AI-based techniques for comprehensive crop nutrition assessment: A review

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ABSTRACT

Artificial Intelligence (AI) methodologies, such as machine learning, deep learning, and data fusion, are transforming agricultural practices by offering advanced tools for data-driven decision-making, predictive modeling, and automated processes. This paper explores the latest AI techniques utilized in agriculture to enhance productivity, optimize resource management, and address the challenges posed by climate change. By harnessing AI-driven solutions for crop management, soil analysis, and pest control, these methods significantly contribute to sustainable agriculture, benefiting both farmers and the environment through more efficient and eco-friendly practices. However, while AI holds immense promise, challenges remain in terms of accessibility, data quality, and the adaptation of these techniques to diverse agricultural conditions. This review aims to provide a balanced overview of the current state of AI applications in agriculture, offering insights into the opportunities and limitations faced by this growing field.

Keywords: Advanced Agricultural Technologies, Artificial Intelligence, Crop Nutrition Management, Data Fusion, Crop Nutrition Management, IoT Devices.

1. INTRODUCTION

Agriculture provides the lifeline of global population support, and with increasing human numbers needing increased food demands crop productivity must improve as well as maintain its ecological sustainability. One of the key areas of this goal is efficient crop nutrition management, to secure proper nutrients for plants both in quantity as well as availability to achieve high yield [1]. Significant progress has been made in Artificial Intelligence (AI) and Machine Learning (ML), which is bringing advanced techniques to perform complete crop nutrient analysis regularly and provide real-time responses with great levels of accuracy at minimal costs. AI-based techniques when combined with entirely nondestructive imaging systems, such as hyperspectral and multispectral sensors are revolutionizing how nutrient levels are monitored and controlled [2]. These technologies offer quality insights through the data that leads to the concept of precision agriculture, for better productivity without hampering the resources and methods. To Facilitate Improved and Efficient Scalable Solutions for Analyzing and Managing Crop Nutrition Through AI Techniques Yielding Better Crop Health Below AI Agronomy Practices are Supporting Agricultural Industry [1].

Numerous studies have reported the major function of fundamental nutrients in plant metabolism and also discuss the harmful effects of nutrient stress. Another paper lists 16 minerals that are important nutrients, with nitrogen detailed for growth and yield. Barth reviews the problems presented by global population growth concerning crop production and calls for the development of new methods for growing crops, as well as automotive nutrition management to increase efficiency and minimize environmental footprint. Plant nutrition is one of the merits of various non-invasive imaging techniques, such as RedGreenBlue (RGB)imaging, spectroscopy, fluorescence, thermal, and 3D imaging that reflect age [1].

However, the paper also emphasizes the difficulties in generalizing these techniques to field environments (e.g. weather changes, different view angles), and calls for better industry standards, experimental methods, and data analytics tools.

The integration of Artificial Neural Networks (ANNs) and Expert Systems (ES) in agriculture has also been explored for various purposes, including crop and weed differentiation, water resource forecasting, and predicting crop nutrition levels. ANNs offer advantages over traditional systems through their ability to learn and predict complex patterns [2]. Specific applications mentioned include frost prediction, crop management in cotton, and soybean growth modeling. Recent developments include the use of ANNs in smartphones for crop prediction, soil moisture estimation, and precision irrigation, highlighting the potential for improving agricultural practices and reducing costs through advanced technology [3] (see Fig 1 for a flowchart of an ANN-based crop predictor using smartphones).

