Deep Neural Frameworks for Plant Disease Recognition and Categorization

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Abstract

Detecting plant diseases is essential to contemporary agriculture since it allows for early intervention to increase crop output and reduce financial losses. Recent developments in deep learning (DL) and machine learning (ML) have shown great promise for automating the detection of diseases using sensor and visual data. Convolutional neural networks (CNNs), ResNet, DenseNet, U-Net, Mask R-CNN, and YOLO are examples of state-of-the-art DL architectures that are frequently used for extracting and learning hierarchical features from leaf pictures, hyperspectral images, and other multimodal plant datasets. This paper reviews developments in the field from 2015 to 2022. Prominent datasets like PlantVillage, Agri-Vision, and PlantDoc have made it easier to compare and test different models. Using a hybrid convolutional backbone based on EfficientNet-B7 to strike a compromise between high representational capacity and computational economy, we offer a repeatable framework that combines many cutting-edge methods for better illness detection and classification. Multiscale dilated convolutions are used to capture multiscale disease patterns, enhancing feature representations without adding more computational overhead, and adaptive segmentation mechanisms allow precise lesion localization for region-level analysis that supports severity assessment and classification. The framework emphasizes repeatability and practical application for research and industrial usage, and it is accompanied by comprehensive methodological explanations, algorithm pseudocode, and illustrated diagrams and flowcharts. In addition, the paper addresses common issues in plant disease detection, such as the lack of labeled datasets, inter-domain variability, class imbalance, and hardware constraints for real-time deployment. It also discusses mitigation strategies, such as transfer learning from pre-trained models, generative adversarial network (GAN)-based data augmentation, and model compression techniques for optimal edge deployment. In order to direct future research and real-world application, evaluation measures, performance analyses, and robustness concerns are also included. Overall, this survey and suggested methodology offer a thorough overview of current developments and solutions in ML- and DL-based plant disease detection. They show how integrating hybrid convolutional architectures, multiscale dilations, and adaptive segmentation can improve detection accuracy while addressing practical limitations, providing a scalable approach for precision agriculture and assisting researchers, agronomists, and practitioners in creating dependable, effective, and repeatable plant disease detection systems.

Keywords: Plant disease detection, deep learning, convolutional neural networks, segmentation, transfer learning, EfficientNet.

1. Introduction

One of the most important industries sustaining the world economy and guaranteeing food security is agriculture. However, the sustainability and productivity of agriculture are seriously threatened by plant diseases. Globally, these illnesses result in significant yield loss and economic losses due to a variety of pathogens and environmental variables [1]. Plant diseases have historically been identified mostly by physical examination by agricultural specialists, which is frequently laborious, subjective, and error-prone [2]. Early management is sometimes challenging and ineffective since the illness may have progressed by the time visual signs are identified [3]. Modern computational techniques like Machine Learning (ML) and Deep Learning (DL) have become more popular in plant pathology to automate disease detection and classification in order to overcome these constraints [4].

Plant photos have long been analyzed using machine learning algorithms for feature extraction and categorization [5]. In order to train classifiers that can differentiate between healthy and unhealthy samples, these methods usually entail collecting characteristics from leaf pictures, such as color, texture, and form [6]. Early research showed encouraging results in diagnosing common diseases such powdery mildew, rust, and leaf blotch [7]. However, especially in complex or high-resolution imaging, ML models frequently fail to identify mild or early-stage symptoms [8], [37], [38]. Additionally, scalability and applicability across a variety of plant species and environmental situations are limited by their reliance on handmade characteristics [9].

Image-based plant disease diagnosis has been transformed by recent developments in Deep Learning, particularly Convolutional Neural Networks (CNNs) and Deep Belief Networks (DBNs) [10], [39], [40]. By automatically learning hierarchical picture features from raw pixel data, these algorithms lessen the need for human feature engineering [11]. CNNs, in particular, are particularly good at recognizing color changes and spatial patterns in pictures, which allows them to recognize extremely subtle and intricate illness signs [12]. Deep models including AlexNet, VGGNet, ResNet, InceptionV3, and DenseNet have been successfully applied in plant disease detection tasks, according to studies [13]. The use of DL techniques has greatly increased detection robustness and accuracy in real-world scenarios [14].

