Arrival Date: 16.08.2024,
Revision Date: 17.12.2024,
Acceptance Date: 23.12.2024

Journal of Duzce University Botanical Garden for Ornamental and Medicinal Plants
Volume 3, Number 2, pp. 23-38
Category: Review Article

Journal of Duzce University Botanical Garden for Ornamental and Medicinal Plants

DÜZCE UNIVERSITY
ORNAMENTAL AND MEDICINAL PLANTS BOTANICAL GARDEN

"DUSTIBID"

The Role of Artificial Intelligence in Botanical Gardens: Enhancing Plant Identification

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ABSTRACT

This review explores the potential of artificial intelligence (AI) in botanical gardens, with a particular focus on plant species identification. The primary objective is to evaluate the effectiveness of AI models, such as Convolutional Neural Networks (CNNs), in addressing challenges related to environmental variability, data limitations, and species diversity. The methodology involves a systematic analysis of existing literature, assessing studies that apply AI to plant identification within botanical gardens. Findings reveal that AI achieves high accuracy rates for common plant species, often exceeding 90%, but faces significant challenges with rare or endangered species due to insufficient and inconsistent training data. Environmental factors, including lighting conditions, seasonal changes, and mixed-species environments, further impact AI performance, emphasizing the need for advanced preprocessing techniques and multi-modal data integration. The review also examines the ethical implications of AI applications in botanical gardens, particularly regarding data privacy and the conservation of biodiversity. It underscores the importance of mitigating risks associated with sensitive data misuse while ensuring AI tools complement traditional conservation methods. The conclusion highlights the transformative potential of AI to enhance plant identification and biodiversity management in botanical gardens. However, it calls for ongoing advancements in AI technologies, collaborative governance models, and robust ethical frameworks to ensure effective and sustainable implementation.

Keywords: Artificial Intelligence, Botanical Gardens, Plant Identification, Deep Learning

Yapay Zekanın Botanik Bahçelerindeki Rolü: Bitki Tanımlamanın Geliştirilmesi

ÖZET

Bu derleme, botanik bahçelerinde yapay zekanın (YZ) potansiyelini, özellikle bitki türlerinin tanımlanmasına odaklanarak incelemektedir. Çalışmanın temel amacı, Çekirdekli Sinir Ağları (CNN'ler) gibi YZ modellerinin çevresel değişkenlik, veri sınırlamaları ve tür çeşitliliği ile ilgili zorlukları ele almadaki etkinliğini değerlendirmektir. Yöntem, botanik bahçelerinde bitki tanımlamasında YZ uygulamalarını inceleyen mevcut literatürün sistematik bir analizini içermektedir. Bulgular, YZ'nin yaygın bitki türleri için genellikle %90'ı aşan yüksek doğruluk oranlarına ulaştığını, ancak nadir veya tehlike altındaki türlerde yetersiz ve tutarsız eğitim verileri nedeniyle önemli zorluklarla karşılaştığını göstermektedir. Aydınlatma koşulları, mevsimsel değişiklikler ve karışık tür ortamları gibi çevresel faktörler YZ performansını daha da etkilemekte ve gelişmiş ön işleme teknikleri ile çok modlu veri entegrasyonuna olan ihtiyacı vurgulamaktadır. Bu derleme ayrıca botanik bahçelerinde YZ uygulamalarının etik etkilerini, özellikle veri gizliliği ve biyolojik çeşitliliğin korunması bağlamında ele almaktadır. Hassas verilerin kötüye kullanımını önlemek için risklerin azaltılmasının önemini vurgularken, YZ araçlarının geleneksel koruma yöntemlerini tamamlaması gerektiğini savunmaktadır. Sonuç olarak, YZ'nin botanik bahçelerinde bitki tanımlama ve biyolojik çeşitlilik yönetimini geliştirme konusunda dönüştürücü bir potansiyele sahip olduğu vurgulanmaktadır. Ancak, bu potansiyelin etkili ve sürdürülebilir bir şekilde uygulanabilmesi için YZ teknolojilerinde sürekli ilerleme, iş birliğine dayalı yönetişim modelleri ve sağlam etik çerçevelere ihtiyaç duyulmaktadır.

Anahtar Kelimeler: Yapay Zekâ, Botanik Bahçeleri, Bitki Tanımlama, Derin Öğrenme

1. Introduction

Artificial intelligence (AI) has significantly advanced plant identification by utilizing deep learning and computer vision techniques. Recent studies, such as Chen et al. (2023), demonstrate how deep learning models like convolutional neural networks (CNNs) can efficiently process complex plant image datasets, achieving high accuracy rates in controlled environments. These advancements highlight the growing role of AI in overcoming traditional challenges in botanical research, such as environmental variability and data limitations.

