

Vegetation health assessment system: towards precise agriculture using artificial intelligence

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ABSTRACT

This paper introduces a Vegetation Health Assessment System (VHAS) that integrates deep learning regression and large language models to improve precision agriculture by predicting and analyzing vegetation health in Southern Nigeria. The VHAS uses a custom-designed Efficient Vision Transformer (EVT) to reliably anticipate vegetation indices from remotely sensed data. The Google Gemini large language model (LLM) then processes these predictions, producing complete reports that include thorough analysis, highlight potential concerns, and provide context-specific management advice. A case study highlights the system's ability to deliver insightful assessments of vegetation health, going beyond simple index numbers and recommending actionable solutions for improving plant health. The VHAS's capacity to combine many data sources and models while generating human-readable reports considerably improves precision agriculture decision-making, outperforming traditional methods, and many other AI-based alternatives. While the work shows encouraging outcomes, it also exposes limitations and proposes future research approaches, with an emphasis on improving model accuracy, data diversity, and quick engineering techniques. The VHAS provides an important step towards more precise and efficient vegetation health monitoring and management in a variety of fields, including agriculture, forestry, and environmental conservation.

1. INTRODUCTION

Precision agriculture, which seeks to increase agricultural yields while minimizing environmental impact, demands efficient and reliable technologies for monitoring vegetation health [15]. Traditional approaches, which rely heavily on manual field surveys and sparse sampling, are frequently time-consuming, labor-intensive, and geographically constrained [22]. These restrictions impede timely interventions and efficient resource management, which is especially important in the context of large-scale agricultural operations and rising food production demands. Manual assessments' intrinsic subjectivity and the possibility of human error undermine the accuracy and consistency of vegetation health assessments. The introduction of remote sensing technology, and the rapid improvements in artificial intelligence (AI), offer new options for addressing these limitations [10].

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Deep learning algorithms, in particular, have shown great promise for automated, large-scale analysis of remotely sensed imagery, with high accuracy in detecting tiny alterations indicating plant stress, disease, or nutritional deficits [10]. Convolutional Neural Networks (CNNs) are particularly well-suited for this purpose because of their ability to extract features and recognize patterns from image data. However, many existing deep learning-based systems frequently fall short of providing the comprehensive, contextually rich insights required to guide educated agricultural decision-making. While these models may accurately categorize vegetative health, they usually lack the ability to incorporate contextual information and generate meaningful recommendations customized to specific scenarios [23]. This constraint emphasizes the importance of having a system that not only predicts, but also identifies areas of concern and provides meaningful interpretation, paving the way for effective vegetation management.

This paper presents a Vegetation Health Assessment System (VHAS) designed to address this critical gap. The system synergistically integrates a custom-designed deep neural regression model, trained on a substantial and diverse dataset of high-resolution vegetation imagery, with the advanced natural language processing capabilities of the Google Gemini large language model (LLM). The deep learning regression model acts as a robust engine for precise prediction of vegetation health indices, while Gemini leverages this information to generate comprehensive and interpretable reports, including detailed analyses, identification of potential problems, and suggestions for specific management actions. This fusion of deep learning regression and large language models allow for the generation of insightful, context-aware analyses that surpass the limitations of existing methods, providing a more holistic understanding of vegetation health and facilitating data-driven decision-making in precision agriculture. We evaluate the performance of this integrated system, demonstrate its capacity for generating in-depth analyses, and discuss its broad implications for optimizing agricultural practices. The scope of this work will focus specifically on the development of a vegetation prediction and analysis system for the Niger Delta areas of Southern Nigeria using the combined synergy of a deep learning regression model and a language model for a complete understandable and actionable insights.

1.1 Contribution of the Study

This work will spur future research into the forces that influence environmental changes. A key relevance of this work is that it will assist relevant government agencies, interested private sectors, and environmental and agricultural stakeholders who are primary beneficiaries, in making real-time decisions and developing policies to mitigate its negative impact. New and easier scientific methods of farm are introduced through this study. As the world population increases; there is a need for food security, this study highlights ways to meet the demands of food with the increase in population [25]. It will serve as a motivator for agricultural re-engineering in order to increase precision agriculture and environmental studies. The proposed study addresses a critical need for precise agricultural practices through advanced green vegetation monitoring in the Niger Delta areas of Southern Nigeria.