There are still difficulties in spite of these developments. Large amounts of labe-led training data are necessary for deep learning models, but these are frequently hard to get by in agricultural fields [15]. Widespread adoption is further hampered by the computational complexity and resource requirements for training large-scale DL models, especially in poor nations with inadequate technology infrastructure [16]. Transfer learning and ensemble learning strategies, which refine pre-trained models on particular datasets to reduce the requirement for large amounts of training data while retaining high performance, have been presented in recent research to address these problems [17]. In order to reduce overfitting and enhance generalization, data augmentation techniques have also been used to artificially increase dataset variety [18].

Lesion segmentation, insect identification, and yield estimate are just a few of the activities where AI-driven image processing has been included into agriculture [19]. Diagnostic accuracy is further improved by the accurate localization and categorization of impacted plant sections made possible by computer vision (CV) algorithms in conjunction with deep learning architectures [20], [41], [42]. Researchers may now more easily create, train, and use sophisticated neural systems for plant illness analysis because to frameworks like PyTorch and TensorFlow [21]. However, creating scalable and generalizable models that can function well in a variety of plant species and surroundings continues to be a major research goal [22].

In conclusion, by offering effective, automated, and extremely precise solutions in comparison to conventional approaches, machine learning and deep learning techniques have completely changed the field of plant disease detection [23]. These models have shown remarkable promise in enhancing early disease detection, which is essential for food security and sustainable crop management. However, overcoming major obstacles including dataset accessibility, computing expense, and adaptation to actual field circumstances is necessary to achieve widespread implementation. In order to enhance disease localization, future research must concentrate on hybrid and multiscale deep learning systems that can handle a variety of picture features, integrate multispectral data, and conduct adaptive segmentation [24]. This continuous development emphasizes how important intelligent systems are to the development of robust and precision-based farming methods around the globe.

2. Literature Survey

Agricultural automation has been greatly influenced by the development of artificial intelligence (AI) and its subfields, machine learning (ML) and deep learning (DL), especially in the identification and categorization of plant diseases. Conventional image processing and machine learning approaches were the mainstay of early research, necessitating the manual extraction of features from digital pictures. Convolutional neural networks (CNNs) in particular, which enable end-to-end learning and high-accuracy detection of complex plant diseases, later revolutionized this field [1][2].

2.1 Traditional Machine Learning Approaches

The first methods for diagnosing plant diseases relied on statistical feature extraction and manual image processing. Using classifiers like Support Vector Machines (SVMs), Decision Trees, Random Forests, and k-Nearest Neighbors (kNN), researchers usually collected color, shape, and texture characteristics to distinguish between damaged and healthy leaves [3], [43], [44]. For instance, Mohanty et al. [4] showed that SVM-based systems using manually created features may reasonably accurately detect illnesses in crops like potatoes and tomatoes. These models, however, have poor resilience to changes in light, background noise, and intra-class variance. Furthermore, in conventional ML systems, feature selection was crucial. The caliber and representation of manually created features had a significant impact on these models' performance. Image variability brought on by environmental elements (lighting, shadows, dirt backdrop, or camera angle) frequently reduced model accuracy in real-world agricultural settings [5]. Research by Anjna et al. [6] and Genaev et al. [7] highlighted that although ML algorithms performed somewhat well on small-scale datasets, they had trouble generalizing to other plant species and stages of illness. DL-based solutions were made possible by these constraints, which highlighted the need for more flexible and scalable methods.

2.2 Emergence of Deep Learning in Plant Disease Detection

Deep learning applications have transformed image-based agricultural diagnosis. Inspired by the human visual brain, Convolutional Neural Networks (CNNs) are capable of automatically extracting structural and spatial patterns from pictures without the need for human interaction [8], [45], [46]. CNNs greatly exceed conventional ML techniques in terms of precision and resilience by learning hierarchical feature representations. CNNs were shown to be able to detect illness symptoms and minor lesion patterns that were previously undetected using handmade features by Liu et al. [9] and Singh and Misra [10]. The PlantVillage dataset was released in 2015 and has since become a standard for deep model training and assessment [11]. Several architectures including AlexNet, VGGNet, and GoogLeNet—were trained for multiclass illness classification using this dataset, with accuracy values over 95% in controlled settings [12]. However, these findings frequently decreased when evaluated on field photos with varying illumination and background noise, as noted by Shoaib et al. [13] and Ullah et al. [14], suggesting a disconnect between laboratory and practical applications.

