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DATA-DRIVEN CROP STRESS, HEALTH AND MOISTURE MONITORING USING SATELLITE IMAGERY FOR PRECISION AGRICULTURE

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ABSTRACT

Precision agriculture demands timely and accurate insights into crop conditions to improve productivity and resource efficiency. This project presents an AI-driven approach for crop stress, health, and moisture monitoring using multispectral and hyperspectral satellite imagery from Sentinel-2 and AVIRIS (Indian Pines) datasets. The solution employs a U-Net-based deep learning architecture to process normalized image patches, eliminating noisy and water absorption bands for accurate spectral representation. Vegetation indices such as NDRE (Normalized Difference Red Edge) and NDMI (Normalized Difference Moisture Index) are integrated to map nutrient stress, disease-prone zones, and soil moisture variability across agricultural fields. By combining AI-based segmentation with remote sensing analytics, the system generates high-resolution maps that provide actionable insights for smart irrigation, nutrient management, and early stress detection. This enables farmers, researchers, and policymakers to make data-driven decisions, reducing water wastage, improving crop yield, and supporting sustainable agricultural practices.

KEYWORDS: Hyperspectral Remote Sensing, Multispectral Imagery, Precision Agriculture, Crop Health Monitoring, Crop Stress Detection, Moisture Mapping, U-Net, Deep Learning, NDRE, NDMI.

1. INTRODUCTION

The rapid advancement of hyperspectral imaging has transformed the landscape of Earth observation by capturing data across hundreds of narrow and contiguous spectral bands. Unlike traditional multispectral sensors that record information in a few broad bands, hyperspectral sensors capture fine-grained spectral details that enable the precise identification of materials and vegetation types based on their unique spectral signatures. This makes hyperspectral remote sensing an indispensable tool for agriculture, forestry, mineral exploration, environmental monitoring, and land-use assessment.

In the context of agriculture, hyperspectral imagery provides a highly detailed view of crop conditions, enabling accurate detection of crop stress, nutrient deficiencies, disease onset, and moisture variations. By leveraging the full spectral profile of vegetation, it is possible to capture subtle biochemical and structural differences that are invisible to conventional multispectral sensors such as those on Sentinel-2 or Landsat missions. Consequently, hyperspectral data has emerged as a critical enabler for precision agriculture, where timely and localized insights are essential for optimizing productivity and sustainability.

However, the enormous volume, high dimensionality, and complex spectral–spatial relationships inherent in hyperspectral data present serious challenges for traditional analytical approaches. Classical methods such as thresholding, band differencing, principal component analysis (PCA), or traditional machine learning models often fail to generalize across varying illumination conditions, soil backgrounds, and atmospheric influences. These techniques rely heavily on handcrafted features, which may not effectively capture nonlinear patterns or intricate correlations among spectral bands. Moreover, the presence of spectral redundancy and water absorption bands further complicates analysis, necessitating robust preprocessing and noise reduction techniques before meaningful information can be extracted.

To overcome these limitations, this project introduces an AI-driven deep learning framework that leverages the power of Convolutional Neural Networks (CNNs) and U-Net architectures to perform efficient, automated, and scalable hyperspectral image analysis. Deep learning methods, unlike traditional algorithms, have the capability to automatically learn hierarchical spatial and spectral representations directly from raw data. The U-Net model, with its encoder–decoder design and skip connections, is particularly effective for pixel-level semantic segmentation, making it ideal for detecting and mapping fine spatial variations in agricultural fields.

The proposed framework integrates data from two complementary satellite sources, the AVIRIS hyperspectral dataset (Indian Pines) and Sentinel-2 multispectral imagery. AVIRIS provides the spectral richness required for accurate modeling of crop characteristics, while Sentinel-2 contributes broad spatial coverage and temporal frequency for near-real-time monitoring.

Once trained, the model is applied to generate pixel-level maps of crop stress, health, and moisture content. The Normalized Difference Red Edge (NDRE) index is employed to quantify vegetation stress and chlorophyll concentration, while the Normalized Difference Moisture Index (NDMI) provides an estimate of vegetation and soil moisture levels. Together, these indices form a comprehensive crop condition monitoring system that can detect early stress signals, water stress, or nutrient imbalances allowing for timely and data-driven agricultural interventions.

