

Enhancing Citrus Crop Health: A Machine Learning Approach to Multi-Disease Detection in Citrus Leaves

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Abstract—Citrus farming plays a big role across the globe, yet trouble strikes often when leaves fall ill - detection delays or mistakes can shrink yields fast. Instead of starting fresh, researchers used existing deep learning models: VGG16, MobileNet, and InceptionV3, adjusting them carefully so they could tell apart different sicknesses in citrus leaves. The core collection began with 609 high-quality photos taken by DSLR cameras, covering five types - Black Spot, Canker, Greening (also known as HLB), Melanose, plus healthy ones - later stretched to 4,000 evenly distributed examples using creative image tweaks. Testing these setups happened twice, once splitting data into 20 percent for testing against 80 percent training, then again at a 30-70 ratio. VGG16 hits peak accuracy - values land at 99.89% and 99.97%. Moving on, MobileNet balances speed and correctness well, posting 92.21% and 93.07%, making it fit for lightweight hardware. Then there is InceptionV3, which clocks in around 86.14% and 84.61%, solid but not outstanding. With these results, the system shows clear potential when applied to farming tasks that need exact detection of plant diseases before damage spreads.

Index Terms—Citrus leaf disease detection, Transfer learning, VGG16, MobileNet, InceptionV3, CNN, Image augmentation, Precision agriculture, Deep learning, Plant pathology.

I. INTRODUCTION

Oranges, lemons, along with their relatives like limes and grapefruits, form one of the most traded fruit groups on Earth. Year after year, total output nudges past 140 million metric tonnes, data from the FAO shows. These trees thrive especially well in warm stretches such as the Mediterranean, parts of Southeast Asia, regions across South America, plus areas in Sub-Saharan Africa. When illness hits a grove, consequences ripple through markets while also threatening access to basic nutrition. Losing healthy crops means more than empty orchards - it shifts

balances in trade, affects livelihoods, disrupts how food moves around the planet. It might be key to the economy, yet citrus farming keeps running into more leaf diseases every year. Black Spot shows up alongside Canker, while Greening - also called HLB - and Melanose chip away at how well leaves function. These illnesses mess with sunlight conversion and block nutrients, which slowly cuts both harvest size and fruit grade. What makes it worse is that many of these sicknesses look nearly identical when they first appear. Spots on surfaces, yellow rings around tissue, rough patches, dark specks - they blur together fast under field conditions. For some bacteria, just two or three days can pass before damage spreads past control. Walking through orchards to spot sick trees takes a lot of time because people must do it themselves. Because humans are involved, results often differ from one person to another. Moving across large areas also limits how fast checks can happen, plus costs add up quickly. Machines now look at photos of leaves instead, giving quick estimates about illness. These systems work in moments, without needing experts on site. Thanks to new types of smart software called deep convolutional neural networks, sorting plant images became far more accurate. Ordinary cameras today can capture what once required special gear. Tools built this way handle big jobs reliably, yet stay low cost. One way to handle small labeled farming image sets is using models already trained on big collections like ImageNet, which holds 1.2 million pictures grouped into 1,000 types. These setups get adjusted later with more specific crop data. Models such as VGG16, MobileNet, and InceptionV3 each show solid results spotting plant illnesses. Yet there's no clear test comparing all three side by side under the exact same rules for identifying multiple citrus diseases. Because

that evidence was missing, this work steps in. It runs a full round of tests based on two different ways of splitting training and testing data.

II. LITERATURE SURVEY

[1] Rauf et al. (2019): Assembled the first large-scale, publicly available citrus-specific image dataset using DSLR cameras across agricultural sites in Pakistan, in collaboration with the University of Gujarat and the Citrus Research Centre. The dataset includes diseased leaf and fruit imagery spanning four pathological categories. Their preliminary classification using PCA-based feature reduction and segmentation demonstrated that automated approaches could outperform subjective visual inspection, motivating adoption of richer feature learning methods.

