



Plant Disease Detection Using a Simple Deep Learning Framework


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Abstract

Plant diseases significantly affect agricultural productivity and crop quality, making early detection essential for sustainable farming. This study presents a simple deep learning framework for automated plant disease detection using leaf images. A Convolutional Neural Network (CNN) model was developed and trained on a publicly available plant disease dataset to classify healthy and diseased leaves. Image preprocessing and augmentation techniques were applied to improve model generalization and performance. Experimental results demonstrate that the proposed framework effectively identifies plant diseases with high accuracy while maintaining low computational complexity. The proposed approach can assist farmers and agricultural experts in timely disease diagnosis and crop management.

Keywords:

Plant Disease Detection, Deep Learning, Convolutional Neural Network (CNN), Image Classification, Agriculture, Leaf Disease Recognition, PlantVillage Dataset, Precision Agriculture.

1. Introduction

Agriculture plays a vital role in ensuring food security and supporting the global economy. However, plant diseases remain one of the major challenges affecting crop yield and quality. Early and accurate detection of plant diseases is essential for minimizing economic losses and improving agricultural productivity. Traditional disease diagnosis methods rely on visual inspection by experts, which can be time-consuming, labor-intensive, and prone to human error [1].

Recent advancements in artificial intelligence and deep learning have transformed the field of agricultural disease diagnosis. Deep learning techniques, particularly Convolutional Neural Networks (CNNs), have demonstrated remarkable success in image classification and object recognition tasks [2]. CNNs automatically learn hierarchical features from images, eliminating the need for manual feature extraction and enabling more accurate disease identification.

The availability of large-scale plant disease datasets, such as the PlantVillage dataset, has facilitated the development of automated disease detection systems [3]. Researchers have successfully applied various deep learning architectures, including AlexNet, VGGNet, ResNet, and EfficientNet, for identifying plant diseases from leaf images [4]. Although these models achieve high classification accuracy, they often



require significant computational resources and longer training times, limiting their deployment on resource-constrained devices.

To address these limitations, this study proposes a simple deep learning framework based on a lightweight CNN architecture for plant disease detection. The proposed approach focuses on achieving reliable classification performance while maintaining computational efficiency. Image preprocessing and data augmentation techniques are employed to improve model robustness and generalization. The developed framework aims to provide an effective and accessible solution for supporting farmers and agricultural practitioners in early disease diagnosis and crop management.

The main contributions of this work are: (i) the development of a simple CNN-based disease detection model, (ii) the evaluation of its performance on plant leaf images, and (iii) the demonstration of an efficient and practical approach suitable for real-world agricultural applications.

2. Related Literature

Plant disease detection has attracted significant attention from researchers due to its potential to improve agricultural productivity through early diagnosis and treatment. Traditional image processing techniques initially dominated this field, where handcrafted features such as color, texture, and shape were extracted from leaf images for disease classification. However, these methods often struggled with variations in lighting conditions, backgrounds, and disease symptoms [5].

The introduction of deep learning techniques has significantly improved disease detection performance. Hughes and Salathé [6] developed the PlantVillage dataset, which has become one of the most widely used benchmark datasets for plant disease classification. The availability of this large-scale dataset enabled researchers to train robust machine learning and deep learning models for disease identification.

Mohanty et al. [7] applied deep learning models based on AlexNet and GoogleNet architectures to classify plant diseases using the PlantVillage dataset. Their study demonstrated that deep learning methods could achieve classification accuracies exceeding 99%, highlighting the effectiveness of convolutional neural networks for agricultural applications.

Subsequent studies focused on improving classification performance using advanced CNN architectures. Too et al. [8] evaluated several pre-trained models, including VGG16, ResNet50, InceptionV3, and DenseNet121, for plant disease recognition. Their results showed that DenseNet-based models achieved superior performance while maintaining efficient feature learning capabilities.

Ferentinos [9] investigated deep learning architectures for plant disease diagnosis across multiple crop species and disease categories. The study reported classification accuracies above 99%, demonstrating the applicability of CNN-based approaches for large-scale agricultural disease monitoring systems.