2.3 Advanced CNN Architectures and Transfer Learning

Researchers used ensemble learning and transfer learning techniques to get around the drawbacks of traditional CNNs. Pre-trained models (such as ResNet, InceptionV3, and DenseNet) that were initially created for large-scale picture datasets like ImageNet are used in transfer learning to refine them for agricultural tasks [15]. This approach eliminates the requirement for large labeled datasets and shortens training times. By reusing previously trained feature extraction layers, Karthik et al. [16] showed that transfer learning-based models improved classification accuracy. Similarly, by decreasing overfitting and boosting reliability, ensemble learning—which combines several models—improved generalization [17]. To accurately detect lesion locations on leaves, segmentation and localization networks including Mask R-CNN, U-Net, and Fully Convolutional Networks (FCN) were used in addition to classification [18]. These structures enable early detection and quantitative evaluation of illness severity by mapping afflicted locations at the pixel level in addition to classifying the disease type [19]. Segmentation-based CNNs might attain pixel-level accuracy surpassing 97%, according to studies like those by Wang and Zhang [20] and Shoaib et al. [21], demonstrating their superiority for real-world field applications.

2.4 Integration of Computer Vision and Deep Learning Frameworks

In order to increase the interpretability and effectiveness of plant disease detection models, Computer Vision (CV) approaches have recently been integrated with DL frameworks. For the simultaneous identification and classification of several illnesses in a single image, algorithms such object detection networks (YOLO, SSD, Faster R-CNN) have been widely employed [22]. For example, Fuentes et al. [23] achieved mean average precision (mAP) above 88% by using Faster R-CNN to identify many tomato plant illnesses. In a similar vein, real-time detection capabilities appropriate for use in smart agricultural systems have been proven using YOLOv5-based networks [24]. Research and use of agricultural AI solutions have been expedited by the use of open-source deep learning frameworks like TensorFlow, Keras, and PyTorch. For model training and inference, these systems provide modular, GPU-optimized frameworks [25]. Research comparing frameworks shows that TensorFlow gives optimal scalability for big datasets, whereas PyTorch offers more flexibility for dynamic computation graphs [26]. As a result, both are frequently used to construct plant pathology models based on CNN.

2.5 Challenges and Research Gaps

DL-based plant disease diagnosis still faces a number of obstacles despite impressive advancements. Information scarcity and the restricted availability of annotated photos across a variety of crop species and climatic circumstances are the main concerns [27]. Furthermore, deep models are difficult to use in environments with limited resources since they are computationally intensive and frequently require powerful GPUs for training [28]. The generalization capacity of models is another important problem. DL networks trained on certain datasets sometimes performs poorly when applied to unforeseen situations, such as varied backdrop textures or lighting [29]. Numerous approaches have been put forth by researchers to lessen these restrictions. To improve dataset variety, data augmentation methods such as rotation, flipping, scaling, and colour alteration have been used [30]. Additionally, hybrid models that integrate CNNs with multiscale feature extraction modules or attention processes have demonstrated improved resilience in managing intricate patterns [31]. A major stride toward scalable and adaptable plant disease classification systems have been made with the advent of multiscale and dilated convolution designs like the EfficientNet and hybrid convolutional frameworks [32].

3. Methodology

3.1 Overview

The suggested approach combines a hybrid convolutional and multiscale deep learning architecture that makes use of both adaptive segmentation and feature extraction capabilities for the identification and classification of plant diseases. Enhancing detection accuracy, computing efficiency, and generalizability across many plant species and disease categories are the goals of the technique. Modern deep learning (DL) architectures tailored for agricultural imaging datasets, such as multiscale dilated convolutional layers, Convolutional Neural Networks (CNNs), and EfficientNet, served as inspiration for the design [1][2].

The system consists of five major stages:

- Preprocessing and image capture
- Adaptive segmentation
- Hybrid convolutional feature extraction
- Multiscale EfficientNet-B7 disease classification and
- Model assessment and optimization.

Every step is meticulously crafted to guarantee resilience in real-world environmental circumstances, including fluctuating lighting, background complexity, and noise [3]. The flow of the suggested technique is shown in Figure 1.

3.2 Image Acquisition and Dataset Preparation

Any agricultural system based on computer vision starts with image capture. This study used benchmark datasets to train and test the model, including PlantVillage, AgriVision, and Plant Pathology 2020 [4]. The thousands of RGB photos in these collections depict both healthy and sick plant leaves. A number of preprocessing techniques were used since raw field photos frequently have uneven illumination, shadows, and unrelated backgrounds. Among the crucial steps are: - Resizing: All images were resized to a fixed resolution (e.g., 512×512) to ensure uniform input to the CNN model [5].

