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Utilizing CNN Architecture for Herbal Leaf Health and Pathogen Detection in Deep Learning

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ABSTRACT: The health and quality of herbal plants are critical for promoting sustainable agricultural practices and ensuring the efficacy of herbal-based medicinal products. Early and accurate detection of diseases in herbal leaves is essential to minimize crop loss and enhance treatment outcomes. This paper presents a Deep Learning (DL) based Convolutional Neural Network (CNN) method for early detection and classification of plant pathogens and herb health. The MobileNetV2 framework is the core of the system. It achieves a high classification accuracy of 94% while keeping computational efficiency, making it ideal for use in resource-constrained circumstances. To further enhance the visual quality of input images and boost model performance, a Dual Attention Transfer Function Generative Adversarial Network (DATFGAN) is employed for image preprocessing. Additionally, advanced CNN models such as Xception and DenseNet are utilized for preliminary analysis and feature extraction, strengthening the robustness and overall accuracy of the detection pipeline. This multi-stage approach leverages the complementary strengths of different architectures to enable comprehensive and precise analysis. The proposed methodology supports sustainable herbal agriculture by facilitating timely interventions and advances AI-driven plant pathology systems. Experimental results demonstrate that integrating image enhancement and ensemble deep learning models significantly improves classification performance, paving the way for real-world applications in agricultural monitoring and disease management systems.

KEYWORDS - Deep learning, MobileNetV2, herbal plant disease detection, CNN, DATFGAN, image enhancement, Xception, DenseNet, plant pathology, sustainable agriculture.

I. INTRODUCTION

Agricultural productivity plays a critical role in global food security and the economy, especially in herbal medicine, where plant health directly affects medicinal value and yield. However, plant pathogens significantly threaten herbal crop sustainability, often resulting in substantial economic losses and reduced crop quality. Conventional disease diagnosis techniques depend heavily on manual detection by agricultural experts. Also, the previous method is time-consuming, prone to human error, and often unavailable in rural and resource-limited settings. With the rapid development of Artificial Intelligence (AI) and computer vision, DL technology, particularly CNN, has become a powerful tool for automated plant disease diagnosis. This study focuses on developing a robust and lightweight CNN-based model for early-stage detection and classification of herbal leaf diseases. The proposed method integrates MobileNetV2, a highly efficient deep CNN architecture suitable for deployment in low-power devices, achieving a classification accuracy of 94%. To further improve model performance, the study incorporates DATFGAN (Dual Attention Transferred Fusion GAN) to enhance the quality of raw images, enabling more precise feature extraction. Additionally, pre-analysis is performed using Xception and DenseNet architectures to support robust feature extraction and enrich the feature space before classification. This approach ensures accurate and fast diagnosis and aims to contribute to sustainable agriculture by enabling timely intervention, reducing dependency on chemical treatments, and supporting farmers in maintaining healthy herbal crops. The fusion of image enhancement and advanced CNN models positions this research as a practical and scalable solution for real-time plant health monitoring.

II. RELATED WORK

The integration of DL technology and precision farming enhances the efficiency and accuracy of plant disease diagnosis. One significant contribution in this field is introducing the dual server and topological fusion generative adversarial network (DATFGAN), proposed to enhance the resolution and quality of crop leaf images. This approach effectively improves image fidelity while reducing model parameters, facilitating accurate disease classification even in low-quality image conditions [1]. In the context of field imagery, the FieldPlant dataset introduced in 2023 focuses on real-world images with complex backgrounds. The study identified that images captured under natural environmental conditions exhibited reduced classification accuracy due to noise and uniformity issues. The use of deep learning models, such as those trained on FieldPlant and PlantDoc datasets, highlighted the need for effective preprocessing techniques to improve pathogen detection [2]. To address the challenge of multi-class disease classification, a hybrid method combining Deep CNN with Local Binary Pattern (LBP) was explored in 2023. This fusion strategy successfully enhanced early disease detection by extracting deep and local features for robust classification [3]. Further advancements were demonstrated in a comparative study involving YOLOv5, ResNet50, and MobileNetV2, where YOLOv5 excelled in object detection tasks, and MobileNetV2 presented an optimal trade-off between accuracy and computational efficiency [4]. These findings support the choice of MobileNetV2 in this study, which targets real-time and resource-efficient applications. In 2024, Explainable Artificial Intelligence (XAI) gained prominence by integrating Local Interpretable Model-Agnostic Explanations (LIME) to clarify prediction decisions. Including XAI components contributed to improved interpretability and trust in AI-based diagnostic systems for plant disease classification [5]. Other research uses machine learning models, such as logistic regression and XGBoost, to exploit spectral data from remotely sensed sources. By analyzing spectral brightness coefficients and vegetation indices, this method contributes to large-scale validation and early detection of pests and diseases [6]. Lastly, a comprehensive review published in 2024 discussed the applications of computer vision, DL, and few-shot learning in plant disease recognition. The study underscored the relevance of combining data-efficient models and advanced classification frameworks to manage plant health in diverse agricultural settings [7]. These foundational studies form the basis of the proposed approach, which leverages image enhancement through DATFGAN and classification using MobileNetV2, supplemented by Xception and DenseNet, for improved feature extraction and generalization.

