Preliminaries on Satellite Image-Based Crop Health Detection

1. Introduction

Satellite-based crop health detection leverages multispectral imagery and machine learning to help farmers rapidly assess field conditions. Using NDVI (Normalized Difference Vegetation Index) and advanced Convolutional Neural Networks (CNNs), this method classifies crop health (e.g., healthy, rust-stressed, or under other stress), enabling smarter, scalable agriculture.

2. Key Terms and Definitions

2.1 Satellite Imagery

Images captured by Earth-observing satellites that record data across multiple spectral bands.

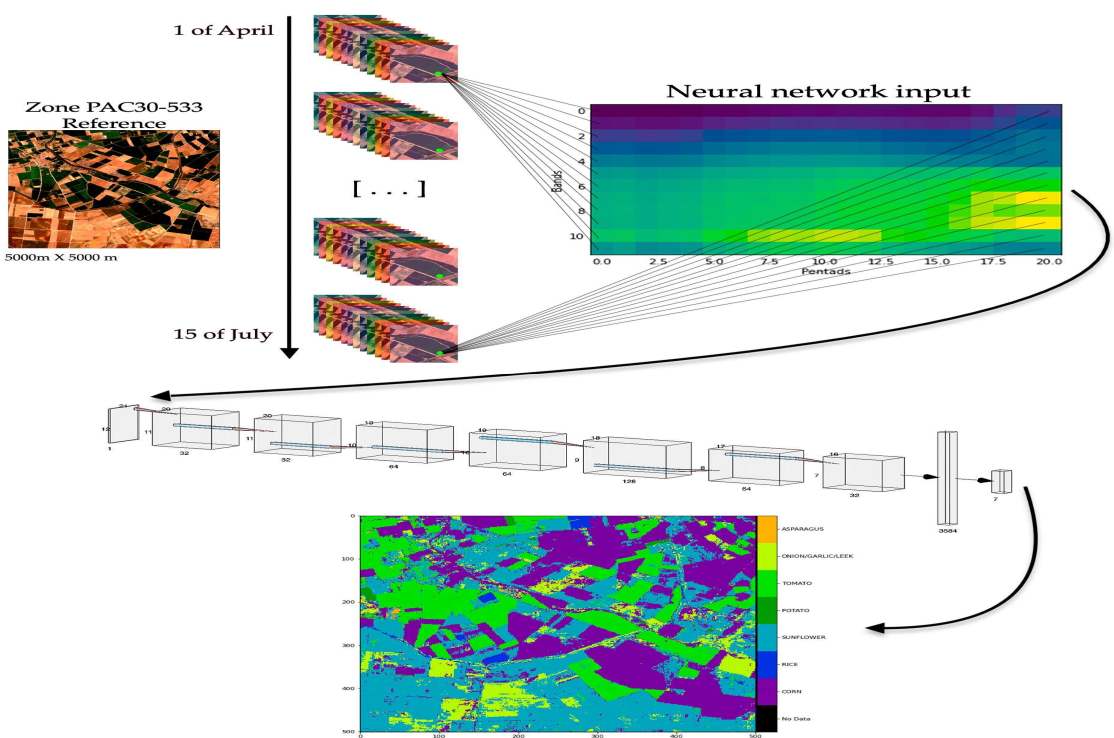

Figure 1.

2.2 Remote Sensing

The technique of acquiring information about an object or phenomenon without physical contact, typically through satellite or aerial sensors.

2.3 NDVI (Normalized Difference Vegetation Index)

A key vegetation index used to assess plant health based on the difference between near-infrared (NIR) and red-light reflectance.

NDVI = (NIR - RED) / (NIR + RED)

- **NDVI (**Normalized Difference Vegetation Index) is a dimensionless metric ranging from −1 to +1.
- High NDVI (≈ 0.6–0.8) indicates dense green vegetation; low/negative values indicate bare ground or water.
- Widely used in agriculture, NDVI tracks plant health, stress, and trends through time.

