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Deep Learning–Based Analysis of Soybean Crop Growth Using Sentinel-2 Vegetation Indices

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Abstract: Remote sensing has become an important technology for crop development monitoring and assessment of vegetation health of current agriculture systems. By combining satellite imagery with advanced data analysis techniques, researchers are able to observe crop conditions on a large scale of agricultural areas with greater efficiency. In recent years, deep learning methodologies have shown a great potential for the decomposition of complex interrelationships between spectral characteristics and crop physiological attributes. The current investigation uses a framework of deep learning to study the growth of soybean using vegetation indices extracted from Sentinel 2 satellite imagery. The field experiment was conducted on a 4 acre soybean field located in Sillod region Maharashtra, India & used Sentinel 2 Multispectral Data collected on 1st October 2022 and 26th October 2022 to determine the temporal variations in crop status. Vegetation indices were extracted from the satellite imagery, Normalized Difference Vegetation Index (NDVI), Green Normalized Difference Vegetation Index (GNDVI), Normalized Difference Red Edge Index (NDRE) and Chlorophyll Index Green (CIgreen) were used to quantify vegetation vigor and chlorophyll activity. A deep learning autoencoder was used to determine latent vegetation features from these indices and identify hidden patterns of crop growth. A resulting model yielded two latent variables, which contained crop condition characteristics for two observation dates. Discernible temporal changes in soybean canopy condition were indicated from analysis of the latent features. DeepFeature1 had a small increase from 0.053 to 0.067 while DeepFeature2 showed a significant decrease from 1.0137 to 0.7911 between the two measurement occasions. The attenuation of DeepFeature2 represents a drop in the vigor and activity of the vegetation and the chlorophyll of the soybean plant at a later stage of its growth. These observations follow the expected phenological path of soybean crops approaching maturity. Consequently, the results validate that the feature extraction with deep learning could be effective for capturing temporal dynamics of crop growth using the vegetation indices derived from satellite remote sensing, and provides nice information for agricultural monitoring and precision farming practices.

Keywords: *NDVI, Deep Learning, Crop Growth, Sentinel-2*

1. Introduction

Remote sensing has become an integral tool for modern agricultural surveillance because of its ability to provide timely, large-scale and non-destructive information on crop condition. Satellite sensors at the spectral reflectance of vegetation, therefore, allow researchers to assess plant vigor, chlorophyll concentration and biomass, as well as stress manifestations. Vegetation indices which are derived from multispectral imagery are widely used to monitor crop development and the identification of spatial heterogeneity within agricultural extents. With the advent of high-resolution satellite platforms like Sentinel-2, remote sensing has had a significant impact on the potential to scrutinize crop condition at both a regional and field scale [1].

In recent years, deep learning approaches have been gradually adopted for agricultural research for the analysis of large and complex datasets. Deep neural

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networks are adept at learning non-linear relationships between spectral features and crop parameters and therefore help in the better modeling of crop growth dynamics. These models have been used in a range of tasks in the agriculture field, such as crop classification, yield predictions, disease detection, and vegetation monitoring. Relative to traditional statistical methods, deep learning methods are able to discover latent patterns within spectral data, and to extract salient features that represent physiological states of crops [2].

Soybean is one of the most important oilseed crop grown in India especially in Maharashtra. The crop plays an important role in providing edible oil, animal fodder and raw material to various food industries. Maharashtra is among the leading soybean producing states of the country with districts like Aurangabad contributing significantly in the production of soybean. Monitoring the health of soybean crops throughout the growing season is extremely important to improve productivity and manage crop stress conditions. Remote sensing technologies offer an efficient and cost-effective option for monitoring the development of crops and identifying differences in the vigor of vegetation in agricultural fields [3].

The present study is aimed at assessing the growth of soybean crop on the basis of satellite imagery of Sentinel 2 and deep learning. A 4 acres of soybean in Sillod region of Maharashtra was selected as the study area. Vegetation indices (NDVI, GNDVI, NDRE and CIgreen) were extracted from Sentinel-II based image acquired on two dates (October 1st, 2022 and October 26th, 2022). A deep learning auto encoder model was designed to extract latent features of vegetation reflective of the growth characteristics of the crops. The objective of the study was to measure the temporal variation of the soybean crop condition using the deep learning-based feature extraction and vegetative index calculation.

2. Literature Survey

Several studies have been done on the use of remote sensing and machine learning for crop monitoring and agriculture analysis. The author looked at the application of Sentinel-2 satellite imagery in the context of precision agriculture. The investigation showed that the multispectral bands and vegetation indices calculated from the Sentinel-2 data can be used to monitor crop variability and crop stress conditions successfully. The results highlighted the importance of red edge bands in Sentinel-2 imagery for the improvement of the detection of physiological changes in the vegetation [4].

