# COMPARATIVE ANALYSIS OF DEEP LEARNING ARCHITECTURES FOR COTTON PLANT DISEASE DETECTION USING GRAD-CAM VISUALIZATION

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***Abstract :***

*Early and accurate identification of plant diseases is critical for improving crop yield and ensuring sustainable agricultural practices. Cotton, being a major commercial crop, is highly vulnerable to leaf diseases that significantly impact productivity. Deep learning has recently emerged as a reliable solution for automated plant disease diagnosis using image-based approaches [1], [2]. This study presents a comparative analysis of two deep learning architectures—DenseNet121 and MobileNetV2—for automated cotton plant disease classification using leaf images. The experiments were conducted on the publicly available Cotton Plant Disease Dataset by Dhamodharan R., consisting of approximately 4,800 images spanning five disease categories and one healthy class. Transfer learning was employed with ImageNet pre-trained weights, and models were trained using a batch size of 32, learning rate of $1\times10^{-4}$, and GPU acceleration. Performance evaluation was carried out using accuracy, macro precision, macro recall, and macro F1-score metrics. DenseNet121 achieved superior performance with an accuracy of 98.32%, outperforming MobileNetV2 while maintaining robust generalization. Additionally, Gradient-weighted Class Activation Mapping (Grad-CAM) was utilized to provide visual interpretability by highlighting disease-affected regions on cotton leaves. The results demonstrate that DenseNet121 offers an effective and explainable solution for cotton disease detection, while MobileNetV2 provides a lightweight alternative suitable for resource-constrained environments.*

**Keywords :** Cotton plant disease, Deep learning, DenseNet121, MobileNetV2, Grad-CAM, Precision agriculture

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**Introduction :**

Cotton plays a vital role in the global agricultural economy; however, its production is severely affected by various leaf diseases such as Aphid, Army Warm, Bacterial Blight, Healthy, Target spot, Powdery Mildew. Conventional disease identification relies on expert knowledge and manual inspection, which is time-consuming, subjective, and impractical for large-scale farming. With the rapid advancement of artificial intelligence, computer vision-based disease detection has emerged as a reliable and scalable alternative. Deep learning has demonstrated remarkable success in plant disease classification using leaf images due to its ability to automatically learn discriminative visual features [1], [2], [3].

Deep learning, particularly Convolutional Neural Networks (CNNs), has demonstrated remarkable success in plant disease classification by automatically learning discriminative features from leaf images. Convolutional neural network architectures such as DenseNet and MobileNet have been widely adopted in agricultural image analysis because of their high accuracy and effectiveness in transfer learning-based applications [4], [5], [6]. Pretrained architectures such as DenseNet and MobileNet have been widely adopted due to their high accuracy and transfer learning capabilities. However, the lack of interpretability in deep models remains a critical concern for real-world agricultural deployment. Despite their high performance, deep learning models are often criticized for their black-box nature, which limits their adoption in real-world agricultural decision-making systems [7], [8]. To address this limitation, explainable AI techniques such as Gradient-weighted Class Activation Mapping (Grad-CAM) are increasingly integrated with CNNs to visualize decision-making regions. Explainable artificial intelligence techniques such as Gradient-weighted Class Activation Mapping (Grad-CAM) enhance model transparency by highlighting disease-relevant regions in plant leaf images [9], [10]. This study focuses on a comparative evaluation of DenseNet121 and MobileNetV2 for cotton leaf disease classification, emphasizing both classification performance and model interpretability.

**Materials and Methods :**

**1. Dataset Description :**

The Cotton Plant Disease Dataset, created by Dhamodharan R. and sourced from Kaggle, was used in this study. The dataset contains approximately 4,800 RGB images categorized into six classes: five disease types and one healthy class. Images exhibit varying illumination, background, and disease severity, making the dataset suitable for evaluating real-world performance. Publicly available plant disease datasets are widely used for benchmarking deep learning-based agricultural disease detection systems due to their reproducibility and standardized evaluation protocols [11], [12]. The complete workflow is illustrated in Figure 1.

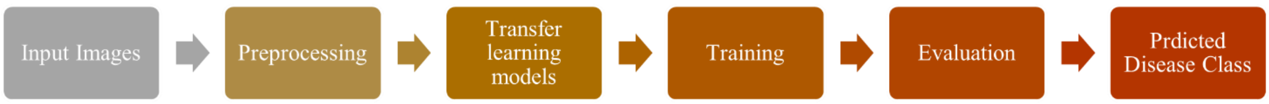



Figure 1: Overall Workflow of the Proposed Methodology

**2. Data Preprocessing :**

All images were resized to 224 × 224 pixels to match the input requirements of the selected CNN architectures. Data augmentation techniques including horizontal flipping, rotation, zooming, and brightness variation were applied to improve generalization and reduce overfitting. Pixel normalization was performed to scale values between 0 and 1.

