Agriculture-Vision

22 October 2025
CS-477 Computer Vision

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INTRODUCTION

Advancements in computer vision and deep learning have opened new possibilities for precision agriculture, enabling automated monitoring of crop growth, disease detection, and yield estimation. Traditional methods of crop inspection are labour-intensive and often fail to provide timely insights into plant health, especially across large farmlands. Vegetation indices such as the Normalized Difference Vegetation Index (NDVI) are widely used to quantify vegetation vigour and stress, but their computation typically requires costly multispectral or near-infrared sensors.

This project aims to overcome that limitation by combining deep learning–based object detection with dataset based NDVI estimation to deliver a low-cost, real-time crop health monitoring solution. Using a YOLO (You Only Look Once) model trained on the **PlantVillage** dataset and validated with NDVI ground truth from the **SEN12MS** dataset, the system will detect crops or diseased leaves and estimate vegetation health using only RGB imagery. The trained model will be optimized and deployed on an **NVIDIA Jetson Nano**, demonstrating the feasibility of performing intelligent agricultural analysis on compact, energy-efficient hardware suitable for field deployment.

Literature Review

Recent advancements in computer vision and deep learning have transformed the field of precision agriculture by enabling automated crop monitoring, vegetation-index computation, and real-time inference on embedded devices.

Wang et al. (2022) proposed a lightweight YOLOv5 model optimized for plant disease detection, achieving a balance between accuracy and speed suitable for edge hardware deployment a methodology closely aligned with this project's implementation approach. The Agriculture-Vision dataset introduced by Chiu et al. (2020) provided a large-scale foundation for aerial agricultural image analysis and vegetation-index benchmarking, establishing an important resource for model training and evaluation. Building upon these developments, Sheng et al. (2020) presented a state of-the-art approach integrating a generalized vegetation index (GVI) into deep models to improve segmentation accuracy in agricultural land-cover tasks.

Recent Works

In summary, recent research shows that deep learning particularly YOLO based models combined with vegetation indices like NDVI offers powerful tools for precision agriculture. Studies highlight the effectiveness of UAV and multispectral data, the adaptability of lightweight models for edge devices such as Jetson Nano, and the strong correlation between vegetation indices and crop health. Collectively, these works validate the feasibility of real-time, embedded crop-health monitoring systems.

