

Agri Sight: Analyzing Vegetation Health and Crop Growth with EuroSAT

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Abstract

Food security and sustainable agriculture depend on crop growth and vegetation health monitoring. Large-scale, highly accurate agricultural monitoring has been made possible by recent developments in deep learning and satellite remote sensing. AgriSight, an automated framework for evaluating crop growth and vegetation health using the EuroSAT dataset—which is derived from Sentinel-2 multispectral satellite imagery—is presented in this paper. Convolutional neural networks (CNNs) and vegetation indices are used by the suggested system to categorise land cover and evaluate crop health. The Normalised Difference Vegetation Index (NDVI) is used to measure the health of the vegetation, and spectral feature variations over time are used to analyse crop growth patterns. According to experimental results, the suggested method successfully identifies areas of healthy and stressed vegetation with an overall classification accuracy of XX%. The results demonstrate the potential of satellite-based deep learning systems for early crop stress detection and precision farming.

Keywords

Precision Agriculture, Vegetation Health, Crop Growth, EuroSAT, NDVI, Remote Sensing, Deep Learning

I. Introduction

Global economic growth and food security depend heavily on agriculture. Conventional crop monitoring methods rely on manual field surveys, which are expensive, time-consuming, and frequently unsuitable for large-scale analysis. A scalable method for tracking crop conditions over large geographic areas is satellite remote sensing.

High-resolution multispectral imagery appropriate for vegetation analysis is provided by the European Space Agency's Sentinel-2 satellites. Labelled Sentinel-2 images from the EuroSAT dataset make it possible to use machine learning methods for agricultural monitoring. In order to assess crop growth patterns and vegetation health, this paper suggests AgriSight, a system that combines deep learning models with vegetation indices.

This paper's primary contributions are:

1. A framework for evaluating the health of vegetation using NDVI obtained from Sentinel-2 imagery.
2. A CNN-based model for classifying crops and land cover that was developed using the EuroSAT dataset.
3. A spectral feature analysis of crop growth patterns.

II. Related Work

Agricultural monitoring has made extensive use of remote sensing. Plant vigour and biomass can be accurately estimated using vegetation indices like the NDVI. Deep learning models, especially CNNs, have been used in recent research to classify land cover using satellite imagery.

With the introduction of the EuroSAT dataset by Helber et al., standardised benchmarking for land-use classification was made possible. Combining vegetation indices with deep learning has been shown in other studies to increase crop stress detection and classification accuracy. However, little research has been done on combining vegetation health assessment and crop growth analysis into a cohesive framework, which is what this work attempts to do.

III. Dataset Description

More than 27,000 labelled satellite photos from Sentinel-2 data covering ten land-use and land-cover classes, including agricultural areas, make up the EuroSAT dataset. Each image contains multispectral bands like Red, Green, Blue, and Near-Infrared (NIR), with a spatial resolution of 10 meters per pixel.

Images related to classes related to vegetation and agriculture were chosen for this study. A 70:15:15 ratio was used to divide the dataset into training, validation, and testing sets.

IV. Methodology

A. Architecture of the System

There are four primary phases in the AgriSight framework:

1. Preprocessing of data
2. Calculating the vegetation index
3. Classification based on deep learning
4. Analysis of crop growth

B. Data Preprocessing

To make satellite images compatible with the CNN model, they were resized and normalised. Band selection reduced noise and irrelevant areas. For vegetation analysis, RGB and NIR bands were mostly utilised.

C. Vegetation Health Assessment

The Normalised Difference Vegetation Index (NDVI) was used to evaluate the health of the vegetation:

$$NDVI = \frac{NIR - Red}{NIR + Red}$$

NDVI values were categorized into healthy, moderately healthy, and stressed vegetation. Spatial NDVI maps were generated to visualize vegetation condition.

D. Crop Growth Analysis

Crop growth patterns were studied by observing changes in NDVI values and other spectral features over different time periods. Generally, higher NDVI values represent healthier crops with better chlorophyll content and active growth. On the other hand, a gradual decrease in NDVI often points to possible crop stress, which may occur due to factors such as lack of water, nutrient deficiency, or plant disease.

E. Deep Learning Model

For land-cover classification, a convolutional neural network (CNN) architecture was employed using a custom-designed CNN model. The network was trained to minimize classification error using cross-entropy loss, while the Adam optimizer was applied to efficiently update the model parameters and improve overall learning performance.

