Journal of Science in Agrotechnology
Vol. 3, No. 1, 2025, pp. 43-53
ISSN: 2986-1411, DOI: https://doi.org/10.21107/jsa.v3i1.30

Global Research Trends on AI and IoT in Precision Agriculture: A VOSviewer Analysis (2021–2024)

Hesti Wulansari [1], Desy Dwi Putri [2,*], Resky Nuralisa Gunawan [3]
[1] Universitas Hasanuddin, Jl. Perintis Kemerdekaan, Kota Makassar, Sulawesi Selatan 90245, Indonesia
[2] Mueang Khon Kaen District, Khon Kaen 40002, Thailand
[3] Peneliti Teknologi Teknik Indonesia
* Corresponding Author

ARTICLE INFO

Article history:

Received August 6, 2025
Revised August 13, 2025
Published August 28, 2025

Keywords:

Crop yield;
Fertilizers;
Irrigation;
Machine-learning;
Smart agriculture;
Vegetation index

ABSTRACT

The integration of Artificial Intelligence (AI) and the Internet of Things (IoT) has significantly transformed precision agriculture, offering data-driven solutions to improve productivity, sustainability, and resource efficiency. This study presents a bibliometric analysis of global research on AI and IoT in precision agriculture from 2021 to 2024, using data from the Dimensions database and visualized through VOSviewer. A total of 674 publications were analyzed, revealing five major thematic clusters: AgriTech Intelligence, AgriVision AI, SkyFarm, RootData, and GeoCrop. Results show a consistent growth in research output and increasing alignment with global sustainability goals, particularly Zero Hunger (SDG 2) and Clean Water and Sanitation (SDG 6). However, research remains geographically concentrated, with limited representation from developing regions. This study highlights critical research gaps and provides valuable insights for researchers seeking collaboration opportunities and emerging topics. For educational administrators and policymakers, the findings offer a strategic reference for curriculum development, investment in digital agricultural education, and informed policymaking to support equitable access to smart farming technologies across diverse socio-economic contexts. Future research should focus on expanding regional inclusion and evaluating the long-term impact of AIoT adoption in agriculture.

Cite Article:

H. Wulansari, D. D. Putri, and R. N. Gunawan, "Global Research Trends on AI and IoT in Precision Agriculture: A VOSviewer Analysis (2021–2024)," *Journal of Science in Agrotechnology*, vol. 3, no. 1, pp. 43-53, 2025, doi: https://doi.org/10.21107/jsa.v3i1.30.

1. INTRODUCTION

Technological innovations, particularly the integration of Artificial Intelligence (AI) and the Internet of Things (IoT), are transforming agriculture by enhancing productivity, sustainability, and efficiency. This transformation, often referred to as "Smart Agriculture" or "Precision Agriculture," leverages AI algorithms, real-time data from IoT sensors, and automation to optimize various farming aspects, including crop monitoring, resource management, and pest control [1], [2], [3], [4], [5], [6]. AI-driven innovations, such as autonomous machinery and predictive analytics, enable farmers to make informed decisions, optimize resource usage, and increase productivity while minimizing environmental impact [7], [8], [9], [10]. IoT devices, including sensors and drones, provide real-time data on crop health, climate conditions, and soil quality, facilitating precise and efficient farming practices. These technologies collectively contribute to higher yields, better resource utilization, and enhanced environmental sustainability, addressing the challenges posed by climate change and resource limitations [11]. However, the adoption of these technologies also presents challenges, such as data security, privacy concerns, and the need for equitable access to technology. Despite these challenges, the integration of AI and IoT in agriculture offers a promising path towards a more sustainable and resilient agricultural future.

In the agricultural context, Artificial Intelligence (AI) refers to the use of algorithms and machine learning models to analyze data, detect patterns, and make data-driven decisions. Internet of Things (IoT) involves the use of interconnected devices and sensors to collect, transmit, and share data in real-time. Together, these technologies form a powerful combination known as AIoT, which significantly enhances agricultural practices. AI and IoT streamline agricultural operations by automating tasks such as irrigation, pest control, and crop monitoring. This automation reduces labor costs and increases operational efficiency [12], [13], [14]. By providing precise data on crop health, soil conditions, and environmental factors, AI and IoT enable farmers to optimize planting schedules, fertilization, and harvesting, leading to higher crop yields[15], [16], [17]. These technologies help in the efficient use of resources like water, fertilizers, and pesticides. For instance, IoT sensors can monitor soil moisture levels and AI can predict the optimal amount of water needed, thus conserving water and reducing waste [18], [19]. AI algorithms analyze vast amounts of data collected by IoT devices to provide actionable insights. This data-driven approach helps farmers make informed decisions about crop management, pest control, and resource allocation, ultimately improving productivity and sustainability [20], [21].