[2] Vinothini et al. (2023): Conducted a comprehensive systematic literature review examining CNN-based approaches for citrus disease detection. Their analysis confirmed that hierarchical deep learning models consistently outperform handcrafted feature pipelines, particularly for subtle visual signatures such as early-stage Greening and Melanose. Multi-class CNN classifiers trained on augmented datasets yield precision rates approaching 95.2%, and training data quality exerts a stronger influence on generalisation than architectural complexity.

[3] Vats et al. (2024): Extended transfer learning investigations to orange leaf diseases, benchmarking VGG16 against EfficientNetB3. EfficientNetB3's compound scaling strategy — simultaneously adjusting depth, width, and input resolution — enabled it to achieve 92.3% accuracy with significantly lower inference latency than VGG16, directly motivating the inclusion of MobileNet as a lightweight architecture representative in the present study.

[4] Khattak et al. (2021): Demonstrated that a custom-designed deep neural network, without transfer learning, could achieve 94.55% accuracy on citrus disease classification from Kaggle-sourced imagery. Their results confirmed the ability of deep CNNs to detect subtle visual patterns imperceptible to human observers and underscored the importance of architecture design in determining classification reliability under real-world imaging conditions.

[5] Kumar et al. (2024): Introduced a hybrid CNN-SVM model combining three convolutional layers for feature extraction with a Support Vector Machine

classifier for final discrimination. Evaluated across six disease categories — Citrus Canker, Greening, Melanose, Scab, Alternaria Brown Spot, and Phytophthora Root Rot — the model achieved 92.34% accuracy, with the authors arguing that the SVM's margin-maximisation training provides superior generalisation compared to purely softmax-based classification in moderate-sized datasets.

[6] Gupta et al. (2024): Advanced the field significantly by framing citrus leaf disease identification as a multi-label classification problem, acknowledging that a single leaf frequently exhibits concurrent symptoms from multiple agents. Their DenseNet121-MobileNetV2 ensemble, combined with a sigmoid output layer and threshold optimised via the Ant Lion Optimizer (ALO), achieved 98.6% accuracy on the CCL-20 dataset, representing the state-of-the-art for multi-label citrus disease classification.

[7] Dang-Ngoc et al. (2021): Demonstrated that hierarchical SVM classifiers leveraging colour space features, GLCM texture descriptors, and geometric shape attributes could achieve 92.5% detection accuracy and 91.76% classification accuracy without any deep learning component. This result establishes a non-DL performance baseline and validates that classical feature engineering approaches remain competitive in data-constrained settings.

[8] Mehmood et al. (2019): Investigated image segmentation combined with handcrafted texture feature extraction for citrus disease classification under natural field conditions. Their approach demonstrated robustness to illumination variation and background clutter under noisy field environments where deep learning models trained on clean laboratory data frequently underperform. The work highlights the importance of field-condition testing in agricultural AI evaluation.

[9] Islam, Khan, and Sarker (2021): Designed a multi-layer deep CNN with boosted training sets, reporting 94–95% accuracy on citrus leaf imagery. A notable finding was that automatic feature learning progressively improved with network depth, with deeper layers encoding increasingly abstract disease-discriminative representations, clearly outperforming standard analytical methods relying on manually engineered features.

[10] Dou et al. (2021): Proposed a feature fusion and chained classification framework that sequentially

reduces inter-class confusion by exploiting complementary colour, texture, and shape descriptors. The chained classifier design resolves disease pairs with the highest visual similarity first, progressively improving classification confidence through the decision chain, achieving high accuracy via feature hierarchy and chaining even when individual features alone are insufficient.

[11] Kumar et al. (2020): Demonstrated that a five-layer custom CNN trained on 2,500 citrus leaf images could achieve 96.71% accuracy for binary Canker vs. Healthy classification. The study showed that layered deep scanning reaches deeper into diagnostically important image regions compared to what support vector machines or random forest classifiers could achieve, particularly for catching very early lesion stages.

