International Journal Of Latest Technology In Engineering & Management (IJLTEM)
Volume 10 - Issue 2 {March-April. 2025} {Page: 26-37}

Advanced Deep Learning Techniques for Effective Plant Disease Classification

Shashi Kumar Gupta[1], Aniket Dutta[2], Harshit Kachhap[3], MD A. Azam[4]
[1,2,3]*(Student, Department of Electronics and Communication, BIT Mesra, Ranchi)*
[4]*(Assistant Professor, Department of Electronics and Communication, BIT Mesra, Ranchi)*

ABSTRACT:*The integration of machine learning techniques in plant disease detection marks a significant advancement in enhancing agricultural productivity and ensuring food security. This research investigates the effectiveness of various Deep Learning (DL) algorithms, particularly Convolutional Neural Networks (CNNs), in accurately identifying plant diseases through image classification. It emphasizes the critical importance of robust preprocessing and data augmentation techniques, which improve model performance and generalization while also influencing the training time. The study highlights the reliance on pre-trained models and transfer learning as valuable strategies that reduce training duration and computational resources, addressing challenges posed by dataset variability and environmental conditions. Findings indicate substantial improvements in disease detection accuracy, with proposed models achieving impressive results while also considering the potential of other algorithms like K-Nearest Neighbor (KNN) for resource-constrained environments. This work emphasizes the essential role of early and precise disease detection in mitigating economic losses and promoting sustainable agricultural practices, with future directions aimed at bridging performance gaps between traditional and advanced methods for more efficient disease management solutions.*

Keywords: *CNN, ML, KNN, Transfer Learning, Fungi*

INTRODUCTION

Plant diseases have a profound economic impact on agriculture, affecting both crop yield and quality. The financial repercussions are multifaceted, encompassing direct losses due to reduced crop productivity and indirect costs related to disease management and control measures. Direct economic losses arise from the diminished quantity and quality of produce. For instance, diseases like black rot, late blight, and early blight can significantly reduce the marketable yield of crops such as tomatoes and peppers. The reduction in yield not only affects the income of farmers but also has a cascading effect on the supply chain, leading to increased prices for consumers and potential shortages in the market.Indirect costs include the expenses incurred in managing and controlling plant diseases. These costs cover a range of activities, from the purchase of fungicides and pesticides to the implementation of advanced disease detection and monitoring systems.

Traditional methods for detecting plant diseases often face significant challenges that limit their effectiveness and efficiency. One of the primary issues is the reliance on visual inspection, which can be subjective and prone to human error. This method requires trained experts to identify symptoms, which can vary widely among different diseases and even among different stages of the same disease. Another challenge is the labor-intensive nature of traditional methods. The manual inspection of large agricultural fields is time-consuming and requires substantial human resources. This process is not only expensive but also impractical for large-scale farming operations. Additionally, the need for continuous monitoring to catch early signs of disease compounds the resource demands.

While traditional methods for plant disease detection face numerous challenges, advancements in ML and data processing techniques offer viable solutions to overcome these limitations. By leveraging these technologies, it is possible to develop more accurate, efficient, and scalable disease detection systems that can significantly enhance agricultural productivity and sustainability. Machine learning algorithms, particularly Convolutional Neural Networks (CNNs), have shown remarkable success in image classification tasks, including the detection of plant diseases. The methodology for CNN-based disease classification typically involves several stages. Initially, available datasets are acquired, which include labeled images of both diseased and healthy plants. This dataset acquisition is crucial as it provides the foundational data required for training and validating the models.To enhance the performance of these models, robust preprocessing pipelines and advanced data augmentation techniques can be integrated. These steps help in improving the generalization capability of the models by artificially increasing the diversity of the training data. Furthermore, state-of-the-art CNN architectures are employed to push the boundaries of fruit disease detection and classification.

In addition to CNNs, other DL algorithms, such as the K-Nearest Neighbor (KNN) -based classifier, have also been explored for plant disease detection. The KNN algorithm, known for its simplicity and interpretability, achieved an accuracy of 86% in fruit disease classification. While it may not match the raw accuracy of CNNs, its low computational overhead and ease of implementation make it a viable option for resource-constrained environments [2]. DL algorithms, particularly CNNs, have shown significant performance in image classification tasks, including the detection of plant diseases.

To enhance the performance of these models, robust preprocessing pipelines and advanced data augmentation techniques are integrated. These steps help in improving the generalization capability of the models by artificially increasing the diversity of the training data. Furthermore, state-of-the-art CNN architectures are employed to push the boundaries of fruit disease detection and classification. Transfer learning, which involves using pre-trained models like MobileNet or ResNet, is another technique that has been effectively utilized for feature extraction. This approach leverages the knowledge gained from training on large datasets to improve the performance of models on specific tasks with limited data. The use of transfer learning can significantly reduce the time and computational resources required for training, making it a practical choice for real-world applications [1].

