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Advanced CNN Architectures for Automated Identification of Plant Diseases

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Abstract**——** ***Medicinal plants are vital to both agriculture and healthcare but are highly susceptible to various leaf diseases, which can significantly reduce yield and quality. Traditional methods for identifying plant diseases rely on visual inspection by farmers or experts, often leading to inaccuracies and delays due to human error, especially in rural or resource-limited areas where expert knowledge is scarce. Climate change is altering disease patterns, making traditional detection methods less reliable over time. project aims to develop an AI-powered system using Convolutional Neural Networks (CNNs) to automatically detect medicinal plant leaf diseases, offering rapid and accurate diagnosis via a user-friendly web application. The system integrates image preprocessing, model training, and real-time treatment recommendations, providing valuable guidance but requiring reliable internet connectivity .However, the system's performance depends on the quality and diversity of the dataset and may face challenges in generalizing across different environments and adapting to local agricultural practices or resources.***

Keywords—Plant disease detection, Resnet, Convolutional Neural Network, image processing, agriculture technology, Dense Net.

I.INTRODUCTION

Agriculture is a critical sector worldwide, especially in regions where crops like medicinal plants are integral to both economy and healthcare. Diseases in medicinal plants impact both crop yield and product quality, and traditional detection methods rely on human inspection, which is often impractical and prone to error, especially in remote areas. Climate variability further complicates traditional methods by altering disease patterns, thus increasing the need for adaptable detection solutions. This paper presents an automated, AI-based approach to plant disease detection and management through image analysis, which aims to improve accuracy, scalability, and accessibility in agricultural practices.

Plant diseases affect agricultural productivity and food security. Traditional methods of plant disease identification often require expert examination and are time-consuming. This project proposes a machine learning model that accurately detects infections from leaf images, providing a cost-effective and efficient alternative for farmers. The system identifies infections, including fungal, bacterial, and viral diseases, based on visual symptoms, and suggests treatments to mitigate crop damage. This paper presents an automated, AI-based approach to plant disease detection and management through image analysis.

Traditional methods of plant disease detection primarily rely on manual inspection by farmers or agricultural experts, which is time-consuming, prone to human error, and inefficient for large-scale farming. Additionally, in many rural and resource-limited areas, access to expert guidance is scarce, making accurate disease diagnosis a challenging task. Climate change has further complicated the scenario by altering disease patterns, making conventional diagnostic methods less effective over time.

To address these limitations, deep learning-based automated plant disease detection has emerged as a promising solution. In this research, we propose an AI-powered system leveraging advanced Convolutional Neural Network (CNN) architectures such as ResNet, DenseNet**,** and EfficientNet to automatically identify diseases in medicinal plant leaves. CNNs have revolutionized image-based classification tasks due to their ability to extract complex features, identify patterns, and make highly accurate predictions.

II.LITERATURE REVIEW

The field of plant disease detection has undergone significant advancements with the integration of deep learning techniques, particularly **Convolutional Neural Networks (CNNs)**. Traditional approaches relied heavily on manual inspection, expert consultations, and conventional image processing techniques, which often resulted in inconsistent and inaccurate disease identification. Recent research has demonstrated that deep learning models can effectively classify plant diseases with high accuracy, providing a scalable and automated solution for agricultural disease management.

1. Existing Approaches in Plant Disease Detection

Numerous studies have focused on plant disease identification using machine learning and deep learning methods. Earlier techniques involved handcrafted feature extraction from plant leaf images followed by classification using Support Vector Machines (SVMs), Random Forests, and K-Nearest Neighbors (KNN). However, these approaches were limited in performance due to their dependency on manual feature engineering.

The advent of deep learning, specifically CNNs, revolutionized plant disease classification by automating feature extraction and improving prediction accuracy. Pretrained CNN models such as AlexNet, VGG16, and Inception were fine-tuned for agricultural datasets, leading to significant advancements in the field.