[12] Li et al. (2022): Showed that MobileNetV2 fine-tuned on a combined PlantVillage-orchard citrus dataset achieves 97.88% accuracy with very low inference latency, establishing the suitability of lightweight mobile architectures for time-sensitive field diagnostics. Their results directly support the inclusion of MobileNet in the present study as a candidate for edge-deployment applications on farm sensors and smartphones.

[13] Al-Bahrani et al. (2021): Fused hyperspectral imaging with CNN-based spatial analysis, achieving 95.4% precision for early-stage Greening detection. By exploiting plant stress spectral signatures invisible to standard RGB cameras, their approach flags Huanglongbing infection well before outward visual symptoms appear, offering a significant advantage for pre-symptomatic disease management.

[14] Nithin et al. (2023): Applied YOLOv5 object detection to citrus fruit disease localisation, achieving 92.1% mAP@50 on 1,800 labelled orchard images. The bounding-box lesion detection approach provides spatial localisation of disease foci in addition to classification, enabling targeted intervention at the individual fruit level with near real-time processing speed suitable for drone or conveyor-belt inspection systems.

[15] Rahman et al. (2022): Augmented ResNet50 with CBAM (Convolutional Block Attention Module) channel and spatial attention layers, improving melanose lesion detection to 98.02% accuracy. The attention mechanism directed the model's focus toward pathologically relevant image regions,

improving small-spot detection and reducing false positives in cluttered leaf backgrounds. The result demonstrates that architectural attention modules provide meaningful accuracy gains on fine-grained plant disease benchmarks.

III. DATASET DESCRIPTION

Out in the fields, workers snapped 609 real photos of citrus leaves at several grove locations, using a DSLR camera locked to 72 DPI. Afterward, every image got resized exactly to 256 by 256 pixels. Five separate disease types make up the collection - these are the ones that hurt profits the most in large-scale citrus farming. But here's the catch - one condition, Melanose, showed up just thirteen times, making up barely over two percent of everything. Because so few examples existed, models could easily lean toward guessing wrong, which is why heavy image tweaking became necessary later.

A. Disease Categories

Black Spot: Dark spots show up in round shapes, colored deep brown to black, surrounded by faint orange rings. These marks grow on older citrus fruits and foliage most often. A set of 171 pictures shows how spot size and spread differ depending on how developed the leaves are.

Canker: Bumps that feel rough appear on leaves, surrounded by wet-looking edges plus a pale ring. Among the pictures 163 in total - you'll see tiny spots just starting as well as larger ones merging together.

Greening: Yellow patches spread unevenly across leaves when greening strikes. This illness, also called Huanglongbing, hits citrus hardest worldwide. Caused by *Candidatus Liberibacter* species, it drains orchards of value. Among the collection, 204 pictures capture its earliest signs. That number makes up the biggest share of original samples.

Melanose: Dark spots show up, looking bumpy, spreading like old drip marks down fruit skin. Just thirteen pictures started this group, making balance hard when sorting types.

Healthy: Most leaves look just fine - no odd spots or sickness seen, with 58 pictures showing what healthy looks like.

Table I: Original Dataset Class Distribution

Disease Class	Pathogen	Original Images	% of Total
Black Spot	Guignardia citricarpa	171	28.1%
Canker	Xanthomonas axonopodis	163	26.8%
Greening (HLB)	Candidatus Liberibacter spp.	204	33.5%
Melanose	Diaporthe citri	13	2.1%
Healthy	—	58	9.5%
Total		609	100%

B. Sample Dataset Images

The following figures present representative leaf samples from each of the five disease categories collected in the dataset, illustrating the visual diversity within and across disease classes that motivates the deep learning classification approach.