The training process involves splitting the dataset into training, validation, and test sets, typically in an 80-10-10 ratio. In the present work, the model is trained using categorical cross-entropy as the loss function, and the Adam optimizer with a learning rate of 0.0001 is used. Early stopping is employed to prevent overfitting by observing the validation accuracy. This ensures that the model does not overfit the training data and maintains its ability to generalize to new, unseen data.In addition to CNNs, other DL algorithms such as the K-Nearest Neighbor (KNN) classifier, have also been explored for plant disease detection. Its low computational overhead and ease of implementation make it a viable option for resource-constrained environments, [2].

The choice of kernel size in convolutional layers is another critical factor in the design of CNNs. Smaller kernel sizes are preferred for extracting local information, while larger kernel sizes are better suited for capturing global information. However, stacking too many convolutional layers can lead to overfitting and vanishing gradient problems. To address this, Inception modules incorporate different kernel sizes within each block, making the network model wider rather than deeper.

The evaluation of model performance is typically conducted by plotting recognition accuracy and model loss over training epochs. For instance, one of the models achieved an accuracy of 99.83% with a model loss of 0.027, outperforming other existing models like Inception V4 and VGG-16.

In summary, the integration of advanced machine learning techniques, robust preprocessing, and data augmentation strategies has significantly advanced the field of plant disease detection. The use of CNNs, transfer learning, and other algorithms like KNN provides a comprehensive method for researchers and practitioners aiming to develop efficient and accurate plant disease detection systems.

LITERATURE REVIEW

The financial repercussions due to plant infections are multidimensional, encompassing direct losses due to reduced crop productivity and indirect costs related to disease management and control measures.The deployment of trained models on edge devices or web platforms for real-time disease detection further adds to the cost. One of the primary issues in detecting plant diseases is the reliance on visual inspection, which is subjective and frequently prone to human error. This method requires experts to identify disease symptoms, including different stages of the same disease.The variations in symptom expression can lead to misdiagnosis or delayed diagnosis, impacting the timely implementation of management strategies.Another challenge is the labor-intensive nature of traditional methods. The manual inspection of large agricultural fields is time-consuming and requires substantial human resources. This process is not only costly but also impractical for large-scale farming operations. Additionally, the need for continuous monitoring to detect early signs of disease impacts the resource demands.Traditional methods struggle with the detection of diseases that do not exhibit clear and visible symptoms. Many plant diseases, such as those caused by viral or bacterial pathogens, may not show observable signs until the infection is well-established. By the time symptoms are visible, the disease may have already caused significant damage, reducing the effectiveness of any subsequent interventions. The accuracy of traditional methods is further compromised by environmental factors. Variations in weather, soil conditions, and other environmental parameters can influence the appearance of disease symptoms, making it difficult to distinguish between disease-related changes and those caused by abiotic stressors. This requires a high levelof expertise and experience, which is not easily available.In addition to these challenges, these methods are not well-suited for the simultaneous detection of multiple diseases. Many plants can be affected by more than one pathogen at a time, and the symptoms of different diseases can overlap. This overlap complicates diagnosis, leading to mistreatment and incorrect recommendations.

Image-processing techniques play a crucial role in the detection and classification of plant diseases. These techniques involve the processing and analysis of images to extract meaningful information that can be used to identify disease symptoms. Data augmentation is a primary method employed in image processing for plant disease detection. This technique involves image transformations,including operations like rescaling, rotating, and flipping to create different versions of the same image. These processes enhance the model's ability to generalize and reduce the risk of overfitting by introducing a wide range of image variations[3].Normalization is another critical preprocessing step in image processing, where pixel values are scaled between 0 and 1. This step ensures that the model receives input data in a consistent range, which can significantly improve training stability and performance. Additionally, techniques such as flipping, rotation, and brightness adjustment are employed to augment the data, further increasing dataset diversity and reducing overfitting.Image binarization, skew detection, noise removal, grayscale conversion, and size normalization are other processing techniques. These steps helpsmooth the images and remove noise, thereby contributing significantly to theoverall accuracy. The integration of local features, such as SIFT (Scale Invariant Feature Transform) and SURF (Speed Up Robust Features), with global features like BOVW (Bag Of Visual Words), has been shown to improve the accuracy of plant disease detection models [4]. By combining differentfeatures, these models can capture a wide range of information from the images, leading to better classification performance.