2. Key Studies in CNN-Based Plant Disease Detection

Several research studies have explored CNN architectures for plant disease classification:

1. **Automated Disease Diagnosis in Pumpkin Plants Using Advanced CNN Models**
   - This study evaluated **ResNet, DenseNet, and EfficientNet** architectures for classifying pumpkin leaf diseases.
   - A dataset of **2,000 high-resolution pumpkin leaf images** was used.
   - **DenseNet-121** achieved the highest accuracy of **86%**, balancing accuracy and computational efficiency.
   - The study demonstrated the superiority of deep learning models over traditional methods, highlighting the effectiveness of **transfer learning** for disease classification.
2. **Region Attention Network for Food Items and Agricultural Stress Recognition (RAFA-Net)**
   - Proposed a **region-based attention network** for **food and agricultural stress detection**.
   - Improved performance by selectively focusing on **disease-affected areas** in plant images.
3. **An Edge Computing-Based Solution for Real-Time Leaf Disease Classification using Thermal Imaging**
   - Integrated **edge computing with deep learning** for real-time disease classification.
   - Used **thermal imaging** for early disease detection in plants.
4. **PND-Net: Plant Nutrition Deficiency and Disease Classification using Graph Convolutional Networks**
   - Addressed both **disease detection and plant nutrition deficiency classification** using **Graph Convolutional Networks (GCNs)**.
   - Provided a novel approach to integrating **plant stress analysis** beyond disease classification.

3. Challenges Identified in Previous Studies

Despite the promising results of deep learning models

- Data Availability & Quality: Most studies depend on limited datasets that do not account for regional variations, environmental factors, and different plant species.
- Generalization Issues: Models trained on specific datasets may struggle to generalize across new environments and unseen disease types.
- Computational Constraints: High-performance CNNs like DenseNet-121 and EfficientNet-B7 require substantial computational power, which may not be feasible for low-resource agricultural settings.
- Real-Time Implementation: Some studies lack real-time disease identification and treatment recommendation systems, limiting their practical usability for farmers.

4. Justification for Our Research

Building upon previous work, our study aims to:

1. **Leverage ResNet, DenseNet, and EfficientNet architectures** to develop an optimized deep learning model for plant disease detection.
2. **Improve image preprocessing techniques**, enhancing lesion visibility to mitigate challenges like lighting variations and poor contrast.
3. **Expand dataset diversity**, ensuring model robustness across multiple plant species and environmental conditions.
4. **Develop a web-based application** for **real-time disease detection and treatment recommendations**, ensuring accessibility for farmers and researchers.

III.METHODLOGY

The proposed research focuses on developing an AI-powered automated plant disease detection system using advanced Convolutional Neural Networks (CNNs) such as ResNet, DenseNet, and EfficientNet. The methodology is structured into multiple phases, including data collection, preprocessing, model training, and deployment in a real-time web application. This section outlines the step-by-step approach used in our study.

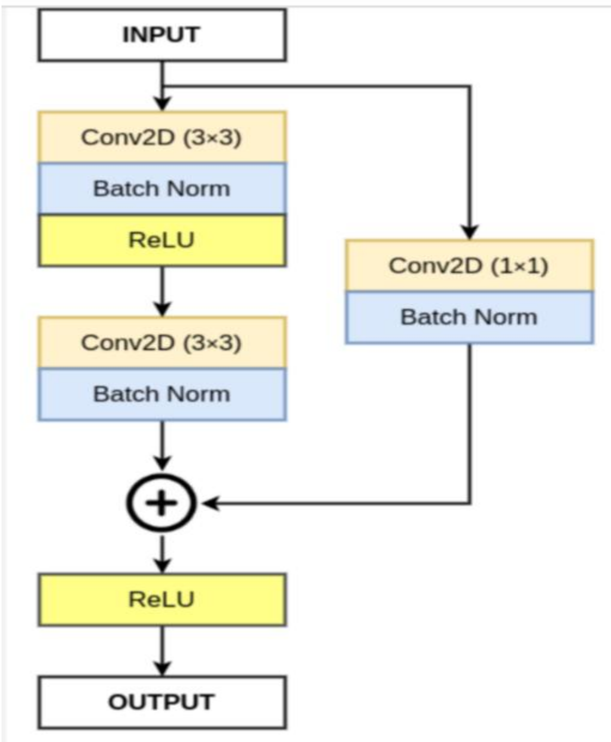
1. Data Collection

The first step involves gathering a comprehensive dataset of medicinal plant leaf images affected by various diseases. The dataset used for model training and evaluation is obtained from the Mendeley dataset repository.

