PROJECT ABSTRACT

Plant Disease Detection using Transfer Learning

MobileNetV2 transfer-learning classifier that identifies crop diseases from leaf photos on the PlantVillage dataset, delivered as a built-to-order student project with code, notebook, report, PPT and viva kit.

01. Title

Plant Disease Detection using Transfer Learning

02. Introduction / Background

Plant diseases cut crop yields every season, and farmers often spot infections only after they have spread. Visual diagnosis by experts does not scale to every field. Transfer learning changes the economics of this problem: a convolutional network pre-trained on ImageNet already knows edges, textures and shapes, so fine-tuning it on leaf images reaches strong accuracy with tens of thousands - not millions - of labeled photos. This project fine-tunes MobileNetV2 on the PlantVillage dataset (54,303 leaf images, 38 crop-disease classes) and serves it through a leaf classifier demo with prediction explanations and treatment notes.

03. Problem Statement

Early, accurate identification of plant disease is the bottleneck in crop protection: extension officers cannot visit every farm, and misdiagnosis wastes pesticide and yield. The project builds a leaf-photo classifier that predicts the crop and disease (or healthy) with a confidence score, shows which leaf regions drove the decision via a Grad-CAM-style overlay, and displays a treatment note for the predicted condition.

04. Objectives

- Fine-tune MobileNetV2 (ImageNet transfer learning, two phases) on PlantVillage for 38-class crop-disease classification at 224x224 input.
- Reach a design target of approx. 90%+ validation accuracy, with the training notebook logging accuracy, per-class F1 and the confusion matrix on a held-out test split.
- Build a demo app with sample-leaf classification, top-3 predictions with confidence bars, region-influence overlay and a treatment-note panel.

- Deliver the complete student kit: source code, training notebook, report, PPT and viva Q&A document.

05. Proposed System / Working

The system has three stages. (1) Data pipeline: PlantVillage images are resized to 224x224 and split 70/15/15; training images get augmentation (rotations, flips, color jitter, random affine) and the loss is class-weighted to handle imbalance. (2) Model: MobileNetV2 pre-trained on ImageNet - phase 1 trains only the 38-way head for 5 epochs with the backbone frozen; phase 2 unfreezes the backbone and fine-tunes for about 15 epochs at a low learning rate with cosine decay. Every epoch logs accuracy, loss and per-class F1. (3) Demo application: the app classifies a leaf image, shows the top-3 classes with confidence bars, overlays a heatmap of influential regions, and displays a treatment note for the top prediction.

06. Technologies / Components Used

- Python 3.10, TensorFlow/Keras with MobileNetV2
- NumPy, scikit-learn (metrics, confusion matrix)
- Matplotlib, Seaborn (curves, per-class analysis)
- Flask-compatible inference module; single-file HTML/CSS/JS demo app
- PlantVillage dataset - Hughes & Salathe (54,303 images, 38 classes, 14 crops)
- Trained weights shipped as .h5 from the included training run

07. Key Features

- 38-class crop-disease classification from a single leaf photo
- Top-3 predictions with confidence bars
- Region-influence overlay showing which leaf areas drove the decision
- Treatment note panel per predicted disease
- Two-phase transfer-learning notebook with logged curves
- Class-weighted training to handle dataset imbalance

08. Applications / Use Cases

- Farmer-facing disease screening demos (prototype scope)
- Teaching material for transfer learning, augmentation and fine-grained classification
- Reference build for other agricultural vision tasks (pest detection, ripeness)
- Extension-service prototype for crop clinics

09. Results & Scope

The deliverable is a design-target-driven build, not a pre-measured product. The training notebook computes accuracy, per-class F1 and the confusion matrix on the held-out test split; the report presents these as the build's measured results. The design target is approx. 90%+ validation accuracy. Scope is classification of the 38 PlantVillage classes from single leaf photos shot in controlled conditions - field photos with cluttered backgrounds are harder, similar-looking diseases (early vs late blight) are the main confusion source, and the system is an educational prototype, not a substitute for agronomist diagnosis.

10. Conclusion

Plant Disease Detection using Transfer Learning delivers a complete applied vision project: a real agricultural problem, the standard PlantVillage benchmark, a MobileNetV2 model fine-tuned through a fully logged two-phase experiment, and a demo app that makes the result visible in seconds. The imbalance handling, Grad-CAM overlays and honest field-photo discussion give the student rich, defensible material for the report and viva.

11. References

- Hughes, D. P. and Salathe, M. - An open access repository of images on plant health to enable the development of mobile disease diagnostics (arXiv:1511.08060); PlantVillage dataset.
- Sandler, M. et al. - MobileNetV2: Inverted Residuals and Linear Bottlenecks (CVPR 2018).
- Selvaraju, R. R. et al. - Grad-CAM: Visual Explanations from Deep Networks (ICCV 2017).
- TensorFlow/Keras applications documentation - MobileNetV2 transfer-learning guide.