The advent of ML and DL techniques offers promising solutions to these challenges. For instance, the use of Convolutional Neural Networks (CNNs) and other advanced algorithms can enhance the accuracy and efficiency of disease detection by analyzing large datasets and identifying patterns that are not easily observable by the human eyes[3], [5]. Novel techniques such as transfer learning allow models to leverage pre-trained networks, improving performance even withlimited data [3], [6]. In addition to that, other methods like SMOTE (Synthetic Minority Over-Sampling Technique) can address class sizeproblems, ensuring that minority classes are adequately represented in the training dataset [5].The use of pre-trained CNN models for feature extraction is a significant method. Common pre-trained models such as MobileNetV2, DenseNet169, EfficientNetB0, and SSD MobileNetV1 are utilized to extract high-level features from images, including edges, textures,and objects. These features are then used as input for classifiers like K-Nearest Neighbors (KNN) to improve classification performance. The advantage of using pre-trained models is their ability to leverage features learned from large-scale datasets, thereby achieving high accuracy even with small-size datasets.Feature extraction is a vital step in deep learning, where relevant features are extracted from raw data to improve classification performance. In the case of plant disease detection, pre-trained deep-learningCNN models are used to extract features from images before feeding them into classifiers like KNN. This approach leverages the strengths of both deep learning and traditional machine learning algorithms to achieve better classification results [5].The effectiveness of machine learning models for plant disease detection is often evaluated using common performance metrics like accuracy, precision, recall, and F1-score. These metrics provide a comprehensive review of the model's performance and help in algorithm improvement. In particular, loss curves and confusion matrices are used to monitor the training and validation progress of CNN-based models, providing insights into how well the model is learning from the data.

The available dataset is typically split into training, validation, and test samples. For instance, 80% of the samples from the PlantVillage datasetwere used for training models like InceptionV4, VGG-16, ResNet, and DenseNet-121.This dataset is widely recognized and extensively usedfor plant disease detection. The dataset includes a vast collection of healthy leaves and diseased plant leaves, which are essential for training and evaluating machine learning models aimed at identifying plant diseases. The dataset also includes images of various plant species, each annotated with the corresponding disease label, thereby providing a rich resource for developing robust classification algorithms.It also contains images of leaves from multiple plant species, including but not limited to tomatoes, potatoes, and apples.This diversity ensures that models trained on this dataset can generalize well to real-world scenarios where multiple plant species and diseases are present.Some sample images of plant leaves from the dataset is shown in Figure 1.

Figure 1: Some images from the dataset: Apple Scab (Left), Apple Black Rot (Center),Cedar Apple Rust (Right)

This work includes the use of synthetic datasets generated through data augmentation techniques.Data augmentation increases the size and diversity of the training dataset by applying various transformations, such as rotation, flipping, and shifting of the original images. Thisapproachhelpspreventoverfittingandimprovesthegeneralizationcapabilityofthemodels. By exposingthe models tovarious augmentedversions ofthesame image, theybecome more robust to variations in the input data [1].

PLANT DISEASES STUDIED

Common Fungal Infections in Plants:

Fungal infections in plants are a significant concern as they can lead to substantial crop losses and affect food quality. These infections are caused by various fungal pathogens that invade plant tissues, leading to diseases that manifest in different forms, such as leaf spots, blights, rusts, and mildew.One of the most common fungal diseases is powdery mildew, which affects a wide range of plants, including cereals and vegetables. This disease is characterized by white, powdery spots on the leaves and stems, which can lead to reduced photosynthesis and stunted growth. The causative agents of powdery mildew belong to the Erysiphaceae family, and they thrive in warm, dry conditions [1].

Figure 2: Mildew Infected Leaf

Another prevalent fungal infection is rust, which is caused by fungi in the Pucciniales order. Rust diseases are named for the rust-colored spores that form on the undersides of leaves. These infections can cause significant damage to crops such as wheat, barley, and beans. Rust fungi have complex life cycles, often requiring two different host plants to complete their development. Spot diseases, caused by various fungal pathogens, are also common. These diseases result in necrotic lesions on the leaves, which can coalesce and cause extensive leaf damage. For instance, the fungus Alternaria alternata is known to cause leaf spots on a variety of plants, including tomatoes and potatoes. These infections can lead to premature leaf drop and reduced yield [1], [2].

Figure 3: Alternaria Infected Leaf

Blight diseases, such as late blight caused by Phytophthora infestans, have a significant impact on plant life. Although it is an oomycete and not a true fungus, it is often grouped with fungal pathogens due to its similar infection mechanisms. Late blight affects potatoes and tomatoes, causing dark lesions on leaves, stems, and tubers. This disease was responsible for the Irish Potato Famine in the 19th century and continues to be a major threat to potato production worldwide.

Figure 4: Blight Infected Leaf

Fungal infections can also affect the vascular system of plants, leading to wilt diseases. Fusarium wilt, caused by Fusarium oxysporum, is a notable example. This pathogen invades the plant's xylem, blocking water transport and causing wilting, yellowing, and subsequent plant death. Fusarium wilt affects a wide range of crops, including bananas, tomatoes, and cucurbits [1], [3].

Common Bacterial Infections in Plants:

The infections caused by various bacterial pathogens that invade plant tissues lead to symptoms such as leaf spots, blights, wilts, and galls. Understanding the characteristics and causes of these infections is crucial for developing an effective plant health monitoring system. A common bacterial disease in plants is bacterial leaf spot, caused by pathogens such as *Xanthomonas* spp. and *Pseudomonas* spp. These bacteria typically enter the plant through natural pores and cause small, water-soaked lesions that eventually turn necrotic. The lesions can coalesce, leading to significant leaf damage and defoliation, which prevents the plant from performing photosynthesis [1], [4].

