Satellite-Based Crop Monitoring Using Hyperspectral Imagery and Deep Learning Approaches

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ABSTRACT

Agricultural crop monitoring plays a crucial role in ensuring food quality and sustainable development, yet traditional field surveys are labor-intensive, time-consuming, and often error-prone. These limitations hinder timely detection of crop stress over large areas. In contrast, satellite-based hyperspectral imagery (capturing hundreds of contiguous spectral bands) offers broad coverage and rich spectral detail, revealing subtle indicators of vegetation health across expansive regions. We propose a novel two-phase methodology combining statistical computer vision techniques with deep learning to improve crop monitoring accuracy and efficiency. In Phase 1, hyperspectral images preprocessed with ENVI software (radiometric calibration and atmospheric correction) undergo histogram analysis and red channel intensity distribution evaluation. The red band (corresponding to near-infrared in false-color composites) is especially indicative of vegetation vitality, as stressed crops exhibit diminished reflectance in this range. Binning red channel intensities into discrete ranges enabled clear differentiation between healthy and unhealthy vegetation. Phase 2 employs a YOLOv11 deep learning model for crop classification. The model was trained on labeled hyperspectral images from multiple Indian states (including Punjab and Gujarat) encompassing major crops such as wheat, rice, and cotton. It achieved ~82% classification accuracy in distinguishing crop types. Integrating these complementary approaches leverages both spectral feature insights and data-driven modeling, enabling accurate crop-type mapping alongside early detection of crop stress. The results demonstrate that this efficient and scalable satellite-driven framework can reliably assess crop condition and species, providing a valuable tool for precision agriculture. In real-world applications, it supports sustainable crop management and informs decision support systems for optimized agricultural practices.

Keywords: Satellite Image Processing; Hyperspectral Imaging; Vegetation Analysis; YOLO Classification; Histogram Analysis

I. INTRODUCTION

Traditional methods of crop assessment, such as manual surveys and field inspections, are time-consuming, limited in scope, and often prone to human error. With the evolution of geospatial technologies [1], satellite image processing has emerged as a powerful tool for monitoring agricultural conditions over large areas with high temporal and spatial accuracy. This study explores the use of hyperspectral imagery [2] to extract meaningful information about crop health and classify vegetation types. Multispectral imagery captures data in a few distinct spectral bands (usually 3 to 12); whereas Hyperspectral imagery captures hundreds of narrow, contiguous bands (often 100–300+). It provides a continuous spectrum for each pixel (Figure 1).

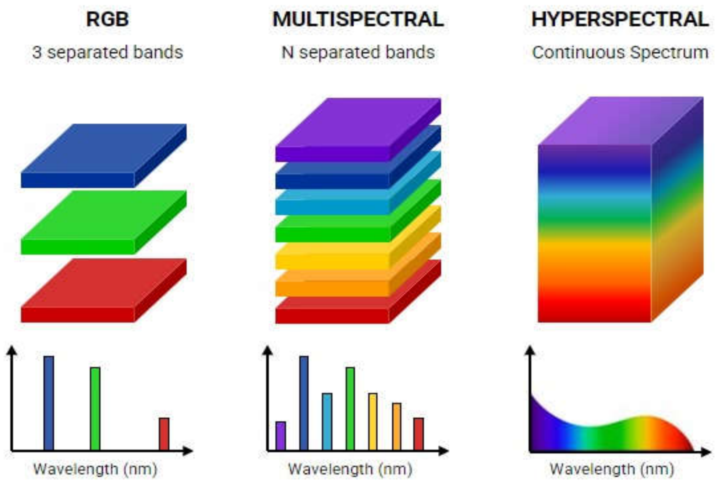

Figure 1: Visual representation of different spectral bands

The methodology includes image preprocessing, histogram-based analysis of red channel intensity distributions, and evaluation of color contributions to detect patterns associated with vegetation to measure the healthiness of crops in an area. By integrating traditional statistical analysis with modern deep learning techniques, this research demonstrates an efficient approach to crop monitoring and prediction. The framework is adaptable and scalable, offering practical utility for precision agriculture and decision support systems in real-world agricultural applications.

