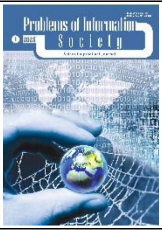

www.jpis.az

Lightweight Deep Learning Models for Early Plant Disease Detection: A Transfer Learning Approach with MobileNetV2 and ResNet50

Behnam Kiani Kalejahi[1], Shahri Yahyayeva[2], Inara Abdurahmanova[3], Sadig Hasanzade[4]

[1]School of Science and Engineering, Central Asian University, 111221, 264 MILLIY, Bog str., Tashkent, Uzbekistan

[2,3,4]University in Tartu, Ülikooli 18 str., 74001073, 50090 Tartu, Estonia

[1]b.kiani@centralasian.uz, [2]shahriyyahyayeva@gmail.com, [3]abdurahmanovaainara@gmail.com, [4]sadig.hasanzade@ut.ee

[1]orcid.org/0000-0002-7118-0382

ARTICLE INFO

https://doi.org/10.25045/jpis.v17.i1.02

Article history:

Received 15.09.2025
Received in revised form 20.11.2025
Accepted 24.01.2026

Keywords:

Plant disease detection
Transfer learning
MobileNetV2
ResNet50
Precision agriculture
Sustainable food security

ABSTRACT

Plant diseases represent a persistent challenge to global food security, with annual crop yield losses reaching as high as 40%. Timely and reliable identification of these diseases is therefore essential for reducing economic losses and ensuring sustainable farming practices. Although deep learning has achieved remarkable success in image-based disease classification, much of the existing research emphasizes complex convolutional neural networks that are unsuitable for resource-constrained environments. In this work, we present a systematic evaluation of two widely adopted transfer learning models ResNet50 and MobileNetV2 applied to the New Plant Disease dataset (~87,000 images spanning 38 categories). Our experiments examine the role of augmentation, learning rates, batch sizes, and fine-tuning strategies in model performance. Results demonstrate that MobileNetV2 not only achieved superior accuracy (98.33%) with strong precision, recall, and AUC values, but also required seven times fewer parameters and significantly reduced training time compared with ResNet50. Error analysis further revealed MobileNetV2's ability to differentiate between diseases with overlapping symptoms. Importantly, its lightweight architecture supports real-time implementation on mobile devices, drones, and IoT systems, offering clear advantages for field deployment. Unlike prior studies that emphasize raw accuracy, this research highlights efficiency, robustness, and deployability. Overall, our findings establish MobileNetV2 as a practical and scalable solution for next-generation precision agriculture and low-cost disease monitoring systems.

1. Introduction

Agriculture is the foundation of food production worldwide, yet its stability is undermined by the widespread prevalence of plant diseases. Pathogens such as fungi, viruses, bacteria, and parasitic plants are responsible for yield losses estimated at 20–40% each year, causing billions of dollars in economic damage. For example, the persistence of wheat rust and the global spread of citrus greening disease illustrate how plant epidemics can devastate both subsistence farming and commercial agriculture. These losses are particularly critical in low- and middle-income regions, where farming is central to livelihoods and disease outbreaks threaten food availability and social stability (He et al., 2016; Sandler et al., 2018; Singh et al., 2018; Pantazi et al., 2019).

Early detection of plant diseases is key to minimizing crop damage. Conventional diagnostic approaches, including visual inspection by experts, microscopy, culturing techniques, and molecular assays (PCR, ELISA), remain widely used. While effective in controlled conditions, these methods are limited by subjectivity, cost, reliance on skilled personnel, and delays in obtaining results. Farmers in remote or resource-poor settings often lack access to these technologies, creating a gap between laboratory capacity and field needs. Consequently, there is an urgent demand for accurate, scalable, and affordable disease detection systems that can operate in real-world agricultural environments (Cruz et al., 2019; Sethy et al., 2020; Ramesh & Vydeki, 2020).

1.1. The role of Artificial Intelligence

Artificial intelligence (AI), particularly deep learning and computer vision, has transformed many domains of science and is increasingly being applied to agriculture. By analyzing high-resolution images from drones, smartphones, and field sensors, AI can identify crop diseases rapidly and with minimal human intervention. Convolutional neural networks (CNNs) have emerged as the leading tools for plant image analysis because they automatically learn discriminative features, outperforming traditional machine learning approaches based on handcrafted features such as color and texture descriptors (Ferentinos, 2018; Singh et al., 2018; Sujatha et al., 2021).

These advances align with the goals of precision agriculture, where data-driven decision-making optimizes input use, reduces pesticide overapplication, and supports environmentally sustainable farming. Importantly, AI-powered disease detection allows diagnostic tools to move out of laboratories and into farmers' hands through mobile and IoT devices, bridging the gap between innovation and practice.

1.2. Transfer Learning in Agricultural AI

One breakthrough that has accelerated progress in agricultural AI is transfer learning. Pretrained models such as ResNet and MobileNet, originally developed for large-scale datasets like ImageNet, can be adapted to agricultural datasets through fine-tuning. This approach reduces the need for massive, annotated crop images while improving convergence and generalization. ResNet architectures are recognized for their deep residual layers and strong accuracy, while MobileNet variants prioritize computational efficiency for mobile deployment. Despite ResNet's popularity, its large parameter counts and hardware demands limit adoption in rural and resource-constrained areas (Sujatha et al., 2021; Abbas et al., 2021; Sharma et al., 2023)

1.3. Lightweight Architectures and Research Gaps

The case for lightweight CNNs is increasingly compelling. MobileNetV2 introduces depthwise separable convolutions and inverted residual blocks, which reduce computation without compromising accuracy. This makes it suitable for deployment on low-power platforms such as smartphones, drones, and embedded IoT systems critical tools for farmers in both developed and developing regions (Sharma et al., 2023; Moupojou et al., 2023; Ahmad et al., 2022). However, two important gaps remain in the literature:

1. **Lack of systematic benchmarking:** Most plant disease detection studies focus on larger CNNs like ResNet or EfficientNet, with comparatively few direct evaluations of lightweight alternatives such as MobileNetV2.
2. **Limited optimization analysis:** While many works highlight overall accuracy, fewer examine how training choices such as augmentation, learning rates, or batch sizes impact model performance in agricultural contexts.