Figure5: Xanthomonas Infected leaf

Bacterial blight is another prevalent infection, often caused by *Xanthomonas campestris* pv. *vesi- catoria*in crops like tomatoes and peppers. This disease manifests as water-soaked spots on leaves, stems, and fruits, which later become brown and necrotic. The bacteria can spread rapidly under favorable conditions, such as humidity and warm temperatures, leading to severe yield losses [2].

Bacterial wilt, caused by *Ralstonia solanacearum*, is anothercommon disease affecting a wide range of host plants, including tomatoes, potatoes, and bananas. The pathogen invades the plant's vascular system, causing wilting and eventual plant death. Infected plants exhibit symptoms such as stunted growth, yellowing of leaves, and wilting, which can occur rapidly, especially under high temperatures. The bacteria can persist in the soil and water, making plant care more challenging [1], [2].Crown gall disease, caused by *Agrobacterium tumefaciens*, is characterized by the formation of tumorlike galls at the crown, roots, and sometimes stems of infected plants. The bacterium infects the plant DNA genome, causing uncontrolled cell division and gall formation. This disease affects a wide range of dicotyledonous plants and can lead to reduced plant health.

Effective removal of bacterial diseases in plants involves a combination of cultural practices, chemical treatments, and the use of resistant varieties of seeds. Cultural practices such as crop rotation and proper irrigation can help reduce the spread of these bacterial pathogens. Chemical treatments, including the use of copper-based bactericides, can provide some control, although their effectiveness may be limited due to the development of resistance in these bacterial populations [1]. In recent years, advances in machine learning and image processing have shown promise in the early detection and diagnosis of bacterial diseases in plants. Techniques such as convolutional neural networks (CNNs) and support vector machines (SVMs) have been employed to analyze images of infected plants and accurately classify the type of bacterial infection. These methods can help in the timely identification and management of bacterial diseases, potentially reducing crop losses andimproving agricultural productivity [1], [2], [4]. Understanding the characteristics of common bacterial infections is essential for developing effective plant health management strategies and ensuring sustainable agricultural practices. Continued research and the integration of advanced technologies will play a crucial role in mitigating the impact of these diseases on global food quality.

Common Viral Infections in Plants:
Viral infections are caused by various viruses that can infect plants, leading to symptoms such as mosaic patterns on leaves, stunted growth, and reduced yield. One of the most common viral infections in plants is the Tobacco Mosaic Virus (TMV). TMV is known for its ability to cause mosaic-like discoloration on the leaves of infected plants, which can severely impact photosynthesis and overall plant health. The virus is highly stable and can persist in plant debris and contaminated tools, making it difficult to control.

Figure6: TMV Infected Leaf

Another notable viral infection is the Tomato Spotted Wilt Virus (TSWV), which affects a wide range of host plants, including tomatoes, peppers, and peanuts. TSWV is transmitted by thrips and can cause symptoms such as necrotic spots, wilting, and stunted growth, leading to significant yield losses. Cucumber Mosaic Virus (CMV) is another widespread virus that has infected over 1,200 plant species, including many important crops like cucumbers, tomatoes, and peppers. CMV is transmitted by aphids and can cause symptoms such as mosaic patterns, leaf distortion, and stunted growth. The virus can also be seed-borne, which complicates its management. Similarly, the Potato Virus Y (PVY) is a major concern for potato growers. PVY can cause a range of symptoms, including mosaic patterns, leaf necrosis, and tuber necrosis, which can significantly reduce the marketability of the crop.In recent years, advancements in molecular biology and biotechnology have provided new tools for managing viral infections in plants. Techniques such as RNA interference (RNAi) and CRISPR/Cas9 have shown promise in developing virus-resistant plants. RNAi involves the use of small RNA moleculesto mute specific viral genes, thereby preventing the virus from replicating. CRISPR/Cas9, on the other hand, allows for the precise editing of plant genomes to introduce resistance genes or to remove susceptibility genes[1].

Common Parasitic Infections in Plants:

Parasitic infections are caused by various pathogens, including fungi, bacteria, viruses, and nematodes, which invade plant tissues and disrupt normal physiological processes. One of the most prevalent parasitic infections is caused by the fungus *Botrytis cinerea*, commonly known as gray mold. This pathogen primarily affects the flower sections of fruits, leading to significant yield losses. The infection is exacerbated by intense humidity conditions, which promote the growth of fungal mycelium on the flower tissues, accelerating their ripening process and causingearly decay.Another notable fungal infection is Black Sigatoka, caused by *Mycosphaerellafijiensis*, which commonly affects banana plants. This disease appears as dark streaks on the leaves, reducing photosynthetic efficiency and leading to substantial yield reductions. Other bacterial infections caused by *Xanthomonas* species, also pose a significant threat to crops. These bacteria can cause leaf spots, blights, and wilts, leading to extensive plant damage. Tomato Yellow Leaf Curl Virus (TYLCV) can cause severe stunting, leaf curling, and yellowing, significantly impacting plant health and productivity. Detection of these viral infections often involves molecular techniques like polymerase chain reaction (PCR) tests, which provide precise identification of the viral pathogens.

