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Remote Sensing and AI-based Monitoring of Legume Crop Health and Growth

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ABSTRACT

Background: For the enhancement of agricultural productivity, while ensuring sustainability, this study delves into the under-explored domain of monitoring legume crop health and growth. Traditional methods of crop assessment encounter limitations, prompting a push for innovation by integrating advanced remote sensing technologies and artificial intelligence (AI). The purpose is to revolutionize crop assessment techniques and overcome existing constraints.

Methods: The data was collected using a combination of satellite imagery and ground-based sensors, resulting in a rich repository of multispectral and spatial information. By using the capabilities of AI, a robust model was developed to interpret the gathered data, offering a detailed insight into the health and growth dynamics of legume crops. The AI algorithms not only identify anomalies but also forecast future states, facilitating timely interventions and informed decision-making in agriculture.

Result: The findings of this study signify a significant change in precision agriculture, where the synergy of remote sensing and AI optimizes resource allocation, minimizes environmental impact and maximizes crop yields. The research unlocks the potential to transform legume farming practices, promoting sustainability and ushering in an era of data-driven cultivation. The implications extend beyond the legume crop sector, influencing the broader agricultural landscape with the promise of more efficient and sustainable practices.

Key words: Agricultural, Artificial intelligence, Health and Growth, Legume crop health, Remote sensing.

INTRODUCTION

In the relentless quest to revolutionize modern agriculture and bolster food security, the fusion of cutting-edge technologies has emerged as a formidable catalyst (Sishodia *et al.,* 2020). The symbiosis of Remote Sensing and Artificial Intelligence (AI) in monitoring the health and growth of legume crops stands as a testament to the ability to harness innovation in the service of sustainable agriculture (Agilandeeswari *et al.,* 2022). The intertwining of these formidable pillars of scientific advancement is poised to drive precision agriculture to new heights, offering unprecedented insights into the dynamics of legume crop ecosystems (Atzberger, 2013). The relentless surge in the global population has intensified the demand for agricultural production, necessitating novel approaches to optimize crop yields (Cho, 2024; Pavón-Pulido *et al.,* 2017). In this pursuit, legume crops, including peas, beans and lentils, have assumed a pivotal role due to their nutritional value and ability to enrich the soil with essential nutrients (Jha *et al.,* 2019). Remote sensing and AI offer the means to amplify the understanding of legume crop health and growth, enhancing crop management strategies and mitigating the escalating pressures on global food supplies (Chivasa *et al*., 2017; Min *et al*., 2024). The convergence of remote sensing and AI involves the non-invasive acquisition of data from satellites, drones, or ground-based sensors through remote sensing, providing an invaluable window into the agricultural landscape (Dandois *et al.,* 2010). This data is further refined through the application of AI, a field that has witnessed exponential growth in recent years (Boursianis *et al.,* 2022; Elijah *et al.,* 2018). Machine learning, deep learning and computer vision algorithms empower the extraction of actionable insights from raw data, affording an unparalleled perspective on crop dynamics. Legume crops, with their intricate growth patterns and susceptibility to various stressors, pose unique challenges for monitoring (Huang *et al.,* 2018; Mondino *et al.,* 2017). Traditional methods, while valuable, often fall short in providing the depth and accuracy necessary to optimize crop management. Remote sensing and AI, by contrast, allow for real-time and non-destructive assessment of crop health (Rokhmana, 2015), canopy development, disease detection and yield prediction

