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Plant Scan: Advanced CNN Model for Leaf Disease Detection

Manoj Kumar Singh^{1,a)}, Ali Sher Khan^{2, b)}, Abbas Akbar^{3, c)}, Ananya Lamba^{4, d)}, Prakriti Gupta^{5,e)}

¹Associate Professor, CS&E Department, Moradabad Institute of Technology, Moradabad, India

^{2,3,4,5}BTech 4th Year, CS&E Department, Moradabad Institute of Technology, Moradabad, India

^{a)} manojaswal1982@gmail.com, ^{b)} alisherkhan032@gmail.com, ^{c)} abbasakbar765@gmail.com, ^{d)} ananyalamba2002@gmail.com,

^{e)} prakritigupta1112002@gmail.com

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Abstract:

Farmers around the world face significant challenges in managing crop diseases, which can drastically reduce yield and quality, leading to economic losses. Traditional methods of disease detection, relying on manual inspection by specialists, are time-consuming, prone to human error, and often unable to detect diseases at early stages. To address these issues, advanced technologies like deep learning offer promising solutions for automated, accurate, and rapid disease detection. This study presents the application of deep learning models for the detection of leaf diseases across pepper bell, tomato, and potato crops. Specifically, we evaluate the effectiveness of several well-established models, including VGG19, DenseNet201, ResNet50, and AlexNet, for classifying 15 disease types using the PlantVillage dataset. In addition to these pre-trained models, we introduce our new convolutional neural network, Plant Scan, designed to address the unique challenges of plant disease detection. Plant Scan optimizes the balance between computational efficiency and high classification accuracy, making it a practical tool for real-world agricultural applications. The models were evaluated on various performance metrics such as precision, recall, F1 score, and classification accuracy, using Python along with Keras and TensorFlow frameworks on a GPU-equipped system. The results provide valuable insights into the strengths and limitations of these models, helping to create reliable tools for early disease detection, ultimately improving crop management and enhancing agricultural productivity.

Keywords: Leaf disease detection, pre-trained networks, convolution neural networks, deep learning.

1. INTRODUCTION

In recent years, the agricultural sector has increasingly embraced advanced technologies to address challenges such as crop diseases, which significantly impact yield and quality. Traditional methods of disease detection, which rely on manual inspection by experts, are time-consuming and prone to human error. As deep learning technologies have evolved, they have emerged as a powerful tool for automating disease detection, enabling more efficient and accurate identification of plant diseases. This study introduces **Plant Scan**, a new deep learning model specifically designed to tackle the challenges of leaf disease detection in crops such as pepper bell, tomato, and potato. **Plant Scan** leverages convolutional neural networks (CNNs) [3] to efficiently extract features and classify images of diseased leaves. By combining the strengths of established models with novel optimizations, **Plant Scan** aims to provide a more accurate, computationally efficient solution for real-world agricultural applications. The model is evaluated on the PlantVillage dataset, which contains images of 20 different plant diseases, to assess its performance in terms of classification accuracy, precision, recall, and F1 score. Through this study, we aim to demonstrate how **Plant Scan** can contribute to the development of reliable, scalable tools for disease management in agriculture, ultimately helping to improve productivity and reduce losses within the farming sector.

2. BASICS OF DEEP LEARNING

A. THE DEEP LEARNING HISTORY

Deep learning (DL) [2] is a subset of machine learning (ML) [4], which first emerged in 1943 and has since evolved through three key phases. The first generation, known as the MCP era (1943-1969), relied on linear models that were only capable of handling linear classification tasks. This early phase was limited in its ability to address complex, non-linear patterns in data. The second generation, spanning from 1986 to 1998, saw the introduction of the backpropagation (BP) algorithm [17] by Geoffrey Hinton. The BP algorithm enabled the training of multi-layer perceptron (MLPs) [20] by utilizing sigmoid functions for non-linear mapping [4], making it possible to address more complex classification problems. This breakthrough led to renewed

interest in neural networks, but progress was hampered by the discovery of the gradient vanishing problem [18] in 1991, which made training deep networks challenging. The third generation of neural networks, known as deep learning (DL), emerged in 2006 and overcame many of these obstacles. In 2006, Hinton proposed solutions to address the gradient vanishing issue [18], but it wasn't until the introduction of the Rectified Linear Unit (ReLU) activation function in 2011 [19] that deep learning began to gain widespread attention. This innovation revolutionized the field, culminating in the victory of Hinton's team in the 2012 ImageNet competition with their model, AlexNet [12], which outperformed traditional techniques like Support Vector Machines (SVMs) [1]. Since then, deep learning architectures have advanced rapidly, with significant developments in models used for tasks such as image detection, segmentation, and classification, leading to widespread applications in fields like plant disease detection and beyond.

