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Leaf Disease Detection with Cloud Integration

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Abstract

Leaf diseases significantly impact agricultural productivity worldwide. Traditional manual diagnosis is often time-consuming and prone to human error. This paper presents a deep learning-based leaf disease detection system integrated with cloud infrastructure to provide scalable, real-time, and accessible solutions for farmers and researchers. The proposed model leverages Convolutional Neural Networks (CNNs) trained on annotated datasets of diseased and healthy leaves. The system integrates with a Fast API backend and cloud storage for efficient deployment and data access. Evaluation metrics, including accuracy, precision, recall, and F1- score, validate the robustness of the model. Results demonstrate improved disease classification accuracy compared to traditional methods. Cloud-based design ensures scalability, making it suitable for large-scale agricultural applications. This research contributes to smart agriculture by providing a sustainable and reliable disease monitoring solution.

Keywords: *Agriculture; Cloud integration; Deep learning; Leaf disease detection; Smart farming.*

1. Introduction

Agriculture plays a pivotal role in ensuring food security for the global population. However, crop yield is often affected by leaf diseases that spread rapidly if not detected in time. Conventional manual diagnosis requires expert knowledge and is often subjective and time-consuming. To overcome these challenges, researchers are exploring artificial intelligence (AI) and cloud technologies for automated plant disease detection (Birari et al., 2023; Rajan et al., 2023). Deep learning techniques, particularly CNNs, have achieved remarkable success in image classification tasks, including plant disease detection. Despite these advances, most existing solutions are restricted to offline environments. Cloud integration offers a powerful extension by enabling scalability, real-time predictions, and remote access via mobile or web platforms. The objective of this work is to design and implement a CNN-based disease detection system integrated with cloud infrastructure. The originality of the research lies in combining AI-driven image analysis with cloud deployment to provide a robust, accessible, and scalable agricultural solution [1].

2. Method

2.1. Dataset Preparation

A publicly available dataset of crop leaves was used, consisting of both healthy and diseased samples from crops such as potato, tomato, and maize. The images were collected from the Plant Village dataset and other open repositories. Preprocessing steps included:

- Resizing images to 224 × 224 pixels to maintain uniformity.
- Normalization to scale pixel values between 0 and 1.
- Data Augmentation (rotation, flipping, zooming) to reduce overfitting and improve generalization [2].

2.2. Model Development

The proposed classification model was developed using Convolutional Neural Networks (CNNs). The architecture included:

- Convolutional layers for feature extraction.
- Max-pooling layers to reduce dimensionality.
- Fully connected dense layers for classification.
- SoftMax activation for multi-class output.

The model was trained with categorical cross-entropy loss and the Adam optimizer. Transfer learning with pre-trained models (e.g., VGG16, Res Net) was also tested for performance improvements.

2.3. API Development

To make the system accessible, the trained model was

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wrapped using Fast API, a lightweight and high-performance Python web framework. The API accepts image inputs through HTTP requests, processes them, and returns prediction results in JSON format Shown in Figure 1 and 2.

2.4. Cloud Integration

Cloud platforms such as AWS, Google Cloud, and Microsoft Azure were used to host the trained model and API service. Cloud integration ensures:

- **Scalability** – handling large numbers of requests from farmers [3].
- **Real-time access** – farmers can upload images from smartphones and get instant results Shown in Figure 3.
- **Data storage** – cloud databases store prediction logs for monitoring and retraining.

