RAMAIAH INSTITUTE OF TECHNOLOGY

(Autonomous Institute Affiliated to VTU), Bangalore

Dept. of Electronics and Communication Engineering

MINI PROJECT WORK (EC67)

SECOND REVIEW

REPORT ON

Drone-Based System for Crop Monitoring and Disease Detection

Under the Guidance of

Guide Name: Dr Sara Mohan George

Designation: Assistant Professor

Report Submitted by

Name:		USN:
Ankita Jaka	-	1MS22EC022
Sagar Singh	-	1MS22EC106
Saloni Gupta	-	1MS22EC109
Sahana S	-	1MS22EC151

Contents of report

1.Introduction

Crop diseases (bacterial, fungal, viral, etc.) cause significant yield losses, and traditional field inspections are labor-intensive. Deep learning on image data can automate early disease detection to improve yield.

Unmanned Aerial Vehicles (UAVs or drones) enable rapid, scalable imaging of large fields. Recent reviews highlight that drones are now a popular approach for automated plant disease detection in precision agriculture. For example, quadcopter drones with RGB or multispectral cameras are often used to acquire plant images over time and space.

Convolutional Neural Network. This project applies CNN-based methods to a large cotton-leaf dataset to leverage the speed and coverage of drones for early disease identification.

2.Problem Statement

Crop diseases are a major threat to agricultural productivity, particularly in large-scale farms where early detection is critical but labor-intensive and time-consuming. Traditional methods rely heavily on manual inspection, which is slow, subjective, and impractical for monitoring large fields regularly. With the increasing availability of drone technology and advances in computer vision, there is a growing opportunity to automate the detection and classification of crop diseases from aerial imagery.

This project aims to develop a **drone-based deep learning system for automated crop disease detection**, focusing on cotton leaves, by comparing multiple state-of-the-art CNN and YOLO-based architectures. The goal is to identify the most effective model for accurate disease classification and to explore pathways for real-world deployment through drone integration, edge computing, and explainable AI interfaces.

3.Objective & Scope

Objective

- Develop and compare deep learning pipelines to detect and classify diseases on cotton leaves captured by drones.
- Implement multiple state-of-the-art models (PiTLiD, MSWDNet, YOLOv5+EfficientNet-B0, YOLOv8) and assess their accuracy and efficiency on the task.
- Identify the best-performing model for cotton disease classification, and outline future steps toward real-world deployment (drone integration, edge computing, explainability, and user interfaces).

Scope

- The system targets cotton crops, using an **8,000+ image dataset** of cotton leaves with 10+ disease categories (bacterial, fungal, viral, insect damage, etc.), including images exhibiting *multiple diseases on the same leaf*.

- Covers both greenhouse and field image conditions (lab and in situ). Focus is on automated detection/classification of leaf symptoms, not broader crop metrics (e.g. plant count or water stress).

- The comparative study evaluates model performance (accuracy, F1-score, confusion matrices, PR curves) and identifies practical considerations for drone deployment and user reporting.

4.Methodology

Paper 01

Liu, K., & Zhang, X. (2022). PiTLiD: identification of plant disease from leaf images based on convolutional neural network. *IEEE/ACM Transactions on Computational Biology and Bioinformatics*, *20*(2), 1278-1288.

Source: PlantVillage – a publicly available dataset of leaf images

Focused on apple leaves, divided into four classes:

