On the fly plant disease Detection and geotagging using Drone

Group No.: 3

Course Code : AR511

Title: Autonomous Mobile Robots

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Date : 7 Nov. 2025

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Introduction

Problem Statement:

Design and implement an autonomous UAV system that uses deep-learning–based visual analysis to detect crop diseases in real time and perform precision spraying of agrochemicals only on affected areas. The system must integrate multispectral imaging, onboard inference, and a variable-rate spraying mechanism to optimize resource utilization and minimize environmental impact.

Literature Review

Existing Method	Key features	Limitations	Reference
Broad literature survey (Scopus, 2004–2022) summarizing UAV platforms, sensors, flight control, and agri-applications.	• Covers full UAV tech stack — from hardware to software and farm use-cases. • Includes trend & bibliometric analysis showing rapid research growth. • Practical checklists for payload, endurance and cost trade-offs.	• Purely descriptive – no performance metrics or quantitative comparison • Limited discussion on regulations and real-field reproducibility.	**Toscano et al., 2024** *“Unmanned Aerial Vehicle for Precision Agriculture: A Review*
Comparative review linking satellite and UAV sensing; analyzes data collection, applications and socio-economic adoption.	• Clearly contrasts satellite vs UAV capabilities (resolution, revisit, cost). • Highlights integration with IoT, RL, multi-UAV systems. • Discusses adoption, training, and policy aspects — good big-picture view.	• Narrative review – no defined search protocol or PRISMA flow. • Lacks quantitative meta-analysis of accuracy/performance. • Technical details on advanced methods kept high-level.	**Phang et al., 2023** *“From Satellite to UAV-Based Remote Sensing: A Review on Precision Agriculture”*
Systematic Literature Review (SLR) of 1,852 papers → 38 studies (using Kitchenham QA and structured extraction).	• Methodologically strong – clear inclusion/exclusion and quality scoring. • Focused on disease detection: CIR/RGB imagery, CNNs dominant. • Lists 38 primary experiments → good map of current work.	• Search string narrow → may miss papers with different terminology. • No meta-analysis of accuracy values. • Excludes non-English studies; minor bias possible.	**Chin et al., 2023** *“Plant Disease Detection Using Drones in Precision Agriculture”*

Literature Review

Existing Method	Key features	Limitations	Reference
UAV-based RGB imaging (4 mm/pix) → Object-Based Image Analysis (OBIA) → extraction of 49 spectral, geometric, and textural features → classification using a **Multilayer Perceptron (MLP)** into *soil / shadow / broad-leaf / grass weeds*.	• Demonstrates **low-cost RGB** sensing can separate broad-leaf vs. grass weeds early in the season. • Employs **object-oriented segmentation** (multiresolution) instead of pixel classification — captures shape and context. • Integrates **height (CHM)** and texture features; interpretable variable-importance analysis. • Tested on **real commercial fields** (sunflower & cotton) with 78–84 % overall accuracy.	• Limited labeled data (30 plots × 1 m²) and **single-expert annotation** → restricted generalization. • Random data split (no spatial cross-validation) inflates accuracy. • Sensitive to segmentation parameters and lighting conditions. • Classical MLP + handcrafted features — lacks modern **CNN/transfer-learning** comparison. • Only early growth stage evaluated.	**Torres-Sánchez et al., Agronomy (2021)***Early Detection of Broad-Leaved and Grass Weeds in Wide-Row Crops Using ANN and UAV Imagery*

