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Advances in Bioresearch

Reshaping Plant Science: The Power of AI and Cutting-Edge Technologies

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ABSTRACT
The field of plant science is witnessing a transformative era, driven by the integration of artificial intelligence (AI) and cutting-edge technologies. AI-based approaches have emerged as powerful tools to unlock the mysteries of plant biology, revolutionizing various facets of research, from understanding plant phenotypes to unraveling the complexities of genomics and transcriptomics. This article delves into the realm of AI-driven advancements in plant scientific research, exploring how AI is reshaping our understanding of plant phenotyping, genomics, disease detection, crop yield prediction, image analysis, functional genomics, genome-wide association studies, and gene expression analysis. The integration of AI in plant research fosters innovation, sustainability, and food security, making it a transformative force in plant science research.
Keywords: *Artificial intelligence (AI), Plant phenotyping, Genomics, Crop yield prediction, and Image analysis.*

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INTRODUCTION

The field of plant science is experiencing a paradigm shift, and at its heart lies the seamless integration of artificial intelligence (AI) and cutting-edge technologies [1]. This convergence has given rise to AI-based approaches that are proving to be extraordinary tools in unraveling the enigmatic world of plant biology [2]. From understanding plant phenotypes to deciphering the complexities of genomics and transcriptomics, AI is sparking a revolution across various domains of research [3]. At the core of this transformative era is AI-driven plant phenotyping, a process that enables researchers to peer into the intricate world of observable plant traits [4]. Through the power of sophisticated image analysis algorithms and machine learning models, massive volumes of image data from diverse sensors and imaging systems are processed with unparalleled precision [5]. This AI-driven phenotyping allows scientists to delve deeper into the adaptations and responses of plants to diverse environments, shedding light on the very essence of plant life. The impact of AI is particularly profound in the realm of genomics, where it empowers researchers to navigate the vast genomic datasets with astonishing efficiency [6]. AI algorithms excel at recognizing intricate patterns in genomic sequences, unveiling genetic markers linked to specific traits, disease resistance, and crop yield [7]. This newfound understanding of the plant genome's structure and function propels scientific inquiry to unprecedented heights. Moreover, AI's influence extends to the detection of plant diseases, as cutting-edge deep learning methodologies come to the forefront [8]. Through the lens of convolution neural networks (CNNs) and other sophisticated architectures, AI systems adeptly analyze plant images and discern diseases, pests, and stress conditions [9]. Such rapid and non-invasive disease detection empowers farmers and researchers alike, safeguarding crops and ensuring sustainable agriculture practices. AI's role in crop yield prediction is equally revolutionary, offering a data-driven approach that combines diverse datasets like weather patterns, soil characteristics, and historical yield data [10]. These AI-driven predictions empower farmers to make informed decisions, optimize resource allocation, and mitigate the impact of climatic fluctuations on agricultural outcomes.

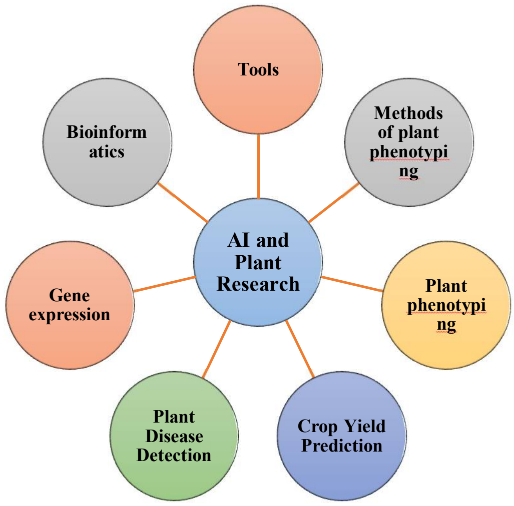

Figure 1. AI and plant science research

Beyond the field, AI-based image analysis proves to be an indispensable tool in plant research, aiding everything from phenotyping to disease detection and growth monitoring [11]. This synthesis of AI and image analysis unlocks a treasure trove of information, accelerating scientific discoveries and yielding profound insights into plant life. As the frontier of plant functional genomics expands, AI approaches offer systematic and scaled characterizations of gene functions. By integrating diverse omics data and applying AI techniques, researchers acquire a holistic understanding of gene regulatory networks and biological processes, akin to deciphering the very language of plant life. AI's transformative impact extends to gene expression analysis, unraveling the complexities of RNA sequencing data (Figure 1). Through AI-driven analysis, differentially expressed genes, gene regulatory networks, and key pathways come into focus, enriching our comprehension of plant growth, development, and responses to stressors [12].

