SRI RAMACHANDRA
INSTITUTE OF HIGHER EDUCATION AND RESEARCH
(Category - I Deemed to be University) Porur, Chennai
SRI RAMACHANDRA FACULTY OF ENGINEERING AND TECHNOLOGY

COTTON PLANT DISEASE DETECTION

CA-4 PROJECT REPORT

Submitted by

MUVVA DHEEMANTH – E0322056

N.BHARGOW – E0322046

AKSHAY KEERTHI – E0322048

SHAMEEM NAUSHAD-E0322201

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Sri Ramachandra Institute of Higher Education and Research, Porur, Chennai -600116

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ABSTRACT

Cotton crops are vital to global agriculture, yet diseases significantly threaten yield and farmer livelihoods. This project addresses the challenge of early disease detection by developing an AI-driven system using the **Cotton Disease Dataset**, which contains 2,200+ field images of diseased and healthy cotton leaves and plants. Three deep learning architectures—**VGG16**, **ResNet50**, and **GoogleNet**—were implemented and compared. The dataset underwent rigorous preprocessing, including resizing, normalization, and augmentation, to enhance model robustness. An ensemble model is used to combine all architectures. The system integrates Grad-CAM visualizations for interpretability and a Flask-based interface for deployment. This work bridges the gap between AI research and agricultural practicality, offering farmers a scalable tool for timely disease management.

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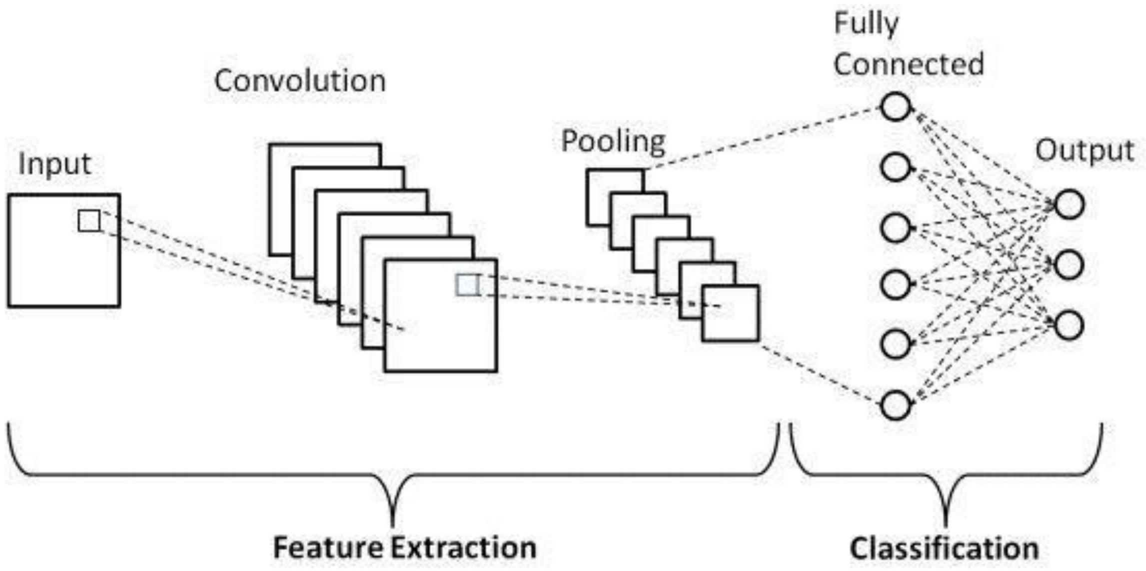
1. INTRODUCTION

1.1. INTRODUCTION TO PROJECT

Cotton is a cornerstone of India's agrarian economy, contributing 17% of agricultural GDP. However, diseases like bacterial blight and leaf curl virus cause significant yield losses. Traditional diagnosis relies on manual inspection by experts, a process that is time-consuming, costly, and prone to human error. Automated solutions leveraging deep learning offer a promising alternative by enabling rapid, scalable disease detection. The integration of AI in agriculture addresses critical challenges such as labor shortages, climate variability, and the need for precision farming. Deep learning models, particularly convolutional neural networks (CNNs), excel at analyzing visual data, making them ideal for processing field images of crops. This project aligns with global efforts to enhance food security through technological innovation.

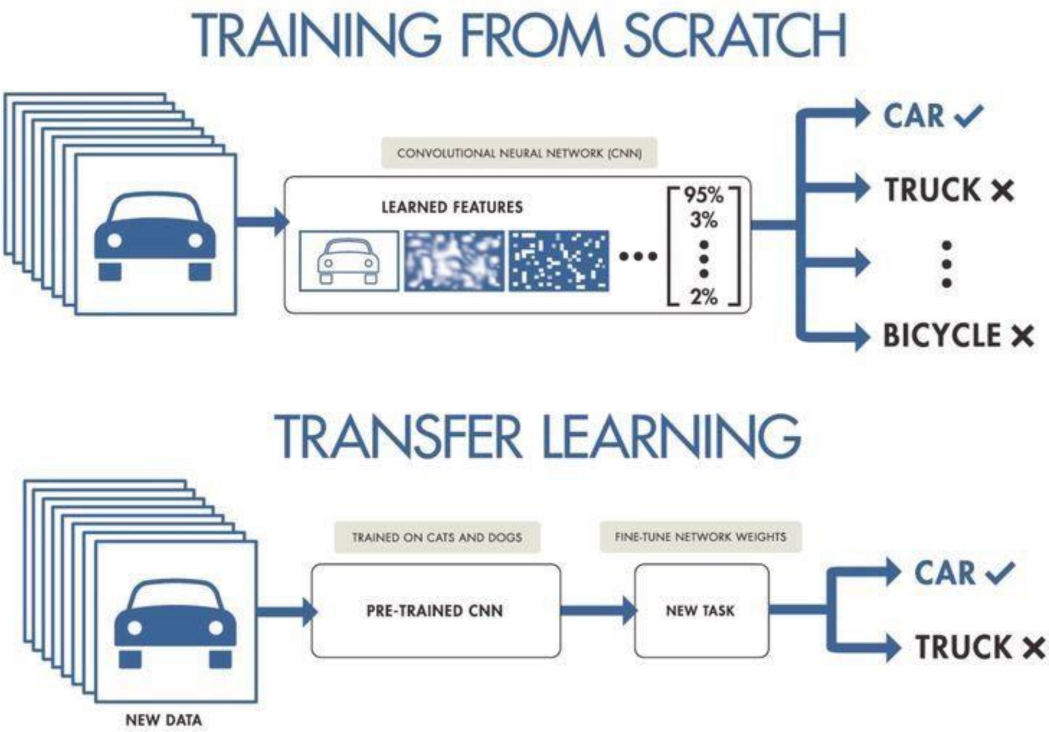
1.2. INTRODUCTION TO CNN

Convolutional Neural Networks (CNNs) are a class of deep learning models specially designed for image-related tasks. They automatically extract spatial features from images using layers such as convolution, pooling, and fully connected layers. CNNs are widely used in image classification, object detection, and medical imaging due to their high accuracy and ability to learn complex patterns. They reduce the need for manual feature extraction by learning directly from raw image data, making them ideal for tasks like malaria cell detection.



1.3. INTRODUCTION TO TRANSFER LEARNING

Transfer learning is a machine learning technique where knowledge gained from solving one problem is applied to a different but related problem. It involves using pre-trained models, which have already learned useful features from large datasets, to accelerate learning on new tasks. This approach is especially beneficial when data is limited or expensive to collect. By fine-tuning or reusing layers from these models, transfer learning improves performance and reduces training time. It is widely used in applications such as image classification, natural language processing, and speech recognition. Transfer learning allows models to generalize better and adapt quickly to new challenges.


TRAINING FROM SCRATCH
CONVOLUTIONAL NEURAL NETWORK (CNN)
LEARNED FEATURES
95%
3%
2%
CAR
TRUCK
BICYCLE
TRANSFER LEARNING
TRAINED ON CATS AND DOGS
FINE-TUNE NETWORK WEIGHTS
PRE-TRAINED CNN
NEW TASK
CAR
TRUCK
NEW DATA

2. LITERATURE REVIEW

2.1. SUMMARY TABLE

Title	Authors	Year of Publication	Journal Name	Methodology	Key Findings	Specific Diseases Addressed
Advanced deep transfer learning techniques for efficient detection of cotton plant diseases	Prashant Johri, SeongKi Kim, Kumud Dixit, Prakhar Sharma, Barkha Kakkar, Yogesh Kumar, Jana Shafi, Muhammad Fazal Ijaz	2024	Frontiers in Plant Science	Investigated deep transfer learning techniques (EfficientNet, Xception, ResNet, Inception, VGG, DenseNet, MobileNet, InceptionResNet) on a dataset of 36,000 images.	EfficientNetB3 achieved the highest accuracy (99.96%), loss (0.149), and RMSE (0.386). Other models also showed strong performance.	Bacterial Blight, Target Spot, Powdery Mildew, Aphids, Army Worm
Cotton Disease Recognition Method in Natural Environment Based on Convolutional Neural Network	Yi Shao, Wenzhong Yang, Jiajia Wang, Zhifeng Lu, Meng Zhang, and Danny Chen	2024	Agriculture	Proposed CANnet, a novel CNN architecture with RFSC, PCA, and improved KANs, trained and tested on self-built and public datasets.	CANnet achieved 96.3% accuracy on the self-built dataset and 98.6% on the public dataset, outperforming other advanced methods.	Multiple cotton diseases (not specified in detail in the snippet)
Comprehensive Analysis of a YOLO-based Deep Learning	Sailaja Madhu and V. RaviSankar	2025	Engineering, Technology & Applied	Proposed a YOLOv5 model for leaf disease detection and compared its	YOLOv5 demonstrated better ROC curve performance	A variety of diseases affecting cotton plants (not