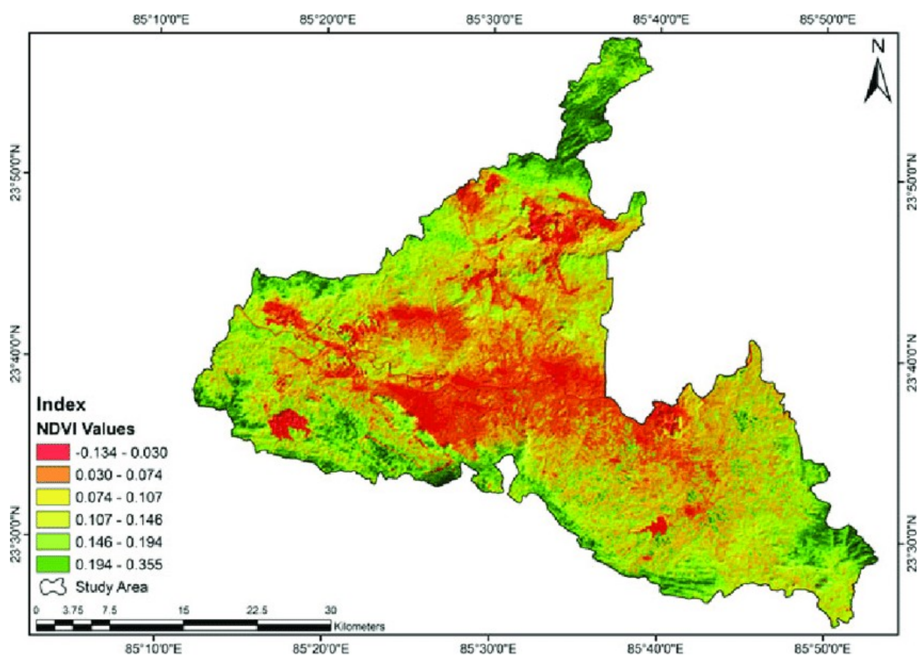

Figure 2. Color-coded NDVI map of a field

2.4 Spectral Bands

Different segments of the electromagnetic spectrum captured by sensors, including visible (Red, Green, Blue), NIR, and SWIR.

Band	Wavelength Range (nm)	Use Case
Red	620–750	Vegetation stress

NIR	750–950	Plant biomass, water content
SWIR	1000–2500	Moisture and soil health

2.5 Others Vegetation Indices

Mathematical combinations of spectral bands used to highlight specific plant characteristics.

Index	Purpose
GNDVI	General vegetation health (uses green + NIR)
EVI	Enhanced Vegetation Index (reduces atmospheric noise)
SAVI	Soil-Adjusted Vegetation Index (corrects soil brightness)

2.6 GIS (Geographic Information System)

A framework for gathering, managing, and analyzing spatial or geographic data.

2.7 Machine Learning in Crop Detection

Algorithms (e.g., Random Forest, CNNs) trained on satellite data to classify crop types or detect anomalies.

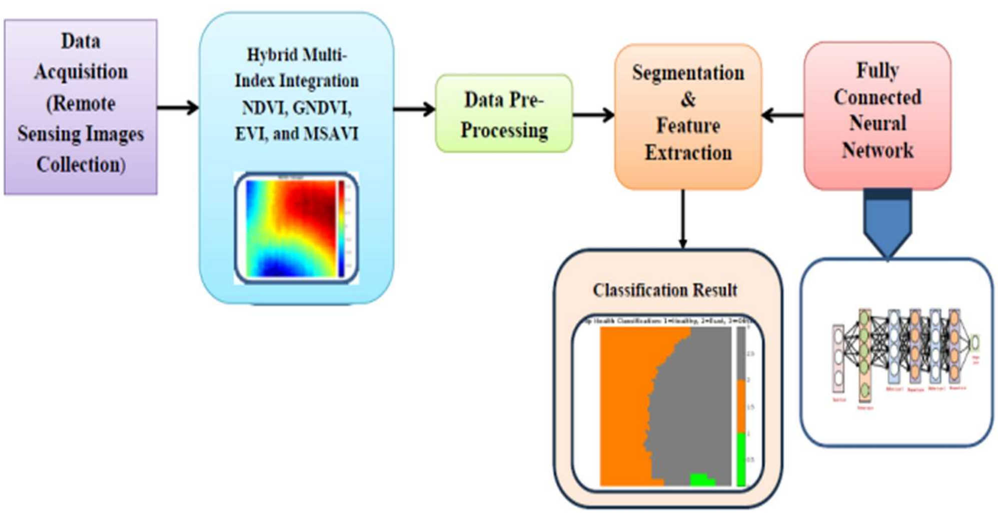

Figure 3. ML workflow

3. Data Sources

Source	Description
Sentinel-2	Free satellite data, 10m resolution
Landsat-8	Long-term Earth observation program
PlanetScope	High-resolution commercial satellite

4. Workflow

4.1 Data Acquisition

- Collect multispectral satellite images (e.g., Sentinel-2, Landsat 8)

4.2 Preprocessing

- Image normalization
- NDVI calculation
- ROI extraction (e.g., fields, patches)

4.3 Feature Extraction

- Use CNNs to extract spatial features
- Combine with NDVI to enhance learning

4.4 Classification

- Train CNN to classify crop patches into health categories
- Evaluate accuracy using labeled ground truth data

5. Expected Outcomes & Benefits

- Spatial crop health maps with real-time alerts.
- Ability to detect early signs of rust or stress.
- Supports targeted interventions (e.g., fertilization, pesticide application).

6. Use Cases

- Early pest/disease detection
- Drought monitoring
- Yield prediction
- Smart irrigation planning
- Large-scale agricultural surveys

7. Future Directions

- Domain Adaptation for Cross-Region Generalization
- Spatiotemporal Fusion & Time-Series Integration
- Satellite-UAV Data Integration
- High-Throughput Stress & Disease Classification
- Integrating Auxiliary Data Sources
- Real-Time Early-Warning Systems

Summery

Satellite Image-Based Crop Health Detection leverages remote sensing and vegetation indices like NDVI (Normalized Difference Vegetation Index) to assess plant health over large agricultural areas. NDVI is calculated using red and near-infrared light reflectance, helping identify healthy, stressed, or diseased crops. This project uses satellite imagery and a deep learning model, specifically a Convolutional Neural Network (CNN), to classify crop health conditions such as rust or nutrient stress. The approach reduces the need for manual inspection, enabling faster and more accurate monitoring. It supports better agricultural decisions, improves productivity, and ensures timely intervention. Overall, it offers a scalable and efficient solution for precision farming.