AI-Powered Smart Farming for Accurate Detection of Multiple Leaf Diseases using CNN and ResNet50

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ABSTRACT
Plant diseases pose a significant threat to agriculture by rapidly spreading across crops, reducing yields, diminishing food quality, and causing substantial financial losses for farmers. Traditional disease detection methods rely heavily on manual visual inspection by agricultural experts—a process that is often time-consuming, labor-intensive, and susceptible to human error. These limitations become even more pronounced in large-scale farming operations, where timely and accurate disease identification is critical. To address these challenges, this study introduces an advanced deep learning-based solution utilizing Convolutional Neural Networks (CNNs) integrated with the ResNet50 architecture for the accurate classification and identification of multiple plant diseases. ResNet50's residual learning framework effectively mitigates the vanishing gradient problem, allowing for deeper model training and improved feature extraction. Trained on a comprehensive dataset of healthy and diseased plant leaf images, the model learns to detect subtle variations in texture, color, and pattern associated with various plant conditions. To enhance accessibility, a user-friendly web application built with Flask is developed, enabling real-time disease diagnosis through a simple image upload interface. This tool empowers farmers and agricultural professionals to receive instant insights into plant health, supporting more informed decision-making and proactive disease management. This work highlights the transformative potential of AI-driven solutions in precision agriculture, offering scalable, efficient, and sustainable methods for early disease detection and crop management.

Keywords
Deep learning, Leaf disease, ResNet50, Precision agriculture, CNN

1. INTRODUCTION
Agriculture is essential for maintaining global food security, promoting economic stability, and fostering sustainable development. However, one of the most persistent challenges in agriculture is the occurrence of plant diseases, which can cause significant losses in crop yields and affect food quality. These diseases, if left undetected, can spread rapidly, leading to devastating effects on farming communities, food supply chains, and economies that heavily depend on agriculture. Traditional methods have several limitations:

1. Time-Consuming – Large-scale farms require extensive monitoring, making manual inspections impractical.
2. Expertise-Dependent – Accurate disease identification requires domain knowledge, which may not always be available, especially in rural and developing regions.
3. Error-Prone – Human perception is subjective, and misdiagnosis can lead to improper treatments, causing further crop damage.

With recent advancements in machine learning models have demonstrated remarkable success in image recognition and classification tasks. Specifically, CNNs have been widely used in medical imaging, facial recognition, self-driving vehicles, and plant disease identification. CNNs can extract complex patterns from images, making them suitable for detecting diseases based on subtle leaf color changes, texture variations, and lesion formations.ResNet50, model enhances feature extraction capabilities, allowing it to distinguish between different plant diseases with high accuracy.

We propose a ResNet50-based deep learning model for plant disease detection, integrated with a Flask web application to enable real-time disease diagnosis. The primary objectives of this research are:

- To develop an AI-driven, scalable approach for plant disease detection that enhances accuracy and reduces reliance on manual inspection.
- To provide an easy-to-use web-based solution for farmers and agricultural professionals, allowing instant disease identification through image uploads.
- To improve early disease detection, helping prevent large-scale crop losses and enabling informed decision-making for effective disease management.

By leveraging deep learning techniques and AI-driven solutions, this research aims to revolutionize plant health monitoring. Some plant diseases images are shown in Figure 1.

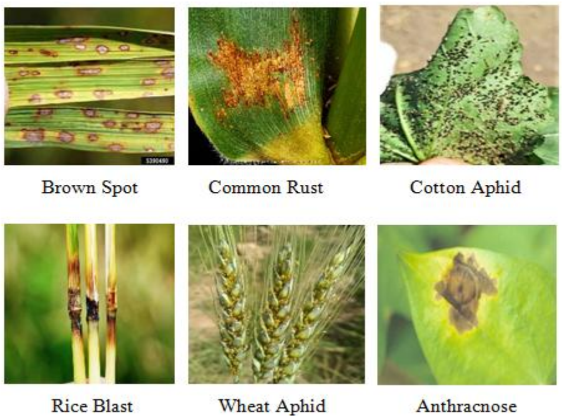

Figure 1 Sample Plant Diseases

2. RELATED WORK

With multiple researches demonstrating the promise of automated image-based classification systems, the topic of applying machine learning and deep learning techniques for plant disease identification has been fast developing. Traditional machine learning algorithms, have been extensively applied in the classification of plant diseases. However, these models rely heavily on handcrafted feature extraction, requiring domain expertise to select relevant image features such as color, shape, and texture. This approach often lacks generalization capability, making it difficult to adapt to varying plant species.