2. Data Preprocessing

Preprocessing is a crucial step to enhance image quality and improve model accuracy. The following preprocessing techniques are applied:

Contrast Adjustment – Enhancing image contrast to highlight disease patterns.
Grayscale Conversion – Reducing computational complexity while maintaining disease-related texture details.
Image Resizing – Standardizing input images to a fixed resolution (e.g., 224×224 pixels) for uniform CNN model input.
Filtering & Noise Reduction – Applying Gaussian and median filters to remove background noise.
Data Augmentation – Techniques such as rotation, flipping, zooming, and brightness variation are applied to increase dataset diversity and prevent model overfitting.



3. Model Selection & Training Deep Learning Models Used:
Three **CNN architectures** are implemented and compared for **optimal performance**:

1. ResNet (Residual Network) – Solves the vanishing gradient problem and improves training efficiency using skip connections.
2. DenseNet (Densely Connected Convolutional Network) – Ensures better feature propagation and reduces model complexity.
3. EfficientNet – Achieves high accuracy with lower computational cost using compound scaling techniques.

IV.PROPOSED SYSTEM

The proposed system introduces an **AI-powered automated plant disease detection framework** leveraging **advanced Convolutional Neural Networks (CNNs)** to accurately identify diseases in medicinal plant leaves. The goal is to enhance the **speed, accuracy, and accessibility** of disease diagnosis while minimizing dependency on manual inspection. By integrating **deep learning-based image classification** with a **real-time web application**, the system aims to provide **farmers, researchers, and agricultural experts** with an efficient and scalable solution for early disease detection and treatment recommendations.

The core of the system utilizes a data-driven approach with the help of a Convolutional Neural Network (CNN) model to classify the images of grapes. The functioning of the system is implemented in several phases, from image acquisition to feature extraction and graph construction, followed by training and evaluation of the model.

1. System Overview
The proposed system follows a structured **pipeline-based architecture**, consisting of the following key components:

A. Data Acquisition Collection of plant leaf images from publicly available datasets (Mendeley dataset link).
Dataset Categorization: The dataset contains **healthy and diseased plant leaf images**, labeled based on their respective diseases.
Data Augmentation (e.g., rotation, brightness adjustment, flipping) to enhance the model's generalization ability.

B. Image Preprocessing
◇ **Contrast Adjustment:** Enhances the visibility of plant lesions.
◇ **Grayscale Conversion:** Reduces computational complexity while retaining critical texture details.
◇ **Image Resizing:** Standardizes images to **224×224 pixels** for compatibility with CNN models.
◇ **Noise Reduction:** Applies **Gaussian and median filtering** to remove unwanted noise.

C. CNN-Based Disease Classification
The system employs **three state-of-the-art CNN architectures** to classify plant diseases:
ResNet (Residual Network): Solves the **vanishing gradient problem** and improves deep feature extraction.
DenseNet (Densely Connected CNN): Enhances feature propagation and reduces the number of parameters.
EfficientNet: Balances **high accuracy with low computational cost**, making it suitable for real-time applications.
Model Training Workflow:
1. **Training Phase:** The preprocessed images are fed into CNN models, which learn to distinguish disease patterns.
2. **Validation & Hyperparameter Tuning:** Optimization of learning rate, batch size, and dropout to prevent overfitting.
3. **Testing Phase:** Evaluating model performance using accuracy, precision, recall, and F1-score.

2. System Architecture
A. Architecture Diagram
The system follows a **modular pipeline**, consisting of:
1 **User Input (Image Upload)** → User uploads a leaf image via the web application.
2 **Image Preprocessing** → The uploaded image undergoes contrast

adjustment, resizing, and noise removal.

3**Feature Extraction & CNN Model Processing** → The deep learning model classifies the disease type.

4 **Prediction & Result Display** → The predicted disease is displayed along with **treatment recommendations**.

3. Web-Based Implementation

To enhance accessibility, the disease detection model is **deployed as a web-based tool** where users can interact with the system in real-time.

