Smart Detection of Medicinal Aloe Vera Leaf Diseases Using DenseNet201 for Precision Agriculture

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***Abstract*—*Aloe vera*, a widely cultivated medicinal plant, is increasingly threatened by foliar diseases such as rust and rot, which significantly impact crop yield and therapeutic quality. Manual disease diagnosis is often subjective and labor-intensive, highlighting the need for automated, accurate, and scalable solutions. This work introduces a classification model based on deep learning and transfer learning with DenseNet201—a convolutional neural network pretrained on ImageNet and fine-tuned for domain-specific identification of *Aloe vera* leaf conditions. To enhance generalization and mitigate overfitting, we incorporate on-the-fly data augmentation using geometric and photometric transformations. A two-phase training protocol is adopted: the custom classification head is initially trained with the backbone frozen, followed by selective unfreezing of deeper layers under reduced learning rates. For robust inference, we implement test-time augmentation (TTA) by averaging softmax outputs across multiple augmented views. The model attains a classification accuracy of 97.37% on the standard test set, which improves to 98.68% with TTA, outperforming baseline methods and demonstrating strong generalization. Optimized for deployment on edge devices, this pipeline is well-suited for real-time, in-field disease monitoring in precision agriculture.**

***Index Terms*—*Aloe vera* classification, plant disease detection, DenseNet201, transfer learning, data augmentation, test-time augmentation, precision agriculture.**

I. Introduction

A. General and Specific Issues

Aloe vera, a succulent plant known for its medicinal, cosmetic, and nutritional applications, plays a crucial role in global agriculture and health markets. Despite its resilience, Aloe vera is highly susceptible to foliar diseases such as rust and rot, which significantly degrade leaf quality, reduce gel yield, and ultimately threaten crop productivity. Conventional diagnostic approaches based on human observation tend to be inefficient, prone to mistakes, and impractical for use in large-scale agricultural settings. This underscores the need for automated, scalable, and reliable disease classification systems for practical deployment in field conditions.

Recent developments in deep learning—especially Convolutional Neural Networks (CNNs)—have significantly advanced visual recognition, including applications in plant disease identification. However, the successful application of these models typically demands large labeled datasets and consistent imaging conditions—requirements that are rarely met in agricultural settings. Field-acquired images often suffer from issues such as lighting variability, occlusions, leaf orientation changes, and background clutter, making the task of robust disease classification considerably more complex. Moreover, there is a clear lack of research focus on medicinal plants like Aloe vera, as most studies concentrate on staple crops (e.g., tomato, maize, wheat), leaving a gap in both datasets and deep learning applications specific to this plant.

B. Literature Review

Several paradigms have shaped automated Aloe vera disease classification:

Early CNN+SVM Pipelines: Muhammad et al. [1] employed pretrained VGG-19 and AlexNet for feature extraction, combining them with discrete wavelet transforms and an SVM classifier. This hybrid pipeline achieved 96.9% accuracy on a three-class task: healthy vs. rust vs. rot. Singh et al. [2] improved robustness by optimizing wavelet parameters, though their approach still relied on separate feature extraction and classification stages.

End-to-End Fine-Tuning of Modern Backbones: To streamline learning and reduce error propagation, later works adopted end-to-end training. Malek et al. [3] fine-tuned EfficientNet-B5, B6, and B7 on a dataset of 2,770 smartphone-captured images, achieving 97.56% accuracy for spot vs. rust classification. These results highlight the effectiveness of compact, high-capacity models. However, **Aloe vera remains underrepresented compared to staple crops like tomato or potato in benchmarking efforts**.

Federated Learning for Privacy and Scalability: Sharma et al. [4] introduced a federated CNN framework that enabled decentralized model training across edge devices while matching the accuracy of centralized methods. Lavenya et al. [5] extended this approach by incorporating class-weighted

aggregation to address imbalance. While these studies advance privacy and fairness, they overlook inference-time robustness in noisy field conditions.