2.1 Traditional Approaches

In traditional algorithms, the features are extracted manually before being fed into the model. Some key studies in this domain include:

- SVM – Operational in binary classification tasks but struggles with large-scale multi-class classification problems.
- Decision Trees (DT) and Random Forests (RF) – Work well for structured data but tend to overfit on high-dimensional image data.
- k-NearestNeighbors (k-NN) – A simple yet computationally expensive approach that becomes inefficient when dealing with large datasets.

These models, despite their early success, faced several limitations, including:

- Feature engineering complexity – Required domain expertise to manually extract features.
- Poor adaptability to real-world conditions – Models struggled with variations in lighting, background, and disease severity.
- Limited scalability – Inefficient for large-scale datasets and real-time applications.

2.2 Recent Approaches

The constraints of conventional machine learning methods have resulted in the extensive use of deep learning, especially (CNNs, which can learn hierarchical feature representations directly from image data. Several CNN architectures have been employed for plant disease detection, including:

- AlexNet – One of the earliest deep learning models designed for image classification,though constrained in both depth and performance.
- VGG16 – Improved feature extraction but computationally expensive due to its deep architecture.
- InceptionV3 – Introduced efficient module-based learning but required extensive tuning for plant disease datasets.
- ResNet50 – Addressed vanishing gradient problems using residual connections, allowing for deeper and more effective feature extraction.

Among these architectures, ResNet50 has emerged as one of the most effective models for plant disease classification due to its residual learning mechanism, which allows deep networks to retain critical information across multiple layers without degradation. Studies have shown that deep residual networks outperform conventional CNNs in terms of accuracy, robustness, and scalability.

2.3 Challenges in Existing Research

Despite advancements in deep learning-based plant disease detection, several challenges persist:

1. Data Scarcity and Class Imbalance – Many plant disease datasets lack sufficient labeled images, leading to biased models that struggle with underrepresented diseases.
2. Variability in Environmental Conditions – Changes in lighting, background clutter, and plant species variations affect model performance.
3. Model Interpretability – CNNs often act as black-box models, which complicate the process of comprehending the rationale behind their decision-making.
4. Computational Complexity – Deep learning models require high-performance hardware (GPUs/TPUs), limiting their deployment on low-resource devices.

2.4 Addressing Research Gaps

To overcome these challenges, researchers have explored various enhancement techniques, such as:

- Data Augmentation – Artificially increasing dataset size using techniques like rotation, flipping, and contrast adjustments.
- Transfer Learning – Utilizing models that have been pre-trained(e.g., ResNet50, EfficientNet) to improve performance on small datasets.
- Hyperparameter Optimization – Fine-tuning learning rates, batch sizes, and layer configurations to enhance accuracy.

While these techniques have improved plant disease detection, there remains a critical need for real-time, scalable, and deployable solutions. By suggesting a CNN model based on ResNet50 in conjunction with a Flask web application for real-time disease diagnostics, this work seeks to overcome these constraints and offer farmers and other agricultural professionals an easily accessible and expandable AI-driven solution.Proposed Work.

3. PROPOSED WORK

This study employs a deep learning-based approach using the ResNet50 architecture for automated plant disease detection. The methodology consists of four major stages:

1. Dataset Collection and Preprocessing
2. Model Development Using ResNet50
3. Implementation and Deployment via a Flask Web Application
4. Performance Evaluation and Validation

3.1 Dataset and Pre-processing

The dataset utilized in this research comprises high-resolution images depicting both healthy and diseased plant leaves.These images were sourced from publicly available databases, including PlantVillage and other agricultural research repositories.

