

Identification Of Plant Leaf Disease Using Deep Learning Algorithm

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ABSTRACT

Plant diseases significantly affect agricultural productivity and crop quality, leading to substantial economic losses for farmers worldwide. Early and accurate identification of plant leaf diseases is essential for effective crop management and disease prevention. Traditional disease detection methods rely on manual inspection by agricultural experts, which can be time-consuming, labor-intensive, and prone to human error. This project presents an automated plant leaf disease identification system using Deep Learning techniques, specifically Convolutional Neural Networks (CNNs). The proposed model is trained on a dataset containing healthy and diseased tomato leaf images, including Bacterial Spot, Early Blight, Tomato Mosaic Virus, and Healthy leaves. Image preprocessing and augmentation techniques are applied to improve model performance and generalization. The CNN model automatically extracts important features from leaf images and classifies them into their respective disease categories. Experimental results demonstrate high classification accuracy of approximately 97.5% on the test dataset, indicating the effectiveness of the proposed approach. The developed system provides a fast, reliable, and cost-effective solution for plant disease diagnosis, helping farmers take timely preventive measures and improve crop yield and quality.

Keywords: Plant Leaf Disease Detection, Deep Learning, Convolutional Neural Networks (CNN), Image Processing, Agricultural Automation, Disease Classification, Computer Vision, Precision Agriculture.

I. INTRODUCTION

Agriculture plays a vital role in the economy of many countries by providing food, employment, and raw materials for various industries. Plant diseases are one of the major challenges faced by farmers, as they can significantly reduce crop yield and quality if not detected and treated at an early stage. Traditionally, disease identification is performed through visual inspection by agricultural experts, which requires extensive knowledge and experience. However, this process is often time-consuming, expensive, and not always accessible to farmers in remote areas. With the rapid advancement of Artificial Intelligence (AI) and Deep Learning technologies, automated disease detection systems have emerged as an effective solution for improving agricultural productivity.

Deep Learning, particularly Convolutional Neural Networks (CNNs), has shown remarkable success in image classification and object recognition tasks. CNNs can automatically learn complex features from images without requiring manual feature extraction, making them highly suitable for plant disease identification. In this project, a CNN-based model is developed to detect and classify diseases in tomato plant leaves using image data. The dataset consists of four classes: Tomato Bacterial Spot, Tomato Early Blight, Tomato Mosaic Virus, and Healthy leaves. The model is trained using thousands of labeled leaf images and

evaluated on separate validation and test datasets. The experimental results achieve an accuracy of 97.5%, demonstrating the capability of deep learning techniques in accurately identifying plant diseases. The proposed system can assist farmers and agricultural experts by providing quick and accurate disease diagnosis, enabling timely treatment and reducing crop losses

II. LITERATURE SURVEY

Plant disease detection has attracted significant attention from researchers due to its importance in improving agricultural productivity. Mohanty et al. [1] utilized deep learning models such as AlexNet and GoogleNet on the PlantVillage dataset and demonstrated that convolutional neural networks can effectively classify plant diseases from leaf images. Ferentinos [2] further investigated deep CNN architectures and achieved classification accuracy exceeding 99%, proving the effectiveness of deep learning in agricultural image analysis. Too et al. [3] conducted a comparative study among VGG16, ResNet50, DenseNet, and Inception architectures and reported that transfer learning significantly improves disease classification performance.

Brahimi et al. [4] focused specifically on tomato leaf disease identification and employed image preprocessing and augmentation techniques to enhance CNN performance. Similarly, Sladojevic et al. [5] proposed a deep neural network model capable of automatically extracting disease-

specific features from leaf images and demonstrated superior performance compared with traditional machine learning approaches. Rahman et al. [6] introduced transfer learning-based CNN models for plant disease identification and reported improved classification accuracy with reduced training requirements.