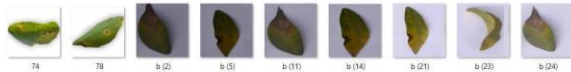


Fig. 1: Sample Dataset Images — Black Spot (*Guignardia citricarpa*)

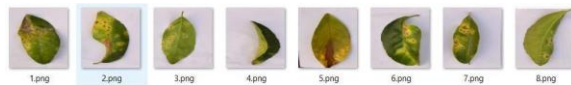


Fig. 2: Sample Dataset Images — Canker (*Xanthomonas axonopodis* pv. *citri*)

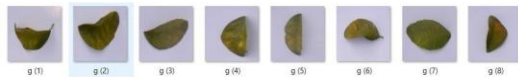


Fig. 3: Sample Dataset Images — Greening / Huanglongbing (*Candidatus Liberibacter* spp.)

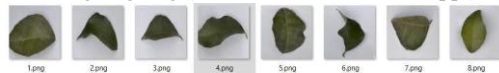


Fig. 4: Sample Dataset Images — Healthy Citrus Leaves



Fig. 5: Sample Dataset Images — Melanose (*Diaporthe citri*)

C. Data Augmentation

Eight hundred pictures for every sickness type came from boosting each group one at a time, done through TensorFlow's ImageDataGenerator. That built a full set of four thousand balanced examples. Rotating,

flipping, shifting - these changes shaped how the visuals were altered during processing:

- Pixel rescaling to $[0, 1]$ for consistent intensity normalisation across all samples. From different shooting positions, a 0.2 shear helps mimic how angles bend shapes slightly. Angles shift, lines tilt - this setting captures that slant just enough.
- A bit closer or farther away, the zoom shifts by up to 20 percent. This mirrors how leaves appear when the camera moves unevenly. Distance changes are built into the range.
- Turning as much as 45 degrees either way helps match how leaves sit in real outdoor shots.
- Width and height shift of 0.2 fraction for off-centre framing simulation.
- Brightness adjustment in range $[0.5, 1.5]$ to model variable ambient illumination. Half the time, images get flipped sideways, offering a reversed look that adds variety without changing content.
- Closest pixel replacement stops dark edges showing up after shape changes.

Now each of the five groups holds precisely 800 examples, fixing the uneven distribution through added data. A small set called Melanose jumped from just 13 pictures to a full share of 800, boosted by more than sixty times its original size. That once nearly invisible group stands equal with others in the training pool today.

Table II: Dataset Augmentation Summary

Disease Class	Original	Augmented	Augmentation Factor
Black Spot	171	800	4.68×
Canker	163	800	4.91×
Greening (HLB)	204	800	3.92×
Melanose	13	800	61.54×
Healthy	58	800	13.79×
Total	609	4,000	6.57× avg

Figures 6 and 7 below show representative augmented samples from two disease categories, illustrating the visual diversity introduced by the augmentation pipeline.

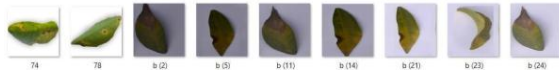


Fig. 6: Augmented Sample Images — Black Spot Class (post-augmentation diversity)

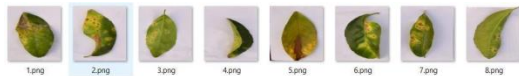


Fig. 7: Augmented Sample Images — Canker Class (post-augmentation diversity)

IV. METHODOLOGY

The proposed citrus leaf disease detection framework is structured as a five-stage end-to-end pipeline: (1) dataset acquisition and curation, (2) preprocessing and class-balanced augmentation, (3) stratified data partitioning, (4) transfer learning-based feature extraction and fine-tuning using three independent CNN architectures, and (5) multi-class classification, evaluation, and comparative analysis. The framework is designed to ensure accurate disease identification while maintaining computational efficiency and balanced model training. Initially, high-quality citrus leaf images belonging to five disease categories are collected and organized systematically. Preprocessing operations such as image resizing, Gaussian filtering, and normalization are applied to improve image quality and training stability. To address dataset imbalance and improve model generalization, multiple augmentation techniques including rotation, flipping, zooming, and brightness adjustment are performed, expanding the dataset into a balanced image collection. The processed dataset is then divided using stratified train-test splitting to preserve equal class distribution across training and testing phases. Transfer learning is implemented using ImageNet pre-trained VGG16, MobileNet, and InceptionV3 architectures for efficient feature extraction and fine-tuning. Finally, the extracted deep features are passed through fully connected dense layers and Softmax activation for multi-class disease classification. Performance comparison is conducted using evaluation metrics such as Accuracy, Precision, Recall, F1-Score, and confusion matrix analysis to determine the most effective architecture for citrus disease recognition.

