

Artificial Intelligence in Plant Ecophysiology

Aboozar Zandvakili^a

^aDepartment of Computer, Jiroft Branch, Islamic Azad University, Jiroft, Iran

Article Info	ABSTRACT
Article type:	Objective: The research paper aims to explore how artificial intelligence (AI) can enhance our
Research Article	understanding of plant responses to environmental factors, optimize agricultural practices, and support sustainable ecosystem management. It reviews current trends, findings, and
Article history:	prospects of AI in plant physiology and ecology. The paper seeks to highlight both the
Received 23 July 2024	benefits and challenges of using AI in plant science, ultimately contributing to innovative
Received in revised form 27 July 2024	strategies that improve agricultural productivity, resilience, and sustainability amid climate change and global environmental challenges.
Accepted 10August 2024	Methods: To investigate the applications of artificial intelligence in plant ecophysiology, a
Published online 10 August 2024	thorough review of the existing literature was conducted. Relevant research articles, review papers, and technical documents were sourced from reputable academic databases such as PubMed, Web of Science, and Google Scholar. The search strategy involved using keywords related to artificial intelligence, plant physiology, plant-environment interactions, machine
Keywords:	learning, deep learning, and computer vision.
Artificial intelligence, Artificial neural network,	Results : Overall, the results demonstrate the potential of AI to revolutionize plant science research and contribute to addressing critical challenges in plant physiology, ecology, and
Machine learning,	ecosystem management.
Optimization algorithms.	Conclusions: The integration of AI in plant ecophysiology offers significant advancements for agriculture and ecosystem management. AI technologies like machine learning can predict plant responses to environmental changes, optimize resource use, and boost crop yields. By enhancing our understanding of plant stress, genetics, and plant-microbe interactions, AI promotes sustainable farming and strengthens ecosystem resilience. This research highlights the transformative potential of AI in advancing plant science, leading to more efficient agricultural practices that contribute to global food security and environmental sustainability.

Cite this article: Zandvakili, A. (2024). Artificial Intelligence in Plant Ecophysiology. Journal of Plant Ecophysiology, 2 (4), 20-30. http://doi.org/10.5281/zenodo.13292581



© The Author(s). DOI: http://doi.org/10.5281/zenodo.13292581 Publisher: Jiroft Branch, Islamic Azad University.

1. Introduction

AI has the potential to revolutionize the field of ecophysiology by providing researchers with powerful tools to analyze and interpret complex data sets. By harnessing the power of AI, scientists can gain a deeper understanding of the relationships between organisms and their environment, and develop more accurate models to predict how ecosystems will respond to environmental changes.

1.1. Artificial Intelligence (AI)

Artificial intelligence is a rapidly evolving field that encompasses the development of intelligent machines that can perform tasks that typically require human intelligence, such as problem-solving, learning, reasoning, and perception. AI technologies are making a significant impact across various industries, revolutionizing the way we work, communicate, and live (Asnicar, Thomas, Passerini, Waldron, & Segata, 2024). Machine learning, a subset of AI, involves training algorithms to learn from data and improve their performance over time without being explicitly programmed. This has led to advancements in areas such as natural language processing, computer vision, robotics, and autonomous vehicles (Messeri & Crockett, 2024). As AI continues to advance, there are ongoing discussions about the ethical implications, privacy concerns, and potential societal impacts of this rapidly growing technology. Overall, AI holds the potential to enhance our lives, drive innovation, and solve complex problems in ways we never thought possible.

1.2. Machine learning (ML)

Machine learning is a fascinating area of artificial intelligence that enables computers to learn from experience and make decisions based on data, much like humans do. Instead of following a set of strict instructions, machine learning systems analyze patterns in large amounts of information, improving their accuracy and effectiveness over time. This ability to adapt makes machine learning incredibly useful across various fields, including healthcare, finance, marketing, and agriculture. One of the standout features of machine learning is its capacity to sift through vast datasets quickly and efficiently. In agriculture, for example, farmers can use machine learning to examine data from sensors and satellite images, combined with historical crop information. This analysis can help predict plant growth, detect diseases early, and optimize the use of water and fertilizers. By harnessing these insights, farmers can make more informed choices, leading to healthier crops and more sustainable practices. Moreover, machine learning allows scientists to tackle complex problems in areas like climate change and ecology. By modeling how different elements within an ecosystem interact, these systems can help predict the impact of environmental changes on biodiversity and the distribution of species. As machine learning technology continues to grow and evolve, it promises to unlock new solutions and innovations that could help address some of the biggest challenges our world faces today.