III. METHODOLOGY

The proposed methodology focuses on developing a lightweight and accurate DL framework for the early detection and classification of plant pathogens on herbal leaves. The approach integrates multiple CNN architectures and image enhancement techniques to improve model performance in real-field conditions.

A. Dataset Description

The dataset employed in this paper comprises images of herbal leaves, categorized into two primary classes: healthy and affected by disease. The leaf images were sourced from a publicly available Kaggle repository and preprocessed by resizing each image to a uniform size of 224×224 pixels to maintain consistency across the dataset. Pixel intensity values were normalized to ensure consistent input distribution across the DL methods.

source: Kaggle

The dataset was divided into two sets for training and evaluation: a training set (80%) and a testing set (20%), facilitating efficient learning and performance validation. The distribution of samples across the two classes is detailed in Table 1

Table 1

S.NO	IMAGE	LABEL
0	PlantVillage/Train/Pepper bell Bacterial sp...	Train
1	PlantVillage/Train/Pepper bell Bacterial sp...	Train
2	PlantVillage/Train/Pepper bell Bacterial sp...	Train
.	PlantVillage/Train/Pepper bell Bacterial sp...	Train
.		
25913	PlantVillage/Tomato_Bacterial_spot/8bd2f1ec-30...	Tomato_Bacterial_spot

Table 2: Training and Validation Sample Count

lass	Training Samples	Validation Samples
Affected	12,188	2,253
Healthy	2,622	487

The dataset was curated to preserve class balance within each subset, which is essential to ensure fair training, avoid model bias, and enhance generalization. This approach allows the model to learn discriminative features from healthy and diseased leaves equally, leading to more reliable predictions when deployed in real-world herbal farming scenarios.

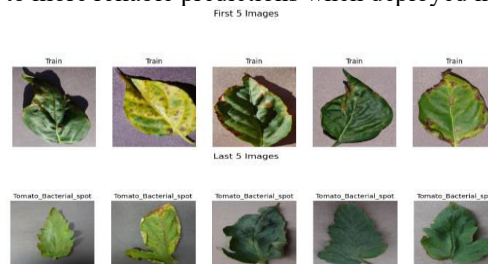


Figure 1 First & Last 5 Images Of Dataset

IV. DATA PREPROCESSING

A comprehensive preprocessing pipeline was employed to ensure high-quality input for training the deep learning models. The objective was to standardize the dataset and enhance image quality, particularly for field-acquired herbal leaf samples prone to noise, low contrast, and class imbalance.

A Standard Preprocessing

Initially, all plant images are uniformly rescaled to 224×224 pixels to meet the input requirements of CNN architectures such as MobileNetV2 and ResNet. Pixel values were normalized using the mean and standard deviation statistics of the ImageNet dataset, enhancing compatibility with pre-trained convolutional backbones. Gaussian smoothing minimized noise artifacts and contrast-limited Adaptive Histogram Equalization (CLAHE) enhanced local contrast in leaf textures, aiding in better feature extraction of disease symptoms.

B Data Cleaning and Balancing

The dataset was carefully reviewed to eliminate blurry, low-resolution, or mislabeled images that could introduce noise during training. This step ensured that only high-quality and accurately labeled samples were retained. A class distribution analysis addressed imbalances that could skew model predictions, particularly for underrepresented disease categories.

