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Deep Learning-Based Detection of Plant Leaf Diseases and Wilting Using a Mobile Application

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Abstract

Plant diseases and wilting are major factors contributing to crop yield reduction and economic losses in agriculture. Early and accurate diagnosis is essential for effective disease management and sustainable crop production. However, manual identification of plant diseases is often time-consuming, labor-intensive, and prone to human error due to the visual similarity of symptoms among different diseases and wilting conditions. This study proposes a deep learning-based mobile application for the detection and classification of plant leaf diseases and wilting using a lightweight MobileNetV2 architecture. Transfer learning was employed to enhance classification performance while reducing computational requirements for mobile deployment. The model was trained using TensorFlow and subsequently converted into TensorFlow Lite (TFLite) format for integration into an Android mobile application. Experimental results demonstrated a testing accuracy of 94.17%, with healthy leaves achieving the highest classification accuracy of 98.12%. The proposed system enables farmers to capture or upload leaf images using a smartphone and obtain real-time disease predictions, while supporting cloud-based data storage and monitoring. Compared with conventional deep learning models that require high computational resources, MobileNetV2 provides an effective balance between accuracy, efficiency, and mobile deployment capability. The proposed solution contributes to

precision agriculture by facilitating early disease diagnosis, timely intervention, and improved crop management.

Keywords:
Plant disease, Leaf Wilting, Convolutional Neural Network, and Crops

Introduction

In recent years, precision farming has been widely adopted in the agriculture industry. This approach uses various technologies and tools to help farmers increase crop survival rates and productivity by detecting plant diseases and placing interventions, such as technological equipment, to assist with tasks. Precision farming is based on observing, measuring, and responding to inter- and intra-field variabilities, such as weather conditions, soil quality, cropping, and plant diseases.

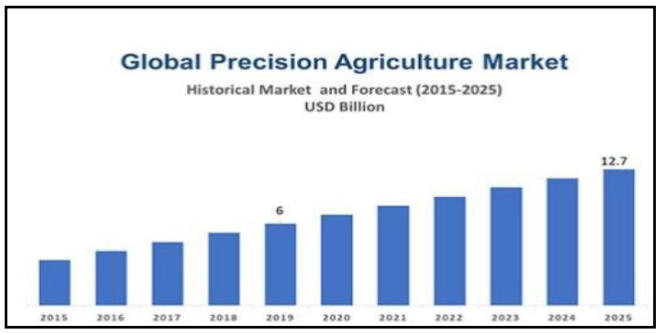


Figure 1. Global precision farming market size [18]

The tools used in precision farming enable farmers to intervene at the right place, at the right time, with the right solution. According to statistics from expertmarketresearch.com, as shown in Fig. 1, the global precision agriculture market was valued at 6 billion dollars in 2020 and is forecasted to reach 12.7 billion dollars by 2026. This growth is expected to continue as more technological advancements are implemented in the industry.

A visitation and interview session were conducted with Dr. Teh regarding the challenges faced in precision farming at the QUEST International University Biotech Farm. One of the major challenges is detecting plant leaf diseases and leaf wilting. This difficulty arises due to the visual similarities between wilting and certain plant leaf diseases, which can lead to misidentification. A reliable solution is to implement computer vision and machine learning techniques, which can accurately detect and distinguish between plant leaf diseases and leaf wilting, as illustrated in Fig. 2.

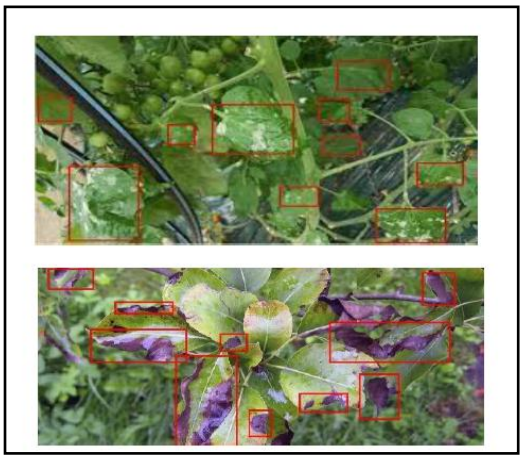


Figure 2. Plant leaf disease and leaf wilting

This proposed project utilizes computer vision techniques and machine learning models, such as Convolutional Neural Networks (CNN), to detect and predict plant leaf diseases and wilting. The system can be deployed on a cloud database server, and a mobile application will be developed to allow farmers to detect specific plant diseases using their mobile phones. This enables farmers to monitor crops and apply timely treatments, thereby reducing crop losses