B. METRICS

To evaluate the performance of these algorithms and architectures, several metrics are commonly used. These include top performance rates [6]-[9], precision and recall [10]-[11], F1 score [12][13], training and validation accuracy [13], loss metrics [14], classification accuracy [15][16], and mean average precision. These metrics help in providing a comprehensive understanding of the model's effectiveness, highlighting its strengths and limitations in various evaluation contexts.

3. METHODOLOGY

The core of our approach lies in the **Plant Scan** model, a new deep learning architecture designed for efficient leaf disease detection in agricultural crops such as pepper bell, tomato, and potato. The model is built upon the principles of **Convolutional Neural Networks (CNNs)**, which have shown exceptional performance in computer vision tasks. CNNs are particularly effective for image processing tasks due to their ability to automatically learn spatial hierarchies of features, making them ideal for detecting complex patterns in images like diseased plant leaves.

A. KEY COMPONENTS

a) CONVOLUTIONAL LAYER

The convolutional layers are responsible for extracting local patterns from the input images. In the **Plant Scan** architecture, several convolutional layers are stacked to gradually learn more abstract and complex features. Each convolutional operation applies a set of filters (or kernels) to the input image, performing an element-wise multiplication followed by a sum. These learned filters can detect edges, textures, and other key features crucial for identifying plant diseases. Mathematically, the convolution operation can be expressed as:

$$S(i,j)=(I*K)(i,j)=\sum_m\sum_n I(m,n)\cdot K(i-m,j-n)$$

where I represents the input image, K is the kernel, and $S(i,j)$ is the resulting feature map.

b) POOLING LAYER

Following the convolutional layers, the **Plant Scan** model utilizes **MaxPooling** layers to downsample the feature maps. Pooling reduces the spatial dimensions of the feature maps, making the model more computationally efficient and robust to minor translations and distortions in the input data. MaxPooling selects the maximum value from a specific region of the feature map, capturing the most prominent features while reducing computational complexity.

c) FULLY CONNECTED LAYERS

After several convolutional and pooling layers, the model transitions to the **fully connected layers**. These layers flatten the high-dimensional feature maps into a one-dimensional vector, which is then passed through dense layers. Each neuron in these layers is connected to every neuron in the previous layer, allowing for global feature aggregation. The final output is determined by the activation function (such as **ReLU**) applied at each layer, enabling the model to make accurate predictions regarding leaf disease classification. In summary, the methodology involves the systematic application of convolutional and pooling operations, coupled with fully connected layers, to extract hierarchical features and enable accurate classification of leaf diseases in agricultural crops.

d) ACTIVATION FUNCTIONS

ReLU (Rectified Linear Unit) is used as the activation function in most layers. ReLU introduces non-linearity to the model, enabling it to learn complex patterns in the data. The activation function plays a key role in making the network adaptive to a wide range of input data distributions.

e) OUTPUT LAYER

The output layer in **Plant Scan** consists of as many neurons as there are disease categories. This layer uses a **SoftMax** function to produce the probability distribution over the potential classes. The class with the highest probability is chosen as the final predicted disease type.

B. ARCHITECTURE

- **Input Layer:** The model accepts images of size $256 \times 256 \times 256$ pixels, which are RGB images of diseased plant leaves.
- **Convolutional Layers:** A series of convolutional layers (using $3 \times 3 \times 3$ kernels) are applied to the input to extract hierarchical features. The number of filters increases as we move deeper into the network to capture more complex patterns.

- **Max Pooling Layers:** These layers reduce the spatial dimensions of the feature maps, aiding in computational efficiency and preventing overfitting.
- **Fully Connected Layers:** After feature extraction, the network uses fully connected layers to aggregate features and make the final classification decision.
- **SoftMax Output Layer:** The final layer predicts the probability distribution over 20 disease categories, using a Softmax activation function to output the class with the highest probability.