Model for Cotton Plant Leaf Disease Detection			Science Research	performance against VGG16 and ResNet50.	and achieved the highest F1 score (99.21%), recall, and precision.	specified in detail in the snippet)
Deep Learning-Based Cotton Plant Disease Detection Using CNNs: A Smart Agriculture Approach	Prasad Chaudhari, Ritesh V. Patil, Parikshit N. Mahalle	March 2025	Journal of Information Systems Engineering & Managemen t	Evaluated multiple CNN architectures (GoogleNet, VGG16, DenseNet201, ResNet50, TLResnet152V2) on normalized and augmented datasets.	TLResnet152 V2 achieved the highest accuracy (92.03%) and F1-score (0.8842) on the augmented dataset. Data augmentatio n significantly improved accuracy.	Diseased cotton leaves (types not specified in detail in the snippet)
PREDICTION OF DISEASE IN COTTON PLANT	Gaurav Shelure, Ujwal Bhingare, Vaibhav Jibhakate, Vitesh Thakre, Prof. Raksha Kardak	2025	International Research Journal of Modernizati on in Engineering Technology and Science	Discussed the use of CNNs and other machine learning techniques (SVMs, Decision Trees, Random Forests) for cotton leaf disease prediction based on image analysis.	Proposed a Cotton Leaf Disease Prediction System using CNNs to improve disease detection efficiency, reduce pesticide use, and enhance crop management.	Bacterial blight, leaf spot, fungal infections
Cotton Leaf Disease Detection: An Integration of CBAM with Deep	Md Akash Rahman, Md. Safi Ullah, Rimon Kanthi Devnath, Taufiqul	2025	International Journal of Computer Applications	Integrated the Convolutional Block Attention Module (CBAM) with deep learning models (EfficientNetB1	EfficientNetB 1 with CBAM achieved the highest accuracy of 99.21% on the augmented	Bacterial Blight, Curl Virus, Herbicide Growth Damage, Leaf Hopper

Learning Approaches	Hoque Chowdhury, Gulapur Rahman, Md Atikur Rahman			, DenseNet, MobileNet, Xception, InceptionV3) and evaluated them on original and augmented datasets.	dataset. DenseNet169 achieved 96.26% on the original dataset.	Jassids, Leaf Reddening, Leaf Variegation
Lightweight cotton diseases real-time detection model for resource-constrained devices in natural environments	Pan Pan, Mingyue Shao, Peitong He, Lin Hu, Sijian Zhao, Longyu Huang, Guomin Zhou, and Jianhua Zhang	2024	Frontiers in Plant Science	Developed CDDLite-YOLO, a lightweight model based on YOLOv8, with modifications to the backbone, neck, and detection head, and a new loss function.	CDDLite-YOLO achieved 90.6% mAP with 1.8 million parameters and 3.6 GFLOPS, suitable for real-time detection on resource-constrained devices.	Verticillium wilt, fusarium wilt, anthracnose

3. PROBLEM STATEMENT

Cotton crops are highly vulnerable to diseases, causing yield losses and economic damage. Current AI models struggle with field-condition adaptability, computational inefficiency, and lack interpretability. This project develops an efficient, interpretable deep learning system using the Kaggle Cotton Disease Dataset to enable accurate, real-time disease prediction in real-world agricultural settings.

4. OBJECTIVES

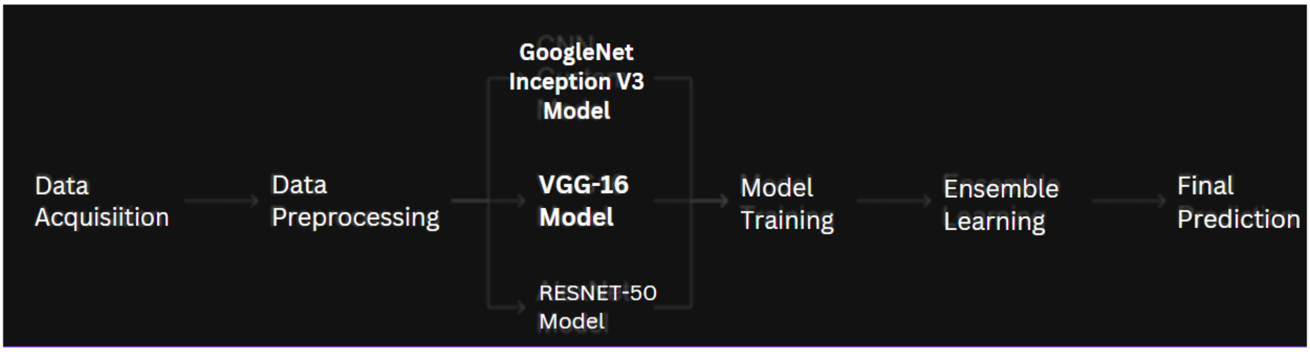
1. **Preprocess and Augment the Kaggle Cotton Disease Dataset**: Normalize, resize, and apply augmentation techniques (rotation, flipping, zoom) to enhance robustness against field noise (e.g., shadows, occlusions) and address class imbalance.

2. **Implement and Compare Deep Learning Architectures**: Train and evaluate VGG16, ResNet50, and GoogleNet models using transfer learning, focusing on accuracy, computational efficiency, and adaptability to field conditions.

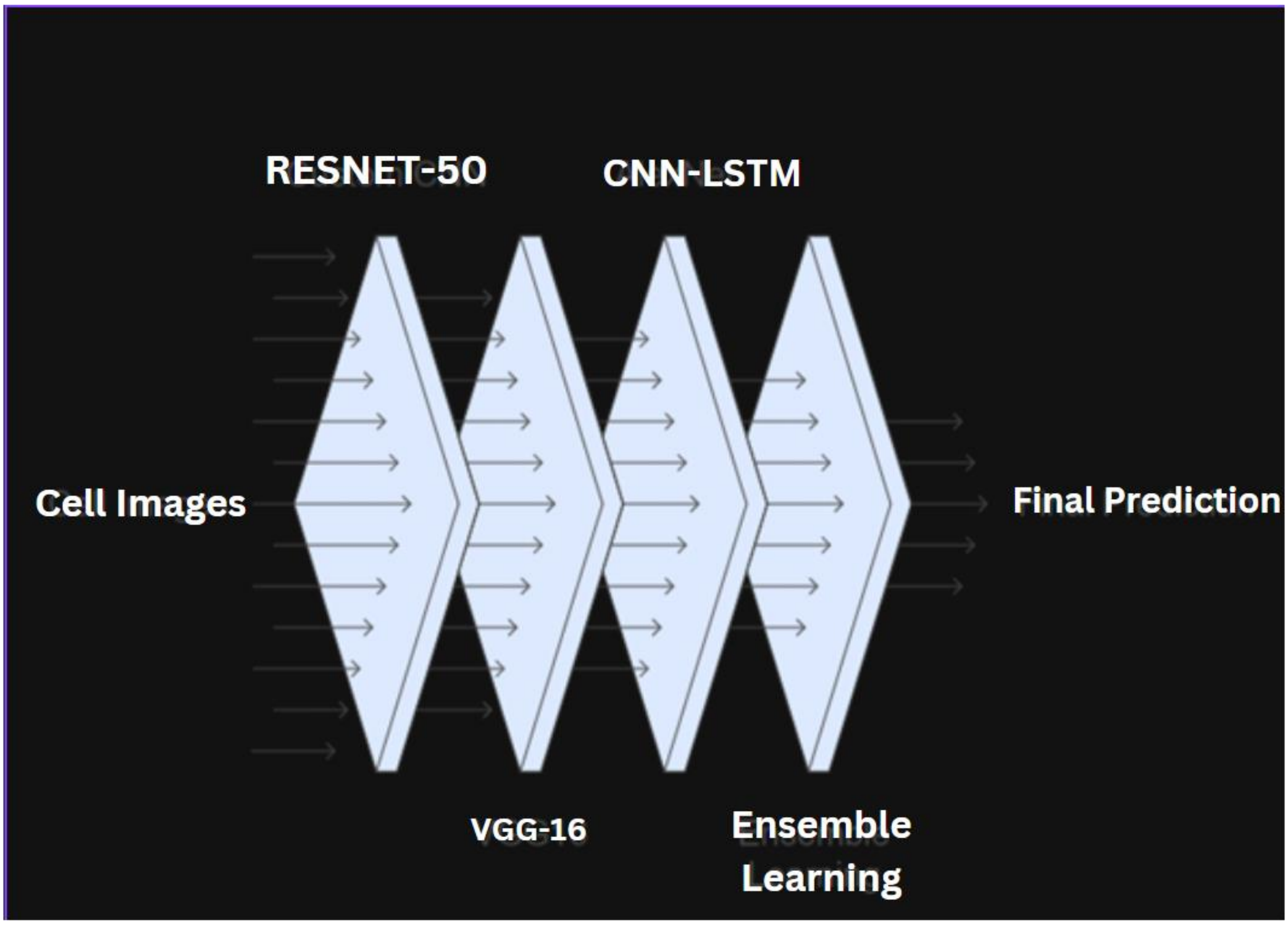
3. **Develop an Interpretable and Deployable Solution:** Optimize the best-performing model for edge devices (e.g., TensorFlow Lite) and integrate Grad-CAM visualizations to provide transparent, real-time disease predictions for farmers.