Another researcher made a comparative analysis of the Sentinel 1 and Sentinel 2 satellite data regarding agricultural vegetation monitoring. The research demonstrated that optical-based vegetation indices are highly effective in determining crop growth condition and plant vigour. The study reaffirmed the fact that indices like NDVI and GNDVI are widely used to monitor crop development and detect the spatial variability in the agricultural fields [5].

The author delved into the combination of the Sentinel-2 vegetation indices combined with machine learning tools for crop variability analysis within agricultural fields. The results showed that machine learning algorithms can well capture the correlations between spectral characteristics and crop conditions and therefore pave the way for better monitoring crop productivity and spatial variability [6].

These projects collectively highlight the importance of using remote sensing data in combination with cutting-edge analytics techniques, such as machine learning and deep learning, to improve crop monitoring and enable better agricultural decision-making.

3. Methodology

The methodology adopted in this study involves the use of satellite imagery, vegetation index analysis, and deep learning techniques to assess soybean crop growth. The workflow consists of dataset acquisition, satellite image preprocessing, feature extraction using vegetation indices, and deep learning-based crop growth analysis.

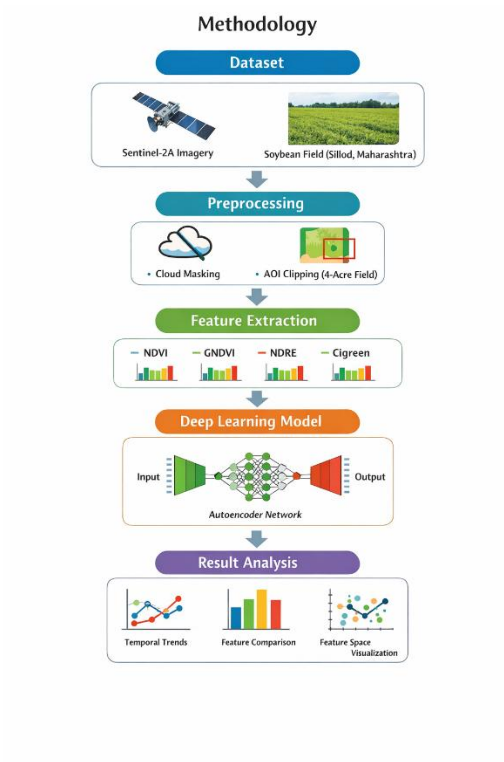

Figure 1: Proposed Methodology

3.1. Dataset

The data used for present investigation is the Sentinel-2A Multi-spectral satellite images and in situ data collected from a soybean plantation in Sillod, Maharashtra, India. Sentinel-2, part of the European Space Agency's Copernicus programmed, provides high resolution multispectral imagery favorable to vegetation monitoring. The sensor covers a number of spectral bands within the visible, near-infrared and red-edge domains that are especially beneficial for agricultural assessment [7].

Two Sentinel-2 images from 1st October 2022 and 26th October 2022 were used to examine temporal changes in the condition of soybean crop. Ground measurements, including geographic coordinates and chlorophyll measurement, were collected from the study area to verify the remote sensing analysis. The selected soybean field is about four acres in size.

3.2. Preprocessing

Preprocessing of the satellite imagery was performed so that the precision of vegetation index calculations is guaranteed. Sentinel-2 Level-2A surface-reflectance products were the basis of this analysis. Cloud masking was applied to remove those pixels that were affected by atmospheric interference and cloud contamination, an indispensable operation in order to avoid errors in the derivation of vegetation index [8].

The study region was defined using a shapefile that represents the perimeter of the four-acre soybean field. The Sentinel-2 imagery was clipped to this area of interest (AOI) so that only pixels dealing with the soybean field were used for further analyses. This preprocessing measure ensured that the derived vegetation indices represented the spectral characteristics of the crop accurately [9].

3.3. Feature Extraction

Vegetation indices have been calculated using spectral bands of Sentinel-2 imagery in order to analyze the crop vigor and chlorophyll status. The following indices are applied in this study:

- NDVI (Normalised Difference Vegetation Index), which is a measure of vegetation vigor, biomass, and is obtained by contrasting near-infrared and red reflectance [10].