DenseNet and Under-Exploration in Aloe Vera: DenseNet's dense skip connections facilitate gradient flow and feature reuse, particularly on limited datasets. Wang et al. [6] reported 97.6% accuracy using DenseNet201 on the PlantVillage tomato dataset. More recently, hybrid variants that integrate attention mechanisms or Bayesian hyperparameter tuning have achieved up to 99.2% accuracy in multi-crop scenarios [7]. Despite this promise, **DenseNet201 remains largely untested on Aloe vera disease datasets.**

Inference Robustness & Test-Time Augmentation (TTA): Real-world Aloe vera imagery is often affected by lighting variations, occlusions, and background clutter. Test-Time Augmentation (TTA)—which ensembles predictions over multiple stochastic transformations—has significantly improved robustness in medical imaging and object detection tasks [8], [9]. Yet, TTA remains underutilized in plant disease pipelines, especially for under-benchmarked crops like Aloe vera.

TABLE I
SUMMARY OF KEY STUDIES ON ALOE VERA DISEASE CLASSIFICATION

Model(s)	Task	Key Outcome
VGG-19/AlexNet + SVM [1], [2]	Healthy vs. rust vs. rot	96.9% accuracy; separate CNN+SVM stages
EfficientNet-B5/6/7 [3]	Spot vs. rust (2,770 images)	97.56% accuracy via full-network fine-tuning
Federated CNNs [4], [5]	Decentralized Aloe vera diagnosis	Privacy-preserving training; class-weighted updates
DenseNet201 (PlantVillage) [6]	Tomato disease classification	97.6% accuracy; superior to ResNet
This Work	Aloe vera with DenseNet201 + TTA	Fine-tuned DenseNet201 with inference-time robustness

Summary and Identified Gap: Over the years, Aloe vera disease classification has progressed from traditional CNN+SVM hybrids to end-to-end deep learning and privacy-aware federated frameworks. Despite these advances, most works focus either on training paradigms or architectural optimization, often overlooking robustness at inference time. Moreover, DenseNet201—while highly effective in plant disease classification—remains underutilized in Aloe vera-specific tasks. **To our knowledge, no existing work combines DenseNet201 fine-tuning with test-time augmentation for robust Aloe vera disease detection.** Our study bridges this gap by proposing a lightweight yet resilient pipeline deployable on edge devices under real-world conditions.

C. Advantages and Implementation

Owing to its dense connectivity, DenseNet201 enables feature reuse and efficient gradient flow, making it well-suited for Aloe vera disease classification on moderate-sized datasets [10]. Compared to architectures like ResNet, it achieves similar or improved accuracy with fewer parameters, making it practical for edge deployment [11], [12].

We leverage transfer learning with ImageNet-pretrained weights. The early layers, trained on diverse images, extract transferable features (e.g., edges, textures), while fine-tuning adapts them to Aloe vera-specific lesion patterns [13], [14]. This accelerates convergence and reduces overfitting on our 3,500-image dataset [15].

To boost generalization, we apply online data augmentation using geometric (rotations, flips, scaling) and photometric (brightness, contrast) transformations [16]. Unlike static methods, this generates new variants each epoch, improving robustness without inflating storage [17].

Training proceeds in two phases:

Phase I: The DenseNet backbone is frozen, and only the classifier head (global average pooling, batch norm, dropout, dense layer) is trained, preserving pretrained features [18].

Phase II: The top 20% of DenseNet blocks are unfrozen and fine-tuned at a low learning rate (1×10^{-5}), allowing refinement of disease-specific patterns like rust blight and necrotic rot [19].

For inference, we use test-time augmentation (TTA): each test image undergoes five random augmentations, and predictions are averaged. This ensemble-like approach improves robustness to lighting, occlusion, and background variation [20], [21].

The final pipeline is lightweight (¡45 MB) and deployable on edge hardware (e.g., smartphones, Jetson Nano), offering scalable, real-time disease detection for field use [22], [23].

D. Detailed Objective

This study focuses on creating a deep learning model that is both lightweight and highly efficient for automated classification of *Aloe vera* leaf conditions—specifically distinguishing healthy, rust-infected, and rot-infected samples—using an optimized DenseNet201-based framework suitable for real-world deployment.