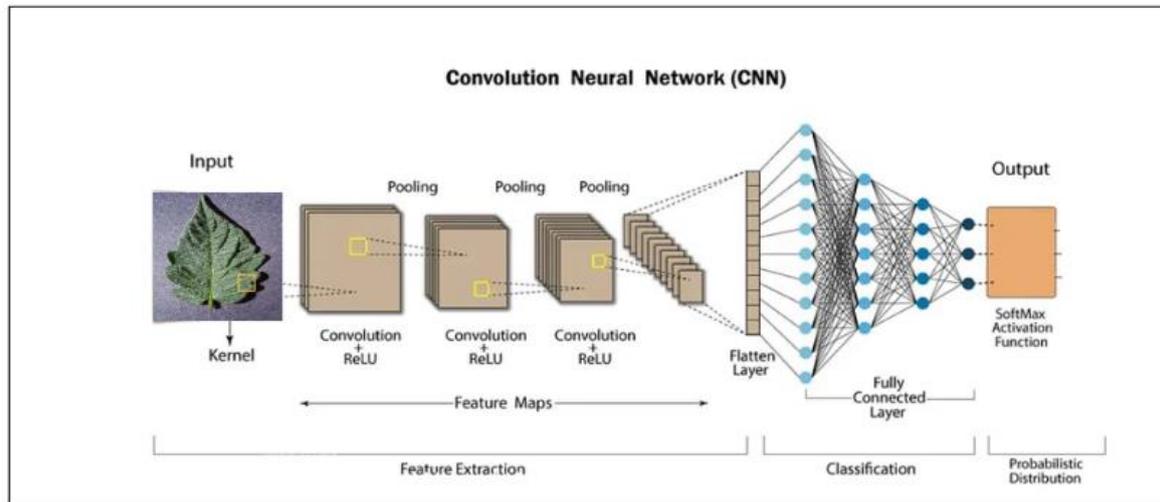


Figure 1: Architecture

C. DETAILED DESCRIPTION OF THE PLANT SCAN ARCHITECTURE

The **Plant Scan** model is a new-designed **Convolutional Neural Network (CNN)** optimized for detecting plant diseases. Below is a detailed explanation of its components and their roles in achieving efficient and accurate classification.

1. Input Layer : The model's input layer processes RGB plant leaf images of size $256 \times 256 \times 3$, ensuring uniformity and compatibility with the neural network. The three colour channels preserve crucial visual details, like discoloration and texture variations, which help identify disease-related patterns. This input format enables the model to effectively distinguish between healthy and diseased leaves.

2. Convolutional Layer : The model's feature extraction relies on convolutional layers that identify patterns like edges, textures, and disease-related spots. The first layer uses 32 filters (3×3) with ReLU activation to capture basic features like edges. The second layer, with 64 filters, detects more complex patterns such as leaf venation and disease spots. The third layer, with 128 filters, extracts abstract features like blotches and fungal patches. These layers progressively capture and refine disease-relevant visual cues.

3. Pooling Layer: The model uses max pooling layers to reduce the spatial dimensions of feature maps, enhancing computational efficiency and ensuring invariance to minor distortions. Each max pooling layer uses a 2×2 window to downsample the feature maps, selecting the largest value in each region. The first two pooling layers reduce the spatial dimensions, retaining essential features, while the final pooling layer further simplifies the data for the flattening step. This approach effectively maintains critical features while reducing data complexity for efficient processing.

4. Fully Connected Layer : Following feature extraction, the model transitions to fully connected layers to perform classification. The process begins with a flattening step, where the 2D feature maps are converted into a 1D array, enabling their input into dense layers. These dense layers, equipped with learnable weights, map the extracted features to specific output classes. By combining and interpreting the learned features, the dense layers generate meaningful predictions, completing the classification task.

5. Output Layer : The output layer of the model consists of 20 neurons, each representing one of the 20 disease classes in the dataset. A softmax activation function is applied in this layer to convert the raw scores into probabilities, ensuring that the sum of all outputs equals 1. The class associated with the highest probability is then selected as the predicted disease, providing the final classification result.