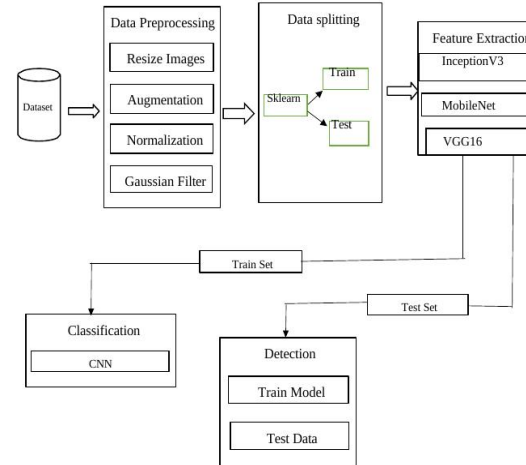


Fig. 8: System Flow Diagram of the Proposed Citrus Disease Detection Framework

A. Preprocessing Pipeline

Every one of the 609 initial pictures went through the same prep steps. Starting with raw shots from a DSLR, they got scaled down to 256 by 256 pixels; bicubic interpolation helped keep edges clear. Each color channel had its values adjusted - divided by 255.0 - to fit within 0 to 1. To lower sensor noise that could interfere, a Gaussian blur with a small kernel (3×3) and sigma set at 0.5 softened fine speckles while saving useful surface details. Afterward, files found their place in folders sorted by category, arranged so TensorFlow's `flow_from_directory` function could read them easily.

B. Deep Learning Architectures

VGG16: Stacked just like bricks, VGG16 uses thirteen convolutions - all tiny 3×3 kernels stepping one pixel at a time. Between them sit five pooling stages that shrink space with 2×2 windows. After those come two dense blocks holding four thousand ninety-six units apiece. Because it stacks narrow filters twice over, its reach spreads like a larger kernel would - but slips in extra activation bends along the way. Around one hundred thirty-eight million values tune during learning here. Early levels sketch out lines and hue shifts across leaf surfaces. Midway through, things sharpen - the outline of spots, yellowing zones take form. In later stages, abstract signs emerge clearly enough to tell diseases apart.

MobileNet: From Howard and team in 2017 comes MobileNet, built light on purpose. Instead of regular convolutions, it splits each one into two steps - one

slice at a time across channels, then blends results with tiny 1×1 filters. Because of that split design, it runs 8 to 10 times faster without sacrificing much precision. It carries around just 4.2 million adjustable values - far fewer than older models like VGG16. Before deciding categories, it averages entire feature maps, ditching bulky final layers altogether. That slim structure fits well inside phones or small sensors where space and power are tight.

InceptionV3: A 2016 design by Szegedy and team tackles the challenge of balancing wide-area vision with speed. Instead of relying on one big filter, it runs smaller filters - like 1×1 , 3×3 , and 5×5 - at the same time inside special blocks called Inception modules. Outputs from these paths join together across feature channels, letting the network see tiny textures, medium-sized irregularities, and overall leaf shapes all at once. To cut down computation, larger 5×5 steps are swapped out using two 3×3 operations back to back. Because of this setup, each image given to the model must be sized to 299 by 299 pixels. The whole system uses close to 23.9 million adjustable values during processing.