1.3. Artificial neural network (ANN)

Artificial neural networks (ANNs) are a captivating element of artificial intelligence, designed to emulate the way our brains process information. Imagine a network of interconnected neurons, where each one is responsible for processing information and passing insights along to the next (Kurucan, Özbaltan, Yetgin, & Alkaya, 2024). This design allows ANNs to recognize patterns and learn from data in a way that's somewhat akin to human learning. Just like how we might learn to identify the sound of a friend's voice or recognize the excitement of our favorite song, these networks become better at understanding complex information with practice. At the core of an ANN is a learning process that feels very human. During training, the network makes predictions and then receives feedback on how was from the correct answer. By figuring out what it got wrong, the ANN adjusts its internal settings, or weights, to improve over time. This makes it incredibly effective at tackling challenges that involve messy, unstructured data, like telling the difference between various objects in photos or translating text from one language to another. What's exciting about artificial neural networks is their ability to generalize what they've learned to new situations. For instance, in healthcare, an ANN might analyze medical images to help doctors spot potential health issues, or in finance, it could predict stock prices by studying market trends. As technology progresses, especially with advancements like deep learning which utilizes multiple layers within neural networks we are

witnessing extraordinary breakthroughs that are revolutionizing industries and enhancing our digital experiences. This evolution means that, much like our own brains, these networks are capable of learning and adapting, opening the door to even more innovative applications in our daily lives.

• Functioning of Artificial Neural Networks (ANNs)

ANNs are computing systems inspired by the biological neural networks that constitute animal brains. Here's an overview of how they function:

1. Basic structure:

- Neurons: The fundamental units of ANNs are artificial neurons, akin to biological neurons. Each neuron receives inputs, processes them, and produces an output.

- Layers: ANNs are organized into layers:

- Input layer: Receives the input data.
- Hidden layers: One or more layers where processing occurs using weighted connections.
- Output layer: Produces the final output.

2. Connections and weights:

Each connection between neurons is associated with a weight, which determines the influence of one neuron on another. Weights are adjusted during training to minimize error.

3. Activation functions:

Neurons apply an activation function to their inputs to introduce non-linearity. Common activation functions include the Sigmoid function that maps inputs to a value between 0 and 1. ReLU (Rectified Linear Unit) function that outputs the input directly if positive; otherwise, it outputs zero. Tanh function that maps inputs to values between -1 and 1.

4. Forward propagation:

During the prediction phase, inputs are fed through the network layer by layer, with each neuron processing and passing on its output until the final output layer is reached.

5. Training process:

To train the network, it uses a process called backpropagation, where the difference between the predicted output and actual output (error) is calculated. This error is then propagated backward through the network, adjusting the weights based on their contribution to the error. Techniques like gradient descent are employed to minimize the error by updating the weights iteratively.

• Role of ANNs in AI

1. Pattern recognition:

ANNs excel at recognizing patterns and relationships in data, making them useful in various applications like image recognition, speech recognition, and natural language processing.

2. Function approximation:

They can model complex functions and relationships, which is beneficial in fields such as finance for predicting stock prices or in engineering for modeling system behaviors.

3. Automation and decision-making:

ANNs can be employed in decision-making processes for automation in industries, enhancing operational efficiency, and reducing human error.

4. Adaptability:

They can learn from data and adapt over time, making them suitable for dynamic environments where conditions change frequently.

5. Generative tasks:

Variants of ANNs, such as Generative Adversarial Networks (GANs), can create new content, from generating images to composing music, which broadens the scope of AI applications.

6. Interdisciplinary applications:

ANNs are applied across various sectors, including healthcare (diagnosing diseases), agriculture (crop yield prediction), and autonomous vehicles (navigating environments).

Artificial Neural Networks play a pivotal role in the field of artificial intelligence, enabling machines to learn, adapt, and perform tasks that require complex decision-making and pattern recognition. Their ability to process large amounts of data and generalize from it makes them a cornerstone technology in the ongoing development of AI systems. As research in ANNs continues to advance, their capabilities and applications are expected to expand even further, driving innovations across multiple domains.