- GNDVI (Green Normalised Difference Vegetation Index) is sensitive to the concentration of chlorophyll and replaces the green band with the red band [11].
- NDRE (Normalised Difference Red-Eod Index) uses the red-edge wavelengths and is especially sensitive to crop chlorophyll content [12].
- CIgreen (Chlorophyll Index Green) calculates chlorophyll concentration using near-infrared and green spectral bands [13].

These indices provide valuable information about the plant health, chlorophyll content and physiological condition of the crop.

Table 1: Vegetation Indices

Vegetation Index	Full Name	Formula	Description
NDVI	Normalized Difference Vegetation Index	(NIR − Red) / (NIR + Red)	NDVI is widely used to measure vegetation vigor and biomass. Higher values indicate healthier and denser vegetation.
GNDVI	Green Normalized Difference Vegetation Index	(NIR − Green) / (NIR + Green)	GNDVI is sensitive to chlorophyll concentration and is useful for detecting variations in plant nitrogen and photosynthetic activity.
NDRE	Normalized Difference Red Edge Index	(NIR − RedEdge) / (NIR + RedEdge)	NDRE uses the red-edge band and is particularly effective for detecting chlorophyll content and crop stress during later growth stages.
CIgreen	Chlorophyll Index Green	(NIR / Green) − 1	CIgreen estimates chlorophyll concentration in plant leaves and is useful for monitoring crop nutrient status and canopy health.

3.4. Deep Learning Technique

In this study, an autoencoder model based on deep learning has been deployed, in order to extract latent features of crop growth information from the vegetation indices. Autoencoders are unsupervised architecture of neural network which learns to learn compact representations of input data by trying to reconstruct the original features [14].

The autoencoder consisted of an input layer, which corresponded to the four vegetation indices (NDVI, GNDVI, NDRE and CIgreen), followed by hidden layers which compressed the data into a lower dimensional latent representation. The compressed latent features represent salient patterns and interrelationships between the vegetation indices which typify the crop growth characteristics.

Training of the autoencoder resulted in 2 latent features, called DeepFeature1 and DeepFeature2, which describe latent vegetation patterns that the neural network has learned. These deep features were used to assess the temporal changes in crop condition of soybeans between the two observation dates.

3.5. Result Analysis and Discussion

The crop growth analysis by deep learning was performed with an autoencoder neural network that was trained on vegetation indices of Sentinel-2 imagery. The autoencoder has learned compressed representations of the vegetation characteristics from NDVI, GNDVI, NDRE and CIgreen. These compressed representations are called DeepFeature1 and DeepFeature2 and they are representations of latent vegetation patterns extracted by the neural network.

The average values of the deep features for the two observation dates are shown in Table 2.

Table 2: Average Values

Date	DeepFeature1	DeepFeature2
1 Oct 2022	0.053064	1.013723
26 Oct 2022	0.067117	0.791102

The results show interesting temporal variations in the learned deep features of the two observation dates. DeepFeature1 showed a small increase from 0.053 to 0.067 that indicates slight changes in canopy structure or spectral interactions that are learned by the neural network. Although this is a relatively small increment, it may indicate small changes in vegetation reflectance patterns in the soybean canopy.

In contrast, the DeepFeature2 showed a large decrease from 1.0137 to 0.7911, which is a decline of about 22%. This diminution suggests the reduction of vigor and the chlorophyll activity of vegetation in the period of the study. Since deep learning models represent the nonlinear relationship among vegetation indices, the decrease in DeepFeature2 implies that the spectral characteristics of the soybean canopy changed significantly between early and late October.

This time-varying pattern in the deep feature values is a natural evolution of soybean crops. During the early October period, soybean plants usually are in the pod-filling period when vegetation vigor and chlorophyll concentration are still relatively high. As the crop approaches maturity stage, the leaf senescence begins and the chlorophyll concentration gradually reduces. This physiological transition leads to reduced reflectance in vegetation indices such as NDVI, GNDVI and CIgreen.

The deep learning analysis managed to capture these dynamics of crop growth by learning latent vegetative features representing the overall state of the canopy. The decreasing DeepFeature2 shows that the soybean crop has experienced a slow decrease in vegetation vigor during the late phase of growth. Such changes in time are generally seen in the cultivation of the soybean when plants are approaching physiological maturity.

Overall, the results show that deep learning models can be useful to extract meaningful vegetation patterns from satellite-derived indices. The model of autoencoder could learn hidden relationships between vegetation indices and show temporal changes in crop condition. These findings highlight the potential of using remote sensing data in conjunction with deep learning methods for monitoring crop growth and evaluating vegetation health at the field scale.

The graphical representations also help to further understand the time evolution of soybean crop condition as captured by the deep learning model.