Amara et al. [7] applied deep learning techniques for banana leaf disease classification, while Ramesh and Vydeki [8] proposed an optimized deep neural network for paddy leaf disease recognition. Both studies confirmed the effectiveness of deep learning approaches for crop disease diagnosis. Picon et al. [9] developed deep convolutional neural networks suitable for mobile-based crop disease detection systems, enabling real-time disease monitoring in agricultural fields. Liu et al. [10] applied CNN models for apple leaf disease identification and achieved promising classification performance.

The success of these disease detection systems is largely attributed to advancements in deep learning architectures. LeCun et al. [11] established the foundations of deep learning, while Krizhevsky et al. [12] introduced AlexNet, which significantly improved image classification performance. Simonyan and Zisserman [13] proposed VGG16, and He et al. [14] introduced ResNet, both of which have become widely used in plant disease classification applications. EfficientNet proposed by Tan and Le [15] further

improved classification efficiency through model scaling techniques, whereas Chollet [16] introduced Xception architecture using depthwise separable convolutions for enhanced feature extraction.

The theoretical foundations of deep learning are extensively discussed by Goodfellow et al. [17], who provide detailed explanations of neural network architectures, optimization techniques, and representation learning. Bishop [18] presents fundamental concepts in pattern recognition and machine learning that underpin modern classification systems.

Image preprocessing and enhancement techniques play an important role in disease detection systems. Gonzalez and Woods [19] provide comprehensive coverage of digital image processing methods, including filtering, segmentation, and feature extraction. Additionally, Russell and Norvig [20] discuss artificial intelligence principles and intelligent decision-making systems that support the development of automated agricultural applications.

Despite significant progress in plant disease identification, existing studies still face challenges related to computational complexity, dataset dependency, environmental variations, and model generalization. Therefore, there is a need for an efficient deep learning framework capable of providing accurate, scalable, and

real-time plant disease diagnosis for smart agricultural applications.

III. COMPARATIVE STUDY OF EXISTING METHODS

A comparative analysis of existing plant disease detection approaches indicates that deep learning models consistently outperform traditional machine learning techniques. Transfer learning architectures such as VGG16, ResNet50, DenseNet, and EfficientNet have demonstrated superior feature extraction capabilities and classification accuracy compared with manually engineered feature-based approaches. Among the reviewed studies, Ferentinos [2] achieved accuracy greater than 99% using deep CNN architectures, while Too et al. [3] reported improved performance through transfer learning techniques. Mobile-oriented approaches proposed by Picon et al. [9] enable practical field deployment, whereas EfficientNet-based models [15] provide a better balance between computational cost and prediction accuracy. Based on this comparative analysis, CNN-based architectures remain the most effective solution for automatic plant leaf disease identification.

IV. EXISTING SYSTEM

The existing plant leaf disease detection systems mainly rely on traditional machine learning techniques and manual inspection by agricultural experts. In these approaches, farmers capture images of affected leaves, and experts analyze the symptoms visually

to identify the disease. Some automated systems use image processing techniques such as colour, texture, and shape feature extraction, followed by conventional classifiers like Support Vector Machine (SVM), Decision Tree, K-Nearest Neighbour (KNN), and Artificial Neural Networks (ANN). These methods require manual feature engineering, where relevant features must be selected and extracted before classification. As a result, the accuracy and reliability of disease detection depend heavily on the quality of extracted features and expert knowledge. Although these systems provide some level of automation, they often struggle with complex disease patterns, varying environmental conditions, and large-scale datasets.

V. PROPOSED SYSTEM

The proposed system utilizes Deep Learning techniques, specifically Convolutional Neural Networks (CNNs), for automatic plant leaf disease identification. The system is trained using a large dataset of tomato leaf images containing both healthy and diseased samples, including Bacterial Spot, Early Blight, and Tomato Mosaic Virus. Unlike traditional approaches, CNN automatically extracts important features from images without requiring manual feature engineering. The leaf images are preprocessed and augmented to improve model generalization and robustness. The trained CNN model learns disease-specific

patterns and accurately classifies leaf images into their corresponding categories. Experimental results show that the proposed model achieves a test accuracy of approximately 97.5%, demonstrating its effectiveness in disease detection. The system provides fast, reliable, and accurate predictions, enabling farmers to take timely preventive measures and improve crop productivity.

