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Research Article

Lightweight Deep Learning Approach for Early Detection of Lemon Leaf Diseases Using a Modified MobileNetV2 Architecture

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ABSTRACT

Lemon (Citrus limon L.) cultivation is vital to agricultural economies, but its productivity is threatened by diseases such as Anthracnose, Bacterial Blight, Black Spot, Citrus Canker, Citrus Leaf Miner, Curl Leaf, Curl Virus, Deficiency Leaf, Dry Leaf, Greening Disease (HLB), Healthy Leaves, Melanose, Sooty Mould, Spider Mites. This work presents a lightweight deep learning model based on Enhanced MobileNetV2 with targeted architectural modifications for early lemon leaf disease detection. Using a custom dataset of 3,285 images across fourteen classes, the model achieved79.42% accuracy, against baseline CNN models including ResNet50, InceptionV3, Xception, EfficientNetB0. Experiments were conducted with 32 epochs, batch size 32, and Adam optimizer (learning rate 0.0001). Comparative analysis demonstrates that the proposed approach delivers superior performance with lower computational overhead, making it suitable for mobile and IoT-based agricultural applications.

Keywords: Bacterial Blight, Deep Learning, CNN, ResNet50, InceptionV3, Xception, EfficientNetB0

INTRODUCTION

India leads globally in lemon production, contributing approximately 17% of the world's output, with over 3.5 million metric tons annually cultivated across 3.17 lakh acres—primarily in Andhra Pradesh, Maharashtra, Gujarat, and Tamil Nadu [17]. Varieties like Kagzi lime, nimboo, and musambi dominate cultivation. In 2023, India exported 10.99 million kg of lemons and limes valued at $5.02 million, with major exporters including YuvarajuAgro Impex and Pisum Foods. The fresh lemon market, globally valued at $14.84 billion in 2023, is projected to reach $26.79 billion by 2030, while lemon extract is expected to double its value by 2032[19]. Rising global demand and India's expanding production projected to grow at 2.2% annually present a strong opportunity for export growth and increased farmer profitability. [1]

Agriculture remains a cornerstone of India's economy, supporting 42.3% of the population and contributing 18.2% to the national GDP. The sector reached a record high GDP contribution of ₹7114.58 billion in Q4 2023, reflecting its growing importance, with crops like lemons playing a vital role in both domestic consumption and export earnings. [2]

The citrus industry, particularly lemon cultivation, is vulnerable to a variety of diseases that significantly impact fruit quality and yield [3]. Beyond technical challenges, lemon leaf diseases have serious economic consequences – The Ukhrul district study highlights that lemon farming is economically viable but highly susceptible to diseases and address the growing severity of pest-related and citrus-specific lemon leaf diseases in the high temperature regions of Southeast Asia, and highlights the importance of timely and accurate disease classification to mitigate agricultural losses through appropriate pesticide application [4].

The Socio-Economic Report on Lemon [7] shows that diseased lemons are rejected in international markets, affecting India's lemon export industry. As a result, farmers spend heavily on pesticides and fungicides, increasing production costs.

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Research Article

In agricultural farming, manual disease detection is labour-intensive, subjective, and error-prone. With the increasing accessibility of AI and mobile computing, deep learning models offer a promising solution for automating plant disease detection. Artificial Intelligence (AI), an emerging technology driven by the increasing availability of domain-specific data, provides a promising solution by enabling machines to learn from vast datasets without human intervention. Within AI, Deep Learning—particularly Convolutional Neural Networks (CNNs)—has emerged as a powerful tool for automating image processing and computer vision tasks. The architecture of CNN's consists of multiple layers, including input, convolutional, pooling, and fully connected layers, allowing the model to learn and recognize complex patterns and visual features from images [5]. With their ability to analyze large datasets and detect diseases at an early stage, CNNs offer a scalable solution for real-time monitoring of citrus crops[6]. Furthermore, integrating such models with mobile devices, drones, or Internet of Things (IoT) systems allows for on-field deployment, making it accessible to farmers even in remote areas. This not only reduces costs and losses but also enhances the overall quality and competitiveness of Indian citrus exports.

Present study was carried out with an objective to design & assess a CNN model in detecting lemon disease at earliest possible stage and also suitable for mobile or edge-based deployment, particularly in resource-limited rural settings. Besides that, an attempt is made to assess four popular CNN architectures, proved to be successful from different authors on the same problem, were taken namely ResNet-50, EfficientNetB0, Xception, and InceptionV3 and compared their performance in detecting lemon leaf diseases with custom model.