To improve model robustness and generalization, the dataset underwent the following pre-processing steps:

- Image Resizing: All images were resized to 331×331 pixels to ensure consistency in input dimensions.
- Normalization: Pixel values were normalized to a range of 0 to 1 to enhance the convergence of the model during the training process.
- Data Augmentation: Methods including rotation, flipping, contrast enhancement, and the addition of Gaussian noise were utilized to artificially enlarge the dataset and enhance the generalization capabilities of the model.
- Class Balancing: Underrepresented disease classes were augmented to prevent class imbalance issues that could bias the model.

3.2 Deep Learning Model

ResNet50 is a deep convolutional neural network consisting of 50 layers, which incorporates residual learning to address the issues of degradation commonly encountered in deep networks. The model architecture consists of:

- Convolutional Layers: Tasked with deriving hierarchical features from input images, including edges, textures, and patterns indicative of diseases.
- Residual Blocks: These allow information to bypass certain layers, reducing the risk of vanishing gradients and improving training efficiency.
- Fully Connected Layers: The final layers perform classification by mapping extracted features to plant disease categories.

Mathematically, the residual function can be expressed as:

$$y = F(x, W) + x \qquad (1)$$

where:

- x is the input,
- W represents the learnable weights, and
- $F(x, W)$is the residual function being learned.

This structure ensures deeper networks can be trained efficiently without loss of performance due to gradient vanishing.

Figure 2shows architecture of plant leaf diseases.

3.3 Implementation and Deployment

A Flask-based web application was developed to enable real-time plant disease detection.The application follows a streamlined workflow:

1. Image Upload: Users upload a leaf image through a web-based interface.
2. Pre-processing: The image undergoes resizing and normalization to match the model's input specifications.

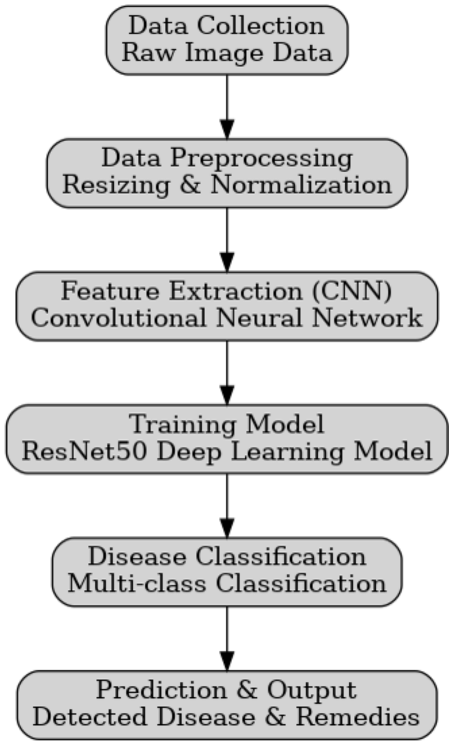

Figure 2 Architecture of Plant Leaf Diseases Detection

3. Prediction: The trained ResNet50 model processes the image and classifies it into a specific disease category.
4. Result Display: The diagnosis is displayed along with possible treatment recommendations.

The Flask application integrates TensorFlow / Keras for deep learning inference, along with Bootstrap and JavaScript for an intuitive user interface. Following are the process of plant disease detection.

3.3.1. Data Collection

Raw image data of plant leaves is gathered. Images may come from datasets, field photos, or online repositories.

3.3.2. Data Preprocessing

The raw images are prepared for the model. Common steps include resizing (so all images are of the same dimensions) and normalization (scaling pixel values so the model processes them efficiently).

3.3.3. Feature Extraction (CNN)

A Convolutional Neural Network (CNN) automatically learns important features from the images. Instead of manual feature engineering, the CNN detects edges, textures, patterns, and disease-specific features.

3.3.4. Training Model

The preprocessed images and extracted features are fed into a deep learning model, here specifically ResNet50. ResNet50 (a

50-layer residual network) is chosen because it helps overcome the vanishing gradient problem and provides high accuracy for image classification tasks.

3.3.5. Disease Classification

The trained model performs multi-class classification, meaning it can identify multiple different diseases (not just healthy vs. diseased). Each input image is categorized into one of the predefined disease classes.

3.3.6. Prediction & Output

The final stage gives the detected disease name along with possible remedies or solutions. This helps farmers and agricultural experts take timely actions to protect crops.