Literature Review

Existing Method	Key features	Limitations	Reference
Systematic Quantitative Literature Review (SQLR) of 103 peer-reviewed papers (2013–2022) from Scopus + WoS, analyzing UAV use for plant-disease detection across sensors (RGB, MS, HS, Thermal) and algorithms (ML, DL, index-based).	• Transparent **PRISMA-compliant methodology**; reproducible search pipeline. • Quantifies research trends → >90 % papers after 2018, **Asia > Europe > NA** in output. • Identifies **dominant sensors** (RGB/MS) and rising **deep-learning** adoption (CNN, U-Net, ResNet). • Provides actionable roadmap: sensor-fusion, annotated datasets, real-time onboard inference, and ethics/data-sharing standards.	• Search string ("UAV AND plant AND disease") may omit domain synonyms → partial coverage. • High **heterogeneity** among primary studies — prevents meta-analysis of accuracy metrics. • Lacks quantitative weighting of sensor-performance trade-offs. • Does not empirically validate proposed frameworks.	**Kouadio et al., Remote Sensing (2023)***A Review on UAV-Based Applications for Plant Disease Detection and Monitoringn Agriculture"*
Integrative survey of **image-processing + machine learning + deep-learning** approaches for weed detection using ground & UAV imagery (RGB, MS, HS). Categorizes by processing level (pixel, object, patch), and task (detection, segmentation, classification).	• Presents **taxonomy** linking classical and DL-based pipelines. • Benchmarks traditional ML (SVM, RF, KNN) vs. CNN and semantic-segmentation (U-Net, DeepLab, Mask R-CNN) .• Highlights the shift from manual features → end-to-end DL with improved robustness to background noise. • Discusses **dataset challenges, domain transfer, illumination variability**, and sensor integration	• Reported results derived from **small, non-standard datasets** → limited comparability. • Many primary works lack **spatially independent or real-field validation**. • Annotation inconsistency and scarce public datasets hinder DL scalability. • Calls for **benchmark creation, data-augmentation strategies, and multisensor fusion** research.	**Wu et al., Computers & Electronics in Agriculture (2021)***A Comprehensive Review of Weed Detection Methods Based on Computer Vision*

Literature Review

Existing Method	Key features	Limitations	Reference
UAV-based RGB imaging (0.35 cm/pixel) → vegetation segmentation → crop-row detection (skeletonization + Hough) → SLIC superpixel masking for auto crop/weed labeling → unsupervised dataset generation → **ResNet-18 (transfer learning)** for weed classification → weed probability mapping via sliding-window inference.	• Fully automatic deep-learning pipeline using UAV RGB images. • Eliminates manual labeling through unsupervised data generation. • Combines classical vision (ExG, Hough) with modern CNN (ResNet-18). • Achieves near-supervised accuracy (≤6 % difference).	• Depends on regular row geometry and accurate line detection. • Tested only on RGB; lacks multispectral robustness. • Slight over-detection at row edges and shadowed zones. • Evaluated on limited crops (bean, spinach).	**Bah, Hafiane & Canals.***"Deep Learning with Unsupervised Data Labeling for Weed Detection in Line Crops in UAV Images"* (*Remote Sensing*, 2018)"
Deep Learning (CNN-based) fruit detection and yield-estimation studies . RGB/UAV orchard images → manual fruit annotation + augmentation → CNN-based detection (YOLO, SSD, Faster R-CNN) → fruit counting + yield estimation → evaluation.	• Evaluates CNNs, YOLO, SSD, Faster R-CNN for fruit counting & yield prediction • Explains training, augmentation, transfer learning • Benchmarks metrics (mAP, F1, IoU) • Highlights dataset creation and annotation issues	• Review only – no UAV/IoT implementation • Occlusion & lighting remain open issues • Dataset scarcity and poor generalization across crops	**Koirala, Anish, et al**. "Deep Learning–Method Overview and Plant Disease Detection Applications."