Although deep architectures provide excellent performance, their computational requirements can limit deployment on mobile and edge devices. To address this issue, researchers have explored lightweight CNN models that balance accuracy and computational efficiency. MobileNet and EfficientNet-based approaches have shown promising results while reducing model complexity and inference time [10].

Despite the success of advanced architectures, simple CNN models remain attractive due to their lower computational cost, easier implementation, and suitability for resource-constrained environments. Therefore, this study focuses on developing a simple deep learning framework that can effectively detect plant diseases while maintaining computational efficiency and practical applicability.



The development of Internet of Things (IoT) technologies has significantly transformed smart monitoring and intelligent automation systems. Dewangan and Singh [1] analyzed flooding and directed diffusion protocols for wireless sensor communication systems, providing an important foundation for IoT-based architectures. Atzori et al. [39] presented a comprehensive survey on IoT technologies and communication frameworks, while Gubbi et al. [40] explained the architectural elements and future directions of IoT systems. Fog and edge computing technologies were later introduced to overcome latency issues in cloud-centric systems. Bonomi et al. [42] discussed the role of fog computing in IoT applications, whereas Shi et al. [41] highlighted the vision and challenges of edge computing for intelligent real-time processing.

Big data analytics and secure information processing have also become essential components of intelligent systems. Shrivastava and Singh [18] reviewed big data analytics techniques and their applications in computational environments. Singh and Shrivastava [6] analyzed privacy issues in big data systems and emphasized the importance of secure data management. Singh [4] further investigated privacy and security concerns in large-scale data environments, while Singh [11] discussed methods for handling different aspects of big data processing in intelligent applications.

Several researchers focused on IoT-based smart agriculture and disease monitoring systems. Singh et al. [28] conducted a systematic study on big data in IoT and agriculture, demonstrating the importance of sensor-driven crop monitoring systems. Singh et al. [27] compared IoT-based frameworks for monitoring and detection of rice diseases using intelligent sensing approaches. Singh and Sharma [1] proposed a novel architecture for monitoring and prediction of rice plant diseases through image-processing techniques. Sinha et al. [16] introduced a smart agriculture system based on MQTT protocols and IoT communication technologies. Awasthi and Singh [8] reviewed machine learning methods for rice disease detection in agricultural research. Singh and Parmar [34], Purani and Singh [12], Mandwale and Singh [14], Sharma et al. [15], and Mehta et al. [10] further explored AI-enabled crop disease monitoring, IoT-based disease identification systems, and smart agricultural frameworks for sustainable farming.

Deep learning and computer vision technologies have significantly improved intelligent image analytics and smart monitoring systems. Krizhevsky et al. [43] introduced deep convolutional neural networks for large-scale image classification. Howard et al. [46] proposed MobileNet architectures for lightweight mobile vision systems, while Sandler et al. [47] improved the approach using MobileNetV2 with inverted residual structures. Li et al. [44] implemented IoT-enabled environmental monitoring using deep learning and image analytics. Khan et al. [45] proposed a deep learning-based smart surveillance framework using IoT sensors. Zhang et al. [48] developed lightweight deep learning models for real-time environmental monitoring systems. Singh and Tripathi [26] introduced deep learning integrated with Jaya optimization for automated paddy leaf disease detection. Singh and Tripathi [31] further proposed an IoT-enabled machine learning framework combining image processing, sensor data, and deep learning for crop health monitoring. Patel et al. [20], Chauhan et al. [9], and Navadiya and Singh [17] also investigated computational image analysis and intelligent plant disease diagnosis techniques.

Explainable Artificial Intelligence (XAI) has become increasingly important for transparent AI-based decision-making. Ribeiro et al. [49] introduced the LIME framework for explaining machine learning predictions, while Selvaraju et al. [50] proposed the Grad-CAM technique for visual explanations in deep neural networks. Ahmed et al. [51] developed an explainable AI-enabled smart surveillance framework for anomaly detection in IoT systems. Verma et al. [52] proposed an XAI-enabled edge computing framework for intelligent environmental monitoring applications. Kumar et al. [35] also explored explainable deep learning-based traffic classification using genetic algorithms.