The specific goals are:

Dataset Preparation: Use a publicly available Kaggle dataset containing ∼3,500 labeled images. A stratified split was performed, allocating 60% for training, 20% for validation, and 20% for testing. All images were resized to 224×224 pixels, and their pixel intensities were scaled to the [0,1] range to ensure compatibility with ImageNet-pretrained models.

Model Customization via Transfer Learning: Adapt DenseNet201 by replacing the classification head with a lightweight layer stack: global average pooling, batch normalization, dropout, and a softmax output for three-class prediction. This retains DenseNet's pretrained feature extractor while reducing complexity.

Two-Stage Fine-Tuning: First, train only the custom classifier while keeping DenseNet frozen. Then, fine-tune the upper ∼40% of DenseNet layers using a lower learning rate to adapt to *Aloe vera*-specific features without overfitting.

Dynamic Data Augmentation: Apply real-time augmentations—random flips, rotations, zooms, and photometric adjustments—during training to improve generalization under real-world variability without expanding the dataset.

Test-Time Augmentation (TTA): Enhance inference robustness by averaging predictions over multiple augmented

versions of each test image. This mitigates prediction variance due to lighting or occlusion, common in field conditions.

Comprehensive Evaluation and Benchmarking: Assess performance using F1-score, recall, precision, and overall accuracy. Benchmark against CNN+SVM and EfficientNet variants. Additionally, evaluate deployment feasibility by measuring inference time, memory usage, and compatibility with edge devices like NVIDIA Jetson Nano.

These objectives support the development of a deployable, domain-optimized model for real-time *Aloe vera* disease monitoring, advancing practical applications in precision agriculture.

II. Methodology

A. Dataset Description

This study utilizes a publicly available Aloe Vera leaf image dataset sourced from Kaggle, comprising 3,482 RGB images categorized into three distinct health conditions: *healthy*, *rust-infected*, and *rot-infected*. The dataset was manually verified and organized into class-specific subdirectories.

A stratified sampling was used to partition the data into training, validation, and test sets in a 60:20:20 ratio while preserving class distributions, resulting in 2,097, 700, and 685 images, respectively. Table II details the number of images per class across each split. This partitioning ensures a balanced representation across all classes and supports robust evaluation.

TABLE II
Class-wise Image Distribution

Class	Training	Validation	Test
Healthy	620	207	207
Rust-Infected	805	268	261
Rot-Infected	674	224	216

Fig. 1. Sample Images from each class

B. Preprocessing and Data Preparation

To meet DenseNet201's input specifications, all images were uniformly resized to 224×224 pixels. Images were loaded using `image_dataset_from_directory` with `label_mode='categorical'` to enable one-hot encoding.

Real-time data augmentation was applied only to the training set using the `tf.keras.Sequential` pipeline, These included random horizontal and vertical flips, rotations up to 20 degrees, and zooming operations that adjusted the height and width by factors in the range of -20% to +10%. Additionally, contrast and brightness variations were introduced with a factor of 0.2, and all pixel values were rescaled to the [0,1] range by dividing by 255.

Since data augmentation is performed dynamically during training, the underlying dataset size remains constant. Nonetheless, the model is exposed to novel image variations in each epoch, thereby enhancing the diversity of the training inputs and promoting better generalization.

Validation and test images were only resized and rescaled. All datasets were cached, prefetched, and shuffled using `AUTOTUNE` for efficient I/O during training.

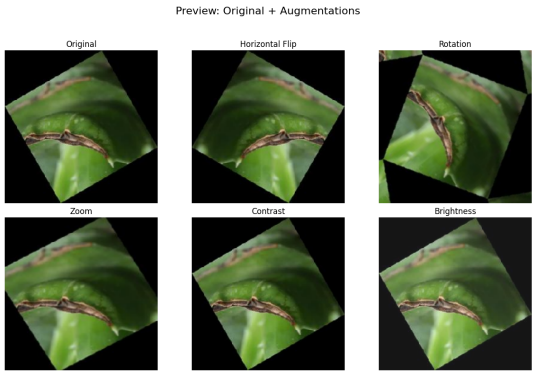

Fig. 2. Original & Augmented Images

C. DenseNet201-Based Deep Learning Architecture

A transfer learning technique was adopted using **DenseNet201** as the backbone with pretrained *ImageNet* weights was used. Its top layers were removed and replaced with a task-specific head using the Functional API. The backbone was initially frozen to preserve its pretrained feature extractors.