Also, further we classify the crop in an area with YOLOv11 to identify which crop is yield in the area; it is very much crucial to identify is any agriculture area yielding sustainable crops or not. In real application, by analyse the healthiness of crops in an agriculture area and which crops is yielding in that area, we can identify the agricultural outcome of that area/land – for example, if the crops status is detected as healthy and the area yielding sustainable crops (Cotton) means here the producer will see good outcomes, but let say in an area the crop health is detected as not good and/or yielding a crop (Sugarcane) which is not suitable for the region means here the producer have to face major losses.

This study explores a structured approach that integrates image pre-image processing and image analysis to enhance the reliability of satellite-based crop health monitor. In the pre-image processing stage, raw satellite data undergoes conversion, atmospheric correction, and radiometric calibration using ENVI to ensure uniformity and minimize noise. These steps are crucial for preparing the hyperspectral and multispectral images for further analysis.

Following this, image analysis phase involves analytical tasks such as histogram generation, red color channel contribution analysis, and extraction of statistical features. These features provide meaningful insights into vegetation variability and healthiness. The processed images also then classified using a deep learning-based YOLOv11 model, to distinguish between crop types with high accuracy.

1.1. Raw Satellite Image

Raw satellite images are the original data files captured by hyperspectral sensors onboard satellites, such as those from NASA's EO-1 Hyperion mission [3]. These images contain hundreds of spectral bands and are typically stored in file formats like .hdr, .dat, or .img. They are not directly viewable without specialized software, and they preserve the complete spectral information required for accurate analysis. The below is an example of raw image proceed with ENVI for visualization.

Figure 2: A raw satellite image

1.2. False Color Image

After obtaining the raw data, the images were processed using ENVI (Environment for Visualizing Images) software to convert the spectral data into a false-color visual format. This step allows us to visually inspect various land features, vegetation, and soil conditions by mapping non-visible spectral bands into the red, green, and blue channels. These false-color images serve as an intermediate step before applying statistical analysis and classification techniques.
A false color image [4] is an image that represents data using colors that do not correspond to the true (natural) colors of the scene as perceived by the human eye. Instead, artificial or "false" colors are assigned to various features to highlight specific characteristics that are otherwise invisible or difficult to distinguish. In false color image, the red brand represents near infrared brand. In false color images, especially in remote sensing (e.g., satellite imagery), vegetation health can be measured using the red (near-infrared) bands, because vegetable strongly reflect near-infrared wavelength. Healthy vegetables reflect more infrared compare to sick vegetables. So, in false color image, healthy vegetables appear brighter (red). This is fundamental concept that we have utilize in this research. Therefore, we have focus on only Red channel to analyze the crops health.

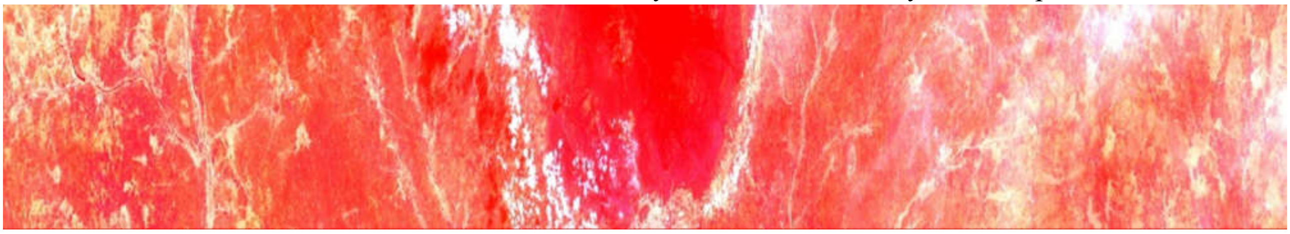

Figure 3: A false color image processed from raw satellite image

II. LITERATURE REVIEW

In recent years, satellite-based image processing has emerged as a crucial tool in agricultural research and monitoring. The increasing availability of high-resolution multispectral and hyperspectral satellite data has enabled researchers to analyze crop conditions, monitor vegetation growth, assess stress levels, and predict yield with greater accuracy.
Hyperspectral imaging, in particular, has shown immense potential due to its ability to capture data across hundreds of narrow spectral bands. These images provide detailed spectral signatures that can be used to differentiate between healthy and unhealthy crops, classify different vegetation types, and detect subtle changes in plant physiology. Many researchers have focused on applying statistical models and machine learning algorithms to this spectral data for classification and prediction tasks.
To gain a deeper understanding of the current trends and advancements in satellite image processing for agricultural applications, several research studies were reviewed. These studies focus on hyperspectral imaging, vegetation analysis, crop health monitoring, and predictive modeling, providing a strong foundation for our work.