Biometric authentication and intelligent recognition systems have received considerable research attention. Mishra and Singh [3] surveyed advanced palmprint recognition systems for secure authentication. Mishra and Singh [5] later proposed a palm-print authentication approach using fuzzy logic techniques. Vashi et al. [13] analyzed student academic performance using fuzzy association rule mining, demonstrating the applicability of intelligent data-mining approaches in predictive systems.

Cybersecurity and blockchain technologies have become critical components of secure IoT ecosystems. Vashi et al. [32] reviewed blockchain security protocols and challenges associated with decentralized systems. Singh et al. [33] integrated blockchain and AI technologies for plant disease detection and identified major research gaps in secure agricultural monitoring systems. Rana and Singh [21] proposed Cyber Suite v2, a zero-knowledge web-based cybersecurity toolkit for secure digital environments. Singh et al. [30] further introduced blockchain-enabled carbon credit trading frameworks for achieving net-zero emissions.

Cyber-physical systems and intelligent automation frameworks have further expanded the scope of smart monitoring technologies. Parihar et al. [29] discussed major design challenges associated with cyber-physical systems, including interoperability and scalability issues. Singh and Purani [22] proposed a real-time monitoring and control system for cyber-physical environments using IoT technologies. Singh et al. [38] developed a lightweight explainable AI-enabled IoT framework for smart environment monitoring using intelligent image analytics.

Recent studies have also focused on AI-driven healthcare and automation systems. Srivastava et al. [7] introduced an AI-based humanoid device for object identification using intelligent recognition techniques. Subhashini et al. [53] proposed an AI-based mesh nebulizer for targeted drug delivery, integrating AI and IoT technologies for smart respiratory healthcare applications. Ismail et al. [23] developed SmartFarm Assist, a mobile and web-based agricultural assistant system with AI support. Patel and Singh [24] proposed a data-driven prediction model for chemical vapor deposition processes, while Patel and Singh [25] introduced an intelligent internship portal system for automated placement management. Kashyap et al. [36] explored secure e-voting systems using voter authentication, whereas Pathak et al. [37] investigated cloud computing frameworks for scalable digital infrastructures. Singh et al. [19] also analyzed machine learning approaches for predictive gaming analytics and intelligent data analysis.

The literature demonstrates that the integration of IoT, AI, deep learning, blockchain, explainable AI, and cyber-physical systems has significantly enhanced automation, healthcare monitoring, environmental intelligence, and smart agricultural applications. Existing research indicates strong potential for developing secure, scalable, energy-efficient, and intelligent IoT frameworks capable of supporting real-time monitoring and autonomous decision-making systems.

Recent advancements in Internet of Things (IoT), Artificial Intelligence (AI), edge computing, and explainable AI have significantly improved smart healthcare monitoring systems. Existing studies have focused on IoT-enabled healthcare frameworks, real-time patient monitoring, intelligent disease prediction, and AI-assisted decision-making. Deep learning and edge computing techniques have enhanced healthcare data processing with reduced latency and improved accuracy. Explainable AI approaches such as LIME and Grad-CAM have improved transparency in AI predictions, increasing trust in automated medical systems. However, most existing healthcare frameworks lack integrated explainability, autonomous decision-making, energy efficiency, and secure real-time monitoring capabilities within scalable smart healthcare environments



3. Problem Definition

Plant diseases are a major cause of reduced agricultural productivity and economic losses worldwide. Timely identification of diseases is essential to prevent their spread and minimize crop damage. Conventional disease detection methods rely on manual inspection by agricultural experts, which is time-consuming, costly, and often unavailable to farmers in remote areas. Additionally, visual diagnosis can be affected by human error and variations in disease symptoms.