METHODOLOGY

In this work, VGG19, Inceptionv3, MobileNetv2, DenseNet121, and KNN-based Deep learning architecturesare employed to perform the classification of plant diseases. VGG19 stands for Visual Geometry Group. It is made up of several convolutional layers followed by a series of dense neural networks. A brief architecture of the VGG19 is shown in Figure 7.

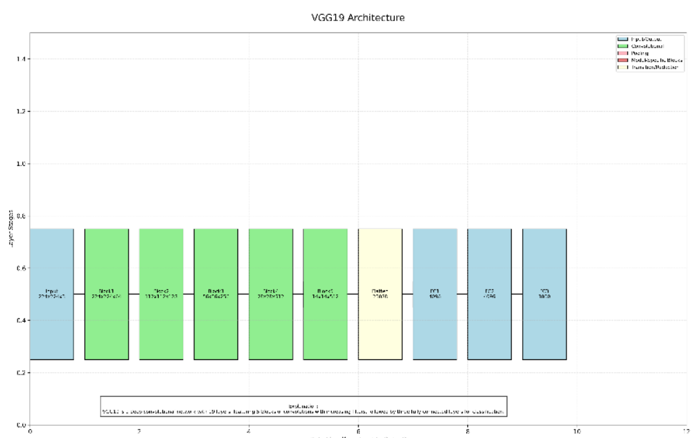

Figure 7: VGG19 Architecture

On the other hand, Inceptionv3 is one of the most powerful CNN architectures. It is generally used for image classification, feature extraction, and object detection. A typical architecture of inceptionv3 employed in this work is shown in Figure 8. MobileNetV2 is a highly efficient and lightweight deep learning model designed for mobile and embedded devices. It is generally used for computer vision applications and transfer learning. In the present work it is trained to classify plant diseases. A typical MobileNetV2 architecture is shown in Figure 9. DenseNet121 is another type of CNN network and is efficient in feature propagation and parameter usage. It is generally used for medical image classification. However, in this work, it has been trained to classify plant diseases and is shown in Figure 10.Some modified KNN-based algorithms have also been used for plant image classification. The typical KNN-based architecture is shown in Figure 11.

