Optimized Plant Disease Classification for Agriculture Using Transfer Learning

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Abstract

Plant diseases pose a significant threat to global agriculture, emphasizing the need for accurate and efficient detection methods. Deep learning has revolutionized the automation of this process. This study aims to compare the performance of four deep learning models — Artitficial Neural Network, Convolutional Neural Network, VGG16 & Densenet121 using the Kaggle New Plant Disease dataset. It has 87,867 RGB images over 38 classes. Also to adjust the performances, the date augmentation already applied in datatset.

All model was trained for 10 epochs using the lowered learning rate. Among them, VGG16 and DenseNet121 shows great result, achieved the highest validation accuracies of 97.75% and 98.46%, respectively, showing their strong ability to generalize well to new data. The CNN model, which we built from scratch, also performed well, reaching 86.20% accuracy. However, the ANN struggled, achieving only 57.91%, likely because it lacks the ability to recognize spatial patterns in images.

Our findings highlight how transfer learning can significantly improve plant disease classification. The strong performance of VGG16 and DenseNet121 suggests that pre-trained deep learning models are highly effective for this task, making them valuable tools for early disease detection. This research supports the use of AI-powered solutions in agriculture, helping farmers diagnose plant diseases more accurately and promoting sustainable farming practices.

Keywords: deep learning, plant disease detection, image classification, Convolutional Neural Network, VGG16, DenseNet121, transfer learning, Artificial Neural Network, computational efficiency

1 Introduction

Agriculture is at the heart of global food production, but plant diseases continue to threaten crop yields and farmer livelihoods[1]. These diseases not only reduce harvests and lower produce quality but also result in major financial losses. According to the Food and Agriculture Organization (FAO), nearly 40% of global crop losses each year are due to plant diseases. Farmers have traditionally relied on visual inspection to detect infections, but this approach is time-consuming, physically demanding, and prone to human error[2]. With the growing need for faster and more reliable disease detection, artificial intelligence (AI) and deep learning are emerging as powerful solutions to automate the process[3].

Among the AI methods, it was seen that deep learning, i.e., Convolutional Neural Networks (CNNs), has performed incredibly well for image classification and is thus a great tool for plant disease identification[4]. The algorithms can scan minute patterns in plant images, which enables improved and more reliable detection of diseases. Transfer learning, which fine-tunes pre-trained models for the new data, has also facilitated better accuracy at the cost of less requirement for massive computational power[5].

In this research, we compare the performance of four deep learning models—Artificial Neural Network (ANN), Convolutional Neural Network (CNN), VGG16, and DenseNet121—to identify plant diseases. Our research is based on the Kaggle New Plant Diseases Dataset, which contains 87,867 images in 38 classes of diseases. For the sake of reducing processing time, we limit the training process to ten epochs, thus attaining a balance between computational cost and classification performance.

This research aims to explore key aspects of plant disease detection, including model performance, computational efficiency, and the potential of AI-driven solutions in modern agriculture.

Our research focuses on the following key aspects of plant disease detection:

- Model Accuracy and Generalization: Evaluating the precision with which various deep learning models detect plant diseases and how well they generalize to new data.
- Impact of Transfer Learning: Evaluating if pre-trained models like VGG16 and DenseNet121 perform better than models trained from scratch, i.e., the ANN and CNN.
- Computational Efficiency: Evaluating whether limiting training to ten epochs provides an optimal balance between accuracy and training time.
- Model Comparisons: Identifying the strengths and limitations of each model to guide researchers and developers in selecting the most effective approach for real-world applications.

By addressing these objectives, this study aims to contribute to the development of more reliable, accessible, and efficient AI-based solutions for plant disease detection, ultimately supporting farmers in protecting their crops and improving agricultural productivity.