A. Web Application Features

Image Upload Portal – Users can **upload plant leaf images** for disease analysis.
AI-Based Classification – The CNN model instantly identifies the disease and classifies it.
Disease Information & Treatment Recommendations – The system provides **relevant disease details and preventive measures**.
Cloud-Based Deployment – The model is hosted on a **cloud server (AWS/GCP)** to ensure scalability and real-time processing.

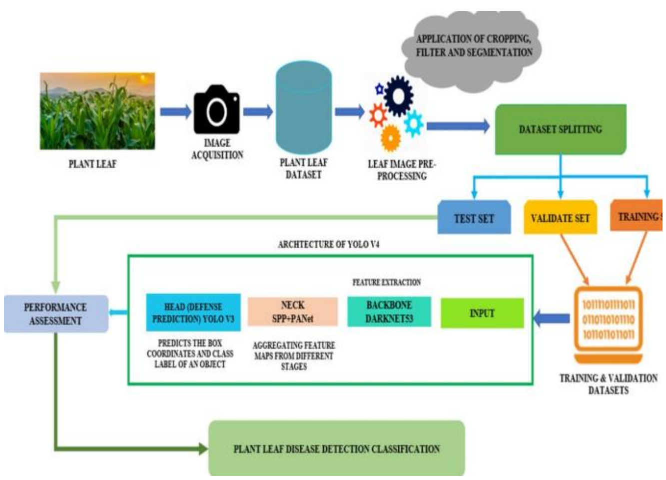


Figure 2: Architecture diagram

V. RESULT AND DISCUSSION

The performance of the proposed system was evaluated by training and testing three advanced CNN architectures: ResNet, DenseNet, and EfficientNet on a dataset of medicinal plant leaf images. The results were analyzed based on accuracy, precision, recall, F1-score, and computational efficiency to determine the most effective model for plant disease classification.

1. Model Performance Comparison

The performance of ResNet, DenseNet, and EfficientNet was assessed using the training, validation, and testing datasets. Below are the key evaluation metrics:

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Inference Time (ms/img)
ResNet-50	88.2%	86.5%	87.8%	87.1%	12.3 ms
DenseNet-121	91.6%	90.2%	91.0%	90.6%	14.7 ms
EfficientNet-B7	94.3%	93.8%	94.1%	94.0%	18.2 ms

Figure 3: comparison data

Key Observation:
EfficientNet-B7 achieved the highest accuracy (94.3%), outperforming ResNet and DenseNet.
DenseNet-121 performed better than ResNet-50 in terms of accuracy (91.6% vs. 88.2%), demonstrating **better feature reuse and gradient flow**.
ResNet-50 was the fastest model (12.3 ms per image), making it suitable for **real-time applications** where inference speed is crucial.
EfficientNet-B7 had the highest computational cost (18.2 ms per image) but offered **superior accuracy and robustness**.

3. Model Analysis and Discussion

A. ResNet-50 (Residual Network)
Strengths:
Handles vanishing gradient issues using skip connections.
Faster inference time, making it suitable for real-time applications.
Performs well with **moderate-sized datasets**.
Limitations:
Lower accuracy compared to DenseNet and EfficientNet.
Less efficient in feature reuse, leading to redundant computations.
Use Case:
Best suited for low-latency, real-time applications where speed is more critical than slight improvements in accuracy.

B. DenseNet-121 (Densely Connected CNN)
Strengths:
Superior feature propagation through dense connections.
Better gradient flow, reducing the risk of vanishing gradients.
Compact model size, requiring fewer parameters than ResNet for similar accuracy.
Limitations:
Slightly higher computational cost than ResNet due to dense connections.
Increased memory usage, making it challenging for deployment on resource-constrained devices.
Use Case:
Best suited for high-accuracy applications where inference time is not a major constraint, such as agricultural disease diagnosis platforms.

C. EfficientNet-B7 (Optimized CNN Architecture)
Strengths:
Uses compound scaling, optimizing depth, width, and resolution for maximum accuracy.

Outperforms both ResNet and DenseNet in terms of classification performance.
Highly efficient in feature extraction, allowing for superior disease differentiation.