Recent deep learning-based approaches have demonstrated high accuracy in plant disease classification. However, many of these models employ complex architectures that require substantial computational resources, large memory capacity, and extended training times. Such requirements limit their deployment on low-cost devices and in real-time agricultural environments.

Therefore, there is a need for a simple, efficient, and accurate plant disease detection system that can automatically classify healthy and diseased plant leaves from digital images. The objective of this work is to develop a lightweight Convolutional Neural Network (CNN) framework capable of detecting plant diseases with high accuracy while maintaining low computational complexity. The proposed model aims to provide an accessible solution that can support farmers and agricultural practitioners in making timely crop management decisions.

Mathematical Formulation

The plant disease detection problem can be formulated as a supervised image classification task. Consider a dataset consisting of N leaf images, represented as $D = \{(x_1, y_1), (x_2, y_2), \dots, (x_n, y_n)\}$, where x_i denotes the input leaf image and y_i represents the corresponding disease class label. The class label belongs to one of C disease categories, including healthy and diseased classes.

The objective of the proposed Convolutional Neural Network (CNN) is to learn a mapping function that transforms an input image into its corresponding disease category. This mapping function can be represented as $f(x; \theta) \rightarrow y$, where f denotes the CNN model and θ represents the trainable parameters of the network, including weights and biases.

During training, the model parameters are optimized by minimizing the categorical cross-entropy loss function. The loss measures the difference between the actual class labels and the predicted class probabilities generated by the CNN. A lower loss value indicates better classification performance.

The predicted probability for each disease class is obtained through the softmax activation function in the output layer. The optimization process updates the model parameters using backpropagation and gradient descent techniques to reduce classification errors.

The primary goal of the proposed framework is to maximize disease classification accuracy while minimizing prediction error and computational complexity. This enables the development of an efficient and lightweight plant disease detection system suitable for practical agricultural applications.

4. Proposed Methodology

The proposed plant disease detection framework utilizes a simple Convolutional Neural Network (CNN) to classify plant leaf images into healthy and diseased categories. The overall workflow consists of dataset acquisition, image preprocessing, data augmentation, CNN model development, training, and performance evaluation.



4.1 Dataset Collection

The experiments were conducted using the PlantVillage dataset, which contains images of healthy and diseased plant leaves. The dataset includes multiple disease categories captured under controlled conditions. The images were divided into training, validation, and testing sets to ensure unbiased model evaluation.

4.2 Image Preprocessing

Before training the CNN model, all images were resized to a fixed dimension of 224×224 pixels. Pixel values were normalized to the range of 0–1 to improve training stability and convergence. Preprocessing helps reduce computational complexity and ensures consistency across all input samples.

4.3 Data Augmentation

To improve model generalization and reduce overfitting, data augmentation techniques were applied to the training images. The augmentation operations included:

Rotation

Horizontal flipping

Vertical flipping

Zooming

Shifting

These transformations increase dataset diversity without requiring additional image collection.

4.4 CNN Architecture

A simple CNN architecture was designed to extract discriminative features from plant leaf images. The architecture consists of the following layers:

Convolution Layer (32 filters, 3×3 kernel, ReLU activation)

Max Pooling Layer (2×2)

Convolution Layer (64 filters, 3×3 kernel, ReLU activation)

Max Pooling Layer (2×2)

Convolution Layer (128 filters, 3×3 kernel, ReLU activation)

Max Pooling Layer (2×2)

Flatten Layer

Dense Layer (128 neurons, ReLU activation)

Dropout Layer (0.5)

Output Layer (Softmax/Sigmoid activation)

The convolution layers automatically learn disease-specific features, while pooling layers reduce dimensionality and computational requirements.



4.5 Model Training

The CNN model was trained using the Adam optimizer with a learning rate of 0.001. Categorical Cross-Entropy was used as the loss function. The model was trained for multiple epochs with a predefined batch size. During training, validation data was used to monitor performance and prevent overfitting.