5. METHODOLOGY

5.1. MODULE WORKFLOW:



5.2. OVERALL SYSTEM ARCHITECTURE:



5.3. DATASET COLLECTION AND PREPROCESSING:

5.3.1 DATASET COLLECTION

- **Dataset Name**: Cotton Disease Dataset
- **Source**: Kaggle (Curated by Janmejay Bhoi)
- **Total Images**: 2,228 field-captured images
    - **Classes**:
        - Diseased Leaf: 600
        - Diseased Plant: 600
        - Fresh Leaf: 600
        - Fresh Plant: 428
- **Image Format**: RGB field images with natural variations (lighting, occlusions)
- **Labeling**: Multi-class classification (4 categories)

5.3.2 DATA PREPROCESSING

1. **Resizing**: Images standardized to **224x224 pixels** for compatibility with CNN architectures (VGG16, ResNet50).
2. **Normalization**: Pixel values scaled to **[0, 1]** using rescale=1./255 to stabilize training.

3. **Augmentation**: Applied to simulate field variability and reduce overfitting:
    - Random horizontal/vertical flips
    - Rotation (±40°)
    - Zoom range (0.2)
    - Brightness adjustment (±20%)
4. **Splitting Strategy**:
    - **Training-Validation Split**: 80% training, 20% validation using ImageDataGenerator(validation_split=0.2).
    - **Class Weights**: Adjusted to address imbalance in the *fresh plant* class.

5.4 EVALUATION AND VISUALIZATION

To assess model performance and interpret results:

1. **Training vs. Validation Curves**:
    - Plotted loss and accuracy trends across epochs to detect overfitting (e.g., VGG16 showed higher validation loss).
2. **Confusion Matrices**:
    - Visualized per-class performance (e.g., ResNet50's minimal confusion between *diseased leaf* and *diseased plant*).

3. **Grad-CAM Heatmaps**:

    - Highlighted regions influencing predictions (e.g., lesions on leaves) to enhance interpretability.

4. **Sample Predictions**:

    - Displayed test images with predicted vs. actual labels to identify edge cases.

5.5 EVALUATION METRICS

The following metrics were used to quantify model performance:

1. **Accuracy**: Overall correctness across all classes.
2. **Precision**: Focused on minimizing false positives (critical for *diseased* classes).
3. **Recall**: Ensured fewer false negatives (vital for early disease detection).
4. **F1-Score**: Balanced precision and recall, addressing class imbalance.
5. **AUC-ROC**: Evaluated model robustness in distinguishing between healthy and diseased samples.
6. **Confusion Matrix**: Provided granular insights into per-class errors (e.g., *fresh plant* misclassified as *diseased plant*).