The graph of temporal variation shows in figure 2,3 and 4 respectively, the change in the extracted deep features between 1 October and 26 October 2022, thus highlighting a prominent decline of DeepFeature2 at the next observation date. The bar chart comparison helps to highlight the difference in the deep feature values for the two dates, and thus drives home the attenuation of the vegetation vigor over time. Furthermore, the deep feature space visualization helps to understand the distribution of the crop condition patterns obtained by the neural network, in which the data points corresponding to the two observation dates gather into separate clusters.

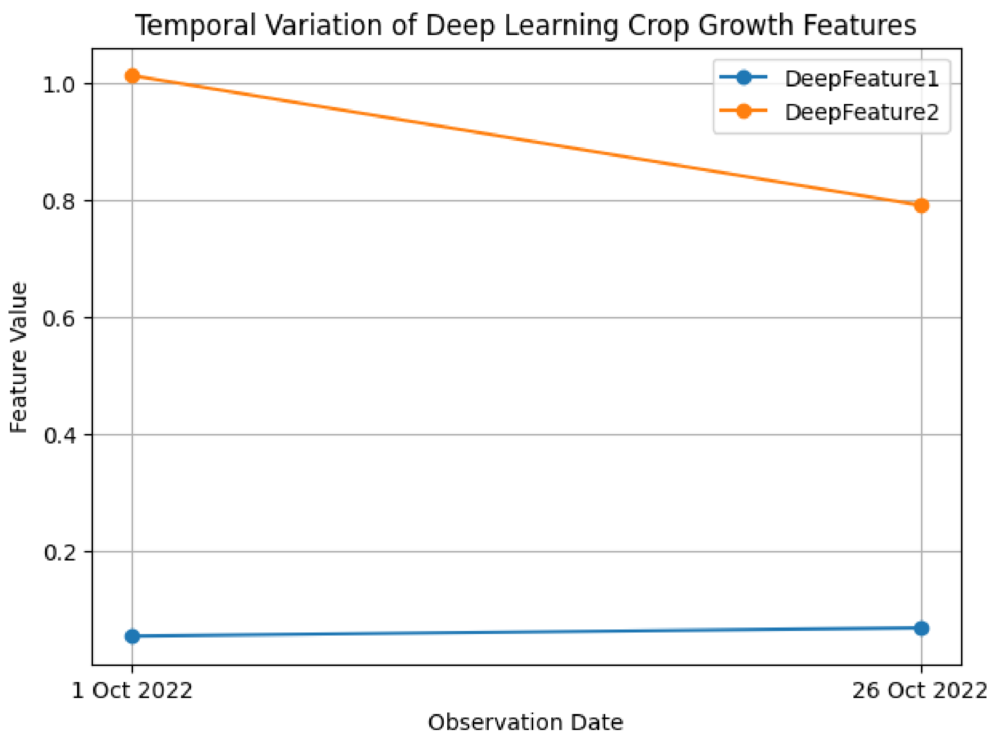

Figure 2: Temporal variation of deep learning crop growth features between 1 October and 26 October 2022.

