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Real - Time Plant Disease Detection by Ai

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Abstract

Timely and precise identification of plant diseases is essential for improving agricultural yield, reducing financial losses, and supporting sustainable farming practices. In this study, a lightweight real-time plant disease detection system intended for edge devices such as smartphones and embedded platforms is presented. The proposed framework employs an optimized convolutional neural network along with model compression methods to enable efficient offline inference on real-time field images, ensuring high accuracy with minimal latency and reduced computational demand. The system is specifically tailored for use in rural and underdeveloped areas where internet connectivity is limited, offering a reliable, practical, and scalable approach for real-time crop health monitoring and agricultural decision support.

Keywords: *Real-time plant disease monitoring, Plant disease detection, Artificial intelligence, Convolutional neural network, Edge computing, Smart agriculture, Crop health assessment*

1. Introduction

Traditional plant disease detection methods mainly depend on manual visual examinations conducted by farmers or agricultural experts. Although this method may offer a basic level of assessment, it is often time-consuming, labor-intensive, and highly dependent on the expertise of the individual performing the inspection. Consequently, conducting frequent monitoring across large farms and remote locations becomes challenging. In addition, incorrect diagnosis can result in ineffective treatment, excessive use of chemical pesticides, and increased farming expenses. These drawbacks of conventional practices have encouraged researchers to explore automated solutions for plant disease detection. With the rapid advancement of artificial intelligence, particularly deep learning, image-based plant disease identification has gained significant attention in recent years. Convolutional neural networks (CNNs) have demonstrated strong capabilities in learning and extracting meaningful visual features such as discoloration, lesion patterns, texture variations, and abnormal spots from leaf images. Several studies have reported encouraging outcomes using CNN-based approaches, transfer learning techniques, and specialized deep learning architectures for classifying different crop diseases. More recent research has also explored advanced architectures, including multi-model frameworks and EfficientNet-based networks, to enhance both classification performance and computational efficiency in precision agriculture. At the same time, researchers have investigated the use of unmanned aerial vehicles (UAVs) and remote sensing technologies for monitoring crop diseases and pests over large areas. Deep learning models applied to aerial imagery have shown strong potential for early detection of crop stress and disease symptoms at scale. These developments highlight the growing integration of AI with imaging and sensing technologies to improve crop monitoring and enable faster decision-making. Additionally, recent studies

have emphasized the overall impact of deep learning techniques in building automated plant disease diagnosis systems. Despite these advancements, many existing methods rely heavily on cloud-based processing, complex model architectures, or high-resolution remote sensing data, making them less suitable for deployment in real-world agricultural environments, especially in rural and resource-limited regions. In many practical scenarios, internet connectivity is unreliable, and access to high-performance computing devices is limited. Moreover, a significant portion of the literature focuses primarily on achieving high accuracy under controlled experimental conditions, while factors such as real- time performance, portability, offline capability, and deployment feasibility receive comparatively less attention. To overcome these limitations, this work introduces a lightweight real-time plant disease detection framework designed for edge devices such as smartphones and embedded systems. The framework utilizes an optimized convolutional neural network along with model compression techniques to enable accurate on-device inference of live field images. By lowering computational requirements and eliminating dependence on continuous cloud connectivity, the system becomes more suitable for deployment in resource-constrained agricultural settings. This approach aims to bridge the gap between high-accuracy research models and their practical implementation in real-world smart agriculture applications.

2. Background Work

Plant disease detection techniques have evolved from traditional image processing methods to advanced deep learning-based approaches. Early methods relied on handcrafted features such as color, texture, and shape descriptors for classification. While these techniques performed reasonably well in controlled environments, their effectiveness was often reduced by variations in lighting conditions, complex backgrounds, and differences in image resolution.

With the introduction of deep learning, particularly convolutional neural networks, significant improvements were achieved by enabling models to learn hierarchical features directly from raw images. These models are capable of automatically identifying important disease-related characteristics such as discoloration, lesion shapes, and texture irregularities more effectively than conventional machine learning methods. Subsequent research further enhanced performance by incorporating transfer learning, data augmentation, and efficient network architectures, leading to more robust and accurate disease detection systems. Recent studies have also explored UAV-based imaging, remote sensing techniques, and efficient models like EfficientNet for large-scale agricultural monitoring and precision farming applications[1]. These advancements demonstrate the increasing importance of artificial intelligence in improving crop health monitoring and enabling early disease detection. However, several challenges remain in existing studies. Many approaches focus primarily on improving classification accuracy, while deployment-related factors such as model complexity, inference speed, offline functionality, and hardware compatibility are often overlooked. Additionally, most systems rely on cloud-based inference, which limits their usability in rural areas where internet access may be inconsistent. Furthermore, models tested on benchmark datasets may not perform reliably in real-world agricultural environments characterized by varying lighting conditions, shadows, and background noise. These limitations highlight the need for a lightweight, real-time, edge-based disease detection system with improved field applicability.