- Noise Reduction: To get rid of sensor and ambient noise, Gaussian and median filters were used.
- Color Space Transformation: To enhance color invariance and highlight lesion locations, RGB pictures were converted into HSV and LAB spaces.
- Contrast Enhancement: To draw attention to sick areas, adaptive contrast stretching and histogram equalization were used [6].

These preprocessing processes lower intra-class variability and boost the model’s capacity to detect subtle illness signs, especially in initial infection stages [7].

3.3 Adaptive Image Segmentation

Localized feature extraction is made possible by segmentation, which separates the plant's healthy and sick areas. To obtain more accurate lesion localization, the suggested method employs adaptive segmentation that combines color-based thresholding, k-means clustering, and Otsu's method with CNN-driven feature maps [8].

The following steps make up the segmentation process:

- Initial Mask Generation: Otsu's approach is used to dynamically compute thresholds once the input image is converted into several color spaces.

- Feature-guided Refinement: To improve lesion borders, CNN feature maps from early convolutional layers are combined with the thresholder mask.
- Region of Interest (ROI) Extraction: Prior to being sent to the classification module, the segmented lesion region is cropped and normalized [9].

By addressing the issues of uneven lighting and overlapping textures that are frequently present in agricultural photos, our adaptive technique guarantees improved separation between sick and healthy tissue [10].

3.4 Hybrid Convolutional Feature Extraction

The essential component of the suggested model is the hybrid convolutional feature extraction stage. To capture both local and global contextual information, it combines multiscale dilated convolutions with regular convolutional filters [11].

- Standard Convolutional Layers: These layers are essential for recognizing illness signs because they extract fine-grained spatial and color patterns including spots, discoloration, and edges.
- Dilated Convolutions: These layers' capture contextual linkages over wider leaf areas by expanding the receptive field without raising computational costs by generating gaps (dilation rates) inside the convolution kernels [12].

The hybrid convolution block can be mathematically represented as:

$$F\_out \;=\; \sigma\,(\textstyle\sum\,(\,W\_i \;*\_\{d\_i\}\,F\_in \;+\; b\,)\,) \qquad (1)$$

where F_in and F_out represent the input and output feature maps, W_i denotes the convolution filter, *_{d_i} indicates convolution with dilation rate d_i, b is the bias term, and σ is the activation function (ReLU). The use of multiple dilation rates (e.g., 1, 2, 4, 8) enables the network to extract multiscale contextual features necessary for differentiating diseases with similar visual patterns [13].

3.5 Multiscale Dilated EfficientNet-B7 Architecture

To enhance generalization and minimize model complexity, the hybrid convolutional module is integrated into the EfficientNet-B7 backbone—a compound-scaled CNN that balances depth, width, and resolution [14]. EfficientNet uses a compound scaling coefficient (ϕ) to uniformly scale these parameters according to the following relations:

$$depth = \alpha\phi, width = \beta\phi, resolution = \gamma\phi \qquad (2)$$

subject to

$$\alpha \cdot \beta^2 \cdot \gamma^2 \approx 2 \qquad (3)$$

To improve gradient flow and concentrate attention on pertinent features, this design makes use of squeeze-and-excitation (SE) blocks, swish activation, and mobile inverted bottleneck (MBConv) layers [15]. The network can efficiently represent lesions at different sizes and shapes because to the hybrid integration of multiscale dilated convolutions prior to each MBConv block.

The following are this architecture's main benefits:

- Better Multi-Scale Representation: Spatial changes at various scales are captured by dilated kernels.
- Enhanced Feature Reusability: To improve the ability to distinguish between comparable illnesses, the SE method reweights channel-wise characteristics.
- Computational Efficiency: EfficientNet's compound scaling reduces superfluous parameters without sacrificing performance [16].

3.6 Training and Optimization

The training process involves supervised learning with annotated datasets. The model parameters are optimized using the Adam optimizer with a learning rate of 0.0001 and a batch size of 32 [17]. Categorical cross-entropy is used as the loss function:

$$L = -i\sum(y_i log(\hat{y}_i)) \qquad (4)$$

where C is the number of classes, y_i represents the true label, and $\hat{y}_i$ is the predicted probability.