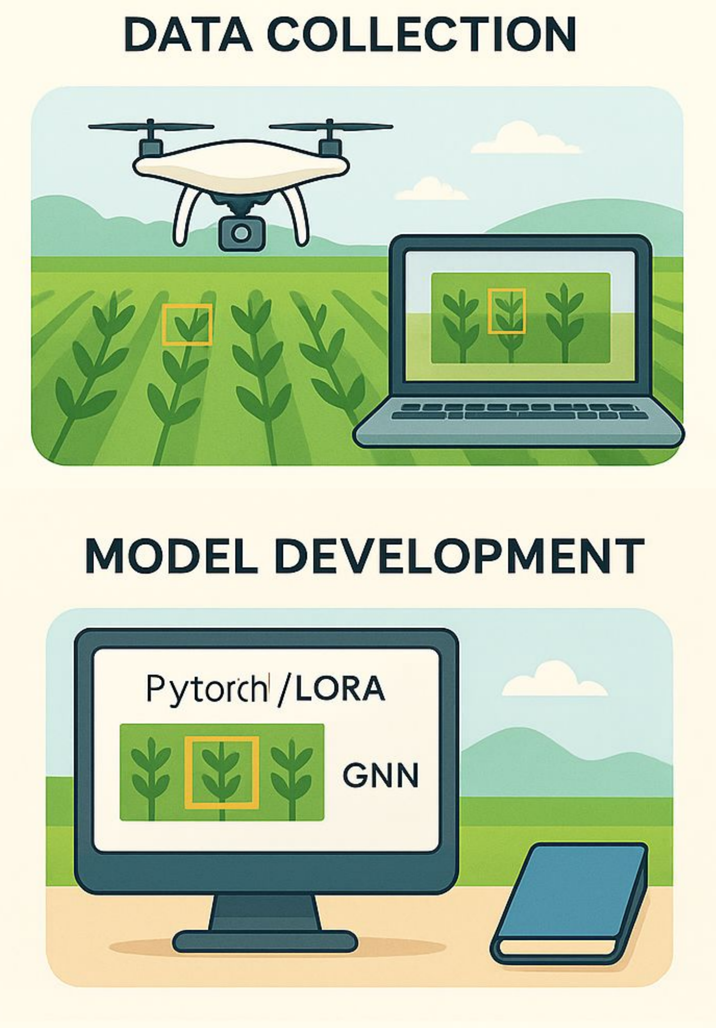
Literature Review

Existing Method	Key features	Limitations	Reference
Object-Based Image Analysis (OBIA) using multispectral UAV imagery and rule-based classification.	• UAV-based multispectral imaging (6 bands) • Automatic **crop row detection** to separate maize and weeds • High spatial resolution (cm-level) • Weed density maps for **site-specific spraying**	• No deep learning (manual rule creation) • Offline processing — **not real-time** • Limited adaptability across crop types • Single modality (multispectral only)	**Peña et al. (2013)***Weed Mapping in Early-Season Maize Fields using OBIA of UAV Images*
Comprehensive **survey of AI + UAV integration** for precision agriculture	• Reviews ML and DL models (SVM, CNN, ResNet, UNet, etc.) • Covers UAV platforms, sensors (RGB, multispectral, hyperspectral) • Discusses data pipelines, training, and evaluation metrics • Identifies challenges (datasets, computation, generalization)	• No real implementation • Lacks experimental validation • Focuses mainly on summarizing previous studies	**Su, Jinya et al.** “AI meets UAVs: A survey on AI empowered UAV perception systems for precision agriculture.”

Proposed Method

- **DATA COLLECTION**
  - RGB image capture via drone
  - Agricultural dataset sourcing
  - Autonomous flight patterns
  - Manual annotation using LabelImg
  - Tensor conversion for training

- **MODEL DEVELOPMENT**
  - Framework: PyTorch Object Detection API
  - Architecture: YOLO SAM+LORA, GNN
  - Technique: Transfer Learning & Fine-tuning
  - Classes: Healthy, Diseased, Multiple Diseases
  - Tools: Google Cloud



Proposed Method

- **GEOTAGGING & MAPPING**
  - Bounding box to GPS coordinate mapping
  - Area-based tagging (polygons, not points)
  - Affected zone calculation
  - Shapefile generation for spraying regions

- **DEPLOYMENT**
  - TensorFlow Lite for edge inference
  - WebAPP for remote monitoring
  - Android APP for field operations
  - Cloud container for data management
  - Real-time processing pipeline