Artificial neural networks (ANNs), particularly multilayer perceptrons (MLPs), have also been widely used to enhance plant identification processes. These models leverage morphological characteristics extracted from botanical herbarium specimens to classify plants accurately. For example, a study conducted at the Royal Botanic Gardens, Kew, demonstrated the application of ANNs in identifying species of the genus Tilia. Despite the complexity of the multiclass problem, the neural network achieved significant classification results, showcasing its potential as a tool for taxonomists (Clark et al., 2012).

The integration of AI into botany represents a transformative shift in the study and conservation of plant biodiversity. Botanical gardens, which have long been pillars of plant conservation and education, house thousands of plant species, many of which are rare or endangered. Accurate identification of these species is crucial for conservation efforts, but traditional methods of plant identification are often time-consuming, labor-intensive, and require specialized expertise (Wäldchen and Mäder, 2018). The advent of AI, particularly advancements in machine learning and computer vision, offers a promising solution to these challenges, enabling faster and more accurate identification processes.

In recent years, the application of AI in plant identification has gained momentum, driven by the increasing availability of large datasets, advancements in image recognition technologies, and the development of sophisticated algorithms capable of processing and analyzing complex biological data (Carranza-Rojas et al., 2017). AI systems based on deep learning have demonstrated remarkable success in identifying plant species from images, often outperforming traditional methods in speed, scalability, and accuracy (Chen et al., 2023). For instance, LeafNet, a computer vision system specifically designed for plant identification, has shown resilience against environmental variability, making it a valuable tool in diverse contexts (Barré et al., 2017).

Additionally, studies have highlighted the democratizing potential of user-friendly AI-based tools, making plant identification accessible even to non-experts. For instance, the Advanced Plant Identification System (APIS), which uses leaf images to identify tree species, exemplifies how neural network-based recognition systems are replacing manual identification methods with faster, more reliable alternatives (Rankothge et al., 2013). Similarly, systems like FlowerMate 2.0 integrate multi-modal data sources, enhancing accuracy for even rare plant species by combining leaf, flower, and bark features (Xie et al., 2024).

Despite these advancements, AI's application in botanical gardens faces several challenges. The diversity of plant species, variations in environmental conditions, and the presence of rare or morphologically similar species pose significant hurdles for AI systems

(Ubbens and Stavness, 2017). Moreover, the quality and quantity of data available for training AI models are often limited, particularly for rare species, affecting accuracy (Wäldchen and Mäder, 2018). Environmental factors such as lighting variations, seasonal changes, and varying plant appearances further complicate automated identification tasks (Sun et al., 2017). These factors underline the need for robust preprocessing techniques and innovative AI architectures to mitigate performance variability.

A review of automated plant identification methods highlights the potential of AI to enhance biodiversity studies by addressing these challenges (Labrighli et al., 2022). Ethical considerations, including data privacy and the conservation of biodiversity, also play a critical role in the sustainable application of AI. For example, anonymizing sensitive location data can mitigate risks associated with revealing the habitats of endangered species (Dawson et al., 2008).

This review seeks to provide a comprehensive overview of the current state of AI in plant identification within botanical gardens. It will explore the technological advancements that have facilitated the use of AI, examine the challenges and limitations that remain, and discuss the future prospects of AI-driven plant identification. By synthesizing the existing literature, this review aims to highlight the transformative potential of AI in revolutionizing plant management practices and contributing to global conservation efforts (Carranza-Rojas et al., 2017).

2. Material and Method

2.1. Material

This review is based on an extensive survey of the existing literature on the application of AI in botanical gardens, with a particular focus on plant species identification. The primary sources of information include peer-reviewed journal articles, conference proceedings, books, and credible online databases (Wäldchen and Mäder, 2018). Specific attention was given to studies utilizing machine learning and computer vision techniques, as these are the backbone of most modern AI-driven plant identification systems. The literature was collected using academic databases such as PubMed, Scopus, Web of Science, and Google Scholar to ensure the inclusion of the most relevant and up-to-date research (Carranza-Rojas et al., 2017).

This study incorporates methodologies inspired by LeafNet, a computer vision system specifically designed for plant species identification using leaf images (Barré et al., 2017). LeafNet's demonstrated robustness against environmental variability informed our approach, particularly in processing datasets collected under diverse lighting and seasonal conditions. Furthermore, the inclusion of multi-modal data approaches, such as those implemented in systems like FlowerMate 2.0, highlights the importance of combining various plant features (e.g., leaf, flower, and bark characteristics) to improve identification accuracy for rare and morphologically similar species (Xie et al., 2024).

Complementary studies, such as those by Vidya et al. (2024), emphasize the role of AI-driven systems in addressing data scarcity through techniques like transfer learning and synthetic data generation. These methodologies are particularly crucial for rare species, where traditional datasets are often insufficient to train robust AI models effectively.