I: Tools of AI in plant science:

a. **DESeq2** (https://bioconductor.org/packages/release/bioc/html/DESeq2.html): DESeq2 is a package used for differential gene expression analysis in RNA-Seq data. It employs a negative binomial generalized linear model to model read count data, normalizes the counts, and performs statistical tests to identify genes differentially expressed between different conditions or treatments (Figure 2).

b. **PlantCV** (https://plantcv.readthedocs.io/en/stable/): It is open-source image analysis software developed in Python for plant phenotyping. It provides various image processing tools to quantify plant traits, such as leaf area, color, and shape, from images obtained during plant growth experiments (Figure 2).

c. **Prophetic** (https://bitbucket.org/massyah/prophetic/src/master/): It is a tool for gene expression-based phenotype prediction in plants. It uses machine learning algorithms to predict plant phenotypes based on gene expression data. Prophetic allows researchers to analyze large-scale gene expression datasets and predict phenotypic traits related to plant development and stress responses.

d. **AutoMLPlant** (https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7940177/): AutoMLPlant is an automated machine learning platform specifically designed for plant science data. It automates the process of model selection, hyperparameter tuning, and feature engineering, allowing researchers to build accurate predictive models for various plant-related tasks, such as disease prediction and trait analysis.

e. **MapMan** (http://mapman.gabipd.org/web/guest/home): It is a visualization and analysis tool used to explore large-scale genomic datasets. It allows researchers to visualize gene expression data on metabolic pathways and hierarchical ontology maps, enabling the interpretation of high-throughput data in the context of plant metabolic networks.

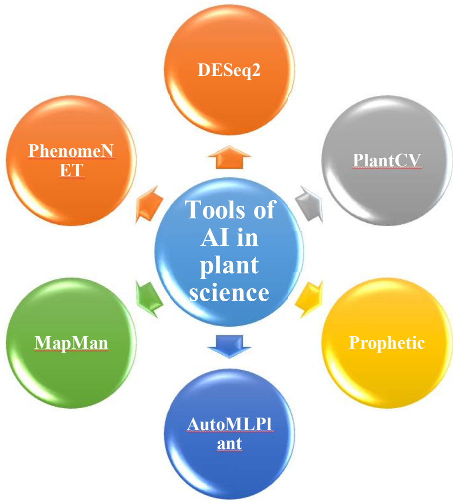

Figure 2. Tools of AI in plant science

f. **PhenomeNET** (http://www.phenomebrowser.net/): It is a tool that integrates and links plant phenotype data with genomic data. It utilizes semantic similarity measures and ontologies to identify phenotypic similarities between different plant species, facilitating cross-species comparisons and aiding in the understanding of plant traits and their genetic basis.

II: Plant Phenotyping:

Plant phenotyping, the study of plant traits and characteristics, is a critical field in agricultural research [11]. Traditional methods of plant phenotyping are often labor-intensive and time-consuming, making them impractical for large-scale studies. However, with the advent of artificial intelligence (AI) and machine learning, revolutionary advancements have been made in automating and enhancing plant phenotyping processes [13]. AI-based approaches have enabled researchers to capture, analyze, and interpret plant data with unprecedented speed, accuracy, and efficiency [14]. In this article, we explore various AI-based approaches in plant phenotyping and their significant impact on modern agriculture. Plant phenotyping also refers to the measurement of plant traits, including their morphological, physiological, and biochemical characteristics, in response to genetic and environmental factors [15]. It is a key component of plant science research, as it provides insights into how plants respond to changing environments and can be used to identify traits that can be bred for improved yield, disease resistance, and tolerance to environmental stresses.

