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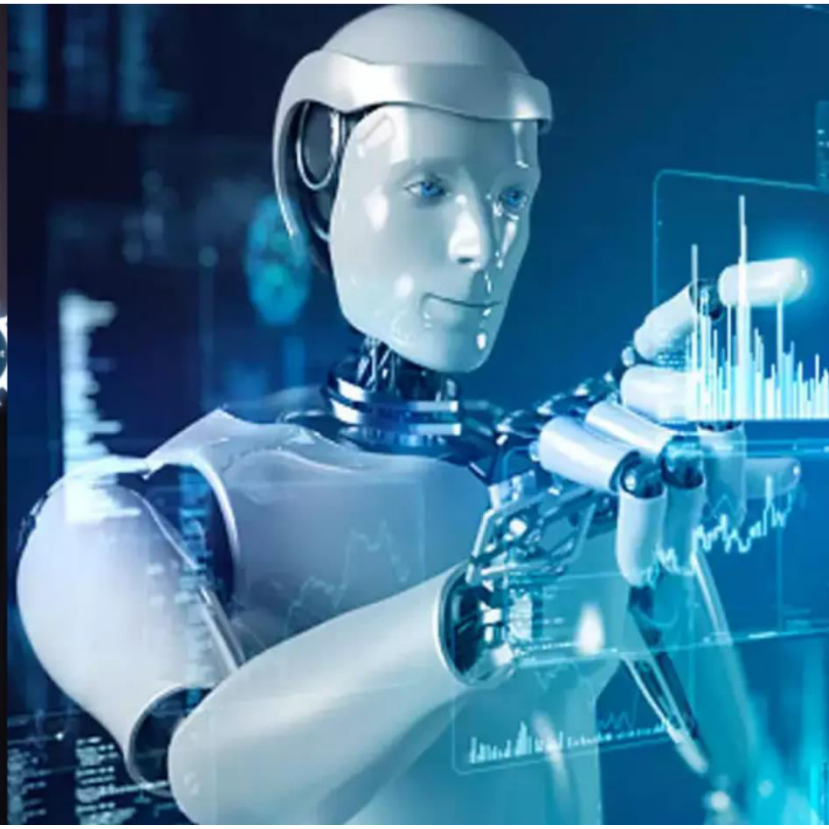

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Plant Leaf Disease Detection using Deep Learning

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ABSTRACT: Plant diseases significantly reduce crop yield and quality, directly affecting food security and farmer income. Early and accurate diagnosis can contain outbreaks and guide timely treatment. This project presents a deep-learning based system for plant leaf disease detection and classification from images. We employ transfer learning with convolutional neural networks (e.g., ResNet50/EfficientNet) trained on curated datasets such as PlantVillage and field images. The pipeline covers image acquisition, preprocessing (resize, normalization, augmentation), model training with class-balanced sampling, and evaluation using accuracy, macro-F1, and confusion matrices. We further apply Grad-CAM to provide visual explanations, improving trust and interpretability. The system can be deployed as a lightweight web or mobile application to assist farmers and agronomists with on-device or edge inference.

I. INTRODUCTION

1.1 Overview

India and many agrarian economies experience substantial crop losses due to foliar diseases such as early blight, late blight, powdery mildew, and rust. Visual diagnosis by experts is accurate but scarce in rural settings; moreover, symptoms can be subtle and confounded by nutrient deficiencies or environmental stress. Recent advances in deep learning for computer vision enable robust image-based diagnosis directly from leaf photos captured by smartphones. This project targets automated classification of plant leaf diseases to aid farmers and extension workers.

1.2 Motivation

Timely disease identification reduces pesticide misuse, lowers costs, and improves yields. Automated tools can standardize diagnosis, reduce dependence on scarce pathologists, and provide decision support in vernacular contexts. With the proliferation of affordable smartphones and improved rural connectivity, an AI-driven solution can be impactful at scale.

1.3 Problem Definition and Objectives

Problem Definition: Build a system that classifies a leaf image into predefined classes (healthy + diseases) with high accuracy and provides interpretable heatmaps indicating symptomatic regions.

Objectives:

- Design a CNN-based classifier using transfer learning (e.g., ResNet50/EfficientNet).
- Create a reproducible data pipeline with augmentation and class balancing.
- Evaluate with accuracy, precision, recall, macro-F1, and confusion matrix.
- Provide Grad-CAM visual explanations.
- Package inference as a simple web/mobile interface for field use.

1.4 Project Scope & Limitations

Scope:

- Supervised multi-class classification on curated leaf images (e.g., PlantVillage).
- Training, validation, and testing using stratified splits.
- On-device/edge-ready inference using quantized models (optional).