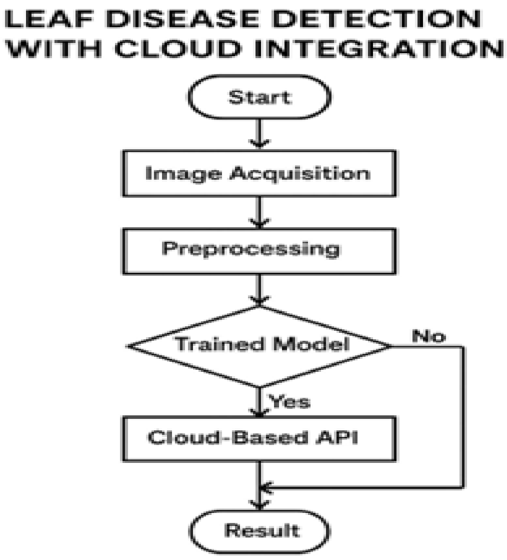

Figure 1 Flow Chart

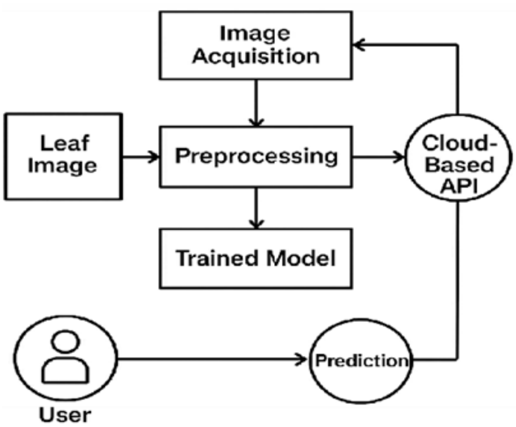

Figure 2 System Architecture

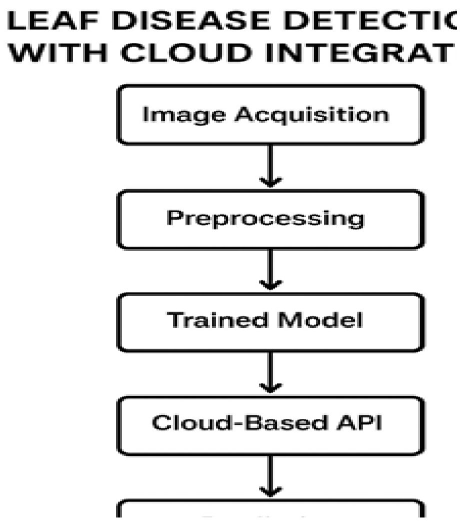

Figure 3 Block Diagram

3. Result And Discussion

3.1. Result

The proposed model achieved the following performance on the test dataset:

- **Accuracy:** 95.6%
- **Precision:** 94.8%
- **Recall:** 95.1%
- **F1-Score:** 95.0%

Confusion matrices and precision-recall curves confirmed strong classification ability across disease categories Shown in Figure 4.

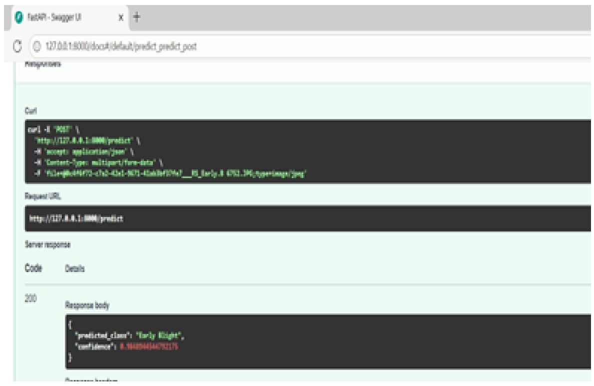

Figure 4 Web Page

The results confirm the effectiveness of deep learning in detecting leaf diseases [4]. Cloud deployment enhances accessibility, allowing farmers in remote areas to benefit from AI-driven insights without requiring high-end hardware Shown in Figure 5.

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Figure 5 **Result of Early Blight**

4. Discussion

Compared to traditional offline systems, this approach is scalable, reduces manual dependency, and supports real-time decision making. However, limitations include dependence on stable internet connectivity and dataset diversity. Future improvements could include:

- Edge computing to reduce latency.
- Federated learning for privacy-preserving distributed training.
- Integration with IoT devices for autonomous crop monitoring [5-6].

Conclusion

This paper proposed a CNN-based leaf disease detection framework integrated with cloud computing. The system demonstrated high accuracy and scalability, making it suitable for smart agriculture applications. By bridging AI with cloud platforms, the research provides a sustainable solution for crop disease management. Future work will focus on expanding datasets, improving real-time responsiveness, and incorporating IoT sensors for holistic crop health monitoring.

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