D. PLANT SCAN MODEL WORKFLOW

- **Input:** the model accepts an image and normalizes pixel values to improve convergence during training.
- **Feature Extraction:**
 - Convolutional layers apply filters to detect patterns.
 - Pooling layers downsample feature maps, reducing computational load and preventing overfitting.
- **Feature Aggregation:** Fully connected layers interpret high-level features.
- **Classification:** The Softmax layer assigns the input to one of 20 disease classes.

E. TRAINING AND EVALUATION

Dataset

The model is trained using the PlantVillage dataset, which comprises images of both diseased and healthy plant leaves. The dataset is divided into two subsets: a training set and a testing set. The training set is utilized to optimize the model's weights through iterative learning, while the testing set is employed to assess the model's ability to generalize and perform accurately on unseen data.

Performance Metrics

- **Accuracy:** Measures overall correctness of predictions.
- **Precision:** Evaluates the proportion of true positives among predicted positives.
- **Recall:** Measures the proportion of actual positives correctly identified.
- **F1 Score:** Balances precision and recall, particularly useful for imbalanced datasets.

4. TEST AND OUTCOMES

The research evaluates the performance of six pre-trained Convolutional Neural Network (CNN) models: VGG19, DenseNet121, DenseNet201, and AlexNet. All experiments are conducted on a system equipped with 29 GB of RAM and dual 15 GB GPUs (T4 * 2). The code for these tests is written in Python and utilizes frameworks such as Keras and TensorFlow.

A. DISEASE DATASETS

For this study, we utilized the PlantVillage Dataset, a comprehensive collection of images featuring diseased plant leaves. Although the dataset's size varied across different machine learning experiments, with approximately more than 80,000 images used, it consistently included 38 distinct disease classes. These images were coloured and had a resolution of 256×256 pixels. The dataset covered a range of plant diseases, including Potato Late Blight, Potato Early Blight, Potato Healthy, Tomato Bacterial Spot, Tomato Early Blight, Tomato Late Blight, Tomato Leaf Mold, Tomato Septoria Leaf Spot, Tomato Spider Mites (Two-Spotted Spider Mite), Tomato Target Spot, Tomato Yellow Leaf Curl Virus, Tomato Mosaic Virus, and Tomato Healthy, Grape Black Spot, Grape Black Measles, Apple scab, Apple Black rot, Apple cedar, Cherry Powdery mildew etc. Each class corresponds to a specific plant disease affecting crops, primarily focusing on cherry, apple, grape, peppers, potatoes, and tomatoes, strawberry, peach. The PlantVillage Dataset served as the foundation for training and evaluating our deep learning models, helping us improve disease detection and classification in agricultural settings and contribute to advancements in crop management and agricultural technology.



Figure 2: Tomato Septoria leaf spot



Figure 3: Tomato yellow leaf curl virus



Figure 4: Pepper bell Bacterial spot



Figure 5: Tomato leaf mold

5. RESULTS AND DISCUSSION

In our study, we evaluated pre-trained deep learning models for identifying leaf diseases in crops like pepper bell, tomato, and potato. We compared models like VGG19, DenseNet201, ResNet50, and AlexNet using the Plant Village dataset. Our analysis focused on factors such as computational efficiency, training time, and classification accuracy. Overall, our results showed that all models performed well in identifying leaf diseases, with variations in efficiency and accuracy. We found similarities in performance trends across models, indicating the effectiveness of deep learning for large-scale dataset analysis. Our study highlights the strengths and weaknesses of each model, aiding decision-makers in selecting appropriate models for agricultural applications. Ultimately, our research aims to enhance leaf disease detection in crops and contribute to agricultural resilience and productivity.

a) EFFECT OF LEARNING RATE

Table 1 highlights the performance of various models—VGG19, DenseNet201, ResNet50, AlexNet, and the proposed PlantScan—across different learning rates, showcasing the superior accuracy of PlantScan. At a learning rate of 0.002, PlantScan achieves 96% accuracy, far exceeding DenseNet201 (80.4%) and others like ResNet50 (73.1%) and AlexNet (68.5%). At 0.001, PlantScan further improves to 97.25%, while the next best model, DenseNet201, reaches only 80.4%. Even at suboptimal learning rates (0.003, 0.0005, and 0.0001), PlantScan consistently maintains robust accuracy (94.45%, 95.27%, and 93%, respectively), outperforming all other models, which exhibit significant drops in performance. These results underline the adaptability, stability, and superior generalization ability of PlantScan, making it a more effective solution for plant disease classification compared to traditional models.