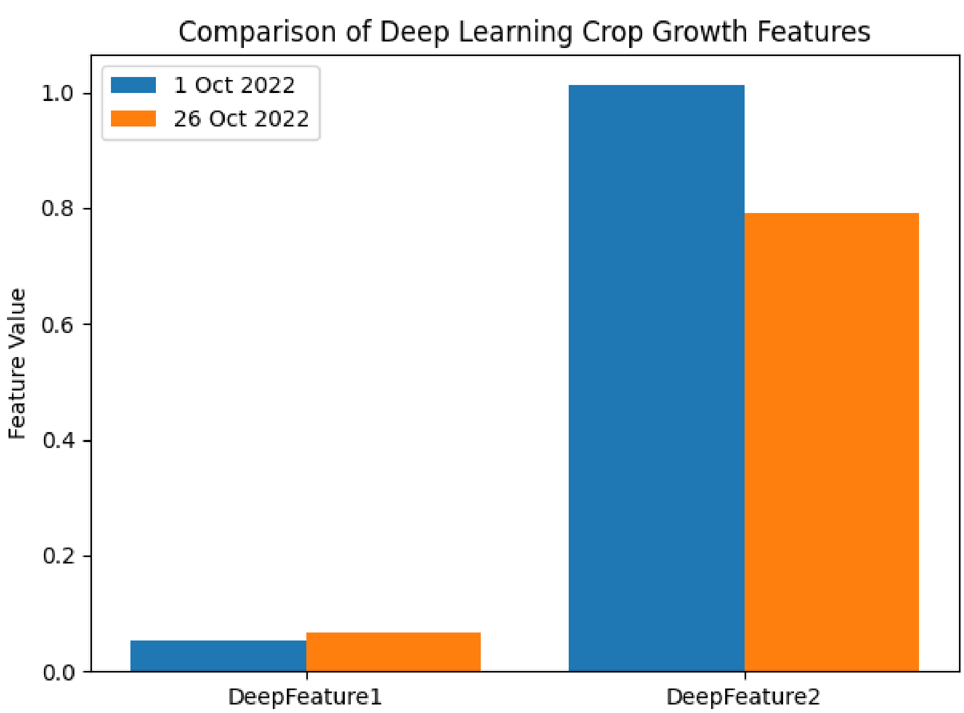

Figure 3: Comparison of deep learning crop growth features extracted from vegetation indices for two observation dates.

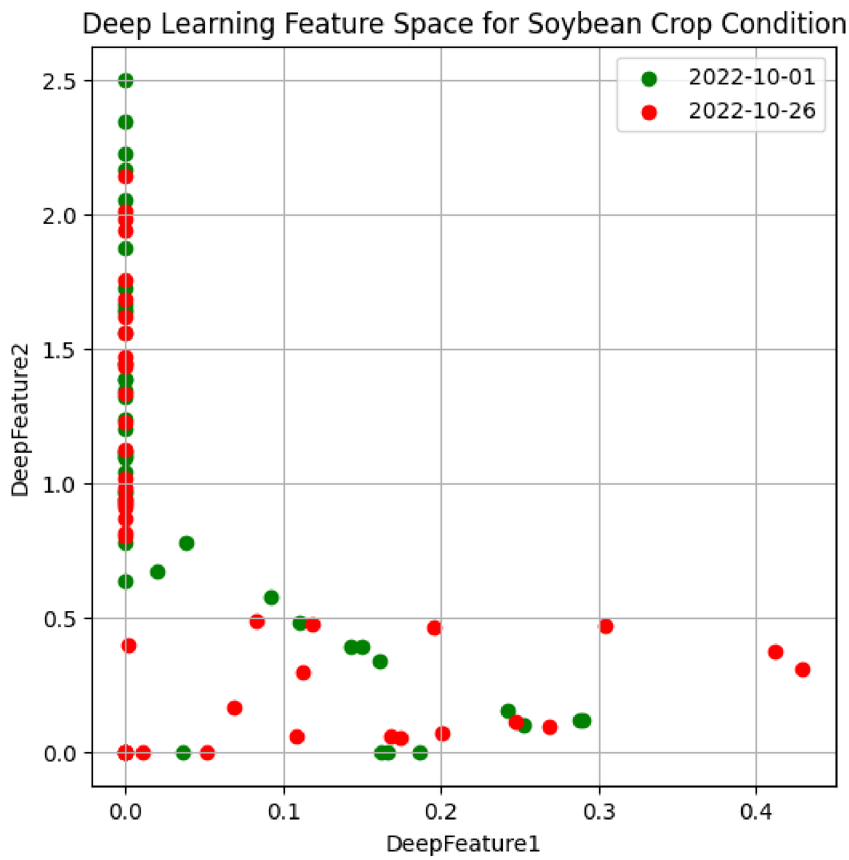

Figure 4: Visualization of deep learning feature space showing crop condition distribution for two observation dates.

Collectively, these visualizations provide an overview of the temporal variation in crop growth and therefore support the deep learning-based analysis of soybean canopy condition.

4. Conclusion

The present study illustrates the use of Sentinel 2 satellite image combined with deep learning algorithms for monitoring growth of soybean crop in 4 acres field in Sillod, Maharashtra. Vegetation indices like NDVI, GNDVI, NDRE and CIgreen were extracted from the Sentinel-2 imagery for measuring the crop vigor and the chlorophyll content. An autoencoder based on deep-learning was used to learn latent representations of the vegetation indicative of crop growth patterns. The resultant deep features showed temporal changes between the two observation dates, which indicated changes in the condition of the soybean canopy over the period of the study. A discernible drop in one latent feature was noted, which suggests a drop in the vigor of the vegetation as the soybean crop reached towards maturity. The results highlight the possibilities of combining satellite remote sensing data and deep learning approaches for the analysis of crop growth dynamics. These techniques can help to improve precision agriculture by providing valuable information about the condition of crops as well as temporal variation in vegetation health. Future studies could use more satellite data, more data and more complex deep learning models to further optimize crop monitoring and agricultural decision-making.

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