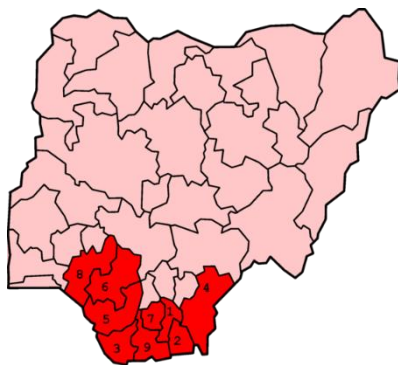


Fig. 1 Map showing locations of interest (Niger Delta of Southern Nigeria in Red) Source: [2]

2. LITERATURE REVIEW

The use of artificial intelligence (AI) in precision agriculture is growing rapidly, with substantial advances in leveraging various AI tools for effective vegetation health monitoring. The vegetation index (VI) as a spectral imaging transformation enables valid geographical and temporal inter-comparisons of terrestrial photosynthetic activity and canopy structural alterations [24]. This transformation is performed for two or more image bands. Many vegetation indices are based on the inverse relationship between red and near-infrared reflectance, which is linked to healthy vegetation. These indicators are calculated using a variety of formulas and procedures,

depending on their intended purpose or historical evolution. The Normalised Difference Vegetation Index (NDVI), Ratio Vegetation Index (RVI), Soil Adjusted Vegetation Index (SAVI), and Enhanced Vegetation Index (EVI) are some commonly used vegetation indices [7]. One of the most commonly used indices is the difference in near-infrared (NIR) and red reflectance divided by the sum of these two values.

The use of vegetation index is essential in a range of fields, including agriculture, environmental monitoring, and climate research. Researchers and resource managers utilise satellite-based vegetation maps to investigate differences in plant growth caused by climate and environmental changes, as well as human activities, and to monitor the health of forests and croplands. These indices are crucial for understanding the carbon cycle and vegetation's involvement in collecting and storing CO₂ from the atmosphere [7], climate change mitigation, wide life preservation and animal husbandry to meet the protein requirement of the rising population. Vegetation indices of various types are used in remote sensing to quantify and analyse vegetative cover using spectral information. These indices are intended to enhance the contribution of vegetation features while also allowing for accurate spatial and temporal comparisons of terrestrial photosynthetic activity and canopy structure changes.

According to literature, several methods have been employed in remote sensing for a variety of applications, including classification, detection, clustering, and segmentation. Image regression, on the other hand, has gotten little attention, despite the fact that it is an important feature of computer vision and has a wide range of applications in remote sensing [19]. The creation of robust, fast, and accurate regression algorithms is an absolute must in the realm of remote sensing. Estimating biophysical characteristics is especially crucial for gaining a better understanding of environmental dynamics at both local and global scales [13]. In general, many researches indicate that the spectral reflectance provided by aerial-based sensors is a mix of signals, especially when the size of scene objects is less than the immediate field of vision [26]. Over the years, a number of approaches to estimating vegetation cover have been developed, which may be broadly grouped into three categories: empirical methods, pixel unmixing models, also known as Spectral Mixture Analysis (SMA), and machine learning methods [14].

Empirical approaches create statistical connections between vegetation cover and vegetation indices or individual band reflectance by gathering enough and reliable data from a large number of samples. When applied to specific vegetation types and on a regional scale, empirical techniques can achieve appropriate accuracy. However, in large-scale regions, empirical approaches become useless because the different vegetation types and land conditions induce uncertainty in the established connections [3]. Pixel unmixing models assume that each pixel is composed of several components, and the fraction of vegetation composition is represented by the pixel's fractional vegetation composition value. Although the linear unmixing method is the most commonly used SMA technique for characterising ground cover at the sub-pixel scale, other approaches have been used, including multi-layer perceptrons neural networks, fuzzy classifiers, maximum likelihood classifiers, and regression trees [1]. In recent years, statistical machine learning approaches have also been widely used in the process of determining vegetation cover values. This is because these strategies are computationally efficient and perform consistently in non-linear fitting [27]. In general, machine learning approaches calculate the vegetation by training on a representative sample database of pre-processed reflectance and related simulated land surface parameter data. This procedure occurs throughout the learning phase [27].