The integration of Artificial Intelligence (AI) and the Internet of Things (IoT) in precision agriculture has sparked interdisciplinary research across environmental sciences, bioenergy management, collaborative learning, and biomedicine. As visualized in the research trends mapping (Fig. 1), the field is characterized by diverse application domains and methodological developments, including the growing use of bibliometric analysis tools such as VOSviewer. This trend reflects a scholarly shift toward understanding the structural evolution of knowledge within this area. By capturing thematic clusters and collaboration patterns, bibliometric approaches offer valuable insights for researchers, practitioners, and policymakers. Therefore, this study aims to map the global research landscape on AI and IoT in precision agriculture between 2021 and 2024 through a VOSviewer-based bibliometric analysis.

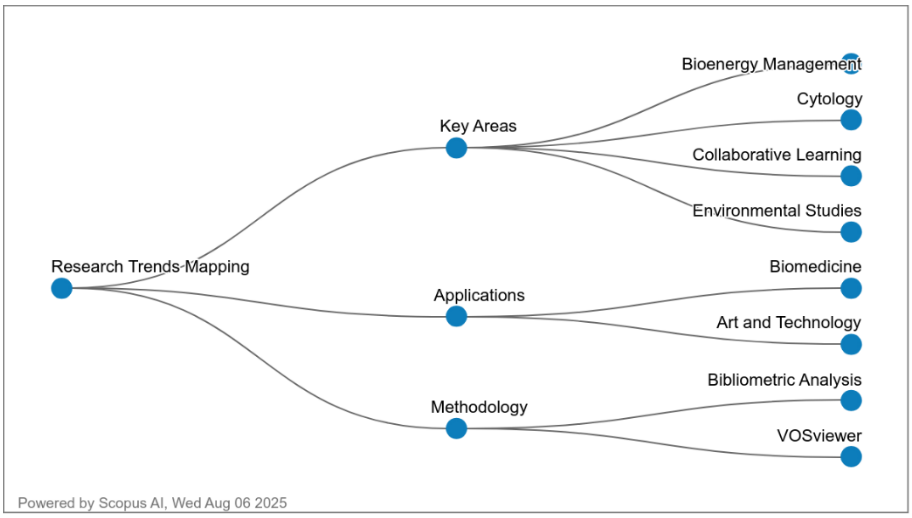

Fig. 1. Research trends mapping in AI and IoT for precision agriculture highlighting key areas, applications, and methodologies (2021–2024) (Source: Scopus database)

Despite the increasing volume of research in the fields of Artificial Intelligence (AI) and the Internet of Things (IoT) within precision agriculture, there remains a notable gap in the synthesis of trends and insights from this body of work. Recent bibliometric analyses have not comprehensively mapped global trends, particularly for the period from 2021 to 2024. This lack of a thorough overview limits the understanding of how these technologies are evolving and being applied in agricultural practices, hindering stakeholders from effectively leveraging the latest advancements and insights to enhance productivity and sustainability in the sector. As such, a detailed bibliometric analysis is essential to illuminate the current landscape and future directions of research in AI and IoT in precision agriculture.

The aim of this study is to map global research trends in the integration of Artificial Intelligence (AI) and the Internet of Things (IoT) within the field of precision agriculture, utilizing VOS viewer as a visualization tool. By focusing on the timeframe from 2021 to 2024, this research highlights the most recent developments and advancements in these technologies, which are increasingly transforming agricultural practices. The study seeks to provide a comprehensive overview of the current research landscape, identifying key areas of interest, influential publications, and emerging trends that are shaping the future of precision agriculture through the application of AI and IoT.

This study offers significant contributions to the field by providing a detailed mapping of global research trends in the integration of Artificial Intelligence (AI) and the Internet of Things (IoT) in precision agriculture for the period 2021-2024. The findings can assist researchers in identifying critical research gaps that require further exploration, thereby guiding future investigations. Additionally, the study facilitates the identification of potential collaborators by highlighting key players and institutions actively engaged in this domain. By tracking thematic evolution, the research enables stakeholders to understand how topics have developed over time, which is essential for informed decision-making. Furthermore, the insights gained from this study can support strategic research planning for policymakers and practitioners, ensuring that resources are allocated effectively to address the most pressing challenges in precision agriculture.