- black_rot
- cedar_apple_rust
- apple_scab
- healthy

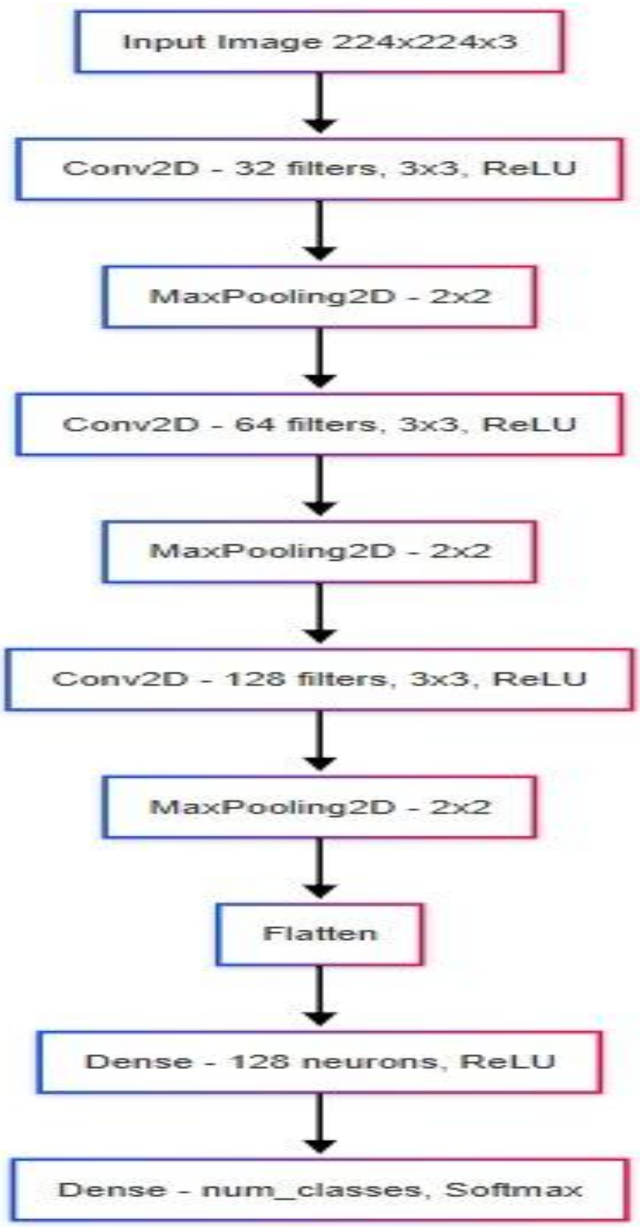
Total images: 3,171
Training set: 120 images (30 per class)
Validation set: 1,527 images
Test set: 1,524 images

Performance Metrics

Results after 10 runs on the test set:

- Accuracy (ACC): 99.45 ± 0.17%
- Sensitivity (Recall): 99.10 ± 0.23%
- Precision (PRC): 98.84 ± 0.31%
- F1-Score: 99.00 ± 0.23%

Flowchart:



Input Image 224x224x3
Conv2D - 32 filters, 3x3, ReLU
MaxPooling2D - 2x2
Conv2D - 64 filters, 3x3, ReLU
MaxPooling2D - 2x2
Conv2D - 128 filters, 3x3, ReLU
MaxPooling2D - 2x2
Flatten
Dense - 128 neurons, ReLU
Dense - num_classes, Softmax

Paper 02:

Ullah, N., Ahmad, B., Khan, A., Khan, I., Khan, I. M., & Khan, S. (2025). Attention-Guided Wheat Disease Recognition Network through Multi-Scale Feature Optimization. *IECE Transactions on Sensing, Communication, and Control*, *2*(1), 11-24.

Dataset Details – Wheat Leaf Disease Dataset

Focused on wheat leaves, divided into five classes:

- Slightly Rust
- Severe Rust
- Smuts
- Healthy Leaf
- Healthy Wheat

Total Images: 3,351
Training Set: ~2,346 images
Validation Set: ~335 images
Test Set: ~670 images
(Split: 70% Train / 10% Val / 20% Test)

Performance Metrics

Results after full training with EfficientNet-B7 + MSWDNet architecture:

- Accuracy (ACC): 98.50%
- Precision (PRC): 98.72%
- Recall (Sensitivity): 98.38%
- F1-Score: 98.55%