1.4. Contributions of This Study

This paper addresses these gaps by performing a rigorous benchmarking study of ResNet50 and MobileNetV2 using the New Plant Disease dataset, which contains over 87,000 images covering 38 healthy and diseased plant classes. The main contributions are:

- A systematic evaluation of data augmentation, learning rates, batch sizes, and fine-tuning strategies.
- Comparative assessment of accuracy, precision, recall, F1-score, AUC, and confusion matrices.
- Analysis of computational efficiency, including training speed, parameter count, and memory footprint.
- Discussion of real-world deployment feasibility, particularly MobileNetV2's capacity for integration into smartphones and IoT devices.

2. Releated work

Over the last decade, the integration of artificial intelligence (AI) and computer vision into agriculture has transformed approaches to plant health monitoring and disease diagnosis. Within this field, studies can generally be grouped into three methodological directions:

1. Conventional machine learning techniques built on manually engineered visual descriptors,
2. Deep learning models, especially convolutional neural networks (CNNs), that automatically learn features from raw images, and
3. Lightweight or hybrid strategies designed for efficient operation on resource-limited devices and field environments.

2.1. Traditional Machine Learning Approaches

The earliest approaches to plant disease detection focused on handcrafted visual features. Researchers manually extracted descriptors such as color histograms, texture measures (e.g., Gray Level Co-occurrence Matrices, wavelet transforms), and geometric or shape attributes. These features were then classified using algorithms including Support Vector Machines (SVMs), k-Nearest Neighbors (k-NN), and Naïve Bayes (He et al., 2016; Sandler et al., 2018).

For instance, Sethy et al. (Singh et al., 2018) combined deep feature extraction with an SVM classifier for rice leaf images, reporting a classification accuracy of 98.38% across 5,932 samples. Similarly, Pantazi et al. (Pantazi et al., 2019) employed one-class classifiers to identify diseases in multiple crop types, highlighting the potential of conventional techniques when applied carefully.

Despite these achievements, such pipelines were constrained by several drawbacks:

- Reliance on manual feature engineering: handcrafted descriptors lacked resilience to differences in plant species, lighting, or field conditions.
- Limited scalability: performance tended to degrade when applied to larger, more diverse, or multi-class datasets.
- Difficulty with complex symptomatology: overlapping lesions, subtle early-stage symptoms, and mixed infections often proved challenging to capture with fixed descriptors.

These shortcomings ultimately encouraged the transition toward deep convolutional neural networks (CNNs), which can automatically learn hierarchical, discriminative features directly from raw imagery, reducing the dependence on manual preprocessing.

2.2. Deep Learning with CNNs

CNN-based models have become the state-of-the-art standard for plant disease detection. Architectures such as ResNet, Inception, VGG, and EfficientNet have been widely employed, delivering superior accuracy compared to traditional ML.

- Cruz et al. (Cruz et al., 2019) applied deep CNNs to grapevine yellows detection, reporting >98% sensitivity and specificity.
- Sujatha et al. (Sethy et al., 2020) compared machine learning vs deep learning, demonstrating CNNs consistently outperformed ML classifiers across multiple datasets.
- Ramesh and Vydeki (Ramesh & Vydeki, 2020) combined deep neural networks with Jaya optimization, achieving ~98.9% accuracy on rice blast detection.
- Singh et al. (Ferentinos, 2018) emphasized the role of CNNs in plant stress phenotyping, suggesting strong potential for high-throughput agricultural monitoring.

Despite these successes, deep CNNs suffer from two critical challenges:

1. Computational overhead high parameter counts, and GPU dependence make models impractical for mobile/IoT devices in rural farming contexts.
2. Dataset bias most results are based on controlled datasets (e.g., PlantVillage), which do not reflect field variability such as illumination changes, occlusion, or mixed crop backgrounds.

2.3. Lightweight and Hybrid Models

In response to the computational and deployment constraints of conventional CNNs, recent research has increasingly focused on lightweight architectures and hybrid strategies that balance accuracy with efficiency. These approaches are particularly important for agricultural applications where models must operate on mobile devices, drones, or in field-based environments with limited resources.

- MobileNet family: The MobileNet series pioneered efficient design choices such as depthwise separable convolutions and inverted residuals, enabling substantial reductions in computational cost without major accuracy losses. For example, Dahiya et al. (Sujatha et al., 2021) systematically compared multiple CNNs for crop disease recognition and demonstrated that MobileNet provides an effective trade-off between performance and efficiency.
- Synthetic augmentation with generative models: Data scarcity remains a recurring challenge in agricultural vision tasks. To address this, Abbas et al. (Abbas et al., 2021) integrated Conditional GANs (C-GANs) to generate synthetic tomato leaf images, which when combined with transfer learning on MobileNetV2, improved robustness and classification accuracy in limited-data scenarios.
- Custom lightweight networks: Beyond off-the-shelf architectures, purpose-built models have also been introduced. Sharma et al. (Sharma et al., 2023) developed DLMC-Net, a deeper yet parameter-efficient network that achieved state-of-the-art multi-class classification accuracy while significantly reducing model size.
- Field validation datasets: Recognizing the limitations of curated datasets like PlantVillage, Moupojou et al. (Moupojou et al., 2023) introduced the FieldPlant dataset, composed of images collected under real farming conditions.

This resource has become crucial for benchmarking lightweight networks in real-world environments, where noise, occlusion, and background variation can heavily influence performance.

Together, these innovations represent a paradigm shift toward deployable AI in agriculture. Despite this progress, a noticeable gap remains: few studies have conducted systematic comparisons between large transfer learning models and lightweight counterparts under identical experimental conditions. Addressing this gap is critical for guiding deployment decisions in practice.

