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Current Trends and Future Prospects in Plant Sciences Apropos Artificial Intelligence (AI)

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ABSTRACT:

The rapid advancement of Artificial Intelligence (AI) in the verdant sphere of plant sciences has been gaining significant traction, and to understand this momentum is undoubtedly imperative. Hence, this paper focuses on highlighting the applications and limitations of AI in the various disciplines of plant sciences. As established in the recent decade, AI can automate plant identification, facilitate comparative studies, analyse results from various tests including genotypical, anatomical and pathological, reform precision agriculture and horticulture, predict outputs and costs, amongst a host of other operatives. In the field of agriculture, AI holds great potential particularly in scrutinizing farm fields for disease identification- pathological and/or physiological, early disease detection, aiding with plant nutrition, and creating superior crop varieties. AI has also proven to be a valuable addition to modern plant propagation techniques by making them more efficient and sustainable. Although current AI models face challenges, such as identifying new species, maintaining heterogeneity in factual and ground data sets, standardization of data and related softwares, providing a definite linkage between predictive analytics and field research, they can be mitigated through machine learning techniques, extensive R&D and collaborative approaches. To reinstitute, AI is rapidly changing the current landscape of the domain in question and stands to revolutionise various aspects of it, but our aim has to be to routinely and ethically integrate it in the fabric of plant sciences in order to open new avenues while focusing on the long-term goal of achieving sustainability and food security.

Keywords: *Artificial Intelligence, AI, Plant Sciences, Machine Learning*

INTRODUCTION:

Artificial Intelligence (AI) has a multifaceted role in cultivating innovative technologies which are being used by scientists to address the urgent issues of a growing population and changing climate. The role of AI in plant sciences is pertinent which includes addressing the problem of food security crisis in the future. From spotting diseases to breeding resilient crops, AI stands as the silent gardener, tending to our botanical bounty with digital finesse. Beyond scientific study, AI in plant sciences affects many facets of our life due to which Next-Gen innovations are speeding up research and cutting down on the time taken to bring an idea to market—from the lab to the field. To make sense of the vast amounts of data generated by these technologies and develop effective plans, scientists need AI. Moreover, AI in plant research has the potential to facilitate our understanding, interpretation, and manipulation of intricate biological processes. It's ability to evaluate large datasets uncovers minute patterns in plant-pathogen interactions, providing crucial information for disease management. Using accessible soil data and auxiliary environmental variables, machine learning algorithms can be used to create prediction models. On the other hand, AI in conservation could be an amalgamation of all the aforementioned uses. Conservationists can improve their ability to maintain ecosystems, and advance global biodiversity conservation efforts by utilizing AI for species monitoring, predictive modelling, planning ecosystem restoration, and citizen science. This work examines the application of various AI technologies, the associated problems (such as model robustness and dataset diversity), and the possible implications for plant sciences and agribusiness research.

LITERATURE REVIEW:

Artificial intelligence (AI) in plant sciences is fast developing with applications ranging from disease detection and crop monitoring to optimization of agricultural practices. The development of climate-resilient crops will accelerate with the integration of genomics and phenomics. These multi-omics are producing enormous, heterogeneous, and complex data far more quickly than can be currently evaluated. First-generation AI is meant to tackle specific tasks of single-omics datasets, which do not require integration of data across various modalities. Hence, better data integration, analysis, and interpretation are made possible by the way that experiments are designed, which can be altered by next-generation AI (Harfouche et al., 2019). The combined influences of genotype and envirotype determine plant performance, or phenotype. By training a model with data gathered from many sources, such as spatiotemporal omics (genomics, phenomics, and enviromics spanning time and place), phenotypes can be predicted and visualised with greater accuracy (Xu et al., 2022, Hati et al.,2021). Additionally, new avenues for environmental monitoring and evaluation have recently become available with the use of AI technologies and data fusion methodologies for the analysis of satellite pictures and remote sensing data. This is made possible because of the development of data mining and Machine Learning (ML) techniques, which make it easier to extract valuable information on a wide scale from heterogeneous and geo-referenced sources (Himeur et al., 2022). ML has considerable promise for bridging the gap between basic research and plant breeding by integrating biological knowledge and omics data. Gene identification and prioritization, plant phenomics analysis, and genomic prediction of plant phenotypes are some of the recent uses of ML in plant sciences and breeding (Yan et al., 2022).