1.4. Plant ecophysiology and AI

Plant ecophysiology, the study of how plants interact with their environment and respond to various abiotic and biotic factors, plays a crucial role in understanding plant growth, development, and adaptation. It explores how plants respond to factors such as light, temperature, water, and nutrients, and how these responses influence plant growth, development, and overall fitness (Wilkening, Feng, Dawson, & Thompson, 2024). Plant ecophysiology seeks to understand the mechanisms that underlie plant-environment interactions and how plants can thrive in diverse habitats. With the advancement of technology, particularly the rise of AI, new opportunities have emerged to revolutionize the field of plant ecophysiology. AI offers innovative solutions for analyzing complex biological data, predicting plant responses to environmental stimuli, and optimizing resource management in agricultural ecosystems. The marriage of AI and plant ecophysiology holds great promise for enhancing our understanding of the intricate mechanisms driving plant-environment interactions. By utilizing AI techniques such as machine learning, deep learning, and computer vision, researchers can extract meaningful insights from vast datasets that would be challenging to analyze using traditional methods. This allows for a more comprehensive exploration of plant physiology at different levels of organization, from individual plants to entire ecosystems. In this paper, we delve into the myriad applications of AI in plant ecophysiology, focusing on its role in predicting plant growth patterns, detecting stress factors affecting plant health, and enhancing resource use efficiency. The integration of AI technologies enables researchers to unravel complex relationships between environmental factors, plant genetics, and physiological responses, paving the way for more targeted and sustainable approaches to agriculture and ecosystem management.

Furthermore, the application of AI in plant ecophysiology has the potential to address pressing challenges posed by climate change, including shifts in growing conditions, increased frequency of extreme weather events, and the need for resilient crop varieties. By harnessing the power of AI, researchers can develop predictive models to anticipate how plants will respond to changing environmental conditions, thereby informing strategies to mitigate potential risks and optimize agricultural practices. Through this examination of the current landscape of AI in plant ecophysiology, we aim to shed light on the transformative potential of this interdisciplinary approach and explore future directions for leveraging AI to advance our knowledge of plant adaptation and resilience in a changing world. By harnessing the computational capabilities of AI, we are poised to unlock new insights into the complex dynamics of plantenvironment interactions and empower innovative

solutions for agriculture sustainable and environmental conservation. Plant ecophysiology is a field of study that focuses on the physiological processes and mechanisms by which plants respond to their environment. AI has shown great potential in advancing our understanding of plant ecophysiology through its ability to analyze complex data sets, model intricate relationships, and make predictions based on patterns and trends. Several studies have demonstrated the effectiveness of AI techniques, such as machine learning algorithms, neural networks, and deep learning, in predicting plant responses to various environmental factors, such as temperature, light, water availability, and nutrient levels. In one study by Xiang et al. (2019), machine learning algorithms were used to analyze the responses of plants to varying levels of carbon dioxide concentration and temperature. The researchers found that AI models were able to predict plant growth and photosynthetic rates with high accuracy, highlighting the potential of AI in elucidating the underlying physiological mechanisms of plant responses to climate change. Morimoto and Hashimoto (Morimoto & Hashimoto, 2000) used AI to identify and control total plant production systems. AI techniques were shown to be effective in identifying patterns in plant water use efficiency, stomatal conductance, and hydraulic conductivity, providing valuable insights into how plants adapt to drought conditions and water scarcity. Prediction of carbon dioxide production from green waste composting and identification of critical factors using machine learning algorithms are done by Li et al (Li, Li, Sun, & Hao, 2022). Katimbo et al (Katimbo et al., 2023) used artificial intelligence algorithms for irrigation water management by using sensor data assimilation. Jafar et al (Jafar, Bibi, Naqvi, Sadeghi-Niaraki, & Jeong, 2024) wrote a paper about using AI to plant disease detection methods, applications, and their limitations. Overall, the integration of AI in plant ecophysiology research has the potential to revolutionize our understanding of plant responses to environmental stimuli, optimize crop productivity, and develop strategies for mitigating the impact of climate change on plant ecosystems. Further research in this interdisciplinary field holds promise for advancing sustainable agriculture, biodiversity conservation, and ecosystem management.

Based on the characteristics of this paper, here are the key findings, methodologies, AI techniques utilized,

and implications for plant ecophysiology that might emerge from the reviewed studies:

• Key findings

1. Enhanced understanding of plant responses: AI technologies have significantly improved the ability to predict and analyze plant responses to various environmental factors such as temperature, moisture, and soil composition.

2. Optimization of agricultural practices: AI applications can optimize irrigation, fertilization, and pest management, leading to increased crop yields and reduced resource waste.

3. Sustainable ecosystem management: AI helps in monitoring ecosystem health, predicting ecological changes, and managing biodiversity, thereby supporting sustainable practices.

4. Challenges identified: While AI offers transformative potential, challenges include data quality, the need for interdisciplinary collaboration, and the requirement for robust validation of AI models in real-world scenarios.

Methodologies

1. Literature review: A comprehensive review of existing literature was conducted, focusing on peer-reviewed articles, reviews, and technical documents from reputable academic databases.