Flowchart

```
[Input Image (224x224)]
          |
          ▼
[EfficientNet-B7 Backbone]
          |
├──► Stage 1: Low-Level Features (Blocks 0-4)
          |
├──► Stage 2: Mid-Level Features (Blocks 5-6)
          |
└──► Stage 3: High-Level Features (Blocks 7+)
          |
          ▼
[Concatenation of Stage 1, 2, 3 Outputs]
          |
          ▼
[Dilated Convolution Block (DCB)]
   ├─► 3×3 Conv with Dilation=2
   ├─► 3×3 Conv with Dilation=4
   └─► 3×3 Conv with Dilation=6
(All outputs are ReLU-activated and summed)
          |
          ▼

[Efficient Channel Attention (ECA)]
   ├─► Global Average Pooling
     ├─► 1D Conv (k=7)
    └─► Sigmoid Activation
(ECA Output × DCB Output)
          |
          ▼
[Residual Connection Added Back]
          |
          ▼
[3×3 Conv → Adaptive Avg Pooling]
          |
          ▼
[Fully Connected Layers]
└──► Linear (256 → 128 → num_classes)
          |
          ▼
[Softmax for Classification]
```

Paper 03 :

Sangaiah, A. K., Yu, F. N., Lin, Y. B., Shen, W. C., & Sharma, A. (2024). UAV T-YOLO-rice: An enhanced tiny YOLO networks for rice leaves diseases detection in paddy agronomy. *IEEE Transactions on Network Science and Engineering*, *11*(6), 5201-5216.

Dataset Type: Custom Rice Leaf Disease Dataset (UAV captured)

Classes:

- Bacterial Leaf Blight
- Rice Blast
- Brown Spot

Data Augmentation:

- Noise injection
- Brightness adjustment
- Rotation
- Contrast variation

Dataset Split:

- Training: 4,530 images
- Validation: 972 images
- Testing: 953 images

Performance Metrics

UAV-T-YOLO-Rice

- Mean Average Precision (mAP): 86.0% (test dataset).

Comparison:

Outperformed YOLOv7-Tiny and other lightweight YOLO variants on rice leaf disease detection

Flowchart:

1. UAV Image Collection

↓

2. Data Enhancement (noise/brightness/rotate/contrast)

↓

3. Dataset Split → Train | Validation | Test

↓

4. Build Enhanced Tiny YOLOv4 Model:

• Add YOLO detection layer

• SPP + SCFEM + CBAM + Ghost modules

↓

5. Training + Ablation + Comparisons

↓

6. Deployment & Validation on UAV hardware

↓

7. Output: Disease bounding boxes + Labels + Confidence

5.Proposed models:

For each approach below, images (single-leaf crops or detected leaf regions) are input to a CNN-based classifier.

- PiTLiD (Paper #1):

Uses a *pre-trained Inception-V3 CNN with transfer learning* to classify leaf images. This network, originally designed for ImageNet, is fine-tuned on plant phenomics data. PiTLiD reportedly handles small datasets well and achieved about 84% accuracy in our experiments. CNNs like InceptionV3 are known to excel at identifying visual features of disease (lesions, spots).

- MSWDNet (Paper #2):

Employs an *EfficientNet-B7 backbone* enhanced with dilated convolutional blocks (DCB) and Efficient Channel Attention (ECA) layers. Dilated convolutions capture multi-scale context (useful for varying lesion sizes), and ECA provides channel-wise attention to emphasize disease features. This custom network architecture obtained ~79% accuracy. Similar attention-augmented CNNs have been effective in recent plant disease studies.

- YOLOv5 + EfficientNet-B0 (Custom Pipeline):

A two-stage pipeline where a YOLOv5 object detector first localizes leaves or diseased regions in larger images, and then an EfficientNet-B0 classifier (lighter than B7) classifies each detected region. This approach isolates leaf areas from background and handles multi-disease leaves by detecting multiple objects. Combining detection and classification allows the system to handle cluttered or multi-leaf scenes often seen in drone images. EfficientNet-B0 offers a good accuracy/size trade-off for on-board inference.