1) Layer-wise Feature Extraction in DenseNet201: DenseNet201 consists of 4 dense blocks with transitional layers for downsampling. Key feature dimensions are:

- **Initial Conv/ReLU/MaxPool:** Outputs feature maps of size $112 \times 112 \times 64$.
- **Dense Block 1:** Outputs $56 \times 56 \times 256$ (after concatenation).
- **Dense Block 2:** Outputs $28 \times 28 \times 512$.
- **Dense Block 3:** Outputs $14 \times 14 \times 1024$.
- **Dense Block 4:** Outputs $7 \times 7 \times 1920$.

2) Task-Specific Head: The backbone's output ($7 \times 7 \times 1920$) is processed as follows:

- **Global Average Pooling:** Reduces spatial dimensions to a **1920-dimensional feature vector**.
- **Regularization:** Batch Normalization + Dropout (0.5).
- **Dense Layers:**
  - A fully connected layer with 512 units and ReLU activation, followed by a 0.3 dropout.
  - A softmax-activated dense layer with 3 output neurons for classification.

Thus, the total number of features extracted from DenseNet201 is **1920**. Its dense connectivity ensures that

each layer receives cumulative knowledge via feature map concatenation from all preceding layers:

$$\mathbf{x}_l = H_l([\mathbf{x}_0, \mathbf{x}_1, \ldots, \mathbf{x}_{l-1}]) \tag{1}$$

where $H_l(\cdot)$ denotes BatchNorm-ReLU-Conv(3×3), and $[\cdot]$ represents channel-wise concatenation [24]. This promotes feature reuse and gradient flow, aiding generalization on moderate-sized datasets.

This architecture is depicted in Fig. 3.

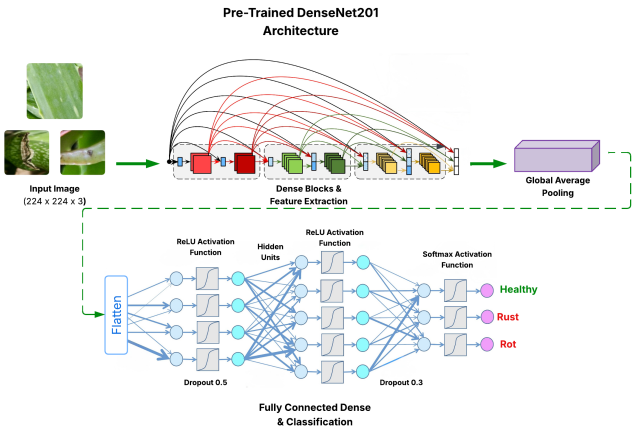

Fig. 3. DenseNet201-Based CNN Architecture

D. Training and Implementation Strategy

The proposed model uses the DenseNet201 architecture pretrained on ImageNet, with the top classification layers removed. A custom classification head was added using the Functional API, consisting of: `GlobalAveragePooling2D`, `BatchNormalization`, `Dropout(0.5)`, `Dense(512, ReLU)`, `Dropout(0.3)`, and a final softmax layer.

Training was conducted in two stages:

- **Stage 1 – Head Training:** The base DenseNet201 was frozen and only the classification head was trained using the Adam optimizer ($\texttt{lr} = 1 \times 10^{-4}$), batch size 32, and categorical cross-entropy loss. Class weights were computed as $w_i = \frac{n}{k \cdot n_i}$ [25] to address class imbalance.
- **Stage 2 – Fine-Tuning:** The top 150 layers of DenseNet201 were unfrozen and fine-tuned using a lower learning rate (1×10^{-5}) for up to 40 epochs to adapt pretrained features to the domain-specific task.