AI is transforming plant genomics, revolutionizing the precision and speed with which new plant varieties are bred. With advancements in high-throughput genomics, phenomics, and breeding methods, AI-driven approaches, particularly ML methodologies, are increasingly utilized in genomic prediction, genomic selection, and marker-assisted selection (Khan et al., 2022). These technologies leverage vast data resources on soil characteristics, seed genetics, and environmental factors to improve agricultural efficiency and crop productivity. Understanding gene regulation in plants requires elucidating the relationships between non-coding regulatory elements and their target genes across different species and ecotypes and the development of various deep learning models has become a time-saving boon that links gene sequence data with mRNA copy number for plants facilitating predictions of the regulatory effects of gene sequence variations across plant species with 80 % accuracy (Peleke, 2024).

The broad application of AI-OA (optimization algorithms) has been found in the improvement of different stages of plant tissue culture. From predicting adequate environmental conditions to achieving maximum productivity to optimization of the length and number of microshoots/ roots, AI-OA models have been considered to be a novel computational method in PTC (Hesami et al., 2020). Furthermore, two important fields where AI is advancing rapidly are plant taxonomy and disease detection. AI methods like computer vision and machine learning are being used to precisely classify plants and detect diseases early on. Scientists are working on algorithms that may identify symptoms of diseases and/or deficiencies and categorize them based on the analysis of plant traits from photos or sensor data. Because AI algorithms have been trained on massive databases of disease patterns, they may accurately predict plant ailments at an early stage, allowing for timely intervention and treatment. For pattern and image recognition, these models make use of ML algorithms like convolutional neural networks (CNN) (Domingues et al., 2022, Hassan et al., 2021). AI in plant disease prediction reduces the overuse of pesticides, which not only increases the efficacy of disease control but also promotes sustainable agricultural practices. Moreover, farmers may diagnose diseases in real-time with the help of AI-powered apps, making this technology available even in isolated farming communities.

In view of the cons of traditional methods of plant disease identification which can lead from being time-consuming to being highly resource-intensive, automated leaf disease diagnosis using AI with Internet of Things (IoT) sensors are considered to be far advanced and effective means for the same task (Dhanaraju et al., 2022, Nayagam et al., 2023, Rajak et al., 2023). For such data-intensive programs, image acquisition, preprocessing, segmentation, feature selection, and classification are predefined processes. Deep Learning (DL), Transfer Learning (TL) and ML detection models are primarily utilized for the necessary actions taken down the road (Mahlein, 2016, Jafar et al., 2024). Furthermore, the usage of DL, specifically Convolutional Neural Networks (CNN), to identify and diagnose plant illnesses is gaining acceptance.

On the same wavelength, by automating feature learning and data integration, integrative taxonomy and artificial intelligence might lessen subjectivity in species delimitation (Karbstein et al., 2024). This strategy will probably hasten the revision and deciphering of eukaryotic biodiversity. Furthermore, AI approaches which combine procedures from plant taxonomy with computer vision techniques, may recognize different species of plants. The internal leaf forms—more especially, the venation system—are the focus of the biometric measurements which help identify species with specific contours and region-based features (De Oliveira Plotze et al., 2009, Mahurkar et al., 2023). Simultaneously, integration of drones and bots into precision agriculture has opened up new possibilities for optimised irrigation, mapping, and field monitoring for crop health, disease or pest presence, targeted application of herbicides and pesticides, etc. (Slimani et al., 2020, Talaviya et al., 2020). The extended capabilities of AI in the sectors of plant taxonomy, plant disease identification and soil monitoring are discussed further.