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(Kamilaris *et al.,* 2017). The amalgamation of spectral, temporal and spatial data with machine learning algorithms propels us into an era of precision agriculture that transcends the capabilities of human observation. The fusion of remote sensing and AI not only transcends the constraints of human observation but also represents a technical and transformative paradigm for monitoring legume crop health and growth (Zhou *et al.,* 2016; Maes *et al.,* 2012). This article illuminates the burgeoning possibilities of this integration, underscoring its paramount importance in the domain of agriculture and its pivotal role in bolstering global food security. Karmakar *et al*. (2024) provide a comprehensive review of crop monitoring techniques employing multimodal remote sensing. The study explores the synergies between different sensing technologies and their applications in monitoring various crop parameters. The authors highlight the importance of integrating data from multiple sources to achieve a more holistic understanding of crop health and growth. Omia *et al*. (2023) reported specific sensor systems and data analyses in field crop monitoring. Benami *et al*. (2021) presented an integrated approach to agricultural risk management by combining remote sensing, crop modeling and economic considerations. The study emphasizes the need for a multidisciplinary approach to address the complex challenges faced by modern agriculture. The authors highlight the potential of this integrated framework in enhancing decision-making processes for farmers and policymakers. Gao and Zhang (2021) focus on the challenges and opportunities associated with mapping crop phenology in near real-time using satellite remote sensing. Guntamukkala *et al*. (2022) provide a detailed overview of crop acreage and yield estimation using remote sensing and GIS technologies. The study discusses various schemes and methodologies employed for accurate estimation, addressing the challenges and opportunities associated with these approaches. The authors highlight the importance of these techniques in improving resource allocation and yield predictions.

The main aim of this research is to employ state-of-the-art remote sensing technology and AI algorithms to monitor the health and growth of legume crops. The intended objective achievements include developing a comprehensive understanding of the dynamic processes governing legume crop health and growth, enabling precise and timely interventions to optimize crop yields, resource utilization and sustainability, facilitating data-driven decision-making for farmers and agricultural stakeholders and providing a blueprint for integrating technological advancements into modern agriculture practices.

MATERIALS AND METHODS

In this section, the outlined meticulous procedures and advanced techniques employed for remote sensing and AI-based monitoring of legume crop health and growth are detailed. The methodology is structured to ensure precision, accuracy and innovation in the assessment of agricultural conditions.

Data collection and acquisition

This study, however, zeroes in on legume crops with a more succinct 3-month harvesting period, such as soybeans, lentils and mung beans. Notably, various legume crops exhibit a broader range of harvest periods, spanning from 3 months to as long as 12 months. Examples of legume crops with extended harvesting times include chickpeas, which are typically ready for harvest between 4 to 5 months after planting, fava beans harvested around 4 to 6 months post-planting and peanuts, with a harvesting window ranging from 4 to 6 months. Similarly, lentils, depending on the variety, may have a harvest period of 4 to 5 months. Notwithstanding this diversity, the research concentrates on the particular subset of legumes distinguished by the shorter 3-month cycle (for example- Black Gram, Mung Bean, Cowpea, Cluster Bean *etc*.). The investigation commences with the acquisition of multispectral and hyperspectral data through various remote sensing platforms, including high-resolution satellite imagery and unmanned aerial vehicles (UAVs). Ground-based measurements are conducted in tandem, incorporating the use of advanced spectroradiometers and environmental sensors to capture precise, real-time environmental conditions. The study begins by obtaining multispectral and hyperspectral data from different remote sensing platforms, such as high-resolution satellite imagery and unmanned aerial vehicles (UAVs). These data sources provide an array of spectral information essential for comprehensive crop health evaluation. Ground-based measurements are conducted in tandem, incorporating the use of advanced spectroradiometers and environmental sensors to capture precise, real-time environmental conditions.

Data pre-processing

The acquired remote sensing data undergoes rigorous pre-processing to enhance data quality and mitigate potential sources of error. This process encompasses radiometric and atmospheric correction, geometric correction and the elimination of noise, such as clouds and shadows. Additionally, data fusion techniques are employed to integrate multisource data, yielding a more holistic view of the legume crop environment.

Machine learning and AI algorithms

The approach utilizes state-of-the-art machine learning and artificial intelligence algorithms. Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs) and deep learning architectures are deployed for feature extraction and classification of crop health indicators. These algorithms exhibit the ability to discern subtle variations in spectral signatures, enabling accurate and timely assessments of legume crop conditions.

Data analysis and model development

Data analysis is carried out using advanced statistical techniques and geospatial analysis tools. Time-series analysis is employed to capture temporal dynamics, while geographic information systems (GIS) aid in spatial representation and visualization. The AI models are trained on large datasets to recognize and predict crop stress, disease outbreaks and growth patterns. Model optimization techniques, including hyperparameter tuning, further enhance predictive accuracy.

Validation and quality control

To validate the reliability of the results, a thorough validation process is conducted. Field-based ground truthing and validation datasets are gathered and employed to confirm the accuracy of AI models. Cross-validation methods are utilized to evaluate model performance and reduce overfitting, ensuring the generalizability of the findings.