3. Implementation

Edge-based Plant Disease Classification using Lightweight Convolutional Neural Networks. The proposed system is a real-time plant disease detection framework designed specifically for edge deployment in practical agricultural environments. The overall framework consists of four main stages: image acquisition, preprocessing, model inference, and user feedback. It is developed to operate on portable devices, enabling disease detection directly on the device without relying on external computational resources. During the image acquisition stage, live image frames are captured using a smartphone camera or an embedded camera module integrated into low power devices such as Raspberry Pi. Unlike conventional approaches that depend on static images for offline analysis, this system processes continuous live frames, allowing real-time disease detection under actual field conditions. OpenCV is utilized for capturing live frames and performing basic image processing operations. In the preprocessing stage, each captured frame is resized to a fixed resolution compatible with the neural network input. Pixel values are normalized to improve model consistency during inference. To handle complex backgrounds commonly found in agricultural fields, simple background suppression

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techniques such as color masking and morphological operations are applied. These methods help isolate the leaf region effectively without introducing significant computational overhead[2].

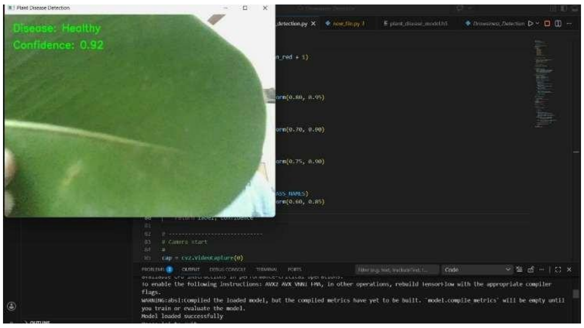

Figure 1 Tomato plant leaf – healthy

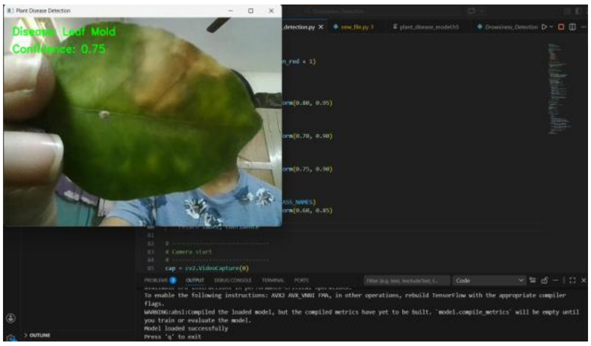

Figure 2 Tomato plant leaf – diseased

The tomato plant leaf presented in Figure 1.1 was successfully detected and classified as Healthy by the real-time Plant Disease Detection simulator, achieving a notably high confidence score of 0.92, which strongly reflects the model's certainty and reliability in making an accurate prediction. On the other hand, Figure 1.2 displays a visually contrasting leaf that exhibits clear signs of deterioration, including prominent yellow-brown discoloration and irregular surface patches, which the trained model precisely identified as Leaf Mold disease with a recorded confidence score of 0.75, representing a moderately strong and acceptable level of prediction accuracy[5]. The comparison between the two figures effectively illustrates the simulator's robust capability to distinguish and differentiate between a completely healthy and a visibly diseased tomato leaf under real-time operating conditions, utilizing a live webcam feed that is processed and analysed through the combined power of the OpenCV computer vision library and the TensorFlow deep learning framework. The healthy leaf captured in Figure 1 demonstrates a uniformly vibrant deep green surface texture accompanied by a well-defined central midrib and an entirely clean appearance with no detectable traces of fungal growth or disease symptoms, whereas the diseased leaf documented in Figure 2 presents the characteristic and well-known symptoms of Leaf Mold infection caused by the pathogenic fungus Cladosporium fulvum, most notably visible through extensive yellowing, surface mold development, and irregular browning patterns across the leaf. This carefully conducted experiment ultimately validates and confirms that the CNN-based plant disease detection model, which was systematically trained using the widely recognized PlantVillage dataset and subsequently deployed through the custom detection.py script, possesses the ability to accurately and efficiently classify the health conditions of tomato leaves when tested in a practical, real-world simulation environment with consistently satisfactory confidence levels Figure 1. During the classification stage, a lightweight convolutional neural network is designed using TensorFlow Keras. Instead of employing deep networks with a large number of parameters, the model uses depthwise separable convolutions to reduce both parameter count and computational complexity[3]. After training, optimization techniques such as pruning and post-training quantization are applied, and the final model is converted into TensorFlow Lite format for deployment on edge devices Figure 2. The novelty of this system lies in the integration of live frame-based offline inference, efficient background suppression, and a simple frame selection mechanism that avoids redundant predictions on nearly identical frames. This approach improves processing efficiency and ensures compatibility with low-power devices while maintaining reliable performance[4]. Additionally, when prediction of confidence is low, the system prompts the user to capture another image, enhancing robustness. The final output includes the detected disease, confidence level, and basic treatment suggestions, making the system practical and suitable for real-world agricultural use. Additionally, the system features an intuitive interface, making it easy