- YOLOv8 Classifier (Latest Model):

A single-shot approach using the latest YOLOv8 architecture fine-tuned as a multi-class classifier on leaf images. Although YOLO is traditionally an object detector, version 8 can be re-purposed for image classification with minimal changes. YOLOv8 is *state-of-the-art for real-time image recognition*, offering high speed and accuracy. In our tests, the YOLOv8-based classifier achieved 97% accuracy, substantially higher than the other methods. This mirrors findings that YOLOv8 delivers significant gains in both precision and inference speed for plant disease tasks

- YOLOv8n Multi Disease detection:

We generated a synthetic dataset by compositing two diseased leaf patches (200×200 px) onto a 640×640 blank canvas at fixed locations. This allowed automatic YOLO-format annotation using known patch positions and class labels. We trained a YOLOv8n object detector using Ultralytics' pipeline with default augmentations. The trained model achieved mAP@0.5:0.95 = 0.995, successfully detecting multiple diseases per image. This method avoids manual annotation and enables real-time drone deployment.

Comparision Table:

Model	**Architecture**	**Methodology**	**Accuracy(%)**	**Key Features**
PiTLiD (Paper #1)	Pre-trained InceptionV3 CNN (transfer)	Classifier on whole-leaf images	84	Transfer learning from large-scale CNN
MSWDNet (Paper #2)	EfficientNet-B7 + DCB + ECA	Single-stage classifier	79	Multi-scale dilated conv. and channel-attention
EfficientNet-B0 + YOLOv5	YOLOv5 detector + EfficientNet-B0 classifier	Detect leaves → classify each leaf	MAP 0.9786	Combines detection and classification, handles multi-object scenes
YOLOv8 Classifier	YOLOv8 (One-Stage Detector/Classifier)	Direct multi-class classification	97	State-of-art real-time model

Results

Model 1 :

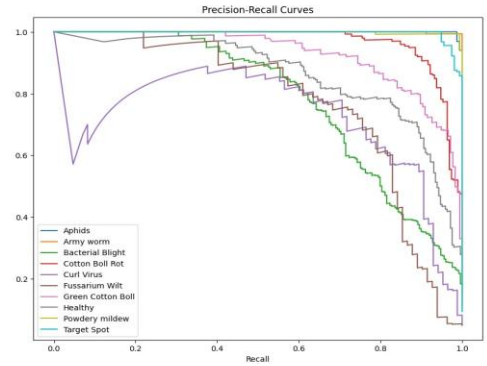


Fig 1 : PR Curve

Fig 1 gives Training Accuracy reaches ~100% by epoch 10.Validation Accuracy plateaus around 84% → model generalizes well but not perfectly.

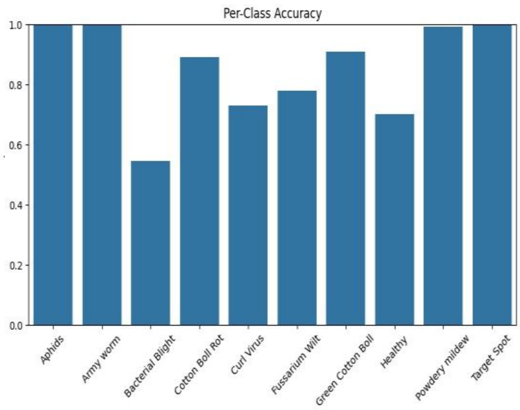
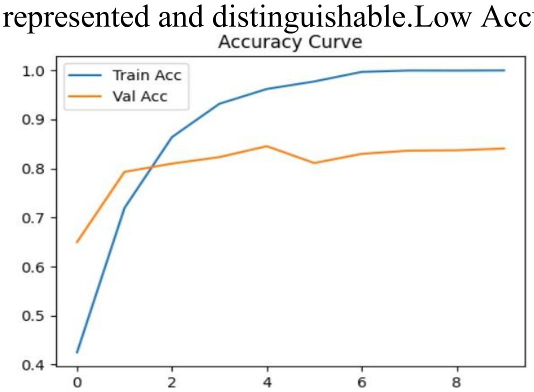


Fig 2 : Per Class Accuracy

Fig 2 says High Accuracy (~100%) :Aphids, Army Worm, Powdery Mildew, Target Spot – well-represented and distinguishable.Low Accuracy:Bacterial Blight (55%), Healthy (71%)