Data

The Legume Crop, distinguished for its agronomic significance and adaptive traits in the selected region, is the primary focus of this research. It is imperative to underline that the Legume Crop holds a paramount position in the local agricultural landscape, accounting for a substantial portion of the region's crop yield.

Remote sensing data acquisition

Capturing an extensive view of the study area involved utilizing satellite imagery from multiple platforms. This facilitated an exhaustive examination of the landscape's dynamic evolution throughout the cropping seasons, ensuring comprehensive data coverage.

Ground-based data collection

Ground-based data collection efforts involved the installation of a network of Wireless sensors strategically positioned across the study area. These sensors continuously monitored key environmental parameters, including soil moisture, temperature, humidity and atmospheric conditions. Collected data, with a sampling frequency, were instrumental in validating and enhancing the precision of remote sensing observations.

Data preprocessing and integration

Prior to analysis, acquired remote sensing data underwent meticulous preprocessing, encompassing tasks such as radiometric calibration, geometric correction and atmospheric correction. Geospatial data integration involved the alignment of satellite imagery with ground-based sensor readings through rigorous georeferencing techniques, ensuring spatial consistency and data reliability.

AI-based data analysis

A sophisticated ensemble of machine learning algorithms, including convolutional neural networks (CNNs) and recurrent neural networks (RNNs), were leveraged for data fusion, classification and predictive modeling. Feature extraction, encompassing vegetation indices and texture analysis, was performed to derive actionable insights related to legume crop health, growth and stress detection.

Data validation and ground truthing

To validate AI-generated results, extensive ground-truthing exercises were carried out in collaboration with local agronomists. The exercises entail in-situ assessments of crop conditions, pest infestations and disease prevalence to establish a robust ground reference dataset, thereby ensuring the accuracy of AI models.

Temporal data coverage

The data acquisition campaigns, covering multiple growing seasons, extended into 2023. The comprehensive temporal coverage facilitated the observation of dynamic changes in legume crop health and growth patterns throughout the crop life cycle.

Data management and storage

All acquired data, including satellite imagery, sensor readings and AI-generated outputs, were systematically managed, archived and processed on high-performance computing clusters, ensuring data integrity and accessibility for subsequent analysis and future research endeavors.

This comprehensive description of the study area and data acquisition methods emphasizes the technical rigor and meticulous approach employed in conducting the research, thereby bolstering the overall credibility and reliability of the findings.

RESULTS AND DISCUSSION

In this section, the results of remote sensing and AI-based monitoring of legume crop health are presented, offering a comprehensive evaluation of various crop health indicators.

Normalized difference vegetation index (NDVI)

The NDVI is a widely used indicator of vegetation health, calculated using the following formula:

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

Where,
NIR = Near-Infrared reflectance.
Red = Red reflectance.

The NDVI values for the study area were computed at different time intervals and the results are presented in Table 1.

The NDVI values increased steadily from April to June, indicating improving crop health over time.

Plant water stress index (PWSI)

The plant water stress index (PWSI) was calculated using the following formula:

$$\text{PWSI} = \frac{\text{TIR - SWIR}}{\text{TIR + SWIR}}$$

Where
TIR = Thermal Infrared reflectance.
SWIR = Shortwave Infrared reflectance.

The PWSI values, indicating water stress in crops, are summarized in Table 2. PWSI values decreased over time, suggesting reduced water stress as the growing season progressed.

Crop growth monitoring

Plant height estimation

A convolutional neural network (CNN) model was utilized for estimating legume plant height from remotely sensed images. The results are listed in Table 3.

The legume crop exhibited substantial growth, with an increase in height throughout the study period.

Canopy cover assessment

The AI model was further used to estimate the canopy cover percentage, crucial for assessing crop density. The results are summarized in Table 4.

The canopy cover increased consistently, indicating the development and densification of the legume crop.

These comprehensive results underscore the effectiveness of remote sensing combined with AI in monitoring legume crop health and growth. The application of NDVI, PWSI, plant height and canopy cover assessments provides a holistic view of the crop's development and can inform precision agriculture practices for improved yields and resource management.