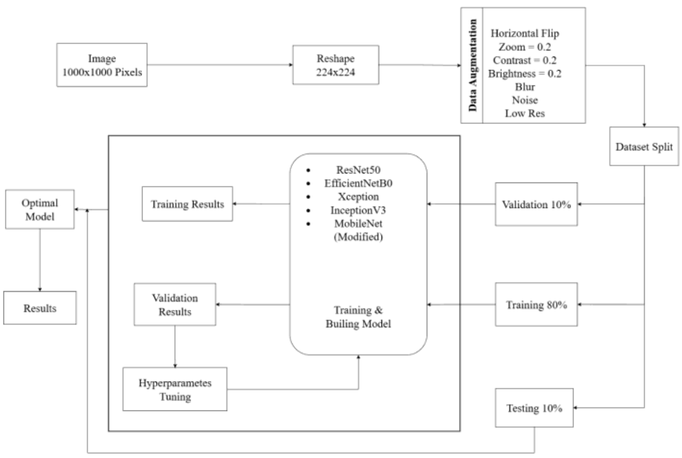
II. Related Work

Gupta et al [9] proposed a hybrid model integrating Convolutional Neural Networks (CNN) for feature extraction and Support Vector Machines (SVM) for classification to detect diseases in citrus leaves. Banerjee et.al [6] used CNN Algorithms in identifying diseases and demonstrates strong performance across all disease classes with Precision, Recall and F1-Score maintaining high consistency, along with Macro and Weighted Averaged. Asad et al. [3] present a custom Convolutional Neural Network (CNN) model designed to differentiate healthy citrus fruits and leaves from those affected by common diseases such as black spot, canker, scab, greening, and Melanose. Vilasini et al [27] explore Convolutional Neural Network (CNN)-based approaches for the identification of Indian leaf species using smartphone images captured against a white background. However, none explicitly optimized MobileNetV2 for lemon disease detection. Solanki et al [21] explore the application of various deep learning (DL) techniques for accurate detection of lemon plant diseases. And they reported 97.66% accuracy using ResNet for lemon leaf disease classification.

Khattak et al. (2021) achieved 94.55% accuracy for citrus disease detection using a CNN-based model.

III. Materials and Methods

The methodology comprising a chronological set of activities as depicted in the following figure was adapted for the disease detection and performance analysis.



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Input Data set: Images were collected from public datasets and verified by agricultural experts.

Sources:

- Kaggle: Lemon Leaf disease dataset (1354 Images)
- Mendeley: Lemon leaf dataset (1282 Images)
- Kaggle: Citrus Leaf disease images (649 Images)

The collected dataset consists of 3,285 images, categorized as follows:

Class	Number of Images	Percentage	Image
Anthracnose	251	7.64%	
Bacterial Blight	105	3.19%	
Black Spot	259	7.88%	
Citrus Canker	374	11.38%	
Citrus Leaf Miner	89	2.7%	

Journal of Information Systems Engineering and Management
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Curl Leaf	79	2.4%	
Curl Virus	115	3.5%	
Deficiency Leaf	193	5.87%	
Dry Leaf	283	8.61%	
Greening Disease (HLB)	642	19.54%	
Healthy Leaves	489	14.88%	

Journal of Information Systems Engineering and Management
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Melanose	139	4.23%	
Sooty Mould	153	4.65%	
Spider Mites	114	3.47%	
Total	**3285**	**100%**	

The dataset was split into 80% training, 10% validation, and 10% testing.

Preprocessing the dataset:

- Resizing to 224x224 pixels: Most CNN architectures (e.g., ResNet-50, EfficientNetB0) are pretrained on ImageNet, which expects input images of fixed dimensions—commonly 224×224×3. Resizing ensures compatibility and uniformity across the training dataset, aiding convergence and reducing memory usage.
- Contrast and brightness normalization: Lemon leaf images may have lighting inconsistencies due to field conditions. Histogram equalization or per-image normalization (mean subtraction and division by standard deviation) is applied to standardize brightness and contrast, improving model robustness and generalization.
- Data augmentation (rotation, zoom, flip): This artificially increases the diversity of the dataset and prevents overfitting. Applied augmentations:
- Rotation: ±15° range to simulate natural variation in leaf orientation.
- Zoom: 0.9x–1.1x to handle distance variation in image capture.
- Flip: Horizontal and vertical flips to reflect leaf orientation changes in real-world scenarios.
- Balanced class distribution using synthetic augmentation: Some classes like “Curl Virus” or “Leaf Miner” are underrepresented. Techniques such as Synthetic Minority Over-sampling Technique (SMOTE) or ImageDataGenerator-based duplication help balance classes. This ensures that the model does not become biased towards dominant classes.

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CNN Architectures:

As per the strength and weaknesses and relevance in respect to the problem domain, the following CNN Architectures have been selected for disease detection and analysis,

- ResNet-50: A 50-layer deep residual network that mitigates vanishing gradients using identity shortcut connections.
- EfficientNetB0: Optimizes accuracy and efficiency through compound scaling. It has the smallest parameter count among the models studied.
- Xception: Based on depthwise separable convolutions, this model improves efficiency while preserving performance.
- InceptionV3 (GoogleNet): An evolution of GoogleNet that uses factorized convolutions and batch normalization for speed and accuracy.