i. A study [1] on peanut quality assessment demonstrated the effectiveness of hyperspectral imaging combined with deep learning models like 3D-CNN and 2D-CNN, achieving over 98% classification accuracy. The use of band selection and data augmentation improved model stability and reduced overfitting. Key spectral features were identified in the 700–850 nm range for precise defect detection. The Snapshot system outperformed traditional push-broom methods in accuracy and processing speed.
ii. According to [2] recent research explored deep learning-based hyperspectral image reconstruction from RGB images to overcome the high cost and complexity of traditional HSI systems. Algorithms like HRNET, HSCNN-D, and MST++ were applied to assess sweet potato quality, with HRNET achieving the best performance metrics. Genetic algorithms and explainable AI were used for feature selection and interpretation.
iii. A study [3] proposed an unsupervised segmentation method for per-field analysis in hyperspectral images, addressing the limitations of manual digitization. By combining spectral similarity with edge detection and watershed segmentation, the method effectively identified spatially homogeneous land segments. Sparse unmixing and dictionary learning were used to compute fractional abundances of

vegetation, soil, and residues. Results showed improved segmentation accuracy using fractional-spectral-similarity and Sobel edge filtering.

iv. This study [4] utilized hyperspectral imaging (HSI) combined with deep learning models to identify hybrid okra seeds across 18 varieties. Spectral data within the 948.17–1649.20 nm range were analyzed using PCA and LDA for clustering and feature analysis. Among various models, CNN achieved the highest accuracy and robustness, maintaining stable performance despite increasing variety complexity.

v. This study [5] presents a hyperspectral imaging (HSI) and deep learning-based approach to identify the infection degree of Fusarium Head Blight (FHB) in wheat kernels. Reflectance spectra were analyzed, and five effective wavelengths were selected using the Random Frog algorithm. The Residual Attention CNN (RACNN) achieved high accuracy using only two key wavelengths (940 nm and 678 nm), demonstrating over 98% classification performance.

vi. This research [6] highlights the use of hyperspectral imaging (HSI) as a non-destructive method for assessing food quality, emphasizing its combination with machine learning techniques. It outlines the advantages and limitations of various algorithms, showing that deep learning offers promising accuracy and real-time application potential. Feature selection is noted as crucial for reducing computation and improving efficiency.

vii. In this study [7] over the past two decades, hyperspectral imaging (HSI) has gained recognition as a powerful non-destructive tool for assessing the quality and safety of horticultural products. By integrating machine vision and spectroscopy, HSI enables precise defect detection, contamination mapping, and internal quality evaluation. This review outlines various imaging modes and discusses data analysis techniques from preprocessing to model building.

viii. This study [8] explores the evolving role of remote sensing technologies in modern agriculture, particularly within the framework of Industry 5.0 (I5.0). By highlighting the collaboration between humans and intelligent machines, the paper underscores enhanced decision-making, sustainability, and resilience in agricultural practices. It reviews various remote sensing applications and their integration with I5.0 principles.

ix. This Study [9] focuses on estimating crop acreage using detailed land use data and GIS spatial technology. It accounts for natural land distribution, crop planting direction, and survey costs to define standard land areas. Irregular land blocks are combined and split into similarly sized standard blocks.

x. In this paper [10] digital plant phenotyping uses advanced non-destructive techniques, like hyperspectral imaging (HSI), to extract structural and physiological traits from plants. HSI offers a unique advantage by capturing both types of information simultaneously. While HSI has been successfully applied to parts like leaves, applying it to whole plants poses challenges due to variations in illumination caused by plant geometry and light scattering.

xi. This study [11] explores the use of hyperspectral imaging to predict internal quality traits—firmness and soluble solids content (SSC)—in Pink Lady apples at different harvest stages. Reflectance data from 300 spectral bands (386–1028 nm) were collected and analyzed using five regression models: ANN, KNN, DT, PLSR, and MLR. The best firmness prediction was achieved using ANN (R^2 = 0.910), while DT and MLR performed better for SSC.