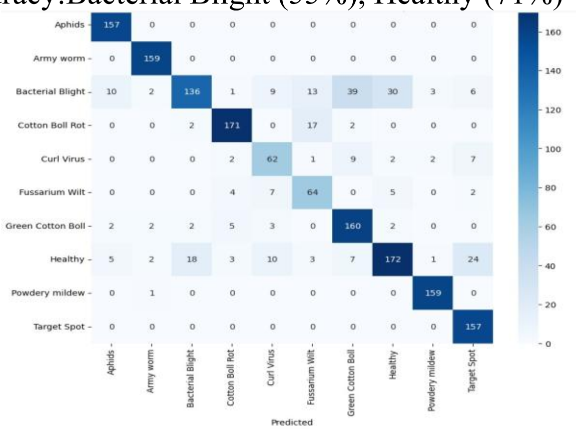


Fig 3 : Accuracy curve

Fig 4 : Confusion matrix

Fig 3 says Training Accuracy reaches ~100% by epoch 10.

Validation Accuracy plateaus around 84% → model generalizes well but not perfectly.

Fig 4 gives Diagonal Dominance (e.g., Aphids 157/157, Army Worm 159/159) → indicates high classification correctness.Misclassifications:Healthy ↔ Bacterial Blight, Fusarium ↔ Curl Virus → overlap in visual features.

MODEL 2: Efficient Net B0 + YOLOV5

.

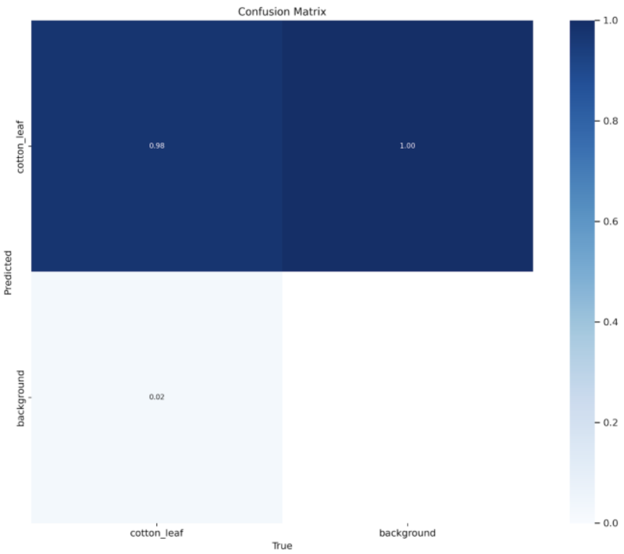


Fig 5 : Confusion matrix

On validation crops vs. background detection:

● True positives ('cotton_leaf') = 98%,

● False positives ('background') = 2%, demonstrating high accuracy in detecting cotton leaves.

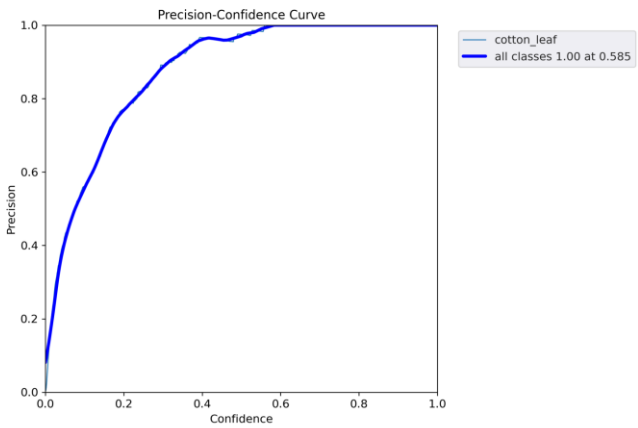


Fig 6: PC curve

Precision reaches 1.0 around 0.585 confidence—model has very low false positives at higher thresholds.