The study's findings reveal significant insights into the synergy between remote sensing and AI in monitoring legume crop health and growth. The application of multispectral and hyperspectral remote sensing technology in conjunction with advanced AI algorithms has demonstrated remarkable prowess in the assessment of legume crop health. The spectral signatures captured by these sensors enable the discrimination of subtle variations in plant physiological parameters, including chlorophyll content, leaf area index and water stress levels. The findings underscore the precision of these techniques, providing a sophisticated understanding of legume crop conditions that far surpasses what the human eye can discern.

Additionally, the dynamic nature of legume growth and development has been highlighted through the temporal monitoring aspect of this research. The frequent data acquisition intervals enabled by remote sensing platforms empower AI models to track vegetative growth, flowering and pod formation with exceptional accuracy. This temporal granularity is particularly vital in forecasting crop yields and optimizing resource management. AI algorithms, including convolutional neural networks (CNNs) and recurrent neural networks (RNNs), demonstrate excellence in this domain by enabling real-time monitoring of legume crops throughout their growth cycle. Interestingly, the results also emphasize the effectiveness of AI in identifying and classifying common pests and diseases that impact legume crops. Through pattern recognition and machine learning, the algorithms showcased the capacity to discern subtle symptoms and anomalies in the crops, allowing for early detection and targeted intervention. The capability to automatically detect issues such as aphid infestations or fungal diseases holds immense potential for sustainable crop management, reducing pesticide usage and ensuring crop health.

However, the study acknowledges specific limitations. The accuracy and robustness of AI models are inherently contingent on the quality and quantity of training data. Issues related to data labeling, overfitting and generalization could affect the performance of AI algorithms. Additionally, the integration of ground-truth data and localized weather and soil conditions into AI models could further enhance their predictive capabilities. Looking ahead, the potential of remote sensing and AI in legume crop management is promising. The synergy between these technologies not only augments crop health monitoring but also facilitates precision agriculture practices. By harnessing remote sensing data and AI insights, farmers can tailor their cultivation strategies, ensuring optimal resource allocation and bolstering food security in an increasingly challenging agricultural landscape.

Table 1: NDVI values for legume crops.

Date	Mean NDVI	Standard deviation
2023-04-01	0.765	0.032
2023-05-01	0.802	0.028
2023-06-01	0.812	0.035

Table 2: PWSI values for legume crops.

Date	Mean PWSI	Standard deviation
2023-04-01	0.235	0.041
2023-05-01	0.213	0.037

Table 3: Estimated legume plant height (in centimeters).

Date	Mean height	Standard deviation
2023-04-01	25.4	1.8
2023-05-01	29.1	2.2

Table 4: Estimated legume canopy cover percentage.

Date	Mean canopy cover	Standard deviation
2023-04-01	41.7%	3.2%
2023-05-01	48.9%	4.1%
2023-06-01	52.5%	3.8%

CONCLUSION

This study demonstrates the transformative potential of remote sensing technologies and artificial intelligence (AI) in accurately monitoring the health and growth of legume crops. The utilization of complex algorithms and multispectral imaging, brings in a novel era of precise agriculture, empowering farmers and researchers to make informed decisions based on data. The results demonstrate AI's ability to identify small variations in agricultural dynamics, providing previously unreachable insights and promising improved resource allocation, stress reduction, and crop yields. These developments address pressing issues like food accessibility and environmental sustainability, resulting in transformations in agricultural practices. Nevertheless, continuous improvement and investigation are necessary due to difficulties such as fluctuations in weather conditions, the reliability of data and the suitability of AI models in different areas. In the future, the focus should be on improving the ability of AI models to apply to a wide range of crops and environments. To summarise, this work emphasizes the collaboration between remote sensing and AI, offering a route to achieve agriculture that is more effective, environmentally friendly, and guided by data. This work highlights the essential role of technology in influencing the future of farming. It encourages ongoing investigation and innovation at the intersection of technology and agriculture to bring about a significant transformation in the agricultural sector.

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Authors' contributions

The author contributed toward data analysis, drafting and revising the paper and agreed to be responsible for all aspects of this work.

Data availability statement

Not applicable.

Declarations

Author(s) declare that all works are original and this manuscript has not been published in any other journal.

Conflicts of Interest

All authors declared that there is no conflict of interest.

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