The contributions of this study are threefold. First, it provides a state-of-the-art overview of global research trends on the integration of Artificial Intelligence (AI) and the Internet of Things (IoT) in precision agriculture through bibliometric visualization using VOS viewer. Second, it offers a novel perspective by identifying and clustering research into five thematic domains Agri Tech Intelligence, Agri Vision AI, Sky Farm, Root Data, and GenCorp based on keyword co-occurrence and citation analysis. Third, this study supports strategic research planning and policy formulation by highlighting regional disparities, emerging research themes, and influential institutions and authors in the field.

To ensure clarity and coherence, the structure of the paper is organized as follows. The Methods section details the systematic data collection process and the bibliometric analysis techniques employed. The Results and Discussion section presents the trends in publication output, the distribution of research across Sustainable Development Goals (SDGs), and an in-depth analysis of the thematic research clusters. Finally, the Conclusion summarizes the key findings, discusses the implications for future research, and provides recommendations for expanding inclusivity and technological adoption in precision agriculture globally.

2. METHODS

This bibliometric study employed a systematic approach to identify, screen, and include relevant publications on Artificial Intelligence (AI) and Internet of Things (IoT) in Precision Agriculture from 2021 to 2024 (Fig. 2). The Dimensions database was chosen exclusively for data retrieval because it offers broad multidisciplinary coverage, includes both peer-reviewed and open-access sources, and integrates publication metadata with citation and research category filters. Unlike some other databases, Dimensions allows for highly refined filtering based on research fields, publication year, and full-title keyword matching making it particularly suitable for bibliometric analyses involving emerging interdisciplinary fields.

This bibliometric study employed a systematic approach to identify, screen, and analyze relevant publications on Artificial Intelligence (AI) and the Internet of Things (IoT) in Precision Agriculture between 2021 and 2024. The Dimensions database was exclusively selected due to its broad multidisciplinary coverage, including open-access and peer-reviewed literature, integration with citation data, and the ability to apply refined filters by research field, publication year, and title-level keyword specificity. Compared to Scopus or Web of Science, Dimensions offers greater flexibility for title-based filtering and more inclusive access to grey literature, which is particularly valuable in an emerging interdisciplinary field like digital agriculture. Furthermore, Dimensions supports real-time bibliometric data export, making it highly compatible with VOSviewer.

The keywords were deliberately chosen to reflect the core intersection of digital technologies and agriculture. “Precision Agriculture” was selected to narrow the scope to data-driven farming practices, while “AI” and “IoT” were included to capture advanced technological dimensions. The title-only filter increased specificity and avoided inclusion of articles that only mentioned the keywords peripherally.

A total of 3,294 records were initially retrieved using the keyword combination:
("Precision Agriculture" AND "AI" AND "IoT") AND (PublicationYear:2021 OR PublicationYear:2022 OR PublicationYear:2023 OR PublicationYear:2024 OR PublicationYear:2025) AND (FieldsOfResearch:"3003 Agricultural Biotechnology" OR "3002 Agriculture, Land and Farm Management" OR "3001 Agricultural, Veterinary and Food Sciences").

This search was limited to articles with the keywords in the title field only, ensuring that only studies explicitly focused on the topic were included. The screening process was conducted in three stages:

1. Initial Screening (n = 3,294): Duplicate and non-English records were automatically removed.
2. Text Screening (n = 1,650): Titles and abstracts were manually reviewed to eliminate irrelevant topics (e.g., articles using “AI” or “IoT” metaphorically or outside the agricultural context).

3. Eligibility Check: Studies were excluded (n = 1,456) if they lacked a direct focus on precision agriculture applications or if they primarily discussed non-agricultural sectors.
4. After applying these criteria, 674 documents were included for bibliometric analysis. This refined corpus represents the most thematically relevant and high-quality research for visual mapping using VOS viewer.

