Intelligent Pesticide Sprinkling System

Determined by Infection Level of a Plant

TEAM GENESIS

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Problem Statement

1. Plant diseases reduce crop yield significantly.
2. Farmers often use pesticides uniformly → wastage, cost, health & environmental risks.
3. Lack of tools to quantify infection level → spraying decision is guesswork.
4. **Need: A Deep Learning model that detects infection levels of plants from images and assists in smart pesticide application.**

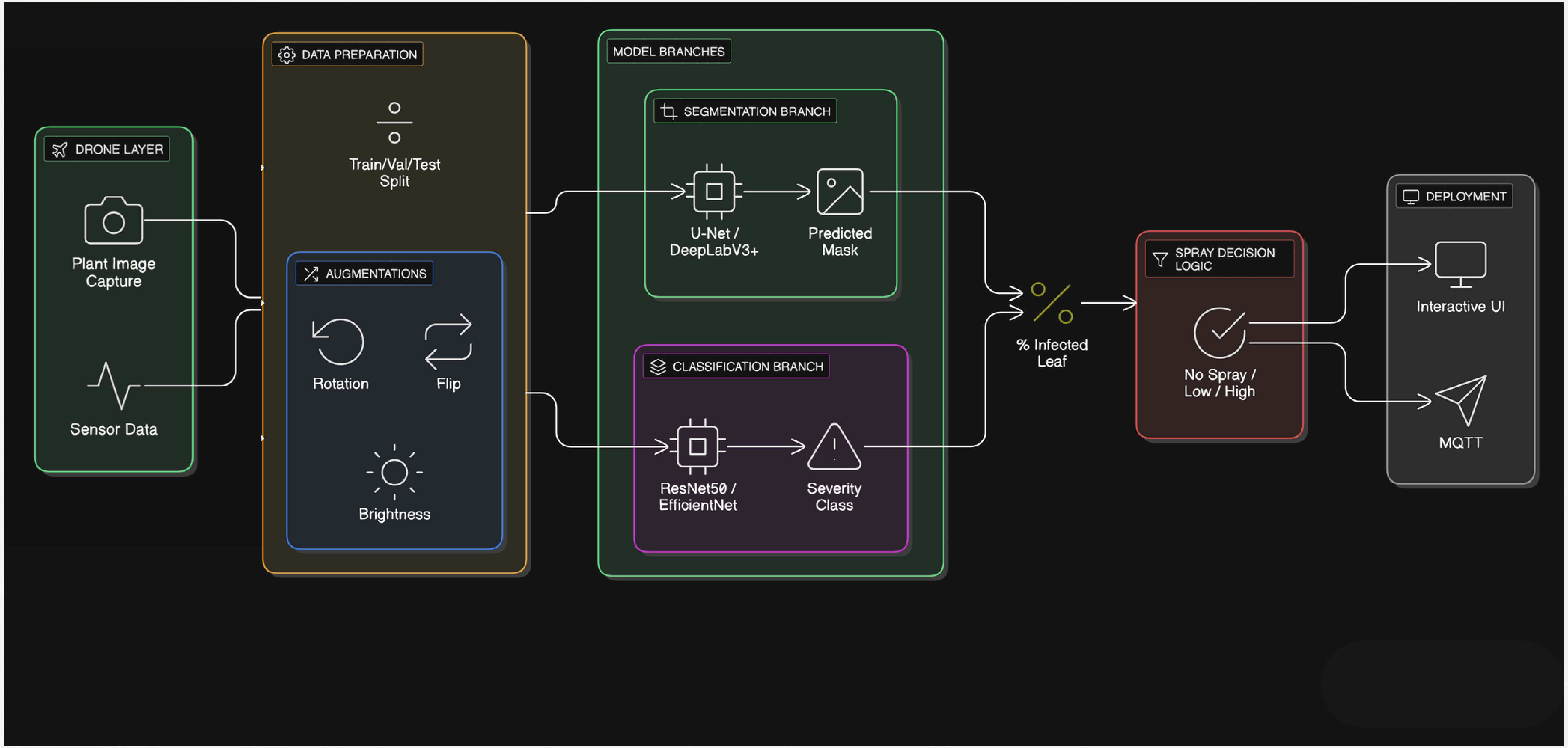
Abstract

- This project applies Deep Learning in Agriculture for infection detection and severity analysis.
- Datasets (PlantSeg, NWRD, DiaMOS) are used for training models.
- **Segmentation models detect infected regions (**where).
- **Classification models determine infection severity** (how much).
- Infection percentage is used as decision logic for spraying.
- This can later integrate with IoT/Drone systems for automation.

Literature Review

- **PlantSeg** → Large in-the-wild dataset with pixel-level segmentation masks for plant diseases, used to calculate infected regions.
- **NWRD (NUST Wheat Rust Disease)** → Real field images of wheat with detailed rust infection masks, useful for severity estimation at field scale.
- **DiaMOS Plant** → Image dataset of diseased leaves with severity levels (low–high), used for classification of infection intensity.
- **Gap**: Most focus on single datasets, offline analysis and many models classify disease but don't calculate infection severity for spraying decisions.
- Whereas our project integrates three datasets and computes infection percentages for real-time actionable decisions like spraying.
- **Multi-dataset training → segmentation → infection-level estimation → spray decision pipeline**.

Architecture Diagram



Proposed Methodology

1. **Dataset Preparation**
   - DiaMOS → Classification (severity levels: none/mild/moderate/severe).
   - PlantSeg + NWRD → Segmentation (pixel-level infection masks).
   - Data Augmentation: rotations, flips, brightness/contrast, random crops, Gaussian noise (use albumentations).
2. **Model Selection**
   - Classification: ResNet50 or EfficientNet (transfer learning) → predict severity class.
   - Segmentation: U-Net (EfficientNet-B0 encoder) or DeepLabV3+ → generate infection masks.
3. **Training Process**
   - Loss Functions: Cross-Entropy (classification), Dice Loss ± BCE (segmentation).
   - Optimizer: Adam.
   - Validation: Early stopping, monitor validation loss, train/val split.
   - Batch size: 8–16 (GPU dependent), input size ~512×512.
4. **Evaluation Metrics**
   - Classification: Accuracy, Precision, Recall, F1-score, Confusion Matrix.
   - Segmentation: IoU/Jaccard, Dice Score, visual inspection of predicted masks.
5. **Result Analysis**
   - Compare classification vs segmentation performance.
   - Compute infection percentage from segmentation masks → map to spray/no-spray decisions.
   - Validate ability to generalize across datasets.