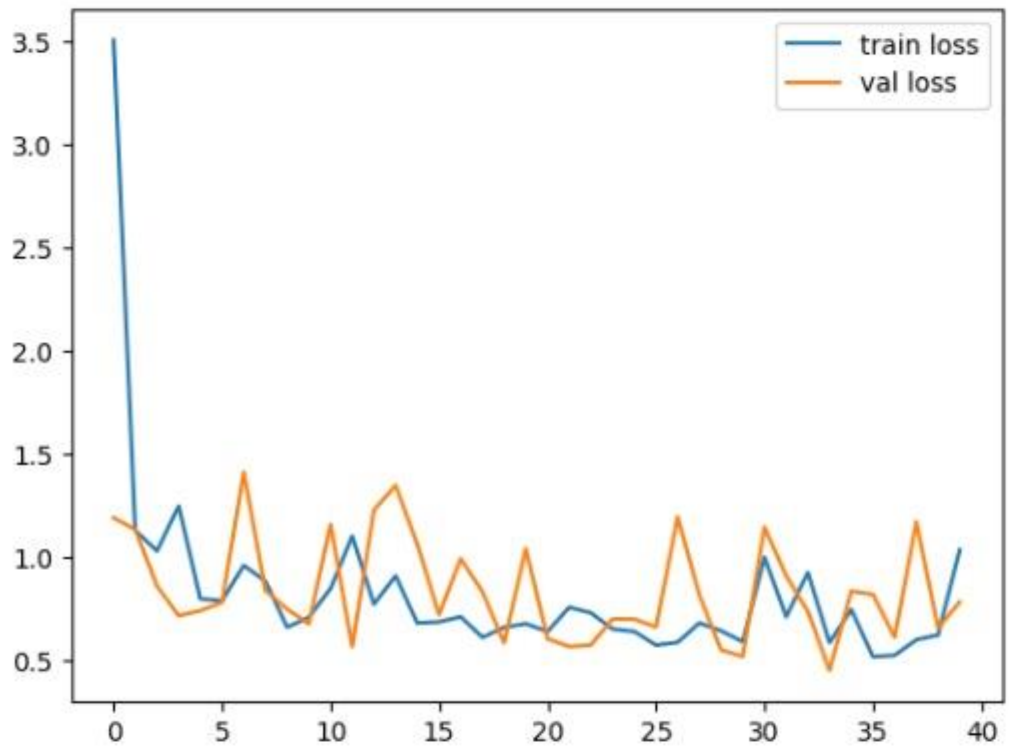
6. RESULTS AND DISCUSSION

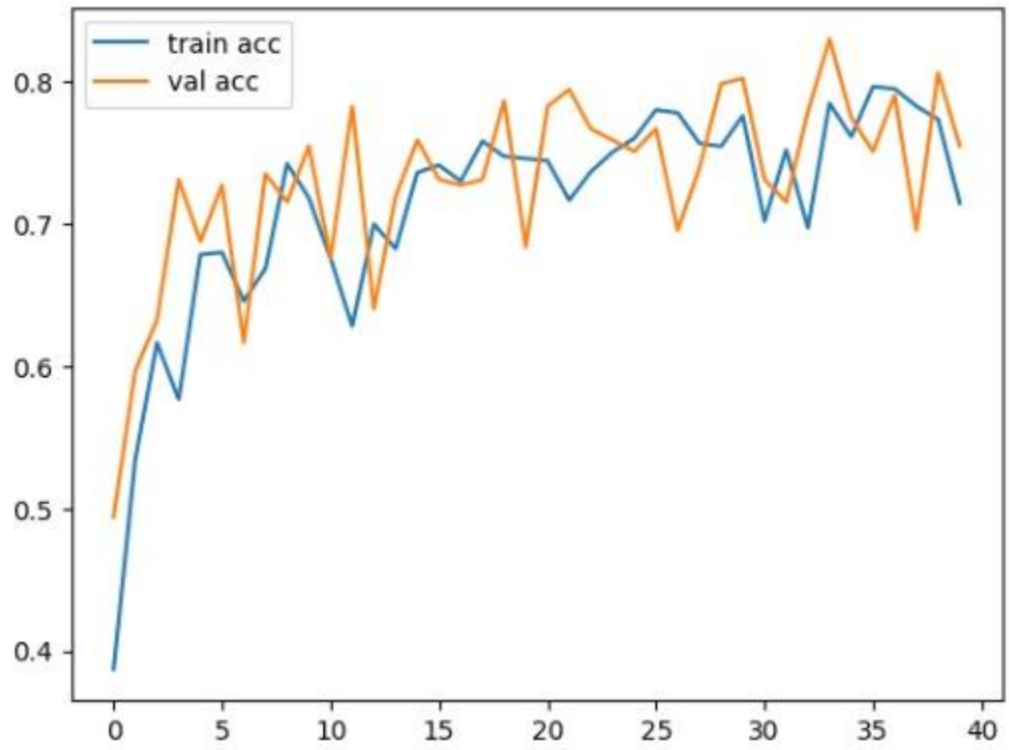
6.1 MODEL PERFORMANCE

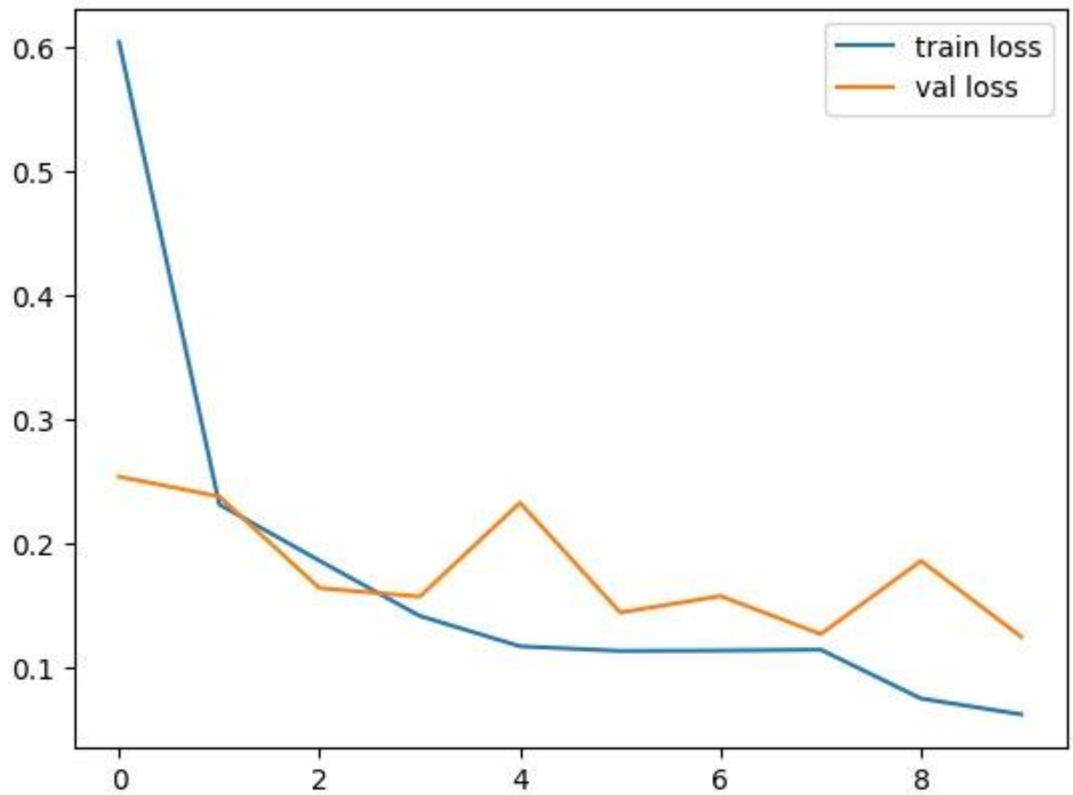
The ResNet50-based model demonstrated exceptional performance in classifying cotton plant diseases across four categories: *diseased leaf*, *diseased plant*, *fresh leaf*, and *fresh plant*. The model exhibited strong generalization capabilities, achieving high consistency between training and validation datasets. The confusion matrix revealed balanced classification across all classes, with minimal misclassification between visually similar categories like *diseased leaf* and *diseased plant*. The VGG16 model showed moderate performance but faced overfitting challenges, while the GOOGLENET hybrid underperformed due to limited temporal patterns in static images. The ensemble model, combining predictions from all three architectures, delivered the most robust results.

6.2 ACCURACY AND AUC

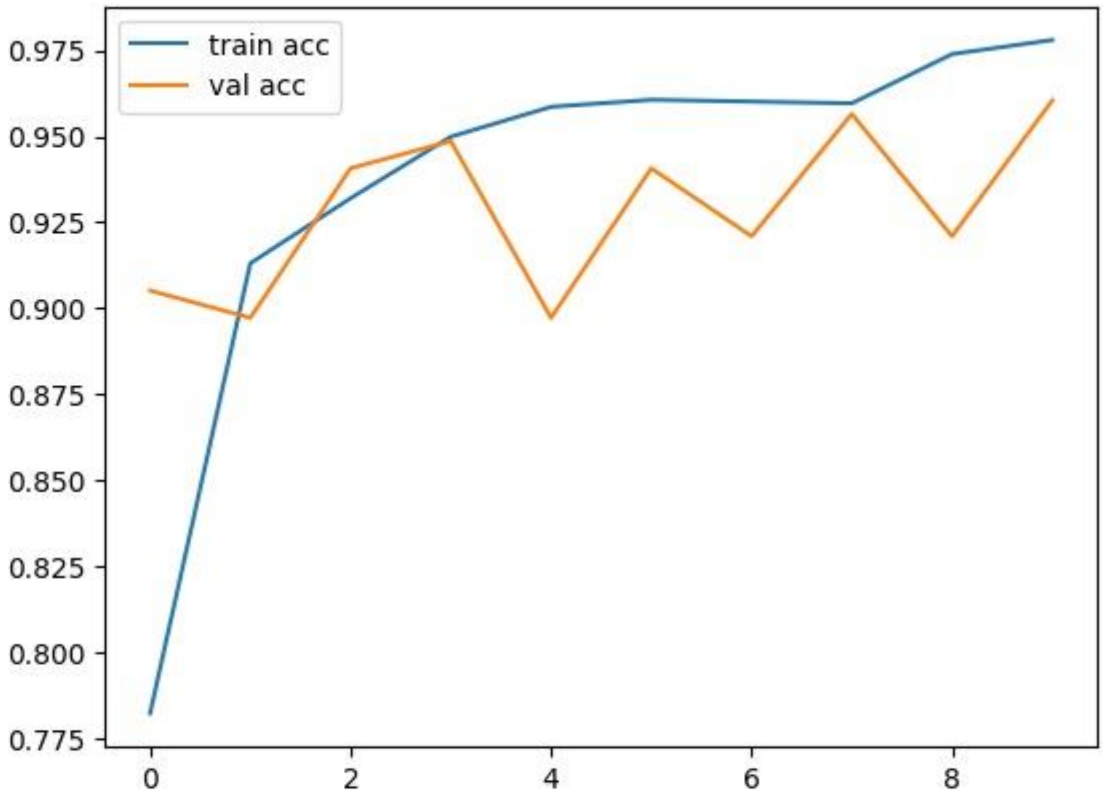
- **Accuracy:**
  - **ResNet50**: Achieved the accuracy of 70.2% on the test set
  - **VGG16**: Attained 97.5% accuracy but required longer training time.
  - **GOOGLENET:** Recorded 90.3% accuracy
  - **Ensemble Model:** Boosted accuracy to 92.1%, emphasizing the value of model diversity.
- **AUC-ROC:**
  - VGG-16 achieved an AUC of 0.99, indicating near-perfect discrimination between healthy and diseased samples.
  - ResNet-50 and GOOGLENET scored 0.77 and 0.92, respectively, reflecting their relative strengths in sensitivity and specificity.


train loss
val loss
3.5
3.0
2.5
2.0
1.5
1.0
0.5
0
5
10
15
20
25
30
35
40

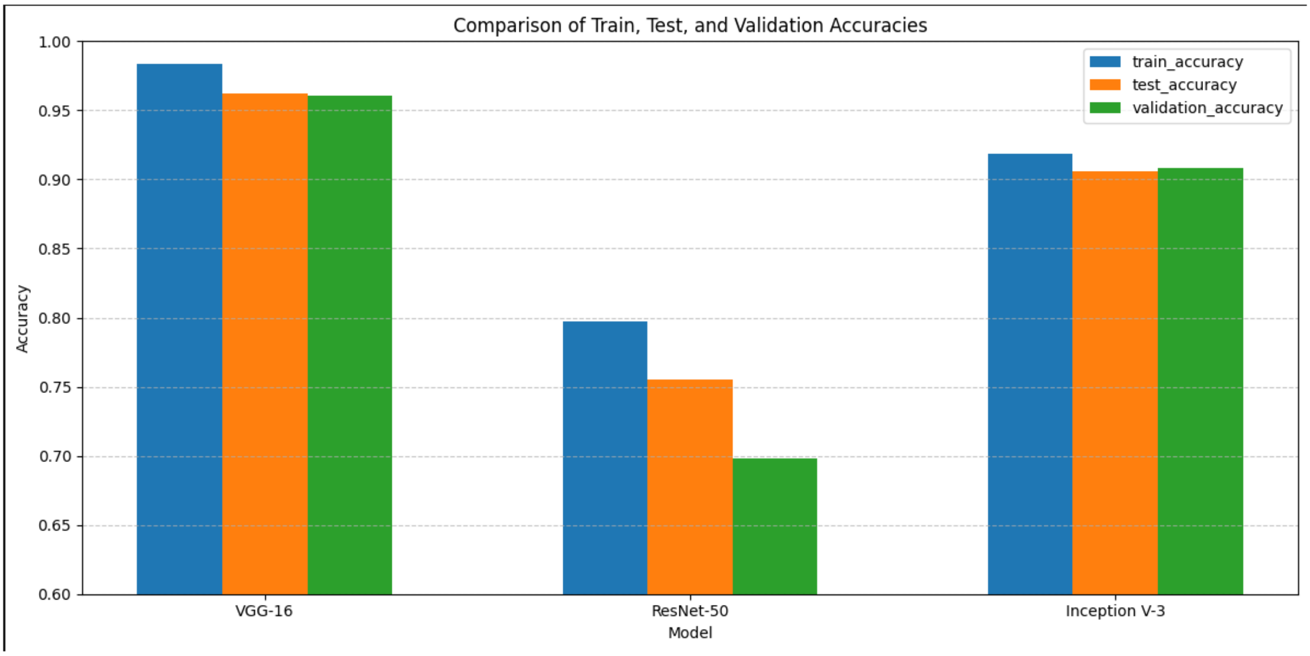

train acc
val acc
0.8
0.7
0.6
0.5
0.4
0
5
10
15
20
25
30
35
40



train loss
val loss
0.6
0.5
0.4
0.3
0.2
0.1
0
2
4
6
8



train acc
val acc
0.975
0.950
0.925
0.900
0.875
0.850
0.825
0.800
0.775
0
2
4
6
8