Proposed Method

SYSTEM WORKFLOW

PHASE 1: DATA ACQUISITION

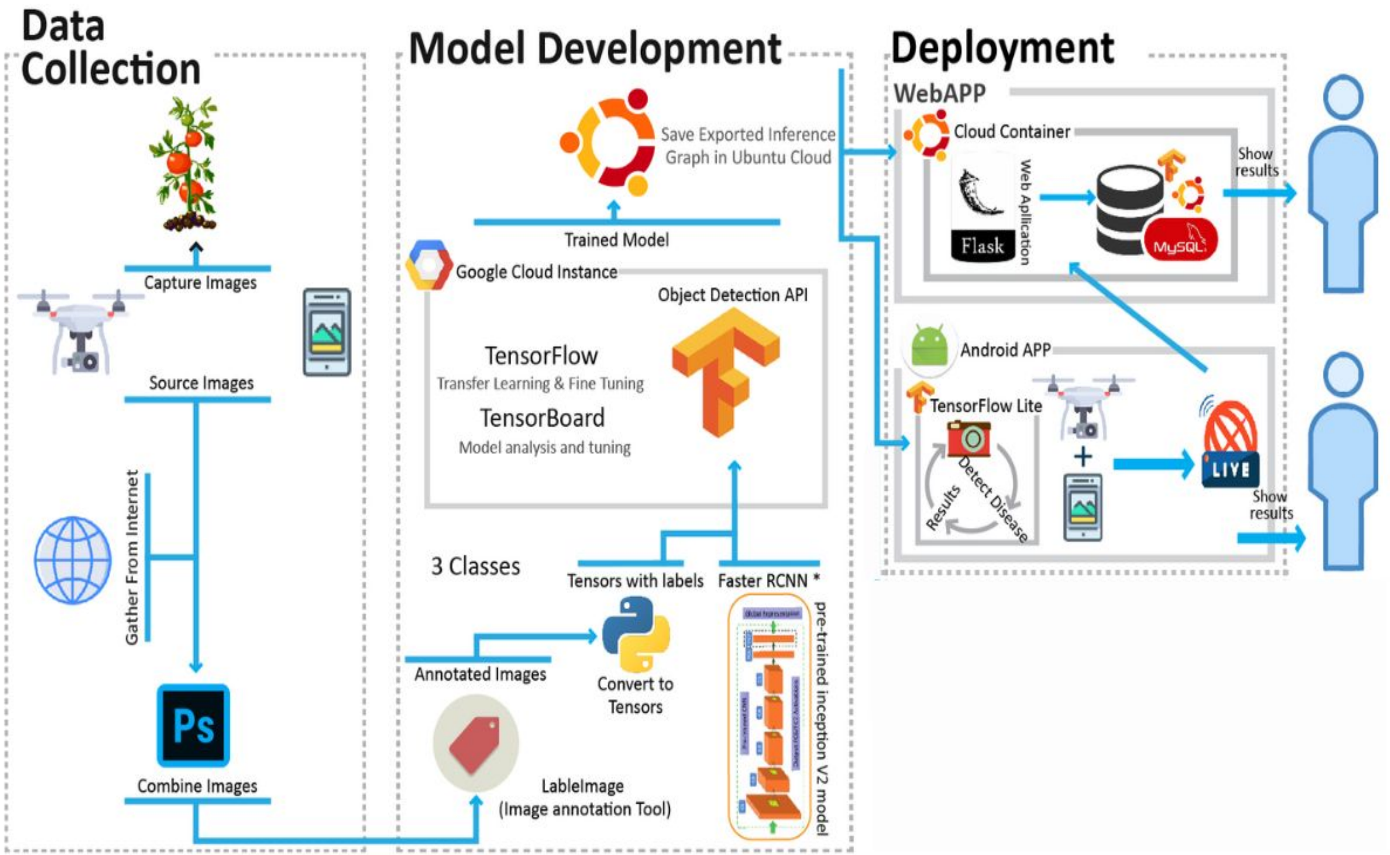
Agricultural Field → Autonomous Flight Mission → Image Capture → Real-Time Preprocessing

PHASE 2: ON-BOARD ANALYSIS

Deep Learning Inference (Disease Detection) → Geotagging (GPS Sync)

PHASE 3: DATA MANAGEMENT

Geospatial Database Logging → GIS Visualization Dashboard → Farmer



Client Server model

Client–Server Model

Client (Flutter App)