xii. According to this paper [12] despite the availability of advanced agricultural technologies, many are underutilized due to their limited design scope. However, hyperspectral remote sensing is increasingly adopted for its cost-effectiveness and ability to provide detailed data. This study proposes a practical hyperspectral imaging model using varied spectral band configurations and introduces a bio-inspired Fly Optimization Algorithm (FOA) for image acquisition.

xiii. According to this paper [13] deep convolutional neural networks (CNNs) are highly effective for hyperspectral image (HSI) classification but face challenges like overfitting and loss of spatial-spectral correlation with increasing depth. This paper proposes an enhanced CNN (e-CNN) that merges successive layer outputs and combines spectral features across four spatial stages for improved feature extraction. A 1×1 convolution is used to integrate hybrid features, and the AdaBound optimizer enhances generalization with limited training data.

xiv. This study [14] investigates the sensitivity of heavy metal prediction (Ni, Zn, Pb) to spectral resolution variations in soil spectra and explores spatial distribution mapping. Using 92 soil samples and airborne HyMap hyperspectral data from Gansu, China, the study compares prediction accuracies across real field spectra and simulated satellite spectra (AHSIGF-5, Hyperion, AHSIZY-1 02D).

xv. This study [15] presents a segmentation-aided methodology for spectral-spatial classification of hyperspectral images. The approach addresses spectral variability, the curse of dimensionality, and spatial dependencies by incorporating local spatial regularization. A contiguity-based segmentation algorithm is used to create object-wise textures, which enhance classifier learning.

III. RESEARCH METHODOLOGY

The proposed model integrates Statistical Computer Vision and Deep Learning-based Classification to analyze satellite imagery for agricultural outcomes. It uses pixel-level statistical features to understand image properties and also leverages a YOLOv11n deep learning classifier to recognize the vegetation.
This hybrid model is divided into two phases:
i. Statistical Computer Vision Phase – analyzes raw image data using histograms, intensity distributions, and pixel-level statistics.
ii. YOLO-based Classification Phase – classifies vegetation types from satellite images using a pretrained neural network.

Flow Chart of Phase 1 **Flow Chart of Phase 2**

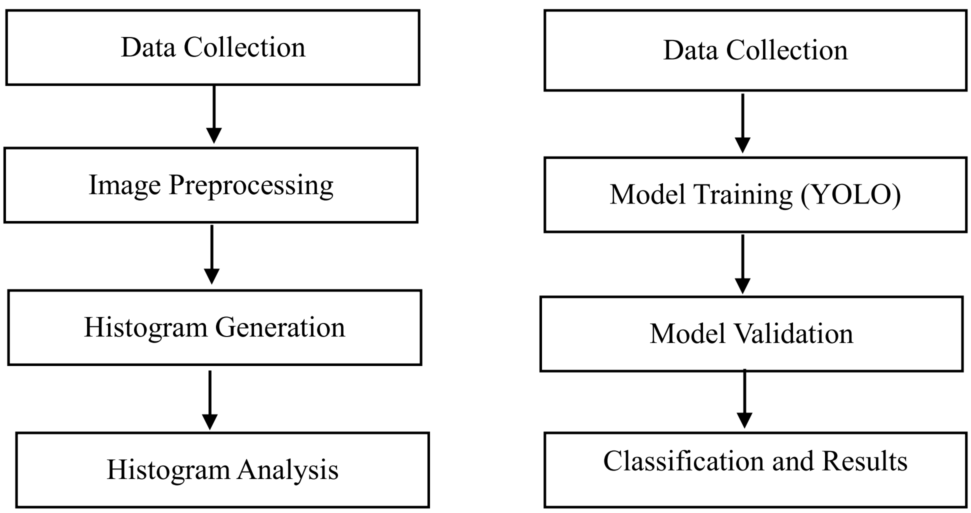

Figure 4: Flowchart of the proposed methodology

3.1. Phase 1: Statistical Computer Vision

Statistical computer vision refers to techniques that use statistical properties of pixels and pixel groups to extract meaningful features from images without learning-based models. In this project, we apply these techniques to study brightness, color dominance, and intensity distributions, which are highly relevant in vegetation analysis.