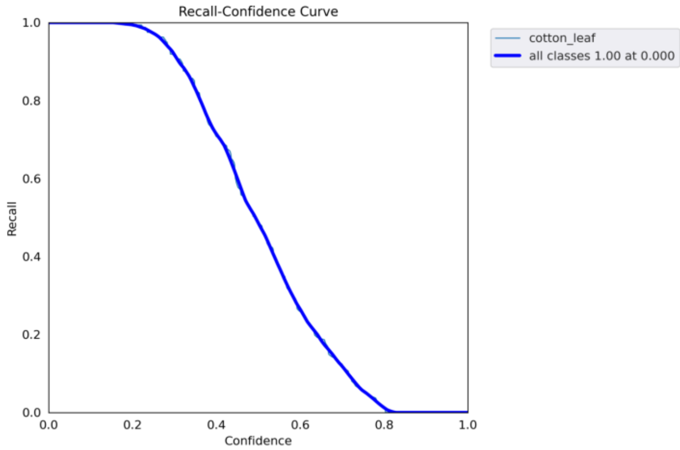


Fig 7: Recall curve

Starts from 1.0 at 0.00 confidence and gracefully decreases—indicating robust detection at lower thresholds.

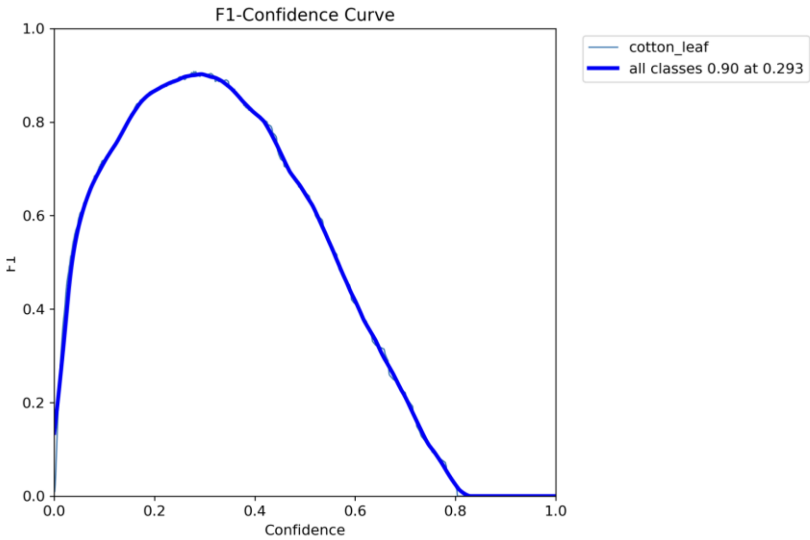


Fig 8: F1 curve

Peak F1 ≈ 0.90 at ~0.293 confidence—ideal threshold for balanced precision and recall.

Fig shows results of stage 1 pipeline output

Fig shows results of stage 2 pipeline output

Epoch Metrics:

- Epoch 1 to 10: Accuracy improves from 27.99% → 100%, with decreasing loss.
- Validation accuracy peaks ~84% → training is successful.

Classification Report:

- **Best Classes:** Aphids (F1 = 0.95), Army Worm (F1 = 0.98), Target Spot (F1 = 0.89)
- **Lowest F1 Scores:** Bacterial Blight (0.64), Curl Virus (0.68), Healthy (0.74)
- **Macro Avg F1 Score:** 0.84 → strong overall performance across classes.

Flowchart:

Start App (Streamlit Launch)

↓

Load Models (YOLOv5 & EfficientNet)

↓

User Uploads Image

↓

Run YOLOv5 Model (Detect Leaves)

↓

For Each Detected Cotton Leaf

↓

Crop Leaf Image

↓

Run EfficientNet Model (Classify Disease)

↓

Annotate Original Image with Detections and Classifications

↓

Display Annotated Image to User

↓

End

MODEL 3: YOLOv8n Multi Occuring Disease Detection

Flowchart :

Collect Disease Patch Images

|

▼

Resize patches to 200x200 px

|

▼

Place 2 patches on 640x640 blank canvas

|

▼

Auto-generate YOLO labels:
Class 0 & 1 with fixed-position bounding boxe

|

▼

Train YOLOv8n using Ultralytics
(with augmentations & transfer learning)

|

▼

Validate on test set
(Evaluate mAP, precision, recall)

|

▼

Detect multiple diseases per image
Enable drone-based inference

Dataset

These figures shows the dataset used for Detection of Multi-Occuring Diseases

Performence Metric

•mAP@0.5:0.95 0.995
•Precision (per class) > 0.99
•Recall (per class) > 0.99
•Accuracy - 0.50
•Macro Avg F1 - 0.17
•Weighted Avg F1 - 0.66