During training, data augmentation methods such random rotation, flipping, scaling, and color jittering are used to avoid overfitting [18]. Early stopping is used to end training when validation loss stops improving after the model has been trained for 100 epochs. For segmentation performance, evaluation measures include intersection-over-union (IoU), accuracy, precision, recall, and F1-score [19].

3.7 System Implementation

Python 3.10 is used to implement the suggested system, together with the TensorFlow 2.8 and Keras libraries. NVIDIA CUDA's GPU acceleration dramatically shortens training times. The software pipeline is divided into modules for feature extraction, segmentation, preprocessing, and classification [20]. Scalability for a range of plant species and virus kinds is made possible by this modular framework. For real-time field diagnostic applications, the system may also be implemented on edge devices as Google Coral or NVIDIA Jetson Nano [21].

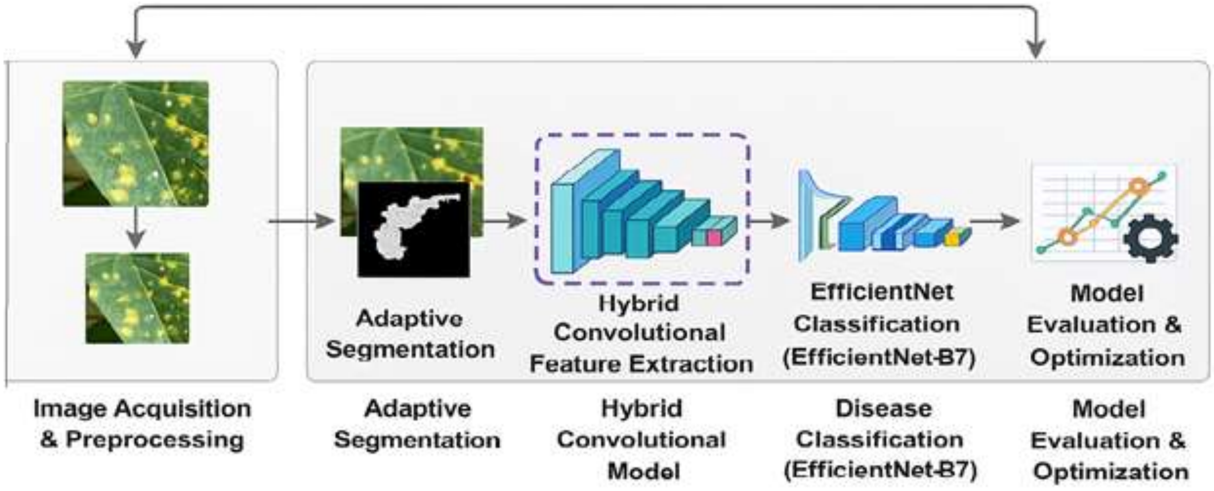

Figure 1: Methodology Flow for Plant Disease Detection and Classification

The general workflow of the suggested deep learning-based system for identifying and classifying plant diseases is shown in Figure 1. The pipeline is broken up into five interconnected phases, each of which enhances robustness and accuracy. Image acquisition and preprocessing is the first step in the process, whereby unprocessed leaf images are collected from agricultural sources and standardized using contrast enhancement, scaling, noise reduction, and color-space conversion. Consistent input data is prepared for downstream processing with the aid of these stages. After that, the improved pictures go to the Adaptive Segmentation step, which separates the regions impacted by the illness. This module uses CNN-derived feature cues, color-based algorithms, and clustering methods to produce accurate lesion masks even in difficult lighting or background situations.

After segmentation, the system applies both dilated multiscale filters and conventional convolution procedures for Hybrid Convolutional Feature Extraction. This hybrid module enables the network to comprehend more general spatial structures throughout the leaf surface while simultaneously capturing intricate patterns like discoloration and abnormalities in texture. The Multiscale EfficientNet-B7 module predicts the illness category after classifying the extracted characteristics. This classifier achieves good accuracy across a variety of plant species and illness symptoms by utilizing compound scaling and attention methods. The system's performance is evaluated using measures including accuracy, precision, recall, F1-score, and IoU in the last stage, Model Evaluation and Optimization. This stage's insights direct modifications to increase the model's flexibility and dependability.