Machine learning has emerged as a powerful tool for analyzing remotely sensed imagery for precise agriculture [5]. Convolutional Neural Networks excel at extracting complex features from high-resolution images, enabling accurate classification of vegetation types, detection of stress indicators (e.g., disease, nutrient deficiencies, water stress), and prediction of yield. These models have been successfully trained on diverse datasets comprising multispectral and hyperspectral imagery acquired from satellites (e.g., Landsat, Sentinel), unmanned aerial vehicles (UAVs), and even ground-based sensors [23]. Various CNN architectures, including but not limited to U-Net [20], ResNet [9], and EfficientNet [21], have been employed, showcasing varying degrees of accuracy and efficiency depending on dataset size, image resolution, and the complexity of the task. Moreover, advancements in transfer learning have allowed researchers to leverage pre-trained models on large image datasets (e.g., ImageNet), accelerating the training process and improving performance, even with limited labeled agricultural data [17]. [28] created a deep learning system utilising the ENVINet-5 model. The deep learning ENVINet-5 model was used to track vegetation coverage in the research area using medium-resolution Landsat Thematic Mapper (TM) and Operational Land Imager (OLI) satellite images. The training and verification samples were manually labelled with the fusion picture and a high-resolution Google Earth satellite image, and labels for four types of ground objects (desert, water body, cultivated land, and building land) were assigned. This data was used to calculate the NDVI for the area of interest.

Despite these successes, several limitations persist. The ENVINet -5 model primarily focused on classification tasks, offering limited insights beyond basic health categorization. Therefore, there is need for models which are capable of providing detailed, and contextually rich analyses that should go beyond simple labels to quantify the severity of stress, identify specific causes, and suggest targeted management interventions [23]. Furthermore, the interpretability of deep learning models remains a challenge. Understanding why a model

predicts a particular outcome is crucial for building trust and ensuring responsible deployment in critical agricultural applications. Explainable AI (XAI) techniques are increasingly being explored to address this limitation, but remain an active area of research.

The efficacy of Large Language Models (LLMs) in generating high-quality, relevant outputs critically depends on the design and formulation of prompts [18]. Prompt engineering, therefore, involves meticulously crafting prompts that guide the LLM's responses towards desired outcomes. This is particularly critical in the agricultural domain, where precision and unambiguous communication are paramount. The selection of vocabulary, sentence structure, and contextual information within the prompt significantly influences the accuracy, completeness, and usefulness of the LLM's response [4]. Effective prompts in agricultural applications need to incorporate precise terminology relating to vegetation indices, environmental factors, specific crops, and agricultural management practices. Moreover, structuring prompts to elicit specific information (e.g., requesting a detailed analysis of a given vegetation index, outlining potential causes of identified issues, or recommending specific actions) is vital for ensuring the LLM's output is directly applicable to real-world decision-making. While prompt engineering is a burgeoning field, further research is necessary to develop robust methodologies for creating optimal prompts for specific agricultural applications, especially within the context of integrating LLMs with deep learning models.

The adoption of Large Language Models (LLMs) and Generative AI in agriculture is rapidly gaining traction. LLMs have shown promise in various agricultural tasks including: generating reports from sensor data, providing expert advice based on user queries, creating detailed summaries of complex research findings, automating disease diagnosis, and predicting crop yields [11]. However, most existing researches focus on isolated applications, lacking a unified framework that integrates LLMs with other deep learning models for a comprehensive and synergistic approach to vegetation health assessment. The integration of LLMs with other deep learning offers several advantages: LLMs can synthesize information from multiple sources (e.g., combining deep learning outputs with weather data, soil information, and historical records), contextualize results within specific agricultural settings, and generate narratives and recommendations that are readily interpretable by agricultural practitioners.