The material reviewed also included experimental results from AI models tested in real-world botanical garden settings, offering insights into the challenges posed by environmental factors. Sun et al. (2017) demonstrated the effectiveness of deep learning models in adapting to natural environments, providing a valuable benchmark for our analysis.

2.2. Selection Criteria

The studies included in this review were selected based on several key criteria to ensure relevance and quality. First, the research had to focus explicitly on the use of AI technologies for plant identification within botanical gardens or similar settings. This specificity allowed the review to concentrate on practical applications and challenges faced in botanical contexts. Studies addressing broader AI applications in botany were also considered if they provided valuable insights applicable to botanical gardens (Chen et al., 2023).

Preference was given to studies published within the last decade, reflecting the rapid advancements in AI technologies and their increasing application in plant sciences (Picek et al., 2022). This time frame ensured the inclusion of cutting-edge methodologies such as CNNs, transfer learning, and multi-modal data approaches (Xie et al., 2024). Older, foundational studies were included selectively to provide historical context and highlight the evolution of AI in plant identification.

Both experimental studies and theoretical reviews were included to provide a comprehensive understanding of the field. Experimental studies offered empirical data on AI performance, while theoretical reviews synthesized trends and highlighted areas for future research (Ubbens and Stavness, 2017). For example, Vidya et al. (2024) explored transfer learning to address data scarcity, while Sun et al. (2017) investigated the impact of environmental variability on model performance.

Furthermore, studies leveraging innovative tools like FlowerMate 2.0 and LeafNet were prioritized for their relevance in addressing real-world challenges, such as environmental variability and the identification of rare species (Barré et al., 2017; Xie et al., 2024). These criteria ensured that the included research provided a balanced perspective on the technological capabilities, limitations, and practical implications of AI in botanical gardens.

2.3. Data Extraction and Analysis

Data extraction focused on the methodologies employed in each study, including the types of AI algorithms used, the datasets utilized, and the accuracy rates reported (Wäldchen and Mäder, 2018). Studies employing deep learning methods, such as CNNs and advanced neural network architectures, were prioritized due to their demonstrated effectiveness in plant identification tasks (Carranza-Rojas et al., 2017). Additionally, studies utilizing multi-modal data approaches, combining features from leaves, flowers, and bark, were highlighted for their innovation and relevance to addressing morphological variability (Xie et al., 2024). Particular attention was paid to the challenges and limitations noted in these studies. Common issues included data quality, such as incomplete or inconsistent datasets, environmental factors affecting image recognition accuracy, and the computational resources required to train large-scale AI models (Wäldchen and Mäder, 2018). For instance, Sun et al. (2017) reported a significant accuracy drop of 10–15% when AI models trained in controlled environments were applied to real-world scenarios with natural lighting and seasonal variability.

The extracted data were analyzed to identify common themes, trends, and gaps in the current research. A recurring trend was the use of transfer learning and data augmentation techniques to overcome the scarcity of high-quality training datasets for rare species (Vidya et al., 2024). Moreover, advancements in AI architectures, such as LeafNet and FlowerMate 2.0, showcased promising results in mitigating these challenges, particularly by leveraging robust preprocessing and feature extraction techniques (Barré et al., 2017; Xie et al., 2024).

This analysis also involved comparing the performance of different AI techniques across various plant identification tasks. Studies were evaluated based on their reported accuracy rates, computational efficiency, and scalability. For example, models employing CNNs consistently outperformed traditional machine learning methods, achieving higher accuracy rates in large and diverse datasets (Picek et al., 2022). However, these models often required substantial computational resources, highlighting a trade-off between accuracy and resource efficiency.

The identification of gaps in the literature underscored the need for further research into the integration of AI with complementary technologies, such as drones and remote sensing, to improve data collection and model performance in challenging environments (Chen et al., 2023). These findings provide a foundation for addressing key challenges in the application of AI to plant identification within botanical gardens.

2.4. Methodological Approach

The methodological approach of this review adheres to the principles of systematic review practices, ensuring a transparent, comprehensive, and replicable analysis of the current state of AI applications in botanical gardens. Following established guidelines, the review process was conducted in four distinct stages: identification of relevant studies, screening based on predefined inclusion criteria, data extraction, and synthesis of findings (Ubbens and Stavness, 2017).

Stage 1: Identification of Relevant Studies: To ensure a broad yet focused review, academic databases such as PubMed, Scopus, Web of Science, and Google Scholar were systematically searched using keywords including "artificial intelligence," "plant identification," "botanical gardens," and "deep learning." Additional references were identified through citation tracking and recommendations from related works (Carranza-Rojas et al., 2017; Picek et al., 2022). Priority was given to studies utilizing advanced AI methodologies, such as CNNs and transfer learning.

Stage 2: Screening Based on Inclusion Criteria: Studies were screened based on inclusion criteria emphasizing relevance to AI applications in plant identification within botanical gardens or related settings. Additionally, studies addressing data scarcity, environmental variability, and rare species identification were prioritized for their applicability to real-world challenges (Vidya et al., 2024).