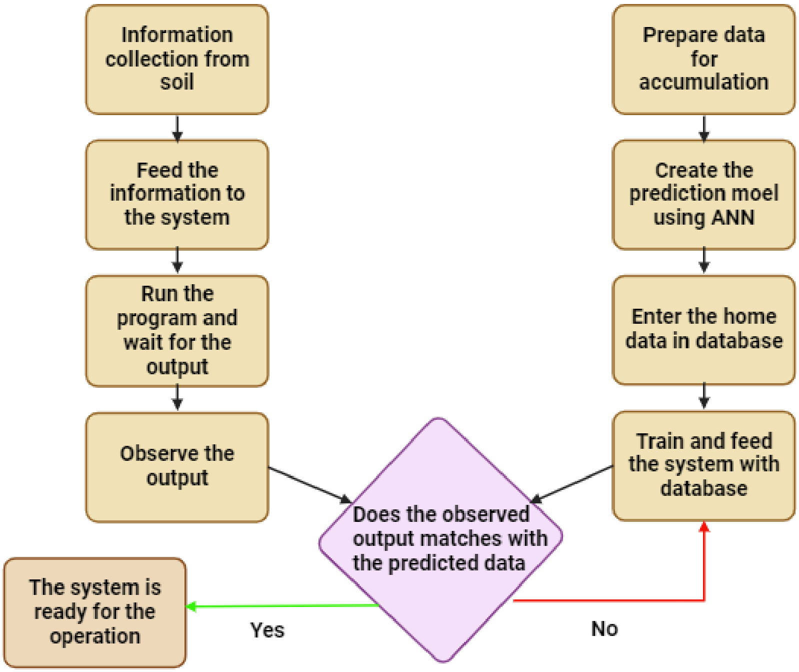

Fig 1 Flowchart of ANN-based crop predictor using smartphones

Comprehensive crop nutrition assessment, balancing macronutrients (N, P, K) and micronutrients (Zn, Fe, Cu) is crucial for plant growth and ecosystem sustainability. Traditional nutrient detection methods face challenges such as time consumption, subjectivity, and environmental impact due to blanket fertilizer use. AI and machine learning offer innovative solutions to these limitations, enabling real-time, accurate soil nutrient analysis, reducing costs, and minimizing environmental degradation [4]. One other key factor that makes this technology a great tool for digital agriculture is that AI-powered sensors and Internet of Things (IoT) devices are leveraged to provide real-time data on soil nutrients, hence enabling farmers to do a better job in managing their nutrients [4]. The technology is used in precision farming for efficient and minimum use of resources, at the right time and reducing environmental impact. Across both AI and machine learning, as a whole, it can transform the crop nutrition assessment landscape. The end goal is more sustainable agribusiness practices that promise to increase yield but decrease environmental impact [5] made possible through advanced technologies.