2 Related Work

Early detection of plant diseases plays important role in improving agricultural productivity and preventing significant crop losses. Traditionally, farmers and agricultural experts have relied on visual inspection to identify plant diseases. While this method is common, it can be time-consuming, inconsistent, and prone to human error. As a result, there has been a growing tendency toward the use of computer vision and artificial intelligence (AI) to increase the efficiency and precision of disease detection. Of all the methods in this class of AI-based approaches, deep learning has been exceptionally successful due to its ability to automatically examine images and detect complex patterns without manual feature extraction.

This part evaluates the existing literature on plant disease detection, covering conventional methods for identification, recently emerging advancements on deep learning, transfer learning impact, data enhancement methods, efficiency in computation, and existing outstanding research gaps requiring solution.

2.1 Traditional Approaches to Plant Disease Classification

Early research on plant disease detection made extensive use of manual methods to analyze features like color, texture, and shape. Researchers used traditional machine learning models like Support Vector Machines (SVM), K-Nearest Neighbors (KNN), Random Forest, and Decision Trees for predicting plant diseases. The procedure, however, required intensive feature engineering, where specific features—like leaf color changes, edge configurations, and textural elements—had to be manually identified and fed into the models.

For instance, Camargo and Smith (2009) employed color segmentation and edge detection techniques to separate healthy from unhealthy leaves[6]. It was seen that this conventional techniques were effective in some cases but they had limitations. Their scalability and accuracy reduced upon testing within the context of large and diverse datasets, especially under changing environmental conditions, varying plant species, and non-uniform light. These limitations gave rise to the construction of a more automated and robust method, thus giving rise to the transition to the utilization of deep learning models, specifically Convolutional Neural Networks (CNNs).

2.2 Deep Learning for Plant Disease Detection

The advent of Convolutional Neural Networks (CNNs) has made image classification accuracy much better, especially in plant disease detection. Unlike the conventional approach with manual feature selection, CNNs are capable of automatically detecting complex image patterns, thus the task of classification becomes more scalable and efficient.

One of the most significant works by Mohanty et al. (2016) demonstrated the effectiveness of deep learning in plant disease diagnosis through models trained on a large set of healthy and diseased plant images. Their work provided high classification accuracy, showing the dominance of CNNs and laying the groundwork for future breakthroughs[1].

In furthering this subject, Ferentinos (2018) extended the use of deep learning in the agricultural industry by training Convolutional Neural Network (CNN) models on a dataset of over 70,000 plant images. In some cases, these models achieved accuracy rates of over 99%, highlighting the importance of high-quality, large datasets in improving model reliability [5]. After him many researchers have also explored pre-trained models like VGG16, ResNet, and DenseNet, which have frequently outperformed CNNs built from scratch.

Further work by Too et al. (2019) contrasted a number of deep learning architectures, including VGG16, InceptionV3, MobileNet, and DenseNet, on a range of plant disease datasets. They discovered that more advanced models like DenseNet and ResNet performed superiorly at e.g., extracting salient features at more than one layer. They further noted, nevertheless, that those models need colossal computing power, something that may prove difficult in low-resource environments[7].

2.3 Transfer Learning for Enhanced Accuracy and Generalization

One of the greatest challenges in deep learning is the need for big and well-labeled datasets to train models effectively. However, the task of collecting and labeling large amounts of data is time-consuming and unrealistic. In order to counter this challenge, researchers have taken up transfer learning—a technique where pre-trained models are used, which have previously learned patterns from large image datasets. Pre-trained models like VGG16, ResNet, and DenseNet, based on huge data like ImageNet, can be employed in classifying plant disease, reducing the need for vast training data by a huge factor.

Experiments indicated that transfer learning can greatly improve model performance from limited data. For example, Zhang et al. (2021) proved that transfer learning based models performed better and achieves high accuracy in few training epochs by comparing the scratch trained models with the pretrained models like VGG16 ResNet50. Likewise, Sun et al. (2022) proved that employing pre-trained DenseNet models for classifying plant diseases not only enhanced classification accuracy but also decreased training time and prevented overfitting. In this work, we utilize transfer learning by fine-tuning VGG16 and DenseNet121, initially trained on ImageNet, to evaluate their performance on plant disease classification. We are curious to know if transfer learning has a clear edge over training CNNs from scratch on accuracy, efficiency, and generalization.