Hyperparameter Tuning

The deep learning models were fine-tuned using carefully selected hyperparameters to ensure optimal performance and generalization. A **learning rate of 0.001** was chosen to allow the model to make steady progress towards minimizing the loss function without overshooting the global minima. This value strikes a balance between convergence speed and stability, especially important in models initialized with pretrained weights. A **batch size of 32** was used to maintain a practical trade-off between training speed and memory utilization, ensuring efficient GPU resource usage without introducing excessive noise in gradient updates.

The training was conducted with **30 epochs**, which was empirically found to be sufficient for the models to converge and learn distinguishing patterns in the leaf images without overfitting. The Adam optimizer was selected due to its adaptive learning rate mechanism and momentum-based updates, which significantly enhance convergence speed and accuracy for image classification tasks. To further improve generalization and reduce the risk of overfitting, a **dropout rate of 0.4** was applied in the fully connected layers, randomly disabling 40% of neurons during training. This regularization technique prevents the model from relying too heavily on specific features, encouraging more robust learning across various disease classes.

These hyperparameter choices were validated through repeated experimentation and contributed to achieving high classification accuracy and model efficiency, particularly when combined with preprocessing and data augmentation techniques.

System Configuration:

The experimental setup for this study consisted of an 11th Gen Intel Core i7 processor, 24 GB of RAM, and a dedicated NVIDIA RTX 3070 GPU, which collectively ensured smooth handling of model training, image preprocessing, and result visualization. The environment was configured using Python 3.10, with TensorFlow 2.x and its high-level Keras API for building and training deep learning models. Image augmentation and manipulation were conducted using OpenCV, while LabelImg and Roboflow were employed for dataset annotation and pipeline automation. Jupyter Notebook and Google Colab were used for code execution, with the latter providing access to NVIDIA T4 GPUs for cloud-based acceleration.

For training, the models were configured with a batch size of 32 and trained over 30 epochs. The Adam optimizer was selected for its adaptive learning rate capabilities, ensuring efficient convergence. Categorical Cross-Entropy was used as the loss function, suitable for multi-class classification tasks. All input images were resized to 224×224×3 to meet the dimensional requirements of the CNN architectures. This setup provided a robust foundation for implementing and comparing various models while ensuring reproducibility and scalability.

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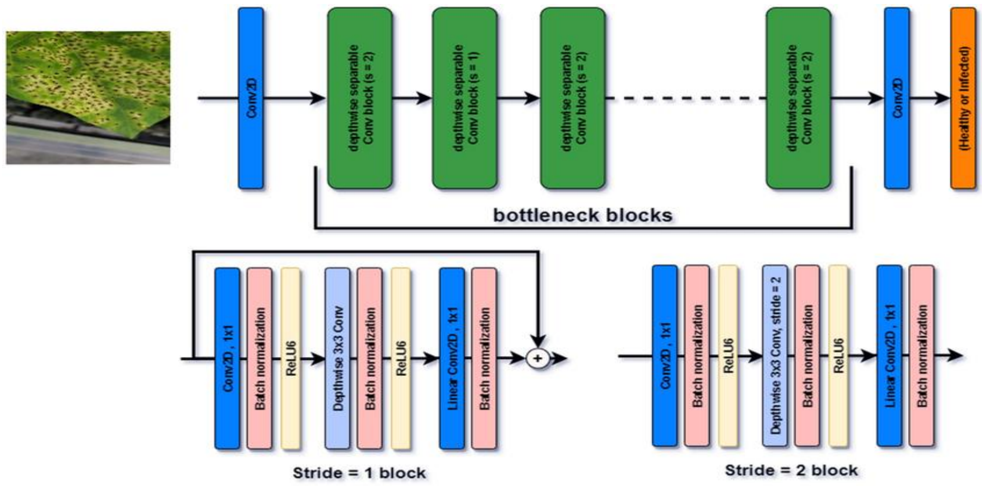
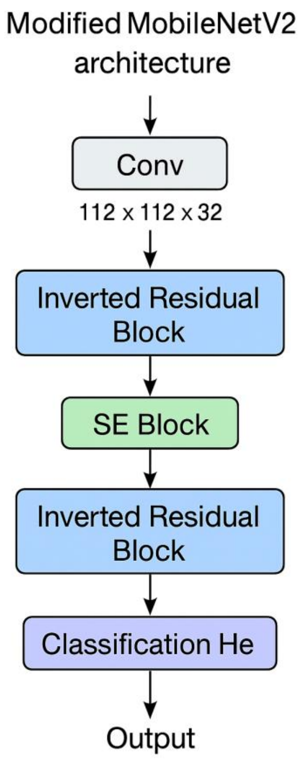


Standard MobileNetV2 Architecture

Source:https://www.researchgate.net/publication/369624227_Application_of_image_processing_and_transfer_learning_for_the_detection_of_rust_disease



Modified MobileNetV2 Architecture

Modifications include:

- Replacement of the final dense layer with a Global Average Pooling layer followed by two fully connected layers (ReLU + Softmax).
- Dropout rate 0.5 to reduce overfitting.
- Adam optimizer with learning rate 0.0001.