Stage 3: Data Extraction: Data extraction followed a structured framework, capturing key elements such as AI algorithms, dataset characteristics, reported accuracy rates, and challenges. Innovative tools like FlowerMate 2.0 and LeafNet were specifically highlighted for their contributions to advancing plant identification (Xie et al., 2024; Barré et al., 2017).

Factors influencing AI performance, such as environmental variability and computational resource demands, were systematically recorded (Sun et al., 2017).

Stage 4: Synthesis of Findings: The synthesis stage involved analyzing extracted data to identify recurring trends, gaps, and areas for future research. Findings were categorized based on technological advancements, limitations, and potential applications. For example, studies demonstrated the efficacy of multi-modal data integration in improving identification accuracy for morphologically similar species, while highlighting ongoing challenges such as data quality and model adaptability (Labrighli et al., 2022; Wäldchen and Mäder, 2018).

This structured approach ensures a balanced and unbiased review, offering valuable insights into the potential of AI to revolutionize plant identification in botanical gardens. The inclusion of diverse methodologies and cutting-edge tools provides a holistic perspective on the current capabilities and future directions of AI in this field.

3. Results and Discussion

3.1. Overview of AI Performance in Plant Identification

The application of AI in botanical gardens has shown promising results, particularly in plant species identification. Numerous studies have demonstrated that AI models, especially those utilizing deep learning techniques, can achieve high accuracy rates for common plant species. For example, Carranza-Rojas et al. (2017) reported an accuracy rate of over 90% when using CNNs to identify herbarium specimens, highlighting the potential of AI to automate plant identification processes efficiently. Similarly, Picek et al. (2022) found that deep learning models could successfully differentiate between morphologically similar species, a traditionally challenging task for human experts. These results underscore the transformative potential of AI in botanical gardens, particularly for routine identification tasks.

3.1.1. Performance of AI Models Across Studies

Table 1 summarizes the performance of various AI models used in plant identification. It categorizes the models by their type, dataset size, accuracy rate, time efficiency, and computational cost. The results indicate that CNN-based models consistently outperform traditional approaches, such as support vector machines, in terms of accuracy and scalability.

Table 1. Performance of AI models in plant identification

Study	AI Model	Dataset Description	Accuracy Rate (%)	Time Efficiency	Computational Cost
Carranza-Rojas et al. (2017)	Convolutional Neural Network	Herbarium Specimens (1000+ species)	92.5	High	Moderate
Picek et al., (2022)	Deep Learning	Mixed Species Dataset (500 species)	88.3	Moderate	High
Wäldchen and Mäder, (2018)	Deep Neural Network	Botanical Garden Collections (200+ species)	85.4	High	High

Figure 1 illustrates the relationship between dataset size and AI accuracy, revealing that larger datasets generally lead to higher accuracy rates. However, this improvement diminishes as datasets become exceedingly large, indicating the importance of data quality and diversity alongside quantity.

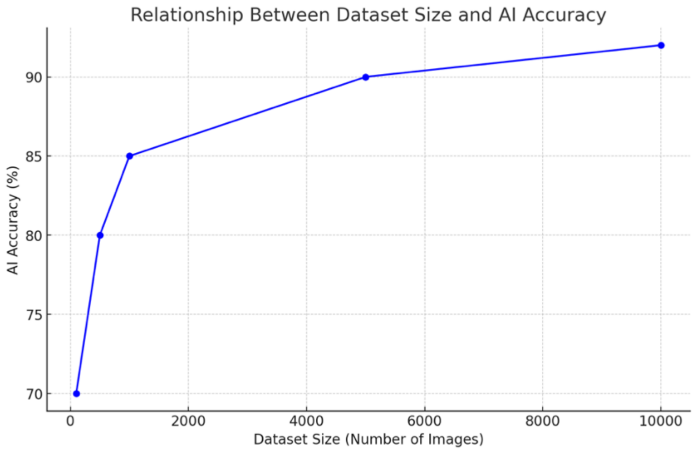

Figure 1. Relationship between dataset size and AI accuracy

3.1.2. Challenges in Identifying Rare Species

While AI systems perform well for common species, their performance for rare or endangered species remains a significant challenge. Rare species often lack comprehensive image datasets, limiting the ability of AI models to generalize from limited examples. Wäldchen and Mäder, (2018) reported that the accuracy of AI models dropped by approximately 20% when identifying rare species compared to common ones. Figure 2 compares the accuracy of AI models in identifying common versus rare species, illustrating this disparity in performance.