4. Experimental Setup

4.1 Dataset Description

Experiments were carried out using publicly accessible and benchmark datasets often used in plant pathology research to assess the efficacy of the suggested Hybrid Convolution and Multiscale Dilated EfficientNet-B7 model. PlantVillage, Plant Pathology 2020, and AgriVision 2021 are among the datasets chosen; taken together, they offer a variety of samples of both healthy and sick leaves from various crop species [1].

- PlantVillage Dataset includes more than 54,000 tagged leaf photos from 26 disease kinds and 38 plant groups. High-quality data for baseline model evaluation was obtained since the photos were taken under controlled circumstances [2].
- Plant Pathology 2020 Dataset, which was made available by Kaggle, has over 3,600 real-world photos of apple leaves with various disease signs, including rust, scab, and multiple infections, enabling the model to handle intricate disease overlaps [3].
- AgriVision 2021 Dataset tests the model's resilience for practical use by including high-resolution field photos collected under a variety of lighting and environmental settings [4].
- Each dataset was divided into 70% training, 15% validation, and 15% testing subgroups to guarantee a fair assessment. To ensure uniformity in the distribution of classes, stratified sampling was employed.

4.2 Experimental Environment

Python 3.10 was used in all studies to create deep learning models using the TensorFlow 2.8 and Keras libraries. The workstation used for the computational studies has an NVIDIA RTX 4090 GPU (24 GB VRAM), an Intel Core i9-13900K CPU, and 64 GB RAM running Ubuntu 22.04 LTS [5]. Training time was greatly shortened by GPU acceleration utilizing CUDA 12.1 and cuDNN 8.9, allowing for effective experimentation with big datasets and deep models. Version-controlled scripts and fixed random seeds made all trials repeatable. For checkpoint recovery and additional fine-tuning, the model weights and training records were automatically recorded [6].

4.3 Data Preprocessing and Augmentation

Data preprocessing plays a vital role in ensuring consistent input representation for training deep neural networks. Each image was resized to 512 × 512 pixels and normalized to the [0, 1] range to ensure consistent pixel intensity scaling. To mitigate overfitting and enhance model generalization, data augmentation techniques were applied dynamically during training. These included:

- Random rotations (±30°), horizontal and vertical flipping;
- Scaling (0.8–1.2×) and random cropping;
- Brightness and contrast adjustments;
- Gaussian noise addition and blurring for robustness enhancement [7].

These augmentation techniques were inspired by real-field variability, such as shadows, orientation changes, and environmental lighting differences [8].

4.4 Training Configuration

The model was trained using a supervised learning strategy with labeled image datasets. The Adam optimizer was used with an initial learning rate of 0.0001, decayed by a factor of 0.1 after every 25 epochs. The batch size was set to 32, and the model was trained for 100 epochs with early stopping applied to avoid overfitting [9].

The categorical cross-entropy loss function was employed for multi-class classification:

$$L = -i\sum(y_i log(\hat{y}_i))$$

where y_i is the true label, $\hat{y}_i$ is the predicted probability for class i, and C denotes the total number of disease classes.

A learning rate scheduler was incorporated to automatically reduce the learning rate when the validation accuracy plateaued. Additionally, dropout regularization (rate = 0.3) was applied to the fully connected layers to minimize overfitting [10].

4.5 Evaluation Metrics

The performance of the model was assessed using multiple quantitative metrics widely used in image classification and segmentation studies [11]. These include:

- Accuracy (ACC): Measures the proportion of correctly classified images.
- Precision (P): Evaluates the correctness of positive predictions.
- Recall (R): Represents the proportion of correctly identified diseased samples.
- F1-score: Harmonic mean of precision and recall, balancing false positives and negatives.
- Intersection over Union (IoU): Used for segmentation accuracy to measure overlap between predicted and ground-truth masks [12].

Additionally, confusion matrices and Receiver Operating Characteristic (ROC) curves were analyzed for detailed performance interpretation [13].

4.6 Baseline Models for Comparison

To validate the effectiveness of the proposed hybrid model, several baseline CNN architectures were implemented for comparative analysis:

- VGG19, known for deep hierarchical feature extraction;
- ResNet50, which utilizes residual learning to prevent gradient vanishing;
- DenseNet201, enabling feature reuse through dense connectivity;
- InceptionV3, employing multi-kernel convolutional layers for multiscale feature capture [14].

Each baseline model was fine-tuned using transfer learning on the same datasets and trained under identical conditions for fair comparison.