AI IN PLANT TAXONOMY:

AI has the potential to completely transform plant taxonomy by increasing the effectiveness, precision, and accessibility of taxonomic data, thereby strengthening our knowledge of plant variety and evolution. Beyond identification of plants, AI can be used in the following aspects of plant taxonomy:

1. **Species Discovery and Classification:** By examining genetic data, physical traits, and ecological variables, AI systems can help find new species or subspecies. This might entail putting similar specimens in groups according to different characteristics in order to suggest new taxonomic categories.
2. **Evolutionary Links:** AI can derive phylogenetic links across plant species by analysing big datasets of genetic sequences or phenotypic features. Building phylogenetic trees and comprehending evolutionary histories are aided by this.
3. **Data Integration and Management:** AI can help with the management of enormous volumes of taxonomic data, including photographs, specimen records, geographic distributions, and ecological information. AI systems can collect, sort and organize different information to enable thorough taxonomic research.
4. **Predictive Taxonomy:** If the field data is insufficient, AI algorithms may predict taxa or forecast taxonomic relationships based on the available data base. For instance, making a

taxonomy guess based on incomplete morphological or genetic data about unknown specimens.

5. **Semantic Annotation and Data Enrichment:** To extract important taxonomic information, AI techniques like Natural Language Processing (NLP) may be used to annotate taxonomic literature, herbarium labels, and digitize records. This contributes structured data to taxonomic databases.
6. **Interactive Identification Keys:** To help users identify unfamiliar plants, AI-powered identification keys can lead users through a succession of morphological or ecological traits. These keys offer real-time feedback and may adjust in response to user inputs.
7. **Quality Control and Standardization:** AI may assist in confirming the precision and coherence of taxonomic information from various sources and databases. This guarantees consistent and trustworthy taxonomic classifications and species descriptions.
8. **Collaborative Taxonomy and Citizen Science:** By combining data from academics, amateur scientists and botanical organizations, AI can support cooperative taxonomic endeavours. This encourages community involvement and free access to taxonomic information.

AI IN PLANT DISEASE IDENTIFICATION:

Currently, automated plant disease detection systems are critical to further development in the agricultural sector. In order to gather and record plant photos, the procedures entail a number of phases, one of which is placing different sensors in the agricultural area. In order to use the acquired pictures as input for machine learning algorithms, they are then segmented and processed. Next, the ML models forecast a leaf's state of health. Specific details include:

1. **Image Recognition and Computer Vision:** AI systems may examine plant photos to identify visual signs of illness, such as lesions, leaf patches, discoloration, or odd growth patterns. In plant pathology, Convolutional Neural Networks (CNN) are frequently employed for image classification applications. With the help of enormous databases of annotated photos, these algorithms are able to precisely detect certain illnesses.
2. **Sensor Data Analysis:** AI can evaluate data from sensors placed in greenhouses or fields to track the health of plants in real-time. Parameters like temperature, humidity, and chlorophyll content may all be measured using sensors. These data may be processed by AI systems to find trends that point towards illness outbreaks or stress. AI is also capable of analysing enormous volumes of historical data on soil conditions, crop management techniques, weather patterns, and crop diseases. These models can detect high-risk locations, forecast disease outbreaks, and recommend preventative actions by establishing correlations between

these factors.

3. **Decision Support Systems:** Equipped with AI, support systems may combine information from several sources (such as weather forecasts, sensor data, and photographs) to offer suggestions to researchers and/or farmers. These systems can recommend the best ways to treat diseases, such as crops rotation or applying pesticides selectively.
4. **Early Warning Systems:** AI models can continuously monitor crops for early signs of diseases. By detecting subtle changes in plant appearance or physiological parameters, AI can provide early warnings, enabling timely interventions to minimize crop losses.