VI. SYSTEM ARCHITECTURE

The system architecture of the Plant Leaf Disease Identification Using Deep Learning project consists of several stages that work together to accurately detect and classify diseases in tomato plant leaves. Initially, a large dataset of tomato leaf images is collected, containing four classes: Bacterial Spot, Early Blight, Tomato Mosaic Virus, and Healthy leaves. The collected images are then passed through a preprocessing stage where image resizing, normalization, and data augmentation techniques such as rotation, flipping, and zooming are applied. These preprocessing steps improve image quality and increase dataset diversity, helping the model learn better features.

After preprocessing, the dataset is divided into training, validation, and testing sets. The processed images are fed into a Convolutional Neural Network (CNN) model consisting of convolution layers, max-pooling layers, a flatten layer, dense layers, and a dropout layer. The convolution layers automatically extract important

features from leaf images, while the pooling layers reduce dimensionality and computational complexity. The extracted features are then passed through fully connected layers, where the final classification is performed using a Softmax activation function. The trained model learns disease-specific patterns and is evaluated using performance metrics such as accuracy, precision, recall, and F1-score.

Once the model training is completed, the trained CNN model is saved and used for disease prediction. When a user uploads a new leaf image, the image undergoes the same preprocessing steps and is provided as input to the trained model. The model automatically extracts features, performs classification, and predicts whether the leaf is healthy or affected by a disease. Finally, the system displays the predicted disease name, leaf status (healthy or diseased), confidence score, and class probabilities. This architecture enables fast, accurate, and automated plant disease detection, assisting farmers in early diagnosis and effective crop management

outputs are subsequently processed by the AFAU, which applies nonlinear activation functions such as sigmoid or tanh to generate the final neuron outputs. All three units operate in a pipelined manner, allowing simultaneous execution of different tasks and maximizing hardware utilization. The tile-based strategy significantly reduces memory access

overhead, while the pipelined architecture improves throughput and minimizes latency. This scalable design enables efficient processing of large neural networks while maintaining low power consumption and high performance on FPGA devices.

The complete implementation workflow consists of the following steps:

1. Dataset Collection
2. Image Preprocessing
3. Data Augmentation
4. Dataset Loading
5. CNN Model Construction
6. Model Compilation
7. Model Training
8. Model Evaluation
9. Performance Analysis
10. Model Saving
11. Disease Prediction

The implementation successfully developed a CNN-based tomato leaf disease classification system capable of identifying Bacterial Spot, Early Blight, Tomato Mosaic Virus, and Healthy leaves with high accuracy and reliability

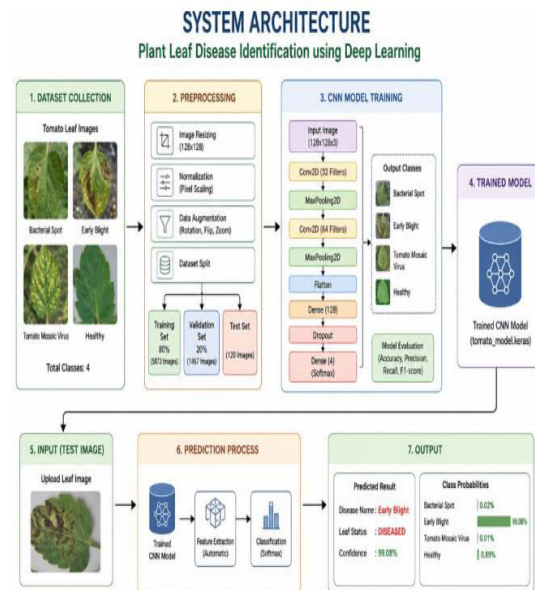


Fig 6.1: System Architecture

VII. IMPLEMENTATION

Fig 7.1: Representative samples from the tomato leaf disease dataset showing four classes: Bacterial Spot, Early Blight, Tomato Mosaic Virus, and Healthy leaves. The images illustrate variations in disease symptoms and leaf appearance used for CNN-based classification