Limitations:

- Lab-like datasets (plain backgrounds) may not fully reflect field variability.
- Class imbalance and visually similar diseases can reduce performance.
- Generalization to new cultivars or lighting requires domain adaptation.

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1.5 Methodologies of Problem Solving

Scope:
- Supervised multi-class classification on curated leaf images (e.g., PlantVillage).
- Training, validation, and testing using stratified splits.
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Limitations:
- Lab-like datasets (plain backgrounds) may not fully reflect field variability.
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II. LITERATURE SURVEY

Deep CNNs have achieved strong performance for plant disease identification. Mohanty et al. reported high accuracies on the PlantVillage dataset using AlexNet and GoogLeNet; subsequent works adopt transfer learning with ResNet/EfficientNet and add attention mechanisms for better localization. Field-deployable approaches incorporate domain adaptation and illumination normalization. Explainable AI methods such as Grad-CAM help visualize discriminative regions to build trust among agronomists.

III. SOFTWARE REQUIREMENTS SPECIFICATION

3.1 Assumptions and Dependencies

- Assumptions: Availability of labeled leaf images; images resized to 224x224; train/val/test split (80/10/10).
- Dependencies: PyTorch/TensorFlow, torchvision/keras, albumentations, scikit-learn, opencv, numpy, matplotlib.

3.2 Functional Requirements

- Upload leaf images or dataset folders.
- Preprocess and augment images.
- Train CNN with checkpointing.
- Evaluate and generate metrics/plots.
- Run single-image inference and output predicted class & confidence.
- Generate Grad-CAM heatmaps.

3.3 External Interface Requirements (If Any)

User Interfaces: Simple web UI to upload an image and view prediction with heatmap.
Hardware Interfaces: Standard CPU/GPU machine; optional mobile device for on-device inference.
Software Interfaces: REST API endpoints for inference; model files stored locally or on server.

3.4 Nonfunctional Requirements

3.4.1 Performance Requirements

Performance: <200 ms per image on GPU; <1 s on CPU (target).
Security: Sanitize uploads; no PII.
Reliability: Deterministic preprocessing; seed control.
Usability: Mobile-friendly UI; clear confidence and guidance messages.

3.4.2 Saystem Requirements

Software: Python 3.10+, PyTorch/TensorFlow, Flask/FastAPI, OpenCV.
Hardware: Minimum Intel i5/8GB RAM; GPU recommended for training.
Database: Not required; optional metadata store (SQLite/PostgreSQL).

3.5 Analysis Models

Agile iterative development with sprints for data, modeling, evaluation, and deployment.
Continuous error analysis guides augmentation and fine-tuning.

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IV. SYSTEM DESIGN

System Design Overview

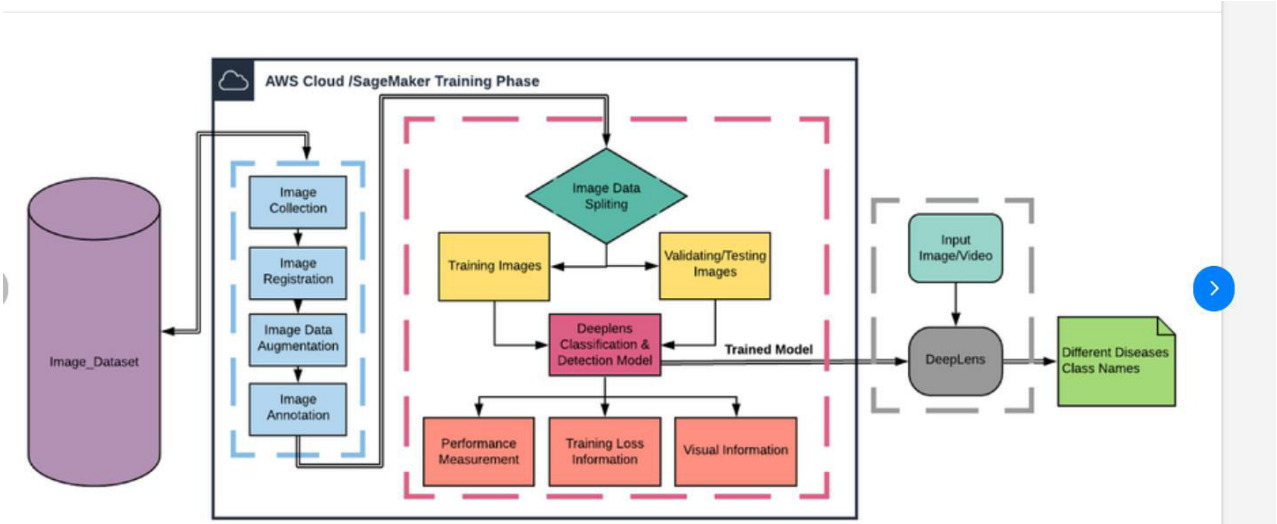
4.1 System Architecture

Modules: Data Loader → Augmenter → CNN Backbone (ResNet50/EfficientNet) → Classifier Head → Metrics & Logger → Grad-CAM → Inference API/UI. Data and model checkpoints stored in structured directories.