The innovation of this project lies in its fusion of hyperspectral and multispectral data, deep learning-based automation, and multi-index mapping capability. By combining spectral, spatial, and temporal information, the system not only enhances accuracy but also ensures scalability and adaptability across different crop types, seasons, and geographical regions. The methodology eliminates the need for manual feature engineering and supports automated decision-making, thereby significantly reducing the time and effort required for agricultural monitoring.

From a broader perspective, this solution contributes directly to the goals of sustainable agriculture and food security. Accurate crop health and moisture maps can help optimize irrigation scheduling, fertilizer management, and yield forecasting, reducing input costs while minimizing environmental impacts.

Furthermore, the insights gained from this system can assist government agencies, agronomists, and researchers in monitoring regional crop performance, identifying drought-prone zones, and supporting climate-resilient agricultural planning.

Ultimately, this project represents a step toward AI-integrated smart farming ecosystems, where data from Earth observation satellites is seamlessly analyzed by intelligent models to deliver actionable insights. By merging hyperspectral science, AI-based analysis, and remote sensing technologies, the proposed solution demonstrates how deep learning can transform raw spectral data into meaningful agricultural intelligence supporting informed decisions, enhancing productivity, and advancing the vision of digital and sustainable agriculture for the future.

2. LITERATURE SURVEY

Author & Year	Technique / Algorithm	Outcomes	Research Gap
Itiya Aneece et al. (2025)	SVM, RF; next-gen hyperspectral sensors; multi-source data fusion (hyperspectral + ancillary).	Demonstrated effectiveness of new hyperspectral sensors in crop type mapping.	Explore additional ML techniques for improved accuracy (Aneece et al., 2024).
Qu Zhou et al. (2024)	RTM-ML; combined radiative transfer models + ML (SVR, RF); included atmospheric correction.	Successfully quantified crop nitrogen and biomass with high accuracy.	Further research needed on atmospheric correction (Zhou et al., 2023).
Nellore Kapileswar et al. (2023)	3D-CNN, RNN; spectral-spatial-temporal feature learning; advanced preprocessing.	Enhanced crop health monitoring; improved F1-score, recall, precision.	Need for more robust preprocessing techniques (Kapileswar et al., 2024).
C. Vairavan et al. (2023)	Hyperspectral imaging; feature engineering (vegetation indices, band ratios); supervised + unsupervised classifiers.	Provided insights into soil and crop monitoring; emphasized national soil spectral library need.	Lack of effective classification algorithms (Vairavan et al., 2024).
Qu Zhou et al. (2022)	RTM-ML; physical modeling + ML; applied preprocessing (noise removal, dimensionality reduction).	Achieved high accuracy in monitoring crop traits and soil properties.	Challenges in processing large data volumes remain (Zhou et al., 2023).
Shiva Mehta & Sunila Choudhary (2022)	ML (RF, Gradient Boosting); integrated with GIS; feature selection + spatial analysis.	Improved resource efficiency by 15%; achieved 90% accuracy in crop health prediction.	Needs high-quality input data, complex algorithms (Mehta & Choudhary, 2024).
Itiya Aneece et al. (2021)	SVM, RF, SAM; supervised classification of DESIS, PRISMA data; used vegetation indices, texture metrics.	Achieved 99% accuracy in crop classification.	Need for more diverse crop datasets (Aneece et al., 2024).

3. MATERIALS AND METHODS

A. Flow Chart

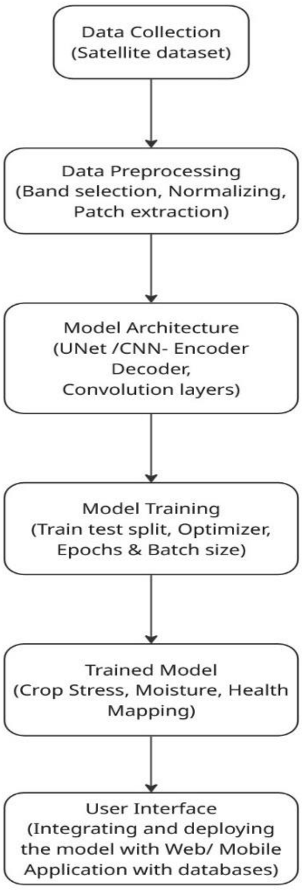

Fig 3.1: Flow Chart.

1. Data Collection

The project begins with the acquisition of high-quality hyperspectral and multispectral satellite datasets. The AVIRIS Indian Pines hyperspectral dataset provides fine spectral resolution across hundreds of contiguous narrow bands, enabling precise identification of crop variations and subtle vegetation differences. In parallel, the Sentinel-2 multispectral data offers broader spatial coverage, allowing the system to generalize and monitor larger agricultural regions effectively. By combining these two sources, the project leverages both spectral richness and spatial context, forming a comprehensive input foundation for training and prediction.