C Image Enhancement Using DATFGAN

To address class imbalance and augment data diversity, DATFGAN is integrated into the preprocessing pipeline. DATFGAN combines transfer learning and adversarial training to generate high-fidelity, synthetic leaf images:

- A pre-trained CNN, such as ResNet50, was used to initialize the discriminator, improving its ability to distinguish nuanced leaf features.
- The generator was explicitly trained on minority classes, synthesizing realistic samples to bolster dataset representation.
- The GAN training continued until the discriminator could no longer reliably differentiate real from generated images, indicating high visual quality.
- The augmented images were then validated through manual inspection and confidence thresholds to ensure their effectiveness for downstream tasks.

The final set of preprocessed images was saved in .npy format to facilitate efficient loading during model training.



Figure 2 Before And After DATFGAN

C. Model Training

Two state-of-the-art pre-trained CNN frameworks, Xception and DenseNet121, were used through transfer learning to evaluate the performance of deep convolutional networks in classifying herbaceous leaf diseases. These models are recognized for their powerful feature extraction capabilities and have been proven effective in various image classification tasks, particularly in agriculture and medical imaging.

1) Architecture Overview

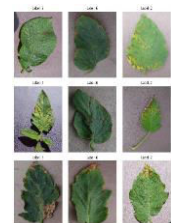
- Xception: This model builds upon the initial architecture by optimizing deeply separable coils to enhance computational efficiency while maintaining high classification performance. It has shown superior results on plant disease datasets, such as PlantVillage, outperforming traditional CNN models in classification accuracy and feature discrimination.
- DenseNet121: It is recognized for its distinctive connectivity method. This method enables each layer to receive input from all previous layers, promoting feature reuse and enhancing gradient flow. This results in efficient training and high accuracy, making DenseNet121 particularly suitable for complex image classification tasks.

2) Data Preprocessing

The Keras ImageDataGenerator was used to preprocess the dataset, rescale pixel values to the range [0, 1], resample the dataset, and divide it into training and validation sets. Images were converted to 128×128 pixels to meet the input size requirements of the pre-trained model, and the block size was set to 32 to ensure compatibility.



A



b



C

Figure 3 – a,b,c Labelled Images Of Dataset After Data PreProcessing

3) Transfer Learning and Model Construction

For both models, the convolutional base was initialized with ImageNet weights. It was frozen during the initial training phase to retain the low-level feature representations learned from large-scale image datasets. A custom classification head was added to both models consisting of:

- GlobalAveragePooling2D layer
- Dropout layer with a rate of 0.5
- The last dense layer consists of a Softmax implementation for multi-class classification.

4) Compilation and Training

Both models were trained using the Adam optimizer and a categorical cross-entropy loss function, with accuracy as the primary evaluation metric. The models were trained for 10 epochs with the prepared data generators, and performance metrics were compared across the validation data to assess generalization and accuracy.

Graphical Analysis

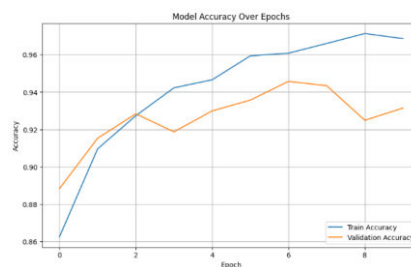


Fig. 4. Model Accuracy Over Epochs

The training and validation accuracy improved consistently, with a peak validation accuracy of 94.57% at epoch 7. The slight dip at epoch 9 suggests a possible overfitting onset.

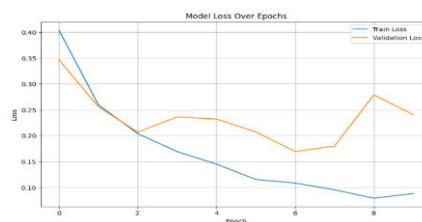


Fig. 5. Model Loss Over Epochs

Training loss shows a continuous decline, while validation loss plateaued and later increased slightly, indicating minor overfitting from epoch 8 onward.