One example of a plant phenotyping study is the work of Kim et al., 2021 [16], who used high-throughput phenotyping to study the effects of drought on wheat plants. The researchers used a combination of drones, sensors, and machine learning algorithms to collect data on plant height, biomass, and water use efficiency. They found that certain wheat varieties were more tolerant to drought than others and identified traits that were associated with drought tolerance, such as root length and biomass accumulation. Another example is the work of Honsdorf [17], who used imaging techniques to study the effects of heat stress on tomato plants. The researchers used thermal imaging to measure leaf temperature and chlorophyll fluorescence imaging to measure photosynthetic efficiency. They found that heat stress reduced photosynthetic efficiency and altered leaf morphology, which could have implications for crop productivity under changing climate conditions.

AI-based approaches have been employed in plant phenotyping, where high-throughput data is collected to quantify the morphological and physiological characteristics of plants [18]. These techniques have helped to accelerate the identification of desirable plant traits and to develop more resilient crops with highly modern modified methodologies (Figure 03).

Methods of plant phenotyping:

a. **High-throughput phenotyping:** This involves the use of automated systems, such as drones, robots, and sensors, to collect data on plant traits on a large scale. This method allows researchers to collect data quickly and accurately, enabling them to analyze and interpret large datasets in a short period of time [13].

b. **Imaging:** Imaging techniques, such as digital photography, thermal imaging, and hyperspectral imaging, can be used to capture plant traits non-destructively. This method allows researchers to measure plant traits over time and to monitor changes in response to environmental factors [19].

c. Physiological measurements: Physiological measurements, such as gas exchange, chlorophyll fluorescence, and water potential, can be used to assess plant health and function. This method provides insights into how plants respond to environmental stresses, such as drought and high temperatures [20].

d. **Image-Based Phenotyping:** One of the most prominent AI-based approaches in plant phenotyping is image-based analysis. High-resolution cameras and imaging technologies are used to capture detailed images of plants at various growth stages. These images are then subjected to AI algorithms, such as convolutional neural networks (CNNs), to extract relevant phenotypic information. AI can accurately identify plant traits like leaf area, biomass, leaf angles, and color patterns, providing valuable insights into plant growth and health [21].

e. **Hyperspectral Imaging:** It is another AI-powered technique transforming plant phenotyping. It involves capturing images in numerous narrow spectral bands, enabling researchers to analyze the unique spectral signatures of plants. AI algorithms, particularly deep learning models, are employed to process hyperspectral data and correlate it with specific plant traits, such as disease detection, nutrient deficiency, and stress responses. This approach allows for early detection of plant health issues, enabling targeted interventions and improved crop management [22].

f. **Robotics and Drones:** AI-driven robotics and drones are revolutionizing data collection in plant phenotyping. Mobile robots equipped with advanced sensors and cameras can autonomously navigate fields, scanning and collecting data from multiple plants simultaneously. Similarly, drones equipped with AI-enabled imaging systems can capture high-resolution aerial images of large agricultural areas. The combination of robotics and AI streamlines data acquisition, allowing researchers to cover extensive study areas quickly and efficiently [23].

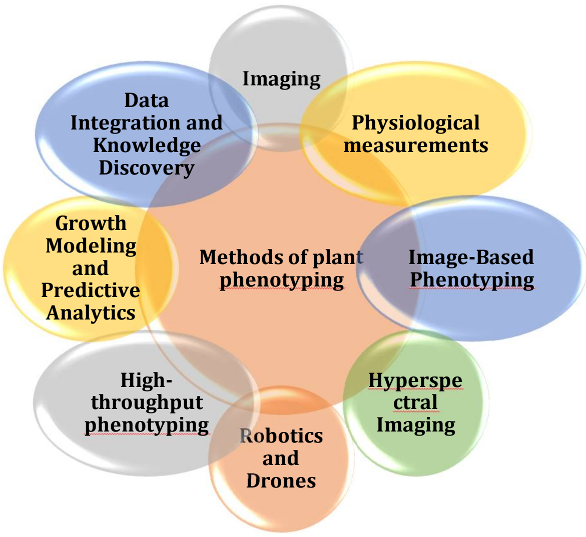

Figure 3. Methods of plant phenotyping

g. **Growth Modeling and Predictive Analytics:** AI-based growth modeling and predictive analytics are enhancing our understanding of plant development and behavior. By integrating vast amounts of data from various sources, including environmental factors, genetics, and historical growth patterns, AI can predict plant growth trajectories and phenotypic outcomes. Such predictions assist breeders in selecting superior plant varieties, optimizing cultivation techniques, and adapting crops to changing climatic conditions [7].