**3. Model Architecture and Training :**

Two pretrained CNN models—DenseNet121 and MobileNetV2—were employed using transfer learning. The final fully connected layers were replaced with a custom classifier consisting of global average pooling and a SoftMax layer corresponding to six output classes. Models were trained for 10 epochs using the Adam optimizer, a batch size of 32, and a learning rate of $1\times10^{-4}$. All experiments were conducted in a GPU-enabled environment. Transfer learning using ImageNet pretrained weights has proven effective for agricultural image classification tasks, particularly when the availability of labelled data is limited [13], [14]. Figure 2 explains the Fine-tuned DenseNet-121 Architecture

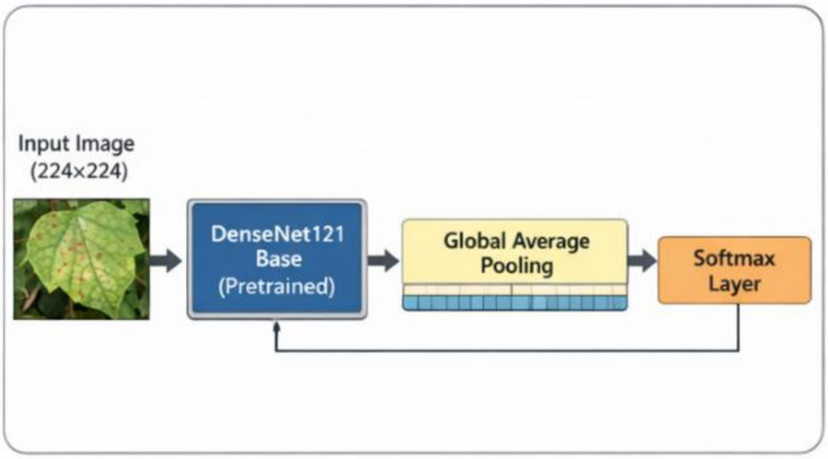



Figure 2 : Fine-tuned DenseNet-121 Architecture

**4. Grad-CAM Based Explainability :**

Grad-CAM was applied to the final convolutional layers of both models to generate class-discriminative heatmaps. These visualizations highlight the regions of cotton leaves that contributed most significantly to disease prediction, thereby improving transparency and trust in the model outputs. Grad-CAM was employed to generate class-discriminative heatmaps by utilizing the gradients of the target class flowing into the final convolutional layers of the network [9], [15]. Figure 3 gives appropriate impression about the Grad-CAM Visualisation.

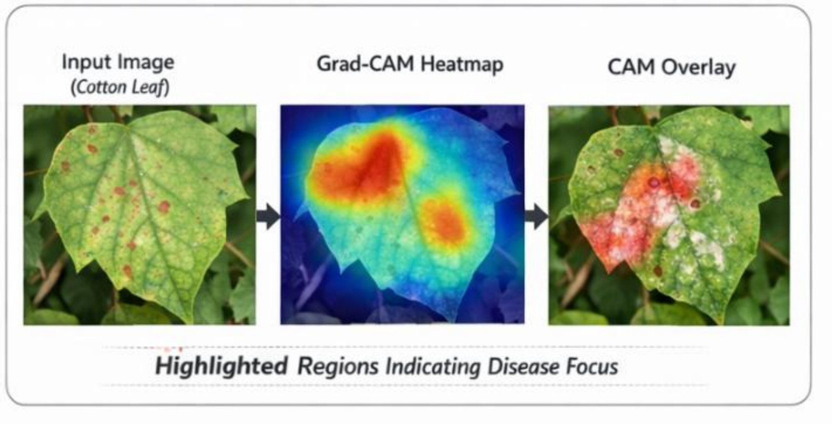



Figure 3: Grad-CAM Visualisation Example

**Results :**

**1. Quantitative Performance Evaluation :**

The performance of DenseNet121 and MobileNetV2 was evaluated using accuracy, macro precision, macro recall, and macro F1-score. The results, obtained from the test dataset, are summarized in Table 1.