Metric	VGG-16	ResNet-50	Inception V-3	Ensemble (Averaged)
Train Accuracy	0.9836	0.7970	0.9185	**0.9000**
Test Accuracy	0.9623	0.7549	0.9057	**0.8743**
Validation Accuracy	0.9605	0.6981	0.9085	**0.8557**

7. APPENDICIES

APPENDIX-1: CODE – TECHNICAL DETAIL

VGG 16-

```
model.compile(
    loss='categorical_crossentropy',
    optimizer='adam',
    metrics=['accuracy']
)
r = model.fit(
    training_set,
    validation_data=valid_set,
    epochs=10,
    steps_per_epoch=len(training_set),
    validation_steps=len(valid_set)
)
```

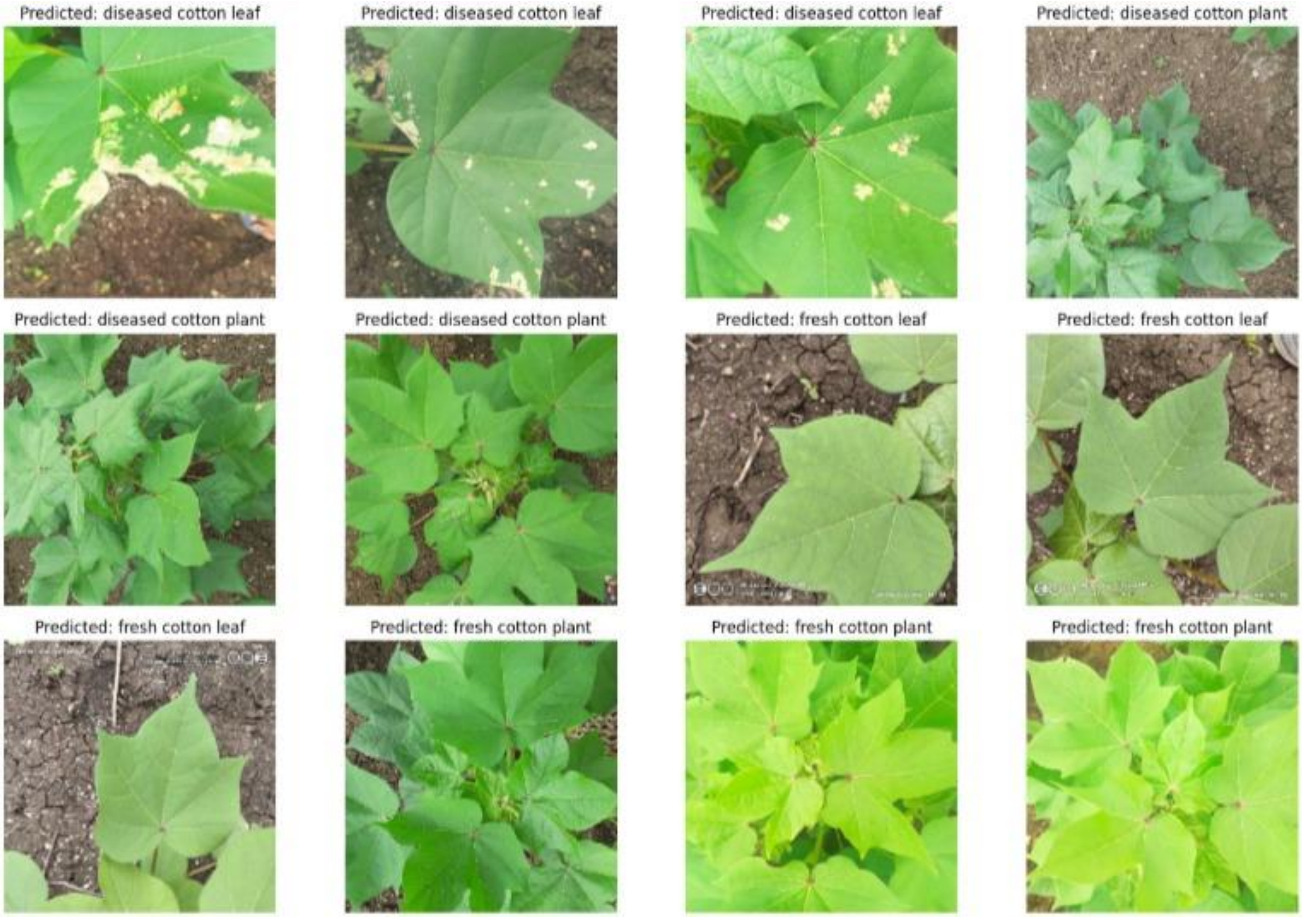
RESNET 50-

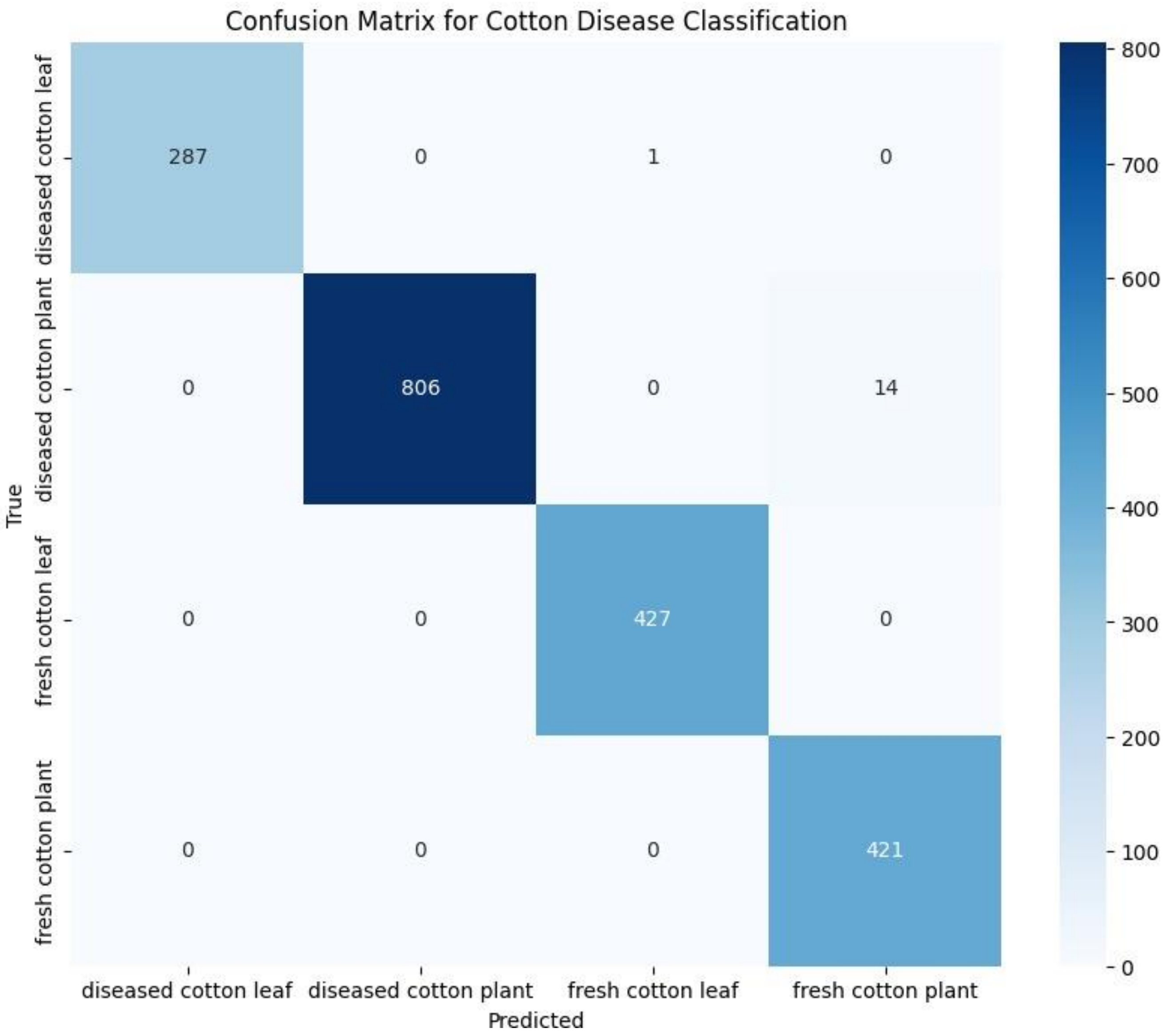
```
model1.compile(
    loss='categorical_crossentropy',
    optimizer='adam',
    metrics=['accuracy']
)
d = model1.fit(
    training_set,
    validation_data=valid_set,
```