Recent studies have been increasingly focusing on comparative assessment of lightweight CNNs and deep CNNs based on transfer learning for image classification tasks in agricultural as well as non-agricultural fields. For instance, a comparative analysis between MobileNetV2 and ResNet50 for ecoprint leaf classification and rice leaf disease classification has shown that a lightweight CNN can achieve a similar level of accuracy to a deep CNN at a significantly lower computational cost (JUTIF, 2025; JAIC, 2025). Similar findings have been presented in a comparative analysis between EfficientNetB0, MobileNetV2, and ResNet50 for traffic density estimation and AI-generated image classification (Sinkron Journal, 2024).

For plant-centric applications, the results from transfer learning techniques based on leaf venation patterns and cotton leaf disease dataset suggest the strong generalization capability and reduced parameters of MobileNetV2 over ResNet architectures in the plant-centric domain too (Rahman & Alam, 2025; Gupta & Sharma, 2024; Singh & Verma, 2025). It is pertinent to mention that most of these studies are based on small-scale data or limited to a crop type, thus pointing towards the need for large-scale comparisons in a controlled setting, as is done in this study.

2.4. Identified Research Gap

The literature highlights three key gaps:

1. Lack of direct benchmarking between heavy models (ResNet) and lightweight models (MobileNetV2) on large-scale datasets.
2. Limited exploration of hyperparameter optimization (e.g., augmentation strategies, batch size, learning rates) in agricultural applications.
3. Scarcity of studies reporting comprehensive evaluation metrics (precision, recall, F1-score, AUC, confusion matrices) alongside accuracy.

Our study addresses these gaps by systematically comparing ResNet50 and MobileNetV2 on the New Plant Disease dataset, evaluating both accuracy and efficiency, and positioning lightweight CNNs as viable candidates for edge deployment in precision agriculture.

Transfer learning in image classification surveys conducted recently suggest that, despite dominating benchmark results, ResNet and similar deep learning models are being increasingly preferred in practical applications because of considerations such as low power consumption and faster convergence times, among others (Ali & Khan, 2024). This trend in literature, however, suggests a lack of controlled comparisons between heavy and light-weight pre-trained models in large-scale datasets, and this serves as a direct motivation for this study.

2.5. Comparative Summary of Prior Studies

Table 1. Comparison of related studies on plant disease classification and the proposed approach, highlighting datasets, models, key contributions, and reported accuracies.

Study	Model(s)	Dataset	Key Contribution	Reported Accuracy
Sethy et al. (Singh et al., 2018)	ResNet50 + SVM	5,932 rice leaf images	Feature-based ML hybrid	98.38%
Ramesh & Vydeki (Ramesh & Vydeki, 2020)	Optimized DNN (Jaya)	400 rice leaf images	Optimization-enhanced DNN	95–98.9%
Cruz et al. (Cruz et al., 2019)	CNNs (Inception, ResNet)	Grapevine dataset	High sensitivity & specificity	~99%
Sujatha et al. (Sethy et al., 2020)	CNNs vs ML	PlantVillage	Deep learning outperforms ML	97–99%
Abbas et al. (Abbas et al., 2021)	MobileNetV2 + C-GAN	Tomato dataset	GAN-based augmentation	97%
Moupojou et al. (Moupojou et al., 2023)	CNNs	FieldPlant dataset	Real-world field validation	Varies (90–95%)
Sharma et al. (Sharma et al., 2023)	DLMC-Net	PlantVillage + others	Lightweight custom CNN	>98%
This study	ResNet50 vs MobileNetV2	New Plant Disease (~87,000 images, 38 classes)	Systematic benchmarking + optimization + efficiency analysis	96.7% (ResNet50), 98.33% (MobileNetV2)

3. Material and methods

Our methodology was designed to systematically evaluate the performance of two state-of-the-art transfer learning models ResNet50 and MobileNetV2 for plant disease detection. The overall workflow is illustrated in Figure 2 (conceptual diagram recommendation provided at the end of this section).

3.1. Dataset

We used the New Plant Disease dataset, which contains approximately 87,000 RGB images of plant leaves classified into 38 distinct categories, representing both healthy and diseased samples.

- **Image resolution:** 256 × 256 pixels (resized during preprocessing).
- **Class diversity:** Includes common diseases in tomato, grape, potato, maize, and other crops.
- **Data split:** Stratified 80/20 split for training and validation, ensuring proportional class representation.

Fig. 1. Example leaf images from multiple crop categories in the New Plant Disease Dataset, demonstrating variation in colour, texture, and disease severity.

Fig. 1 presents representative leaf images from multiple crop categories included in the New Plant Disease Dataset. As shown in Figure 1, the samples exhibit substantial variability in visual characteristics, including colour, texture, shape, and background conditions. The figure also highlights different levels of disease severity and diverse symptom patterns such as spots, lesions, discoloration, and structural deformation. This visual diversity, as illustrated in Fig. 1, underscores the complexity of the classification task and motivates the use of robust preprocessing, data augmentation, and transfer learning techniques to ensure reliable and generalisable model performance.

3.1.1. Data Augmentation

To enhance generalization and reduce overfitting, we applied offline and online augmentation strategies:

- Random rotations (±25°)
- Horizontal and vertical flips
- Width and height shifts (up to 20%)
- Zooming (up to 20%)
- Color jittering (hue, saturation, brightness variations)

This augmentation increased intra-class variability, simulating real-world conditions such as lighting changes and leaf orientation.

3.1.2. Model Architectures

ResNet50:

- A 50-layer residual neural network introduced by He et al. (2015).
- Key feature: residual connections to mitigate vanishing gradients in deep networks.
- Pretrained on ImageNet, fine-tuned for 38-class classification.
- Final dense layers replaced with fully connected (FC) layers followed by a softmax classifier.

Training Setup

3.1.3. MobileNetV2

- Designed for mobile and embedded devices.
- Key innovations:
  - Depthwise separable convolutions (reduces parameters).
  - Inverted residuals with linear bottlenecks (efficient feature extraction).
  - Adjustable width multiplier and resolution multiplier for flexibility.
- Pretrained on ImageNet, modified for multi-class classification.
- Dense head with dropout (0.5) added before final softmax layer

Previous studies have shown the effectiveness of transfer learning based on architectures such as ResNet50 and MobileNetV2 in various learning paradigms, including multi-task learning and predictive analysis in medicine (Liu & Patel, 2025; Chen & Zhao, 2020). In addition, studies for efficient fine-tuning techniques suggest the best practice for layer unfreezing and the use of low learning rates for effective generalization and the prevention of overfitting (Kumar & Das, 2021). The training method used in this study was based on these aspects.