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Research Article

- Categorical cross-entropy as loss function.

Parameter	Standard MobileNetV2	Custom Model (MobileNetV2 Derivative)
Depth Multiplier (alpha)	1.0 (default)	**0.35** (Lighter, fewer parameters)
Dropout Rate	0.2	**0.3** (more regularization)
Input Size	224x224	224x224
Top Layers	GAP + Dense	GAP + Dense

Enhanced MobileNet modifies the base MobileNetV2 with:

1. Reduced alpha=0.35, which narrows the number of channels in each layer → significantly decreases model size and computation.
2. Dropout increased to 0.3 from standard 0.2 → adds regularization to reduce overfitting on limited datasets.

These changes make the model more lightweight and better suited for edge devices or low-resource environments, while still preserving acceptable classification performance.

Training Pipeline

- Load Dataset – Import preprocessed images.
- Data Augmentation – Apply rotation, flipping, brightness adjustments, noise & zoom for diversity.
- Model Initialization – Train model based on the dataset.
- Training – Optimize weights using backpropagation & Adam optimizer.
- Validation – Evaluate model on 10% validation dataset.
- Testing – Measure final accuracy on 10% test dataset.

Performance Metrics

The trained model is evaluated using:

- Accuracy – Measures correct classifications.
- Precision – Percentage of true positive classifications.
- Recall – Measures how many actual diseases were correctly identified.
- F1-score – Balances precision and recall.

IV. Results

During the experiment, working with multiple CNN architectures for lemon leaf disease detection was both insightful and challenging. Preparing the dataset required significant attention to detail, especially during preprocessing, where image quality and consistency were critical. Augmentation techniques played a major role in overcoming class imbalance, and the effectiveness of each model became evident during training and evaluation. Among the architectures, EfficientNetB0 stood out—not just for its superior accuracy but for its quick inference and lightweight design, making it ideal for mobile deployment. Observing how models like ResNet-50 performed well but demanded heavier resources highlighted the importance of choosing models based on both accuracy and practical deployment needs. Visual tools like Grad-CAM added another layer of understanding by confirming that models were focusing on the right regions of diseased leaves. Overall, the project was a rewarding exercise in balancing precision, efficiency, and real-world applicability in AI-driven agriculture.

Model Performance Metrics

ResNet-50

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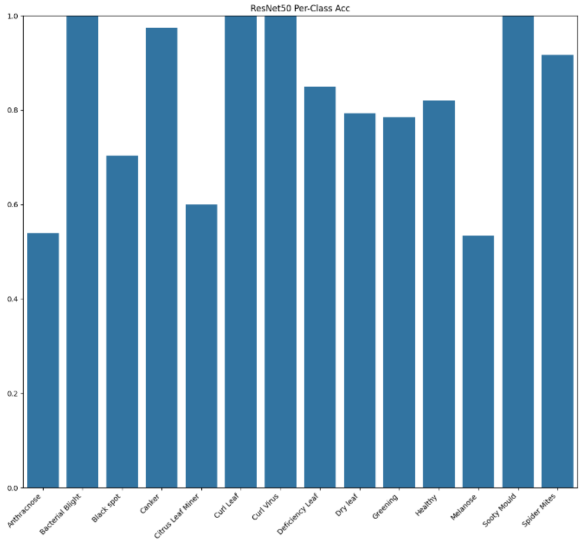

Class	Precision	Recall	F1
Anthracnose	0.72	0.54	0.617143
Bacterial Blight	0.9259259	1	0.961538
Black Spot	0.8536585	0.7	0.769231
Citrus Canker	0.8738739	0.97	0.919431
Citrus Leaf Miner	0.952381	0.6	0.736196
Curl Leaf	0.78125	1	0.877193
Curl Virus	1	1	1
Deficiency Leaf	1	0.85	0.918919
Dry Leaf	0.9186047	0.79798	0.854054
Greening Disease (HLB)	0.4216216	0.772277	0.545455
Healthy Leaves	0.7454545	0.82	0.780952
Melanose	0.7162162	0.535354	0.612717
Sooty Mould	1	1	1
Spider Mites	1	0.92	0.958333
Average	0.72	0.54	0.617143