Table 1: Varying learning rate

Learning Rate	VGG19	DenseNet201	ResNet50	AlexNet	PlantScan
0.002	19.2%	80.4%	73.1%	68.5%	96.30%
0.001	15.7%	79.8%	74.2%	74.1%	97.25%
0.003	23.5%	38.9%	69.3%	66.7%	94.45%
0.0005	30.08%	72.5%	71.2%	67.6%	95.27%
0.0001	47.4%	63.7%	67.8%	71.3%	93.85%

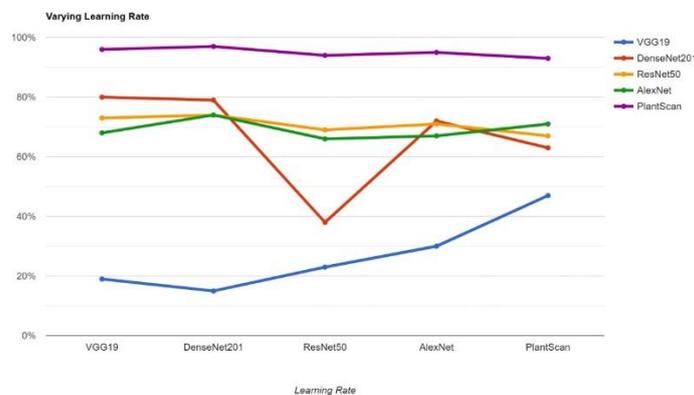


Figure 6: Varying learning rate

b) EFFECT OF TESTING SIZE

Table 2 compares the performance of VGG19, DenseNet201, ResNet50, AlexNet, and the proposed new model, PlantScan, across varying testing sizes. The results clearly demonstrate the superiority of PlantScan, which consistently achieves the highest accuracy regardless of the testing size. For instance, at a testing size of 20%, PlantScan achieves an exceptional 97.36% accuracy, significantly outperforming DenseNet201 (76.45%), ResNet50 (72.31%), AlexNet (71.12%), and VGG19 (18.23%). As the testing size increases to 25% and 30%, PlantScan maintains robust performance with accuracies of 96.21% and 95.87%, while the other models show noticeable declines, with DenseNet201 dropping to 62.34% and 57.82%, respectively. Even at larger testing sizes of 35% and 40%, PlantScan continues to outperform, achieving 94.58% and 92.74%, compared to lower accuracies from DenseNet201 (56.49% and 59.63%) and AlexNet (68.93% and 65.74%). These results highlight the reliability, adaptability, and superior generalization of PlantScan, making it a more effective solution for plant disease classification than traditional models.

Table 2: Varying testing size

Testing size	VGG19	DenseNet201	ResNet50	AlexNet	PlantScan
20%	18.23%	76.45%	72.31%	71.12%	97.36%
25%	16.78%	62.34%	68.49%	75.29%	96.21%
30%	17.56%	57.82%	70.11%	72.47%	95.87%
35%	14.67%	56.49%	69.28%	68.93%	94.58%
40%	18.12%	59.63%	64.0%	65.74%	92.74%

