

# Development of a Deep Learning-based Application for Assessing Plant Leaf Images and Predicting Crop Diseases

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**Abstract:** Agriculture is a cornerstone of any country's economy, providing essential crops and supporting livelihoods. A key element in ensuring a healthy agricultural industry is the timely and accurate detection of plant diseases. Early recognition of plant diseases is essential for protecting the health, optimizing production, and avoiding the waste of valuable resources, including time, labor, and finances. Each year, agricultural producers face significant economic losses due to various plant diseases, making efficient disease management crucial for agricultural sustainability. Deep learning technology offers a powerful solution to this challenge by enabling detection of diseases in plant leaves, helping users in taking proactive measures to protect their crops. The study compared the performance of ResNet-50 and VGG-19 deep learning models, using a dataset called PlantVillage, which comprises over 10,000 images. The results demonstrated impressive accuracy rates of 98.98% for ResNet-50 and 96.15% for VGG-19, highlighting the models' effectiveness in identifying crop diseases. Building on these findings, we developed an intelligent web application using the ResNet-50 model for real-time crop disease prediction. Proposed method is designed to support farmers by providing fast and accurate disease detection, enabling timely application of appropriate treatments. This technology helps farmers save resources, reduce economic losses, and promote a more efficient and sustainable agricultural industry.

**Keywords:** Deep Learning, Plant Leaf Analysis, Crop Disease Prediction, Image Assessment, and Agricultural Technology

## 1. Introduction

As the backbone of every country, agriculture continues to evolve alongside the industrial revolution, with crops being essential for human survival [1]. Food insecurity, primarily caused by crop diseases, represents one of the most serious global challenges facing modern humanity. Plant diseases not only present a global threat to food security but also have a profound impact on our everyday lives. As such, ensuring crop health is vital for both economic stability and food safety. The growth and condition of leaves serve as critical indicators of a crop's overall health. Studying leaf image symptoms can provide valuable insights into various plant diseases [2]. Diseases affecting vegetables

such as potatoes, tomatoes, and peppers cause significant financial losses for farmers annually. For example, blight exists in two forms: early blight, caused by fungi, and late blight, caused by specific bacteria. Early disease detection allows farmers to take preventive measures, saving both money and resources.

With the world population expected to surpass 9 billion within the next 25 years, food production must increase by 70% to meet demand. Crop diseases pose a formidable challenge, especially in agrarian economies where crops like potatoes, tomatoes, and peppers are vital. Inspired by the adage, "prevention is better than cure," agricultural scientists are exploring DL techniques to combat potato crop diseases. Machine learning techniques have shown promise by utilizing real-time image processing to extract data, thanks to advancements in computing technology.

### A. Contribution of Deep Learning to Advancements in Agriculture

Deep learning's importance continues to grow, enhancing daily life and agricultural practices [3], [4], [5]. Plant diseases affect crop quality and yield by damaging leaves, fruits, stems, and roots, leading to reduced vegetable consumption globally. Crop diseases are responsible for a significant 16% reduction in annual crop yield. In the realm of smart farming, deep learning is widely used, embracing new algorithms, devices, and techniques [6]. ML addresses essential issues like pattern recognition, picture categorization, and feature extraction [7], [8].

This project aims to develop a CNN methodology for the early identification and categorization of agricultural diseases. The research aims to substantially diminish agricultural output losses via the real-time use of this method.

### B. Challenges in Crop Disease Detection

In rural areas of countries like India, Bangladesh and other, farmers often rely on traditional knowledge to identify crop diseases. Disease identification by experts can be time-consuming, labor-intensive, and expensive, making it less feasible in developing countries. Artificial intelligence (AI) solutions, including DL and ML, offer faster disease detection, reducing crop damage.

For instance:

[9] proposed a CNN-based framework achieving 98.02% accuracy in leaf disease detection.

[10] developed a 15-layer custom CNN with 93% accuracy.

[11] utilized DenseNet121 and EfficientNetB0 to extract features from plants, with models like ResNet152 achieving up to 98.56% accuracy.

[12] introduced a dense-optimized CNN for corn leaf classification, with 98.06% accuracy.

[13] employed the VGG-19 for detecting potato leaf diseases, achieving an accuracy of 97.8% through “logistic regression”.

[14] used a particle swarm optimization algorithm for sunflower leaf disease classification, reaching 98% accuracy.

Most existing solutions use default deep learning models without tuning, and their accuracy levels leave room for improvement. A dedicated application offering preliminary treatment recommendations could significantly reduce crop loss.

### C. Research Objective

The goal of this study is to create a deep learning-based detection framework that ensures high accuracy and offers initial treatment suggestions for farmers.

### D. Research Questions

The research aims to find the effective solution of below listed questions:

1. How can we reduce the impact of preventable crop diseases?
2. Which deep learning strategies are effective for identifying crop diseases?
3. Can deep learning models match the accuracy of human experts in disease detection?
4. What are the most efficient methods for identifying crop diseases?

### E. Contributions

This research contributes to the field in two primary ways:

*Development of a Deep Learning Framework:* A framework for crop disease detection using DL models ResNet-50 and VGG-19 has been studied. The models' performance was tested extensively using the PlantVillage dataset, which includes over 10,000 images of vegetable leaves (tomatoes, peppers, potatoes).