Literature Review

Plant diseases significantly threaten global agricultural productivity and food security, causing an estimated 20–40% annual crop loss worldwide. Early and accurate disease detection is therefore essential to reduce yield and economic losses [1]. In cucumber and tomato cultivation, diseases often exhibit similar visual symptoms, making manual diagnosis difficult. Major cucumber diseases include anthracnose (*Colletotrichum* spp.) [2], alternaria leaf spot (*Alternaria* spp.) [3], bacterial leaf spot (*Xanthomonas* spp.) [4], downy mildew [5], and powdery mildew [6], while bacterial wilt (*Ralstonia solanacearum*) [7] and fusarium wilt (*Fusarium oxysporum*) [8] disrupt water transport, causing irreversible wilting. Tomato crops are also susceptible to early blight (*Alternaria solani*) [9], late blight (*Phytophthora infestans*) [10], and septoria leaf spot (*Septoria lycopersici*) [11], all of which reduce plant health and crop productivity.

Artificial intelligence has greatly enhanced automated plant disease diagnosis. Unlike traditional machine learning methods that rely on handcrafted features and are sensitive to lighting and background variations, Convolutional Neural Networks (CNNs) automatically learn hierarchical image features, providing superior classification performance [12]. Previous studies have demonstrated that CNN-based models consistently outperform conventional approaches by learning disease-specific visual characteristics directly from images [13], [14].

Several deep learning architectures, including VGG16, ResNet50, DenseNet121, EfficientNetB0, and MobileNetV2, have been successfully applied for plant disease detection. Although deeper networks generally achieve higher classification accuracy, they require substantial computational resources, limiting their deployment on mobile devices [15]. MobileNetV2 has emerged as a preferred architecture for mobile agricultural applications because its lightweight design incorporates depthwise separable convolutions and inverted residual bottleneck blocks, significantly reducing computational complexity while maintaining competitive classification accuracy [16]. These characteristics make MobileNetV2 particularly suitable for real-time plant disease diagnosis using smartphones and other edge devices.

Comparison of State-of-the-Art Deep Learning Models

A variety of CNN architectures have been investigated for plant disease detection. Table 1 summarizes the characteristics of commonly used models.

Table 1. Compariosn of Deep Learning Models for Plant Disease Detection

Model	Advantages	Limitations
VGG16	High feature extraction capability	Large model size and high memory consumption
ResNet50	Excellent performance on deep architectures	Higher computational requirements
DenseNet121	Strong feature reuse and improved gradient flow	Increased training complexity
EfficientNetB0	High accuracy-to-parameter ratio	Requires careful hyperparameter tuning
MobileNetV2	Lightweight, fast inference, mobile deployment	Slightly lower accuracy than larger models
ShuffleNet	Very efficient for edge devices	Lower performance on complex datasets

Among these architectures, MobileNetV2 was selected because the primary objective of this study was to develop a real-time mobile application for disease diagnosis. Compared to VGG16, ResNet50, and DenseNet121, MobileNetV2 requires fewer parameters and computational resources while maintaining competitive accuracy. Therefore, it provides an appropriate balance between classification performance and deployment efficiency on mobile devices [16].

MobileNetV2-Based Disease Detection Framework

The proposed framework uses MobileNetV2 transfer learning to classify plant diseases and wilting conditions. MobileNetV2 applies depthwise separable convolutions and inverted residual layers to reduce computational cost while maintaining accuracy [16]. The workflow includes image acquisition, preprocessing, feature extraction, and Softmax-based classification. The trained model was converted to TensorFlow Lite (TFLite) and integrated into an Android application for real-time field diagnosis without specialized equipment.