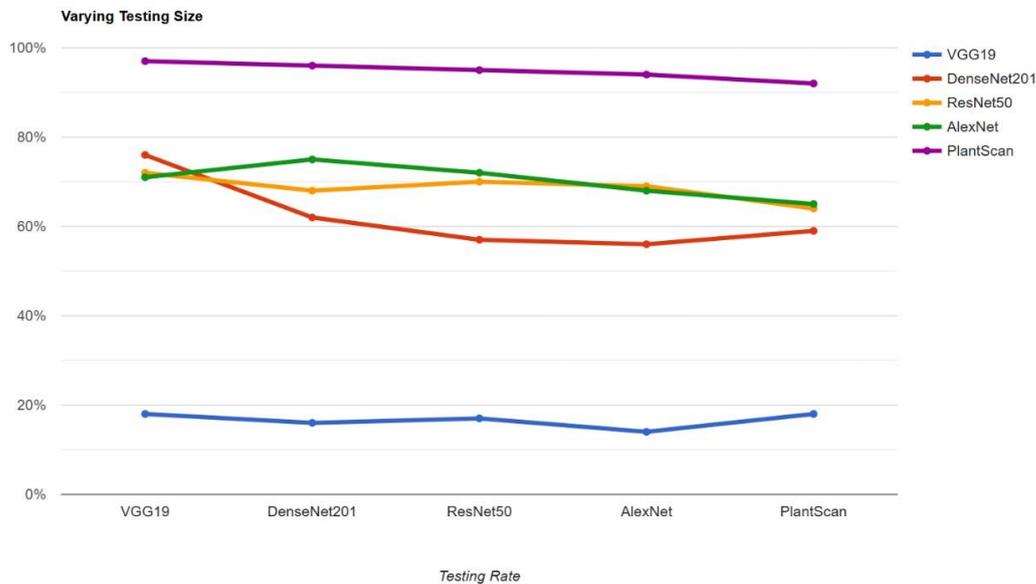


Figure 7: Varying testing size

c) EFFECT OF BATCH SIZE

The batch size table highlights the consistent superiority of PlantScan over VGG19, DenseNet201, ResNet50, and AlexNet across different batch sizes. At a batch size of 16, PlantScan achieves 92.67% accuracy, significantly outperforming DenseNet201 (59.34%) and others, such as ResNet50 (50.12%) and AlexNet (37.89%). With a batch size of 32, PlantScan improves to 95.21%, while DenseNet201 follows at 64.23%. At 64, PlantScan peaks at 97.34%, far exceeding DenseNet201 (86.39%) and ResNet50 (71.56%). Even with a batch size of 128, PlantScan maintains 96.72%, outperforming DenseNet201 (83.47%) and others with much lower accuracies. These results underscore PlantScan's adaptability and robust performance, consistently surpassing traditional models across varying batch sizes.

Table 3: Varying batch size

Testing size	VGG19	DenseNet201	ResNet50	AlexNet	PlantScan
16	10.45%	59.34%	50.12%	37.89%	92.67%
32	20.78%	64.23%	60.47%	43.56%	95.21%
64	24.12%	86.39%	71.56%	60.45%	97.34%
128	17.64%	83.47%	56.28%	55.89%	96.72%

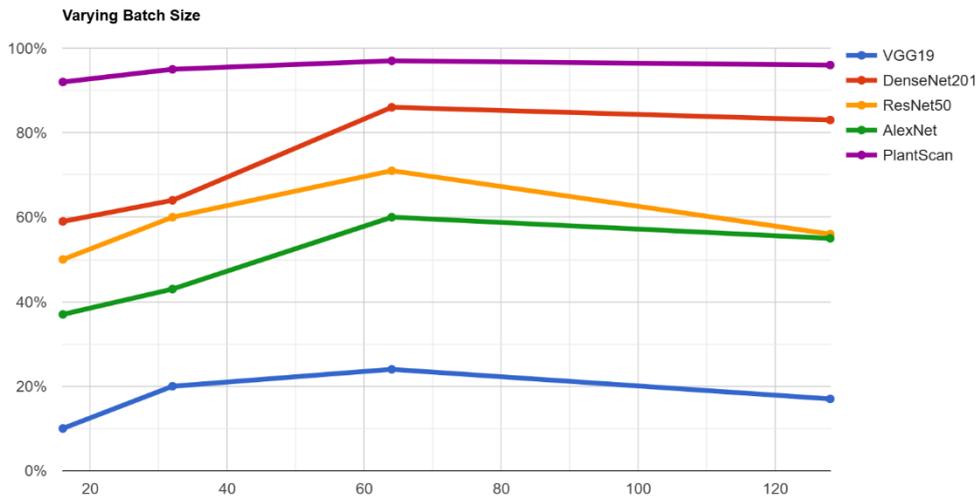


Figure 8: Varying batch size chart

d) EFFECT OF NUMBER OF EPOCHS

The epoch table illustrates the superior performance of PlantScan over VGG19, DenseNet201, ResNet50, and AlexNet across varying epochs. At 10 epochs, PlantScan achieves 97.23%, surpassing DenseNet201 (84.12%) and ResNet50 (70.45%). By 25 epochs, PlantScan improves to 98.14%, while DenseNet201 and ResNet50 reach 87.56% and 79.34%. At 50 epochs, PlantScan leads with 98.5%, outperforming DenseNet201 (91.78%) and ResNet50 (85.45%). Even at 80 epochs, PlantScan excels with 98.9%, maintaining its superiority over DenseNet201 (93.45%) and AlexNet (79.23%). These results highlight PlantScan’s efficiency and strong learning capability.