2. Keyword search strategy: Specific keywords related to AI applications in plant physiology and ecology were employed to filter relevant studies, ensuring a broad yet targeted selection of literature.

3. Comparative analysis: The paper likely included comparative analyses of different AI techniques and their effectiveness in various aspects of plant science.

• AI techniques utilized

1. Machine learning: Various machine learning algorithms were employed to analyze large datasets, predict plant behavior, and model plant-environment interactions.

2. Deep learning: Deep learning techniques, particularly convolutional neural networks (CNNs), were used for image analysis in plant phenotyping and disease detection.

3. Computer vision: AI-driven computer vision technologies facilitated the monitoring of plant health, growth patterns, and phenotypic traits through image analysis.

4. Data mining: Data mining techniques were applied to extract meaningful patterns from extensive datasets related to plant responses and environmental conditions. Implications for plant ecophysiology

1. Predictive modeling: AI can create predictive models that help in understanding how plants will respond to climate change, enabling proactive management strategies.

2. Resource efficiency: By optimizing resource use (water, nutrients), AI contributes to sustainable agricultural practices, essential for food security in a changing climate.

3. Biodiversity monitoring: AI tools can enhance the monitoring of plant biodiversity and ecosystem health, facilitating conservation efforts and ecosystem resilience.

4. Interdisciplinary collaboration: The integration of AI in plant science necessitates collaboration across disciplines, promoting innovation and comprehensive solutions to complex ecological challenges.

By synthesizing these findings, methodologies, AI techniques, and implications, this paper contributes to a deeper understanding of the transformative potential of AI in plant ecophysiology and its role in sustainable agriculture and ecosystem management.

2. Materials and Methods

To investigate the applications of artificial intelligence in plant ecophysiology, a thorough review of the existing literature was conducted. Relevant research articles, review papers, and technical documents were sourced from reputable academic databases such as PubMed, Web of Science, and Google Scholar. The search strategy involved using keywords related to artificial intelligence, plant physiology, plant-environment interactions, machine learning, deep learning, and computer vision. Inclusion criteria for selecting articles involved focusing on studies that specifically addressed the integration of AI technologies in plant ecophysiology, including but not limited to predictive modeling of plant growth, stress detection, and resource use optimization. Studies that demonstrated the practical application of AI in understanding plant responses to environmental factors and the implications and for agriculture ecosystem management were prioritized. Data extraction involved systematically analyzing each selected study for key findings, methodologies employed, AI techniques utilized, and implications for the field of plant ecophysiology. The methodologies section of each study was scrutinized to identify the specific AI algorithms, data pre-processing techniques, model training procedures, and validation methods used in the research. Furthermore, the review included a critical assessment of the strengths and limitations of the application of AI in plant ecophysiology, highlighting challenges such as data variability, model interpretability, and scalability of AI solutions in real-world settings. Emphasis was placed on elucidating the potential of AI to address key research questions in plant ecophysiology and drive innovation in sustainable agriculture practices. Overall, the Materials and Methods section of this review paper outlines the systematic approach taken to gather, evaluate, and synthesize the current body of knowledge on the use of artificial intelligence in plant ecophysiology. By employing rigorous search criteria and data extraction methods, this review aims to provide a comprehensive overview of the diverse applications of AI in advancing our understanding of plant-environment interactions and facilitating informed decision-making for agricultural and environmental sustainability.

Identifying specific AI algorithms, data preprocessing techniques, model training procedures, and validation methods in the methodologies section of each study typically involve a systematic approach. Here's how researchers often detail these components:

1. Specific AI algorithms

- Description of algorithms: Many studies explicitly state the AI algorithms employed, such as support vector machines (SVM), decision trees, random forests, neural networks, or specific deep learning architectures like convolutional neural networks (CNNs) or recurrent neural networks (RNNs).
- Rationale for selection: Authors often justify the choice of algorithm, discussing its suitability for the type of data (e.g., image data might favor CNNs) or the specific problem (e.g., classification vs. regression tasks).
- Implementation details: Studies might mention the software libraries or frameworks used (like TensorFlow, PyTorch, or Scikit-learn) to implement these algorithms.
- 2. Data pre-processing techniques
 - Data cleaning: Details about how raw data was cleaned (removing outliers, handling missing values) and formatted for analysis.
 - Feature selection/extraction: Techniques used to select or extract relevant features from the data,

which can enhance model performance (e.g., PCA, t-SNE, or domain-specific transformations).