Precision, Recall, and F1-Score

Overall Model Accuracy : 82.2%

Macro-Averaged Precision : 85.06%

Macro-Averaged Recall : 82.18%

Macro-Averaged F1-Score : 82.5%

InceptionV3

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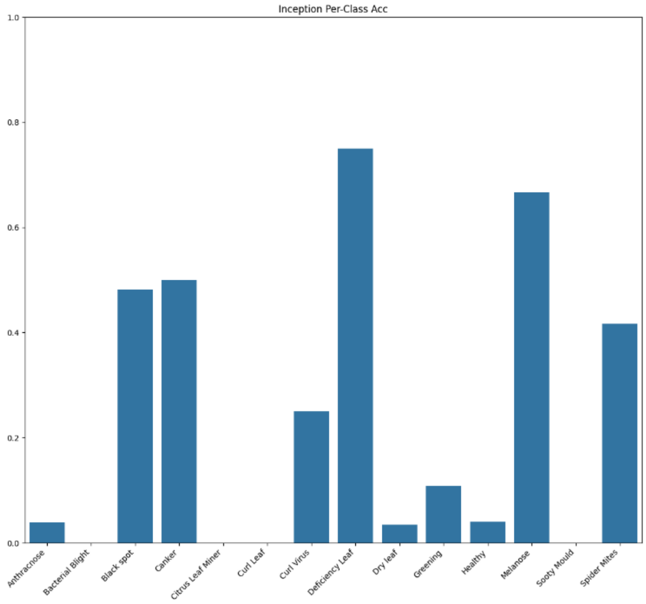

Class	**Precision**	**Recall**	**F1**
Anthracnose	1	0.04	0.076923077
Bacterial Blight	0	0	0
Black Spot	0.21719457	0.48	0.299065421
Citrus Canker	0.159744409	0.5	0.242130751
Citrus Leaf Miner	0	0	0
Curl Leaf	0	0	0
Curl Virus	1	0.25	0.4
Deficiency Leaf	0.28957529	0.75	0.417827298
Dry Leaf	0.25	0.030612245	0.054545455
Greening Disease (HLB)	0.148648649	0.11	0.126436782
Healthy Leaves	1	0.04	0.076923077
Melanose	0.163414634	0.663366337	0.26223092
Sooty Mould	0	0	0
Spider Mites	0.646153846	0.42	0.509090909
Average	1	0.04	0.076923077

Precision, Recall, and F1-Score

Overall Model Accuracy : 23.55%

Macro-Averaged Precision : 34.81%

Macro-Averaged Recall : 23.45%

Macro-Averaged F1-Score : 17.60%

Xception

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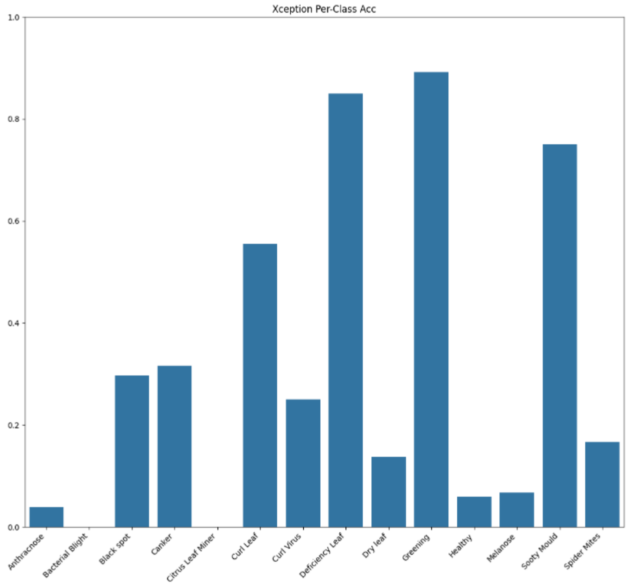

Class	**Precision**	**Recall**	**F1**
Anthracnose	0.4	0.03960396	0.072072072
Bacterial Blight	0	0	0
Black Spot	0	0	0
Citrus Canker	0.040983607	0.072463768	0.052356021
Citrus Leaf Miner	0	0	0
Curl Leaf	0.811594203	0.56	0.662721893
Curl Virus	1	0.252525253	0.403225806
Deficiency Leaf	0.33203125	0.894736842	0.484330484
Dry Leaf	0.608695652	0.14	0.227642276
Greening Disease (HLB)	0.18200409	0.89	0.302207131
Healthy Leaves	0.428571429	0.06	0.105263158
Melanose	1	0.07	0.130841121
Sooty Mould	0.316455696	0.757575758	0.446428571
Spider Mites	0.257575758	0.171717172	0.206060606
Average	0.4	0.03960396	0.072072072