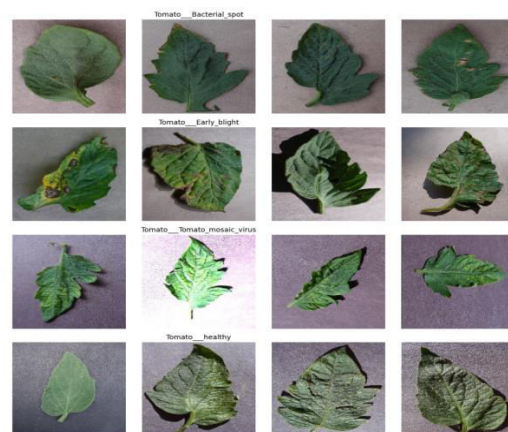


Fig 7.1 Data set

The Fig 7.2 illustrates the performance of Training and validation accuracy and loss curves of the CNN model over 10 epochs. The increasing accuracy and decreasing loss values indicate successful model learning, good convergence, and strong generalization performance for tomato leaf disease classification.

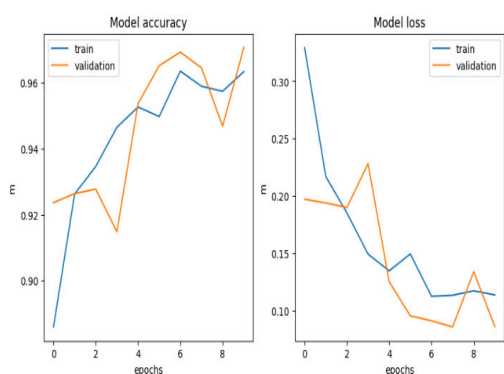


Fig 7.2 Training results

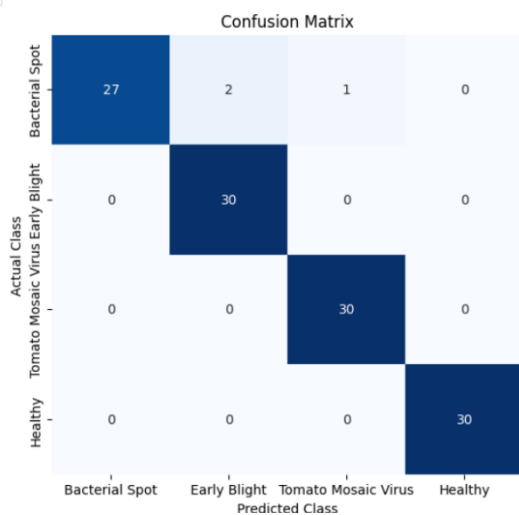


Fig 7.3 Confusion Matrix

Fig 7.3 Confusion matrix of the CNN model for tomato leaf disease classification. The

model correctly classified 117 out of 120 test samples, achieving an overall accuracy of 97.5%. Most misclassifications occurred within the Bacterial Spot class, while Early Blight, Tomato Mosaic Virus, and Healthy leaves were classified with 100% accuracy.

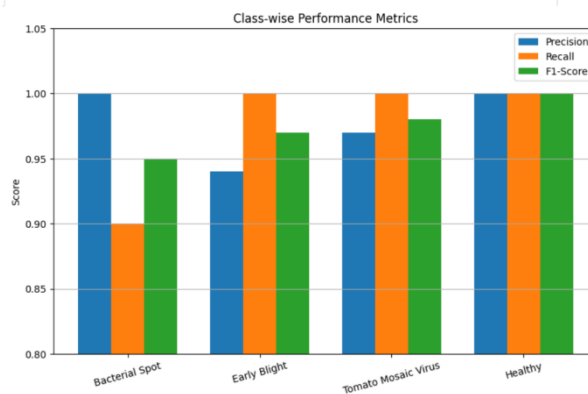


Fig 7.4 Bar Graph Results

The Fig 7.4 shows Class-wise Precision, Recall, and F1-Score of the CNN model for tomato leaf disease classification.