2. Data Preprocessing

Before model training, the raw satellite data undergo extensive preprocessing to improve its quality and reduce redundancy. Noisy and irrelevant spectral bands, particularly those affected by water absorption or atmospheric interference, are removed to retain only informative wavelengths. The remaining data is then normalized to a uniform scale to minimize lighting and sensor variability. Subsequently, the large hyperspectral images are divided into smaller patches to maintain spatial continuity and improve computational efficiency during training. This process ensures the dataset is spectrally consistent, balanced, and optimized for deep learning analysis.

3. Model Architecture

The preprocessed image patches are then fed into a deep learning model designed using a hybrid U- Net/CNN architecture. The encoder part of the model captures spatial and spectral features using multiple convolutional and pooling layers, while the decoder reconstructs these features into detailed segmentation maps. The inclusion of skip connections in U-Net allows the network to retain fine-grained details that are crucial for accurate boundary detection in agricultural fields. This architecture is specifically chosen for its ability to perform pixel-level semantic segmentation, making it highly effective for mapping crop stress, health, and moisture variations.

4. Model Training

The model is trained using the normalized hyperspectral patches, where the dataset is split into training and testing subsets to ensure robust evaluation. The training process involves optimizing the model parameters using techniques such as the Adam optimizer and fine-tuning hyperparameters like learning rate, batch size, and number of epochs. Loss functions such as categorical cross-entropy or Dice loss are minimized to improve pixel-wise classification accuracy. This stage allows the model to learn the complex spectral- spatial relationships within hyperspectral data, improving its ability to generalize across different crop types and conditions.

5. Trained Model

Once the training phase is complete, the model is capable of generating detailed predictive maps that visualize different crop conditions. The NDRE-based stress map highlights early signs of vegetation stress due to nutrient deficiency or disease, while the NDMI-based moisture map estimates soil and plant water content to guide irrigation decisions. Additionally, a crop health confidence map indicates overall vegetation vitality, distinguishing between healthy and weak growth zones. These outputs collectively provide actionable insights that can help optimize farming operations, reduce water wastage, and improve crop yields.

6. User Interface

The final stage involves integrating the trained model into a user-friendly web or mobile application to make the technology accessible to farmers, researchers, and policymakers. Through this interface, users can upload satellite data, run predictions, and visualize crop stress, moisture, and health maps in real time. The platform can also connect with databases and APIs to automate continuous monitoring and historical analysis. By combining the power of deep learning with an intuitive interface, the system empowers users to make informed, data-driven agricultural decisions at both local and regional scales.

7. Tools and Technologies Used

The system development and analysis were carried out using advanced AI and remote sensing tools. The implementation utilized Python as the core programming language, leveraging libraries such as TensorFlow and Keras for deep learning model development (U-Net and CNN architectures). NumPy, Pandas, and Scikit-learn were used for data preprocessing and normalization, while Matplotlib and Seaborn supported visualization and statistical analysis. For satellite data handling, Rasterio and GDAL were employed to process and manage multi-band raster datasets such as AVIRIS (Indian Pines) and Sentinel-2 imagery. Model training and testing were performed on GPU-enabled hardware for faster computation. The final outputs, including crop health, stress, and moisture maps, were generated using Python-based visualization frameworks, with potential integration into a web or mobile-based interface for real-time access and decision support.

4. RESULTS AND DISCUSSION

The results obtained from the proposed deep learning framework demonstrate the system's capability to accurately analyze and visualize critical crop conditions through pixel-level mapping derived from hyperspectral and multispectral satellite data.

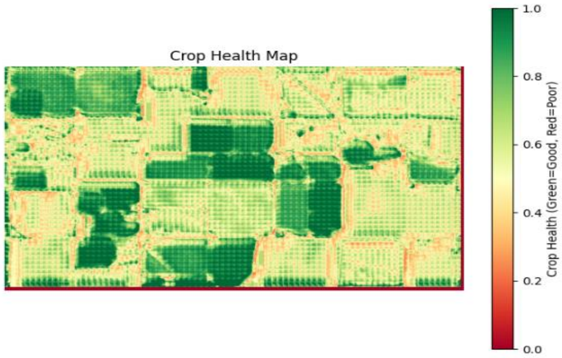

Fig. 4.1: Crop Health Map.