*Web Application Development:* The experimental results led to the selection of the ResNet-50 model for developing an intelligent web application. This web-based application will to assist farmers in detecting “plant diseases using leaf images,” allowing for timely intervention and reducing both resource waste and economic losses.

## 2. Related works

Recent advancements in artificial intelligence (AI) have revolutionized disease detection in both healthcare and agriculture, with imaging technologies playing a pivotal role. Deep learning (DL) and machine learning (ML) techniques, in particular, have demonstrated remarkable potential in automating plant disease identification, offering scalable solutions to enhance agricultural productivity.

### Traditional Machine Learning Approaches

Early studies primarily relied on image processing combined with classical ML algorithms for disease diagnosis. For instance:

- Reference [18] employed AI and image processing for plant disease detection.
- Reference [19] integrated artificial neural networks (ANNs) with image processing to assess fruit quality and disease presence.
- Reference [20] developed a smartphone-based system using computer vision to detect insect pests and plant diseases.

Feature extraction techniques such as the **Grey Level Co-occurrence Matrix (GLCM)** were commonly used alongside classifiers like **Support Vector Machines (SVM)** and **Convolutional Neural Networks (CNNs)**. For example:

- Reference [21] achieved 99% accuracy in apple leaf classification using CNN and SVM, demonstrating superior performance over traditional methods.
- In rice disease detection, Decision Trees (J48) outperformed Logistic Regression, Bayesian Networks, and K-Nearest Neighbors (KNN), reaching 97% accuracy in identifying bacterial leaf blight, leaf blast, and brown spot [22].
- Wheat disease studies [23] highlighted ML's effectiveness in categorizing infections caused by fungi, bacteria, and pests, improving large-scale agricultural monitoring.

### Deep Learning Advancements

DL models, particularly CNNs, have surpassed traditional ML methods by automating feature extraction and improving accuracy:

- A CNN-based model achieved 95.81% accuracy in general plant disease detection [24].
- For maize disease diagnosis, Random Forest (79.23%) outperformed SVM, Naive Bayes, and KNN [25].
- Reference [26] combined K-means clustering, GLCM, and SVM for leaf disease segmentation and classification.
- Grapevine disease studies further validated these approaches:
- Reference [27] used color segmentation and SVM to classify scab, rust, and healthy leaves with high precision.
- Another study [28] reported 88.89% accuracy using SVM alone.
- Tomato Disease Detection: A Case Study
- Tomato leaf disease identification has seen significant DL integration:
- Reference [29] introduced an open-source system combining image segmentation and clustering for precise diagnosis.
- Reference [30] leveraged AlexNet and SqueezeNet (trained on PlantVillage and validated on Nvidia Jetson TX1) for field-based disease detection.
- A transfer learning-based CNN achieved 95.75% accuracy, while Faster R-CNN reached 80%, with empirical tests confirming 91.67% reliability [31].

### Challenges and Research Gaps

Despite progress, several limitations persist:

- Manual Feature Dependency: Traditional ML requires labor-intensive feature engineering, which may not capture complex patterns.
- Overfitting: Small datasets (e.g., [29, 32, 35, 36]) lead to poor generalization in CNNs.
- Limited Scope: Many studies restrict classification to 5–6 disease types [32, 33], lack real-time applications, or use single pre-trained models [13, 33].

**Proposed Contributions**

This study addresses these gaps by:

- Utilizing multiple pre-trained DL models on an expanded dataset covering 8 disease categories.
- Developing a web-based application for real-time disease prediction, aiding farmers in timely intervention.
- Providing a comparative analysis (Table 2.1) of existing methodologies, datasets, and accuracy benchmarks to contextualize advancements.

Future research should explore hybrid DL architectures, attention mechanisms, and larger multi-disease datasets to further enhance model robustness and field applicability.

Table 2.1: Related works in leaf disease detection using DL & ML

Reference	Authors	Focus	Methodology	Data set	Accuracy	Key Findings
[18]	Sanjiv Sanna kki et al.	AI and image processing for disease diagnosis	AI based image processing for disease detection	N/A	N/A	Developed a diagnostic tool using AI for disease identification.
[19]	Monika Jhuria et al.	Fruit grading and disease identification	Image processing with Artificial Neural Networks (ANN) for grading and disease classification	N/A	N/A	Used ANN to improve accuracy in disease identification and fruit grading.
[20]	Kaiyi Wang et al.	Identification of insect	Image processing and comput	Smart phone image	N/A	Enhanced pest and

		pests and plant diseases using smartphone images	er vision techniques for pest and disease identification	es		diseases identification using smartphone - captured images.
[21]	Unspecified	Differentiating diseased and healthy leaves	Image processing, GLCM for feature extraction, SVM for classification, and CNN for improved accuracy	Apple leaves	CNN : 99%, Plant classification: 97.71 %	CNN improved recognition accuracy significantly over SVM, achieving high accuracy for apple leaves and plant classification.
[22]	Unspecified	Rice leaf disease detection	Decision Tree with 10-fold cross-validation, Logistic Regression, Bayesian Network, Decision Tree (J48), Image preprocessing	Rice leaves	Decision Tree: 97%	Decision tree technique achieved high accuracy with proper pre-processing and machine learning techniques.