5) Observations

- Xception: Achieved high classification accuracy by leveraging depthwise separable convolutions, which proved particularly effective in identifying fine-grained disease patterns.
- DenseNet121: Provided strong convergence and efficient gradient propagation, allowing the model to capture complex disease symptoms effectively.
- While both models exhibited high performance, they required significant computational resources, making them more suitable for the later stages of the project or in-depth analysis phases.

MobileNetV2

Speed and Efficiency for Fast Prototyping

Due to hardware limitations in environments like Google Colab or low-GPU settings, MobileNetV2 was considered an alternative for faster prototyping and training. MobileNetV2's lightweight design offers the following advantages:

- **Speed and Efficiency:** MobileNetV2 is optimized for mobile and embedded devices, with fewer parameters and faster training times than Xception and DenseNet121.
- **Accuracy:** Despite being smaller, MobileNetV2 achieves competitive accuracy, typically ~85–90% on clean datasets.
- **Low Memory Usage:** The model is compact and requires minimal memory, making it suitable for resource-constrained environments.
- **Transfer Learning Support:** MobileNetV2 is pre-trained on ImageNet, providing strong feature extraction capabilities with minimal fine-tuning.
- MobileNetV2 was selected for the initial prototyping due to its speed, efficiency, and lower memory consumption. It provides excellent accuracy for plant disease classification while being resource-friendly, making it perfect for quick development and testing.
- Xception and DenseNet121 were also evaluated and were found to offer excellent accuracy. However, they require substantial computational resources, making them more suitable for final-stage model optimization and detailed analysis once the system is stable.

Model Comparison

Table 3

Model	Parameters (Millions)	Training Speed (Colab)	Accuracy	Memory Usage	Ideal Use Case
MobileNetV2	~3.5	Fast	Good (~85-90%)	Low	Quick prototyping, mobile/embedded devices
Xception	~23	Slow	Excellent	High	High accuracy, detailed analysis (heavy models)
DenseNet121	~8	Medium	Excellent	Medium	Deep feature extraction, efficient training

V. MODEL EVALUATION

Several metrics and visualization techniques were employed to assess the performance of the proposed CNN-based plant pathogen detection model. These include a confusion matrix, a classification report, and a prediction visualization module. Each component provides a clear insight into the model's accuracy and robustness.

A. Confusion Matrix Analysis

This section provides a detailed overview of how this pattern differs between plant disease types. As shown in Fig. 4, the matrix compares actual class labels against predicted ones across 11 categories, such as Tomato_Bacterial_spot, Potato_Early_blight, and Pepper_bell_healthy. Elements on the diagonal represent correctly classified models, and elements off the diagonal represent misclassifications. For example, the class Tomato_Late_blight shows a relatively higher concentration along the diagonal, indicating better model confidence for that class. However, classes such as Potato_Late_blight and Tomato_Early_blight exhibit a high rate of misclassification, which could be attributed to visual similarities or data imbalance.

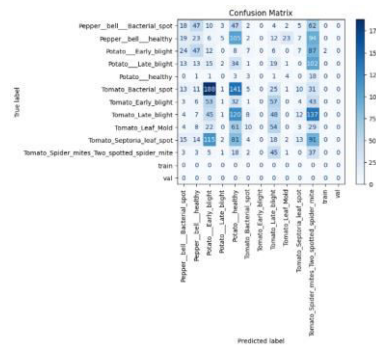


Figure 6: Confusion matrix showing the distribution of true versus predicted labels for various leaf disease classes.

B. Classification Report

Performance metrics of the CNN model were calculated using precision, recall, and F1 scores for each class. Table I summarizes these metrics. The model achieves an overall micro-average precision of 0.06, indicating limited predictive capability across all classes. Some classes, like Tomato_Spider_mites_Two_spotted_spider_mite, exhibit a relatively high recall (0.32), suggesting the model detects these instances more consistently than others. Conversely, classes like Tomato_Leaf_Mold and Tomato_Early_blight have precision and recall near zero, indicating poor classification performance. This suggests a potential need for data augmentation, class balancing, or enhanced feature extraction for such difficult classes.