4.2 Mathematical Model

Given input image x, CNN f_θ outputs logits $z = f_\theta(x)$. Softmax yields class probabilities $p_i = \exp(z_i)/\Sigma_j \exp(z_j)$. Loss: weighted cross-entropy $L = -\Sigma_i w_i y_i \log p_i$ where w_i accounts for class imbalance. Prediction $\hat{y} = \text{argmax}_i p_i$. Grad-CAM uses gradients of target class score with respect to feature maps to compute heatmap.

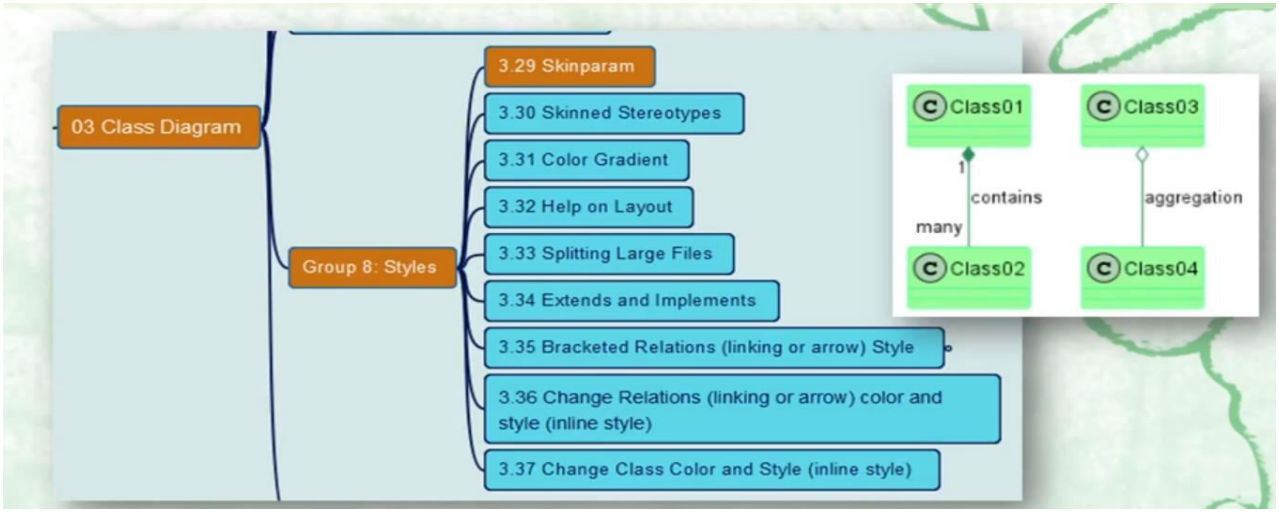
4.3 Data Flow Diagram



The data flow diagram of the DCDM that illustrates the process of our proposed disease diagnosis

4.4 UML Diagram

Entities: Image, Label, Model, Checkpoint, Metric. UML: Classes for DatasetManager, Trainer, Evaluator, InferenceService.



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V. PROJECT PLAN

5.1 Risk Management

Risk Identification: Class imbalance; overfitting; domain shift from lab to field; limited GPU resources; data licensing. Risk Analysis: High likelihood of overfitting on small classes; domain shift impacts generalization. Mitigation: Class-weighted loss, focal loss, heavy augmentation, mixup/cutmix, collecting field images, validation on held-out farms, model distillation for edge.

5.2 Project Schedule

Project Task Set: Requirement Analysis (2w), Data Preparation (2w), Modeling & Training (4w), Evaluation & Explainability (2w), Deployment Prototype (2w), Documentation (2w). Timeline tracked via Gantt chart.

VI. CONCLUSION

6.1 Conclusion

We developed the design for an end-to-end deep learning system to detect plant leaf diseases from images with emphasis on accuracy and interpretability. Transfer learning with modern CNNs, robust augmentation, and Grad-CAM explanations form the core. The approach is suitable for practical deployment as an assistive tool for farmers and agronomists.

6.2 Future Scope

Collect diverse field datasets; integrate few-shot domain adaptation; incorporate self-supervised pretraining; support multilingual advisory; on-device quantization (TensorRT, TFLite) and offline mode.

6.3 Applications

Smartphone-based crop advisory; greenhouse monitoring; extension worker toolkit; integration with precision agriculture platforms for targeted spraying.

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