						but highlighted the need for further improvement.			disease diagnosis in tomatoes	Neural Networks and F-models for disease detection using motor-controlled image capture	(Diamante Max)	95.75%, F-RCN N: 80%, Real-world : 91.67%	achieved high accuracy; real-world testing confirmed model reliability in disease identification.
[29]	Unspecified	Tomato leaf disease detection with image segmentation	image segmentation Open-source algorithms,, clustering for tomato disease detection	Tomato leaves	N/A	Created an accurate method for tomato leaf disease detection using image segmentation techniques.							
[30]	Durmuş et al.	Deep learning for greenhouse/field-grown tomato disease detection	AlexNet and SqueezeNet architectures, real-time detection using Nvidia Jetson TX1, PlantVillage database for training	Tomato leaves (Plant Village)	N/A	Real-time disease detection using deep learning models enhanced accuracy and efficiency in tomato disease identification.			Addressing limitations in ML models for leaf disease detection	Highlighted issues like handcrafted feature extraction, overfitting in small datasets, and limited model tuning. Proposed large datasets and multiple pre-trained deep learning models for improved accuracy and generalization.	Various (small datasets)	N/A	Suggested using large datasets, multiple models, and tuning to improve classification accuracy and prevent overfitting in applications.
[31]	Unspecified	Camera-assisted	RCNN CNN Convolutional	Tomato leaves	Transfer Learning:	Transfer learning			Smart web application for	Utilized multiple pre-	Plant Village (>10,	ResNet-50: 98.98%,	Proposed model
[32], [35], [36]	Various												
Proposed	Unspecified												

	crop disease detection	trained DL models (VGG-19, ResNet-50) with large datasets. Developed an intelligent web application for real-time disease detection and initial treatment recommendations for farmers.	000 images)	VGG-19: 96.15%	significantly improved accuracy and introduced a web application for farmers to detect and manage crop diseases, reducing losses and resource waste.
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used during the training and evaluation phases of the framework.

*C. Preprocessing*

Raw images may contain noise, making preprocessing essential before feeding them into the learning module. The phase involves applying techniques like as rotation, resizing, and shearing to enhance image quality and ensure consistency across the dataset.

*D. Training and Model Building*

This phase consists of two main stages:

- *Training Phase:* Transfer Learning (TL) models are trained using a labeled dataset of training images.
- *Validation Phase:* The model's architecture is tested with a separate set of test images to validate performance and confirm accuracy.

*E. Model Construction*

The predictive model is built through the following steps:

- *Image Collection:* Gather images from the dataset representing different leaf types.
- *Image Preprocessing:* Resize and rotate images to standardize inputs.
- *Feature Extraction:* “Apply convolutional layers to extract features, followed by connection to Fully Connected Layers (FCL). The convolutional features are flattened into a one-dimensional (1D) array and joined to one or more fully connected layers.”
- *Feature Classification:* Extract the features of different leaf classes and perform the classification task.

*F. Evaluation of the Model*

To assess the model, we implement the following steps:

- In the ideal dataset, 80% of the images are used for training, with the remaining 20% allocated for testing.
- Validation data helps measure accuracy by using the predict function and carefully extracting features.
- Images are captured to verify detection after satisfactory validation findings.
- Ultimately, features are extracted to ascertain the infection status of the leaves.

*G. Assessment of Performance*

“At this stage, we select the optimal model by analyzing the results of extensive tests. Key performance indicators like accuracy, precision, recall, F1 score, training accuracy, training loss, validation accuracy, and validation loss were considered. This will facilitate the development of a sophisticated web application with deep learning support.”

*H. Deep Learning Models*

The proposed approach utilizes deep transfer learning with two key architectures: **ResNet50** and **VGG-19**.

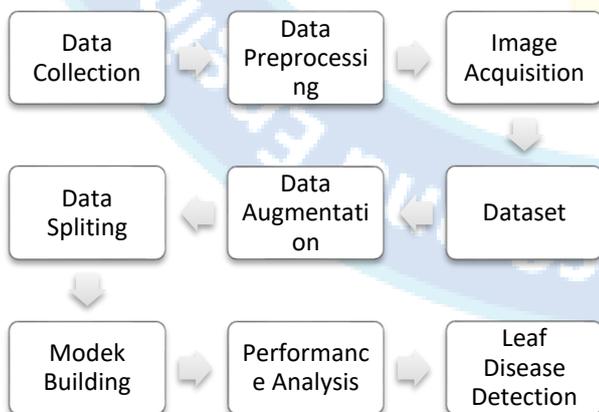
**ResNet50** consists of 48 convolutional layers, along with max pooling and average pooling layers, making it widely used for image classification. Its structure is divided into four stages:

- **Stage 1:** Three repeated blocks (1x1, 3x3, and 1x1 kernels) with 64, 64, and 256 filters, totaling nine layers.