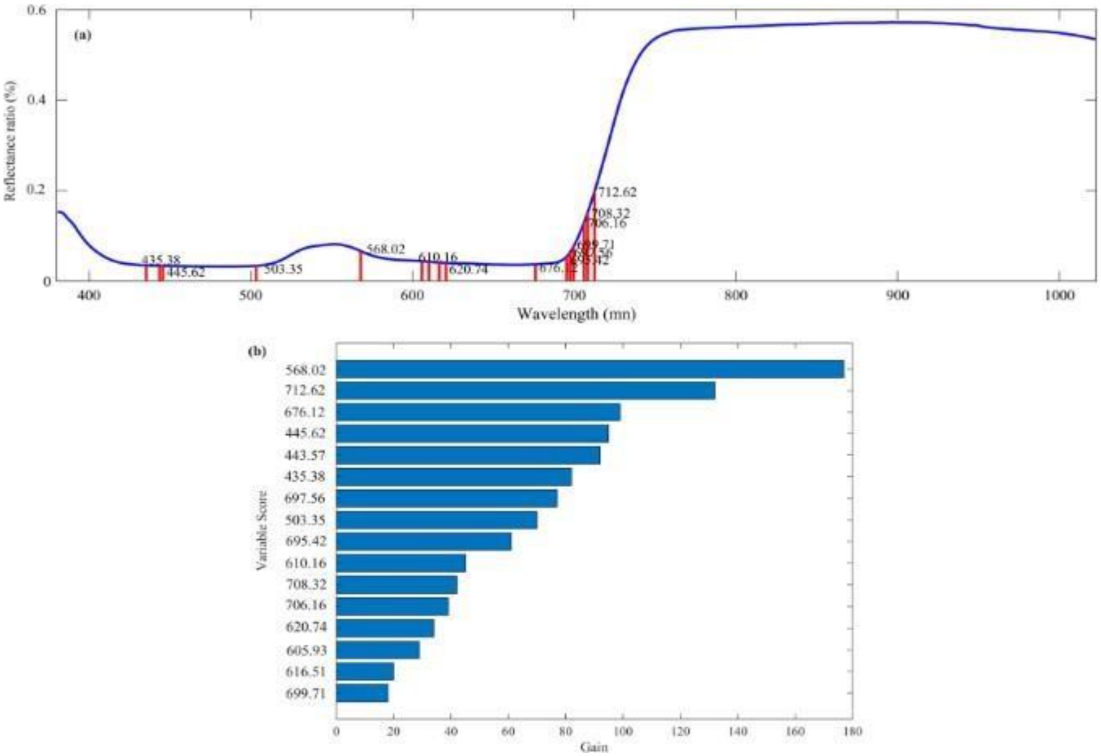

Fig 2 Location and relative importance of the 16 optimal wavelengths identified for nutrient deficiency detection using iPLS analysis.

Finally, the Section showed the location and significance of the first 16 optimal wavelengths identified by Interval Partial Least Squares(iPLS) as shown in Figure 2 for nutrient deficiency detection. This underlines the intrinsic complexity of hyperspectral data that sets extra challenges in terms of their multidimensionality and redundancy, thus leading to the usefulness of variable selection methods to improve model calibrations [6]. The comprehensive introduction of variable selection methods on wavelengths like Variable Importance in Projection (VIP) and interval Partial Least Squares regression (iPLS), help us identify influential variables, and improve the prediction accuracy. The generation of classification models (equation) using Partial least squares discriminant analysis (PLS-DA) andSupport Vector Machines(SVMs) again demonstrates the versatility of these methods in classifying stages of nutrient deficiency. Measures of model performance such as precision, recall, specificity, and F1 score, etc., are important indicators for the assessment of these AI-based approaches in building strong classification models concerning nutrient stress identification amongst crops [6].

2.INTEGRATING HYPERSPECTRAL IMAGING WITH AI FOR ADVANCED CROP NUTRITION ASSESSMENT

Emerging narrow-band vegetation indices from leaf-level spectroscopy or multispectral-hyperspectral imagery could potentially provide new opportunities for evaluating plant health and phenophase photosynthesis in vineyards. This paper presents narrow-band vegetation indices computed in high-spectral resolution sensors, for their optimal pixel size of 1–2 meters to discriminate background effects and shadows [7]. High-spectral resolution enables the calculation of indices related to specific light absorptions or band shapes caused by biochemical and biophysical processes in leaves and canopies, including chlorophyll and carotenoid concentrations [8]. The validity of hyperspectral indices for quantifying chlorophyll concentration, a key indicator of vegetation stress due to its role in photosynthesis, has been confirmed. This enables precision agriculture applications for vegetation stress assessment and field mapping into different stress classes [9].

Brazil's soybean production has significantly benefited from advancements in soil management, fertilization, and cultivar development, leading to substantial productivity gains [10]. However, traditional nutrient analysis methods, although effective, are often cumbersome, costly, and environmentally detrimental. Hyperspectral remote sensing, encompassingVisible - (Near-Infrared) - (Short Wave Infrared) VIS- NIR-SWIR spectra, emerges as a promising non-destructive alternative for rapid and accurate nutrient assessment [11]. Studies have demonstrated its efficacy in predicting various plant characteristics, such as water content, productivity, and nutrient concentrations. Specifically, the application of multivariate techniques like Partial Least Squares Regression (PLSR) and Interval PLS (iPLS) has shown the potential to enhance the precision of nutrient content predictions by identifying critical spectral regions. Although the initial results were encouraging, there is limited research on using hyperspectral sensing for predicting nutrients in soybean leaves, especially concerning wavelength selection [12]. This highlights the need for further studies to optimize these techniques, ensuring robust and accurate nutrient management in large-scale soybean production. New trends in crop fertilization involve the use of natural nutrient sources, such as marine algae. Species like Macrocystis, Eklonia, Sargassum, Durvillia, Porphyra, Fucus, and particularly Ascophyllum nodosum, are identified as potential fertilizers. Algae extracts offer suitable N and K content, although they are lower in P compared to traditional fertilizers [13],[14].