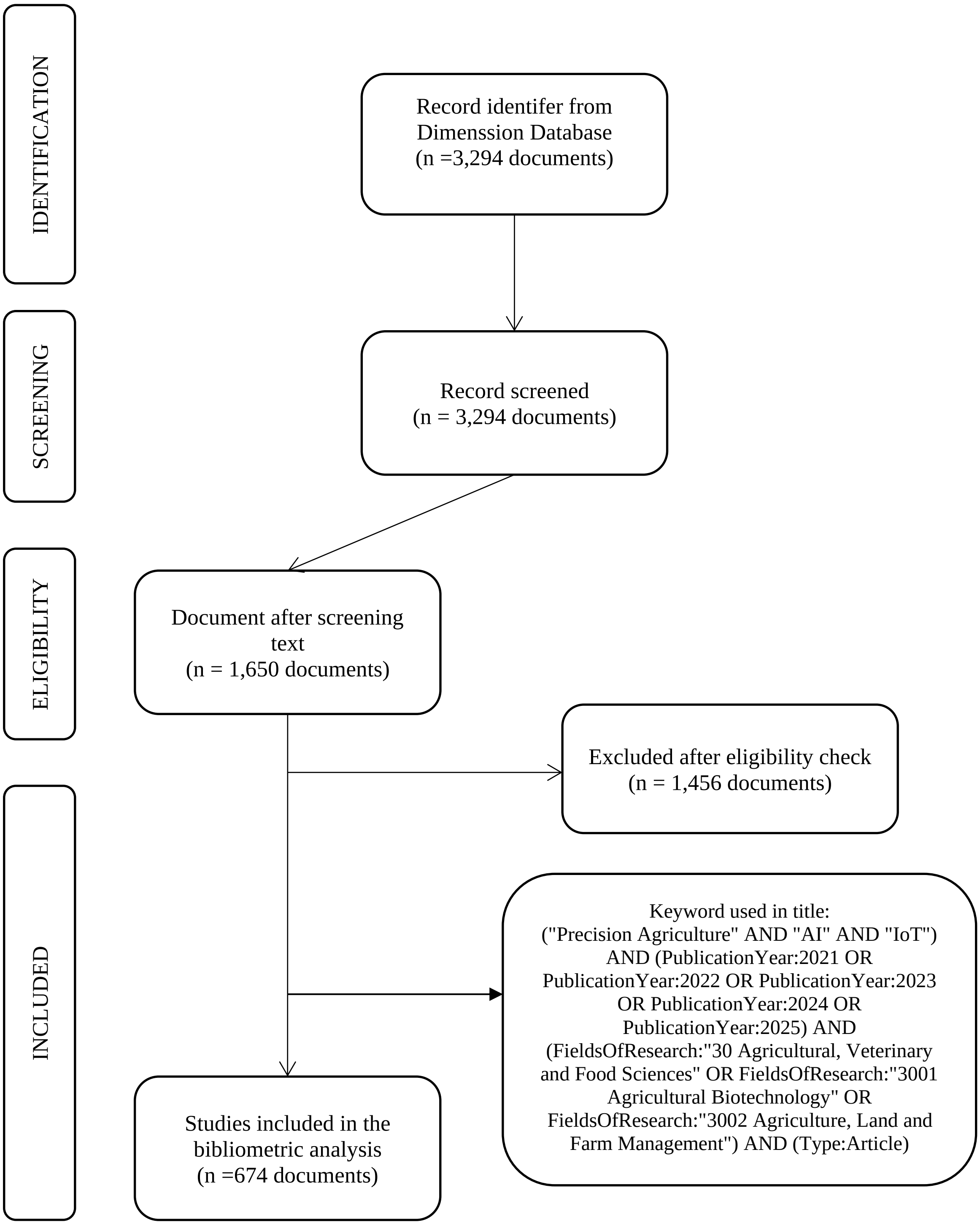

Fig. 2. Flow diagram of the bibliometric study selection process based on dimensions database records from 2021 to 2024

3. RESULTS AND DISCUSSION

3.1. Number of Publications Published

The visualization shows the number of publications published in each year shown in Fig. 3. The chart illustrates a steady and significant increase in the number of publications on AI and IoT in precision agriculture from 2021 to 2024, rising from approximately 11 to over 50 publications, with a projected continuation into 2025. This trend reflects a growing global interest in the application of advanced digital technologies to agriculture, driven by the need for more efficient, data-driven, and sustainable farming practices. The consistent rise in research output suggests that AI and IoT are becoming central components in addressing agricultural challenges, such as optimizing crop yields, improving resource management, and adapting to climate change, while also indicating an expanding interdisciplinary research focus in this evolving field.