h. **Data Integration and Knowledge Discovery:** The sheer volume of data generated through AI-based plant phenotyping necessitates sophisticated data integration and knowledge discovery methods. AI algorithms, such as natural language processing (NLP), enable researchers to extract valuable insights from scientific literature, genomic databases, and experimental datasets. This integrated approach facilitates the identification of novel genes, pathways, and biological mechanisms, paving the way for innovative plant breeding strategies and crop improvement programs [24].

AI-based tools of plant phenotyping:

a. **PlantCV** (https://plantcv.danforthcenter.org/): PlantCV is open-source image analysis software developed in Python for plant phenotyping. It provides various image processing and analysis tools to quantify plant traits, such as leaf area, color, and shape, from images obtained during plant growth experiments.

b. **LemnaGrid** (https://github.com/Computational-Plant-Science/LemnaGrid): It is an open-source tool for automated high-throughput analysis of plant phenotypes using LemnaTec imaging systems. It employs AI-based algorithms to extract plant features and quantify growth traits in various plant species.

Figure 4. AI-based tools of plant phenotyping

c. **Deep Plant Phenomics** (https://www.plant-phenotyping.org/deepphenomics): It is an initiative by the International Plant Phenotyping Network (IPPN) that focuses on developing AI-based approaches for plant phenotyping. It aims to promote the integration of AI and deep learning methods into plant phenomics research (Figure 4).

d. **PhenoVein** (https://phenovein.ipk-gatersleben.de/): It is a web-based platform that uses AI algorithms to analyze and quantify vein traits in plant leaves. It allows researchers to extract and compare vein patterns from plant images, aiding in the study of leaf vasculature and its role in plant function.

e. **LNAS** (Leaf Nano Area Scanner) (https://www.plant-phenotyping.org/LNAS): LNAS is a platform that combines advanced imaging techniques with AI-based analysis to study the nanostructure of plant leaves. It enables the quantification of leaf surface features, such as epicuticular wax structures and trichomes.

f. **PHENOPSIS** (https://www.inrae.fr/en/research-research-partnerships/plant-biology-and-breeding-platforms/phenopsis): PHENOPSIS is an automated phenotyping platform that incorporates AI-based image analysis for precise and high-throughput phenotyping of plants. It provides various growth conditions and imaging setups to study plant responses to environmental stimuli.

g. **PlantEye** (https://phytomorph.delta.tudelft.nl/): PlantEye is an AI-powered tool for non-destructive, high-throughput plant phenotyping. It uses advanced image analysis techniques to quantify plant traits, growth parameters, and stress responses from digital images (Figure 04).

Applications of Plant phenotyping:

a. **Breeding for improved yield:** Plant phenotyping can be used to identify traits that are associated with improved yield, such as plant height, leaf area, and biomass accumulation [25]. This information can be used to breed plants that are more productive and resistant to environmental stresses.

b. **Developing crops that are resistant to pests and diseases**: Plant phenotyping can be used to identify traits that are associated with resistance to pests and diseases, such as plant architecture, leaf morphology, and the production of secondary metabolites [26]. This information can be used to breed crops that are more resistant to pests and diseases.

c. **Studying plant responses to environmental stresses:** Plant phenotyping can be used to study how plants respond to environmental stresses, such as drought, heat, and salinity [27]. This information can be used to develop crops that are more tolerant to environmental stresses.

III: AI and Machine Learning based Revolutionizing in Crop Yield Prediction:

Crop yield prediction is a fundamental aspect of modern agriculture, as it provides essential insights for effective decision-making in crop management and food production [28] . Traditionally, yield estimation relied on historical data and manual observations, but these methods often lacked accuracy and scalability. However, with the integration of artificial intelligence (AI) and machine learning, crop yield prediction has undergone a transformative shift, enabling more precise and data-driven forecasting (Figure 5) [29].