AI IN SOIL MONITORING:

Robust infrastructure for collecting data, interaction with current agricultural systems, and ongoing model validation and improvement are necessary for implementing AI for soil monitoring. Agriculture may progress toward more resilient, sustainable, and effective soil management techniques by utilizing AI's capabilities. Compelling prospects exist to improve agricultural output, maximize resource usage, and advance sustainable farming methods through the application of AI in soil monitoring. Mentioned below are a few ways in which AI can be utilised in this domain:

1. **Soil Health Assessment:** AI is capable of analysing a range of soil characteristics, including pH, organic matter content, soil texture, and nutrient levels (such as NPK). ML algorithms are capable of analysing data obtained from laboratory tests or soil sensors in order to evaluate indicators of soil health and spot patterns over time.
2. **Precision Agriculture:** By producing high-resolution soil maps, AI can facilitate precision agriculture methods. AI models are able to build precise maps of soil attributes (such as fertility and moisture levels) by integrating data from satellite photography, soil sensors, and historical data. With the use of this knowledge, farmers may better manage their crops using crop management techniques that are suited to their particular soil types and fertilizer applications.
3. **Early Soil Disease and Pest Detection:** AI algorithms are capable of analysing data on soil microbiomes to identify diseases or pests that compromise crop yield and soil health. AI may be used to enhance targeted management methods and offer early warnings by detecting microbial signatures linked to soilborne illnesses or pests.
4. **Optimization of Soil Amendments:** Based on soil analysis and crop requirements, AI may suggest the best kinds and amounts of soil amendments (such as fertilizers, nutrients, organic matter, etc.). In order to provide specialized soil management techniques, AI models may take into account variables including nutrient availability, soil structure, and environmental circumstances.

5. **Predictive Modelling for Soil Erosion and Degradation:** Using information from topography, land use, and weather patterns, AI can forecast the hazards of soil erosion and degradation. AI algorithms can predict erosion hotspots and suggest erosion control strategies to minimize soil loss by evaluating historical data and real-time inputs.
6. **Real-time Monitoring and Alerts:** Large agricultural regions can have real-time soil condition monitoring provided by AI-powered sensor networks. When ideal soil parameters are not fulfilled, alerts may be set up to enable quick corrections that preserve soil health and avoid crop losses.

FUTURE PROSPECTS IN PLANT SCIENCES WITH AI:

1. **Generative Genomics**: A rapidly advancing domain where generative AI (Gen AI) models are applied to genomic research, allowing scientists to analyse and design genetic sequences with precision (Esposito et al., 2019). By training these models on extensive DNA and RNA datasets from diverse organisms, researchers can detect complex patterns, structures, and functional elements within genetic material. Once trained, Generative AI models will have the capability to create novel genetic sequences with tailored properties. This enables the optimization of gene sequences for enhanced expression and regulation, and drafting of custom proteins for potential applications in medicine, biotechnology, and synthetic biology. Through these developments, generative genomics can shift biology from a descriptive science to one that is increasingly predictive and engineering-oriented.
2. **Genome Editing:** AI can contribute to the optimization of genome editing techniques such as CRISPR-Cas9, where ML algorithms can analyse large-scale genetic datasets to enhance the accuracy of editing methods by predicting off-target effects. These advancements underscore the potential of AI in addressing complex challenges within plant genomics, providing insights into gene regulation, variability, and genetic improvement.
3. **3-D Printing:** Also known as additive manufacturing, it's a revolutionary technology that aids in tissue engineering and organogenesis (Nath et al., 2020). With the addition of AI to the fold, scientists can design, create and organise complex structures that mimic the architecture of plant tissues and organs. Additionally, the combination of AI and 3-D printing could revolutionize the process of micropropagation by enabling the production of customized growing media and plant culture containers.
7. **Precision Agriculture:** The usage of Unmanned Aerial Vehicles (UAV), Computer Vision (CV) approaches and Machine Learning has proven to be useful in weed management (Fragassa et al., 2023, Punithavathi et al., 2023). Furthering the same technology, the addition of IoT and Robotics can transform precision agriculture by programming robotics to carry out

activities like targeted soil treatments or fine-tuned soil sampling, real-time imaging of field for diseases, pest and weed identification, etc., eliminating ambiguity amongst available resources and streamlining the technology with the aim of reducing the usage of water, nutrients, and herbicides and/or pesticide along with assisting farmers and agronomists by offering data-driven decision support systems that evaluate intricate soil data and offer practical insights. These methods can increase total farm profitability, decrease negative effects on the environment, and maximize resource usage efficiency to make agriculture truly smart.