**3. Proposed methodology**

*A. Key Metrics*

A set of experiments was undertaken to evaluate the framework's performance. The key metrics considered were: “Average Training Loss, Training Accuracy, Validation Accuracy, and Prediction Accuracy on Test Data”. The process of detecting plant diseases is shown in Fig. 3.1. The following section outlines each step of the proposed approach:



**Fig. 1: Proposed Method**

*B. Dataset*

The collected input images of several leaf types can be captured in real-time through a camera. For model development and testing, a publicly available dataset was

- **Stage 2:** Four repetitions of 1x1, 3x3, and 1x1 kernels with 128, 128, and 512 filters, forming 12 layers.
- **Stage 3:** Six iterations of 1x1, 3x3, and 1x1 kernels with 256, 256, and 1024 filters, resulting in 18 layers.
- **Stage 4:** Three cycles of 1x1, 3x3, and 1x1 kernels with 512, 512, and 2048 filters, producing nine layers.

VGG-19, another transfer learning model, classifies images into 1000 categories using 19 layers, including 16 convolutional layers and 3 fully connected layers. It is known for its repeated use of 3x3 filters in convolutional networks, enhancing its effectiveness in image prediction tasks.

The proposed model is illustrated in the figure below:

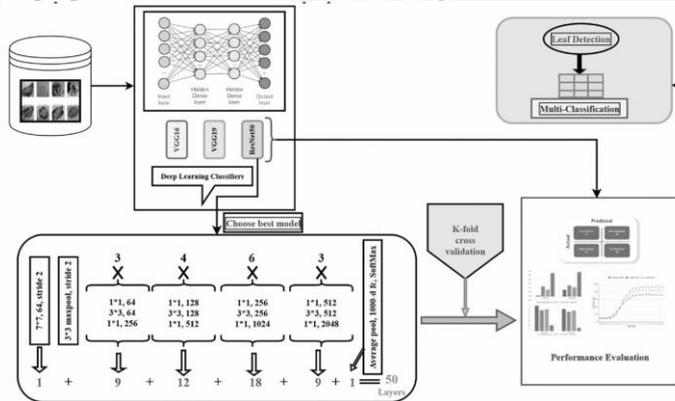


Fig. 2: Our Developed model

I. Architectural Analysis

This study compares three transfer learning architectures—VGG-19, ResNet50, and CNN—trained on ImageNet (1,000 classes) to enhance classification performance. Model accuracy and training errors depend on factors like dataset type, image size, layer configuration, epochs, and batch size. VGG-19 achieves high precision due to its deep structure but suffers from the vanishing gradient problem as depth increases.

ResNet50 overcomes this issue using residual connections, enabling stable training across its 50 layers. This design improves accuracy, data representation, and generalization on new datasets, making it superior to VGG-19 for high-performance tasks.

A comparative analysis of these architectures is provided in Table 1, highlighting ResNet50’s advantages in optimization and classification accuracy.

Table 1: Comparison of VGG-19 and ResNet50

SL	Properties	ResNet-50	VGG-19
1	Activation function	Softmax	softmax
2	Max pool	1	5
3	Convolution layer	48	16
4	Total layers	50	19
5	Model size	102 MB	574 MB
6	weight	imagenet	imagenet
7	image	224*244*3	224*244*3
8	Total parameters	25.6 million	143.7 million

4. Implementation and Result

The parameters used in the experiments are presented in Table 2:

Table 2 Configuration of Experimental Parameters

Parameters	Values
Validation split	0.2
Batch Size	32
Zooming	0.5 to 1.5
Rotating	-10 to +10
Horizontal flipping	True
Shearing	-0.3 to +.3
Optimizer	Adam
Drop out	0.01
Learning Rate	.001

A. Dataset

We obtained image data from the Plant-Village competition (Kaggle, 2018) to test our approach. The annotated images were divided into two subsets, with 80% used for training the model and the remaining 20% allocated for validation or testing.

Several example photos are shown in figure below.



Fig. 3. Few Diseased image

B. Results analysis

The average training and validation accuracy and loss for the three experiments are summarized in Tables 3, 4, and 5.

Table 3: Accuracy results from Experiment-1.

Model Name	Validation Accuracy	Validation loss	Training Accuracy	Training Loss
ResNet-50	93.51%	0.2654	94.38%	0.0212
VGG19	92.18%	0.2751	93.28%	0.1402

Table 4: Accuracy results from Experiment-2.

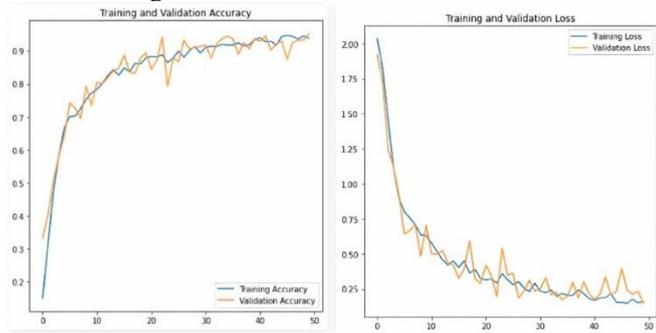
Model Name	Validation Accuracy	Validation loss	Training Accuracy	Training Loss
VGG19	92.45%	0.2943	95.16%	0.1721
ResNet-50	96.55%	0.0987	95.14%	0.1247

Table 5: Accuracy results of Experiment-3.