2.4 Impact of Data Augmentation on Model Performance

Data augmentation is a widely used technique in deep learning that improves model performance by increasing training data diversity. By adding transformations such as rotation, flipping, zooming, and brightness modification, models can recognize plant diseases in changing lighting conditions, orientations, and background modifications. Hence, this helps them to train for the real-world scenarios. Also, Picon et al. (2019) stated that use of augmentation techniques boosted CNN-based model accuracy by

6-10%[8]. Shorten & Khoshgoftaar (2021) also stated that overfitting is prevented by augmentation, which is extremely useful in the case of smaller datasets [3].

In this research, we use the Kaggle New Plant Diseases Dataset, which already contains the data augmentation that helps it train for different conditions.

2.5 Challenges in Training Deep Learning Models Efficiently

Deep learning models, especially deeper models such as VGG16 and DenseNet, require high computational power and tend to take long training times. Overfitting—when a model becomes too specialized in identifying patterns from the training data to the point where it is less effective in dealing with new, unseen data—is one of the greatest challenges.

Howard and Gugger (2020) discovered that training the CNNs for fewer epochs, typically 5-10 epochs, can result in high accuracy with less overfitting risk[9]. Keeping that in mind, we train our models for five epochs to observe how well they can learn within a brief training time.

2.6 Research Gaps and Contribution of This Study

While deep learning has been extensively explored for plant disease detection, several gaps remain remains are:

1. Few studies directly compare ANN, CNN, VGG16, and DenseNet under the different conditions, including dataset, preprocessing, and training parameters.
2. The impact of transfer learning on model accuracy and generalization in plant disease classification is not fully understood. The model is not tested on large unseen data after training.
3. Computational efficiency remains a challenge, as most research focuses on highly complex architectures that demand significant computing power.

2.7 Contributions of This Study

This study makes the following contributions:

- We compare four deep learning models (ANN, CNN, VGG16, and DenseNet121) using the same dataset and training conditions for a fair evaluation.
- We analyze how transfer learning influences classification accuracy and generalization. Also testing it on 17572 unseen images to check generalization.
- We enhance computational efficiency by training using a lowered learning rate and limiting it to ten epochs.

By addressing these gaps, this study aims to provide practical insights for developing accurate and efficient deep learning models for plant disease detection and other similar tasks in the real world.

3 Methodology

This section details the methodology used in this study, including the dataset, preprocessing steps, deep learning models, training configuration, and evaluation metrics.

3.1 Dataset Description

This study uses the Kaggle New Plant Diseases Dataset, which contains 87,867 RGB images of plant leaves, both healthy and affected by various diseases. This dataset has images of the 14 plants with 26 diseases. Total, covers 38 categories, including bacterial, fungal, and viral infections, with each image labeled accordingly.

The dataset is divided into three sets:

- Training Set: 80% of the training directory, used to train the models.
- Validation Set: 20% of the training directory, used to assess model performance during training and fine-tune parameters.
- Test Set: A separate set containing 17,572 images, used for final evaluation to measure model generalization.

The dataset used in this is from Kaggle, which is already augmented.