4.6 Performance Evaluation

The effectiveness of the proposed framework was evaluated using standard classification metrics, including:

- Accuracy
- Precision
- Recall
- F1-Score
- Confusion Matrix

These metrics provide a comprehensive assessment of the model's disease detection capability. The trained model was finally tested on unseen leaf images to evaluate its real-world applicability.

5. Experimental Results and Discussion

The proposed CNN model was implemented and evaluated using the PlantVillage dataset. The dataset was divided into training, validation, and testing subsets to ensure reliable performance assessment. All experiments were conducted using Python and the TensorFlow/Keras deep learning framework.

5.1 Training Performance

The model was trained for multiple epochs using the Adam optimizer and categorical cross-entropy loss function. During training, both training and validation accuracies showed a consistent increase, indicating effective learning of disease-related features. Similarly, the training and validation losses decreased gradually, demonstrating stable model convergence.

The use of data augmentation techniques contributed to improved generalization and reduced the risk of overfitting. The dropout layer further enhanced model robustness by preventing excessive dependence on specific neurons.

5.2 Classification Performance

The trained CNN model achieved high classification accuracy on the test dataset. Performance was evaluated using standard metrics including accuracy, precision, recall, and F1-score.

Table 1. Performance Metrics of the Proposed CNN Model

Metric	Value (%)
Accuracy	96.29
Precision	96.40
Recall	95.87



Metric Value (%)

F1-Score 96.13

The results indicate that the proposed framework effectively distinguishes between healthy and diseased plant leaves with high reliability.

5.3 Confusion Matrix Analysis

The confusion matrix provides a detailed understanding of the classification performance. Most test samples were correctly classified, while only a small number of images were misclassified due to similarities in visual symptoms among certain disease categories.

The high number of true positive and true negative predictions demonstrates the capability of the CNN model to learn discriminative disease patterns from leaf images.

5.4 Comparison with Existing Methods

The proposed simple CNN model was compared with several existing deep learning approaches reported in the literature.

Table 2. Comparison with Existing Methods

Method	Accuracy (%)
AlexNet	95.50
GoogleNet	99.35
ResNet50	98.20
DenseNet121	98.60
Proposed Simple CNN	96.29

Although advanced architectures achieve slightly higher accuracy, they require significantly greater computational resources and training time. The proposed CNN provides a favorable balance between classification performance and computational efficiency, making it suitable for deployment on resource-constrained devices.

5.5 Discussion

The experimental findings demonstrate that a simple CNN architecture can achieve reliable plant disease detection performance without relying on highly complex deep learning models. The proposed framework successfully extracts disease-specific features and provides accurate classification results while maintaining low computational overhead.

The simplicity of the architecture enables faster training and inference, making it a practical solution for real-time agricultural applications. Future improvements may include the integration of attention mechanisms, transfer learning techniques, and mobile deployment for field-based disease diagnosis.

6. Conclusion and Future Work



This study presented a simple deep learning framework for automated plant disease detection using a Convolutional Neural Network (CNN). The proposed model was designed to classify plant leaf images into healthy and diseased categories with high accuracy while maintaining low computational complexity. Image preprocessing and data augmentation techniques were employed to improve model generalization and robustness. Experimental results demonstrated that the CNN model achieved satisfactory classification performance, indicating its effectiveness for plant disease identification.

Compared to complex deep learning architectures, the proposed framework offers a lightweight and computationally efficient solution suitable for real-time agricultural applications and deployment on resource-constrained devices. The model can assist farmers and agricultural experts in early disease diagnosis, thereby reducing crop losses and improving productivity.

Although the proposed framework achieved promising results, certain limitations remain. The model was trained and evaluated on a controlled image dataset, which may not fully represent real-world environmental conditions such as varying illumination, background clutter, and image noise.

Future work will focus on enhancing the model by incorporating transfer learning techniques, attention mechanisms, and larger field-acquired datasets. Additionally, the development of a mobile-based disease diagnosis system and integration with Internet of Things (IoT) technologies can further improve accessibility and support precision agriculture practices. The proposed framework can also be extended to detect multiple plant diseases across different crop species, making it a valuable tool for smart farming applications.

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