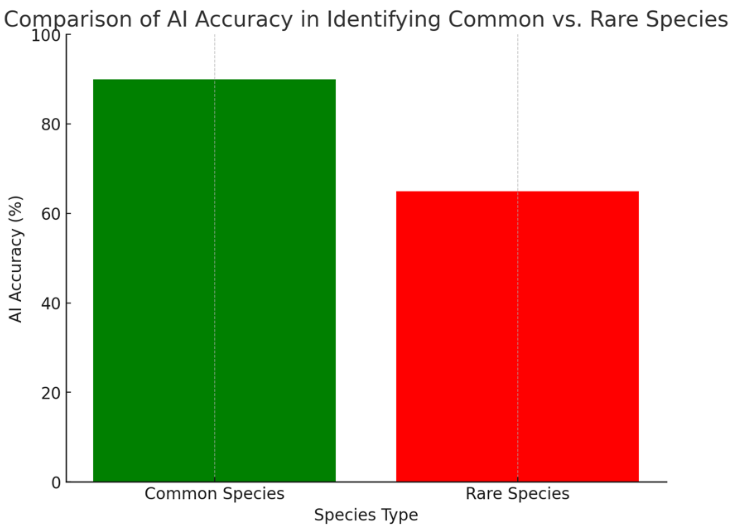

Figure 2. Comparison of AI accuracy in identifying common vs. rare species

Studies like Sun et al. (2017) have further highlighted the need for preprocessing techniques, such as data augmentation, to enhance model robustness under variable conditions, including rare species datasets. Similiariy, Vidya et al. (2024) emphasized the importance of transfer learning and synthetic data generation as potential solutions to this issue, enabling AI systems to learn from limited datasets.

3.1.3. Technological Innovations

To address these challenges, innovative systems such as LeafNet and FlowerMate 2.0 have demonstrated the effectiveness of multi-modal data integration in improving identification accuracy. By combining features from leaves, flowers, and bark, these systems overcome the morphological similarities that often confuse AI models (Barré et al., 2017; Xie et al., 2024). These advancements are pivotal for expanding the scope of AI applications in botanical gardens, particularly for conservation efforts targeting endangered species.

3.2. Environmental and Contextual Challenges

Environmental factors present another layer of complexity in AI-based plant identification. Variations in lighting conditions, seasonal changes, and differences in plant appearances due to growth stages can significantly affect the accuracy of AI models. For example, Sun et al. (2017) demonstrated that deep learning models trained under controlled conditions often exhibit a 10–15% accuracy drop when applied to real-world scenarios with variable lighting and seasonal changes. Table 2 summarizes the impact of these environmental factors on AI-based plant identification.

Table 2. Impact of environmental factors on AI accuracy

Environmental Factor	Effect on Accuracy	Percentage Decrease in Accuracy (%)	Study Reference
Lighting Variations	High	10-15%	Ubbens & Stavness (2017)
Seasonal Changes	Moderate	5-10%	Wäldchen and Mäder, (2018)
Plant Growth Stage	Moderate	7-12%	Picek et al., 2022
Background Noise	Low	3-5%	Carranza-Rojas et al. (2017)

Figure 3 illustrates how accuracy rates decrease as environmental variability increases, based on data from Ubbens and Stavness (2017).

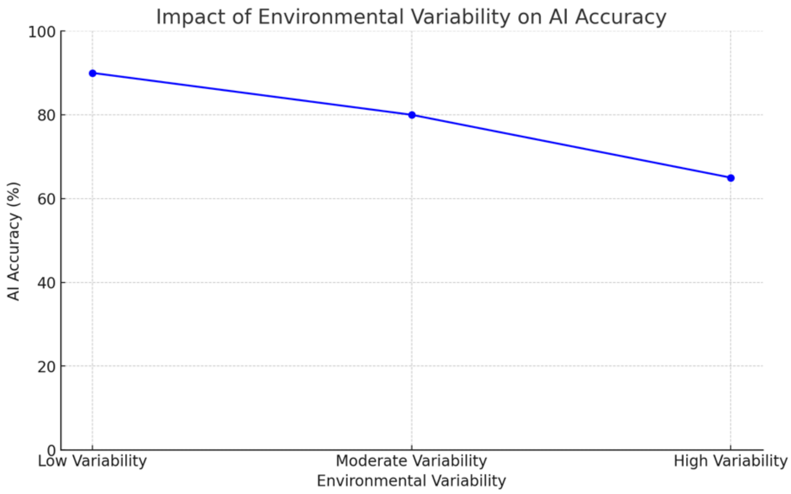

Figure 3. Impact of environmental variability on AI accuracy

3.2.1. Contextual Challenges

The context in which plants are found can also significantly influence AI performance. Plants growing in mixed-species environments, such as dense forests or multi-species displays in botanical gardens, pose challenges for AI systems that rely on clear, isolated images for identification. Studies by Wäldchen and Mäder (2018) have shown that these systems often struggle to distinguish between overlapping or closely situated plants, leading to higher rates of misidentification. Table 3 outlines the challenges faced by AI models in different contextual settings and the potential solutions proposed in the literature.