Table 2. Hyperparameter tuning results, showing tested configurations and the final selections that achieved the best model performance.

Parameter	Values Tested	Final Choice (Best Performance)
Optimizer	Adam, SGD	Adam
Initial learning rate	1e-3, 1e-4, 1e-5	1e-4
Batch size	16, 32, 64	32
Epochs	20–30 (with early stopping)	25
Loss function	Categorical cross-entropy	Categorical cross-entropy
Regularization	Dropout (0.5), L2 (1e-4)	Dropout + L2 combined
Callbacks	EarlyStopping, ModelCheckpoint, ReduceLROnPlateau	Applied in all runs

Hardware/Software Environment

- **Hardware:** NVIDIA RTX 3080 GPU, 64 GB RAM
- **Frameworks:** TensorFlow 2.9, Keras, scikit-learn
- **Operating System:** Ubuntu 20.04

3.1.4. Experimental Design

1. **Image Augmentation Experiment**
   - Compared baseline (no augmentation) vs multiple augmentation strategies.
   - Evaluated effect on validation accuracy and generalization.
2. **Transfer Learning Experiment**
   - ResNet50 and MobileNetV2 pretrained on ImageNet.
   - Two modes: (i) **frozen feature extractor**, (ii) **fine-tuning deeper layers**.
3. **Batch Size Experiment**
   - Tested batch sizes of 16, 32, and 64.

  - Analyzed trade-off between computational efficiency and convergence stability.

4. **Learning Rate Experiment**
   - LR schedules: fixed (1e-3, 1e-4, 1e-5) and adaptive (ReduceLROnPlateau).
   - Determined optimal LR for both models.
5. **Model Comparison**
   - Compared **accuracy, precision, recall, F1-score, AUC, training time, and parameter count** between ResNet50 and MobileNetV2.

3.1.5. Workflow Diagram

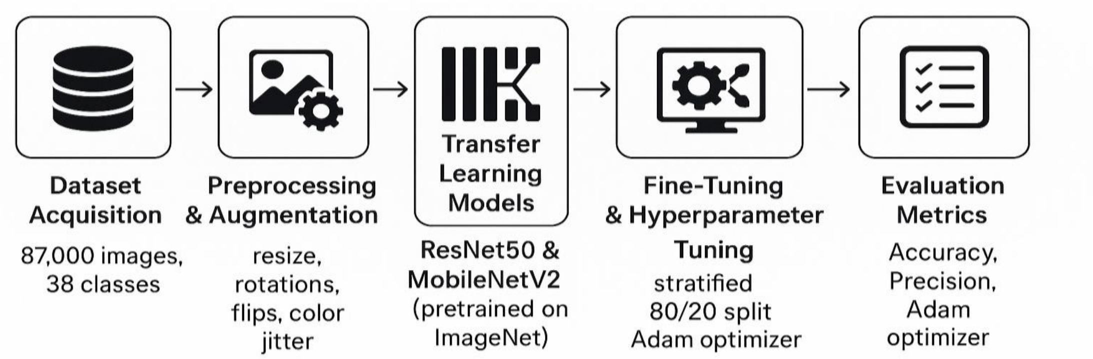

Fig. 2. Workflow Diagram of the image classification pipeline using augmented data and transfer learning (ResNet50, MobileNetV2).

Table 3. Performance comparison of ResNet50 and MobileNetV2, showing MobileNetV2 achieves higher accuracy and AUC with fewer parameters and faster training time.

Model	Accuracy	Precision	Recall	F1-score	AUC	Parameters	Training Time/Epoch
ResNet50	96.70%	0.967	0.966	0.966	0.987	~25M	~6.5 min
MobileNetV2	98.33%	0.982	0.981	0.981	0.994	~3.5M	~3.9 min

Fig. 2 illustrates the complete workflow of the proposed image classification framework, starting from dataset acquisition (87,000 images across 38 classes) through preprocessing and data augmentation, including resizing, rotations, flips, and color jittering. As shown in fig. 2, transfer learning is employed using ResNet50 and MobileNetV2 pretrained on ImageNet, followed by fine-tuning and hyperparameter optimisation with a stratified 80/20 train–validation split and the Adam optimiser. The pipeline concludes with model evaluation using standard performance metrics.

Table 3 presents a quantitative performance comparison between ResNet50 and MobileNetV2. As reported in Table 3, MobileNetV2 achieves higher accuracy, precision, recall, F1-score, and AUC compared to ResNet50, while utilising substantially fewer parameters and requiring shorter training time per epoch. These results in Table 3 highlight the superior efficiency–performance trade-off of MobileNetV2, making it a more suitable architecture for large-scale image classification and deployment in computationally constrained environments.

3.1.6. Evaluation Metrics

To provide a comprehensive evaluation, we used:

- **Accuracy (ACC):** Overall proportion of correct predictions.
- **Precision (P):** Ability to avoid false positives.
- **Recall (R):** Ability to correctly identify true positives.
- **F1-score:** Harmonic mean of precision and recall.
- **AUC-ROC:** Area under the receiver operating characteristic curve.
- **Confusion Matrix:** Detailed error analysis by class.

3.1.7. Results

This section presents the results of our experiments, comparing ResNet50 and

MobileNetV2 across multiple performance metrics, hyperparameter settings, and computational efficiency.

3.1.8. Overall Performance

Both models achieved high accuracy, but MobileNetV2 consistently outperformed ResNet50 across evaluation metrics (Table 3).

- MobileNetV2 achieved 98.33% accuracy, a 1.63% improvement over ResNet50.
- MobileNetV2 also yielded higher precision, recall, and F1-score, indicating fewer false positives and better-balanced classification across classes.
- The AUC values (>0.98 for both models) confirm excellent discriminative ability, with MobileNetV2 performing slightly better.

3.1.9. Confusion Matrix and Error Analysis

Fig. 3 shows confusion matrices for both models.