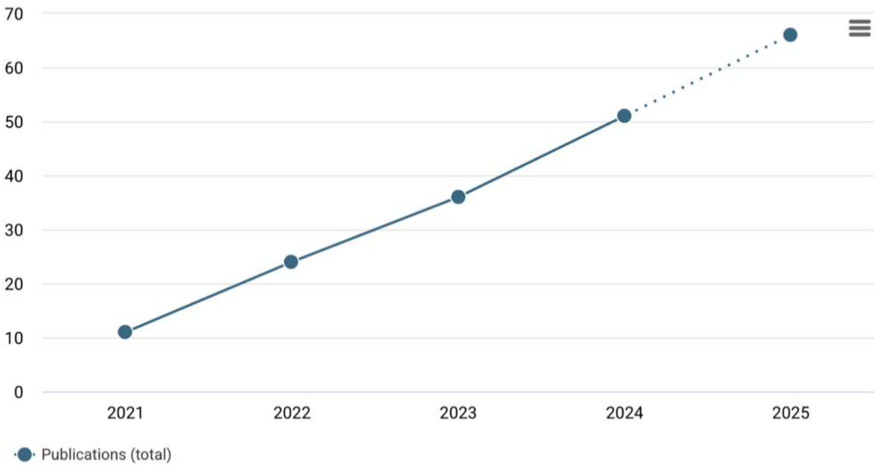

Fig. 3. Annual trend of global publications on AI and IoT in precision agriculture from 2021 to 2024, with a projected increase in 2025

The annual trend shows a steady increase in publications related to AI and IoT in precision agriculture, rising from approximately 11 in 2021 to over 50 in 2024, with a projected continuation into 2025. This upward trend can be attributed to several factors: post-pandemic recovery stimulating investment in digital infrastructure, broader access to open-source AI tools, and rising global concerns over climate-resilient agriculture. Notably, publication peaks in 2023 and 2024 suggest a transition from experimental applications to field-level implementation, supported by real-time sensing, cloud computing, and wireless networks.

Furthermore, the increasing research interest is consistent with earlier studies that predicted AI and IoT would become key enablers of smart farming systems. Subeesh A and Chend D [22], [23] noted the early promise of deep learning and sensor networks in optimizing crop management, while Alkhayyal M [24] outlined emerging applications of AI in yield prediction, pest detection, and precision irrigation. The 2023 and 2024 publication peaks suggest that these technologies have moved from experimental stages to more widespread field implementations, supported by advancements in real-time data processing, cloud computing, and wireless sensor networks. These developments demonstrate a maturing field that is increasingly interdisciplinary combining agronomy, computer science, environmental science, and engineering.

Additionally, recent bibliometric and regional studies show that research is no longer concentrated in a few industrialized nations. Instead, there has been a global diffusion of innovation, with growing contributions from Asia, Africa, and Latin America. This reflects broader awareness of how precision agriculture, supported by AI and IoT, can contribute to food security, climate adaptation, and sustainable development goals. Researchers such as Sakib Sizan N and Ahmad N [25], [26] have highlighted how low-cost IoT devices and open-source AI platforms are helping smaller farms access cutting-edge technologies. As projected for 2025, the continued growth in publications is expected to further diversify research themes, including ethical concerns, data governance, and scalability of smart farming systems in various socio-economic contexts.

3.2. Classification: Sustainable development goals

Table 1 presents the alignment of publications on AI and IoT in precision agriculture with the United Nations Sustainable Development Goals (SDGs). The most dominant contribution is to SDG 2 Zero Hunger, with 83 publications and 2,225 citations, showing a strong focus on addressing global food security. Although fewer in number, SDG 6 Clean Water and Sanitation has the highest mean citations per publication (112), indicating a high impact of research addressing water related agricultural challenges. Other relevant goals include Climate Action (SDG 13), Affordable and Clean Energy (SDG 7), and Responsible Consumption and Production (SDG 12), reflecting the multidisciplinary and sustainability-oriented nature of precision agriculture research.