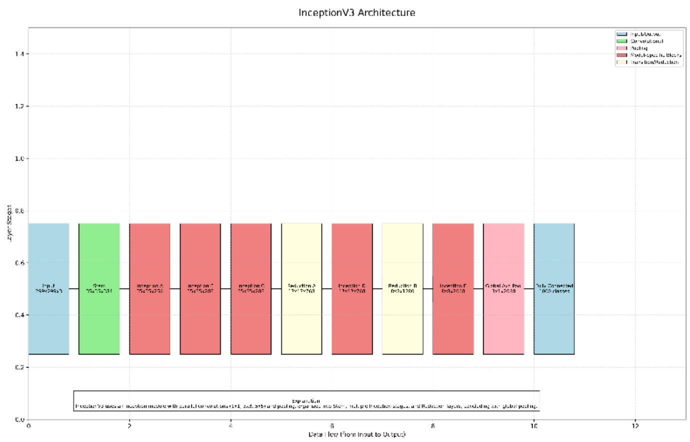

Figure 8: InceptionV3 Architecture

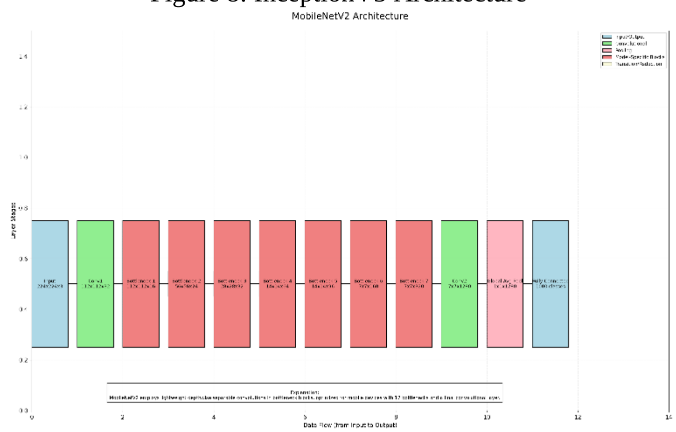

Figure 9: MobileNetV2 Architecture

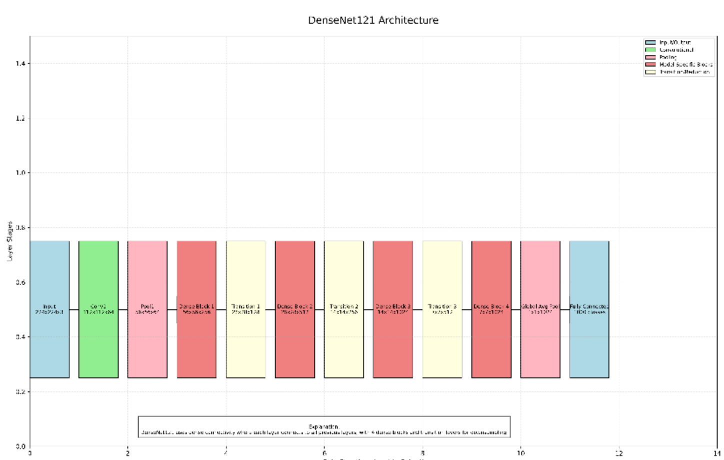

Figure 10: DenseNet121 Architecture

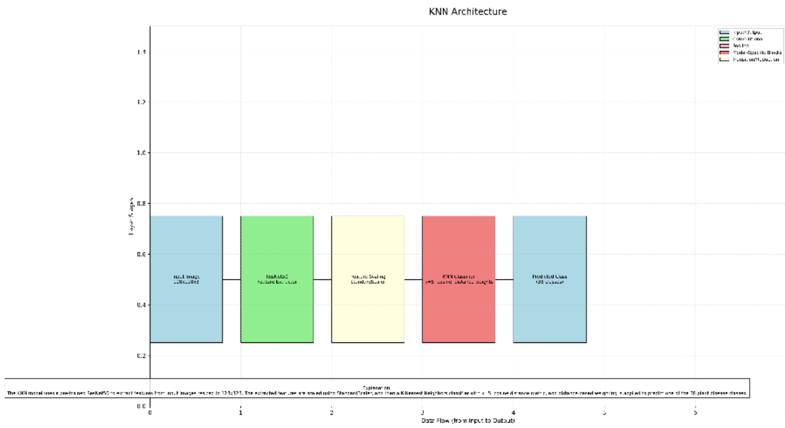

Figure 11: KNN based DL Architecture

RESULTS AND DISCUSSION

Performance Metrics for Evaluation:

Performance metrics are important for evaluating ML/DL algorithms in the detection of plant diseases. These metrics provide insights into how well a model can predict the correct class labels for given inputs, which is essential for determining the model's effectiveness and reliability.One of the primary metrics used is accuracy, which measures the proportion of correctly predicted instances out of the total instances. This metric is straightforward and provides a general sense of the model's performance. However, accuracy alone can be misleading, especially in cases of imbalanced datasets where one class may dominate the others.To address this limitation, other metrics such as precision, recall, and the F1-score are also used. Precision is the ratio of true positive predictions to the total predicted positives, indicating the model's ability to avoid false positives. Recall, on the other hand, is the ratio of true positive predictions to the total actual positives, reflecting the model's ability to capture all relevant instances. The F1-score is the harmonic mean of the precision and recall, providing a balanced measure that considers both false positives and false negatives.

The confusion matrix is another valuable tool for evaluating model performance. It provides a detailed breakdown of true positives, true negatives, false positives, and false negatives, allowing for a more granular analysis of the model's predictions. By analyzing the confusion matrix, one can identify specific areas where the model may be underperforming and subjectto further improvements.

MobileNetV2 has been shown to achieve high accuracy with minimal overfitting, making it a suitable choice for plant disease detection tasks. In contrast, other models like ResNet50 may have lower accuracy and higher overfitting risks, highlighting the importance of appropriate algorithm selection based on specific requirements. On the other hand, the use of pre-trained models can significantly impact the accuracy. DenseNet- 121, for example, has demonstrated high validation accuracy and F1 scores in various studies, outperforming other network models such as Inception V4, VGG-16, and ResNet-50. These pre-trained models leverage transfer learning, which allows them to benefit from prior knowledge gained from large datasets, thereby improving their performance on specific tasks like plant disease detection. The achieved accuracy of the developed algorithms is shown in Table 1 and Table 2, respectively.

Precision,alsoknownaspositivepredictivevalue,measurestheproportionoftruepositivepredictions among all positive predictions made by the model.It is defined as:

$$\text{Precision} = \frac{\text{True Positives}}{\text{TruePositives+FalsePositives}}$$

Recall, orsensitivity, measurestheproportionoftruepositivepredictionsamongall actualpositive instances.It is defined as:

$$\text{Recall} = \frac{\text{True Positives}}{\text{TruePositives+FalseNegatives}}$$

TheF1-scoreistheharmonicmeanofprecisionandrecall,providingasinglemetricthatbalances both aspects.It is defined as:

$$\text{F1-score} = 2\times\frac{\text{Precision}\times\text{Recall}}{\text{Precision+Recall}}$$