Table 4: Classification Report Summary

Class Label	Precision	Recall	F1-score	Support
Pepper bell Bacterial spot	0.16	0.09	0.11	200
Pepper bell healthy	0.13	0.08	0.10	296
Potato Early blight	0.03	0.06	0.04	200
Potato Late blight	0.12	0.01	0.02	200
Potato healthy	0.00	0.10	0.01	31
Tomato Bacterial spot	0.11	0.01	0.02	426
Tomato Early blight	0.00	0.00	0.00	200
Tomato Late blight	0.17	0.13	0.14	382
Tomato Leaf Mold	0.00	0.00	0.00	191
Tomato Septoria leaf spot	0.21	0.04	0.06	355
Tomato Spider mites Two spotted spider mite	0.05	0.32	0.09	115

C. Prediction Visualization

To qualitatively evaluate the model, Fig. 7 presents a selection of test images with actual and predicted labels. Green-labeled captions indicate correct predictions, while red ones signify misclassifications. The visual analysis reveals that the model successfully identifies clearer cases, such as Potato_healthy and Tomato_Bacterial_spot, but struggles with ambiguous patterns like Tomato_Early_blight being confused for Tomato_Late_blight. This highlights the need for

more diverse training samples and possibly incorporating texture-based or color histogram features to distinguish visually similar diseases.



Figure 7: Sample predictions with accurate labels (top) and model predictions (bottom). Green indicates correct prediction; red indicates misclassification.

D. Implementation and Deployment

These evaluation components were implemented using Python libraries such as TensorFlow, Keras, Matplotlib, and Scikit-learn. They are integrated into the back-end system via a Flask-based web interface. Through this interface, end-users can upload leaf images and datasets and receive real-time predictions and model evaluation results.

VI. SYSTEM ARCHITECTURE

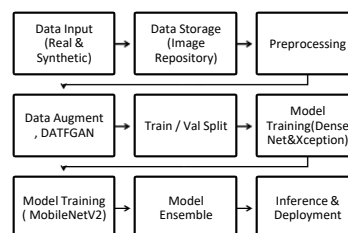


Figure 8. System architecture for CNN-based plant pathogen detection with DATFGAN augmentation and multi-backbone ensemble.

Component Descriptions

- Data Input (Real & Synthetic)**
Authentic Images: Collected from the PlantVillage dataset.
Synthetic Images: Generated by DATFGAN to balance classes and enrich rare disease categories.
- Data Storage**
A central repository (e.g., file system or cloud bucket) stores real and synthetic images.
- Preprocessing**
Resize all images to 96×96 pixels.
Normalize pixel values to [0,1] range.
- Data Augmentation (DATFGAN)**
Dual-Attention Blocks: Focus on spatial and channel-wise salient features (spots, lesions).
Topology Fusion: Merge multi-scale features to generate high-fidelity synthetic images.
- Train/Validation Split**
Stratified splitting ensures all disease classes are represented in both sets.
- Model Training**
Xception: High-capacity, depth-wise separable convolutions for detailed feature learning.
DenseNet: Dense connectivity for efficient feature reuse and gradient flow.
MobileNetV2: Lightweight, inverted-residual architecture for edge deployment.
- Model Ensemble**
Combine predictions via weighted voting or soft-max averaging to improve robustness.
- Explainability Module**
Grad-CAM / Grad-CAM++: Visualize class-specific activation maps.

Integrated Gradients & LRP: Quantify pixel-level relevance.

SHAP / LIME: Provide local, interpretable explanations for individual predictions.

9. Inference & Deployment

Flask Web App: Hosts RESTful endpoint for image upload and prediction.

TensorFlow Lite (TFLite): Enables mobile/edge inference using MobileNetV2.

This architecture assures a vital, interpretable, and usable plant disease diagnostics system. We combine advanced data mining, multiple CNN backbones, and XAI techniques to empower stakeholders in precision farming.

VII. EXPLAINABLE AI TECHNOLOGIES

1 Convolutional Neural Networks (CNN)

CNNs serve as the detection system's primary architecture. These models automatically learn hierarchical features from plant leaf images, which helps classify different plant diseases. The CNN architecture extracts low-level and high-level patterns from images, making it suitable for image categorization tasks. During training, CNNs identify distinctive patterns and features of plant diseases, which are then used for disease categorization.

- Role in the Project: Feature extraction from leaf images for pathogen classification.