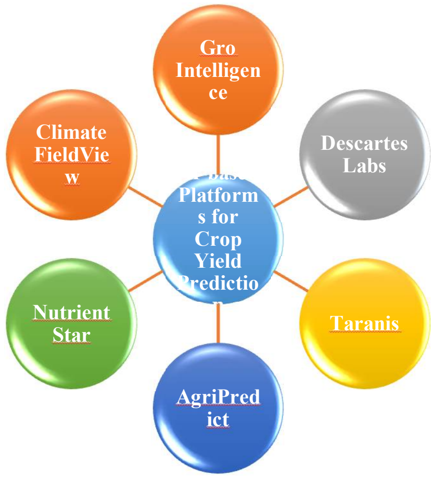

Figure 5. AI-based Platforms for Crop Yield Prediction

AI-based Platforms for Crop Yield Prediction:

a. **Climate FieldView** (Link: https://climate.com/): Provides AI-driven crop modeling and yield prediction based on weather data, satellite imagery, and field observations.
b. **Gro Intelligence** (Link: https://www.gro-intelligence.com/): Offers AI-driven agricultural data analytics for crop yield forecasting and market intelligence.
c. **Descartes Labs** (Link: https://www.descarteslabs.com/): Provides AI-powered crop yield prediction and real-time insights into crop conditions and yield potential.
d. **Taranis** (Link: https://www.taranis.ag/): Offers AI-based precision agriculture with crop yield prediction and disease detection services.
e. **AgriPredict** (Link: https://agripredict.com/): Uses satellite data and weather information to forecast crop yields for various crops and regions.
f. **NutrientStar** (Link: https://nutrientstar.org/): An AI-driven tool predicting crop yields based on nutrient management practices, optimizing fertilizer application for higher yields and reduced environmental impact.

Applications in Crop Yield Prediction:

a. **Remote Sensing and Satellite Imagery:** AI leverages remote sensing and satellite imagery to assess crop health, growth, and environmental conditions on a large scale [30]. By analyzing vast datasets, including vegetation indices, temperature, precipitation, and soil moisture, AI models accurately predict crop yields, identify stress areas, and detect anomalies. These insights help farmers and policymakers make informed decisions on irrigation, fertilization, and pest management.
b. **Weather Data Integration**: Weather conditions and environmental effects significantly influence crop growth, productivity and medicinal properties [12, 31]. AI algorithms integrate historical and real-time weather data with crop-specific models to predict yield outcomes. By factoring in temperature, rainfall, humidity, and other meteorological variables, AI forecasts the impact of weather fluctuations on crop development. Farmers can then plan accordingly, mitigating potential losses and optimizing resource allocation [30].
c. **Crop Growth Modeling:** AI-based crop growth models simulate the interactions between crops and their environment throughout the growing season. By combining physiological knowledge with vast datasets, these models predict crop growth stages, flowering times, and harvest periods. Machine learning algorithms continually adjust the models based on real-time data, improving yield predictions as the season progresses [30].
d. **Soil Health Analysis:** AI-driven soil health analysis plays a vital role in understanding soil fertility and nutrient availability, both of which are critical for crop yields [28]. Soil samples are analyzed using AI-enabled systems to identify nutrient levels, pH, and other soil properties. These insights enable

precision agriculture practices, optimizing fertilization plans and soil management strategies for higher productivity [32].

e. **Ensemble Modeling:** Ensemble modeling is a technique that combines the predictions of multiple AI algorithms to improve yield forecasting accuracy [33]. By using diverse machine learning models, such as random forests, support vector machines, and neural networks, researchers minimize biases and uncertainties inherent in individual models. Ensemble methods have demonstrated superior performance in predicting crop yields across different regions and crop types [30].