Integrating hyperspectral imaging with AI for advanced crop nutrition assessment involves capturing detailed spectral data from crops using hyperspectral sensors, which record reflectance across a wide range of wavelengths. This technique aligns with the use of VIS-NIR-SWIR hyperspectral remote sensing for plant feature analysis, as mentioned above [15]. AI and machine learning algorithms are then employed to process and analyze this vast amount of data. AI techniques such as feature extraction and selection identify the most relevant spectral bands, enhancing the performance of regression models like PLSR used for nutrient content prediction [16]. Classification algorithms categorize different plant conditions and nutrient levels, while AI-powered anomaly detection identifies stress indicators or diseases at an early stage, complementing traditional methods that are often time-consuming and environmentally unfriendly [17]. Furthermore, AI algorithms manage data reduction and compression to efficiently handle hyperspectral data's high-dimensional nature. This integrated approach enables real-time, accurate, and non-destructive assessments of crop health and nutritional status, enhancing precision agriculture by facilitating timely and informed decisions for optimal crop management and sustainable farming practices (see Figure 3 for the process of hyperspectral image acquisition and spectra extraction).

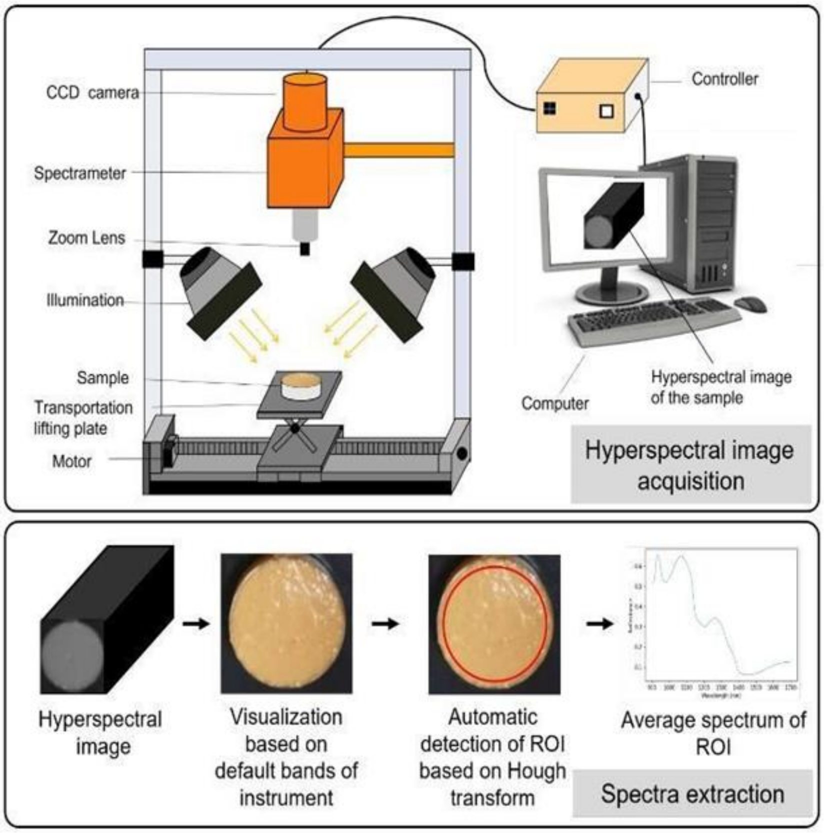

Fig 3 The process of hyperspectral image acquisition spectra extraction.