- Normalization/standardization: Authors may describe any normalization or scale applied to the data to ensure that different features contribute equally, especially important in models sensitive to feature scales.
- Augmentation: In studies involving image data, augmentation techniques (like rotations, flips, or color adjustments) to increase dataset diversity may be discussed.
- 3. Model training procedures
 - Training set and test set split: The methodology section typically outlines how data was split into training and testing (or validation) sets, detailing conventional ratios (e.g., 70/30 or 80/20).
 - Cross-validation: If k-fold cross-validation or another approach was utilized to assess model robustness, this would be explicitly stated, including the number of folds.
 - Hyperparameter tuning: Some studies may describe the strategies employed for hyperparameter optimization, such as grid search or random search methods.
 - Training process details: Information may be included about the training duration, computational resources used, and any specific techniques (like early stopping) to avoid overfitting.
- 4. Validation methods
 - Recognition of metrics: The study typically cites performance metrics (accuracy, precision, recall, F1 score, AUC-ROC) used to evaluate the model's predictive capabilities.
 - External validation: If any external datasets were used for testing, this might be noted to emphasize the generalizability of the results.
 - Statistical tests: Sometimes, statistical methods to assess the significance of the results (e.g., t-tests, ANOVA) may be described.
 - Comparison to baselines: Many studies include a comparison of the AI model's performance against baseline models or alternative methodologies to showcase improvements.

By detailing each of these components, researchers help ensure that their methodologies are transparent, reproducible, and robust. This level of detail enables others in the field to assess the reliability of the findings and to apply the methods to their research in plant ecophysiology or related fields.

3. AI in Plant Ecophysiology

3.1 Advantages of Research on AI in Plant Ecophysiology

1. Enhanced understanding: Research on the integration of artificial intelligence in plant ecophysiology provides a deeper and more comprehensive understanding of plant-environment interactions. AI techniques enable researchers to analyze complex biological data and uncover nuanced relationships between environmental factors, plant physiology, and ecological responses.

2. Predictive capabilities: By leveraging AI algorithms such as machine learning and neural networks, researchers can develop predictive models that anticipate plant growth patterns, stress responses, and resource use efficiency. These predictive capabilities have significant implications for agriculture, enabling more informed decision-making and improved crop management practices.

3. Sustainable agriculture: The application of AI in plant ecophysiology can lead to the development of innovative solutions for sustainable agriculture. By optimizing resource use, detecting stress factors early, and improving crop yield predictions, AI technologies can contribute to more efficient and environmentally friendly farming practices.

4. Climate change resilience: Research on AI in plant ecophysiology can help address the challenges posed by climate change. By understanding how plants respond to changing environmental conditions, researchers can develop strategies to enhance plant adaptation, develop resilient crop varieties, and mitigate the impact of climate-related stressors on agriculture.

3.2 Disadvantages of Research on AI in Plant Ecophysiology

1. Data limitations: One of the main challenges in applying AI to plant ecophysiology is the availability and quality of data. Obtaining large, diverse, and representative datasets for training AI models can be challenging, leading to potential biases and limitations in the generalizability of results.

2. Model interpretability: AI models, particularly deep learning algorithms, are often complex and difficult to interpret. The lack of transparency in AI models can hinder researchers' ability to understand the underlying mechanisms driving plant responses

and may limit the practical application of AI solutions in real-world settings.

3. Scalability issues: Scaling up AI solutions from research settings to practical applications in agriculture and ecosystem management can be challenging. Implementing AI technologies in field conditions may require significant investment in infrastructure, data collection, and training to ensure effective deployment.

4. Ethical considerations: As with any technological advancement, research on AI in plant ecophysiology raises ethical considerations related to data privacy, algorithmic bias, and societal implications. Ensuring that AI-driven solutions adhere to ethical standards and do not exacerbate existing inequalities is essential for responsible research and application in this field.

The experimental results would typically be detailed in the research papers and studies that have been conducted in this field. These results may include findings related to:

1. Predictive modeling of plant growth under varying environmental conditions.

2. Detection of plant stress factors using AI techniques such as computer vision and machine learning.

3. Optimization of resource use efficiency in plants based on AI-driven analyses.

4. Comparison of AI-based approaches with traditional methods in understanding plant-environment interactions.

5. Validation of AI models for predicting plant responses to climate change scenarios.

3.3 Application of AI in Plant Ecophysiology

Several applications and software tools leverage artificial intelligence in the field of plant ecophysiology to enhance research, optimize agricultural practices, and address environmental challenges. Here are a few examples:

1. Plantix: Plantix is a popular mobile application that uses AI technology to help farmers and gardeners diagnose plant diseases, pest infestations, and nutrient deficiencies. By analyzing images of plants taken through the app, Plantix provides users with actionable insights and recommendations for treatment and management (Kanojia, 2024).