Feasibility Analysis

1. Hardware Feasibility

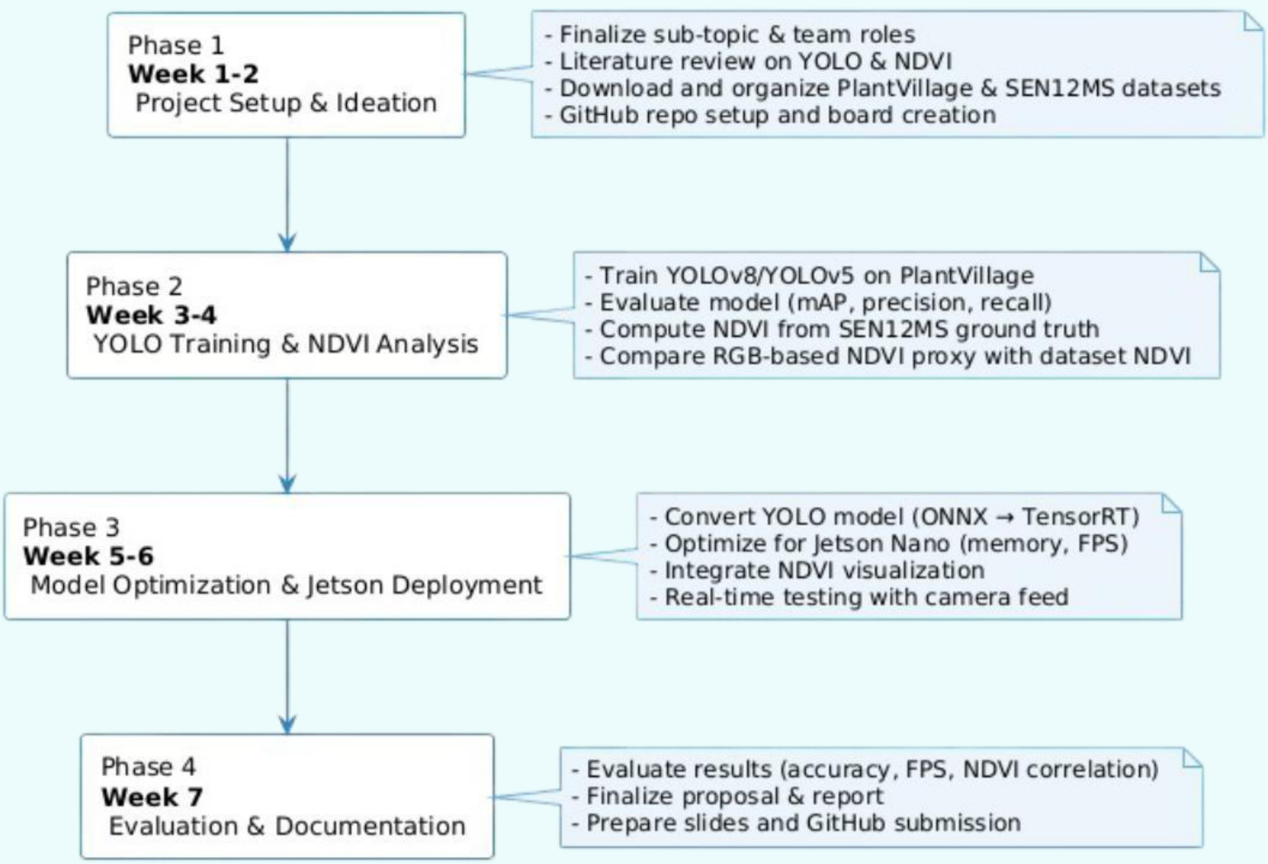
Item	Specification	Relevance
Processor	Quad-core ARM CortexA57 @1.43 GHz	Handles real-time control and I/O tasks
GPU	128-core NVIDIA Maxwell	Supports CUDA acceleration for YOLOv5/v8 inference
RAM	4 GB LPDDR4	Sufficient for lightweight models (YOLOv5s, YOLOv8n)
Supported Frameworks	PyTorch, TensorRT, OpenCV, CUDA 10.x	Required toolchain available in JetPack SDK
Power Requirements	5 V ⎓ 4 A	Compatible with standard adapters and lab setup

2. Dataset Feasibility

Dataset	Description	Usage in Project	Size and Format	Availability
PlantVillage	~50k RGB images (14 crops, healthy + diseased)	YOLO model training and validation	1–2 GB (JPEG)	Public (Kaggle / Penn State)
SEN12MS	Multispectral (RGB + NIR) Sentinel-2 imagery with NDVI ground truth	NDVI estimation, correlation study	280k image patches (256×256)	Public on GitHub

The Jetson Nano, equipped with a 128-core NVIDIA Maxwell GPU and 4 GB of LPDDR4 RAM, provides sufficient computational capacity for employing lightweight YOLO variants such as YOLOv8-nano or YOLOv5s. Its compatibility with CUDA, cuDNN, and TensorRT ensures smooth inference acceleration and real-time processing within the owner and thermal limits of the embedded platform. For datasets, the plant Village collection offers over 50,000 RGB images of healthy and diseased leaves suitable for YOLO training, while the SEN12MS dataset supplies multispectral imagery with NDVI ground truth to validate vegetation health indices. Both datasets are open-source, well- annotated, and easily accessible through Kaggle and GitHub, enabling reproducible experimentation without the need for additional sensors. Overall, the hardware and dataset combination is technically feasible and fully supports the proposed system's training and deployment goals.