To prevent overfitting and encourage generalization, the training was regulated using:

Regularization Techniques:

- `EarlyStopping` (patience=6)
- `ReduceLROnPlateau` (factor=0.3, patience=3, minimum learning rate=1×10^{-6})
- `ModelCheckpoint` (it preserves the best model based on validation accuracy)

All models were implemented in TensorFlow 2.14. This two-stage approach ensured stable convergence while retaining pretrained feature representations for domain-specific learning.

E. Full Pipeline Overview

The complete Aloe Vera disease classification workflow (Fig. 4) follows these key stages:

1) **Data Preparation:** Images are collected, split into training/validation/test sets, resized to 224×224, and batched (size 32).
2) **Data Augmentation:** Training images undergo random zooms and brightness/contrast shifts to increase diversity and boost generalization.
3) **Dataset Loading:** Augmented data is loaded using caching and prefetching to maximize GPU utilization and training efficiency.
4) **Model Construction:** A DenseNet201 backbone (pretrained on ImageNet) is combined with a custom classification head.
5) **Initial Training:** The classifier head is trained while keeping the DenseNet backbone frozen.
6) **Unfreezing Layers:** The top layers of DenseNet201 are selectively unfrozen to allow domain-specific fine-tuning.
7) **Fine-Tuning:** A decreased learning rate is applied during training of the partially unfrozen model for better optimization.
8) **Inference:** The final model outputs a softmax vector classifying each leaf as *healthy*, *rust-infected*, or *rot-infected*.

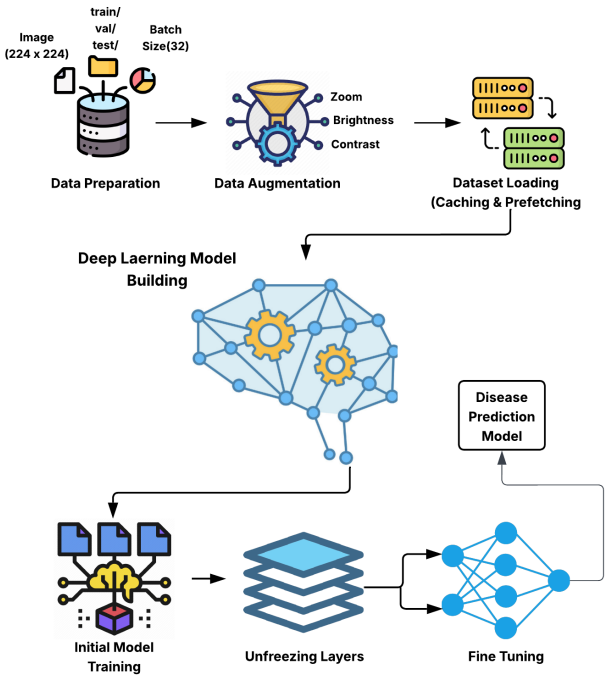

Fig. 4. Complete Disease Classification Pipeline

F. Inference-Time Robustness with Test-Time Augmentation

To improve prediction reliability under varying field conditions (e.g., inconsistent lighting, occlusions, background noise), Test-Time Augmentation (TTA) was utilized during the inference phase. Each test image underwent ten stochastic augmentations (flips, rotations, zooms, brightness, contrast shifts), consistent with training transformations.

The model generated predictions for each augmented view, and the final output was obtained by averaging the softmax probabilities across all views. This ensemble approach reduces sensitivity to visual noise and enhances prediction stability.

As a result, TTA improved the test set classification accuracy to **98.68%**, outperforming single-view predictions and demonstrating enhanced robustness in real-world scenarios.

G. Evaluation Metrics

The evaluation phase employed an isolated test partition, preserved from the outset using commonly adopted classification metrics to assess overall accuracy as well as per-class effectiveness.

1) Accuracy: Accuracy quantifies the proportion of correctly classified instances out of the total number of predictions. It is defined as:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{2}$$

Here, TP, TN, FP, and FN denote the counts of true positives, true negatives, false positives, and false negatives, respectively, aggregated over all classes [26].