Model Name	Training Loss	Training Accuracy	Validation loss	Validation Accuracy
VGG19	0.0871	97.13%	0.1439	93.47%
ResNet-50	0.0711	95.84%	0.2143	96.51%

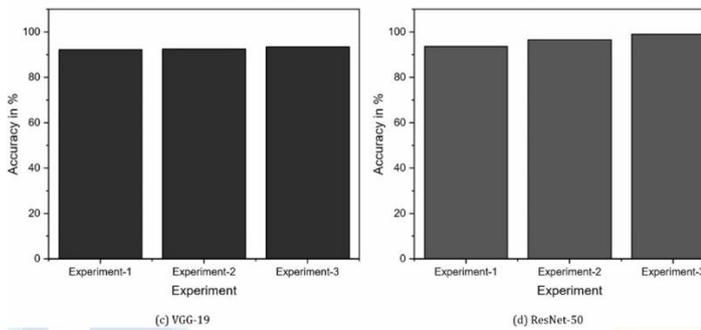
As illustrated in Fig. 4, the ResNet50 model demonstrates stable performance, with minimal fluctuations in validation accuracy and loss. Both training and validation losses decline consistently, maintaining a narrow gap between them, which suggests effective learning without overfitting. Figure 4 further depicts the model’s accuracy and loss trends, revealing steady improvements in training and validation accuracy despite minor variations in the latter.

The closely aligned training and validation loss curves confirm a stable convergence pattern, indicating robust model training.



(a) Accuracy curve vs epoch. (b) Loss curve vs epoch. **Fig. 4: ResNet-50 Training & Validation**

The recommended model's accuracy for many tests is shown in Fig. 4.3. The accuracy of any model increases with the number of photos, but ResNet50 beats the others in Table 4.5.



(c) VGG-19 (d) ResNet-50 **Fig. 5: Accuracy results**

**Table 6: "Set-wise Accuracy Results"**

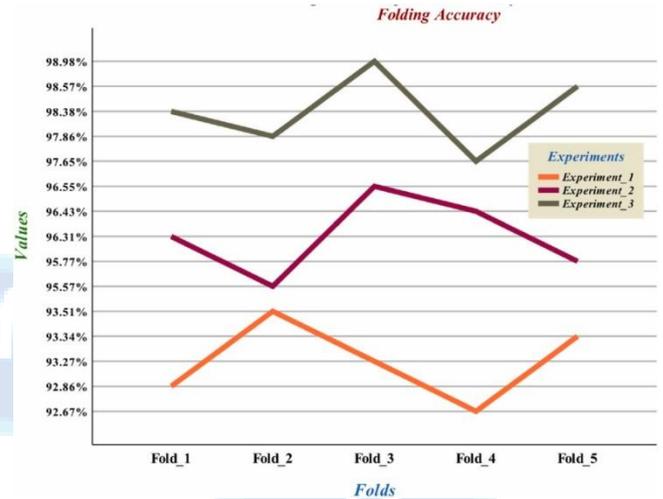
Model	Experiment-3	Experiment-2	Experiment-1
ResNet-50	98.98%	96.55%	93.51%
VGG-19	93.47%	92.45%	92.18%

Summary findings for experiment-3's accuracy, precision, f1-score, and recall are in Table 4.6. ResNet50 outperforms every model, as seen in the table. We used 5-fold cross-validation on each ResNet50 experiment to further verify it. Thus, 80% of data are utilized for training and 20% for testing. Fig. 4.4 shows fold accuracy. On experiments 1, 2, and 3, we averaged fold accuracies of 93.13%, 96.126%, and 98.288%.

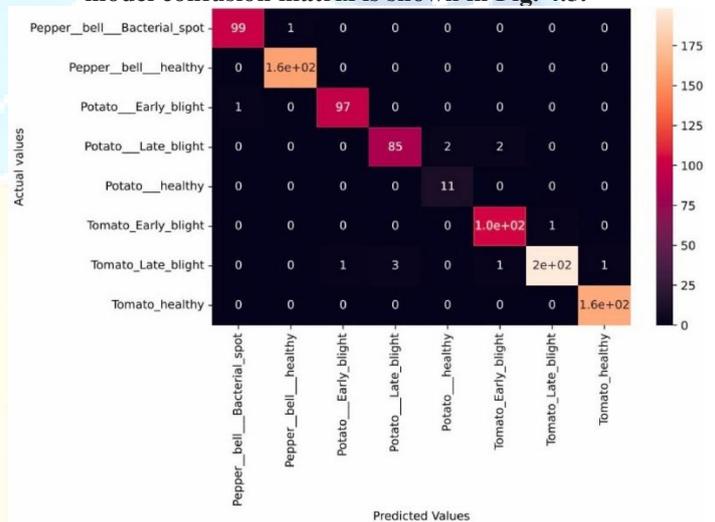
**Table 7: Results of Experiment-3**

Model	f1score	Recall	Precision	Testing Accuracy
ResNet-50	98.98%	99.05%	98.96%	98.99%
VGG-19	96.60%	97.06%	96.42%	96.15%

For all crop leaves, experiment 3 has superior average accuracy. This is because accuracy performance increases linearly with training set size.