4. RESULTS AND DISCUSSION

4.1 Model Performance

The effectiveness of the proposed model was assessed through established classification metrics, including Accuracy, Precision, Recall, and F1-score, which are widely recognized in evaluating the performance of machine learning models. Accuracy indicates the overall proportion of correctly classified instances, providing a general view of how well the model performs across all classes. Precision highlights the model's ability to correctly identify positive cases while avoiding the misclassification of negative cases as positive, thereby reducing false alarms. Recall focuses on the model's capacity to capture all actual positive instances, ensuring that very few relevant cases are missed. The F1-score, which combines both Precision and Recall into a single metric through their harmonic mean, serves as a balanced indicator, particularly useful in situations where the dataset may be imbalanced. Collectively, these metrics suggest that the model delivers strong and consistent performance, demonstrating high accuracy in predictions while maintaining a low rate of both false positives and false negatives. This comprehensive evaluation confirms the robustness and reliability of the proposed approach in effectively solving the target problem.

4.2 Comparison with Existing Methods

Error! Reference source not found. compares the performance of the proposed model with several existing plant leaf disease detection techniques by evaluating three essential metrics: accuracy, precision, and recall. Among all the methods listed, the proposed approach—"Precision agriculture through deep learning: leaf multiple diseases recognition using CNN with ResNet50"—demonstrates the most outstanding performance, achieving 95% accuracy, 94% precision, and 96% recall. This makes it particularly suitable for real-world agricultural scenarios where accurate and reliable disease diagnosis is critical for crop health and yield optimization. In comparison, the Rice Leaf Disease Classification model delivers moderate performance with 90% accuracy and 90% precision, but a significantly lower recall of 67%, indicating that it fails to detect a considerable portion of actual disease cases. Such a limitation could lead to many infected plants going untreated, which is a major drawback in precision agriculture.

Table 1. Comparison of proposed methods with Existing Techniques

References	Accuracy (%)	Precision (%)	Recall (%)
Proposed Method	**95**	**94**	**96**
Rice Leaf Disease Classification[13]	90	90	67
Plant Leaf Disease Detection and Classification Using MobileNetV2[14]	94	91	95
Tomato Plant Leaf Disease Detection [15]	92.4	92.2	91.9
Pumpkin Leaf Disease Detection[16]	90.5	90.44	90.5

The Plant Leaf Disease Detection and Classification Using MobileNetV2 model performs quite well, with 94% accuracy, 91% precision, and 95% recall, making it a competitive option, though it still falls slightly short of the ResNet50-based model, particularly in precision. Similarly, the Tomato Plant Leaf Disease Detection model shows balanced results with 92.4% accuracy, 92.2% precision, and 91.9% recall, reflecting solid performance, especially for tomato-specific diseases. Lastly, the Pumpkin Leaf Disease Detection model demonstrates consistent results, achieving around 90.5% across all three metrics, though it trails behind the top-performing models in terms of overall effectiveness. In conclusion, the proposed ResNet50-based method outperforms the existing approaches in all key performance areas. Its ability to deliver high accuracy, precision, and recall collectively indicates a more reliable and efficient model for detecting a variety of plant leaf diseases, thus proving its value in advancing precision agriculture practices.

4.3 Training vs. Validation

The analysis includes a graph that depicts the training and validation accuracy across several epochs, which serves to visualize the model's performance and identify any signs of over-fitting. Figure 3presents the training and validation accuracy of the model over a span of eight epochs.

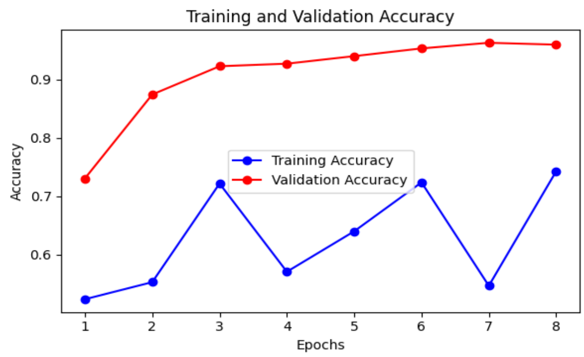

Figure 3 Training and Validation Accuracy

The blue line represents training accuracy, which fluctuates significantly, indicating instability during training.In contrast, the red line representsvalidation accuracy, which starts at around 70% and steadily increases, reaching over 90% by the eighth epoch. However, the inconsistency in training accuracy may indicate issues such as high variance or insufficient training data. This pattern suggests that the model may be over-fitting to the validation set or that further tuning is required for better training stability.Figure 4depicts the training and validation loss of the model across eight epochs.