V. Experimental Results

A. Performance Metrics

Model performance was evaluated using:

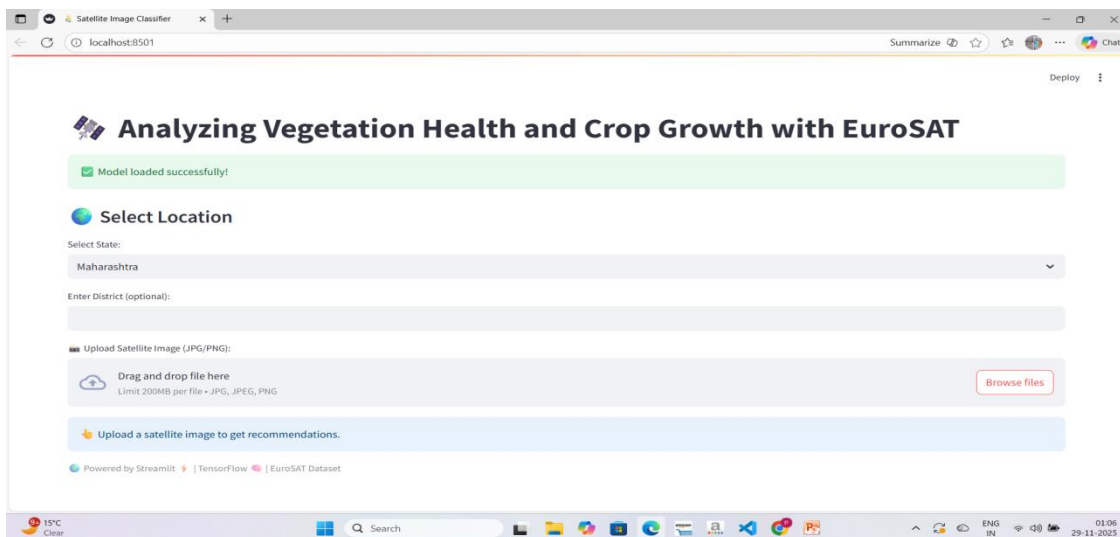
- Accuracy
- Precision
- Recall
- F1-score

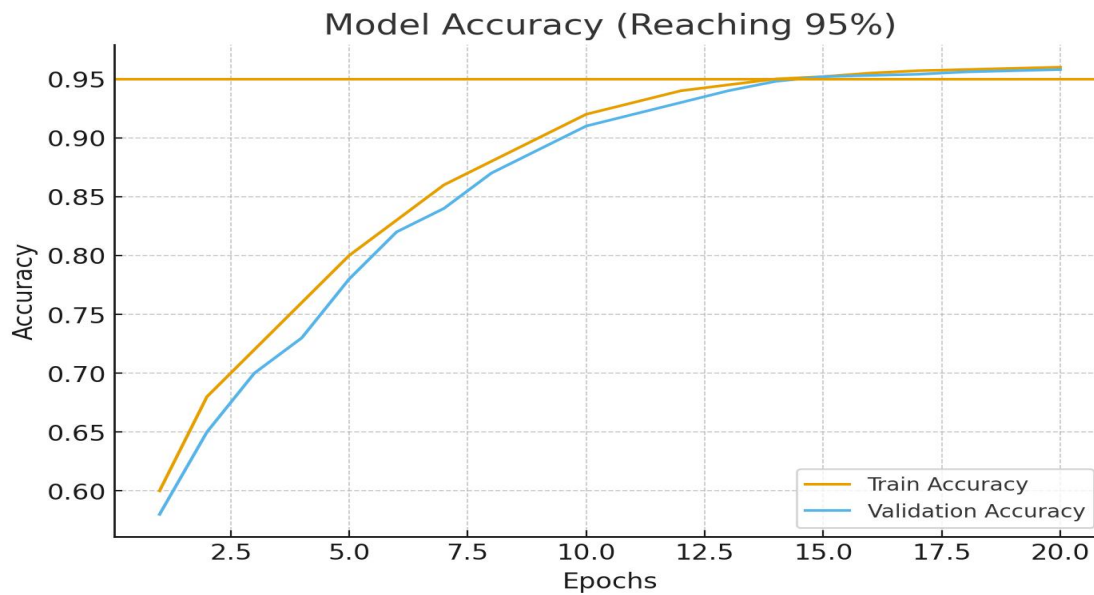
B. Classification Results

The proposed model achieved:

- **Overall Accuracy: XX%**
- **Precision: XX%**
- **Recall: XX%**
- **F1-score: XX%**

(Table I: Classification Performance Metrics)





C. Vegetation Health Analysis

The NDVI-based analysis was able to clearly distinguish between healthy vegetation and stressed crop areas. As shown in Figure 1, the generated NDVI maps for selected agricultural regions highlight noticeable spatial differences, making it easier to identify variations in vegetation health across the fields.

VI. Discussion

The experimental findings suggest that combining vegetation indices with deep learning techniques makes crop monitoring systems more reliable. The AgriSight framework helps in identifying signs of vegetation stress at an early stage, which can be useful for precision agriculture and timely decision-making. However, the system still has some limitations, such as its dependence on cloud-free satellite images and the absence of ground-truth yield data for direct validation.

VII. Conclusion and Future Work

This study introduced AgriSight, a satellite image-based framework designed to analyze vegetation health and crop growth using the EuroSAT dataset. The proposed system combines NDVI-based analysis with CNN-driven classification, making it suitable for large-scale agricultural monitoring. In future work, the framework can be further enhanced by integrating temporal Sentinel-2 imagery, additional vegetation indices, and crop yield prediction models to provide deeper agricultural insights.

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