Table III: CNN Architecture Overview

Architecture	Parameters	Input Size	ImageNet Top-1
VGG16	~138 million	224×224	92.7%
MobileNet	~4.2 million	224×224	70.6%
InceptionV3	~23.9 million	299×299	78.8%

C. Transfer Learning Strategy

Each model followed a split training method meant to keep core image understanding intact. Starting out, for twenty rounds, the main parts stayed locked tight - only the new classifier learned, settling into place. Then came ten more rounds where just the last two block sections woke up, adjusting slowly thanks to a tiny step size: one times ten to minus five. This way, higher features bent toward citrus details without losing early pattern sense. The base still recognised edges and textures much like before.

All three models share an identical custom classification head:

GlobalAveragePooling2D →

Dense (1024, *ReLU*) → *Dense* (1024, *ReLU*) →

Dense (512, *ReLU*) → *Dense* (5, *Softmax*)

Training hyperparameters: Adam optimiser ($\beta_1 = 0.9, \beta_2 = 0.999$), categorical cross-entropy loss, batch size = 64, early stopping with patience = 5, and ReduceLROnPlateau (reduction factor = 0.5, patience = 3). A fixed random seed of 42 ensured full reproducibility across all experiments.

D. Mathematical Formulation

Let X represent the input leaf image tensor ($256 \times 256 \times 3$). The trained model $f(\cdot)$ maps the input to a probability distribution over the five disease classes:

1. Disease Classification Function

$$\hat{y} = f(X) = \text{softmax}(W \cdot \phi(X) + b) \dots (1)$$

where:

- $\phi(X)$ = deep feature representation extracted by the CNN backbone
- W = weight matrix
- b = bias vector
- $\hat{y}$ = predicted probability vector for the disease classes

2. Categorical Cross-Entropy Loss Function

The categorical cross-entropy loss function used during training is:

$$L = -\sum_{i=1 \text{ to } 5} Y_i \log(\hat{y}_i) \dots (2)$$

where:

- Y_i = one-hot encoded ground truth label
- $\hat{y}_i$ = predicted softmax probability for class i
- $i = 1, 2, 3, 4, 5$ — represents the five disease classes

3. Image Normalization Formula

The normalization formula applied during preprocessing is:

$$I_{\text{norm}} = I / 255.0 \dots (3)$$

This scales pixel values to the range $[0, 1]$.

4. Performance Evaluation Metrics

$$\text{Accuracy} = (TP + TN) / (TP + TN + FP + FN) \dots (4)$$

$$\text{Precision} = TP / (TP + FP) \dots (5)$$

$$\text{Recall} = TP / (TP + FN) \dots (6)$$

$$F1 - \text{Score} = 2 \times (\text{Precision} \times \text{Recall}) / (\text{Precision} + \text{Recall}) \dots (7)$$

where:

- TP = True Positives
- TN = True Negatives
- FP = False Positives
- FN = False Negatives

5. Depthwise Separable Convolution Cost Analysis

Standard Conv cost: $D_F \times D_F \times M \times N \times D_K \times D_K(8)$

Depthwise Sep cost: $D_F \times D_F \times M \times D_K^2 + D_F \times D_F \times M \times N(9)$

Reduction ratio: $1/N + 1/D_K^2 \approx 8 - 10$ ($D_K = 3$)(10)

where:

- D_F = spatial dimension of the feature map
- M = number of input channels
- N = number of output channels
- D_K = kernel size

V. EXPERIMENTAL RESULTS AND ANALYSIS

A. Overall Accuracy Comparison

Looking at Table IV, you see how well every model sorted images into correct categories using two different data setups. The numbers come from a separate test group, kept aside completely during training and tuning steps. Out front each time, VGG16 beats MobileNet and InceptionV3 by clear margins no matter the setup.