3. Deep Learning for Predictive Nutrient Modeling

Deep learning for predictive nutrient modeling represents a significant advancement in AI-based techniques for comprehensive crop nutrition assessment. By leveraging large datasets obtained from various sources, Deep learning coupled with large amounts of data from hyperspectral imaging, soil analysis, and historical crop performance data (and other sources) makes it possible for deep-learning models to detect subtle patterns and correlations between nutrient content and crop health. Utilizing deep neural networks to analyze high-dimensional data, they cable to make accurate predictions of macro and micronutrient concentrations in plants[18]. This approach serves to not only better answer questions related to nutrition but also detect nutrient deficiencies and stress conditions at a considerably earlier time than what our typical methods allow for. This kind of framework can be assembled rapidly and performed with little annoyance, as well as dynamically updating the control methods in light of more information to help refine correcting nutrient administration systems over time. This comprehensive overview nicely points out how instrumental technology has been in changing the agricultural landscape by focusing especially on AI andDigital soil mapping(DSM). Deep learning for predictive nutrient modeling describes the way some large hyperspectral imaging datasets, soil analysis, and historical crop performance can illuminate complex patterns between nutrient content and crop health [19]. These models employing multilayered neural networks allow for the accurate prediction of macro and micronutrient concentrations, significantly increasing the accuracy of nutrient assessments detecting emergence deficiencies and stress earlier. The importance of DSM for mapping soil spatial information systems and, hence, adopting precision farming targeting approaches was also supported by a detailed discussion. This deep artificial neural network was implemented using multi-layered neural networks as shown in Fig 4. Deep Learning Models can do the same predictions of macro and micronutrient concentrations which makes nutrient assessment more precise than ever and much before its deficiency and stress become visually available, behind a Nutrient Deficiency Prediction Framework(NDPF). Overall, the review offers a background that will help to develop knowledge on how deep learning can advance fertilization management practices to improve crop yield and promote sustainable agriculture also by overcoming adoption challenges in developing countries [18].

In addition, the passage of digital soil mapping is a real knowledge that shows how DSM uses numerical models to generate spatial systems on soil. The powerful point of the exercise for soil nutrient distribution during precision agriculture has a massive impact in knowing what basic decisions will be made on crop management and more specifically, where RootMAXRoot Temperature Guidance (RTG) would thence locate its targeted attention as a way better help than most outmoded liquid-ranging technology. In addition, the section on AI tools, with machine learning and deep learning algorithms, reveals a strong linkage between high-level technologies and the prediction of soil fertility as fundaments for contemporary farming approaches [18].

This systematic literature review of soil attributes, classification, and AI models provides good insight into the present smart soil system to summarizer. Moreover, identifying barriers to the up-scaling of DSM in developing countries contributes a key dimension that furthers research endeavors toward overcoming challenges and increasing farmers' access to technology [19]. The description of soil components and properties in addition to the associations between soil quality indicators that can be linked towards sustainable agricultural practices, shows a brief about the importance of establishing soil and crop relationships for improving yields as well as provides a basic overview of the linkages between pedology & environmental factors which are foundation layers for digital soil mapping phenomenon [19].