3.1.1. Collection of Dataset

The initial and crucial step of this research involves collecting high-resolution hyperspectral satellite images to serve as the foundation for vegetation analysis using Statistical Computer Vision techniques. The images were sourced from the Earth Explorer portal of the United States Geological Survey (USGS), specifically from the Hyperion sensor onboard the EO-1 satellite. This sensor captures data across 242 spectral bands, covering the Visible (VIS), Near-Infrared (NIR), and Short-Wave Infrared (SWIR) regions within a spectral range of 0.4 µm to 2.5 µm. Such dense spectral coverage allows for fine-grained detection of vegetation traits such as chlorophyll content, water stress, and biomass variation. We selected major agricultural regions in India based on crop density and climatic diversity, including the states of Gujarat, Uttar Pradesh, West Bengal, Bihar, Jharkhand, Punjab, and Uttarakhand. For each region, multiple hyperspectral scenes were collected—each comprising 6 to 10 image layers depending on the capture specifics. The datasets were stored in region-wise directories for streamlined processing and reproducibility.

3.1.2. Pre-processing

Hyperspectral imaging (HSI) captures reflectance information across hundreds of narrow and contiguous spectral bands, providing detailed spectral signatures for each pixel in a scene. While this spectral richness is invaluable for tasks such as material identification, vegetation health monitoring, and mineral mapping, hyperspectral data is inherently high-dimensional and not visually interpretable in its raw form. False color imaging serves as a dimensionality reduction and visualization technique, enabling researchers to explore and analyze HSI data in a human-interpretable RGB format.
In the pre-processing, at first raw sensor images are converted to radiance or reflectance using ENVI's Radiometric Calibration tool for radiometric correction. Then, use tools like FLAASH within ENVI for surface reflectance derivation (atmospheric correction). And finally, band selection is performed to generate the False Color image.

3.1.3. RGB Histogram Generation

Histograms provide a non-parametric estimate of the probability distribution of pixel intensities.

$$H_c(i) = \sum_{x=1}^{W} \sum_{y=1}^{H} \delta(I_c(x,y) = i)$$

Where,
$H_c(i)$: Histogram count at intensity i for channel c
δ: Indicator function (1 if intensity matches i, else 0)
This helps in understanding how intensity values are distributed, which can indicate plant health, shadow presence, or image brightness variations.

3.1.4. Histogram Analysis:

i. Channel-Wise Contribution Analysis
We calculate the percentage contribution of each color channel (Red, Green, Blue) to understand which spectral component dominates.

$$\text{Contribution}_{c} = \frac{\sum I_c(x,y)}{\sum(I_R + I_G + I_B)} \times 100$$

This helps us determine the dominant spectral band, which is important in agriculture: in false color image, higher contribution of red channel means the captured area has larger agriculture land, means this area could contribute largely in agriculture outcome.

ii. Red Channel Intensity Binning (Statistical Segmentation)
To analyze red channel variations, pixel intensities are grouped into discrete bins:

$$\text{Bin}_i = [I \in (a_i, b_i)], i = 1,2, \dots ,5$$

We then compute:

$$P_{\text{bin}\ i} = \frac{\text{Number of pixels in Bin } i}{\text{Total pixels}} \times 100$$

This helps to understand the healthiness of the vegetation. Bins dominated in higher intensity groups indicates good quality of the crop.

3.2. Phase 2: Deep Learning-Based Classification (YOLOv11n)

we also perform classification using a deep learning based YOLO model. YOLOv11 is a light-weight, efficient convolutional neural network (CNN) designed for classification tasks. It learns spatial patterns and classifies images into specific vegetation classes.

3.2.1. Data Collection

Also to classify the crops a large dataset of various hyperspectral images of labelled crops (including Wheat, Sugarcane, Cotton, soyabean, Rice) is collected from various sources. This dataset is splited into 3:1 ratio for training and testing.
This robust dataset serves as the backbone for evaluating vegetation status and projecting crop outcomes across diverse geographical zones. By integrating hyperspectral imagery with labelled training data, we created a rich multidimensional dataset suitable for advanced feature extraction, classification, and predictive modelling.