The class-wise performance metrics confirm that the proposed CNN model provides robust and accurate classification across all disease categories. The high Precision values indicate a low false-positive rate, while the high Recall values demonstrate the model's ability to correctly identify diseased leaves. The F1-Scores ranging from 95% to 100% highlight the balanced and reliable performance of the model, making it suitable for practical tomato disease diagnosis applications.

The overall evaluation in Fig 7.5 confirms that the CNN-based approach is highly suitable for automated tomato leaf disease

diagnosis. With performance metrics above 97%, the model can accurately identify disease symptoms from leaf images and support early disease management in agricultural environments. Such high-performance results indicate the potential for practical deployment in smart farming and precision agriculture applications.

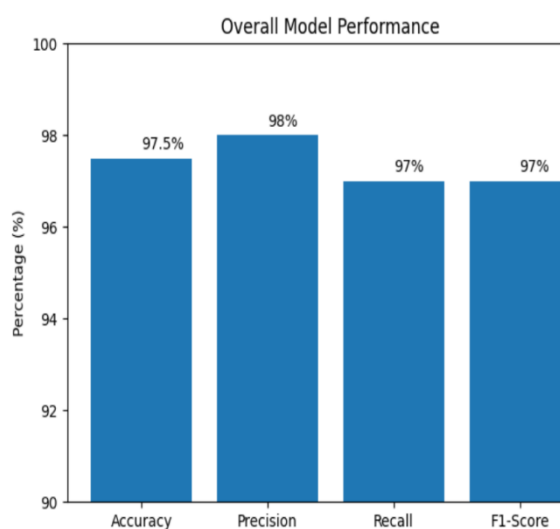


Fig 7.5 Model Performance

VIII. CONCLUSION

The **Plant Leaf Disease Identification Using Deep Learning Algorithm** project successfully demonstrates the effectiveness of Convolutional Neural Networks (CNNs) in detecting and classifying diseases from tomato leaf images. The proposed system automates the disease diagnosis process by analyzing leaf images and identifying whether they are healthy or affected by diseases such as Bacterial Spot, Early Blight, and Tomato Mosaic Virus. Through image preprocessing, data augmentation, and deep feature extraction, the CNN model achieves

high classification performance with an accuracy of approximately **97.5%**. The developed system reduces the dependency on manual inspection and agricultural experts while providing fast, reliable, and accurate disease predictions. Early detection of plant diseases enables farmers to take timely preventive measures, minimize crop losses, and improve overall agricultural productivity. Therefore, the proposed deep learning-based approach serves as an efficient and cost-effective solution for modern smart agriculture and precision farming applications.

IX. FUTURE SCOPE

The future scope of the Plant Leaf Disease Identification Using Deep Learning Algorithm project is extensive and can significantly contribute to the advancement of smart agriculture. The current system is limited to the classification of a few tomato leaf diseases; however, it can be extended to detect diseases in multiple crop species by training the model on larger and more diverse datasets. Advanced deep learning architectures such as ResNet, EfficientNet, and Vision Transformers (ViTs) can be integrated to further improve detection accuracy and robustness. The system can also be deployed as a mobile application, enabling farmers to capture leaf images using smartphones and receive instant disease diagnosis in real time. Additionally, integration with Internet of Things (IoT) devices, drones, and cloud-based platforms

can facilitate large-scale crop monitoring and automated disease surveillance. Future enhancements may include disease severity estimation, treatment recommendations, pesticide suggestions, and multilingual support to make the system more practical and accessible for farmers worldwide. These improvements will help promote precision agriculture, reduce crop losses, and enhance food production sustainability.

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