**Fig. 5: Folding accuracy findings from 5-folding cross validation on all experiments. The testing scenario CNN model confusion matrix is shown in Fig. 4.5.**



**Fig. 6: Confusion matrix for sequential CNN**

This research evaluates the performance of three deep transfer learning models—VGG-19 & ResNet50—for crop leaf disease detection across multiple crop types using extensive datasets. The VGG-16 and VGG-19 models, consisting of 16 and 19 layers respectively, are popular image classification models. However, both struggle with the vanishing gradient problem, leading to subpar accuracy levels that fall below acceptable thresholds. In contrast, ResNet50 effectively addresses the vanishing gradient issue, significantly reducing testing errors and demonstrating superior performance in experimental scenarios. Consequently, ResNet50 outperforms both VGG models, making it the most effective model in this study.

**5. Development of Web Based Application**

This project developed a web service to assist farmers in remotely diagnosing plant leaf diseases and selecting effective treatments. Built using the Flask Python framework, the web application integrates deep learning to provide real-time disease prediction. The ResNet50 model, known for its superior accuracy, powers the application. The web app operates on localhost, allowing users to upload images of plants—whether healthy or diseased. The application resizes the images to fit model specifications and

uses the ResNet50 model to classify the plant's health status. It then informs the user if the plant is healthy or infected and, if diseased, recommends appropriate treatment options. This automated online system offers farmers and users valuable insights into plant health and practical guidance for disease management. It enhances the early detection of plant diseases, helping farmers take timely measures to prevent productivity loss and improve agricultural output.

## 7. Conclusions

Due to its exceptional performance in reliably detecting plant leaf diseases, the ResNet-50 model was chosen for the development of a web-based agricultural diagnostic application. This online tool serves as an intelligent system that helps users accurately diagnose plant issues and implement timely interventions. The proposed technique outperformed previous research in evaluating symptom severity and overall disease classification accuracy, demonstrating its practicality and reliability.

Looking ahead, future research will focus on further improving accuracy by developing a hybrid deep learning architecture that incorporates attention mechanisms. Additionally, techniques for disease area identification or localization will be employed to precisely identify affected regions on leaves. To enhance model generalization and resilience, more extensive, multi-leaf disease datasets will be utilized to ensure coverage of all recognized plant leaf diseases.

Early detection and classification of plant and leaf diseases remain significant challenges in modern agriculture. Our research addresses these challenges by leveraging Convolutional Neural Network (CNN) architectures for accurate disease identification. We evaluated two advanced models—VGG-19 and ResNet-50—using the PlantVillage dataset, a publicly available benchmark for leaf disease analysis. The experimental results showed that ResNet-50 achieved an accuracy of 98.98%, outperforming VGG-19, which achieved 96.15%, highlighting ResNet-50's superior disease detection capabilities.

Given its high performance, ResNet-50 was integrated into a web-based agricultural diagnostic tool, empowering users to quickly identify leaf diseases and take corrective actions. Our approach surpassed existing methods in symptom severity assessment and classification accuracy, further validating its practical utility. Future work will focus on enhancing precision with hybrid deep learning models, using attention mechanisms, disease localization techniques, and expanding datasets to improve model generalization and robustness.

## References

- [1]. Bidwell, P. W. (1921). The agricultural revolution in New England. *American Historical Review*, 26(4), 683–702. <https://doi.org/10.2307/1843770>
- [2]. Husin, Z. B., Shakaff, A. Y. B. M., Aziz, A. H. B. A., & Farook, R. B. S. M. (2012). Feasibility study on plant chili disease detection using image processing techniques. In *2012 Third International Conference on Intelligent Systems Modelling and Simulation* (pp. 291–296). IEEE. <https://doi.org/10.1109/ISMS.2012.69>
- [3]. Talukder, M. A., Islam, M. M., Uddin, M. A., Akhter, A., Pramanik, M. A. J., Aryal, S., Almoyad, M. A. A., Hasan, K. F., & Moni, M. A. (2023). An efficient deep learning model to categorize brain tumor using reconstruction and fine-tuning. *Expert Systems with Applications*, Article 120534. <https://doi.org/10.1016/j.eswa.2023.120534>
- [4]. Ahmed, N., Ahammed, R., Islam, M. M., Uddin, M. A., Akhter, A., Talukder, M. A., & Paul, B. K. (2021). Machine learning-based diabetes prediction and development of smart web application. *International Journal of Cognitive Computing in Engineering*, 2, 229–241. <https://doi.org/10.1016/j.ijcce.2021.05.003>
- [5]. Uddin, M. A., Islam, M. M., Talukder, M. A., Hossain, M. A. A., Akhter, A., Aryal, S., & Muntaha, M. (2023). Machine learning-based diabetes detection model for false negative reduction. *Biomedical Materials & Devices*, 1–17. <https://doi.org/10.1016/j.bmd.2023.01.001>
- [6]. Bah, M. D., Hafiane, A., & Canals, R. (2018). Deep learning with unsupervised data labeling for weed detection in line crops in UAV images. *Remote Sensing*, 10(11), 1690. <https://doi.org/10.3390/rs10111690>
- [7]. Talukder, M. A., Islam, M. M., Uddin, M. A., Akhter, A., Hasan, K. F., & Moni, M. A. (2022). Machine learning-based lung and colon cancer detection using deep feature extraction and ensemble learning. *Expert Systems with Applications*, 205, Article 117695. <https://doi.org/10.1016/j.eswa.2022.117695>
- [8]. Talukder, M. A., Hasan, K. F., Islam, M. M., Uddin, M. A., Akhter, A., Yousuf, M. A., Alharbi, F., & Moni, M. A. (2023). A dependable hybrid machine learning model for network intrusion detection. *Journal of Information Security and Applications*, 72, Article 103405. <https://doi.org/10.1016/j.jisa.2023.103405>
- [9]. Jasim, M. A., & Al-Tuwaijari, J. M. (2020). Plant leaf diseases detection and classification using image processing and deep learning techniques. In *2020 International Conference on Computer Science and Software Engineering (CSASE)* (pp. 259–265). IEEE. <https://doi.org/10.1109/CSASE49868.2020.9207150>
- [10]. Pawar, S., Shedge, S., Panigrahi, N., Jyoti, A., Thorave, P., & Sayyad, S. (2022). Leaf disease detection of multiple plants using deep learning. In *2022 International Conference on Machine Learning, Big Data, Cloud and Parallel Computing (COM-IT-CON)* (pp. 241–245). IEEE. <https://doi.org/10.1109/COM-IT-CON53732.2022.9783204>
- [11]. Amin, H., Darwish, A., Hassanien, A. E., & Soliman, M. (2022). End-to-end deep learning model for corn leaf disease classification. *IEEE Access*, 10, 31103–31115. <https://doi.org/10.1109/ACCESS.2022.3167217>
- [12]. Waheed, A., Goyal, M., Gupta, D., Khanna, A., Hassanien, A. E., & Pandey, H. M. (2020). An optimized dense convolutional neural network model for disease recognition and classification in corn leaf. *Computers and Electronics in Agriculture*, 175, Article