Training Process

$$\mathcal{L}_{\text{CE}} = -\sum_{i=1}^{C} y_i \cdot \log(\hat{y}_i)$$

Cross-entropy loss is used to optimize predictions.

Softmax for Prediction

$$\hat{y}_i = \frac{e^{z_i}}{\sum_{j=1}^{C} e^{z_j}}$$

The class with the highest probability is selected as output.

4. EXPERIMENT AND RESULTS

In this section, we present a comprehensive analysis of the experimental outcomes derived from applying the proposed methodology to hyperspectral satellite images collected for multiple Indian states, including Gujarat, Uttar Pradesh, West Bengal, Bihar, Jharkhand, Punjab, and Uttarakhand. The experiments were designed to evaluate the capability of the model in accurately assessing crop health and predicting future growth trends using spectral data derived from Hyperion sensors.

i. Original Histogram

A false color image was loaded and slightly darkened using a brightness factor of 0.6 to analyze pixel intensity behavior under reduced illumination. The image was then split into its three primary color channels: Red, Green, and Blue. For each channel, a histogram was computed that represents the frequency of pixel intensities ranging from 0 (black) to 255 (maximum intensity) shown in Fig 5.

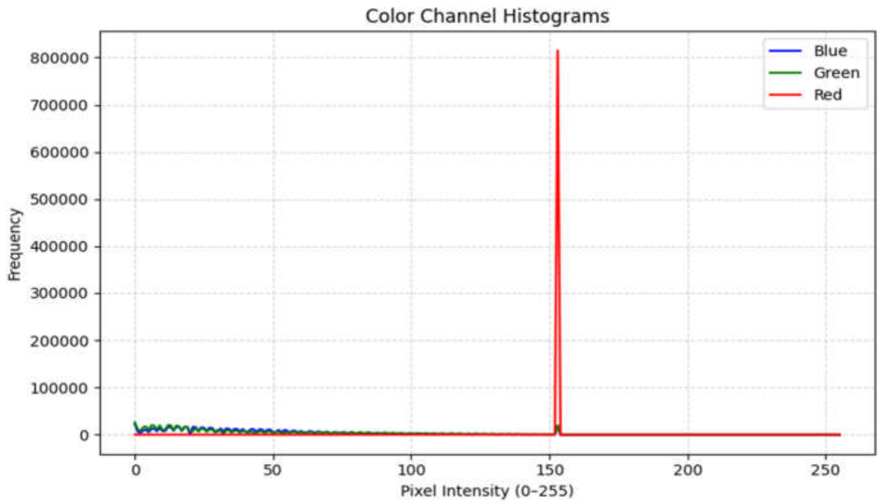

Figure 5: Histogram Representing of a Hyperspectral Satellite Image (loaded False Color Image)

- Each color channel shows a unique intensity distribution pattern.
- Peaks indicate the most frequent intensity levels per channel.
- Comparison highlights informative wavelength ranges.
- Lower intensities suggest shadow or low-light areas.

ii. Color Channel Contribution Analysis

This experiment aimed to analyze the relative contribution of each color channel (Blue, Green, Red) in the satellite image. The process involved computing the total sum of pixel intensities for each channel after applying a brightness factor of 0.6 to uniformly reduce overall brightness without distorting color relationships. Hence, we find out the channel wise contribution of the original histogram.

