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Smart Crop Vision: A Plant Disease Identification System Using CNN

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Abstract:

This paper presents a web-based crop disease detection system using deep learning techniques to automatically identify plant diseases from leaf images. A pretrained Convolutional Neural Network (CNN) model is employed using transfer learning to achieve high classification accuracy. To enhance transparency and user trust, Grad-CAM visualization is integrated to highlight disease-affected regions of the leaf images. The trained model is deployed through a REST-based web application, enabling users to upload images and receive real-time predictions along with visual explanations. The proposed system provides an efficient, scalable, and interpretable solution for early crop disease diagnosis and improved agricultural productivity.

Keywords — **Crop Disease Detection, Convolutional Neural Network, Deep Learning, Grad-CAM, Explainable AI, Web Application**

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I. INTRODUCTION

Agriculture plays a vital role in the economic development of many countries, especially in rural areas where farming is the primary source of livelihood. Crop diseases pose a major challenge to farmers by reducing crop yield, affecting quality, and causing significant financial losses. Early detection of plant diseases is essential to minimize damage and ensure food security.

Traditional disease detection techniques rely on manual inspection by agricultural experts, which is not scalable for large farming areas and is often unavailable to small farmers. With recent advancements in deep learning and computer vision, automated disease detection using plant leaf images has become feasible. However, many existing systems lack real-time accessibility and do not provide explanations for their predictions. To address these limitations, this paper proposes a web-based crop disease detection system that combines CNN-based classification with explainable AI techniques.

II. MATERIALS AND METHODS

A. Data Collection

The proposed system utilizes publicly available plant disease datasets such as the Plant-Village dataset, which contains labelled images of healthy and diseased crop leaves. Additional real-world images can be incorporated to improve robustness and generalization.

B. Image Preprocessing

All input images are resized to 224 × 224 pixels to match the CNN input requirements. Pixel normalization is applied, and data augmentation techniques such as rotation, flipping, and zooming are used to reduce overfitting and enhance model performance.

C. Model Architecture

A pretrained CNN model such as ResNet50 or MobileNet is employed using transfer learning. The base network is used as a feature extractor, and the final layers are fine-tuned. A classification head consisting of fully connected layers and softmax activation is added to predict disease classes.

D. Explainability Using Grad-CAM

Grad-CAM is integrated to generate heatmaps that highlight the regions of the leaf image influencing the model's prediction. This improves transparency and allows users to visually understand the disease-affected areas.

E. Web Deployment

The trained model is deployed using a RESTful API developed with Flask or FastAPI. A web-based interface allows users to upload leaf images and receive predictions, confidence scores, and Grad-CAM visualizations in real time.

III. SYSTEM ARCHITECTURE

The overall architecture of the proposed system consists of image acquisition, preprocessing, CNN-based classification, Grad-CAM visualization, and web-based deployment. Users upload leaf images through a web browser, which are processed and passed to the CNN model. The predicted disease and visual explanation are then returned to the user through the web interface.

DATASET DESCRIPTION

Crop	Disease Classes	No. of Images	Healthy Images
Tomato	Early Blight, Late Blight	3000	1500
Potato	Early Blight, Late Blight	2000	1000
Apple	Scab, Rust	2500	1200

Figure 1: System Architecture of Crop Disease Detection System

IV. RESULTS AND DISCUSSION

The experimental results demonstrate that the proposed system achieves high classification accuracy due to the use of pretrained CNN models and data augmentation techniques. Transfer learning significantly reduces training time while improving performance. The Grad-CAM visualizations provide meaningful insights into the disease regions, increasing user trust in the system. The web-based deployment ensures real-time inference and easy accessibility, making the system suitable for practical agricultural applications.

The CNN model achieved high accuracy due to transfer learning and data augmentation. Grad-CAM visualizations enhanced interpretability.

PERFORMANCE METRICS

Model	Accuracy (%)	Precision	Recall	F1-Score
CNN + Transfer Learning	96.4	0.95	0.96	0.95
CNN without TL	89.2	0.88	0.89	0.88