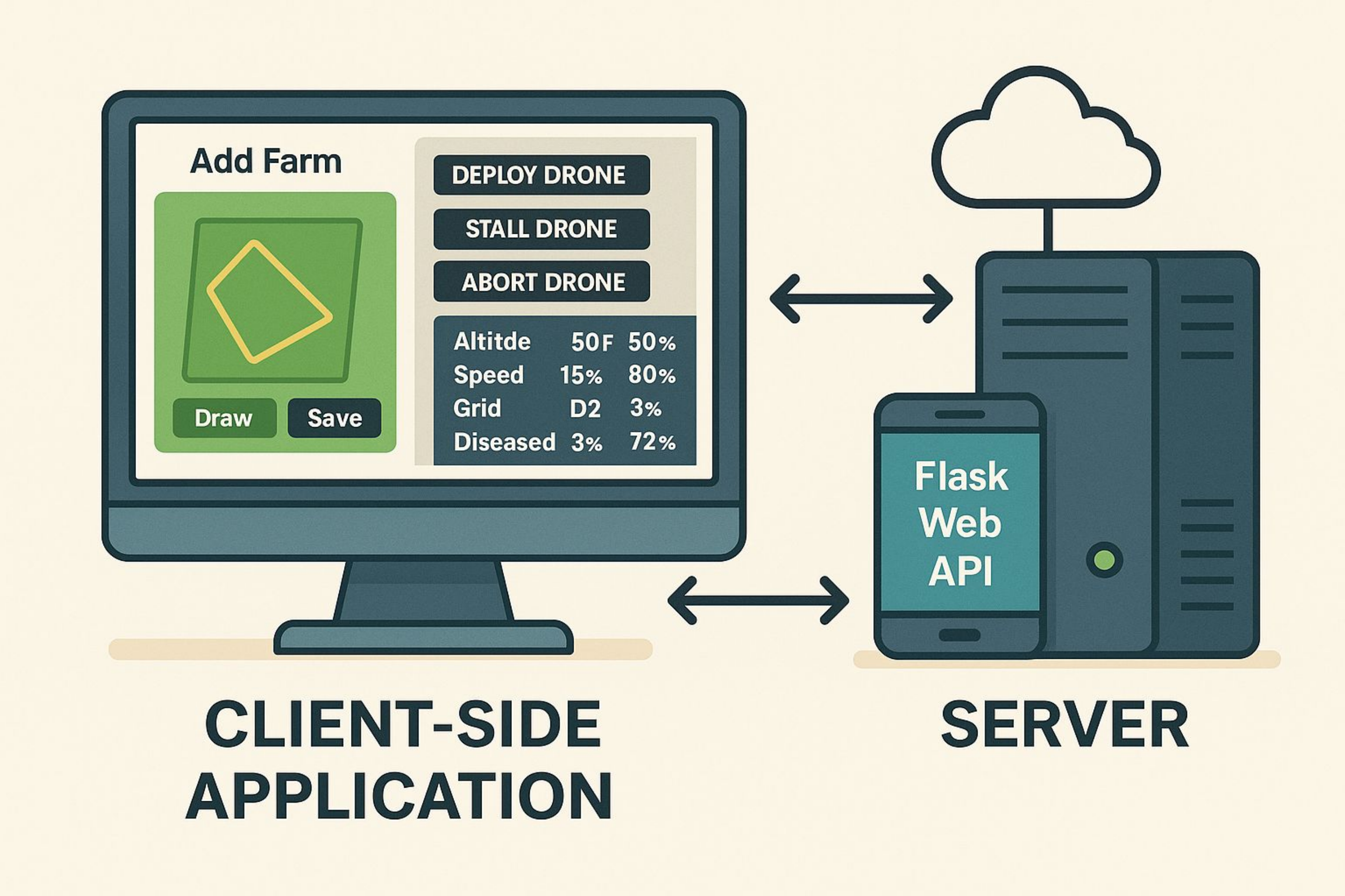
- Cross-platform (desktop/mobile)
- **Add Farm:** mark boundaries, save to DB
- **Monitor Farm:** deploy/stall/abort drone, view live stats

Server (Flask + SQL + Azure)

- Flask API links app, drone & database
- Manages data, ensures integrity, enables scalability