Table 3. Contextual challenges and potential solutions for AI in plant identification

Contextual Challenge	Effect on AI Performance	Proposed Solutions	Study Reference
Mixed-Species Environments	High Error Rate	Context-aware AI models	Wäldchen and Mäder, (2018)
Overlapping Plant Structures	Moderate Error Rate	Enhanced image segmentation algorithms	Picek et al., (2022)
Dense Foliage	Moderate Error Rate	Use of depth sensing and 3D imaging	Ubbens & Stavness (2017)

Recent advancements have proposed innovative solutions to address these challenges. For instance, Xie et al. (2024) highlighted the use of multi-modal data integration, combining features from leaves, flowers, and bark, to improve accuracy in complex environments. Additionally, Vidya et al. (2024) emphasized the importance of transfer learning and synthetic data augmentation to adapt AI models for mixed-species contexts.

3.2.2. Emerging Solutions

Systems like FlowerMate 2.0 leverage advanced AI techniques, including depth sensing and 3D imaging, to navigate dense foliage and overlapping plant structures (Xie et al., 2024). These advancements, combined with robust preprocessing techniques like data augmentation and enhanced segmentation algorithms, provide promising avenues for improving AI performance in challenging environmental and contextual conditions.

3.3. Ethical Considerations and Conservation Implications

The integration of AI into botanical gardens raises critical ethical considerations, particularly concerning data privacy and biodiversity conservation. August et al. (2020) highlighted the potential risks associated with AI applications, including unintended consequences of extensive data collection and the misuse of sensitive biodiversity information. For instance, revealing the locations of rare or endangered species through public datasets could inadvertently increase their vulnerability to poaching or habitat destruction (Dawson et al., 2008).

3.3.1. Framework for Ethical AI in Botanical Gardens

Figure 4 illustrates a comprehensive ethical framework for AI applications in botanical gardens. This framework balances conservation goals with privacy concerns by emphasizing transparent data handling, anonymization protocols, and collaboration with conservation experts to minimize risks (Dawson et al., 2008).

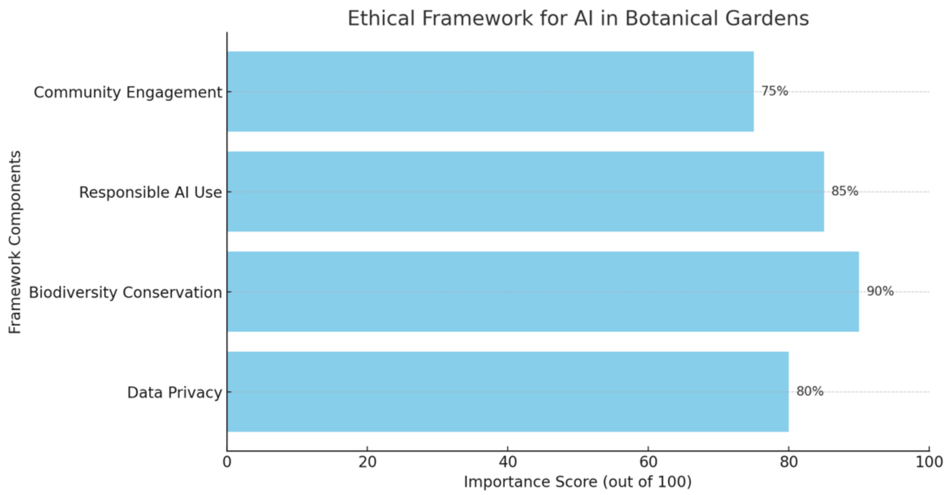

Figure 4. Ethical framework for AI in botanical gardens

3.3.2. AI's Role in Conservation

Beyond plant identification, AI has the potential to significantly enhance conservation efforts by providing real-time data on species distribution, health, and population dynamics. These insights enable botanical gardens to make informed decisions regarding conservation priorities and resource allocation (August et al., 2020). For example, AI systems such as FlowerMate 2.0 have been used to monitor endangered species, leveraging multi-modal data to track health indicators and respond rapidly to environmental changes (Xie et al., 2024).

Table 4 provides an overview of the potential benefits and risks associated with AI applications in conservation efforts within botanical gardens.

Table 4. Potential benefits and risks of AI in botanical conservation

Potential Benefit	Associated Risk	Mitigation Strategy
Enhanced Species Monitoring	Data Privacy Concerns	Implementation of strict data protocols
Improved Resource Allocation	Over-reliance on AI Predictions	Regular cross-checking with expert assessments
Faster Identification Processes	Potential for Misidentification	Continuous model updates and training

The use of AI must also be balanced against its limitations. Over-reliance on AI predictions without adequate cross-validation by human experts can lead to misidentifications or skewed conservation priorities. Studies by Picek et al. (2022) suggest that regular updates to AI models, incorporating expert feedback and adaptive learning strategies, are essential for maintaining reliability.