**Table 1. Performance comparison of DenseNet121 and MobileNetV2**

| Model | Accuracy | Macro Precision | Macro Recall | Macro F1-score |
|---|---|---|---|---|
| DenseNet121 | **0.9832** | **0.9836** | **0.9834** | **0.9833** |
| MobileNetV2 | 0.9749 | 0.9765 | 0.9748 | 0.9751 |

DenseNet121 outperformed MobileNetV2 across all evaluation metrics, demonstrating superior feature extraction and classification capability. This is clear from the figure 4 and figure 5

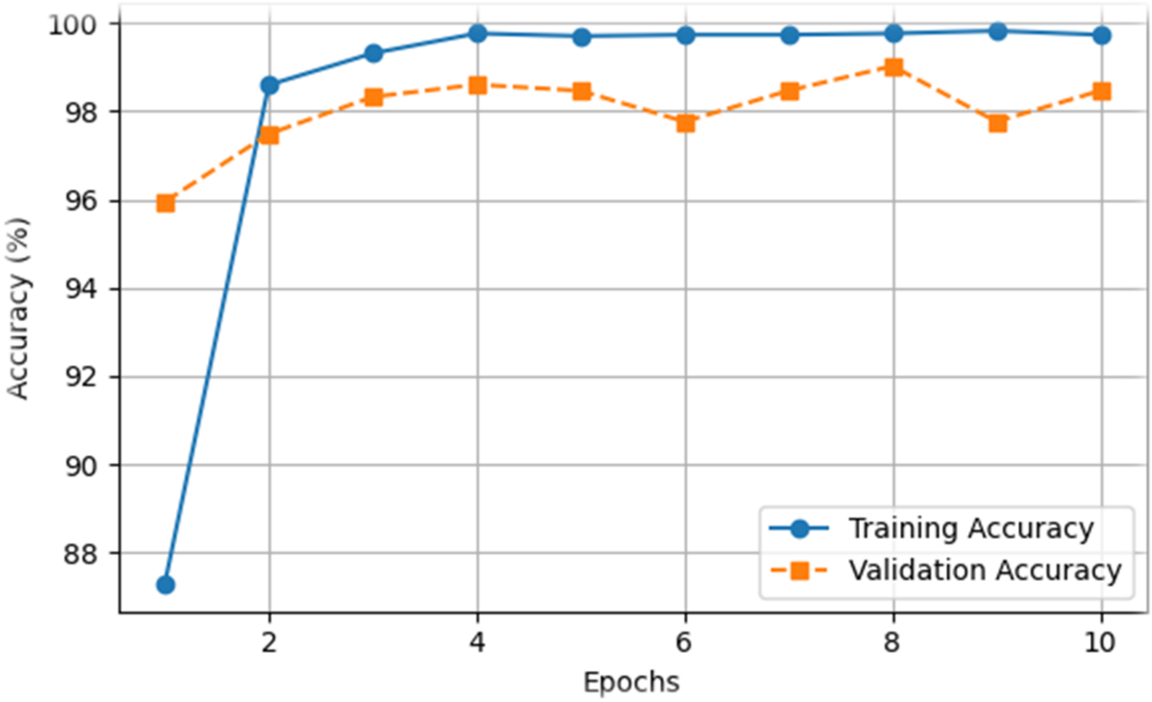



Figure 4: DenseNet121 Accuracy Vs Validation Accuracy

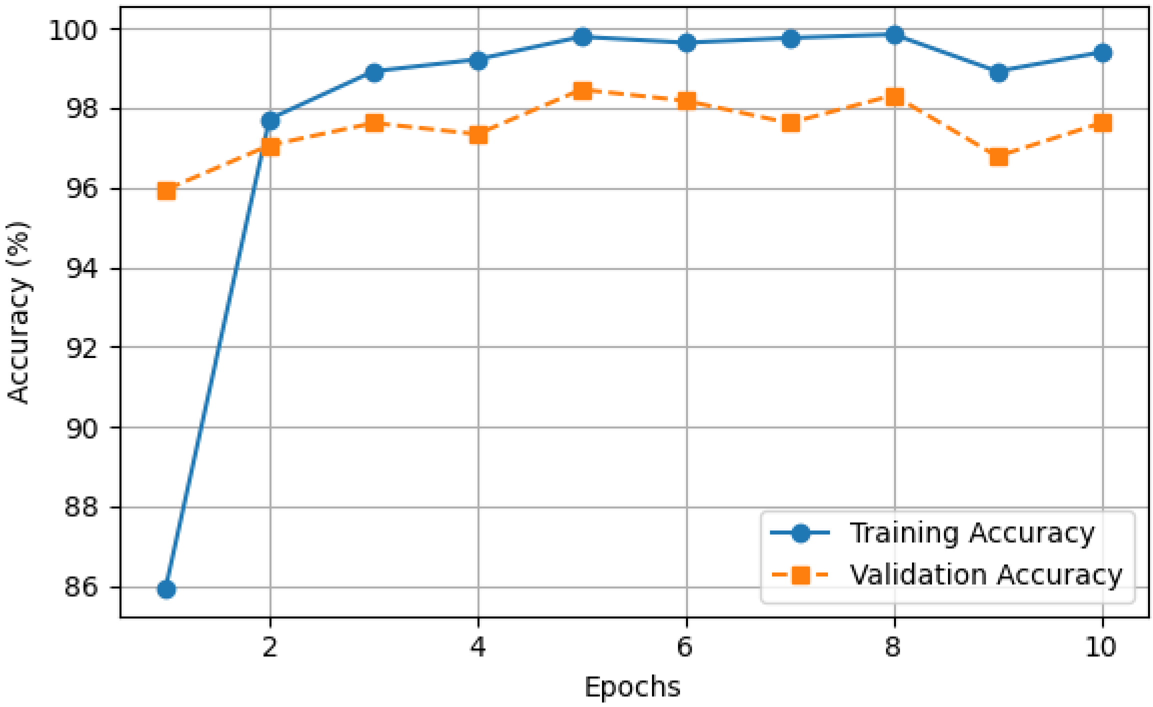
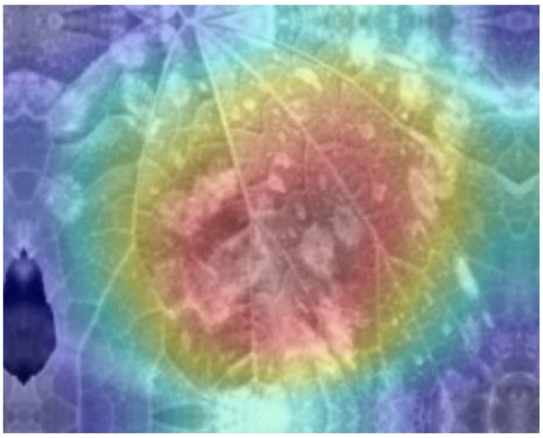



Figure 5: MobileNetV2 Accuracy Vs Validation Accuracy

**2. Grad-CAM Visualization Results :**

Grad-CAM visualizations revealed that DenseNet121 consistently focused on disease-affected regions such as lesions and discoloration patterns, whereas MobileNetV2 occasionally showed broader attention areas. These findings confirm that DenseNet121 not only achieves higher accuracy but also provides more reliable visual explanations. This is very well verified by the Figure 5 a) & b)



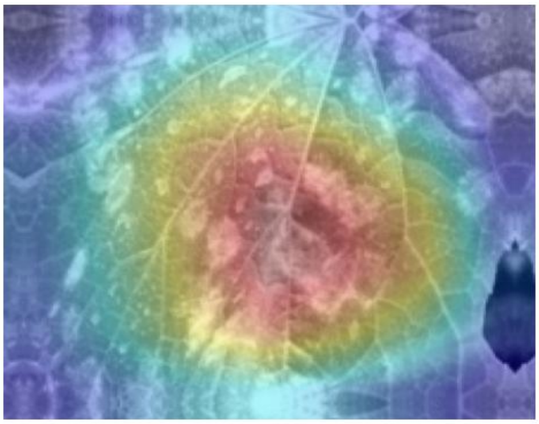


Figure 5: a) Grad-CAM for DenseNet121 Figure5:b) Grad-CAM for Mobile Net121

**Discussion :**

The experimental results indicate that DenseNet121 is highly effective for cotton plant disease detection due to its dense connectivity and efficient feature reuse. This architecture enables improved gradient flow and captures fine-grained disease characteristics, leading to superior classification performance. The superior performance of DenseNet121 can be attributed to its dense connectivity, which enhances feature reuse and improves gradient propagation, as reported in similar agricultural image classification studies [16], [17].

MobileNetV2, while slightly less accurate, offers advantages in terms of reduced computational complexity and faster inference, making it suitable for mobile or edge-based agricultural applications. The integration of Grad-CAM significantly enhances model interpretability, which is essential for real-world adoption by farmers and agricultural experts.

Compared to existing plant disease detection studies, the proposed approach achieves competitive accuracy while emphasizing explainability, an aspect often overlooked in earlier works. The classification accuracy achieved in this study is comparable to or exceeds recent deep learning-based plant disease detection approaches reported in the literature [18], [19], [20].