4. **Seed Priming:** AI and ML may assist with Infrared spectroscopy and X-ray image data mining and curation further optimizing seed priming technology based on chemi-analytic profiling for heat and moisture content, thereby assisting in breaking seed dormancy. Post nano-priming of seeds, AI feedback tools may aid in soil management, irrigation, and water use, all of which contribute to efficient production adding to food security (Yan et al., 2022).
5. **Predictive Analytics:** It can be applied to a variety of data types in the field of plant sciences, such as genetic, phenotypic, environmental, and historical crop production data. Researchers and farmers may make well-informed decisions regarding crop management, disease prevention, crop yield optimization, and resource allocation by using predictive analytics to analyse these statistics (Singh et al., 2024). Crop yield prediction is arguably one of the most significant uses of predictive analytics in plant sciences. AI algorithms can discover patterns and associations that can be utilized to forecast future agricultural yields by examining historical crop yield data in conjunction with environmental variables like weather, soil quality, and fertilizer availability. Furthermore, detecting and preventing diseases can become easier due to predictive analytics significantly impacting the crop output and overall agricultural productivity. In addition to these applications, predictive analytics can also be used for genomic selection, crop breeding, trait prediction, climate change impact assessment, etc. (K.K., 2023, Singh et al., 2023)
6. **Intelligent Agents:** These are essentially computer programs that can perceive the environment, draw conclusions, and take action to achieve a specific goal (Atefi et al., 2021). Theseagents in the form of autonomous robots equipped with sensors, actuators, and imaging systems can automate tasks such as data collection, analysis, and decision-making. Later, AI algorithms can be used to analyse the collected data and provide real-time insights to farmers and agronomists.
7. **Landscape Designing:** Yesteryears have also seen the emergence of AI offering customised recommendations, visualisations and smart implements for landscape/ garden planning.

Microsoft Copilot, Rescape AI, AITwo, etc. are just some of the go-to tools from a plethora of options available online. With the onset of Image-Generator AI Models that not only create but enhance an idea, the field of landscape designing is set to be transformed into an efficient, energy and labour-saving domain.

8. **Plant Genome Project:** With the mapping of Arabidopsis thaliana genome, Plant Genome Project was institutionalised in 2000 and since then, large-scale initiatives have been underway to sequence hundreds of thousands more plant genomes, but they are extremely complex, varying in size and structure and can be 100 times larger than mammalian genomes, have large amounts of repetitive sequences, and many crop species are polyploid which makes genome assembly intricate and tedious. With accurate data sets, AI can be endlessly beneficial to this project by bridging the gap with identification, marking, visualisation, error correction, filtering and assembly of genes, facilitating studies of plant biology, functional genomics, evolution, domestication processes, phylogenetic relationships, etc., which will culminate into breakthrough discoveries like the identification of receptor molecules that bind to plant hormones and their site of action amongst many requisite findings.
9. **Conservation and Biodiversity Studies:** To help guide conservation efforts, AI may examine species distributions, habitat suitability models, and trends in biodiversity. This involves determining the conservation priority regions according to the rarity, availability and richness of species, mapping changes in ecosystems, tracking illegal activities, monitoring the population of endangered species and their threats, identifying patterns of changes in habitats and providing solutions to niche challenges concerning conservation of species and their ecosystems.