105456.  
<https://doi.org/10.1016/j.compag.2020.105456>
- [13]. Tiwari, D., Ashish, M., Gangwar, N., Sharma, A., Patel, S., & Bhardwaj, S. (2020). Potato leaf diseases detection using deep learning. In *2020 4th International Conference on Intelligent Computing and Control Systems (ICICCS)* (pp. 461–466). IEEE. <https://doi.org/10.1109/ICICCS48265.2020.9120909>
- [14]. Singh, V. (2019). Sunflower leaf diseases detection using image segmentation based on particle swarm optimization. *Artificial Intelligence in Agriculture*, 3, 62–68. <https://doi.org/10.1016/j.aiaa.2019.06.004>
- [15]. Ahamed, M., Uddin, K., Islam, M. M., Uddin, M., Akhter, A., Acharjee, U. K., Paul, B. K., & Moni, M. A. (2023). Dtlx: An improved ResNet architecture to classify normal and conventional pneumonia cases from COVID-19 instances with Grad-CAM-based superimposed visualization utilizing chest X-ray images. *Diagnostics*, 13(3), 551. <https://doi.org/10.3390/diagnostics13030551>
- [16]. Ahamed, K. U., Islam, M., Uddin, A., Akhter, A., Paul, B. K., Yousuf, M. A., Uddin, S., Quinn, J. M., & Moni, M. A. (2021). A deep learning approach using effective preprocessing techniques to detect COVID-19 from chest CT-scan and X-ray images. *Computers in Biology and Medicine*, 139, Article 105014. <https://doi.org/10.1016/j.compbiomed.2021.105014>
- [17]. Ahmad, A., Saraswat, D., & El Gamal, A. (2022). A survey on using deep learning techniques for plant disease diagnosis and recommendations for development of appropriate tools. *Smart Agricultural Technology*, Article 100083. <https://doi.org/10.1016/j.atech.2022.100083>
- [18]. Sannakki, S. S., Rajpurohit, V. S., Nargund, V., & Kulkarni, P. (2013). Diagnosis and classification of grape leaf diseases using neural networks. In *2013 Fourth International Conference on Computing, Communications and Networking Technologies (ICCCNT)* (pp. 1–5). IEEE. <https://doi.org/10.1109/ICCCNT.2013.6726696>
- [19]. Jhuria, M., Kumar, A., & Borse, R. (2013). Image processing for smart farming: Detection of disease and fruit grading. In *2013 IEEE Second International Conference on Image Information Processing (ICIIP-2013)* (pp. 521–526). IEEE. <https://doi.org/10.1109/ICIIP.2013.6721457>
- [20]. Wang, K., Zhang, S., Wang, Z., Liu, Z., & Yang, F. (2013). Mobile smart device-based vegetable disease and insect pest recognition method. *Intelligent Automation & Soft Computing*, 19(3), 263–273. <https://doi.org/10.1080/10798587.2013.805444>
- [21]. Fulari, U. N., Shastri, R. K., & Fulari, A. N. (2020). Leaf disease detection using machine learning. *Seybold Report*, 1533, Article 9211.
- [22]. Ahmed, K., Shahidi, T. R., Alam, S. M. I., & Momen, S. (2019). Rice leaf disease detection using machine learning techniques. In *2019 International Conference on Sustainable Technologies for Industry 4.0 (STI)* (pp. 1–5). IEEE. <https://doi.org/10.1109/STI47771.2019.8965614>
- [23]. Dixit, A., & Nema, S. (2018). Wheat leaf disease detection using machine learning method—a review. *International Journal of Computer Science and Mobile Computing*, 7(5), 124–129.
- [24]. Trivedi, J., Shammani, Y., & Gajjar, R. (2020). Plant leaf disease detection using machine learning. In *International Conference on Emerging Technology Trends in Electronics Communication and Networking* (pp. 267–276). Springer. [https://doi.org/10.1007/978-981-15-6093-4\\_23](https://doi.org/10.1007/978-981-15-6093-4_23)
- [25]. Panigrahi, K. P., Das, H., Sahoo, A. K., & Moharana, S. C. (2020). Maize leaf disease detection and classification using machine learning algorithms. In *Progress in Computing, Analytics and Networking* (pp. 659–669). Springer. [https://doi.org/10.1007/978-981-15-3757-9\\_59](https://doi.org/10.1007/978-981-15-3757-9_59)
- [26]. Prakash, R. M., Saraswathy, G., Ramalakshmi, G., Mangaleswari, K., & Kaviya, T. (2017). Detection of leaf diseases and classification using digital image processing. In *2017 International Conference on Innovations in Information, Embedded and Communication Systems (ICIECS)* (pp. 1–4). IEEE. <https://doi.org/10.1109/ICIECS.2017.8074905>
- [27]. Meunkaewjinda, A., Kumsawat, P., Attakitmongkol, K., & Srikaew, A. (2008). Grape leaf disease detection from color imagery using hybrid intelligent system. In *2008 5th International Conference on Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology* (Vol. 1, pp. 513–516). IEEE. <https://doi.org/10.1109/ICEE.2008.4600156>
- [28]. Padol, P. B., & Yadav, A. A. (2016). SVM classifier based grape leaf disease detection. In *2016 Conference on Advances in Signal Processing (CASP)* (pp. 175–179). IEEE. <https://doi.org/10.1109/ICCASP.2016.7859132>
- [29]. Ashok, S., Kishore, G., Rajesh, V., Suchitra, S., Sophia, S. G., & Pavithra, B. (2020). Tomato leaf disease detection using deep learning techniques. In *2020 5th International Conference on Communication and Electronics Systems (ICCES)* (pp. 979–983). IEEE. <https://doi.org/10.1109/ICCES48766.2020.9137923>
- [30]. Durmuş, H., Güneş, E. O., & Kırıcı, M. (2017). Disease detection on the leaves of the tomato plants by using deep learning. In *2017 6th International Conference on Agro-Geoinformatics* (pp. 1–5). IEEE. <https://doi.org/10.1109/Agro-Geoinformatics.2017.8079935>
- [31]. De Luna, R. G., Dadios, E. P., & Bandala, A. A. (2018). Automated image capturing system for deep learning-based tomato plant leaf disease detection and recognition. In *TENCON 2018 - 2018 IEEE Region 10 Conference* (pp. 1414–1419). IEEE. <https://doi.org/10.1109/TENCON.2018.8650084>
- [32]. Sujatha, R., Chatterjee, J. M., Jhanjhi, N., & Brohi, S. N. (2021). Performance of deep learning vs machine learning in plant leaf disease detection. *Microprocessors and Microsystems*, 80, Article 103615. <https://doi.org/10.1016/j.micpro.2020.103615>