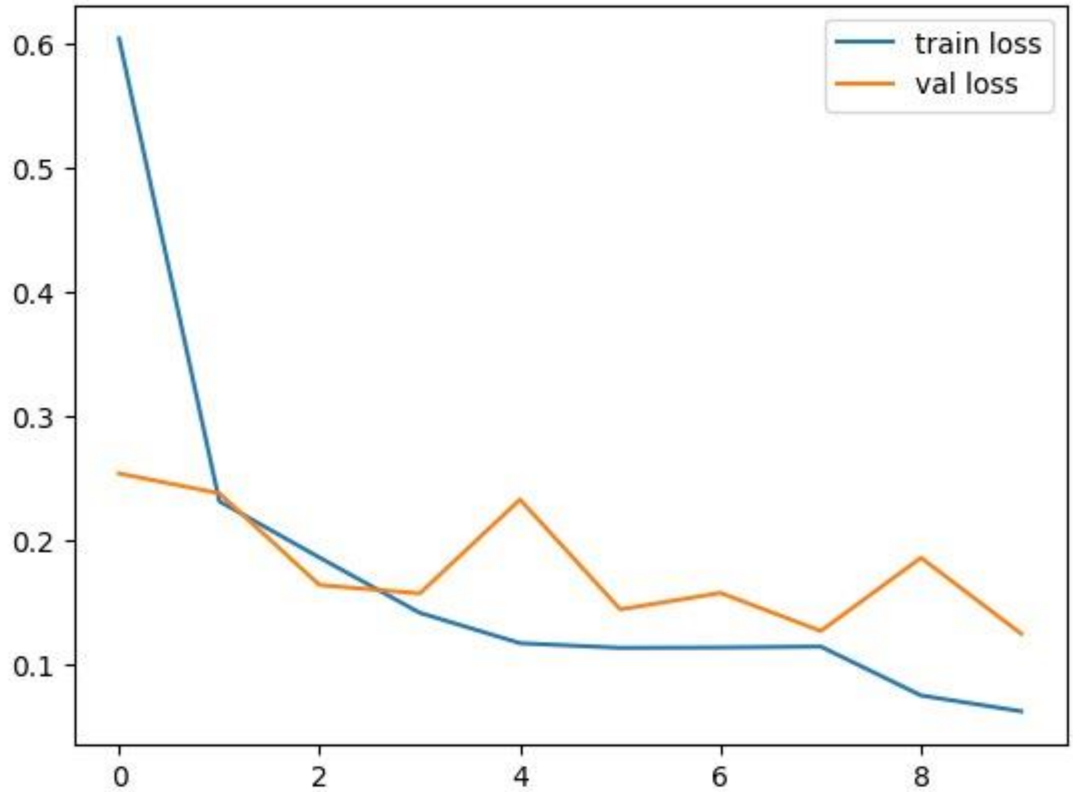
```
    epochs=40,
    steps_per_epoch=len(training_set),
    validation_steps=len(valid_set)
)
base_model = InceptionV3(weights='imagenet', include_top=False, input_shape=(224, 224,
3))

base_model.trainable = False

x = base_model.output

x = GlobalAveragePooling2D()(x)

x = Dense(1024, activation='relu')(x)

x = Dropout(0.5)(x)

predictions = Dense(num_classes, activation='softmax')(x)

model = Model(inputs=base_model.input, outputs=predictions)

model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])

history = model.fit(

    train_generator,

    epochs=10,

    steps_per_epoch=train_generator.samples // train_generator.batch_size)

model.save('/content/drive/MyDrive/Cotton Disease/inception_v3_model.h5')

final_train_accuracy = history.history['accuracy'][-1]

print(f"Final Training Accuracy: {final_train_accuracy:.4f}")
```