Generative AI models, such as Generative Adversarial Networks (GANs) and Variational Autoencoders (VAEs), hold significant potential for advancing precision agriculture [8],[12]. These models can be used to synthesize training data for deep learning models, addressing data scarcity issues which are common in agricultural contexts. They can also be employed to simulate various scenarios, enabling predictive modeling and supporting optimized decision-making under varying conditions [16]. However, the full potential of generative AI in precision agriculture remains largely unexplored. For that reason, further research is needed to develop robust generative models tailored to specific agricultural applications and to address challenges related to data quality, model interpretability, and computational cost.

3. METHODOLOGY

This section details the methodology employed in developing and evaluating the proposed Vegetation Health Assessment System (VHAS), encompassing the deep learning regression model, the large language model (LLM) integration, system architecture, and image preprocessing techniques.

The core of the VHAS is a custom-designed Efficient Vision Transformer (EVT) network implemented in [6], an architecture combining the strengths of Convolutional Neural Networks (CNNs) for localized feature extraction with the global context modeling capabilities of Transformers. The EVT architecture comprises a convolutional layer for patch embedding, followed by a Transformer encoder (six (6) encoder layers, eight (8) attention heads, and a feedforward dimension of 2048) for feature extraction and a linear decoder to regress a single vegetation index value. The ReLU activation function is implicitly used within the Transformer layers. The model was trained using the Mean Squared Error (MSE) loss function, optimized via the Adam algorithm with learning rate $lr = 0.0001$.

The EVT was trained on a dataset of 4000 images representing diverse vegetation settings, sourced from custom UAV imagery. Images were pre-processed and labelled with corresponding vegetation indices calculated using pixel values. Data augmentation, including random horizontal and vertical flips were applied to enhance model robustness. The dataset was stratified into training (3700), validation (281), and testing (19) sets. Model performance was rigorously evaluated using the Root Mean Squared Error (RMSE) on the held-out test set. See Table 1.

Table 1: Statistics on Test data for EVT

1	Mean Square Error	0.00209
2	Root Mean Square Error	0.04582

Source: [6]

The Google Gemini LLM is integrated to provide detailed analysis and actionable recommendations based on the EVT's vegetation index forecasts. The system workflow is as follows: A pre-processed image is sent into the EVT, which predicts the vegetation index. This value is then utilized to dynamically generate a prompt for the Gemini LLM. The prompt was carefully designed to collect particular information about vegetation health, potential stressors, and recommended management actions. Gemini's JSON response is parsed to extract and organize relevant information for the final report.

3.1 System Architecture:

The VHAS workflow proceeds as follows:

1. Image Input: User uploads an image via a user-friendly interface.
2. Image Preprocessing: The uploaded image undergoes resizing (600x600), tensor conversion, normalization, and MinMax scaling to the range (1.8 and 7.10). This preprocessing pipeline is critical to ensure model input consistency and to optimize model performance.
3. EVT Model Inference: The preprocessed image is fed to the trained EVT model, generating a vegetation index prediction.
4. Prompt Generation: A prompt tailored to the predicted vegetation index is dynamically created for the LLM.
5. LLM Interaction: The prompt is submitted to the Gemini LLM for analysis and recommendation generation.
6. Report Generation: Relevant information from the LLM's JSON response is extracted and formatted into a structured report.
7. Output Presentation: The final report, including the predicted vegetation index, LLM-generated analysis, and recommended actions, is presented to the user via a user-friendly interface.

4. RESULTS AND DISCUSSION

The analysis focuses on a representative example to illustrate the system's capabilities and highlight the importance of integrating deep learning with large language models for comprehensive vegetation health assessment. The system's deep learning model (EVT) predicts a vegetation index between 0-1. This vegetation index value, as interpreted by the integrated Gemini LLM, indicates remarkably healthy and thriving vegetation if vegetation is above 0.5 threshold, suggesting abundant green biomass and robust plant health. LLM-Generated Analysis of Vegetation Index is presented in Table 2.