2) Per-Class Metrics: For each class $i \in \{\text{healthy}, \text{rust}, \text{rot}\}$, the following metrics were computed:

$$\text{Precision}_i = \frac{TP_i}{TP_i + FP_i} \tag{3}$$

$$\text{Recall}_i = \frac{TP_i}{TP_i + FN_i} \tag{4}$$

$$\text{F1-score}_i = \frac{2 \cdot \text{Precision}_i \cdot \text{Recall}_i}{\text{Precision}_i + \text{Recall}_i} \tag{5}$$

These metrics assess both correct identification and the penalty for incorrect classifications across classes [26].

3) Confusion Matrix and Macro Averaging: A 3×3 confusion matrix was generated to illustrate the relationship between predicted and actual class labels, allowing for the identification of common misclassification trends. To ensure balanced evaluation across all categories—irrespective of class distribution—macro-averaged precision, recall, and F1-score were also computed alongside individual class metrics.

These measures offer a holistic assessment of the model's effectiveness in the context of disease classification.

H. Model Comparison and Benchmarking

To assess the effectiveness of our DenseNet201-based pipeline, we benchmarked it against several popular CNN architectures. To maintain fairness in model evaluation, all architectures were pretrained on ImageNet and subsequently fine-tuned using the same training protocol, including augmentation and optimization settings, on the Aloe vera dataset.

The evaluated models include:

- **DenseNet201** – Our proposed model, utilizing dense connectivity for efficient feature reuse and gradient flow.
- **MobileNetV2** – A resource-efficient architecture leveraging depthwise separable convolutions for lightweight inference on mobile platforms.
- **EfficientNetV2S** – A resource-efficient model offering fast training and low inference cost.
- **ResNet50** – A widely used residual network known for its depth and skip connections.

Each model outputs softmax probabilities for the three target classes: healthy, rust-infected, and rot-infected. This comparison highlights the generalization capabilities of different backbones for Aloe vera disease classification under uniform experimental conditions.

III. Results and Discussion

A. Test Performance

The final evaluation on the test dataset yielded a accuracy of **97.37%** and a loss of **0.0795**, indicating the model's strong generalization capability. The detailed classification report is presented below.

TABLE III
CLASSIFICATION REPORT OF DENSENET201 ON TEST DATA

Class	Precision	Recall	F1-score	Support
healthy_leaf	0.99	0.98	0.98	207
rot	0.96	0.96	0.96	216
rust	0.97	0.98	0.98	261
Accuracy	-	-	**0.97**	684
Macro Avg	0.97	0.97	0.97	684
Weighted Avg	0.97	0.97	0.97	684

High and balanced precision, recall, and F1-scores were recorded for all classes, with the *healthy_leaf* and *rust* categories showing particularly strong results.

Confusion Matrix: A confusion matrix was used to illustrate the distribution of accurate and erroneous classifications across all classes.

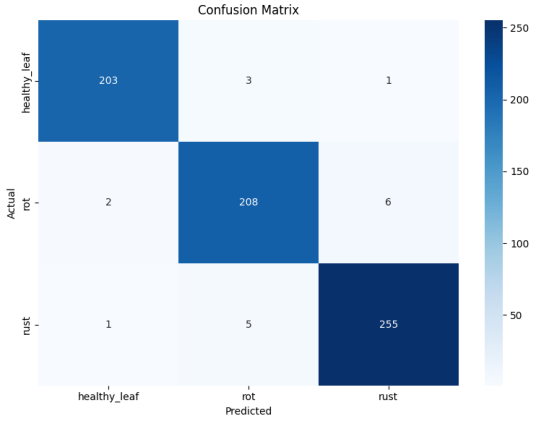

Fig. 5. Confusion Matrix Heatmap of DenseNet201 on Test Data.

The confusion matrix (Fig. 5) showed minimal misclassification, mainly between rot and rust due to visual similarities. Healthy leaves were consistently well-classified, confirming strong feature extraction.

B. Training and Validation Trends

The curves (Fig. 6) depicting training and validation accuracy and loss exhibit smooth convergence with validation loss consistently lower than training loss. This behavior is attributed to the use of real-time data augmentation during training, which introduces challenging variations, slightly increasing training loss. In contrast, the validation set remains unaugmented and cleaner, leading to lower loss and higher accuracy while improving robustness.