**Conclusion :**

This study presented a refined comparative analysis of DenseNet121 and MobileNetV2 for automated cotton plant disease detection using deep learning and Grad-CAM visualization. DenseNet121 achieved the highest performance with an accuracy of 98.32%, demonstrating its suitability for high-precision agricultural diagnostics. MobileNetV2 serves as a lightweight alternative for deployment in resource-constrained environments. The incorporation of Grad-CAM ensures transparency and trust in model predictions. Future work will focus on real-time field deployment, model compression, and integration with mobile-based agricultural advisory systems.

**References :**


- A. Kamilaris and F. X. Prenafeta-Boldú, "Deep learning in agriculture: A survey," *Computers and Electronics in Agriculture*, vol. 147, pp. 70–90, 2018.
- S. P. Mohanty, D. P. Hughes, and M. Salathé, "Using deep learning for image-based plant disease detection," *Frontiers in Plant Science*, vol. 7, pp. 1–10, 2016.
- E. C. Too, L. Yujian, S. Njuki, and L. Yingchun, "A comparative study of fine-tuning deep learning models for plant disease identification," *Computers and Electronics in Agriculture*, vol. 161, pp. 272–279, 2019.
- G. Huang, Z. Liu, L. van der Maaten, and K. Q. Weinberger, "Densely connected convolutional networks," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pp. 4700–4708, 2017.
- M. Sandler, A. Howard, M. Zhu, A. Zhmoginov, and L. Chen, "MobileNetV2: Inverted residuals and linear bottlenecks," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pp. 4510–4520, 2018.
- K. P. Ferentinos, "Deep learning models for plant disease detection and diagnosis," *Computers and Electronics in Agriculture*, vol. 145, pp. 311–318, 2018.
- W. Samek, G. Montavon, A. Vedaldi, L. K. Hansen, and K.-R. Müller, "Explainable artificial intelligence: Understanding, visualizing and interpreting deep learning models," *Information Fusion*, vol. 48, pp. 1–15, 2019.
- A. B. Arrieta et al., "Explainable artificial intelligence (XAI): Concepts, taxonomies, opportunities and challenges," *Information Fusion*, vol. 58, pp. 82–115, 2020.
- R. R. Selvaraju et al., "Grad-CAM: Visual explanations from deep networks via gradient-based localization," *International Journal of Computer Vision*, vol. 128, no. 2, pp. 336–359, 2020.
- A. Singh, S. Ganapathysubramanian, S. Sarkar, and A. Singh, "Explainable deep learning models for crop disease detection," *Computers and Electronics in Agriculture*, vol. 203, 2023.
- J. G. A. Barbedo, "Plant disease identification from individual lesions and spots using deep learning," *Biosystems Engineering*, vol. 180, pp. 96–107, 2019.
- Y. Lu, S. Yi, N. Zeng, Y. Liu, and Y. Zhang, "Identification of rice diseases using deep convolutional neural networks," *Neurocomputing*, vol. 267, pp. 378–384, 2017.
- S. J. Pan and Q. Yang, "A survey on transfer learning," *IEEE Transactions on Knowledge and Data Engineering*, vol. 22, no. 10, pp. 1345–1359, 2019.
- G. Wang, Y. Sun, and J. Wang, "Automatic image-based plant disease severity estimation using deep learning," *Computers and Electronics in Agriculture*, vol. 174, 2020.
- A. Chattopadhay, A. Sarkar, P. Howlader, and V. N. Balasubramanian, "Grad-CAM++: Improved visual explanations for deep convolutional networks," in *Proceedings of IEEE WACV*, pp. 839–847, 2018.
- S. Zhang, S. Zhang, C. Zhang, X. Wang, and Y. Shi, "Cucumber leaf disease

identification with global pooling dilated convolutional neural network," *Computers and Electronics in Agriculture*, vol. 162, pp. 422–430, 2019.

- M. A. Khan et al., "An optimized method for multi-class plant disease recognition using deep learning," *Expert Systems with Applications*, vol. 186, 2022.
- Y. Li, H. Wang, and L. Dang, "Crop disease image recognition based on deep learning algorithms," *Computers and Electronics in Agriculture*, vol. 205, 2023.
- I. Ahmed, M. Ahmad, and G. Jeon, "An IoT-based deep learning framework for early plant disease detection," *IEEE Access*, vol. 9, pp. 17184–17199, 2021.
- J. Chen, X. Liu, and Y. Wang, "Explainable artificial intelligence for smart agriculture: A review," *Computers and Electronics in Agriculture*, vol. 212, 2024.

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