Table 1. Distribution of publications on AI and IoT in precision agriculture classified by relevant Sustainable Development Goals (SDGs), showing the highest contribution to SDG 2 (Zero Hunger) and the highest citation impact for SDG 6 (Clean Water and Sanitation)

SDG Name	Publications	Citations	Mean Citations
2 Zero Hunger	83	2,225	26.81
13 Climate Action	10	250	25.00
7 Affordable and Clean Energy	9	121	13.44
9 Industry, Innovation and Infrastructure	7	245	35.00
3 Good Health and Well Being	5	149	29.80
12 Responsible Consumption and Production	5	248	49.60
6 Clean Water and Sanitation	3	336	112.00
8 Decent Work and Economic Growth	2	23	11.50
15 Life on Land	1	5	5.00
16 Peace, Justice and Strong Institutions	1	8	8.00

The concentration of research under SDG 2 (Zero Hunger) is consistent with the global imperative to improve food production systems through smart farming technologies. This aligns with studies such as Sharma K [27] , which emphasized how precision agriculture supported by AI and IoT optimizes crop yields, reduces waste, and increases food availability. The significant citation count here reflects the field's maturity and relevance, especially in developing efficient and scalable solutions for global food demand. Moreover, the presence of research tied to SDG 13 (Climate Action) suggests that the technologies are also being employed to monitor and mitigate the environmental impacts of agriculture, such as carbon emissions, deforestation, and unsustainable land use.

Interestingly, despite having only 3 publications, research aligned with SDG 6 (Clean Water and Sanitation) shows an exceptional mean citation rate, signaling high scholarly impact. This could be attributed to the increasing role of smart irrigation systems, soil moisture monitoring, and water use optimization [28], [29], [30], [31]. Similarly, contributions to SDG 12 (Responsible Consumption and Production) and SDG 9 (Industry, Innovation and Infrastructure) demonstrate the broader implications of precision agriculture in promoting sustainable supply chains and rural innovation. These findings support the view that AI and IoT in agriculture do not only serve food production but also contribute significantly to achieving environmental and infrastructural sustainability targets.

3.3. Focus research

Table 2 shown clustering from network visualization and Fig. 4 visualized network map, enhanced with labeled cluster names, illustrates the thematic structure of research on AI and IoT in Precision Agriculture. The map is divided into five focus areas: AgriTech Intelligence (red), AgriVision AI (yellow), SkyFarm (green), RootData (blue), and GeoCrop (purple). Each cluster represents a distinct yet interconnected research domain. AgriTech Intelligence focuses on integrating machine learning and IoT for smart agriculture. AgriVision AI emphasizes deep learning and computer vision. SkyFarm deals with aerial technologies like UAVs and drones. RootData is centered on data analysis related to soil and crop inputs, while GeoCrop connects remote sensing and vegetation analytics. These clusters reveal a multidisciplinary approach, where advanced computing meets agricultural needs.

Table 2. Clustering from network visualization

No.	Cluster Color	Short Name	Brief Description
1	Red	AgriTech Intelligence	Focused on the application of AI, IoT, and machine learning in smart agriculture.
2	Green	SkyFarm	Use of drones and UAVs for aerial monitoring of fields and crops.
3	Yellow	AgriVision AI	Deep learning and computer vision technologies for object detection and analysis.
4	Blue	RootData	Data-driven farming using soil analysis, fertilizers, and vegetation indices.
5	Purple	GeoCrop	Remote sensing applications for crop monitoring and yield estimation.