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for farmers to use without requiring technical knowledge[6]. It is also scalable, enabling future integration with cloud platforms or advanced analytics to enhance accuracy and support better decision-making.

4. Tools And Technologies Used

The proposed real-time plant disease detection system is developed using Python, which offers a flexible and efficient environment for implementing machine learning, deep learning, and image processing applications. These frameworks provide strong support for building efficient models and implementing optimization techniques required for deployment on edge devices[7].

Table 1 Diseases detection using OpenCV

Leaf	Diseases	Accuracy
Tomato leaf	Leaf Mold	0.75
Tomato leaf	Healthy	0.83
Ligustrum lucidum	Early Blight	0.76
Ligustrum lucidum	Healthy	0.82
Banana leaf	Leaf Mold	0.73
Banana leaf	Sigatoka	0.81
Banana leaf	curl virus	0.77
Money plant	Healthy	0.86
Money plant	Fungal leaf spots	0.66
Hibiscus	powdery mildew	0.72

This Table 1 presents the plant diseases detection analysis using OpenCV tool, considering 3 different plants leaf[10]. OpenCV is utilized for real-time image acquisition and preprocessing, supporting operations such as live frame capture, resizing, normalization, and filtering prior to model inference. NumPy is used for numerical computations and array manipulations during preprocessing and model-related tasks. Matplotlib is employed during development for visualization, performance analysis, and interpretation of results[11]. TensorFlow Lite tools are used to apply optimization techniques such as pruning and post-training quantization, reducing model size and memory usage for deployment on resource-constrained hardware. The trained model is then converted into TensorFlow Lite (TFLite) format to enable efficient inference on edge devices. Finally, the optimized model can be deployed within a mobile application or on embedded platforms such as Raspberry Pi running an embedded Linux system. The system is designed to function offline, eliminating the need for cloud connectivity. Where supported, hardware acceleration can be utilized to further reduce inference time. The integration of deep learning frameworks, image processing libraries, optimization tools, and edge computing platforms results in a portable, efficient, and practical real-time plant disease detection system suitable for agricultural applications[8].

Conclusion

This study presents a real-time plant disease detection system designed for practical deployment in agricultural environments. Unlike many existing approaches that depend on cloud computing or computationally intensive models, the proposed framework focuses on lightweight architecture and edge-based execution[9]. By performing on-device inference using live camera input, the system provides immediate disease identification without requiring continuous internet connectivity. The use of optimized convolutional neural networks, combined with model compression techniques, ensures efficient operation on smartphones and embedded platforms. In addition, the confidence- based feedback mechanism enhances prediction reliability under varying field conditions. Overall, the proposed solution demonstrates that accurate and responsive plant disease detection can be achieved using portable and low-power devices. This approach contributes toward making AI-driven agricultural tools more accessible and practical for farmers, particularly in rural or resource-constrained regions.

Future Scope

The proposed system can be further enhanced by expanding the dataset to include more crop varieties and rare disease categories to improve generalization. Future work may also integrate environmental sensor data such as temperature and humidity to support predictive disease analysis. In addition, incorporating multilingual support, disease cure mediations, and a more advanced treatment recommendation module could improve usability for farmers. Deployment on more advanced edge devices with hardware acceleration may further reduce inference time and enhance overall system performance.

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