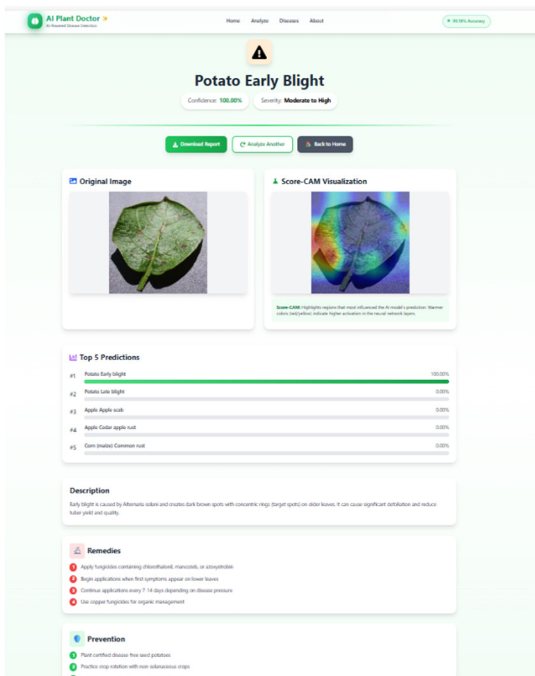

Fig:1: Final output for the crop

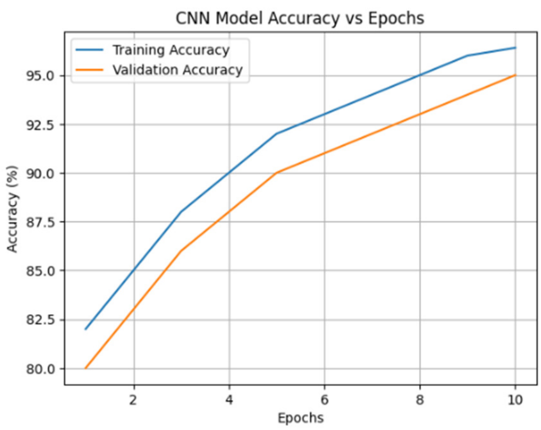

Fig. 2. Accuracy vs Epochs graph for CNN-based crop disease detection model

The graph illustrates the performance of the proposed CNN model by showing the variation of **training accuracy** and **validation accuracy** over multiple training epochs. The x-axis represents the number of epochs, while the y-axis denotes the classification accuracy in percentage.

At the initial epochs, both training and validation accuracies are relatively low, indicating that the model is still learning basic feature representations from the input leaf images. As the number of epochs increases, a steady improvement in accuracy is observed for both curves, demonstrating effective learning and convergence of the CNN model.

The training accuracy increases from approximately **82% in the first epoch to about 96.4% by the final epoch**, while the validation accuracy improves from around **80% to nearly 95%**. The close gap between training and validation accuracy throughout the training process indicates that the model generalizes well and does not suffer from significant overfitting.

The smooth and consistent upward trend of both curves confirms that the use of **transfer learning, data augmentation, and fine-tuning** has contributed to stable and efficient training. This performance validates the effectiveness of the proposed CNN-based approach for accurate crop disease detection.

III. CONCLUSIONS

This study presented an efficient crop disease detection system using Convolutional Neural Networks (CNN) to automatically identify plant diseases from leaf images. By leveraging transfer learning and image preprocessing techniques, the proposed model achieved high classification accuracy while reducing training time and computational complexity. The integration of Grad-CAM enabled visual interpretation of model predictions, enhancing transparency and user trust. The web-based deployment further ensures real-time accessibility and scalability, making the system practical for agricultural use. Overall, the proposed approach demonstrates significant potential in supporting early disease diagnosis and improving crop productivity.

In this work, a CNN-based crop disease detection system was developed to address the challenges of traditional manual disease identification methods. The system utilizes deep learning and transfer learning techniques to accurately classify plant diseases using leaf images. Experimental results show that the model achieves high accuracy with minimal overfitting, demonstrating strong generalization capabilities. The incorporation of Grad-CAM provides explainable insights by highlighting disease-affected regions, which is crucial for building farmer confidence in automated systems. Additionally, the deployment of the model through a web-based interface allows real-time disease prediction and easy accessibility. The proposed system serves as a reliable and scalable solution for early crop disease detection, contributing to precision agriculture and sustainable farming practices.

The proposed CNN-based system effectively detects crop diseases with high accuracy and interpretability. The integration of explainable AI and web deployment makes the solution practical for real-world agricultural applications.

This paper presented a CNN-driven crop disease detection system that delivers accurate and interpretable disease diagnosis through leaf image analysis. The results confirm the effectiveness of transfer learning and Grad-CAM in improving both performance and transparency. Future enhancements include mobile application development, integration with IoT-based sensors, expansion to additional crop varieties, and real-world field validation. Such improvements can further strengthen the role of artificial intelligence in smart and sustainable agriculture.

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