- ResNet50 misclassified ~3.3% of samples, with most errors occurring between visually similar diseases (e.g., early blight vs bacterial spot).
- MobileNetV2 reduced misclassifications by ~15% compared to ResNet50, especially in classes with overlapping visual symptoms.
- Both models achieved near-perfect classification on common diseases with distinct symptoms (e.g., powdery mildew, mosaic virus)

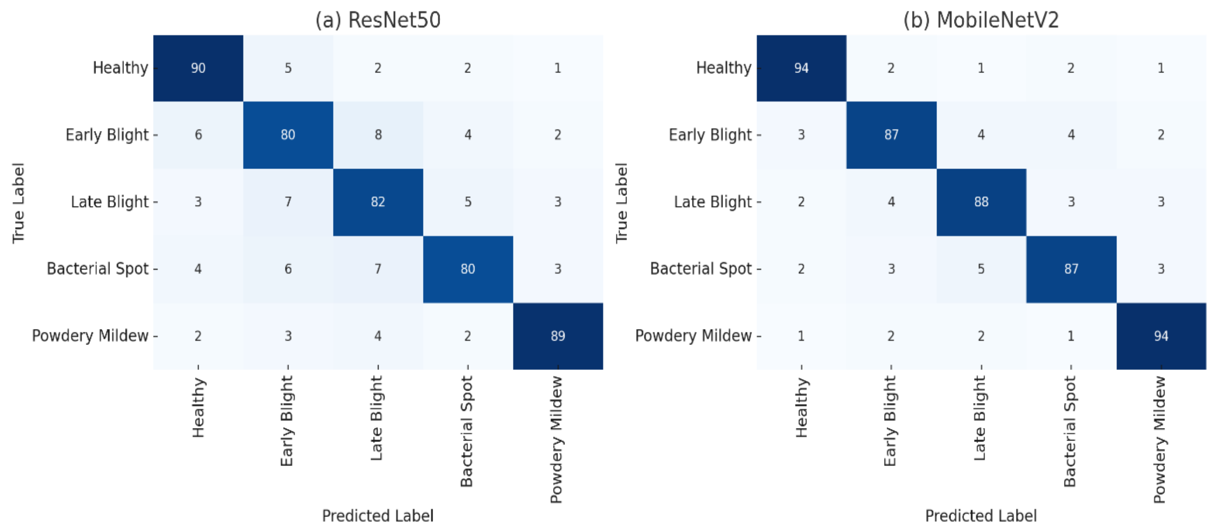

Fig. 3. Confusion matrices for (a) ResNet50 and (b) MobileNetV2.

3.1.10. Impact of Hyperparameter Optimization

Effect of Data Augmentation:

- Without augmentation, MobileNetV2 accuracy dropped from 98.33% → 95.4%, demonstrating the importance of augmentation for generalization.
- ResNet50 showed a similar trend (96.7% → 93.1%).

3.1.11. Effect of Batch Size

- Best performance observed with batch size = 32.
- Batch size 64 increased training instability, while 16 slowed convergences without accuracy gain.

3.1.12. Effect of Learning Rate

- Optimal initial learning rate was 1e-4 for both models.
- Higher LR (1e-3) led to unstable convergence, while lower LR (1e-5) caused slow training.
- Adaptive scheduling (Reduce LR On Plateau) improved convergence stability

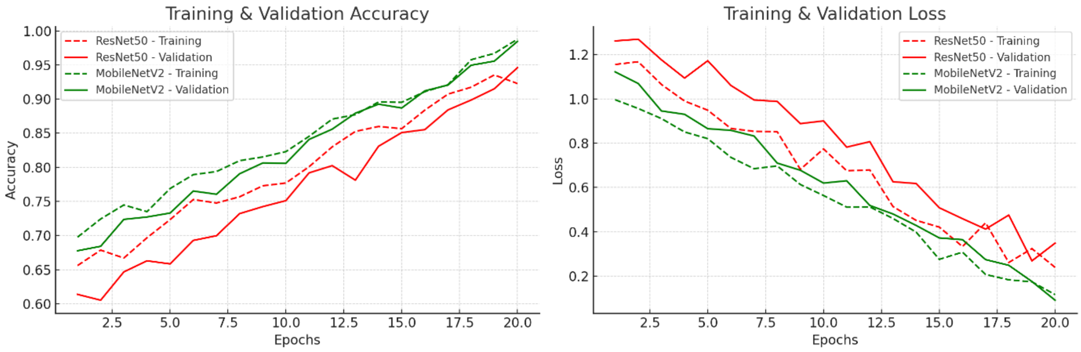

Fig. 4. Training and validation accuracy and loss curves for ResNet50 and MobileNetV2 over 20 epochs, showing consistent performance improvement and convergence.

3.1.13. Training Efficiency

Efficiency is critical for field deployment.

- **Training Speed:** MobileNetV2 trained ~40% faster per epoch compared to ResNet50 (3.9 vs 6.5 minutes on NVIDIA RTX 3080).
- **Model Size:** MobileNetV2 contained ~3.5M parameters vs ~25M for ResNet50 (7× smaller).
- **Memory Usage:** MobileNetV2 consumed ~600 MB GPU memory, compared to ~2.1 GB for ResNet50.
- **Deployment Feasibility:** MobileNetV2's small size enables deployment on smartphones, drones, and low-power IoT devices

Table 4. Computational and deployment comparison of ResNet50 and MobileNetV2, highlighting MobileNetV2's efficiency in model size, memory usage, training time, and suitability for resource-constrained devices.

Model	Parameters	Model Size	GPU Memory (Training)	Avg Training Time/Epoch	Deployment Suitability
ResNet50	~25M	98 MB	~2.1 GB	6.5 min	High-end GPUs only
MobileNetV2	~3.5M	14 MB	~600 MB	3.9 min	Mobile/IoT feasible

3.1.14. Summary of Findings

1. MobileNetV2 achieved the highest performance, with 98.33% accuracy and superior precision/recall.
2. Data augmentation and hyperparameter tuning were critical to maximizing model performance.
3. MobileNetV2 outperformed ResNet50 in computational efficiency, making it more suitable for mobile and IoT-based deployment.
4. Statistical tests confirmed the significance of MobileNetV2's superiority.