Drone & Simulator

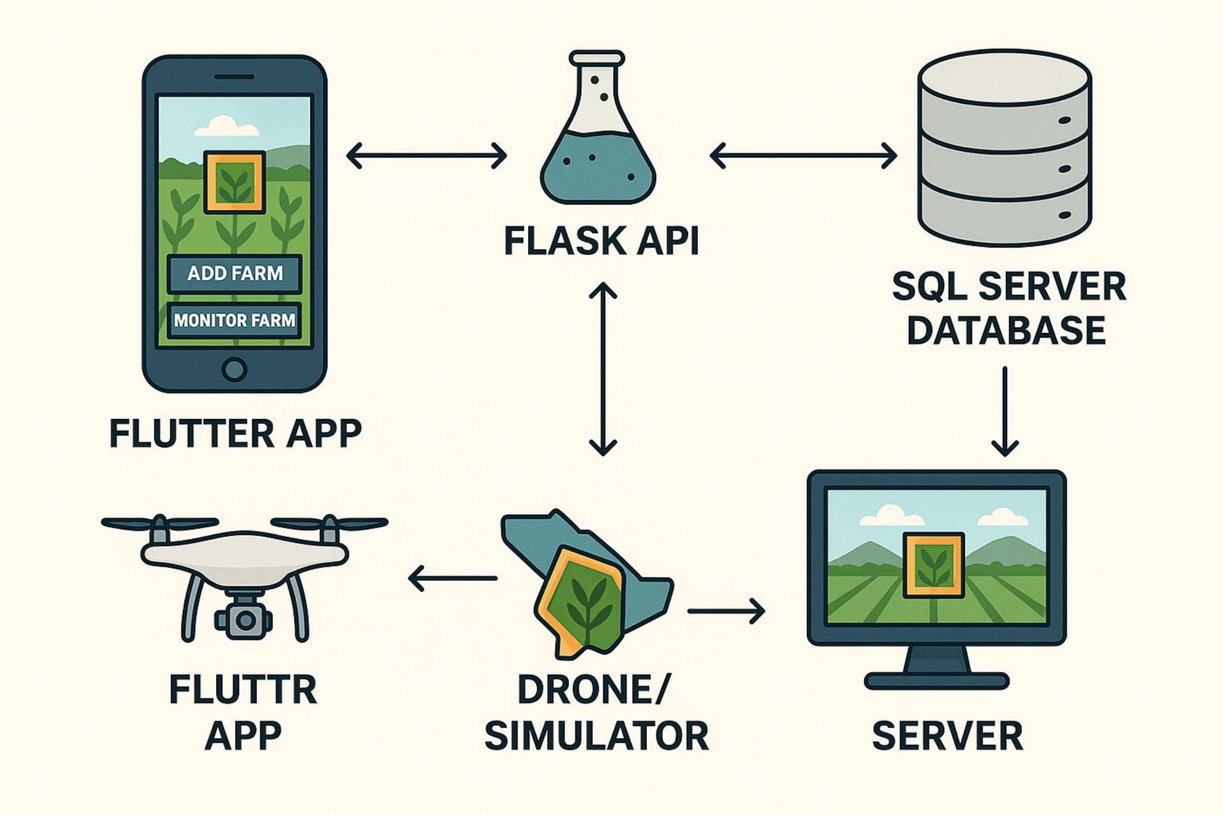
- Drone fetches grids & uploads imagery
- 3D simulator: AWSD control, live camera feed, disease detection