3.3.3. Ethical Mitigation Strategies

To address these risks, Dawson et al. (2008) recommend anonymizing sensitive data, such as the geographic coordinates of rare species, to prevent misuse while retaining its utility for conservation efforts. Additionally, Hardwick et al. (2011) propose integrating AI with traditional conservation methods to ensure a holistic approach that leverages both technology and human expertise. Emerging technologies like blockchain-based data verification have also been suggested to enhance data transparency and prevent unauthorized use of sensitive information. Collaborative governance models, involving stakeholders such as botanical garden managers, AI developers, and conservationists, can further ensure that AI is deployed responsibly and adaptively in conservation contexts (August et al., 2020).

3.4. Future Directions and Research Opportunities

Looking ahead, several key areas offer significant potential for advancing the application of AI in botanical gardens. By addressing existing challenges and exploring innovative approaches, future research and development can enhance the effectiveness and accessibility of AI technologies.

3.4.1. Integration with Emerging Technologies

One promising direction is the integration of AI with other emerging technologies, such as drones and remote sensing. These tools can provide comprehensive data on plant populations across large areas, enabling more efficient monitoring and management. For example, drones equipped with AI-powered cameras can capture high-resolution images of plant canopies, while remote sensing technologies can offer additional insights into environmental conditions and vegetation health (Chen et al., 2023). Figure 5 outlines a proposed model for the integration of AI, drones, and remote sensing in plant monitoring, emphasizing their complementary roles in biodiversity management.

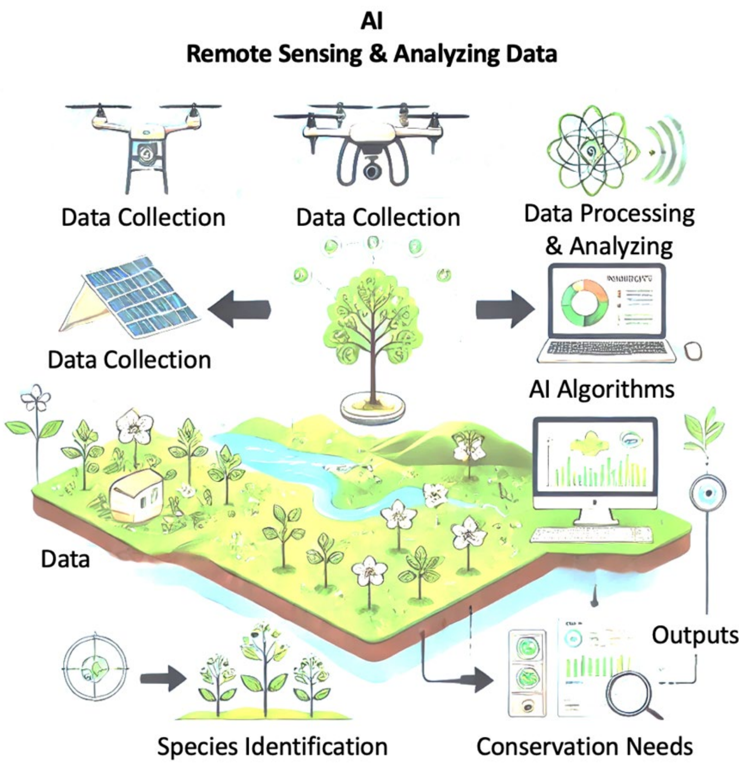

Figure 5. Integration of AI, drones, and remote sensing in plant monitoring

3.4.2. Advancements in AI Algorithms

Future research should focus on advancing AI algorithms to address current limitations. For instance, transfer learning and unsupervised learning hold great promise for overcoming issues related to data scarcity and environmental variability. These techniques enable models to learn from smaller or less comprehensive datasets by leveraging pre-trained networks or identifying patterns without labeled data (Picek et al., 2022). Additionally, techniques such as synthetic data generation and data augmentation can be explored to improve model robustness for rare species and underrepresented environments (Vidya et al., 2024).

3.4.3. Development of User-Friendly Tools

Another critical area of focus is the development of user-friendly AI tools that botanical gardens with limited technical expertise can adopt easily. Wäldchen and Mäder, (2018) emphasized the importance of intuitive interfaces and customizable models tailored to the specific needs of different gardens. Systems like FlowerMate 2.0 have demonstrated the potential for integrating multi-modal data sources, improving the accessibility and accuracy of AI tools for non-experts (Xie et al., 2024). Similarly, mobile applications designed for plant identification, such as those highlighted by Jones (2020), further expand the reach of AI technologies, making them more practical for fieldwork.