To enhance generalization, DenseNet201 was fine-tuned with a low learning rate (1×10^{-5}), and regularization was reinforced through early stopping, learning rate scheduling, and best-model checkpointing. These strategies collectively prevent overfitting and reflects a well-generalized model and ensure strong performance on unseen data.

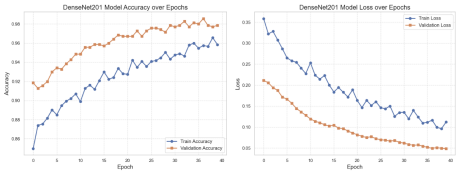

Fig. 6. Training and validation accuracy/loss

C. Test-Time Augmentation (TTA)

To enhance robustness, Test-Time Augmentation (TTA) with 10 randomized transformations was applied. Aggregated predictions improved accuracy to **98.68%**, reinforcing the model's generalization capability.

D. Model Comparison

Other pre-trained models—MobileNetV2, EfficientNetV2S, and ResNet50—were evaluated under the same setup. DenseNet201 outperformed all, as shown in Table IV.

TABLE IV
ACCURACY COMPARISON OF DIFFERENT MODELS

Model	**Test Accuracy (%)**
DenseNet201	97.37
MobileNetV2	95.32
EfficientNetV2S	62.43
ResNet50	61.40

EfficientNetV2S and ResNet50 underperformed, likely due to insufficient depth or over-aggressive downsampling. Such architectures may struggle with fine-grained visual cues crucial for leaf disease classification.

E. Qualitative Results

Representative images from the test set were examined qualitatively to evaluate the model's performance in practical scenarios. This assessment provides insight into the model's capability to differentiate disease classes based on visual features.

(Fig. 7) showcases representative samples from the three classes—healthy leaf, rot, and rust—displaying both ground truth and predicted labels. The model reliably predicted the correct class, including in difficult cases with subtle or partially obscured symptoms.

These qualitative results visually confirm the model's strong discriminative capability and robustness in handling intra-class variability and visual noise. Such visual validation is particularly valuable in real-world agricultural applications, where interpretability and trust in AI predictions are critical for informed decision-making.

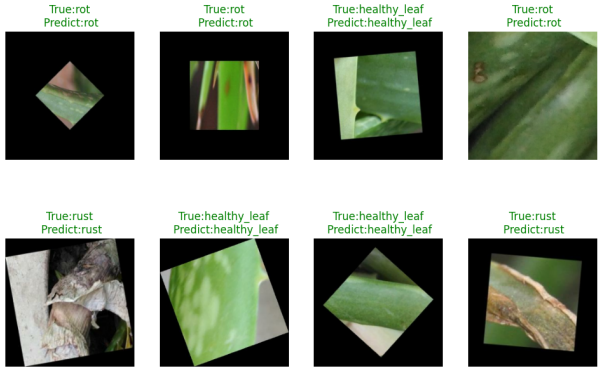

Fig. 7. Predictions with ground truth labels

IV. CONCLUSION

In this work, we propose a deep learning-based method utilizing convolutional neural networks to automatically identify diseases in Aloe Vera leaves. Among the models evaluated, DenseNet201 delivered the best performance with a test accuracy of **97.37%**, further enhanced to **98.68%** through Test-Time Augmentation (TTA). The model consistently achieved high precision and recall across all disease classes, demonstrating its effectiveness in real-world classification tasks.

Given Aloe Vera's wide use as a medicinal plant—valued for its therapeutic properties in skincare, wound healing, digestion, and other health applications—early and accurate disease detection is critical. Leaf infections can compromise the plant's bioactive compounds, affecting both crop yield and medicinal quality. Thus, the proposed system has direct implications not only for precision agriculture but also for maintaining the pharmacological integrity of Aloe Vera products.

This work contributes toward sustainable cultivation practices by enabling timely intervention and reducing dependence on manual monitoring. Future efforts could focus on deploying the model on mobile or edge devices for in-field use, expanding to other medicinal plants, and incorporating explainable AI to assist agricultural and healthcare professionals with trustworthy insights.

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