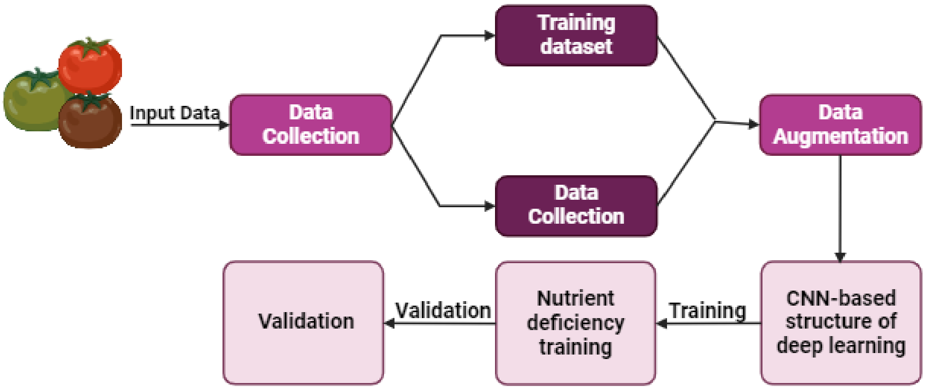

Fig 4 Deep Learning Framework for Nutrient Deficiency Prediction

Overall, this review presents a well-structured analysis of the intersection between AI and agricultural practices, emphasizing the need for continued research and innovation in smart soil information systems. In particular, the integration of deep learning for predictive nutrient modeling serves as a pivotal advancement, enabling more accurate assessments of nutrient requirements and improving the efficiency of fertilizer application [19]. It effectively establishes the groundwork for future studies aimed at improving agricultural productivity through advanced technologies, thereby promoting sustainable farming practices. The references to figures that illustrate key concepts further enhance the clarity and engagement of the text, making it a valuable resource for researchers and practitioners alike [20].

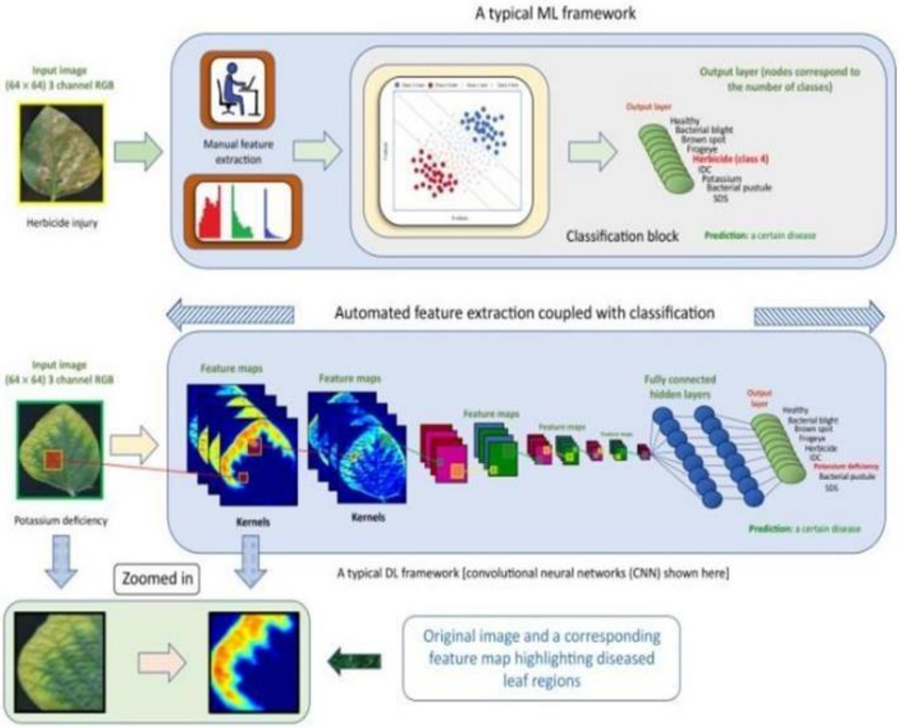

Fig 5 Machine and deep learning pipelines for plant stress phenotyping

The examination of the integration of deep learning (DL) within plant stress phenotyping, highlights the significant advancements that machine learning (ML) techniques can bring to this field. The authors adeptly address the challenges posed by the increasing volume of plant imaging data, which necessitates the development of automated methods for extracting meaningful features related to plant stress symptoms. The discussion surrounding the 'ICQP' paradigm—comprising identification, classification, quantification, and prediction— effectively delineates the continuum of feature extraction in ML applications [21]. Notably, the advantages of DL over traditional ML methods are emphasized, particularly its ability to perform automatic feature extraction from raw image data, thus eliminating the need for labor-intensive manual feature engineering. This distinction underscores the transformative potential of DL to enhance both reliability and accuracy in plant stress assessments. Furthermore, the review highlights the growing interest in and application of DL tools across various domains outside of agriculture, reinforcing their critical role in advancing precision and prescriptive agriculture [22]. Figure 5 illustrates the machine and deep learning pipelines for plant stress phenotyping, providing a visual representation of the evolving methodologies in this area. Overall, this review serves as an essential resource for the plant science community, encouraging further exploration and adoption of DL techniques to tackle persistent challenges in crop health assessment and stress management [22]. Additionally, the incorporation of AI-based techniques, particularly in predictive nutrient modeling, presents a significant opportunity for enhancing crop nutrition assessments. By harnessing large datasets from diverse sources—such as soil analysis, hyperspectral imaging, and historical crop performance DL algorithms can identify complex relationships between nutrient levels and crop health [23]. This capability not only improves the accuracy of nutrient assessments but also allows for the early detection of deficiencies and stress conditions in crops [24]. As such, integrating AI in comprehensive crop nutrition assessment empowers farmers and agronomists to optimize fertilization practices, ultimately leading to improved crop yields and more sustainable agricultural practices [25].