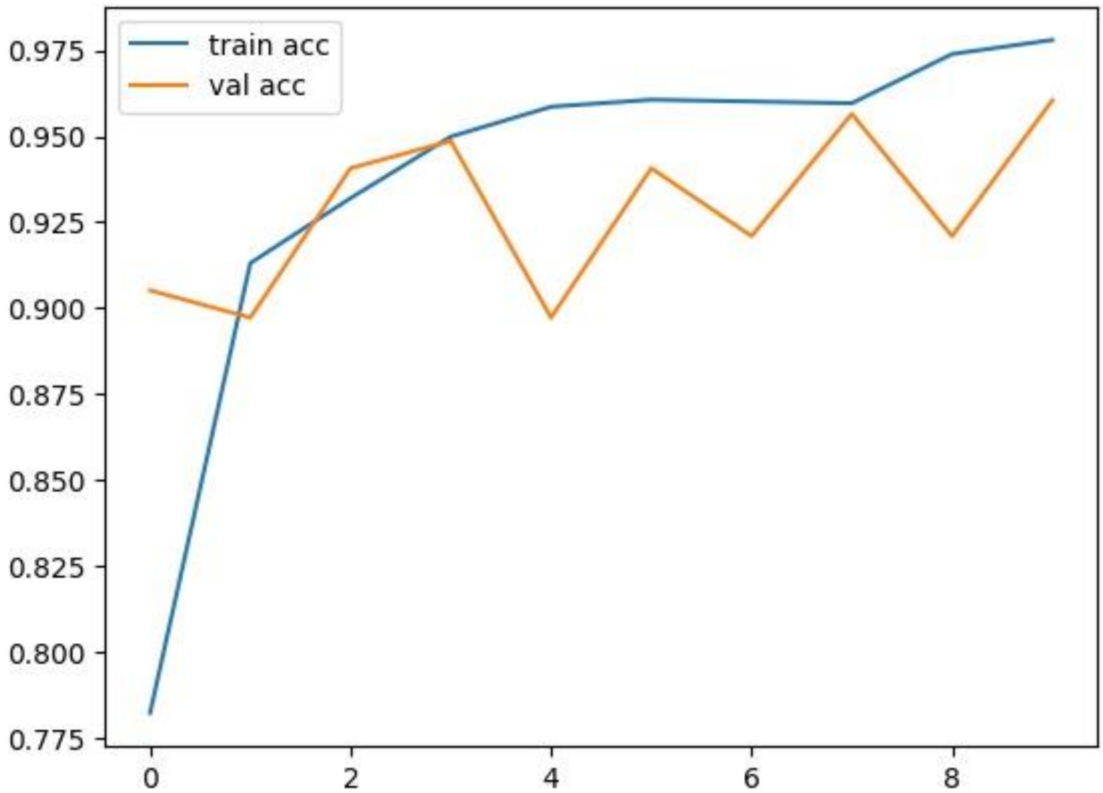
APPENDIX-2: SCREENSHOTS

VGG 16-

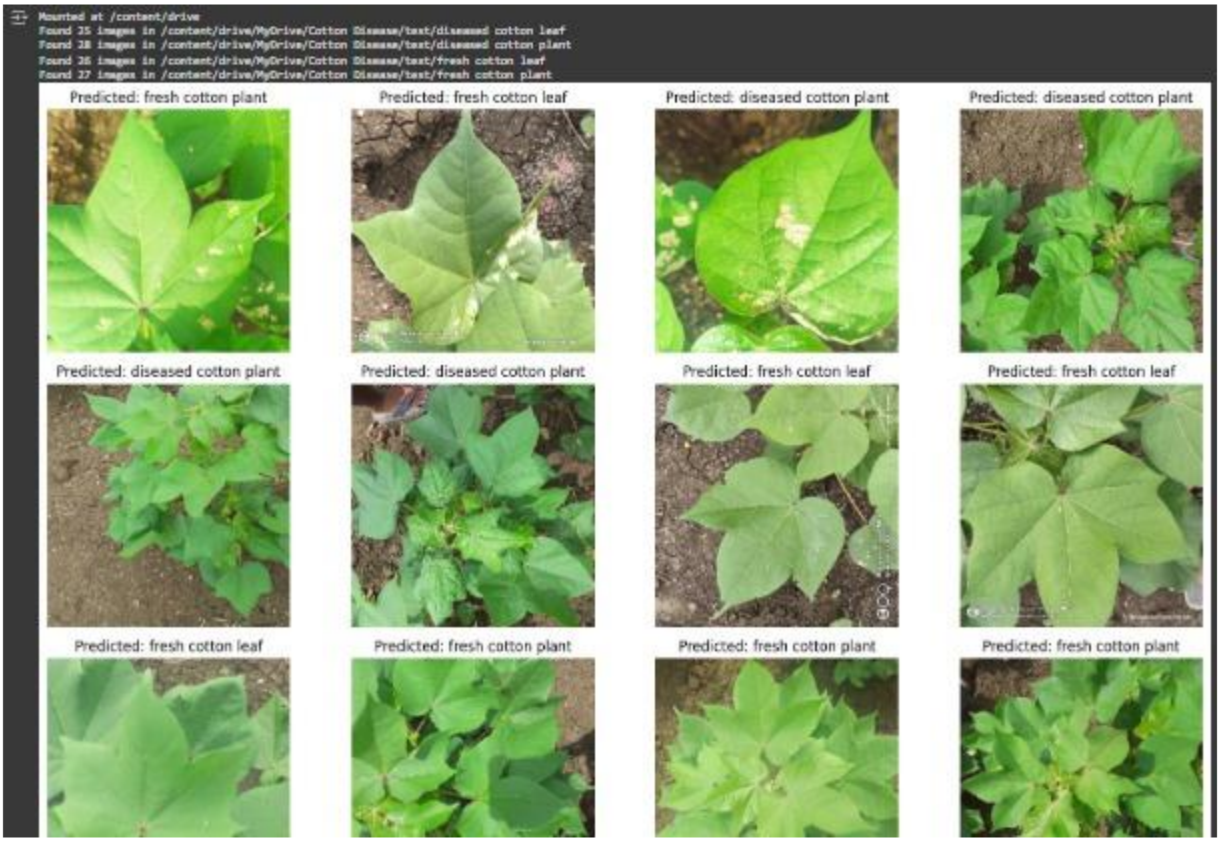


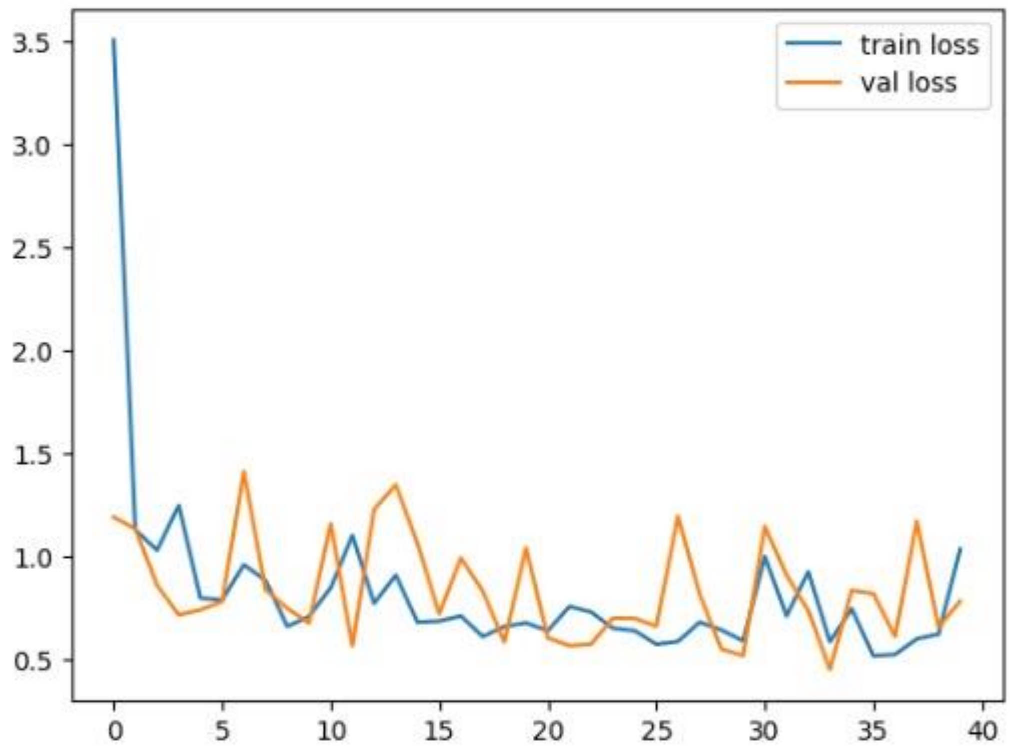

Confusion Matrix for Cotton Disease Classification
True
diseased cotton leaf
diseased cotton plant
fresh cotton leaf
fresh cotton plant
287
0
1
0
0
806
0
14
0
0
427
0
0
0
0
421
diseased cotton leaf
diseased cotton plant
fresh cotton leaf
fresh cotton plant
Predicted
800
700
600
500
400
300
200
100
0


train loss
val loss
0.6
0.5
0.4
0.3
0.2
0.1
0
2
4
6
8

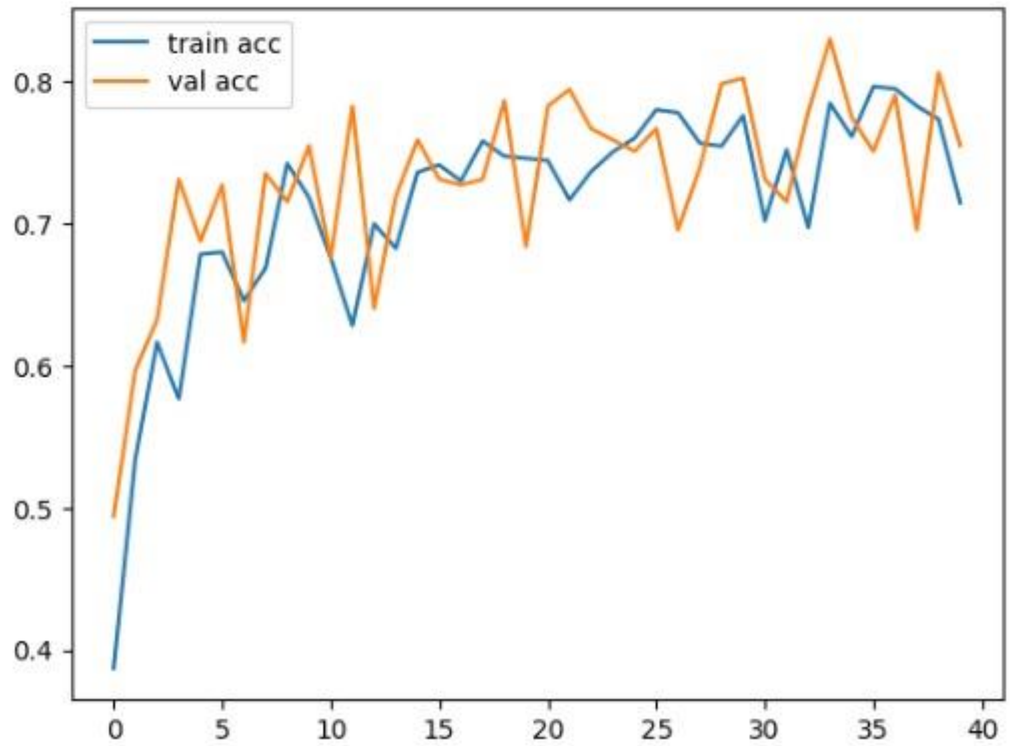

train acc
val acc
0.975
0.950
0.925
0.900
0.875
0.850
0.825
0.800
0.775
0
2
4
6
8