Client Server model

Data Flow

App ↔ Flask API ↔ SQL Server ↔ Drone/Simulator



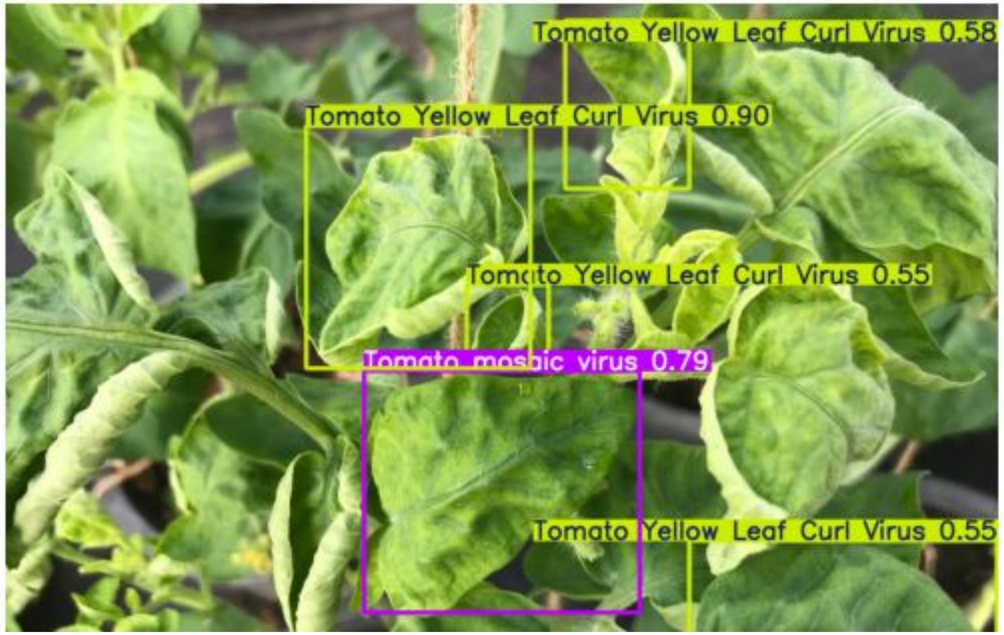
Highlights

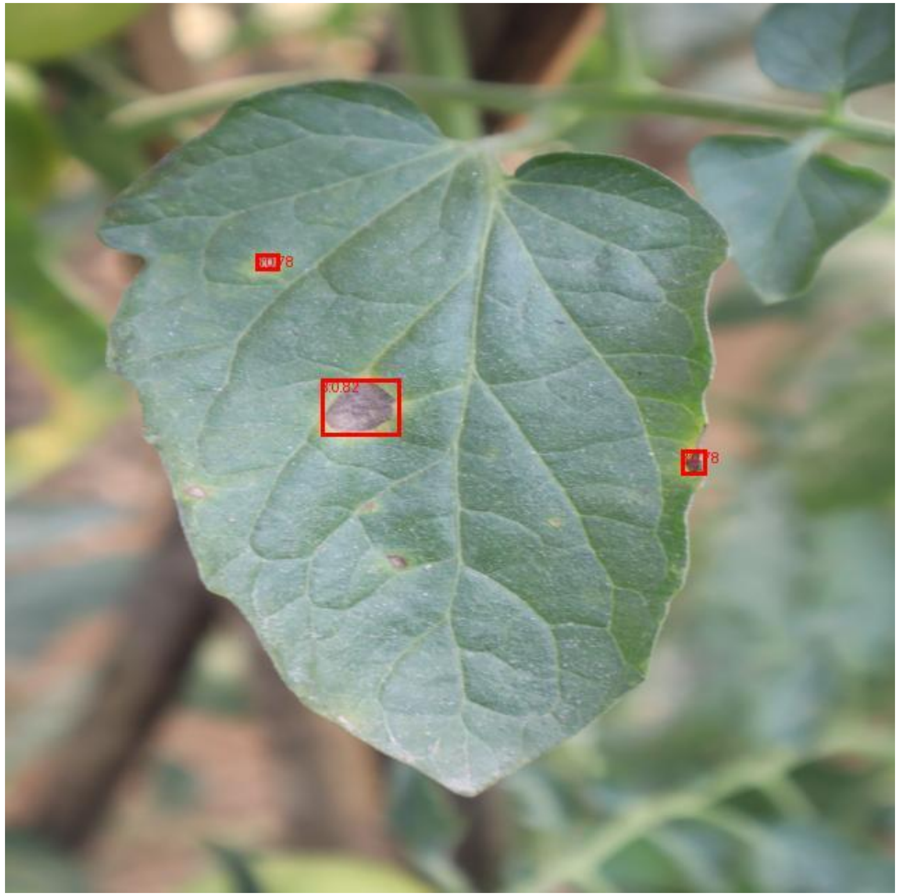
- Real-time monitoring
- Scalable & reliable
- Interactive 3D visualization

Initial Results

```
0: 448x640 4 Tomato Yellow Leaf Curl Viruss, 1 Tomato mosaic virus, 12.8ms
Speed: 2.3ms preprocess, 12.8ms inference, 1.5ms postprocess per image at shape (1, 3, 448, 640)
```

Prediction Result





Thank you