Project Timeline



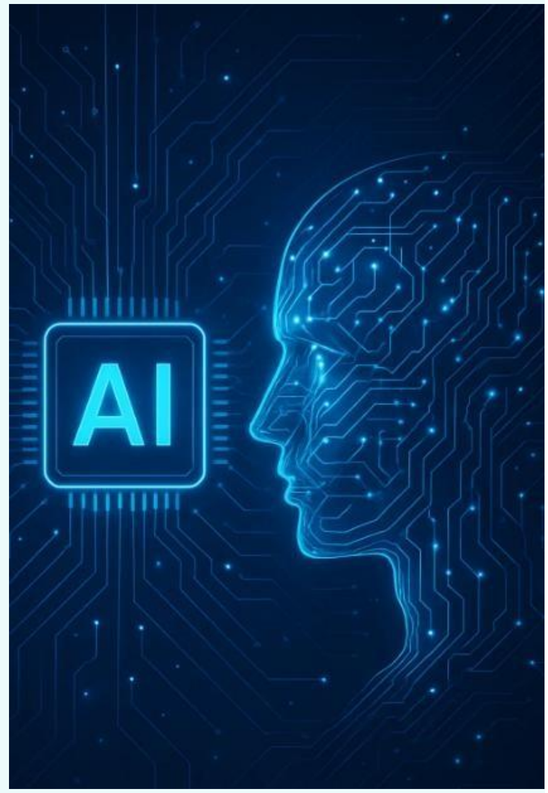
Team Responsibilities

Member Name	Role/ Domain	Core Responsibilities	Key Deliverables
M. Sufyan Haider	Algorithms and Simulations	Train YOLO model on PlantVillage dataset; implement NDVI/VARI scripts using SEN12MS; analyse accuracy and performance.	Trained YOLO model; results graphs; pipeline diagram.
M. AbuBaker Ahmed Rafiq	Hardware Implementation	Set up Jetson Nano; convert model to TensorRT; integrate camera feed and measure FPS, latency.	Optimized model; working demo; performance report.
Abeer Fiaz	Report writing and Documentation	Write proposal and final report; manage GitHub repo; prepare figures and references.	Proposal & final reports; GitHub repo; presentation slides.

The expected outcomes of this project include a **YOLO-based deep learning model** capable of accurately detecting healthy and diseased crop regions using RGB imagery, alongside an **NDVI estimation module** validated against the **SEN12MS ground truth**. The trained model will be **optimized and deployed on Jetson Nano** for real-time inference, enabling on-device crop health monitoring. Additionally, the project will deliver a **visualization interface** that overlays vegetation health indices on detected regions, demonstrating the system's applicability for precision agriculture.

Use of AI Tools (Declaration)

- The team acknowledges the use of **AI assisted tools** during the preparation of this proposal report.
- **Grammarly** was used for minor grammar and formatting corrections.
- **GitHub Copilot** assisted with autocompletion of small Python code snippets for dataset preprocessing.
- All AI-generated outputs were **critically reviewed, verified, and modified** by the team to ensure correctness and originality.
- No AI tool was used to fabricate data, citations, or experimental results.
- The team members remain the **primary authors and intellectual contributors** to all project ideas, design, and written material.



Papers Reviewed

[1] Wang et al., "Plant Disease Detection and Classification Method Based on the Optimized Lightweight YOLOv5 Model," Agriculture (MDPI), 2022.

[2] Chiu et al., "Agriculture-Vision: A Large Aerial Image Database for Agricultural Pattern Analysis," CVPR 2020.

[3] Sheng et al., "Effective Data Fusion with Generalized Vegetation Index for Agricultural Land Cover Segmentation," arXiv 2020.

[4] Chandra et al., "Computer Vision with Deep Learning for Plant Phenotyping in Agriculture: A Survey," arXiv 2020.

[5] Xue and Su, "Significant Remote Sensing Vegetation Indices: A Review of Developments and Applications," Sensors 2017.

[6] Mazzia et al., “UAV and Machine Learning-Based Refinement of a SatelliteDriven Vegetation Index for Precision Agriculture,” IEEE TGRS 2020.

[7] Kerkech et al., “Vine Disease Detection in UAV Multispectral Images with Deep Learning Segmentation Approach,” Computers and Electronics in Agriculture 2019.

[8] Khan et al., “Plant Disease Detection Model for Edge Computing Devices,” Frontiers in Plant Science 2023.

[9] Atila et al., “Plant Disease Classification Using EfficientNet Deep Learning Model,” Computers and Electronics in Agriculture 2021.

[10] Khose et al., “UAV-Based Multispectral Image Analytics and Machine Learning for Predicting Crop Nitrogen and SPAD,” Remote Sensing 2024.

Among the reviewed works, three papers form the foundation of this project: **Wang et al. (2022)**, which guides the YOLO-based implementation for plant disease detection; **Chiu et al. (2020)**, serving as the key survey and dataset reference through the Agriculture-Vision benchmark; and **Sheng et al. (2020)**, representing the state-of-the-art approach by integrating vegetation indices with deep-learning models for agricultural analysis.