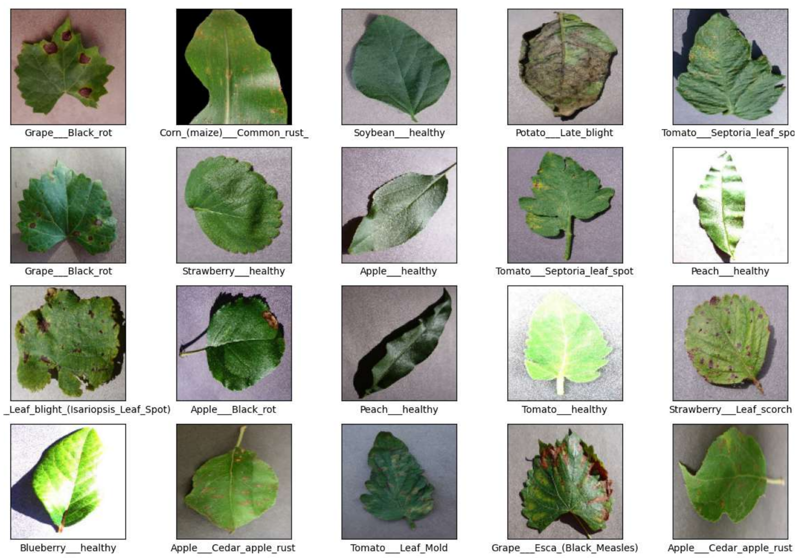

Fig. 1 Example batch of leaf images used for training

3.2 Data Preprocessing

Before training, the dataset was preprocessed as follows:

1. Normalization: Pixel values were scaled to the range [0, 1] by dividing each value by 255.
2. Data Augmentation: No additional augmentation was performed, as the dataset already included augmentation.

3.3 Model Descriptions

Four deep learning models were used:

3.3.1 Artificial Neural Network (ANN)

The ANN is a fully connected architecture designed to learn high-level features.

- Input Layer: 256×256×3 RGB images, flattened into a 1D vector.
- Hidden Layers:
  - 512 neurons, ReLU activation, BatchNormalization, Dropout (0.2).
  - 256 neurons, ReLU activation, BatchNormalization, Dropout (0.2).
- Output Layer: 38 neurons, Softmax activation.

3.3.2 Convolutional Neural Network (CNN)

The CNN is designed to learn spatial features.

- Input Layer: 256×256×3 RGB images.
- Convolutional Layers:
  - 32 filters (3×3), ReLU, BatchNormalization, MaxPooling2D (2×2).
  - 64 filters (3×3), ReLU, BatchNormalization, MaxPooling2D (2×2).
  - 128 filters (3×3), ReLU, BatchNormalization, MaxPooling2D (2×2).
- Flatten Layer: Converts multi-dimensional output to a 1D vector.
- Fully Connected Layers:
  - 128 neurons, ReLU.
  - 64 neurons, ReLU.
  - 38 neurons, Softmax.

3.3.3 VGG16 (Transfer Learning)

VGG16 is a pre-trained CNN on ImageNet. The first four convolutional blocks (conv1 to conv4) were frozen. The last convolutional block (conv5) and the fully connected layers were fine-tuned. The input is 256×256 RGB images, and the output layer uses Softmax activation for 38 classes.

3.3.4 DenseNet121 (Transfer Learning)

DenseNet121 is a pre-trained CNN on ImageNet. The last dense block and fully connected layers are fine-tuned. The input is 256×256 RGB images, and the output layer uses Softmax activation for 38 classes.