- [33]. Zhong, Y., & Zhao, M. (2020). Research on deep learning in apple leaf disease recognition. *Computers and Electronics in Agriculture*, 168, Article 105146. <https://doi.org/10.1016/j.compag.2019.105146>
- [34]. Agarwal, M., Singh, A., Arjaria, S., Sinha, A., & Gupta, S. (2020). ToLeD: Tomato leaf disease detection using convolution neural network. *Procedia Computer Science*, 167, 293–301. <https://doi.org/10.1016/j.procs.2020.03.190>
- [35]. Nalini, S., Krishnaraj, N., Jayasankar, T., Vinothkumar, K., & Sagai, A. (2021). Paddy leaf disease detection using an optimized deep neural network. *Computers, Materials & Continua (CMC)*, 68(1), 1117–1128. <https://doi.org/10.32604/cmc.2021.013513>
- [36]. Syed-Ab-Rahman, S. F., Hesamian, M. H., & Prasad, M. (2022). Citrus disease detection and classification using end-to-end anchor-based deep learning model. *Applied Intelligence*, 52(1), 927–938. <https://doi.org/10.1007/s10489-021-02668-0>
- [37]. Yang, H., Ni, J., Gao, J., Han, Z., & Luan, T. (2021). A novel method for peanut variety identification and classification by improved VGG16. *Scientific Reports*, 11(1), 1–17. <https://doi.org/10.1038/s41598-021-85520-2>
- [38]. Simonyan, K., & Zisserman, A. (2014). Very deep convolutional networks for large-scale image recognition. *arXiv preprint arXiv:1409.1556*. <https://arxiv.org/abs/1409.1556>
- [39]. He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition* (pp. 770–778). <https://doi.org/10.1109/CVPR.2016.90>
- [40]. Khamparia, A., Saini, G., Gupta, D., Khanna, A., Tiwari, S., & de Albuquerque, V. H. C. (2020). Seasonal crops disease prediction and classification using deep convolutional encoder network. *Circuits, Systems, and Signal Processing*, 39, 818–836. <https://doi.org/10.1007/s00034-019-01174-5>