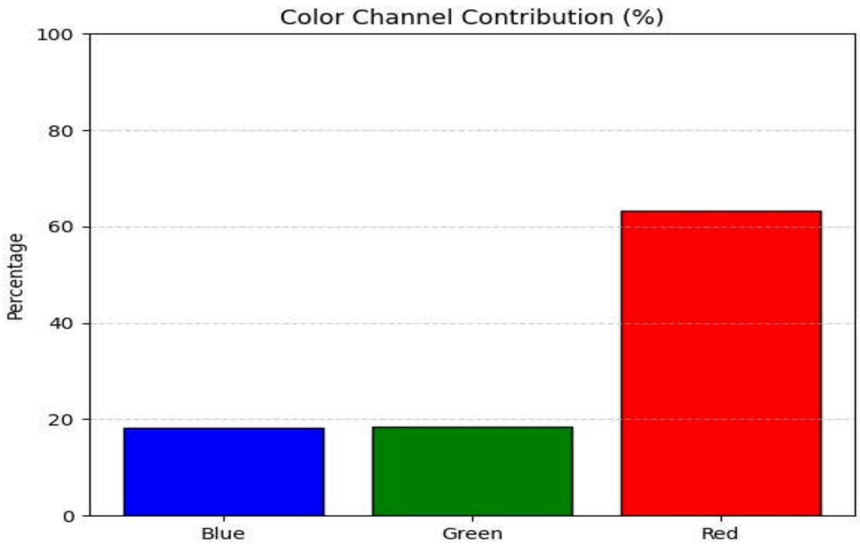

Figure 6: Color Channel Contribution of Histogram

In the obtained channel-wise histogram the Red channel contributed most (~60%), that is the taken image contains agriculture land largely.

iii. Red Channel Intensity Distribution Analysis

This part of the histogram analysis focuses specifically on understanding how the intensity levels in the Red channel are distributed across the image. This is crucial in agricultural satellite image analysis, as vegetation stress and crop health often manifest as changes in red reflectance.

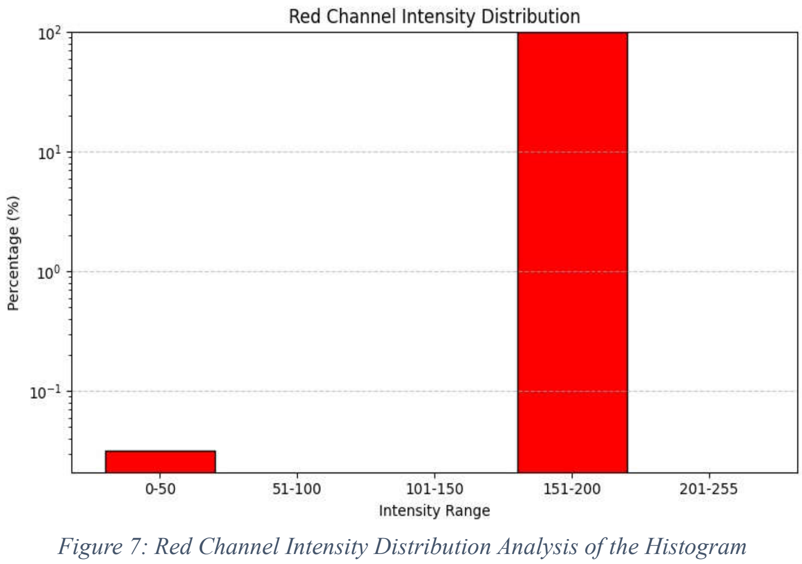

Figure 7: Red Channel Intensity Distribution Analysis of the Histogram

- Bin 1 (0-50) intensity range is very high: Means crops health is very poor, the agriculture land yielding sicked crops. The outcome of the agriculture land is very poor.
- Bin 2 (51-100) intensity range high: Means the is crop health is not so good.
- Bin 3 (101-150) intensity range high: Means the crop health is moderate, the outcome of the agriculture land is moderate.
- Bin 4 (151-200) intensity range high: Means the is crop is healthy and the area is entirely agricultural.
- Bin 5 (151-200) intensity range high: Means the is crop is very healthy and fine. The outcome of the agriculture land is dramatic.

For the sample image (that we have selected to demonstrate), intensity of bin-4 is high, that is crops health is good in the land. Since, the sample image contains large agriculture land and healthy crops the outcome of this land could be high.

CLASSIFICATION SECTION

i. Classification Training Using YOLOv11

The YOLOv11 model was trained using labeled satellite images of crops to accurately classify vegetation types. The images were resized to 256x256 and fed into the model to learn spatial and spectral patterns. Through iterative optimization of loss functions and confidence scoring, the model achieved efficient and high-accuracy classification.

ii. Model Validation Using YOLOv11

The YOLOv11 model was validated using a separate set of hyperspectral images not seen during training to assess its generalization capability. Performance was evaluated using metrics like accuracy, confusion matrix, and confidence scores. The classification model archived 82% accuracy in validation. This validation ensured the model's robustness in real-world agricultural prediction tasks.