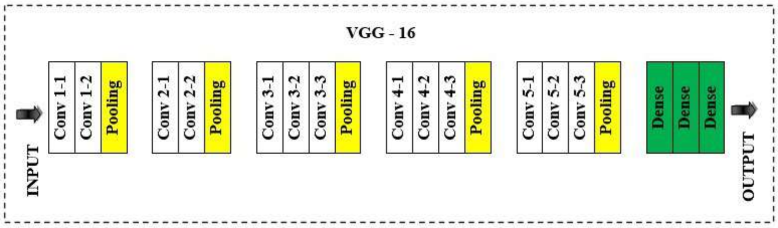

Fig. 2 Architecture Diagram of VGG16 Model

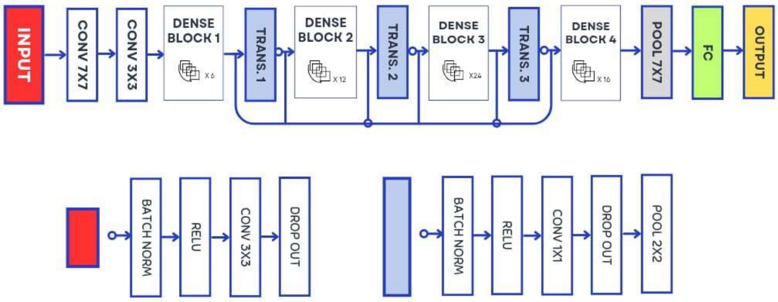

Fig. 3 Architecture of Densenet121 Model

3.4 Training Configuration

- Batch Size: 32
- Optimizer: Adam (learning rate :0.00001)
- Loss Function: Categorical Cross-Entropy
- Epochs: 10
- Hardware: GPU

3.5 Evaluation Metrics

1. Accuracy
2. Loss (Categorical Cross-Entropy)
3. Precision, Recall, F1-Score (average of all classes)

4 Results

4.1 Performance of the Models

This section presents the performance of the deep learning models—ANN, CNN, VGG16 (with the last convolutional block trainable), and DenseNet121 (with the last convolutional block trainable)—on the Kaggle New Plant Diseases Dataset. The models were evaluated based on their accuracy, loss, and generalization capabilities using the validation set. All models were trained for five epochs using the default learning rate, and their performance was compared across the following metrics:

Table 1 Training and validation metrics for all four models.

Model	Training Accuracy (%)	Validation Accuracy (%)	Training Loss	Validation Loss
ANN	53.85	57.91	1.5893	1.4615
CNN	97.57	86.20	0.0867	0.6891
VGG16	99.78	97.75	0.0075	0.0814
DenseNet121	99.87	98.46	0.0043	0.0593

4.2 Testing Results

Table 2 Testing metrics for all four models.

Model	Accuracy (%)	Precision	Recall	F1-score
ANN	57	0.62	0.57	0.57
CNN	86	0.88	0.86	0.86
VGG16	98	0.98	0.98	0.98
DenseNet121	98	0.98	0.98	0.98

From the tables, it is evident that VGG16 and DenseNet121 achieved the highest validation and testing accuracy, both surpassing 98%, demonstrating their superior ability to generalize. CNN also performed well, reaching 86% testing accuracy. ANN, being a fully connected network without convolutional operations, lagged behind with 57% testing accuracy, indicating its limited ability to capture spatial dependencies in plant images.

4.3 Accuracy and Loss Curves

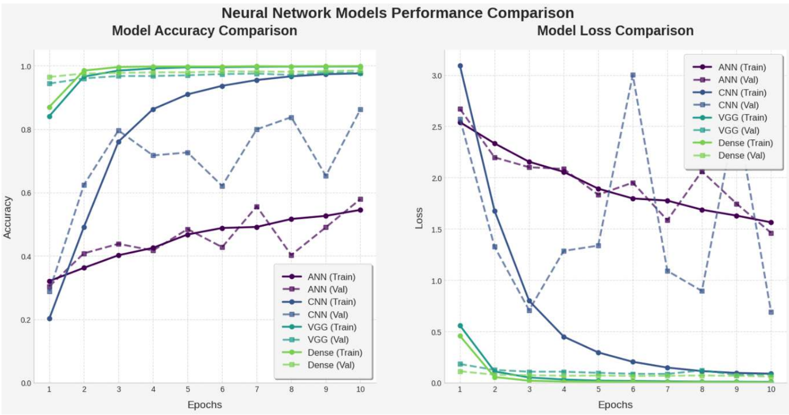

Fig. 4 Training and validation accuracy and loss for ANN, CNN, VGG16, and DenseNet121.

The accuracy curves (Figure 4) indicate that VGG16 and DenseNet121 rapidly achieved high validation accuracy, while CNN showed a strong learning curve but stabilized at a lower validation accuracy. ANN struggled to generalize effectively, showing significant fluctuations in accuracy.Also VGG16 and DenseNet121 maintained the lowest validation loss, confirming their superior learning capabilities. CNN had relatively low loss but showed fluctuations in validation accuracy, suggesting potential overfitting. ANN exhibited high validation loss, which indicates poor generalization ability.