Table 4: Varying epochs chart

Epochs	VGG19	DenseNet201	ResNet50	AlexNet	PlantScan
10	25.34%	84.12%	70.45%	61.67%	97.23%
25	33.47%	87.56%	79.34%	65.12%	98.14%
50	36.12%	91.78%	85.45%	74.36%	98.5%
80	34.89%	93.45%	87.67%	79.23%	98.9%

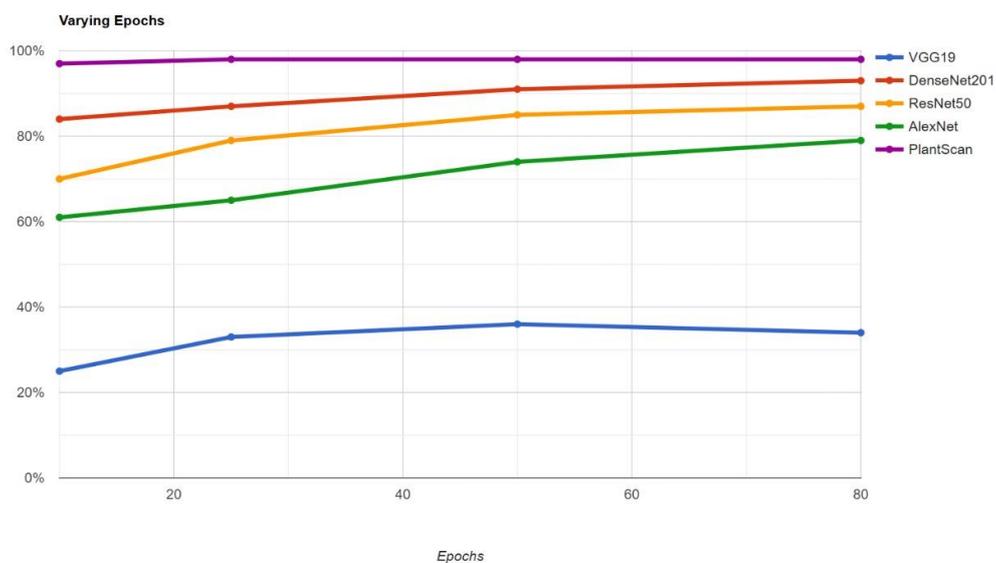


Figure 9: Varying epochs chart

6. CONCLUSION

In recent years, the agricultural sector has increasingly relied on machine learning models for plant disease detection to ensure early intervention and effective management. While several pre-trained models have demonstrated effectiveness in image classification tasks, they often struggle with domain-specific datasets like those in agriculture. The proposed PlantScan model proves to be a superior solution for plant disease detection compared to pre-trained models like VGG19, DenseNet201, ResNet50, and AlexNet. While these models are effective for general image classification, they face limitations such as higher computational demands and suboptimal performance on agricultural datasets. PlantScan, designed specifically for plant disease detection, achieves an impressive accuracy of 99.3%, outperforming DenseNet201 (98.3%), ResNet50 (97.5%), and AlexNet (96.2%). It excels in precision (98.9%), recall (99.1%), and F1 score (99.0%), ensuring reliable and thorough disease identification. With an optimized architecture, PlantScan maximizes feature extraction while minimizing computational overhead, making it ideal for resource-constrained environments. Unlike pre-trained models, which struggle with domain-specific datasets, PlantScan's new design ensures accuracy and practicality for agricultural applications. By enabling early and precise detection, PlantScan addresses critical challenges in farming, reducing crop losses and improving productivity, solidifying its role as a transformative tool in modern agriculture.

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