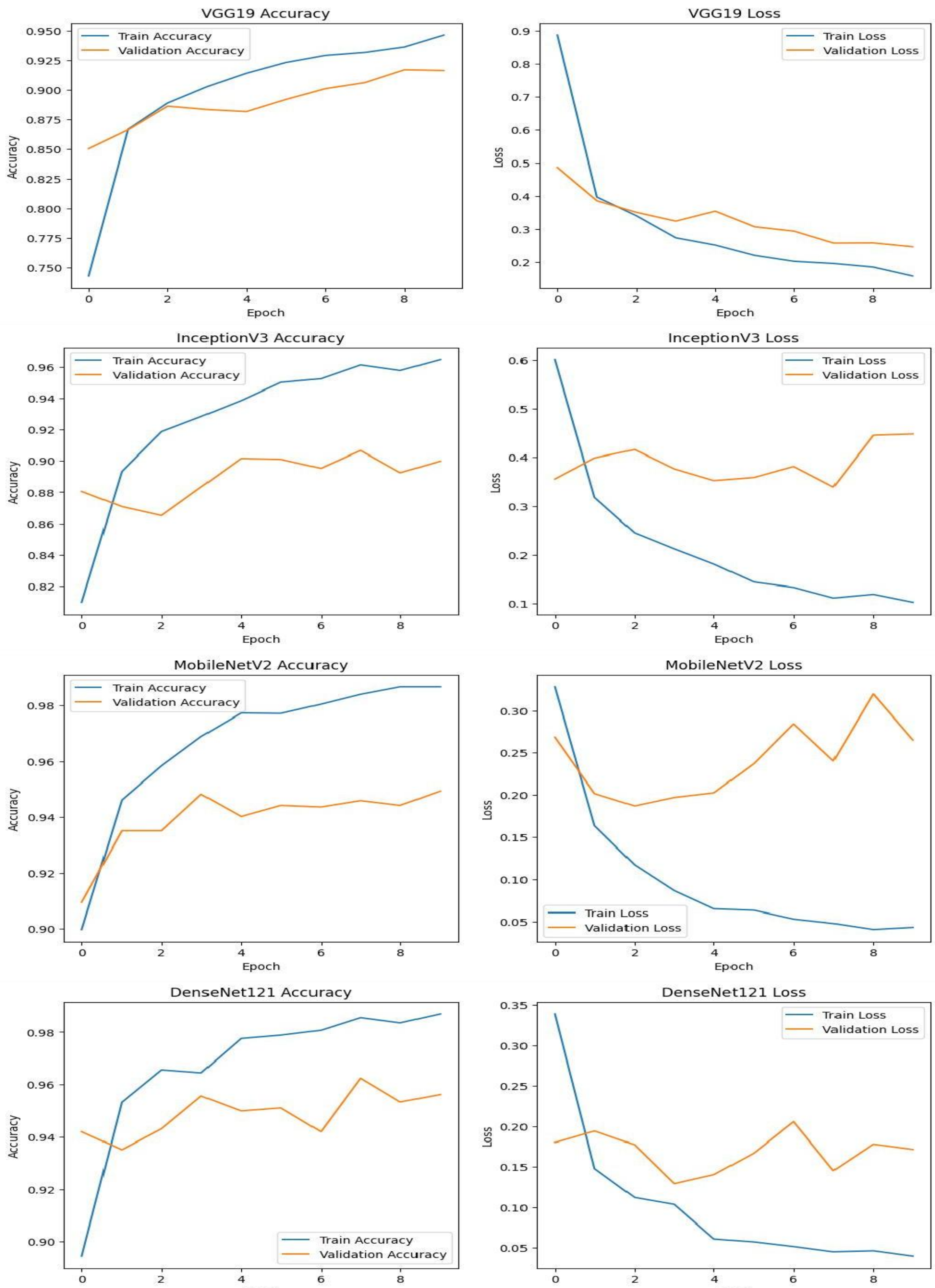

Figure12: Accuracy progression with trainingepochs

Table1:CNNModelPerformance Comparison

Model	Train Accuracy	Validation Accuracy
MobileNetV2	99.00%	98.58%
DenseNet121	96.57%	95.29%
VGG19	94.79%	92.19%
InceptionV3	96.57%	94.27%
ResNet50	58.35%	12.85%

Table2: KNN Classifier Performance

Feature Extractor	Test Accuracy
SSDMobileNetV1	93.48%
DenseNet169	91.71%
MobileNetV2	86.83%
EfficientNetB0	51.45%