5 Discussion

5.1 Comparison of Model Performance

The results highlight that complex deep learning architectures such as VGG16 and DenseNet121 significantly outperform simpler architectures like ANN. The use of pre-trained models played a crucial role in enhancing performance, particularly for VGG16 and DenseNet121, as they leveraged transfer learning to extract meaningful features from the dataset. CNN, despite being trained from scratch, achieved impressive performance, suggesting that its convolutional layers were effective in learning spatial patterns from plant images. However, it did not surpass VGG16 and DenseNet121, likely due to the benefits of transfer learning in those models. VGG16, while performing well, slightly trailed behind DenseNet121. This could be attributed to the resolution of the dataset (256×256 pixels), which may have limited the effectiveness of VGG16's densely connected layers. Additionally, fine-tuning only the last convolutional block may have restricted its full potential. ANN, lacking convolutional layers, was the weakest performer. Its fully connected structure struggled to learn spatial hierarchies, making it less effective for image classification tasks.

5.2 Training Epochs

Training all models for ten epochs provided an efficient balance between computational cost and performance. The ANN model exhibited potential overfitting as training accuracy increased, but validation accuracy remained relatively low. In contrast, VGG16 and DenseNet121 reached near-optimal performance within the ten epochs, with minimal signs of overfitting. This underscores the effectiveness of transfer learning in achieving high accuracy in fewer training iterations.

5.3 Transfer Learning and Model Generalization

The success of VGG16 and DenseNet121 highlights the advantage of transfer learning, where pre-trained weights help the model generalize better to unseen data. These models leveraged knowledge from large-scale datasets, allowing them to extract more robust features for plant disease classification. CNN, while trained from scratch, still performed well, proving that it can be a viable alternative when pre-trained models are unavailable.

5.4 Limitations and Future Work

Despite promising results, certain limitations must be considered: Image Resolution: Higher-resolution images could potentially improve model performance, especially for DenseNet121, which benefits from detailed feature extraction. Class Imbalance: Some disease categories had fewer samples, which may have affected model performance. Future work could explore techniques like class weighting, oversampling, or generative adversarial networks (GANs) to balance the dataset. Extended Training: Although ten epochs provided efficient results, further training may help improve CNN and ANN performance. Future studies could experiment with early stopping and adaptive learning rates to optimize training.

6 Conclusion

This study evaluated the performance of four deep learning models—ANN, CNN, VGG16, and DenseNet121—for plant disease classification using the Kaggle New Plant Disease Dataset. The models were compared in terms of accuracy, loss, and generalization capabilities.

VGG16 and DenseNet121 both emerged as the best-performing model, achieving the highest validation and testing accuracy, largely due to its deep architecture and use of transfer learning. CNN, despite being trained from scratch, demonstrated strong performance, indicating that convolutional networks can effectively learn plant disease features. ANN performed the weakest, highlighting the limitations of fully connected networks in image classification tasks. DenseNet121 is very lightweight as compared to the VGG16, which makes it the more suitable model to use.

Future work should explore higher-resolution images, advanced data augmentation techniques, and other deep learning approaches to further enhance model performance. Overall, this study demonstrates the effectiveness of deep learning models in plant disease classification and emphasizes the trade-offs between model complexity, computational efficiency, and classification accuracy.

Declarations

Authors' Contributions

All authors contributed equally in all the aspects.

Funding

Not Applicable.

Data Availability

The dataset used in this study was obtained from Kaggle. The data can be accessed at: https://www.kaggle.com/datasets/vipoooool/new-plant-diseases-dataset/data.

Code Availability

The code used can be accessed in this repository https://github.com/pranavmittal07/plant-disease-classification

Conflict of Interest

The authors declare no conflict of interest.

Ethical Approval

This article does not contain any studies with human participants or animals performed by any of the authors.

Informed Consent

Not Applicable.

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