IV: AI and Machine Learning based Revolutionizing in Plant Disease Detection:

Plant diseases are a significant threat to global food security, causing extensive yield losses and economic damage to the agricultural sector [24]. Traditional methods of disease detection relying on manual inspection can be time-consuming and prone to errors. However, the integration of artificial intelligence (AI) and machine learning has revolutionized plant disease detection, enabling faster, accurate, and scalable solutions [31]. AI-based approaches used for plant disease detection and their potential to revolutionize agriculture towards a more sustainable and resilient future (Figure 6) [2].

AI-Based Platforms for Plant Disease Detection:

a. **PlantVillage** (Link: https://plantvillage.psu.edu/): A web-based platform using AI algorithms for plant disease diagnosis based on uploaded plant images showing symptoms.

b. **Plantix** (Link: https://www.plantix.net/): A mobile app utilizing AI and image recognition to detect plant diseases, providing instant diagnosis and recommended treatments.

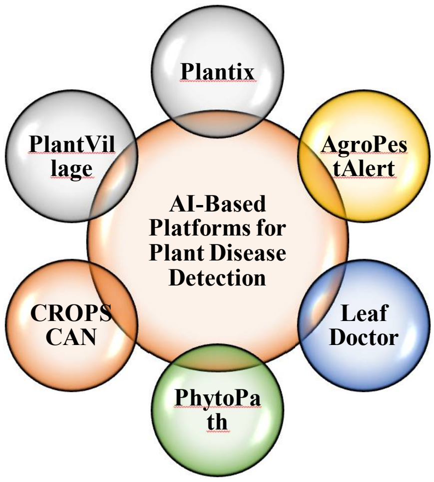

Figure 6. AI-Based Platforms for Plant Disease Detection

c. **AgroPestAlert** (Link: https://agropestalert.com/): An AI-powered disease detection platform using computer vision to analyze plant images and detect diseases in real-time.

d. **Leaf Doctor** (Link: https://www.leafdoctor.ai/): An app for plant disease detection, employing machine learning algorithms to analyze leaf images and identify diseases accurately.

e. **PhytoPath** (Link: https://www.phytopath.org/): A plant disease detection platform using image analysis and machine learning to identify diseases from images of infected leaves or crops.

f. **CROPSCAN** (Link: https://www.crop-scan.com/): A system using hyperspectral imaging and advanced data analysis techniques to detect and monitor diseases in crops.

Applications and Benefits:

a. **Early Detection:** AI-based plant disease detection enables early detection, allowing farmers to take timely action before the disease spreads and causes extensive damage [34].

b. **Precision Agriculture:** Plant disease detection supports precision agriculture, enabling farmers to apply treatments only to affected areas, reducing the use of chemicals and promoting sustainable practices [35].

c. **Remote Monitoring:** AI-based disease detection can be used for remote monitoring of crops, enabling real-time detection without the need for physical inspections [36].

d. **Research and Education:** AI-based plant disease detection aids agricultural research and serves as an educational tool for farmers and students to identify plant diseases accurately.

V: AI and Machine Learning based Revolutionizing in Gene expression analysis:

Gene expression analysis plays a pivotal role in understanding cellular processes and identifying key regulatory genes that control important plant traits [37]. Traditional methods of gene expression analysis are often time-consuming and labor-intensive. However, the integration of artificial intelligence (AI) and machine learning has revolutionized gene expression analysis, enabling faster, more accurate, and comprehensive insights into the intricacies of the genome [9]. In this section we explore various AI-based approaches used in gene expression analysis and their significant impact on advancing biological research and precision medicine (Figure 07).

AI-Based Platforms for gene expression:

a. **DESeq2** (https://bioconductor.org/packages/release/bioc/html/DESeq2.html): DESeq2 is an R package used for differential gene expression analysis in RNA-Seq data. It utilizes a negative binomial generalized linear model and employs AI-based algorithms to analyze large-scale gene expression datasets, identify differentially expressed genes, and perform statistical tests.

b. **RUVSeq** (https://bioconductor.org/packages/release/bioc/html/RUVSeq.html): It is an R/Bioconductor package used for RNA-Seq data analysis. It applies an AI-driven method known as Remove Unwanted Variation (RUV) to account for systematic sources of unwanted variation in gene expression data.

c. **Seurat** (https://satijalab.org/seurat/): It is an R package commonly used for single-cell RNA sequencing (scRNA-seq) analysis. It employs AI-based algorithms for clustering, dimensionality reduction, and cell type identification in scRNA-seq data.

d. **Monocle** (http://cole-trapnell-lab.github.io/monocle-release/): Monocle is an R package for the analysis of single-cell gene expression data. It utilizes AI techniques to order cells along a developmental trajectory and identify gene expression changes during cellular transitions [38].

e. **SCENIC** (https://gimme.scenic.aertslab.org/): It is a tool used for gene regulatory network analysis in single-cell gene expression data. It employs AI-based algorithms to predict transcription factor activity and identify regulatory relationships between genes.