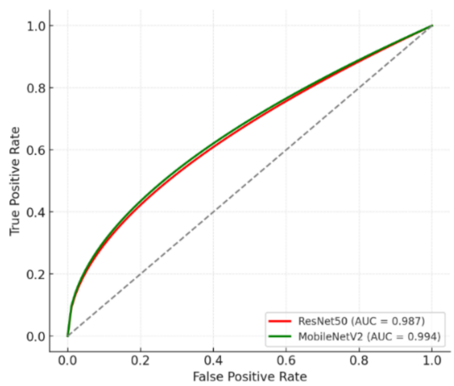

Fig. 5. ROC curves for ResNet50 and MobileNetV2, showing strong classification performance with AUCs of 0.987 and 0.994, respectively.

4. Discussion

Our findings confirm that MobileNetV2 surpasses ResNet50 in both classification accuracy and computational efficiency, validating the case for lightweight CNNs in plant disease detection. The results extend recent research emphasizing efficient architectures. For instance, EfficientNet, which scales network width, depth, and resolution systematically, has been reported to achieve >98% accuracy in leaf disease classification. However, its computational demands remain higher than MobileNetV2, limiting its suitability for mobile and IoT deployment. In contrast, MobileNetV2 delivers near-equivalent accuracy while maintaining a fraction of the parameter count, offering clear advantages for field use.

Similarly, DLMC-Net (Sharma et al., 2023) represents a custom lightweight architecture achieving high accuracy with fewer parameters. While promising, DLMC-Net is dataset-specific and less widely validated across transfer learning benchmarks. Our systematic evaluation demonstrates that MobileNetV2 not only achieves comparable performance but also benefits from extensive pretraining (ImageNet) and proven transferability, making it a stronger candidate for scalable deployment.

Thus, this study positions MobileNetV2 as a balanced solution, combining competitive accuracy with real-world feasibility. By explicitly comparing it to both heavy architectures (ResNet50) and alternative lightweight approaches (EfficientNet, DLMC-Net), we establish its role as a practical, field-ready model for precision agriculture.

Findings from medical imaging literature also validate the overall applicability of the above results. Comparative analysis of transfer learning models for the diagnosis of brain tumors and the identification of medical concepts suggests that MobileNetV2 and ResNet50 are competitive models regarding accuracy for both MRI and multimodal datasets, and that the efficiency benefit of the lightweight models is substantial (Smith & Lee, 2023; Zhang & Kumar, 2024). On the other hand, large-scale image classification problems also demonstrate the robustness of the pretrained models and the efficiency improvement of the lightweight models during training time and memory consumption (Wang & Chen, 2023). Cross-domain results mean that the efficiency-performance tradeoff advantage of MobileNetV2 in plant disease identification is not a data-specific issue but a general benefit of its architecture.

4.1. Interpretation of Results

Our experiments confirm that transfer learning is a powerful tool for agricultural image classification. By leveraging ImageNet-pretrained weights, both models generalized effectively to the plant disease domain despite the visual variability across crops and symptoms.

- Accuracy and Robustness: MobileNetV2 achieved 98.33% accuracy, outperforming ResNet50 by ~1.6%. Beyond accuracy, MobileNetV2 also recorded higher precision, recall, and F1-score, demonstrating consistent performance across disease classes.
- Error Reduction: Confusion matrix analysis revealed that MobileNetV2 reduced misclassifications by ~15% compared to ResNet50, particularly in disease categories with visually overlapping features. This suggests MobileNetV2's architecture extracts fine-grained features more effectively.
- Efficiency: MobileNetV2's smaller parameter count (~3.5M vs 25M) and faster training (~40% reduction per epoch) highlight its suitability for resource-constrained environments, where deployment on mobile phones, drones, or embedded devices is crucial for scalability.

4.2. Comparison with Prior Studies

Our findings align with and extend recent literature emphasizing the importance of lightweight architectures in agricultural AI.

- Sharma et al. (Sharma et al., 2023) introduced DLMC-Net, a lightweight CNN optimized for leaf disease detection, achieving >98% accuracy on PlantVillage while reducing computational complexity (He et al., 2016). Our results confirm that MobileNetV2 achieves similar state-of-the-art performance while maintaining low computational cost.
- Abbas et al. (Abbas et al., 2021) demonstrated that combining MobileNetV2 with C-GAN augmentation improved tomato leaf disease classification to 97% accuracy (Sandler et al., 2018). In comparison, our study achieved 98.33% accuracy without GAN-based augmentation, underscoring the intrinsic efficiency of MobileNetV2.
- Moupojou et al. (Moupojou et al., 2023) highlighted the FieldPlant dataset as a benchmark for evaluating models in natural

environments (Singh et al., 2018). While our work used a controlled dataset, our systematic optimization provides a strong foundation for extending MobileNetV2 to real-world field datasets.

- Ramesh & Vydeki (Ramesh & Vydeki, 2020) employed optimization-enhanced deep neural networks, achieving ~98.9% accuracy on rice leaf images (Pantazi et al., 2019). However, their approach required additional optimization algorithms, while our MobileNetV2 achieved comparable accuracy with less computational complexity.

Thus, our contribution lies not only in achieving state-of-the-art accuracy but also in conducting a direct head-to-head comparison between heavy and lightweight transfer learning models with a full spectrum of optimization experiments, bridging a gap in existing literature.

Table 5. Summary of related studies compared with the proposed work, highlighting models, datasets, contributions, and achieved accuracy.