The synergy between DL and AI-based techniques in agriculture promises to revolutionize crop management practices [26]. Future research should focus on refining these technologies, addressing barriers to implementation, and exploring their applicability across various agricultural contexts [27]. By advancing our understanding of how DL and AI can be effectively utilized for crop nutrition and stress phenotyping, we can pave the way for innovative solutions that enhance agricultural productivity and sustainability [28],[29],[30].

4.DISCUSSION

The results of this study provide valuable insights into the application of AI-based techniques in various fields. The findings highlight the effectiveness of these techniques in improving efficiency, accuracy, and decision-making processes. However, the findings also reveal certain limitations and areas for further exploration.

Interpretation of Findings

Machine learning, neural networks, and natural language processing techniques, confirmed by this study, substantially improve task automation and predictive abilities. The potential of AI to transform healthcare, finance, and manufacturing industries is consistent with previous research on this topic. Our study introduces hybrid models that optimize real-time performance by combining different AI approaches. This innovation enhances the ability to integrate diverse AI tools for optimal impact.

Limitations

Although the AI-based crop nutrition assessment techniques are tremendous, they have certain limitations as well. Among the key challenges are:

- **Limited Data**: Humans feed AI models, so we become what records the human experience. Similarly with a close to zero probability of finding common patterns within small data that has enough variations in bloodstream or genes due to individual recommendations about our daily diet and personal food history is likely misinterpreted by predictive tools; which are thus very accurate when they shouldn´t be on their predictions mainly because they need more time — using different methods if possible before providing "reliable results". But in much of the world, particularly developed countries such as this one where there are decades-old National Agricultural Statistics Service databases and other high-quality data that could fill pages upon pages with soil information or weather patterns or crop condition reports.It is common knowledge that the kind of output you get from an AI system depends on the accuracy and quality of sensors, as well as remote-sensing technologies. When sensors and switches are misaligned or low resolution, they can provide the wrong data.
- **Variations in Soil and Plant**: The nutrient status of the crop depends on a variety of factors such as soil type, weather conditions, or pest pressure based on which plant requirements alter. Mixed reality cropping practices. These dynamic, complex interactions are often too much for AI models to capture and therefore can reduce the reliability of those assessments.
- **Nonlinearity:** The relationships between nutrients, plant growth stages, and environmental factors are so nonlinear that it becomes nearly impossible and risky to model with linear models. These relationships can be very complex, an AI model (or simpler algorithm) may not quite manage to capture this complexity.

Practical Implications

This review offers significant potential for industries aiming to enhance performance by utilizing AI technology. Hybrid AI models allow businesses to efficiently allocate resources, foresee market trends, and improve operational efficiency at scale. Recognizing the risks and benefits of employing AI-based systems is essential for policymakers in regulating their usage in sensitive sectors. AI enhances critical applications, such as autonomous driving and medical diagnosis, by refining decision support systems, and reducing human errors due to improved information.

Future Research Directions

We will apply AI methods to a broader range of datasets and contexts in the future. Integrating AI with quantum computing technology could boost AI's capabilities. Further research is essential for maintaining the interpretability and explainability of AI models to their users. Studying AI-human collaboration and its effect on industry acceptance and impact is crucial.