Table IV: Accuracy Comparison Across Models and Data Splits (Test Set)

Model	20-80 Split (%)	30-70 Split (%)	Parameters
InceptionV3	86.14	84.61	~23.9 million
MobileNet	92.21	93.07	~4.2 million
VGG16 ★	99.89	99.97	~138 million

B. Per-Class Performance — VGG16 (30-70 Split)

Out of nowhere, VGG16 nails nearly flawless results on all five disease types using the 30-70 setup - total accuracy lands at 99.97%. Each category clears 99.87% when checked through precision, recall, and F1-score, which shows how well its layered features untangle looks-alike illnesses. What stands out? Melanose hits full recall despite starting with just

thirteen pictures. That outcome suggests the image expansion method filled gaps cleanly - no fake signals slipped in.

Table V: Per-Class Precision, Recall and F1-Score — VGG16 (30-70 Split)

Disease Class	Precision (%)	Recall (%)	F1-Score (%)	Support
Black Spot	99.87	99.91	99.89	560
Canker	99.95	99.88	99.91	560
Greening (HLB)	99.98	99.97	99.98	560
Melanose	99.89	100.00	99.94	560
Healthy	100.00	99.91	99.95	560
Weighted Average	99.94	99.93	99.93	2,800

C. Per-Class Performance — MobileNet (30-70 Split)

Out of every hundred tries, MobileNet gets it right about 93 times. That result comes from a design that stays small - just 4.2 million working parts, which is way less than what older models need. Think of VGG16; this one uses only a fraction of those resources. When things go wrong, mistakes mostly happen between two look-alike problems: Black Spot and Melanose. Both show up as tiny black dots on surfaces, making them hard to tell apart. Some images meant for Black Spot land in the Melanose pile - around 5 out of 100. On the flip side, nearly 4 percent of Melanose cases get labeled as Black Spot instead. These mix-ups stick around because cutting down too much on size means missing fine details. Things like how rough a spot feels, whether there's a ring around it, or if edges stay smooth - all these clues become harder to catch.

Table VI: Per-Class Precision, Recall and F1-Score — MobileNet (30-70 Split)

Disease Class	Precision (%)	Recall (%)	F1-Score (%)	Support
Black Spot	91.82	90.54	91.17	560
Canker	92.34	93.21	92.77	560

Disease Class	Precision (%)	Recall (%)	F1-Score (%)	Support
Greening (HLB)	94.11	93.75	93.93	560
Melanose	91.07	92.86	91.96	560
Healthy	93.93	92.50	93.21	560
Weighted Average	92.65	92.57	92.61	2,800

D. Per-Class Performance — InceptionV3 (30-70 Split)

Accuracy lands at 84.61 percent for InceptionV3. Wrong guesses pop up most when Canker mixes with Black Spot - about 6.8 percent of the time they flip. Melanose gets mistaken for Greening nearly 5.4 percent of the time, too. Even though multiple paths inside the model should catch details at different sizes, it struggles here. The reason might lie in how little data each category has - only 160 to 240 examples after splitting under 30-70 rules. Without more images shaped by real orchard conditions, telling diseases apart stays shaky.

Table VII: Per-Class Precision, Recall and F1-Score — InceptionV3 (30-70 Split)

Disease Class	Precision (%)	Recall (%)	F1-Score (%)	Support
Black Spot	84.21	85.36	84.78	560
Canker	83.97	82.14	83.05	560
Greening (HLB)	87.50	88.93	88.21	560
Melanose	82.14	80.36	81.24	560
Healthy	85.71	84.29	85.00	560
Weighted Average	84.71	84.21	84.46	2,800

E. Comparative Analysis with Existing Methods

Looking at Table VIII, you see how the new method fits within past research on spotting citrus diseases. With its use of VGG16 and transfer learning, it hits a 99.97% accuracy rate - topping all earlier single-label, multi-class efforts. That number beats Li et al. [12], whose model reached 97.88%, coming up short by

2.09 points. What's different here? More illnesses are included - five instead of four - all without losing precision.