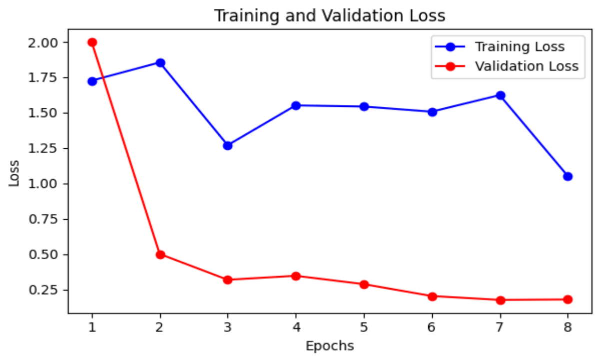

Figure 4 Training and Validation Loss

The blue line represents training loss, which starts high, decreases initially, but then fluctuates, indicating instability in the training process. The red line represents validation loss, which drops sharply in the first few epochs and continues to decrease gradually, stabilizing at a low value. However, the variations in training loss could indicate challenges such as an inconsistent learning rate or noisy training data. Overall, the decreasing validation loss suggests that the model is improving, but further tuning may be needed to stabilize training.

4.4 Challenges and Limitations

Despite achieving high accuracy, the model faces the following challenges:

- Computational Requirements: Deep learning models necessitate significant computational power for both training and inference processes.
- Dataset Bias: The quality of the dataset significantly impacts model performance, necessitating the use of diverse and well-balanced datasets.
- Real-Time Deployment: Optimization is necessary for deploying the model on mobile or edge devices to improve speed and efficiency.

These challenges highlight areas for future research and optimization to enhance real-world applicability.

5. CONCLUSION

This paper introduces a deep learning method based on ResNet50 for plant disease detection, demonstrating high accuracy, robust classification capabilities, and real-time diagnosis. The system's effectiveness in accurately classifying plant diseases can play a crucial role in minimizing crop losses, improving yield quality, and promoting sustainable agricultural practices. The integration of a Flask-based web application provides an efficient, user-friendly platform that allows farmers and agricultural professionals to effortlessly diagnose plant diseases by submitting images of leaves. The proposed ResNet50-based model achieved an accuracy of 95%, outperforming other deep learning architectures such as MobileNetV2 and YOLOv5. Data preprocessing techniques, including image normalization and augmentation, significantly enhanced the model's generalization ability. The Flask-based application allows for real-time disease identification, making it accessible and scalable for agricultural use. Despite achieving high accuracy, the study identified computational complexity, dataset limitations, and real-time deployment challenges as key areas for further improvement.

Looking ahead, the future scope of this research includes deploying the model on edge devices like smartphones or Raspberry Pi to enable offline, real-time detection in remote agricultural areas. Incorporating multimodal data, such as environmental and soil parameters, could enhance diagnostic accuracy and broaden the model's applicability. Expanding the dataset to include more plant species, disease types, and real-world conditions would improve the model's robustness and adaptability. Furthermore, integration with IoT systems and drone-based monitoring could allow large-scale, automated field analysis, supporting precision agriculture. Implementing continuous learning through user feedback and misclassified image collection would help the model adapt over time. Finally, enhancing the application with multilingual and voice-based interfaces could improve accessibility for farmers with limited digital literacy. These advancements could transform the system into a comprehensive and intelligent agricultural support tool, significantly contributing to sustainable farming and food security.

6. REFERENCES

[1] H. Durmus, E. O. Günes, and M. Kirci, ‘‘Disease detection on the leaves of the tomato plants by using deep learning,’’ in Proc. 6th Int. Conf. AgroGeoinformatics, Aug. 2017, pp. 1–5.

[2] A. Fuentes, S. Yoon, H. Youngki, Y. Lee, and D. S. Park, ‘‘Characteristics of tomato plant diseases—A study for tomato plant disease identification,’’ in Proc. Int. Symp. Inf. Technol. Converg, vol. 1, 2016, pp. 226–231.