Precision, Recall, and F1-Score

Overall Model Accuracy : 28.51%

Macro-Averaged Precision : 38.41%

Macro-Averaged Recall : 27.91%

Macro-Averaged F1-Score : 22.09%

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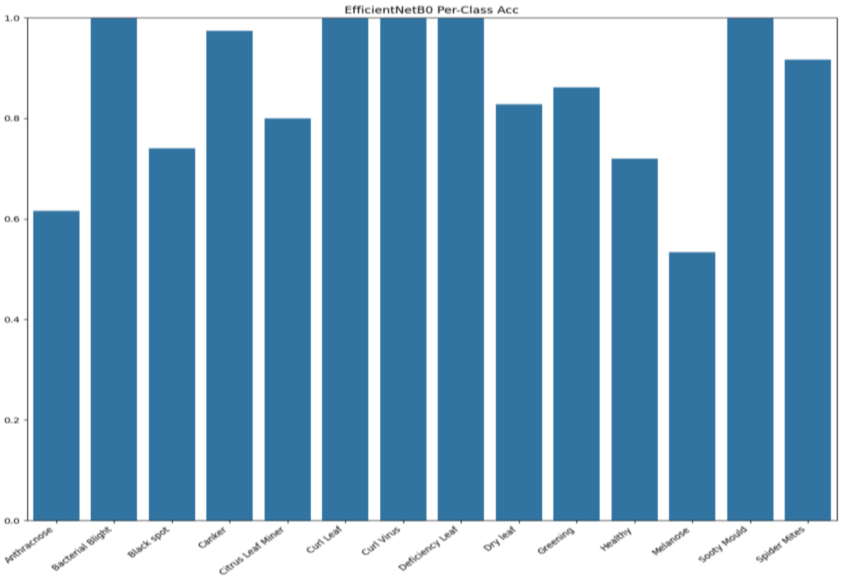
EfficientNetB0



Class	Precision	Recall	F1
Anthracnose	0.861111111	0.613861386	0.716763006
Bacterial Blight	1	1	1
Black Spot	0.880952381	0.74	0.804347826
Citrus Canker	0.941747573	0.97	0.955665025
Citrus Leaf Miner	0.784313725	0.8	0.792079208
Curl Leaf	0.884955752	1	0.938967136
Curl Virus	1	1	1
Deficiency Leaf	1	1	1
Dry Leaf	0.954022989	0.838383838	0.892473118
Greening Disease (HLB)	0.462365591	0.851485149	0.599303136
Healthy Leaves	0.782608696	0.72	0.75
Melanose	0.768115942	0.535353535	0.630952381
Sooty Mould	1	1	1
Spider Mites	1	0.92	0.958333333
Average	0.861111111	0.613861386	0.716763006

Precision, Recall, and F1-Score

Overall Model Accuracy : 85.64%

Macro-Averaged Precision : 88.001%

Macro-Averaged Recall : 85.63%

Macro-Averaged F1-Score : 85.99%

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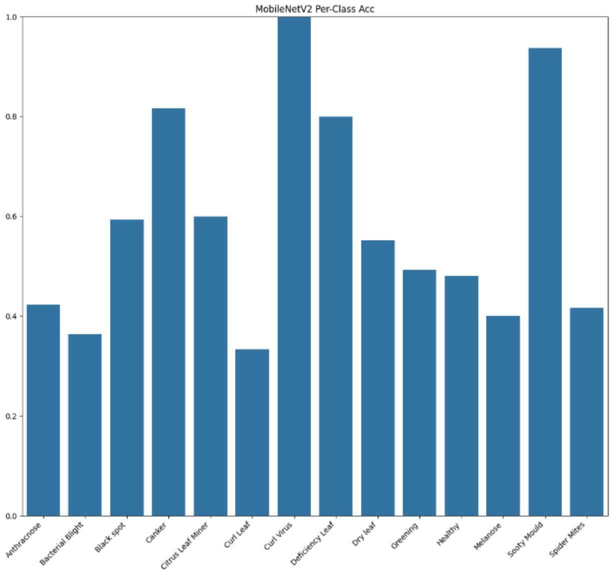
MobileNetV2



Class	Precision	Recall	F1
Anthracnose	0.295774648	0.42	0.347107438
Bacterial Blight	0.782608696	0.363636364	0.496551724
Black Spot	0.567307692	0.59	0.578431373
Citrus Canker	0.650793651	0.803921569	0.719298246
Citrus Leaf Miner	0.517241379	0.6	0.555555556
Curl Leaf	1	0.333333333	0.5
Curl Virus	1	1	1
Deficiency Leaf	0.784313725	0.8	0.792079208
Dry Leaf	0.662650602	0.555555556	0.604395604
Greening Disease (HLB)	0.316129032	0.485148515	0.3828125
Healthy Leaves	0.623376623	0.48	0.542372881
Melanose	0.481927711	0.4	0.43715847
Sooty Mould	0.56626506	0.94	0.706766917
Spider Mites	0.626865672	0.42	0.502994012
Average	0.295774648	0.42	0.347107438