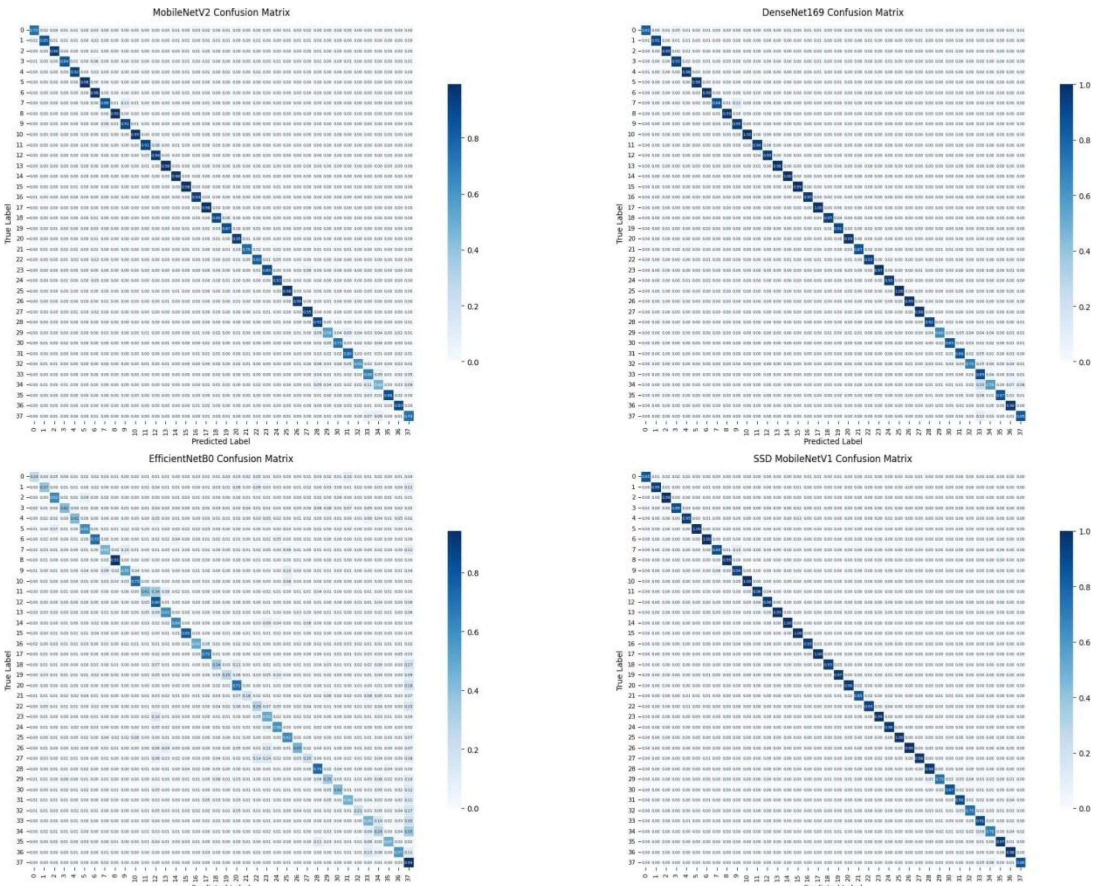

Figure13: Normalizedconfusion matrix forMobileNetV2(OverallAccuracy:86.8%)

CONCLUSION

In the present work, several types of plant diseases were studied. An effective dataset of plant leaf images was used to represent various disease classes. Several deep learning algorithms were developed based on pre-existing CNN and KNN-based architectures. The discussed architectures were trained and used to classify plant diseases. It was found that CNN-based MobileNetV2 has the highest performance in terms of classification accuracy. Compared to that, KNN-based classifiers achieved lower classification accuracy. The development of KNN and other classifiers for plant disease classification and the Android-based app development for plant disease classification are some of the future work.

REFERENCES

[1] *A. J., J. Eunice, D. Popescu, M. Chowdary, and J. Hemanth, "Deep learning-based leaf disease detection in crops using images for agricultural applications", Agronomy, vol. 12, no. 10, Oct. 2022. doi: 10 . 3390 / agronomy12102395. [Online]. Available: https : / / doi . org / 10 . 3390 /agronomy12102395.*

[2] *Y. Benlachmi, A. E. Airej, and M. L. Hasnaoui, "Fruits disease classification using machine learning techniques", Indonesian Journal of Electrical Engineering and Informatics (IJEEI), vol. 10, no. 4, Dec. 2022. doi: 10 .52549 / ijeei. v10i4 . 3907. [Online]. Available: http :// section .iaesonline.com/index.php/IJEEI/index.*

[3] *S. Ramesh, N. M, P. R, et al., "Plant disease detection using machine learning", Apr. 2018. doi: 10.1109/ICDI3C.2018.00017.*

[4] *K. Mojho, "Detecting plant disease using cnn and knn", Dec. 2023. doi: 10.13140/RG.2.2.24040.65285. [Online]. Available: https://www.researchgate.net/publication/376415019.*

[5] *Lu, Jinzhu, Lijuan Tan, and Huanyu Jiang. "Review on convolutional neural network (CNN) applied to plant leaf disease classification." Agriculture 11.8 (2021): 707.*

[6] *Barbedo, Jayme Garcia Arnal. "Impact of dataset size and variety on the effectiveness of deep learning and transfer learning for plant disease classification." Computers and electronics in agriculture 153 (2018): 46-53.*