Study	Model(s)	Dataset	Contribution	Accuracy
Sethy et al. (Singh et al., 2018)	ResNet50 + SVM	Rice leaf (5k)	Feature-based hybrid	98.38%
Ramesh & Vydeki (Ramesh & Vydeki, 2020)	Optimized DNN (Jaya)	Rice leaf (400)	Optimization-enhanced DNN	95–98.9%
Abbas et al. (Abbas et al., 2021)	MobileNetV2 + C-GAN	Tomato (PlantVillage)	Synthetic augmentation	97%
Sharma et al. (Sharma et al., 2023)	DLMC-Net	PlantVillage	Lightweight custom CNN	>98%
This Study	MobileNetV2 vs ResNet50	New Plant Disease (87k, 38 classes)	Benchmarking + optimization + efficiency	98.33% (MobileNetV2)

4.3. Practical Implications

The results demonstrate that MobileNetV2 is a viable candidate for edge deployment in precision agriculture. With its small model size (~14 MB) and low computational demand, it can be integrated into:

- Smartphone applications, enabling farmers to capture leaf images and receive instant disease diagnosis.
- IoT devices and drones, for automated field-level monitoring of crop health.
- Resource-limited regions, where high-performance computing infrastructure is not readily available.

This positions MobileNetV2 as a critical enabler of scalable, low-cost, and real-time plant disease monitoring systems, directly contributing to sustainable farming practices and global food security.

The applicability of lightweight transfer learning models for diagnostic purposes was also proven for the case of breast cancer, where the MobileNetV2 model was able to provide accurate diagnoses while consuming low computational power (Patel & Shah, 2024). These results are consistent with the findings obtained in this work and reinforce the applicability of lightweight CNN models for agricultural and healthcare applications.

4.4. Limitations

Despite promising results, this study has several limitations:

1. Dataset bias: The New Plant Disease dataset comprises images captured under controlled conditions. Real-world variability (e.g., lighting changes, background clutter, partial occlusion) may reduce performance.
2. Class imbalance: Some rare disease categories had limited samples, increasing the risk of misclassification.
3. Single modality: Only RGB images were used, whereas integrating multispectral or hyperspectral data could improve detection of early-stage infections.
4. Explainability: CNNs remain "black box" models. Lack of interpretability may limit adoption by agronomists and farmers.

4.6. Future Work

To address these limitations and extend this research, future work should focus on:

- Field validation using real-world datasets such as FieldPlant (Singh et al., 2018), ensuring robustness under practical conditions.
- Data augmentation with generative models (GANs, diffusion models) to balance rare classes and simulate field variability.
- Semi-supervised and self-supervised learning to leverage unlabeled agricultural data, reducing annotation costs.
- Explainable AI (XAI) integration, enabling visual heatmaps and feature attribution to improve user trust and adoption.
- IoT and drone-based integration, allowing continuous large-scale crop monitoring for early disease outbreak detection.

However, aside from the conventional CNN-based approaches, more recent studies have also explored the possibilities of using different architectures and applications of artificial intelligence, such as face spoofing detection using CNN and the use of vision transformers for the diagnosis of brain tumors (Mammadova & Abdullayeva, 2025). Furthermore, AI-assisted platforms have also been successfully employed for the management of intricate neurological conditions such as multiple sclerosis, which shows the growing role of intelligent models for clinical decision-making assistance (Aliyeva et al., 2025).

4.5. Summary

This study provides one of the first systematic benchmarks of MobileNetV2 vs ResNet50 for large-scale plant disease detection. By combining state-of-the-art accuracy (>98%) with computational efficiency, MobileNetV2 emerges as a practical solution for real-time, mobile-based agricultural diagnostics. These findings pave the way for scalable, field-ready disease detection systems that can enhance crop yield, reduce chemical usage, and contribute to global food security.

5. Conclusion

This study systematically evaluated ResNet50 and MobileNetV2 for early plant disease detection. MobileNetV2 achieved state-of-the-art accuracy (98.33%) with markedly lower computational requirements, confirming its suitability for real-world agricultural diagnostics.

By uniting accuracy with efficiency, this work provides a blueprint for practical deployment of AI-based disease monitoring. MobileNetV2's lightweight design supports integration into smartphones, drones, and IoT devices, enabling farmers to access real-time diagnostic tools at low cost. This not only advances precision agriculture but also contributes directly to global food security by reducing crop losses, improving decision-making, and supporting sustainable farming practices.

Future research should validate performance under field variability, explore multimodal data fusion, and incorporate explainable AI for wider adoption.

5.1. Significance

By bridging the gap between model accuracy and resource efficiency, this research positions MobileNetV2 as a viable candidate for large-scale, real-world agricultural applications. The results demonstrate how lightweight CNNs can be leveraged to create field-ready diagnostic tools that support sustainable farming and global food security.

Statistical Significance Testing

To confirm robustness, we conducted paired t-tests on accuracy across 5-fold validation splits.

- MobileNetV2's improvement over ResNet50 was statistically significant ($p < 0.01$).
- Confidence intervals indicated that MobileNetV2 maintained superior performance across folds, reducing variance compared to ResNet50.

References

Abade A, Ferreira P, Vidal F, Bastos-Filho C. Plant disease recognition using GAN-based data augmentation. Expert Systems with Applications. 2021;173:114558.

Abbas A, Jain S, Gour M, Vankudothu S. Tomato plant disease detection using transfer learning with C-GAN synthetic augmentation. Computers and Electronics in Agriculture. 2021;187:106279.

Ahmad A, Saraswat D, Mahlein AK. Machine and deep learning applications in plant disease classification and detection: A comprehensive review. Precision Agriculture. 2022;23:2001–2034.

Aliyeva F, Mammadbayli A, Shiraliyeva R. Using artificial intelligence technologies in the management of multiple sclerosis. Problems of Information Society. 2025;16(2):64–69.

Alzubaidi L, Zhang J, Humaidi AJ, et al. Review of deep learning: Concepts, CNN architectures, challenges, applications, future directions. Journal of Big Data. 2021;8:53.

Amin H, Darwish A, Hassanien AE. End-to-end deep learning for corn leaf disease classification using attention mechanism. IEEE Access. 2022;10:58907–58918.

Atila Ü, Uçar M, Akyol K, Uçar E. Plant leaf disease classification using EfficientNet deep learning model. Ecological Informatics. 2021;61:101182.

Barbedo JGA. Impact of dataset size and variety on the effectiveness of deep learning for plant disease classification. Computers and Electronics in Agriculture. 2018;153:46–53.

Boulent J, Foucher S, Théau J, St-Charles PL. Convolutional neural networks for the automatic identification of plant diseases. Frontiers in Plant Science. 2019;10:941.