Conclusion

We implemented a deep learning-based pipeline using YOLOv5 + EfficientNet-B0 for cotton plant disease detection:

- YOLOv5 was used for real-time detection and localization of cotton leaves in field images. Its lightweight architecture and fast inference make it ideal for drone-based deployment in agriculture.
- EfficientNet-B0 was selected for classifying individual leaves as healthy or diseased, offering an excellent trade-off between performance and computational efficiency.

Epoch Metrics:

- Epoch 1 to 10: Accuracy improves from 27.99% → 100%, with decreasing loss.
- Validation accuracy peaks ~84% → training is successful.
- Best Classes: Aphids (F1 = 0.95), Army Worm (F1 = 0.98), Target Spot (F1 = 0.89)
- Lowest F1 Scores: Bacterial Blight (0.64), Curl Virus (0.68), Healthy (0.74)
- Macro Avg F1 Score: 0.84 → strong overall performance across classes.

- We're actively working to improve performance on multi-occurring diseases (leaves showing more than one disease), which remains a challenge due to overlapping symptoms.

This combined approach shows strong promise for real-time, scalable disease monitoring using drones in precision agriculture

Future scope

Drone Integration
Integrate model into UAVs for automated image capture (e.g., grid-based scanning) and on-board inference using multispectral drone imagery.

Fine-Tuning on Drone Imagery
Train with aerial images from varied altitudes/angles to improve robustness to scale, lighting, and real-field conditions.

Edge Deployment (Jetson Nano, etc.)
Optimize YOLOv8 using quantization and TensorRT for real-time inference (20+ FPS) on low-power devices like Jetson Nano.

Explainability with LLMs
Use LLMs to interpret model outputs, explain predictions with saliency maps, and generate natural-language crop health reports.

Interactive User Dashboard
Develop a web/mobile dashboard to display disease maps, confidence scores, and LLM-based recommendations for farmers.

References

[1] Liu, K., & Zhang, X. (2022). PiTLiD: identification of plant disease from leaf images based on convolutional neural network. *IEEE/ACM Transactions on Computational Biology and Bioinformatics*, *20*(2), 1278-1288.

[2] Ullah, N., Ahmad, B., Khan, A., Khan, I., Khan, I. M., & Khan, S. (2025). Attention-Guided Wheat Disease Recognition Network through Multi-Scale Feature Optimization. *IECE Transactions on Sensing, Communication, and Control*, *2*(1), 11-24.

[3]Zhao, Y., Chen, Z., Gao, X., Song, W., Xiong, Q., Hu, J., & Zhang, Z. (2021). Plant disease detection using generated leaves based on DoubleGAN. *IEEE/ACM transactions on computational biology and bioinformatics*, *19*(3), 1817-1826.

[4] Sangaiah, A. K., Yu, F. N., Lin, Y. B., Shen, W. C., & Sharma, A. (2024). UAV T-YOLO-rice: An enhanced tiny YOLO networks for rice leaves diseases detection in paddy agronomy. *IEEE Transactions on Network Science and Engineering*, *11*(6), 5201-5216.

[5] Qadri, S. A. A., Huang, N. F., Wani, T. M., & Bhat, S. A. (2024). Advances and challenges in Computer Vision for Image-based plant disease detection: a Comprehensive Survey of Machine and Deep Learning approaches. *IEEE Transactions on Automation Science and Engineering*.

[6] Tian, L., Zhang, H., Liu, B., Zhang, J., Duan, N., Yuan, A., & Huo, Y. (2022). VMF-SSD: A Novel v-space based multi-scale feature fusion SSD for apple leaf disease detection. *IEEE/ACM Transactions on Computational Biology and Bioinformatics*, *20*(3), 2016-2028.

.