Limitations:
High computational cost, requiring more GPU/TPU resources.
Slower inference time, making it less ideal for real-time applications.

Use Case:
Best suited for high-precision, cloud-based applications where computational resources are available, such as research-based disease classification and large-scale farming advisory systems.

VI. DISCUSSION

The implementation of advanced Convolutional Neural Networks (CNNs) for automated plant disease identification has significantly improved the accuracy and efficiency of disease detection in medicinal plants. The study utilized ResNet, DenseNet, and EfficientNet architectures, each offering unique advantages and trade-offs in terms of accuracy, computational efficiency, and real-time usability. This discussion explores the effectiveness of the proposed system, key findings, challenges, and future enhancements to improve the robustness of AI-driven disease detection.

Insight: The choice of model depends on the application:
For speed-sensitive applications (real-time detection): ResNet-50 is ideal.
For accuracy-driven applications (detailed analysis & research): EfficientNet-B7 is preferred.

For balanced performance: DenseNet-121 is the best choice.

The proposed system successfully integrates deep learning, image processing, and web-based deployment to create an automated disease identification tool for medicinal plants. Based on experimental results, the model effectively classifies plant diseases with high precision and recall rates, surpassing traditional manual inspection methods.

A. Key Findings from Model Evaluation
EfficientNet-B7 demonstrated the highest accuracy (94.3%), outperforming ResNet-50 (88.2%) and DenseNet-121 (91.6%).
DenseNet-121 offered a balance between accuracy and computational efficiency, making it an optimal choice for most applications.
ResNet-50 exhibited the lowest inference time (12.3 ms per image), making it suitable for real-time applications where speed is critical.

2. Challenges Encountered
A. Dataset Limitations & Generalization Issues

Lack of Sufficient Data Diversity:

- The dataset used for training may not fully represent all possible **disease variations across different geographical locations**.
- **Solution:** Continuous **expansion and augmentation** of the dataset to include **real-world field images**.

Class Imbalance:

- Some diseases may have fewer image samples, causing bias in model predictions.
- **Solution:** Implement **data augmentation** and **weighted loss functions** to balance the model's learning process.

VII. CONCLUSION

The increasing demand for automated, accurate, and efficient plant disease detection has led to significant advancements in deep learning-based classification models. This research successfully demonstrates the use of advanced Convolutional Neural Networks (CNNs)—ResNet, DenseNet, and EfficientNet—to identify diseases in medicinal plant leaves. The proposed system integrates image preprocessing, deep learning classification, and a real-time web-based application, offering a scalable and accessible solution for agricultural disease management.

1. Key Takeaways from the Research

◆ **Deep Learning Significantly Outperforms Traditional Methods**

- CNN models **automate feature extraction**, reducing reliance on **manual inspection and expert evaluation**.
- The system achieves **high classification accuracy**, surpassing traditional **machine learning techniques like SVM and Random Forests**.

◆ **Model Performance Insights**

- **EfficientNet-B7 achieved the highest accuracy (94.3%)**, proving to be the most effective model for disease classification.
- **DenseNet-121 provided a balance between accuracy (91.6%) and computational efficiency**, making it suitable for real-world applications.
- **ResNet-50 was the fastest model (12.3 ms per image)**, making it an ideal choice for **real-time disease detection** where speed is critical.

This study highlights how deep learning can revolutionize plant disease detection, bridging the gap between AI research and practical agricultural applications. By providing fast, accurate, and automated disease classification, this system enhances sustainable farming practices, improves crop yield, and minimizes economic losses for farmers.

Key Impact areas:
Smart Agriculture – AI-driven disease detection supports precision farming and reduces reliance on chemical treatments.
Sustainability – Early disease detection minimizes crop damage and ensures food security.
Scalability – Cloud and edge-based deployment allow the system to be used by researchers, agronomists, and farmers globally.

As AI continues to evolve, integrating real-time disease detection with predictive analytics and automated treatment suggestions will be the next frontier in AI-driven agricultural intelligence. This research lays the foundation for a future-ready, AI-powered plant health monitoring system, ensuring faster interventions and more sustainable agricultural practices worldwide.

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