Capstone Thesis Document

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Created time	@June 25, 2025 5:01 PM
Last edited time	@June 25, 2025 5:27 PM
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1. Context and Motivation

In rural India, timely identification of plant diseases remains a major challenge for small-scale farmers, leading to **crop losses up to 100%** during outbreaks and threatening food security and livelihoods (arxiv.org). Smartphone penetration crossed **5 billion users by 2020**, and mobile broadband reached **69% coverage** globally (arxiv.org)—making AI-powered smartphone diagnostics more accessible than ever, even for small-scale farmers.

However, while numerous AI tools for plant disease detection exist—and many demonstrate impressive accuracy in controlled environments—they often fall short in **three critical aspects** when applied in real-world farming contexts: (1) **reliance on internet connectivity**, which remains intermittent or costly for many rural users; (2) **lack of contextual adaptation**, as many tools are trained on non-regional crops (especially for Indian crops) or assume ideal image conditions (test accuracy); and (3) **poor explainability**, where predictions are presented without interpretable justification.

Tools like **Plantix** or **Nuru** have shown impact in certain regions, but evaluations show that users still struggle with partial leaf input, non-standard disease appearances, or understanding what action to take. Furthermore, **peer-reviewed benchmarks (e.g., Mohanty et al., 2016)** indicate that models trained on curated datasets can see performance drop by **up to 70%** when tested on field conditions—suggesting that *accuracy alone* does not guarantee *utility*. This project does not seek to reinvent what works, but rather to **adapt and extend** those models into a **modular, explainable, and robust pipeline** specifically designed for real-world usability in India’s resource-constrained agricultural settings.

Inspired by direct conversations with distressed farmers near Sullurpeta and validated through our national hackathon win, this capstone seeks to build **PlantGuard** — an app-based, modular AI system that detects plant diseases offline, explains its predictions, and delivers actionable insights in a user-friendly, multilingual interface.

2. Related Work

Mohanty et al. (2016) used transfer-learning with CNNs (AlexNet, GoogLeNet) on the PlantVillage dataset (54,306 images across 26 diseases, 14 crops), achieving **99.35% accuracy**, though it dropped to **31.4%** when tested on field-like images (researchgate.net). Subsequent studies leveraged architectures like EfficientNet, Xception, and MobileNet, sustaining above **97% accuracy** but still trained on synthetic or lab data . Visual explainability techniques like Grad-CAM (Selvaraju et al., 2017) reveal which image regions influence CNN decisions, improving user trust and error analysis (arxiv.org). Yet, the integration of explainability with modular pipelines (leaf detection → crop ID → disease classification) remains rare in agriculture-focused tools, especially when evaluated under real-world conditions.

3. Research Problem Statement

Despite high lab-based performance, current plant disease models **fail in trust, explainability, and deployment** aspects:

- **Trust**: Outputs lack confidence estimations or fail gracefully in noisy or unseen settings.
- **Explainability**: Farmers see a label but not *why* — making it difficult to act.
- **Deployment**: Tools need full offline functionality, multilingual support, and responsiveness across conditions.

Therefore, this thesis will explore:

> How can we design a modular, explainable, and robust plant disease detection pipeline that generalizes to real-world conditions, offers actionable explanations, and remains accessible for resource-limited farmers?

4. Solution Approach & Methods

The proposed system follows a **modular classification pipeline**, combining classical CNN-based techniques with transformer-based models for experimentation and benchmarking:

1. **Leaf Detection**

   A lightweight YOLOv5 model verifies that the input image contains a valid, centered leaf and crops it for downstream use.

2. **Crop Identification**

   A **ResNet-50** model (transfer learning) classifies the plant type using a fine-tuned model on PlantVillage + real-world augmentations. In parallel, we explore **Vision Transformers (ViTs)** — particularly **DeiT** and **ViT-B/16** — which offer strong spatial attention capabilities and robustness under occlusion and lighting noise. ViTs remain underutilized in agriculture, and this project critically evaluates their potential in this context.

3. **Disease Classification**

   Once the plant is identified, a disease-specific classifier (ResNet or ViT, based on comparative performance) predicts the condition. Grad-CAM is used for CNNs, while **attention map visualization** is implemented for ViTs to maintain interpretability.

Each step produces a **confidence score** and, where applicable, a **visual explanation overlay** (e.g., Grad-CAM or attention map) that shows which regions influenced the model's decision. The multilingual frontend presents outputs in an intuitive, farmer-friendly format, including:

- Detected plant and disease
- Confidence score (e.g., 94%)
- Heatmap or attention overlay
- Suggested actionable steps (e.g., “Use copper-based fungicide”)

5. Validation Strategy

To evaluate PlantGuard’s performance and generalizability:

- **Accuracy**: Top-1 and top-3 accuracy on real-world datasets, including augmented samples (blur, poor lighting, occlusion, rotation).
- **Model Benchmarking**: Direct comparison between **ResNet** and **ViT variants** for disease classification accuracy, robustness to noise, and computational efficiency.
- **Explainability Effectiveness**: Conduct small-scale studies ($n \approx 10$) with users evaluating the system **with and without visual explanation overlays**, measuring trust and perceived clarity.
- **Robustness**: Measure output stability under field-simulated degradation.
- **Modularity/Generalizability**: Add a new crop and disease category to assess plug-and-play ability and retraining

requirements.