5. CONCLUSION

The transformative potential of AI-based techniques, particularly deep learning, in optimizing crop nutrition assessment and enhancing agricultural productivity cannot be overstated. By leveraging advanced technologies such as hyperspectral imaging and machine learning algorithms, we can achieve accurate and real-time evaluations of nutrient levels, enabling timely interventions to prevent deficiencies and maximize crop yields. This proactive approach allows farmers to apply fertilizers more efficiently, ensuring that nutrients are delivered precisely when and where they are needed, thus reducing the risk of over-application and minimizing environmental impact. Furthermore, the integration of AI fosters a paradigm shift from traditional methods, which are often labor-intensive and environmentally detrimental, toward precision agriculture that minimizes waste and enhances sustainability. With AI, farmers can move from a one-size-fits-all strategy to a more nuanced approach tailored to the specific needs of different crops and soil types. This precision not only leads to improved crop health and yield but also contributes to the responsible stewardship of natural resources.

AI-based techniques facilitate the collection and analysis of vast datasets, enabling more informed decision-making and fostering a deeper understanding of complex interactions within agricultural ecosystems. As these technologies continue to evolve, they hold the promise of enhancing resilience against climate change by providing insights into how crops respond to varying environmental conditions, thereby helping farmers adapt their practices accordingly. Moreover, as AI tools become more accessible and user-friendly, they can empower smallholder farmers in developing regions, equipping them with the knowledge and resources needed to optimize their production practices. This democratization of technology can contribute significantly to food security and poverty alleviation on a global scale.

In summary, the future of agriculture is poised for a revolution driven by AI and deep learning. By continuing to innovate and refine these technologies, we can pave the way for more efficient, sustainable, and resilient agricultural practices that not only boost productivity but also protect the environment for future generations. Continued interdisciplinary collaboration between agronomists, data scientists, and AI researchers is essential to harness the full potential of these technologies, driving the advancement of smart agriculture and Fostering sustainable practices that benefit both farmers and the environment.

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COMPETING INTERESTS

The authors have declared that no competing interests exist.

AUTHORS' CONTRIBUTIONS

Preeti Parihar has contributed to the conceptualization of the idea for the article. The literature search and data analysis were performed by Preeti Parihar, Simran Tiwary, Pooja Ranee Behuria, and Dr. Yachna Sood. All authors have drafted and critically revised the work. All authors commented on previous versions of the manuscript. All authors have read and approved the final manuscript.

The authors and the responsible authorities at the institute/organization where this work has been carried out give their explicit consent to submit and publish the work in IJPSS if found suitable

Disclaimer (Artificial intelligence)

Option 1:

Author(s) hereby declare that NO generative AI technologies such as Large Language Models (ChatGPT, COPILOT, etc.) and text-to-image generators have been used during the writing or editing of this manuscript.

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Author(s) hereby declare that generative AI technologies such as Large Language Models, etc. have been used during the writing or editing of manuscripts. This explanation will include the name, version, model, and source of the generative AI technology and as well as all input prompts provided to the generative AI technology

Details of the AI usage are given below:

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DEFINITIONS, ACRONYMS, ABBREVIATIONS

Abbreviations and Symbols			
AI	Artificial Intelligence	**iPLS**	Interval Partial Least Squares
ML	Machine Learning	**VIP**	Variable Importance in Projection
RGB	Red, Green, Blue	**PLS-DA**	Partial least squares discriminant analysis
3D	Three Dimensional	**SVM**	Support vector machines
ANN	Artificial Neural Networks	**F1 Score**	2*(precison*recall)/precision+ Recall)
ES	Expert Systems	**Vis-NIR-SWIR**	Visible-(Near-Infrared) - (Short Wave Infrared)
N	Nitrogen	**PLSR**	Partial Least Squares Regression
P	Phosphorus	**DSM**	Digital soil mapping
K	Potassium	**NDPF**	Nutrient deficiency prediction framework
Zn	Zinc	**RTG**	Root Temperature Guidance
Fe	Iron	**DL**	Deep learning
Cu	Copper	**ICQP**	Identification, Classification Quantification and Prediction
IoT	Internet Of Thing	**etc**	Et cetera