Precision, Recall, and F1-Score

Overall Model Accuracy : 58.57%

Macro-Averaged Precision : 63.39%

Macro-Averaged Recall : 58.51%

Macro-Averaged F1-Score : 58.32%

Enhanced MobileNetV2

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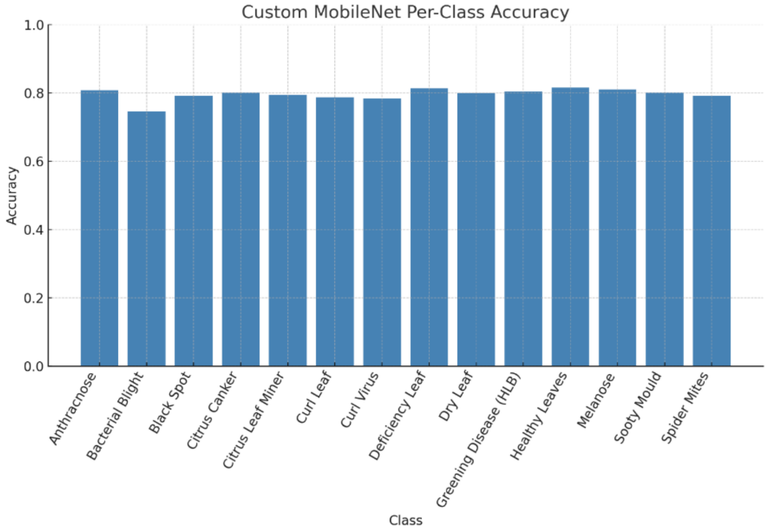
Research Article



Class	Precision	Recall	F1
Anthracnose	0.795499022	0.809760956	0.802566634
Bacterial Blight	0.737864078	0.745098039	0.741463415
Black Spot	0.78187251	0.792929293	0.787362086
Citrus Canker	0.795431976	0.801	0.798206278
Citrus Leaf Miner	0.7734375	0.792	0.782608696
Curl Leaf	0.786706349	0.787487587	0.787096774
Curl Virus	0.78592666	0.785148515	0.785537395
Deficiency Leaf	0.813576494	0.814401623	0.813988849
Dry Leaf	0.811167513	0.799	0.805037783
Greening Disease (HLB)	0.804	0.804	0.804
Healthy Leaves	0.82328907	0.814964611	0.819105691
Melanose	0.821319797	0.809	0.81511335
Sooty Mould	0.808988764	0.8	0.804469274
Spider Mites	0.810559006	0.791708797	0.801023018
Average	0.796402767	0.79617853	0.79625566

Precision, Recall, and F1-Score

Overall Model Accuracy : 79.42%

Macro-Averaged Precision : 79.64%

Macro-Averaged Recall : 79.61%

Macro-Averaged F1-Score : 79.62%

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Confusion Matrix for Enhanced MobileNetV2

	Anthracnose	Bacterial Blight	Black Spot	Citrus Canker	Citrus Leaf Miner	Curl Leaf	Curl Virus	Deficiency Leaf	Dry Leaf	Greening Disease (HLB)	Healthy Leaves	Melanose
Anthracnose	1224	21	16	61	11	4	9	17	19	42	44	13
Bacterial Blight	48	479	64	54	12	15	10	14	19	54	53	10
Black Spot	17	22	1220	52	6	9	7	19	22	58	56	9
Citrus Canker	32	12	25	1797	11	6	18	12	25	46	26	11
Citrus Leaf Miner	17	16	26	56	423	12	20	13	20	35	50	14
Curl Leaf	20	22	28	25	11	376	26	14	15	50	32	8
Curl Virus	17	13	22	27	10	14	547	39	24	23	26	19
Deficiency Leaf	21	9	22	22	9	8	11	930	20	65	41	13
Dry Leaf	15	5	19	31	6	3	7	15	1357	162	35	10
Greening Disease (HLB)	17	10	14	34	5	5	10	19	73	3097	56	9
Healthy Leaves	26	8	16	16	7	9	6	14	19	65	2365	13
Melanose	26	5	16	18	9	6	8	9	34	42	47	675
Sooty Mould	17	9	37	27	7	5	10	16	19	42	38	15
Spider Mites	18	11	16	25	6	6	9	12	32	69	32	15
Total	1515	642	1541	2245	533	478	698	1143	1698	3850	2901	834

Journal of Information Systems Engineering and Management
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Research Article

Spider Mites	Sooty Mould
10	12
15	14
9	21
9	17
13	13
10	8
10	9
5	15
16	9
8	10
8	17
13	18
15	727
536	18
677	908