3.4.4. Real-World Applications and Conservation

In line with the findings of Chen et al. (2023), this study reaffirms the potential of deep learning in plant species identification. While CNN-based models demonstrate high accuracy under controlled conditions, their adaptability to real-world settings, including mixed-species environments, remains an ongoing area of research. For example, LeafNet's demonstrated resilience to environmental variability highlights the importance of robust preprocessing techniques to improve accuracy in challenging contexts (Barré et al., 2017). Additionally, systems like FlowerMate 2.0 underscore the value of integrating diverse data sources to tackle the challenges posed by rare species and complex environments (Xie et al., 2024).

Botanical gardens play a crucial role in biodiversity conservation. Hardwick et al. (2011) emphasized their function as hubs for ecological restoration, where AI can be leveraged to enhance conservation capabilities. For instance, AI tools can unlock new biodiversity insights from digital images, as demonstrated by August et al. (2020), complementing traditional fieldwork methods and enabling more effective resource allocation.

4. Conclusion

4.1. AI Accuracy in Plant Identification

The analysis of existing research demonstrates that AI models, particularly those leveraging deep learning, have shown remarkable promise in accurately identifying plant species within botanical gardens. CNNs and Deep Neural Networks (DNNs) are among the most effective tools, often achieving accuracy rates exceeding 90% for well-represented plant species in comprehensive datasets (Carranza-Rojas et al., 2017; Wäldchen and Mäder, 2018). For instance, Carranza-Rojas et al. (2017) achieved a 92.5% success rate using a CNN-based approach to identify herbarium specimens.

However, the performance of AI models is inconsistent across species. Rare and endangered plants, which are often underrepresented in training datasets, exhibit significantly lower identification accuracy, with rates dropping to approximately 65% in some studies (Wäldchen and Mäder, 2018). This disparity highlights the critical need for more inclusive datasets encompassing a broader range of species. Multi-modal approaches, such as integrating leaf, flower, and bark data, as seen in systems like FlowerMate 2.0, offer a viable path forward to enhance AI performance for these species (Xie et al., 2024). Additionally, techniques like data augmentation, transfer learning, and synthetic data generation have demonstrated potential in addressing data scarcity challenges (Clark et al., 2012; Vidya et al., 2024).

Social media platforms like Flickr also present an innovative opportunity for biodiversity data augmentation, enabling AI systems to improve rare species recognition by integrating diverse data sources (August et al., 2020). The combination of advanced methodologies and diverse datasets underscores the transformative potential of AI in species conservation efforts within botanical gardens.

4.2. Impact of Environmental Factors

Environmental variability emerged as a key challenge influencing AI accuracy in plant identification. Variations in lighting conditions, seasonal changes, and plant growth stages significantly impact model performance. Studies have shown that CNN-based models trained under controlled conditions can experience a 10–15% drop in accuracy when applied to natural settings with non-uniform lighting (Rankothge et al., 2013; Sun et al., 2017).

Seasonal changes, such as leaf coloration or the absence of flowers, further reduce accuracy by 5–10% (Govindaraj, 2024).

Moreover, the physical context in which plants are situated—such as mixed-species environments in botanical gardens—adds another layer of complexity. Dense foliage, overlapping plant structures, and closely situated species can lead to higher error rates (Wäldchen and Mäder, 2018). For example, Ubbens and Stavness (2017) highlighted the challenges of identifying plants in mixed-species environments, where AI systems trained on isolated images struggle to adapt.

To address these challenges, robust preprocessing techniques and innovations in AI architectures are essential. Data augmentation strategies, enhanced segmentation algorithms, and the integration of depth sensing and 3D imaging have shown promise in mitigating environmental variability and improving model resilience (Picek et al., 2022; Xie et al., 2024).

4.3. Ethical and Conservation Implications

The ethical considerations surrounding AI applications in botanical gardens are integral to their responsible implementation. August et al. (2020) emphasized the importance of balancing technological advancements with ethical concerns, particularly regarding data privacy and biodiversity conservation. The potential misuse of sensitive data, such as the geographic locations of rare species, underscores the need for strict anonymization protocols and collaborative governance models (Dawson et al., 2008).

AI-driven conservation efforts extend beyond identification to encompass monitoring and management of plant populations. Real-time data on species distribution and health can guide informed decision-making, optimizing resource allocation and conservation priorities (Wäldchen and Mäder, 2018). However, these advancements must complement, rather than replace, traditional conservation methods. Studies by Hardwick et al. (2011) advocate for the integration of AI tools with human expertise to ensure holistic ecological restoration approaches.

Concrete mitigation strategies, such as blockchain-based data verification, have been proposed to enhance data transparency and prevent unauthorized access. Collaborative frameworks involving botanical garden managers, AI developers, and conservationists can ensure that AI applications align with biodiversity conservation goals while addressing ethical challenges (Labrighli et al., 2022; Gan et al., 2011).

Acknowledgements

The author would like to thank Duzce University for its support throughout this research. Special thanks are also extended to the colleagues and reviewers who provided valuable feedback and insights, helping to improve this manuscript.

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