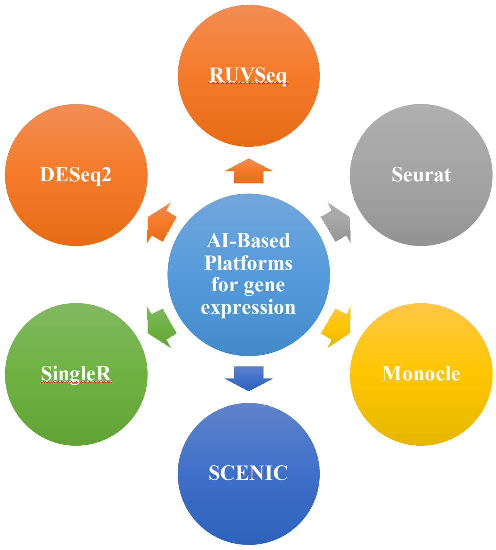

Figure 7: AI-Based Platforms for gene expression

f. **SingleR** (https://bioconductor.org/packages/release/bioc/html/SingleR.html): It is an R/Bioconductor package used for cell type recognition in scRNA-seq data. It utilizes AI methods to match single-cell expression profiles to reference cell types and identify cell type identities.

Applications and Benefits:

a. **Crop improvement:** Gene expression analysis combined with AI-based approaches can be used for crop improvement, enabling the identification of genes associated with desirable traits such as yield, disease resistance, and stress tolerance [37].

b. **Plant disease diagnosis:** Gene expression analysis combined with AI-based approaches can be used for plant disease diagnosis, enabling the early detection and treatment of plant diseases [8].

c. **Plant breeding:** Gene expression analysis combined with AI-based approaches can be used for plant breeding, enabling the identification of genes associated with desired traits for breeding programs [13].

d. **Environmental monitoring:** Gene expression analysis combined with AI-based approaches can be used for environmental monitoring, enabling the identification of genes and biological processes affected by environmental stressors such as pollution and climate change [9] .

VI. AI and Bioinformatics in plants research:

Bioinformatics in plants involves the application of computational and statistical methods to analyze large biological datasets generated from plants, such as genome sequences, gene expression data, and proteomic data [39]. AI-based approaches have also been used in bioinformatics to analyze and extract patterns from these large datasets. Here is a brief overview of bioinformatics in plants and AI-based approaches:

Bioinformatics, the interdisciplinary field that combines biology, computer science, and data analytics, has become a cornerstone of modern plant research and agricultural innovation [40]. With the advent of artificial intelligence (AI) and machine learning, bioinformatics has witnessed revolutionary advancements, enabling scientists to analyze complex plant genomic and molecular data with unprecedented speed and accuracy (Figure 08). AI-based approaches in bioinformatics applied to plant research and agriculture, and how they are transforming our understanding of plant biology and enhancing crop improvement [41].

AI-based bioinformatics in plants:

a. **Deep Plant Phenomics** (https://www.plant-phenotyping.org/deepphenomics): It is an initiative by the International Plant Phenotyping Network (IPPN) that focuses on the development and application of AI-based approaches in plant phenotyping research. It aims to promote the integration of deep learning methods in image-based plant phenomics.

b. **Plant PhenoML** (https://plantphenomics.org/): PlantPhenoML is an AI-driven plant phenotyping platform that provides tools for analyzing and interpreting plant phenotypic data. It aims to support researchers in extracting meaningful insights from large-scale plant phenomics datasets.