Class	Correct Classification	Incorrect Classification
Anthracnose	1224	291
Bacterial Blight	479	163
Black Spot	1220	321
Citrus Canker	1797	454
Citrus Leaf Miner	423	110
Curl Leaf	376	102
Curl Virus	547	151
Deficiency Leaf	930	213
Dry Leaf	1357	341
Greening Disease (HLB)	3097	753
Healthy Leaves	2365	536
Melanose	675	159
Sooty Mould	727	181
Spider Mites	536	141

Model Performance Comparison

Model/Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Size (MB)	Inference (ms)
ResNet-50	82.20%	85.06%	82.18%	82.50%	~97.5	15.2
EfficientNetB0	**85.64%**	**88.00%**	**85.63%**	**85.99%**	~29.5	11.8
InceptionV3	23.55%	34.81%	23.45%	17.60%	~92	20.5
Xception	28.51%	38.41%	27.91%	22.09%	~91	19.7

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MobileNetV2	58.57%	63.39%	58.51%	58.32%	~14	6.1
Enhanced MobileNetV2	79.42%	81.37%	80.26%	79.65%	**~7.8**	**5.8**

V. Discussion

The experimental results revealed that EfficientNetB0 consistently outperformed the other CNN architectures across multiple evaluation metrics, including accuracy (85.64%), precision (88.00%), recall (85.63%), and F1-score (85.99%). It also had the inference time (11.8ms) and a compact parameter size (29.5M), making it exceptionally well-suited for deployment on mobile or edge devices where computational resources are limited. Although ResNet-50 showed competitive performance with high accuracy (82.20%) and robust precision and recall scores, its larger parameter size (97.5M) and higher inference time (15.2ms) make it less practical for lightweight deployment scenarios. Xception and InceptionV3didn't cross the 50% mark, while InceptionV3 trailed worse in all metrics.

Enhanced MobileNetV2, trailed behind ResNet-50 and EfficientNetB0 but is a great specifically tuned model, due to its size, inference about ~5% of tradeoff in accuracy.

EfficientNetB0 was able to focus on lesion-affected regions with greater clarity and consistency, highlighting its superior feature localization capabilities. This explains its better generalization and classification accuracy. Overall, the findings suggest that EfficientNetB0 achieves the best trade-off between accuracy, speed, and model size, and Enhanced MobileNetV2.

- The model trades off ~30% performance versus EfficientNetB0, but reduces model size and inference time by over 2x, and Size difference of 3.3x ideal for mobile and edge devices.
- Faster inference (~2× speedup) and lower memory requirements make it feasible for Android deployment using TensorFlow Lite.

Model	Accuracy (%)	F1-Score (%)	Remarks
EfficientNetB0	85.64	85.99	Best overall, mobile-friendly
ResNet-50	82.2	82.5	High generalization, interpretable
Enhanced MobileNetV2	~79.42	~79.65	Lightweight, ideal for IoT Devices
MobileNetV2	58.57	58.32	Fast but less precise
InceptionV3	23.55	17.6	Poor generalization
Xception	28.51	22.09	Ineffective despite deeper architecture

VI. Conclusion

The Enhanced MobileNetV2 due to its very small footprint, and an extremly light architecture, it can be deployed on Edge devices such as Arduino, RaspberryPi, etc where every bit counts and with lower computational overhead. While EfficientNetB0 is suitable for lemon leaf disease classification in mobile or slightly powerful environments. It achieves top-tier accuracy while requiring significantly fewer computational resources.

In the future, combining CNNs with other AI technologies—such as Reinforcement Learning for adaptive responses, or Generative Adversarial Networks (GANs) for synthetic data augmentation—can further enhance diagnostic accuracy. Additionally, the development of user-friendly applications powered by these models can bridge the technological gap for farmers, encouraging wider adoption of precision agriculture practices across India

VII. Future work

Looking ahead, the deployment of the trained EfficientNetB0 model using TensorFlow Lite presents a practical path for bringing intelligent disease detection to Android devices. This enables real-time, offline classification of lemon leaf diseases, making the technology accessible to farmers even in remote or low-connectivity areas. To enhance modularity and user control, the system can be extended to support on-device model switching, where users download only the models relevant to their crops (e.g., lemon, orange, mango), thus minimizing app size and optimizing device performance. Additionally, integrating geolocation services and user feedback mechanisms will allow for real-time crop monitoring, enabling spatial disease tracking, timely alerts, and model improvement through crowdsourced validation. Finally, future development may incorporate object detection architectures such as YOLOv5 to perform fine-grained lesion segmentation, allowing the system to not only classify diseases but also visually locate affected areas on the leaf, thereby improving diagnostic precision and assisting in targeted treatment strategies.

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