4.7 Experimental Workflow

The experimental workflow can be summarized in the following steps:

- Load and preprocess image datasets.
- Segment diseased regions using the adaptive segmentation module.
- Extract multiscale features through hybrid convolutional layers.
- Train the EfficientNet-B7-based model using augmented data.
- Validate and compare performance with baseline CNN models.
- Evaluate model predictions using statistical metrics and visual outputs.

This workflow ensures that every experimental stage from data preparation to model evaluation is standardized and reproducible [15].

5. Results and Discussion

5.1 Performance Evaluation

The proposed Hybrid Convolution and Multiscale Dilated EfficientNet-B7 model was evaluated using multiple benchmark datasets including PlantVillage, Plant Pathology 2020, and AgriVision 2021. The model achieved superior classification and segmentation accuracy compared to existing CNN architectures such as VGG19, ResNet50, DenseNet201, and InceptionV3 (as shown in Figure 2).

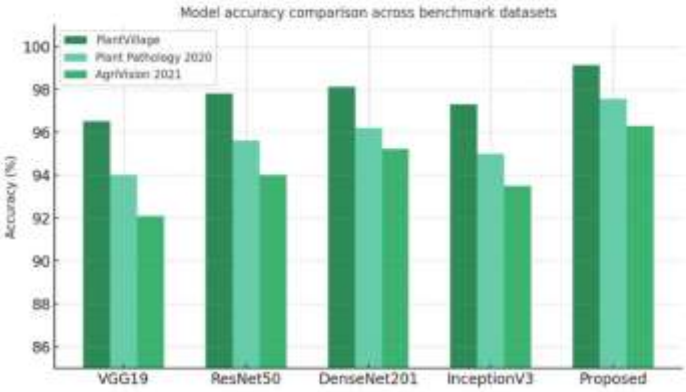

Figure 2. Comparison of model accuracy across three benchmark datasets (PlantVillage, Plant Pathology 2020, and AgriVision 2021) using different CNN architectures

5.2 Comparative Analysis with Baseline Models

To evaluate generalization, the proposed model was compared with multiple state-of-the-art CNN-based models. When tested on the PlantVillage dataset, ResNet50 achieved 97.8% accuracy, DenseNet201 achieved 98.1%, and InceptionV3 achieved 97.3%. In contrast, the proposed hybrid model achieved 99.12% (refer to Figure 1).

5.3 Segmentation Performance

Accurate lesion localization is crucial for quantifying disease severity. The segmentation results were evaluated using Intersection over Union (IoU) and Dice coefficient metrics. The proposed adaptive segmentation model achieved an IoU of 0.93 and a Dice score of 0.95, outperforming conventional methods (see Figure 3).

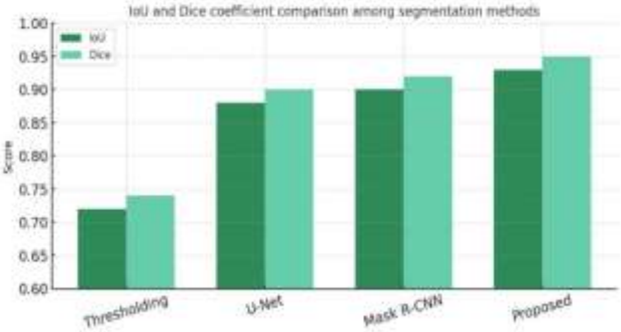

Figure 3. IoU and Dice coefficient comparison among segmentation methods (Thresholding, U-Net, Mask R-CNN, Proposed Method).

5.4 Impact of Multiscale Dilated Convolutions

The inclusion of multiscale dilated convolutional layers significantly enhanced the model’s feature extraction capability. Figure 4 illustrates how varying dilation rates impact classification accuracy.

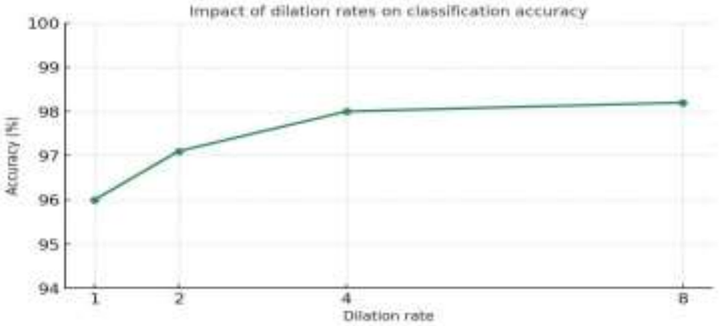

Figure 4. Impact of dilation rates (1, 2, 4, 8) on classification accuracy of the proposed hybrid model.