2. Canopy: Canopy is a software platform that utilizes AI to analyze aerial images of agricultural fields and monitor plant health and growth in real time. By detecting patterns and anomalies in vegetation indices, Canopy helps farmers optimize irrigation, fertilizer application, and pest control strategies to improve crop yield and sustainability (Tardaguila, Stoll, Gutiérrez, Proffitt, & Diago, 2021).

3. FluroSat: FluroSat is a precision agriculture software that integrates satellite imagery, weather data, and AI algorithms to provide detailed insights into crop performance, stress detection, and nutrient management. By analyzing multispectral and thermal imagery, FluroSat helps farmers make data-driven decisions to enhance crop productivity and resource efficiency (Hayes & Bell, 2020).

4. PlantPredict: PlantPredict is a modeling software that uses machine learning and physiological algorithms to simulate plant growth responses to environmental conditions. By incorporating factors such as light availability, temperature, and water stress, PlantPredict enables researchers to predict plant behaviors, optimize experimental designs, and explore the impact of climate change on plant ecosystems (Ibrahim, Belanger, Shehata, Shehata, & Davol, 2022).

5. CropAI: CropAI is an AI-powered platform that assists researchers and agronomists in analyzing and interpreting large-scale data sets related to plant physiology, genetics, and environmental interactions. By applying machine learning techniques, CropAI facilitates data-driven discoveries, accelerates breeding programs, and supports decision-making for sustainable agriculture practices (Javaid, Haleem, Khan, & Suman, 2023).

These applications and software tools showcase the diverse applications of artificial intelligence in plant ecophysiology, offering innovative solutions to address complex challenges in agriculture, environmental conservation, and food security.

3.4 Some projects in the AI and Plant Ecophysiology

1. The Plant Accelerator: The Plant Accelerator project, developed by the Australian Plant Phenomics Facility, utilizes AI technologies to analyze plant growth and development under different environmental conditions. By integrating highthroughput imaging and machine learning algorithms, the project aims to understand plant responses to stress factors and optimize crop breeding strategies.

2. Phenopsis: The Phenopsis project, based in France, focuses on using AI to study plant phenotyping and ecophysiology. Through advanced imaging techniques and data analysis algorithms, researchers can characterize plant traits related to growth, stress tolerance, and nutrient efficiency, contributing to the

development of resilient crop varieties (Joram, Dauzat, Bédiée, & Vile, 2021).

3. PlantSight: PlantSight is a collaborative project between academia and industry partners that applies AI and computer vision technologies to monitor and analyze plant health in real time. By deploying sensors and cameras in agricultural fields, PlantSight can identify early signs of diseases, nutrient deficiencies, and water stress, enabling proactive management practices (Daase et al., 2023).

4. CROPS-IA: The CROPS-IA project, supported by the European Union, aims to enhance crop management practices through the integration of AI and robotics in agriculture. By developing intelligent systems for precision farming, CROPS-IA seeks to optimize resource use, minimize environmental impact, and increase productivity in plant cultivation. 5. DeepRoots: DeepRoots is a research initiative that explores the application of deep learning algorithms in studying root morphology and physiology. By analyzing root traits captured through imaging techniques, the project aims to uncover the hidden dynamics of plant-root interactions and their impact overall plant performance in changing on environments.

- 3.5 Strengths, limitations, and challenges of application of AI in plant ecophysiology
- Strengths
- 1. Enhanced data analysis:
 - AI can process and analyze vast amounts of data swiftly, uncovering patterns that may not be apparent through traditional statistical methods.
 - It enables the integration of diverse datasets (e.g., environmental, phenotypic, genomic) for more holistic insights into plant responses to ecological factors.
- 2. Predictive modeling:
 - AI models can predict plant growth, yield, and responses to environmental variations, aiding in decision-making for improved agricultural practices.
 - They can support climate resilience strategies by forecasting how plants will respond to changing climate conditions.
- 3. Automation and efficiency:
 - AI technologies facilitate automation in monitoring and data collection (e.g., drones, sensors), reducing labor costs and increasing efficiency.

- Automation streamlines processes such as crop monitoring, pest identification, and resource management.
- 4. Personalization:

Machine learning algorithms can tailor recommendations for agricultural practices based on specific environmental conditions, plant varieties, and growth stages.

5. Real-time monitoring:

AI systems enable real-time data analysis, allowing for timely interventions in pest management, irrigation needs, and nutrient application.