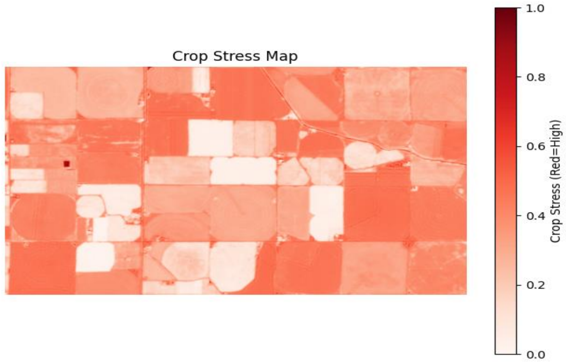

Fig. 4.1: Crop Stress Map.

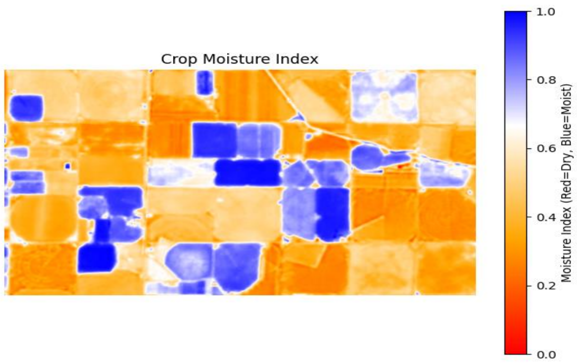

Fig. 4.1: Crop Moisture Map.

1. Crop Health Map

The generated crop health map provides a detailed visualization of overall vegetation vigor across the agricultural landscape. By analyzing spectral patterns through the trained U-Net model, the system effectively differentiates between healthy and weak vegetation zones. Healthier regions display higher spectral reflectance in the near-infrared bands, indicating dense and active chlorophyll content, while low- reflectance zones suggest poor growth or sparse vegetation. This map serves as an essential decision-support tool for monitoring crop performance, assessing field variability, and identifying areas that require targeted management interventions.

2. Crop Stress Map (NDRE-Based)

The NDRE (Normalized Difference Red Edge)–based stress map effectively highlights early signs of crop stress related to nutrient deficiency, pest infestation, or disease occurrence. The model’s spectral sensitivity to red-edge and near-infrared bands allows it to detect subtle changes in chlorophyll content before visible symptoms appear. High-stress zones are represented in red shades, whereas healthy vegetation areas appear in lighter tones, enabling farmers to take preventive measures such as adjusting fertilization or pesticide use. This early stress detection capability significantly enhances field-level management and prevents potential yield losses.

3. Moisture Map (NDMI-Based)

The NDMI (Normalized Difference Moisture Index)–based moisture map provides an accurate spatial distribution of crop and soil moisture levels using near-infrared (B8A) and shortwave infrared (B11) bands from Sentinel-2 imagery. Regions with high moisture content are clearly depicted in blue tones, while drier areas are shown in lighter hues. This allows precise irrigation scheduling and helps prevent both drought stress and waterlogging conditions. By integrating this moisture information with crop health indicators, the system enables efficient water resource management and contributes to sustainable agricultural practices.

Overall Performance and Insights

Across all indices, the model exhibited strong generalization on unseen data and successfully integrated hyperspectral and multispectral features to produce smooth and interpretable maps. The combined outputs enable a comprehensive understanding of crop conditions linking plant health, stress, and moisture dynamics. Such integration empowers decision-makers to adopt site-specific management strategies, enhancing productivity while conserving natural resources.

5. CONCLUSION

The proposed AI-driven system successfully demonstrates the potential of deep learning and satellite- based hyperspectral–multispectral integration for precision agriculture. By leveraging U-Net and CNN architectures, the framework effectively maps crop health, stress, and moisture variations at high spatial detail, offering actionable insights for farmers and policymakers. The generated maps based on NDRE, NDMI, and vegetation health indices enable early detection of crop stress, efficient irrigation planning, and optimized resource utilization.

This approach bridges the gap between traditional remote sensing and intelligent agricultural monitoring, reducing the need for manual field surveys while improving data accuracy and timeliness. The scalable and automated nature of the system ensures it can be applied across different crop types, seasons, and geographical regions. Ultimately, the solution contributes to sustainable agriculture by promoting better decision-making, increasing yield reliability, and supporting environmental conservation through informed management practices.

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