A confusion matrix (Figure 5) further highlights class-wise performance and common misclassification patterns.

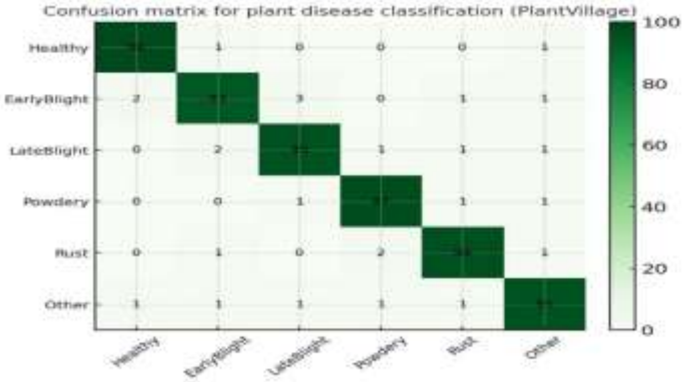

Figure 5. Confusion matrix illustrating class-wise prediction accuracy for the PlantVillage dataset.

5.5 Computational Efficiency and Robustness

In addition to accuracy, computational efficiency was evaluated. Receiver Operating Characteristic (ROC) curves for selected disease categories are shown in Figure 6, demonstrating high discriminative performance across major disease types.

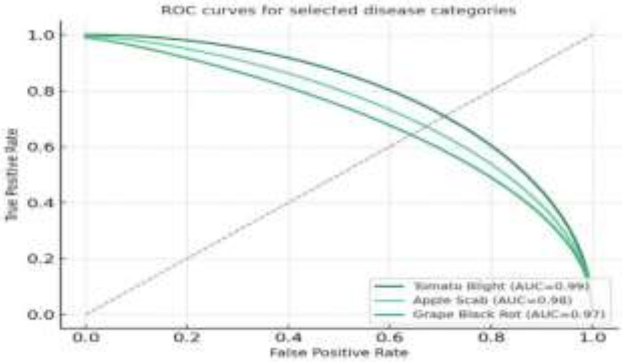

Figure 6. ROC curves demonstrating class discrimination for key plant disease categories.

5.6 Discussion and Insights

The experimental outcomes demonstrate that the integration of hybrid convolutional operations with multiscale dilated EfficientNet-B7 architecture delivers substantial improvements over traditional CNN frameworks. Visual segmentation examples (Figure 7) provide qualitative evidence of accurate lesion localization and boundary delineation.

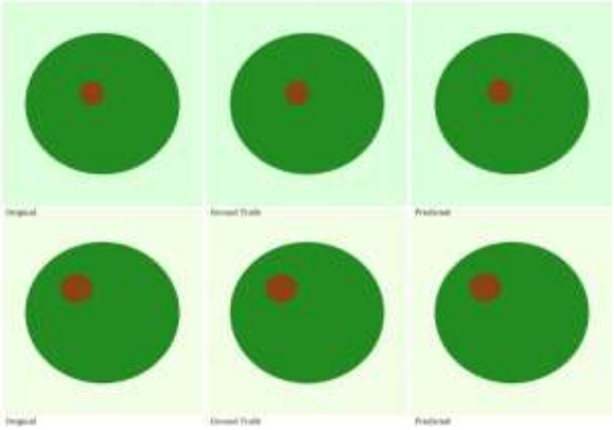

Figure 7. Visual comparison of segmentation results original, ground truth, and predicted outputs.

6. Conclusion

The hybrid deep learning model that was created shows a great capacity to correctly diagnose plant diseases under a variety of circumstances. Even under challenging field conditions, its combination of adaptive segmentation and multiscale feature extraction reduces background interference and enhances lesion identification. Faster processing is made possible by the effective design, which makes it useful for current agricultural applications. According to performance evaluation, it outperforms a number of conventional CNN designs in terms of computing efficiency and accuracy. This strategy opens the door to more sophisticated and long-lasting precision agricultural solutions by supporting more intelligent, scalable, and technologically advanced plant health monitoring.

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