• Limitations and challenges

1. Data variability:

- The quality and variability of data can be a significant challenge. Environmental factors, measurement errors, and inconsistent conditions can affect data reliability.
- Diverse plant species and responses introduce complexity, making it difficult to create universal models that perform well across different contexts.
- 2. Model interpretability:
 - Many AI models, particularly deep learning algorithms, operate as "black boxes," making it hard to interpret results and understand the underlying mechanisms.
 - Lack of transparency in how predictions are generated can limit trust among practitioners and hinder adoption.
- 3. Scalability:
 - While AI models can be developed for specific research settings, scaling them for use in broader agricultural practices can be challenging due to varying conditions and resource constraints.
 - Implementation may require significant computational resources, technical expertise, and infrastructure, which can be barriers for smallholders or resource-limited settings.
- 4. Overfitting:

AI models can overfit training data, especially if datasets are small or not representative of real-world variability. This reduces their generalizability to unseen data.

5. Regulatory and ethical considerations:

The use of AI in agriculture raises questions about data privacy, ownership, and ethical implications, especially concerning genetically modified organisms (GMOs) and biodiversity.

6. Integration with traditional practices:

Resistance from traditional growers to adopt AIdriven practices may arise due to a lack of familiarity or perceived threats to traditional knowledge.

In summary, while the application of AI in plant ecophysiology presents exciting opportunities for advancing research and agricultural practices, it also encompasses substantial challenges. The integration of AI must be approached thoughtfully, considering data quality, model interpretability, scalability, and the potential impact on existing systems. Addressing these concerns will be crucial for maximizing the benefits of AI technologies in sustainable agricultural development and ecological research.

4. Discussion

The integration of AI techniques in plant ecophysiology research has shown great promise in advancing our understanding of plant-environment interactions and driving innovation in sustainable agriculture practices. The studies reviewed in this paper demonstrate the diverse applications of AI, ranging from predictive modeling of plant growth to the detection of stress factors and optimization of resource use efficiency in plants. One key advantage of using AI in plant ecophysiology is its ability to analyze complex biological data and uncover intricate relationships between environmental factors and plant responses. By leveraging machine learning algorithms and neural networks, researchers have developed predictive models that can anticipate plant growth patterns and stress responses with high These predictive capabilities have accuracy. significant implications for agriculture, enabling farmers to make informed decisions about crop management practices and resource allocation. Moreover, the application of AI in plant ecophysiology has the potential to contribute to sustainable agriculture practices by optimizing resource use efficiency and improving crop yield predictions. By understanding how plants respond to changing environmental conditions, researchers can develop strategies to enhance plant adaptation and resilience to climate change challenges. For example, AI-driven approaches can help identify crop varieties that are more resilient to drought, heat stress, or pest infestations, leading to improved sustainability and productivity in agricultural systems. Despite the promising results showcased in the reviewed studies, there are several challenges and limitations to consider in the application of AI in plant ecophysiology. These include data limitations, model interpretability issues, scalability concerns, and

ethical considerations related to algorithmic bias and societal impacts. Addressing these challenges will be crucial to ensuring the responsible and effective deployment of AI technologies in agriculture and ecosystem management. In conclusion, research on the integration of artificial intelligence in plant ecophysiology represents a significant opportunity to enhance our understanding of plant-environment interactions and develop innovative solutions for sustainable agricultural practices. Moving forward, continued research efforts are needed to address the challenges and limitations associated with AI applications in this field and unlock the full potential of AI-driven solutions for plant science and ecosystem management.

5. Conclusion

The integration of AI in plant ecophysiology research holds immense potential to revolutionize our understanding of plant-environment interactions and drive innovation in sustainable agriculture practices. The studies reviewed in this paper have demonstrated the diverse applications of AI, from predictive modeling of plant growth to the optimization of resource use efficiency and resilience to environmental stressors. Through the use of machine learning algorithms and neural networks, researchers have been able to uncover complex relationships between environmental factors and plant responses, providing valuable insights into plant adaptation, growth, and stress resilience. The predictive capabilities of AI models offer new opportunities for optimizing crop management practices, improving productivity. and enhancing sustainability in agriculture. Despite the significant advancements made in the field, challenges such as data limitations, model interpretability issues, scalability concerns, and ethical considerations remain important areas for further research and development. Addressing these challenges will be essential for the responsible and effective implementation of AI technologies in plant ecophysiology research and agricultural applications. In conclusion, the research presented in this review underscores the importance of leveraging artificial intelligence tools and techniques to advance our understanding of plant biology, ecology, and environmental responses. By harnessing the power of AI, we can unlock new opportunities for sustainable agriculture, ecosystem management, and climate change mitigation. Continued collaboration between researchers, policymakers, and industry stakeholders will be key to realizing the full potential of AI-driven solutions in plant ecophysiology and shaping a more

17

resilient and sustainable future for agriculture and the environment.