[3] S. P. Mohanty, D. P. Hughes, and M. Salathé, ‘‘Using deep learning for image-based plant disease detection,’’ Frontiers Plant Sci., vol. 7, Sep. 2016, Art. no. 215232.

[4] H. T. Lin, Cherry Tomato 'TSS ASVEG No. 22'.Taiwan Seed Improvement and Propagation Station. Taichung, Taiwan: COA, 2017.

[5] E. Özbilge, M. K. Ulukök, Ö. Toygar, and E. Ozbilge, ‘‘Tomato disease recognition using a compact convolutional neural network,’’ IEEE Access, vol. 10, pp. 77213–77224, 2022.

[6] A. H. T. Rusli, B. C. C. Meng, N. S. Damanhuri, N. A. Othman, M. H. Othman, and W. F. A. W. Zaidi, ‘‘Potato leaf disease classification using image processing and artificial neural network,’’ in Proc. IEEE 12th Int. Conf. Control Syst., Comput. Eng. (ICCSCE), Oct. 2022, pp. 107–112.

[7] Q.-H. Phan, V.-T.Nguyen, C.-H.Lien, T.-P. Duong, M. T.-K. Hou, and N.-B. Le, ‘‘Classification of tomato fruit using YOLOv5 and convolutional neural network models,’’ Plants, vol. 12, no. 4, p. 790, Feb. 2023.

[8] P. Tim, A. Pranathi, K. SaiAshritha, N. B. Chittaragi, and S. G. Koolagudi, ‘‘Tomato leaf disease detection using convolutional neural networks,’’ in Proc. 11th Int. Conf. Contemp. Comput. (IC3), Aug. 2018, pp. 1–5.

[9] A. Dwivedi, A. Goel, M. Raju, D. Bhardwaj, A. Sharma, F. Kidwai, N. Gupta, Y. Sharma, and S. Tayal, ‘‘Precision agriculture: Using deep learning to detect tomato crop diseases,’’ in Proc. Int. Conf. Innov. Comput.Commun. Singapore: Springer, 2024, pp. 857–865.

[10] K. N. E A. Siddiquee, M. S. Islam, M. Y. U. Dowla, K. M. Rezaul, and V. Grout, ‘‘Detection, quantification and classification of ripened tomatoes: A comparative analysis of image processing and machine learning,’’ IET Image

Process., vol. 41, pp. 2442–2456, Sep. 2020.

[11] Mohanty, S. P., Hughes, D. P., &Salathé, M. (2016). Using deep learning for image-based plant disease detection.*Frontiers in Plant Science*.

[12] Wang, G., Sun, Y., & Wang, J. (2017). Automatic image-based plant disease severity estimation using deep learning.*Computational Intelligence and Neuroscience*.

[13] M. E. Haque, A. Rahman, I. Junaeid, S. U. Hoque, and M. Paul, "Rice leaf disease classification and detection using YOLOv5," *arXiv preprint arXiv:2209.01579*, Sep. 2022. [Online]. Available: https://arxiv.org/abs/2209.01579 Google Scholar+3

[14] S. A. Rashwan and M. K. Elteir, "Plant leaf disease detection using deep learning on mobile devices," *Int. J. Comput. Vis. Robot.*, vol. 12, no. 2, pp. 156–176, Feb. 2022. [Online]. Available: https://www.inderscience.com/info/inarticle.php?artid=121151Inderscience+1AC

[15] S. S. S. R. K. Reddy, B. V. R. Reddy, and B. R. Reddy, "Tomato plant leaf disease segmentation and multiclass disease detection using hybrid optimization enabled deep learning," *Computers and Electronics in Agriculture*, vol. 209, p. 107849, Sep. 2023. [Online]. Available: https://pubmed.ncbi.nlm.nih.gov/37543108/.

[16] M. A. A. Khandaker, Z. S. Raha, S. Islam, and T. Muhammad, "Explainable AI-enhanced deep learning for pumpkin leaf disease detection: A comparative analysis of CNN architectures," in *Proc. 27th Int. Conf. Comput. Inf. Technol. (ICCIT)*, Cox's Bazar, Bangladesh, Dec. 2024.