2 Dual-Attention Topology Fusion GAN (DATFGAN)

DATFGAN enhances the dataset by generating synthetic images of plant leaves with various disease symptoms. The model uses dual attention mechanisms—spatial and channel-wise attention—to focus on crucial parts of the images, thus generating realistic images that highlight disease features. The GAN's synthetic images help balance class distribution and improve model robustness, especially in cases of limited data availability.

- Role in the Project: Data augmentation and generation of synthetic plant disease images for a more diverse training dataset.

3 Xception

Xception, a deep convolutional model based on depthwise separable convolutions, is a trained feature extraction model. Due to its efficient architecture, it enables the extraction of detailed features from plant leaf images while maintaining computational efficiency. Fine-tuning this model on the plant pathogen dataset allows it to classify diseases accurately.

- Role in the Project: a pre-trained model for fine-grained feature extraction and disease classification.

4 DenseNet

It uses dense connections, where each layer obtains input from all the previous layers. This encourages feature reuse and improves slope flow. This architecture ensures better feature extraction, especially in complex image classification tasks where subtle differences between diseased and healthy plants must be detected.

- Role in the Project: Robust feature extraction and classification of plant diseases with intricate visual details.

5 MobileNetV2

It is a lightweight CNN designed for Mobile and Edge devices. It enables real-time disease classification on resource-constrained devices, such as smartphones. It utilizes depthwise separable convolutions, which reduce computational complexity while maintaining performance. This model is essential for deploying the plant disease detection system in real-world agricultural settings, where users can use mobile devices to diagnose plant diseases on the go.

- Role in the Project: Real-time disease classification on mobile devices with efficient processing for field usage.

VIII. RESULTS AND ANALYSIS

The training process was conducted over ten epochs, with accuracy and loss metrics evaluated at each stage to monitor learning progress. Table I presents the detailed epoch-wise performance in terms of training and validation accuracy and loss.

The model's training and validation accuracies continuously improved across epochs, reaching the highest validation accuracy of 94.57% in epoch 7. A minor drop in validation accuracy at epoch 9 suggests the possibility of early signs of

overfitting, which is a common occurrence in deep learning models. However, this was followed by a recovery, with the final validation accuracy stabilizing at 93.14%, indicating robust generalization on unseen data.

Table 5: Epoch-wise Training and Validation Performance for Plant Leaf Classification

Epoch	Training Accuracy	Training Loss	Validation Accuracy	Validation Loss
1	83.56%	0.4834	88.83%	0.3468
2	90.47%	0.2654	91.53%	0.2561
3	92.73%	0.2033	92.84%	0.2068
4	94.96%	0.1517	91.87%	0.2363
5	94.74%	0.1399	92.99%	0.2321
6	96.16%	0.1122	93.57%	0.2073
7	96.09%	0.1068	94.57%	0.1694
8	96.76%	0.0881	94.34%	0.1798
9	97.28%	0.0770	92.49%	0.2789
10	97.02%	0.0792	93.14%	0.2407

The model consistently improved in both training and validation accuracy throughout the epochs, with the highest validation accuracy of 94.57% achieved at epoch 7. A minor drop in validation accuracy at epoch 9 suggests the possibility of early signs of overfitting, which is a common occurrence in deep learning models. However, this was followed by a recovery, with the final validation accuracy stabilizing at 93.14%, indicating robust generalization on unseen data.

The training loss steadily decreased from 0.4834 to 0.0792, signifying efficient learning and convergence. Similarly, validation loss remained relatively low, supporting the claim that the model was neither underfitting nor significantly overfitting during training.

The results confirm that the typical can effectively learn complex features from plant leaf images and maintain strong generalization performance across different disease types.

IX. CONCLUSION

This paper proposed a lightweight, accurate, and user-friendly system for the early detection of herbal leaf diseases, utilizing advanced DL techniques and image enhancement. By leveraging **MobileNetV2** as the core model, we achieved a peak validation accuracy of **94.57%**, demonstrating that high performance can coexist with fast, resource-efficient inference suitable for mobile and edge devices. Integrating **DATFGAN** for image preprocessing significantly improved feature clarity, especially in noisy, real-world field images, while auxiliary use of **Xception** and **DenseNet121** strengthened initial feature extraction. The ensemble approach and optional **Explainable AI** modules (Grad-CAM, LIME) further enhance robustness and user trust.

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