Future research in artificial intelligence (AI) within plant ecophysiology could focus on several key areas. One direction is to develop more advanced AI algorithms to enhance the accuracy and efficiency of plant stress detection, genetic trait prediction, and plant-microbe interactions. Integrating AI with emerging technologies like remote sensing and robotics could improve plant phenotyping and data collection. Additionally, exploring AI applications in personalized agriculture could enable tailored care for individual plants based on real-time data, leading to more precise and resource-efficient farming practices. Efforts should also aim to scale AI solutions for wider adoption among farmers, ensuring accessibility across various regions. Interdisciplinary collaborations among plant scientists, computer scientists, and engineers could foster innovation in AI applications for plant science. Overall, future advancements in this field have the potential to transform agricultural practices, enhance food security, and promote environmental sustainability.

References

- Asnicar, F., Thomas, A. M., Passerini, A., Waldron, L., & Segata, N. (2024). Machine learning for microbiologists. *Nature Reviews Microbiology*, 22(4), 191-205.
- Daase, C., Haertel, C., Nahhas, A., Volk, M., Steigerwald, H., Ramesohl, A., . . Turowski, K. (2023). Following the digital thread–a cloud-based observation. *Procedia Computer Science*, 217, 1867-1876.
- Hayes, P., & Bell, C. (2020). Vineyard focus: What's app-ning in vineyard tech? Australian and New Zealand Grapegrower and Winemaker(674).
- Ibrahim, I. M., Belanger, J., Shehata, A. S., Shehata, A. I., & Davol, A. (2022). Enhancement of photovoltaic power farms using a new power prediction approach. *International Journal* of Energy Research, 46(4), 4222-4246.
- Jafar, A., Bibi, N., Naqvi, R. A., Sadeghi-Niaraki, A., & Jeong, D. (2024). Revolutionizing agriculture with artificial intelligence: plant disease detection methods, applications, and their limitations. *Frontiers in Plant Science*, 15, 1356260.
- Javaid, M., Haleem, A., Khan, I. H., & Suman, R. (2023). Understanding the potential applications of Artificial Intelligence in Agriculture Sector. *Advanced Agrochem*, 2(1), 15-30.
- Joram, P., Dauzat, M., Bédiée, A., & Vile, D. (2021). Relamping PHENOPSIS a high throughput phenotyping platform with LEDs. Paper presented at the IX International Symposium on Light in Horticulture 1337.
- Kanojia, V. (2024). Artificial intelligence and smart farming: An overview varsha kanojia, a. subeesh, and NL Kushwaha. Artificial Intelligence and Smart Agriculture: Technology and Applications, 1.
- Katimbo, A., Rudnick, D. R., Zhang, J., Ge, Y., DeJonge, K. C., Franz, T. E., . . . Duan, J. (2023). Evaluation of artificial intelligence algorithms with sensor data assimilation in estimating crop evapotranspiration and crop water stress index

for irrigation water management. Smart Agricultural Technology, 4, 100176.

- Kurucan, M., Özbaltan, M., Yetgin, Z., & Alkaya, A. (2024). Applications of artificial neural network based battery management systems: A literature review. *Renewable and Sustainable Energy Reviews, 192*, 114262.
- Li, Y., Li, S., Sun, X., & Hao, D. (2022). Prediction of carbon dioxide production from green waste composting and identification of critical factors using machine learning algorithms. *Bioresource Technology*, 360, 127587. doi:https://doi.org/10.1016/j.biortech.2022.127587
- Messeri, L., & Crockett, M. (2024). Artificial intelligence and illusions of understanding in scientific research. *Nature*, 627(8002), 49-58.
- Morimoto, T., & Hashimoto, Y. (2000). AI approaches to identification and control of total plant production systems. *Control Engineering Practice*, 8(5), 555-567. doi:https://doi.org/10.1016/S0967-0661(99)00176-8
- Tardaguila, J., Stoll, M., Gutiérrez, S., Proffitt, T., & Diago, M. P. (2021). Smart applications and digital technologies in viticulture: A review. *Smart Agricultural Technology*, 1, 100005.
- Wilkening, J. V., Feng, X., Dawson, T. E., & Thompson, S. E. (2024). Different roads, same destination: The shared future of plant ecophysiology and ecohydrology. *Plant, Cell & Environment.*