Table 2: LLM-Generated Analysis of Vegetation Index between 0-1

Aspect	Highlights of Detailed Analysis
Area of Concern	This feature outputs areas of concern in the input data that require attention.
Needed Attention	This feature identifies the needed attention with respect to the input data.
Recommended Actions	Gives a comprehensive recommendation of actions to be taken.

The LLM's detailed analysis template (Table 2) further contextualizes the predicted vegetation index emphasizing the need for a nuanced interpretation. While a higher vegetation index is generally positive, it does not provide a complete picture. The system highlights several crucial points requiring further investigation. The LLM-generated report in Table 2 above, emphasizes the importance of considering spatial variability. A uniformly high vegetation index across the entire area would indicate optimal conditions. However, the presence of localized areas with lower vegetation indices could signify potential stress points requiring targeted interventions. Similarly, comparing the current vegetation index with historical data for the same area is crucial to assess whether the observed high vegetation index represents a long-term trend or a recent improvement. Understanding the influence of environmental factors such as rainfall, temperature, and soil conditions is also essential for a comprehensive interpretation of the vegetation index. The LLM's recommendations, including regular monitoring schedules and additional measures like ground truthing, reinforce this need for context-specific analysis.

The VHAS successfully integrates regression model and LLM to provide a detailed analysis that surpasses the limitations of traditional methods. The regression model accurately predicts the vegetation index, while the LLM interprets this prediction within a broader context, offering comprehensive insights and actionable recommendations. This integrated approach enhances interpretability and facilitates data-driven decision-making. The generated report, exemplified in this case study, demonstrates the VHAS's ability to not

only identify areas of concern but also to suggest practical management strategies. The system's recommendations, including regular monitoring, investigation of spatial variability, environmental impact analysis and ground truthing, underscore a proactive and adaptive management approach critical for optimizing vegetation health and maximizing yields. The identified applications (agriculture, forestry, conservation, climate change research) showcase the VHAS's broad potential across diverse fields.

While promising, the VHAS has certain limitations. The accuracy of the vegetation index prediction depends on the quality of the input imagery and the training data. The LLM's analysis is dependent on the quality of prompts and the availability of relevant information in its knowledge base. Future work will focus on improving model accuracy, incorporating additional data sources with actionable context, integrating the Retrieval Augmented Generation (RAG) system, and refining prompt engineering techniques.

5. CONCLUSION

This research presented the development and evaluation of a Vegetation Health Assessment System (VHAS) designed to enhance precision agriculture practices. The VHAS integrates a custom-designed Efficient Vision Transformer (EVT) for accurate vegetation index prediction with the powerful analytical capabilities of the Google Gemini large language model (LLM) for comprehensive report generation and actionable recommendations. The results demonstrate the system's ability to provide detailed, context-aware analyses of vegetation health, surpassing the limitations of traditional methods and many existing AI-based approaches.

Despite its promising capabilities, the VHAS has certain limitations. The accuracy of the system relies on the quality of input images and training data, and the LLM's analysis is influenced by the quality of prompts and the completeness of its knowledge base. Future research will focus on enhancing the model's robustness and accuracy by exploring advanced deep learning architectures, expanding the training dataset to include a wider range of vegetation types and environmental conditions, and refining prompt engineering techniques for more effective interaction with the LLM. Incorporating additional data sources, such as weather data, soil information, and historical records, could further improve the comprehensiveness and precision of the VHAS. Furthermore, research into explainable AI (XAI) methods could enhance the transparency and trustworthiness of the system's predictions and recommendations.

In conclusion, the VHAS represents a significant step towards achieving more precise and efficient vegetation health monitoring and management. Its ability to integrate deep learning and large language models offers a powerful new tool for data-driven decision-making in diverse agricultural and environmental applications. The continued development and refinement of this technology hold significant promise for improving agricultural practices, resource management, and environmental sustainability.

Declarations

Ethical Statement: The submitted work should be original and has not been published elsewhere in any form or language to our knowledge.

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Code availability (software application or custom code): Not Applicable

Consent to participate: Not Applicable

Consent for publication: Not Applicable

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