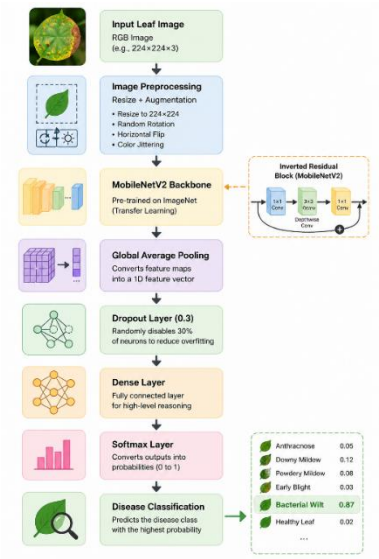


Figure 3. Proposed MobileNetV2 Disease Detection Architecture

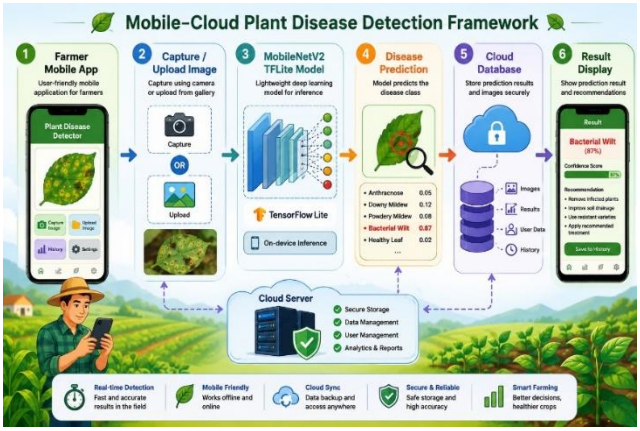


Figure 4. Mobile-Cloud Detection Framework

Methods

The proposed plant leaf disease and wilting detection system employs a Convolutional Neural Network (CNN) with MobileNetV2 transfer learning for efficient image classification. MobileNetV2 was selected because it requires approximately half the computational operations, 30% fewer parameters, and achieves 30–40% faster inference than MobileNetV1 on mobile devices [17]. Images were preprocessed using segmentation and data augmentation before training. A total of 4,797 images were divided into 80% training and 20% testing datasets. The model was trained for 50 epochs (batch size = 32; dropout = 0.3), converted to TensorFlow Lite, and integrated into an Android application supporting live detection, image capture, and gallery-based prediction.

Results

During the model training, the initial training accuracy in the first epoch was 42.24%, with a validation accuracy of 67.50%. By the 50th epoch, the model achieved a training accuracy of 99.25% and a validation accuracy of 95.83%.

Table 2. Training and Validation Accuracy of the model for every 10 EPOCHS

Epoch	Training Accuracy	Validation Accuracy
1st	42.24%	67.50%
10th	96.34%	95.83%
20th	98.06%	95.00%
30th	98.49%	96.67%
40th	99.35%	95.00%
50th	99.25%	95.83%

The model achieved an overall accuracy of 94.17% on the testing dataset after training was completed. It was then implemented into a mobile application to conduct real-world tests. The table below shows the classification and accuracy of the model for various leaf diseases and wilting conditions.

Table 3. Leaf Disease and Wilting Classification and Accuracy

Leaf Disease/Wilting	Classification	Accuracy
Anthracnose	Anthracnose	93.15%
Alternaria Leaf Spot	Alternaria Leaf Spot	89.11%
Bacterial Leaf Spot	Bacterial Leaf Spot	89.64%
Bacterial Wilt	Bacterial Wilt	88.14%
Downy Mildew	Downy Mildew	87.47%
Powdery Mildew	Powdery Mildew	88.30%
Fusarium Wilt	Fusarium Wilt	87.74%
Early Blight	Early Blight	81.64%
Late Blight	Late Blight	82.12%
Septoria Leaf Spot	Septoria Leaf Spot	91.46%
Healthy Leaf	Healthy	98.12%

Based on the testing of real-world cases, the model correctly predicted all images in the test dataset. However, some predictions were accurate but had lower confidence scores. Factors such as image brightness, shadows on the leaves, or low-resolution images contributed to this. In real-world scenarios, the model's accuracy may be lower compared to the 94.17% average observed during development.

Conclusions

The proposed system offers numerous benefits to farmers, particularly in the classification of plant leaf diseases and wilting. This capability enables farmers to quickly identify specific disease types, saving considerable time compared to the manual analysis of leaves, which is time-consuming. Additionally, the system improves the accuracy of disease prediction through the use of computer vision techniques. Traditional methods of diagnosing leaf diseases are labour-intensive and place a heavy workload on farmers. By leveraging computer vision, the proposed system simplifies this process and enhances prediction accuracy. Furthermore, the

system's portability as a mobile application allows farmers to conveniently diagnose leaf diseases using their mobile devices while on the move.

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