The confusion matrix of the classification result (obtained in validation) is shown below:

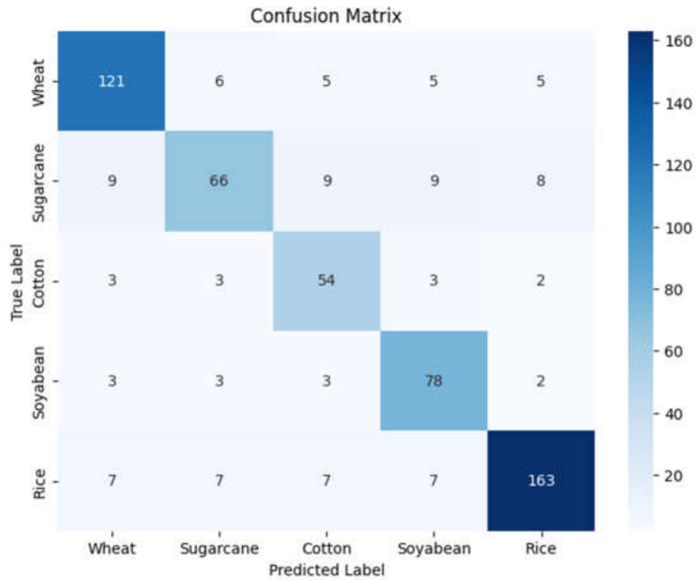

Figure 8: Confusion Matrix for Classification Results

The classification report is show below

Overall Accuracy: 0.82

	precision	recall	f1-score	support	Class-wise Accuracy
Wheat	0.69	0.83	0.76	65	0.85
Sugarcane	0.91	0.85	0.88	191	0.65
Cotton	0.76	0.88	0.82	89	0.83
Soyabean	0.78	0.65	0.71	101	0.88
Rice	0.85	0.85	0.85	142	0.85
accuracy			0.82	588	
macro avg	0.80	0.81	0.80	588	
weighted avg	0.82	0.82	0.82	588	

The histogram analysis revealed red channel dominance indicating vegetation traits, while YOLOv11 classification showed high-confidence, fast, and accurate crop-type predictions. Together, these validate the strength of combining statistical and deep learning methods for satellite-based agricultural analysis.

V. CONCLUSION

This study demonstrates that combining satellite-based hyperspectral imagery with statistical computer vision techniques and deep learning yields an effective framework for crop monitoring. By preprocessing raw Hyperion satellite data in ENVI (including radiometric calibration and atmospheric correction) to ensure spectral quality, we obtained reliable false-color composites for analysis. Focusing on the red channel of these images proved particularly insightful – healthy vegetation showed stronger near-infrared reflectance (appearing brighter red) compared to stressed crops, validating red-band intensity as a robust indicator of crop health. Leveraging these spectral insights, our YOLOv11-based classifier distinguished crop types with high accuracy; the model achieved about 82% classification accuracy on the validation set. These results confirm that integrating statistical histogram analysis with a state-of-the-art deep learning model can effectively assess crop health and classify crop types from hyperspectral data. These findings carry significant implications for precision agriculture. The developed satellite monitoring approach enables scalable, non-invasive crop health assessment over large areas, which is especially beneficial for agrarian regions like India. By automatically evaluating vegetation condition and crop type from spectral imagery, the system supports data-driven decision-making for sustainable crop management across diverse agricultural zones. In our experiments, the method was successfully applied to satellite data from multiple states in India (e.g. Gujarat, Uttar Pradesh, West Bengal, Punjab), underscoring its applicability to varied geographic and climatic contexts. This capability can help farmers and policymakers optimize resource allocation and intervention timing, aligning with the growing use of remote sensing to monitor crops, assess stress, and improve yield predictions. In essence, the proposed framework can enhance precision farming by providing timely insights into crop conditions at regional and national scales. Despite its promise, the approach has certain limitations. It is dependent on high-quality hyperspectral imagery, which can be costly and limited in coverage – specialized satellite sensors (such as NASA's Hyperion) are required to capture the rich spectral data. The reliability of the model under different atmospheric conditions or across seasons remains to be fully assessed; unmodeled atmospheric effects or seasonal shifts in crop spectra could impact accuracy. Additionally, the current training dataset encompasses a limited range of crop varieties, which may constrain the model's generalizability to other crop types or regions not represented in the training data. These factors highlight the need for cautious interpretation of the results and targeted improvements going forward.

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