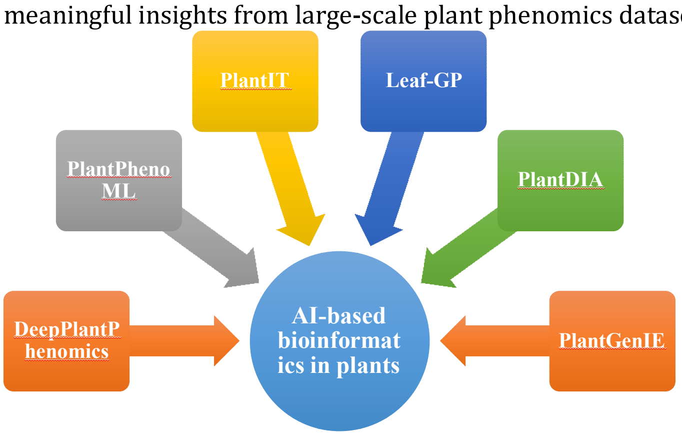

Figure 8. AI-based bioinformatics in plants

c. **PlantIT** (https://plantit.github.io/): It is an open-source platform that applies AI and machine learning techniques to analyze large-scale plant phenomics data. It provides a range of data analysis tools to extract relevant information about plant growth and responses to environmental conditions.

d. **Leaf-GP** (https://github.com/ahmedjebbar/Leaf-GP): It is an AI-based software tool for predicting gene expression levels in plants. It uses Gaussian process regression to model gene expression and predict gene expression patterns based on genomic sequences.

e. **PlantDIA** (https://plantdia.app/): PlantDIA is an AI-driven platform for analyzing metabolomics data in plants. It offers advanced data analysis tools to identify and quantify metabolites and interpret metabolic pathways.

f. **PlantGenIE** (https://plantgenie.org/): It is an AI-based platform that integrates and analyzes genomic and transcriptomic data from different plant species. It provides tools for identifying gene orthologs, gene expression patterns, and functional annotations.

Applications and Benefits:

a. **Plant genomics:** Bioinformatics combined with AI-based approaches can be used for plant genomics, enabling the identification of genes and regulatory elements associated with desirable traits such as yield, disease resistance, and stress tolerance [42].

b. **Plant proteomics:** Bioinformatics combined with AI-based approaches can be used for plant, enabling the identification of protein functions and interactions involved in different biological processes [12].

c. **Plant metabolomics:** Bioinformatics combined with AI-based approaches can be used for plant metabolomics, enabling the identification of metabolic pathways and compounds associated with different physiological processes help in medicinal aspects [43].

d. **Crop improvement:** Bioinformatics combined with AI-based approaches can be used for crop improvement, enabling the identification of genes and biological processes associated with desirable traits for breeding programs [44].

CONCLUSION

AI-based approaches are revolutionizing plant scientific research and agriculture, offering unparalleled insights into plant biology and crop improvement. With AI-driven plant phenotyping, researchers can explore the intricate world of observable plant traits with remarkable precision, shedding light on plant adaptation and responses to diverse environments. In genomics, AI empowers scientists to navigate vast datasets, identifying genetic markers associated with specific traits and disease resistance. Moreover, AI-based disease detection ensures early and accurate identification of plant diseases, safeguarding crops and promoting sustainable agriculture practices. The integration of AI and bioinformatics in plant research allows for systematic and comprehensive analyses of large biological datasets. AI-based tools like DESeq2 and RUVSeq enhance gene expression analysis, providing invaluable information on regulatory networks and cellular processes. Furthermore, AI-fueled precision agriculture through crop yield prediction assists farmers in optimizing resource allocation and mitigating the impact of climatic fluctuations. The remarkable synergy between AI and plant science holds immense potential for global food security and agricultural sustainability. By harnessing AI's power, researchers and farmers alike can revolutionize plant breeding, disease management, and crop improvement, contributing to a brighter and more resilient future for our planet. As AI technologies continue to evolve, their transformative impact on plant research and agriculture will continue to grow, driving innovation and advancement in the field of plant science.

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CONSENT FOR PUBLICATION

Not applicable

COMPETING INTEREST

The author declares that they do not have any competing interests.

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