LIMITATIONS OF AI:

Robotics, Internet of things (IoT) devices, Area-Specific Algorithms and Machine Learning systems, as well as the functioning of the amalgamation of these components in the agricultural sector is an extremely sophisticated process. As such, the biggest complication that any AI model faces is the size and quality of the dataset needed for the AI to give accurate results which depends on several factors, including the complexity of the task, the variability within the data, and the specific AI algorithms used, specifically in a country like India where environmental conditions along with soil types differ greatly in different locations, and its practical applications. Here are some considerations:

1. **Task Complexity:** Larger datasets are often needed for more complicated tasks in order to capture the nuance and variety seen in real-world circumstances. For instance, compared to uncommon diseases or diseases with modest signs, diagnosing common diseases in crops

may need a smaller dataset.

2. **Variability in Data:** A wide variety of examples that capture the variability seen in the intended application should be included in the dataset. This covers differences in crop species, disease kinds, soil types, and environmental factors. An expanded dataset enables the AI model to identify resilient patterns and adapt well to novel, unobserved data.
3. **Data Quality:** In addition to quantity, data quality is essential. An uncontaminated, properly labelled dataset free of biases and mistakes greatly increases the accuracy of AI models. Model performance is enhanced by ensuring high-quality annotations and reducing noise in the data. For example, the existence of multiple concurrent diseases might affect the results even if the data set is substantial, giving rise to biases. Such obstacles can only be cleared with the help of targeted data sets.
4. **Algorithm and Model Complexity:** The amount of dataset required for various AI algorithms and models varies. Comparing deeper learning models to simpler machine learning methods like decision trees or support vector machines, such as CNNs for image identification in soil or crop research, one might see that the latter frequently require bigger datasets.
5. **Heterogeneity in Data Used:** Ensuring sufficient linkage between biological materials and data used for AI applications remains a veritable challenge that can be overcome by clear documentation of material provenance and developing new procedures for priority setting that selects data in a bias-free manner.
6. **Standardisation of Data and Related Software:** Some plant data (e.g. phenotypic observations) remain very difficult to standardise to a level that is appropriate for usage by AI applications. Standardisation of data at the point of collection and development of semantic standards can be the solutions to this challenge which can also give rise to reusable multi-source data sets while making validation amongst peers easier.
7. **Promoting Practical Applications:** While AI's potential in the field of plant sciences is adequately acknowledged, its practical application needs scaling. Conducting large-scale on-ground implementations and pilot projects in combination with promoting multidisciplinary research and enhancing collaborative efforts between academia, industry, and agricultural communities can curb this challenge.

Sturdy datasets are necessary for AI model testing, validation, and training when implementing AI in any sector. Therefore, it's still difficult to guarantee the scalability and dependability of AI systems in many agricultural contexts. AI algorithms are still being improved by researchers and developers, who will then incorporate them into more approachable solutions that can effectively promote food security and sustainable agriculture.

CONCLUSION:

The integration of Artificial Intelligence (AI) in plant sciences marks a transformative shift, offering unprecedented opportunities for advancements in research and agriculture. AI's ability to automate and enhance processes such as plant identification, disease detection, and crop yield prediction demonstrates its immense potential to revolutionise this field. The application of Machine Learning algorithms and advanced data analysis techniques facilitates more accurate and efficient genotypical, anatomical, and pathological studies, thus accelerating scientific discoveries and practical applications. Despite its numerous benefits, AI in plant sciences also faces significant challenges, including the accurate identification of new species and the need for large, high-quality datasets. Addressing these challenges will require continuous advancements in machine learning models, improved data collection methods, and interdisciplinary collaboration among scientists, technologists, and agricultural experts. Moreover, the integration of AI with other technologies, such as the Internet of Things (IoT), robotics, and satellite imaging, will enable more comprehensive and real-time monitoring of agricultural systems. This holistic approach will pave the way for smarter and more sustainable farming practices. In conclusion, while AI in plant sciences is still in its nascent stages, its potential is vast. Continued research, investment, and collaboration will be essential to harness the full power of AI, ultimately leading to significant advancements in plant sciences and agriculture, benefitting society at large.

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