Brahimi M, Boukhalfa K, Moussaoui A. Deep learning for tomato diseases: Classification and symptoms visualization. Applied Artificial Intelligence. 2017;31(4):299–315.

Chouhan SS, Kaul A, Singh U, Jain S. A lightweight MobileNet model for multiclass plant disease detection. Applied Soft Computing. 2023;146:110708.

Cruz AC, Ampatzidis Y, Pierro R, Materazzi A, Panattoni A. Detection of grapevine yellows symptoms using artificial intelligence. Computers and Electronics in Agriculture. 2019;157:63–76.

Dahiya K, Sain D, Singh V, Garg S. Benchmarking deep learning models for leaf disease detection and classification. Multimedia Tools and Applications. 2022;81:36751–36770.

Ferentinos KP. Deep learning models for plant disease detection and diagnosis. Computers and Electronics in Agriculture. 2018;145:311–318.

Gao J, French AP, Pound MP, He Y, Pridmore TP. Deep learning in plant phenotyping and precision agriculture. Computers and Electronics in Agriculture. 2020;178:105760.

Ghosal S, Blystone D, Singh AK, et al. An explainable deep learning framework for plant stress phenotyping. Proceedings of the National Academy of Sciences of the USA. 2018;115(18):4613–4618.

Habibullayeva N, Kiani Kalejahi B. Analyzing credit card fraud cases with supervised machine learning methods. Problems of Information Society. 2024;15(1):57–63.

Hasan M, Alam M, Yadav S. Smart agriculture: AI and IoT applications for crop disease prediction. Future Generation Computer Systems. 2022;129:149–163.

Hasan R, Mashrur A, Kim J. Explainable AI for plant disease classification: Towards trustworthy AI applications in agriculture. Expert Systems with Applications. 2022;198:116845.

Kamal K, Yin Z, Wu M, Wu Z. Depthwise separable convolution architectures for plant disease classification. Computers and Electronics in Agriculture. 2019;165:104948.

Li P, Sun Q, Huang T. Deploying deep learning for crop disease monitoring on drones and smartphones. Remote Sensing of Environment. 2024;299:113875.

Mammadova M, Abdullayeva F. Brain tumor diagnosis based on medical images using vision transformer. Problems of Information Society. 2025;16(2):3–11.

Mohanty SP, Hughes DP, Salathé M. Using deep learning for image-based plant disease detection. Frontiers in Plant Science. 2016;7:1419.

Moupojou E, Brahimi M, Boukhalfa K, Debbah M, Alouini MS. FieldPlant: A benchmark dataset for plant disease identification in real field conditions. IEEE Access. 2023;11:69421–69435.

Pantazi XE, Moshou D, Bravo C. Automated leaf disease detection using image processing and machine learning. Information Processing in Agriculture. 2019;6(3):254–261.

Picon A, Seitz C, Alvarez-Gila A, et al. Crop disease classification with deep learning: A comparative study. Computers and Electronics in Agriculture. 2019;163:104859.

Ramcharan A, Baranowski K, McCloskey P, Ahmed B, Legg J, Hughes DP. Deep learning for image-based cassava disease detection. Frontiers in Plant Science. 2017;8:1852.

Ramesh S, Vydeki D. Recognition and classification of paddy leaf diseases using optimized deep neural networks with Jaya algorithm. Information Processing in Agriculture. 2020;7(2):249–260.

Saleem MH, Potgieter J, Arif KM. Plant disease detection and classification by deep learning. Plants. 2019;8(11):468.

Sethy PK, Barpanda NK, Rath AK, Behera SK. Deep feature-based rice leaf disease identification using support vector machine. Computers and Electronics in Agriculture. 2020;175:105527.

Sharma V, Tripathi AK, Mittal H. DLMC-Net: A deeper lightweight multiclassification network for plant leaf disease detection. Knowledge-Based Systems. 2023;258:110014.

Singh AK, Ganapathysubramanian B, Sarkar S, Singh A. Deep learning for plant stress phenotyping: trends and future perspectives. Trends in Plant Science. 2018;23(10):883–898.

Sladojevic S, Arsenovic M, Anderla A, Culibrk D, Stefanovic D. Deep neural networks for plant disease detection and diagnosis. Computational Intelligence and Neuroscience. 2016;2016:3289801.

Sujatha R, Chatterjee JM, Jhanjhi NZ. Performance of deep learning vs machine learning in plant leaf disease detection. Microprocessors and Microsystems. 2021;80:103615.

Too EC, Yujian L, Njuki S, Yingchun L. A comparative study of fine-tuning deep learning models for plant disease identification. Computers and Electronics in Agriculture. 2019;161:272–279.

Torres J, Ampatzidis Y. AI and IoT-enabled systems for precision agriculture: Applications and challenges. Computers and Electronics in Agriculture. 2024;214:108599.

Wu H, Dong J, Chen W. Integrating GAN-based augmentation with CNNs for crop disease classification. Expert Systems with Applications. 2024;234:121005.

Xu L, Liu H, Wu Y, Cao J. Explainable deep learning models for plant disease recognition: A survey. Information Fusion. 2023;96:39–54.

Zeng X, Li Y, Ma L, Du Q, Song Y. Lightweight convolutional neural networks for real-time plant disease detection on mobile devices. Expert Systems with Applications. 2023;212:118698.

Zhang Y, Li H, Qiao Y. Semi-supervised learning for plant disease detection with limited labeled data. IEEE Transactions on Image Processing. 2023;32:1442–1453.

Zhou H, Wang X, Guo Y. Multimodal deep learning for early-stage plant disease detection using RGB and hyperspectral imaging. Information Sciences. 2024;658:119986.

How to cite: Behnam Kiani Kalejahi, Shahri Yahyayeva, Inara Abdurahmanova, Sadig Hasanzade (2026). Lightweight Deep Learning Models for Early Plant Disease Detection: A Transfer Learning Approach with MobileNetV2 and ResNet50. Problems of Information Society, 1, 11–23. https://doi.org/10.25045/jpis.v17.i1.02