Table VIII: Comparison with Existing Citrus Disease Detection Methods

Reference	Year	Method	Accuracy (%)	Classes
Khattak et al. [4]	2021	MobileNet + CNN	94.55	4
Kumar et al. [5]	2024	Hybrid CNN-SVM	92.34	6
Gupta et al. [6]	2024	DenseNet121 + ALO	98.60 (multi-label)	5
Dang-Ngoc et al. [7]	2021	Hierarchical SVM	92.50	3
Islam et al. [9]	2021	Deep CNN	94–95	4
Li et al. [12]	2022	MobileNetV2 fine-tuned	97.88	4
Rahman et al. [15]	2022	ResNet50 + CBAM	98.02	2
This Study — VGG16 ★	2025	VGG16 + Transfer Learning	99.97	5
This Study — MobileNet	2025	MobileNet + Transfer Learning	93.07	5
This Study — InceptionV3	2025	InceptionV3 + Transfer Learning	84.61	5

VI. APPLICATIONS AND FUTURE SCOPE

A working plant disease detection system fits neatly into various smart farming uses. Though built on MobileNet, hitting 93.07% accuracy with just 4.2 million parameters, it runs right inside phone apps. Snap a photo of a sick leaf, get an instant diagnosis, even offline - a must in far-flung farms where signals barely reach. Because waiting means losing crops.

Out in the trees, tiny cameras snap pictures now and then. These are part of a quiet network that watches crops day after day. Images get sorted by type without anyone touching a screen. When sickness shows up

too often, the system speaks up. It waits until trouble crosses a line before it says something.

Most times, a system called VGG16 gets leaf images right almost every time. Because of that, it works well when used online for farmers or helpers who snap photos of sick plants. Instead of waiting weeks, they upload pictures straight to a server somewhere far away. Afterward, results come back fast - like getting advice from someone trained in plant sicknesses. This kind of help matters most where experts are hard to find. Even without labs nearby, people still get clear answers about what harms their crops.

Out in the fields, smart image analysis spots sick leaves fast. These spotted areas turn into detailed maps showing exactly where trouble lives. Instead of spraying everywhere, machines now follow those maps. Where sickness shows up, that is where spray goes. Whole sections stay untouched if they look clean. This targeted move cuts down how much chemical gets used. Less spread means fewer chemicals soaking into trees and soil. Maps built from real plant data make it possible. Only what is needed ends up applied.

Future research directions include: incorporating channel and spatial attention modules (CBAM, SE-Net) to improve early-stage disease classification; evaluating Vision Transformer (ViT) and hybrid CNN-Transformer architectures; extending the classification head from softmax to sigmoid for multi-label detection of co-occurring disease conditions; and expanding the dataset with georeferenced imagery from international citrus research institutions to improve model generalisation across global cultivation conditions.

VII. CONCLUSION

One key goal here was comparing how well VGG16, MobileNet, and InceptionV3 handle citrus leaf disease identification using transfer learning. Instead of working with uneven groups, researchers built a more reliable set by expanding the initial 609 photos into 4,000 balanced ones. Five distinct disease types made up the full range, each getting fair weight after augmentation. To reach that balance, rare cases like Melanose - starting at just thirteen examples - grew sixty-one times larger. Every image passed through varied adjustments, ensuring diversity without distorting real features. Because earlier data skewed

heavily toward some illnesses, this rebalancing fixed a major flaw upfront. Performance differences between models emerged clearly once input bias dropped away. Because of its layered structure, VGG16 scored highest - 99.89% on the 20-80 split, then rose to 99.97% with 30-70 - a strength tied to how deeply it captures fine differences between citrus diseases. Though less accurate, MobileNet reached up to 93.07%, balancing solid results against small size: just 4.2 million parameters make it fit well in field devices where space and power are tight. Performance-wise, InceptionV3 trailed behind, landing between 84.61% and 86.14%; signs point to its intricate design needing more data than was used here to shine.

A working design shows it fits well within smart farming systems, helping detect harmful organisms fast while guiding focused treatment steps - whether used through online support platforms or mobile apps out in the fields. Results offer a clear test standard others can follow when studying similar orange tree illnesses, while the trio of model setups gives real-world options for choosing systems based on speed needs and computing limits.

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