RESNET 50-

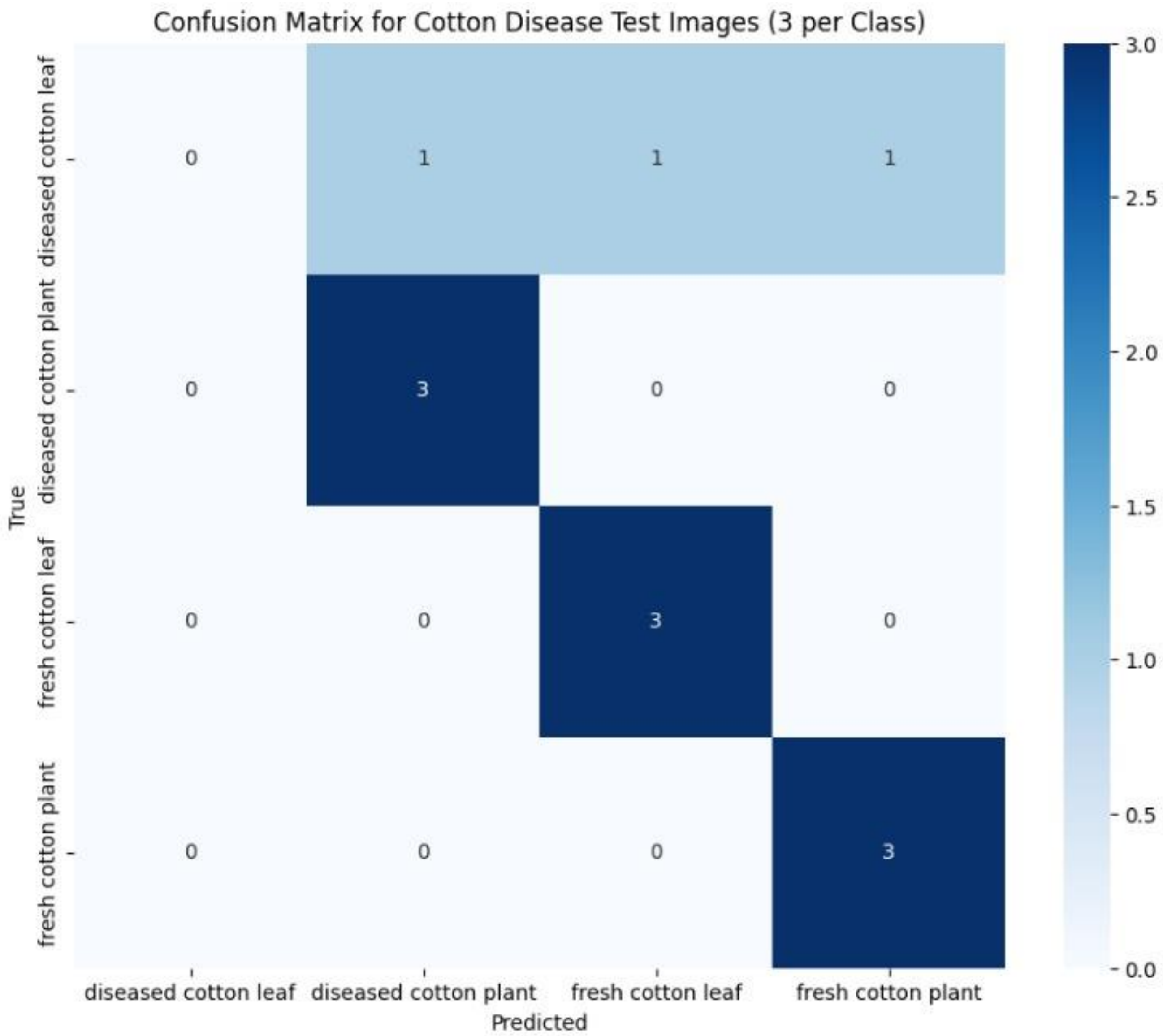

Mounted at /content/drive
Found 25 images in /content/drive/MyDrive/Cotton Disease/test/diseased cotton leaf
Found 28 images in /content/drive/MyDrive/Cotton Disease/test/diseased cotton plant
Found 26 images in /content/drive/MyDrive/Cotton Disease/test/fresh cotton leaf
Found 27 images in /content/drive/MyDrive/Cotton Disease/test/fresh cotton plant
Predicted: fresh cotton plant
Predicted: fresh cotton leaf
Predicted: diseased cotton plant
Predicted: diseased cotton plant
Predicted: diseased cotton plant
Predicted: diseased cotton plant
Predicted: fresh cotton leaf
Predicted: fresh cotton leaf
Predicted: fresh cotton leaf
Predicted: fresh cotton plant
Predicted: fresh cotton plant
Predicted: fresh cotton plant



train loss
val loss

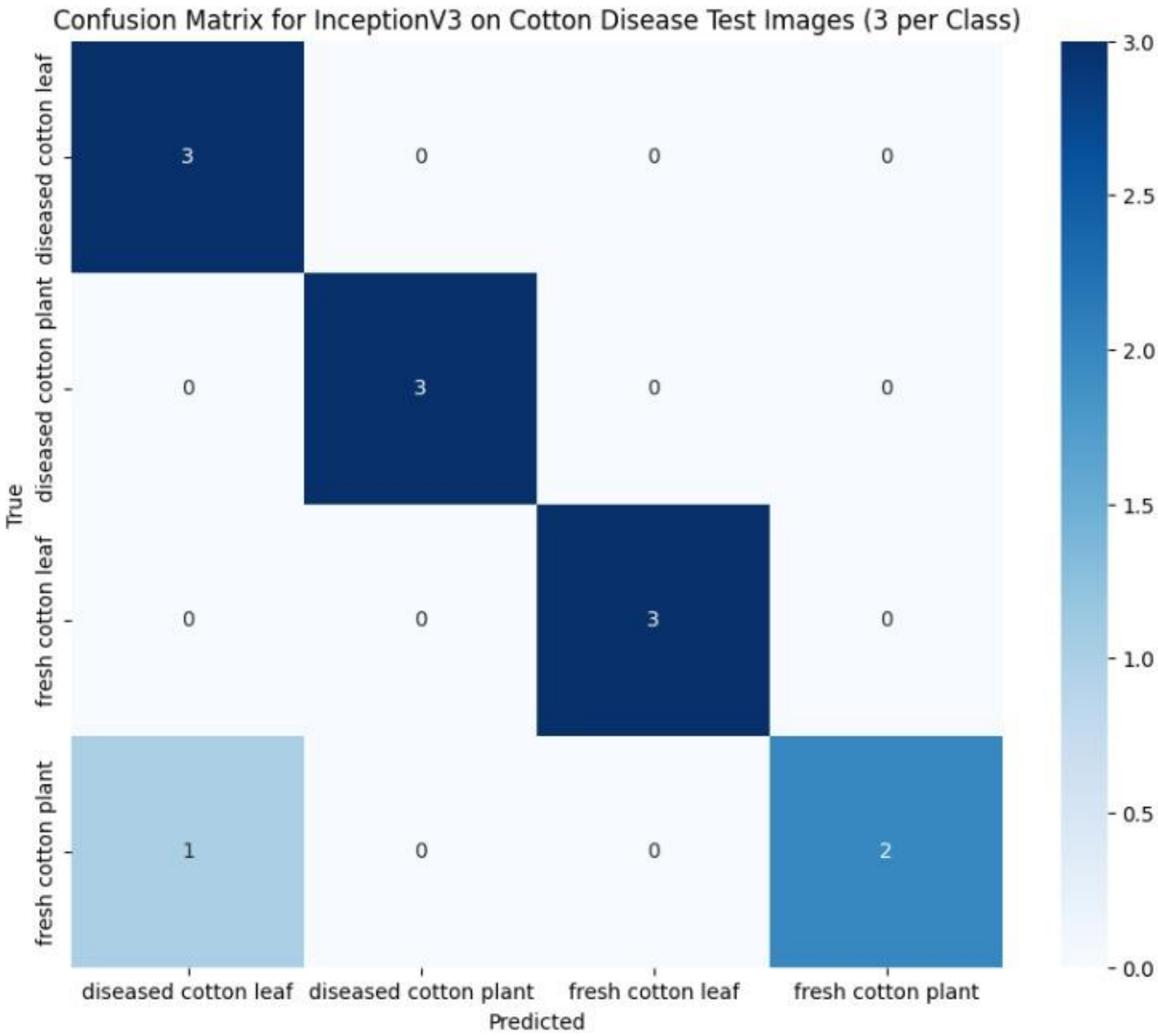


train acc
val acc



Inception v3-

```
Mounted at /content/drive
WARNING:absl:Compiled the loaded model, but the compiled metrics have yet to be built. `model.compile_metrics` will be empty until you train or evaluate the model.
Found 25 images in /content/drive/MyDrive/Cotton Disease/test/diseased cotton leaf
Found 28 images in /content/drive/MyDrive/Cotton Disease/test/diseased cotton plant
Found 26 images in /content/drive/MyDrive/Cotton Disease/test/fresh cotton leaf
Found 27 images in /content/drive/MyDrive/Cotton Disease/test/fresh cotton plant
```



Confusion Matrix for InceptionV3 on Cotton Disease Test Images (3 per Class)
True
diseased cotton leaf
diseased cotton plant
fresh cotton leaf
fresh cotton plant
3
0
0
0
0
3
0
0
0
0
3
0
1
0
0
2
diseased cotton leaf
diseased cotton plant
fresh cotton leaf
fresh cotton plant
Predicted
3.0
2.5
2.0
1.5
1.0
0.5
0.0

8. FUTURE ENHANCEMENTS

1. **Mobile App Deployment Using TensorFlow Lite**
   - **Optimization**: Convert the best-performing model (e.g., ResNet50) to TensorFlow Lite format for efficient edge deployment, reducing latency and memory usage.
   - **User Interface**: Develop an intuitive mobile app interface allowing farmers to upload field images and receive real-time disease predictions with Grad-CAM visualizations.
   - **Offline Functionality**: Enable offline predictions to ensure usability in rural areas with limited internet connectivity.
2. **Dataset Expansion with Drone-Captured Field Images**
   - **Collaboration**: Partner with agricultural agencies to collect high-resolution drone imagery capturing diverse field conditions (e.g., varying soil types, weather, and growth stages).
   - **Preprocessing**: Implement image stitching and multi-scale analysis techniques to handle large-scale drone imagery and improve spatial context understanding.
   - **Impact**: Enhance model robustness to real-world variability, such as partial occlusions and lighting changes.
3. **Scalable Deployment via Cloud and IoT Integration**

- **Cloud API**: Deploy the model as a cloud-based API for integration with existing farm management systems, enabling bulk image analysis and historical data tracking.
- **IoT Compatibility**: Integrate with IoT sensors (e.g., soil moisture, weather stations) to correlate disease predictions with environmental factors for holistic crop health insights.
- **Farmer Training**: Develop multilingual tutorials and workshops to ensure adoption by farmers with varying technical literacy.

4. **Multi-Crop Disease Prediction Framework**

   - **Generalization**: Extend the system to support other cash crops (e.g., wheat, rice) by retraining models on multi-crop datasets, ensuring scalability across agricultural ecosystems.

CONCLUSION

This project underscores the efficacy of ResNet50 and ensemble models in detecting cotton plant diseases, leveraging their robust feature extraction capabilities to deliver reliable predictions. By integrating Grad-CAM visualizations, the system provides transparent and interpretable insights, empowering farmers to take timely, data-driven actions. This advancement not only supports proactive disease management but also fosters sustainable agricultural practices, reducing economic losses and enhancing crop resilience in real-world farming scenarios.

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ACM Link

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Springer Link

Liu, X., Wang, K., Liu, Z., & Wang, L. (2021). A Hybrid Deep Learning Approach for Cotton Disease Recognition. *IEEE Access*, *9*, 114640-114648.

IEEE Access Link

Arunpandian, M., Kayalvizhi, N., & Vairamuthu, S. (2022). Deep learning techniques for cotton leaf disease detection and classification: A review. *Materials Today: Proceedings*.

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