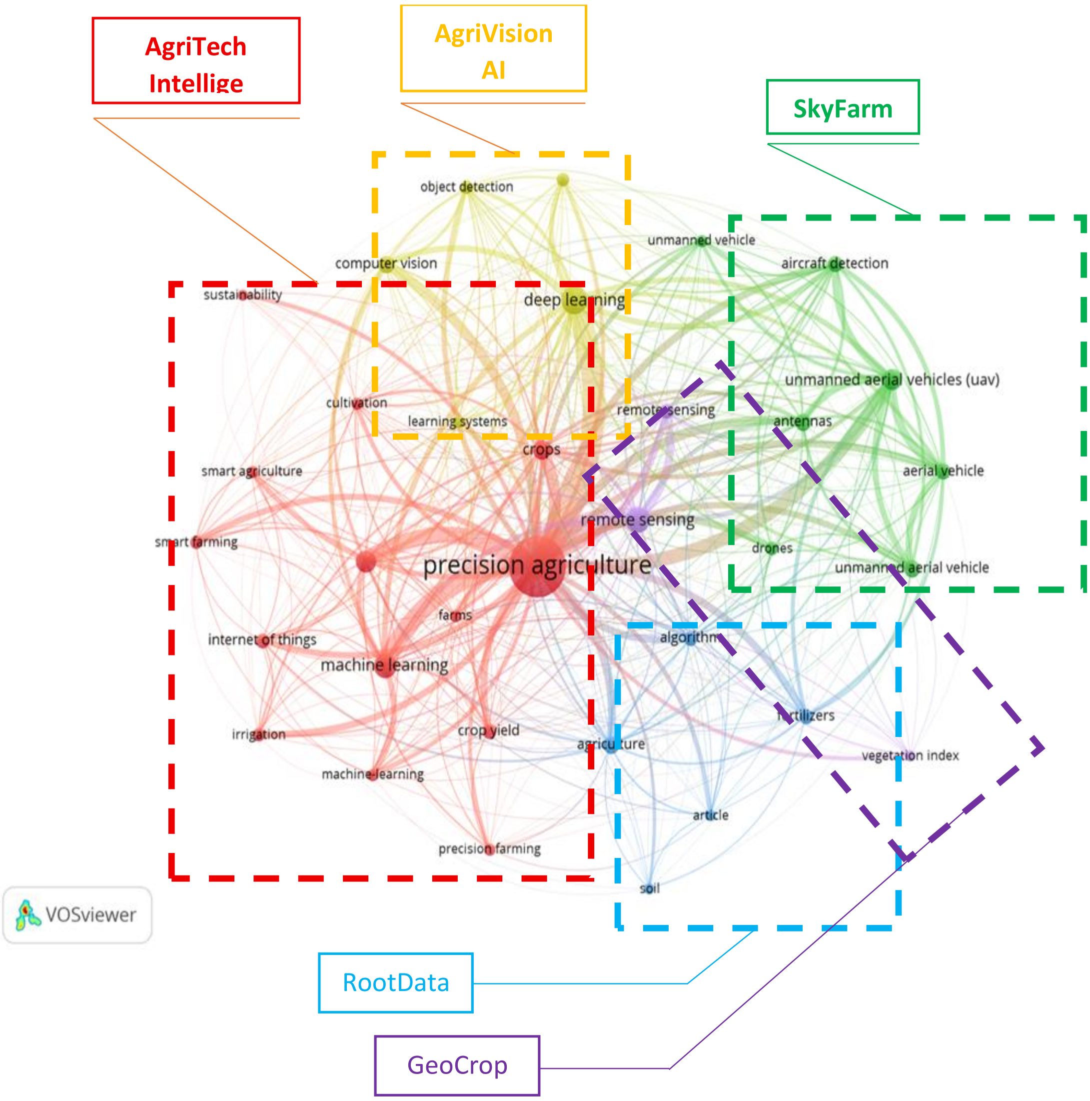

Fig. 4. Network visualization of research clusters in AI and IoT-based precision agriculture, categorized into five thematic areas: AgriTech Intelligence, AgriVision AI, SkyFarm, RootData, and GeoCrop

The AgriTech Intelligence cluster reflects the heart of smart farming innovation, where machine learning, IoT, and automation technologies converge to optimize agricultural operations. This aligns with Qin T [32] who described the digital transformation of agriculture through data-driven technologies. The cluster's inclusion of terms like "smart farming," "irrigation," and "crop yield" highlights efforts to increase efficiency in resource usage and productivity. As Fuentes-Penailillo [33] noted, machine learning techniques are now widely used to predict harvest times, detect diseases, and support decision-making in real time, making this area fundamental for food security and sustainability.

The AgriVision AI and SkyFarm clusters show how AI-powered vision systems and UAVs are transforming agricultural monitoring. The presence of terms like "object detection," "computer vision," and "unmanned aerial vehicle" in these clusters emphasizes how remote sensing and aerial imaging are used for crop mapping, pest detection, and land surveillance. According to Lacerda C [34], combining UAVs with AI models enables high-resolution crop assessment at low cost, particularly beneficial in large-scale farms or inaccessible areas. The strong interconnection between AgriVision AI and SkyFarm in the network suggests a growing integration of aerial data with machine learning algorithms.

RootData and GeoCrop point to the increasing importance of data analytics and environmental monitoring in agriculture. RootData focuses on soil characteristics, fertilizers, and algorithms echoing Huda S [35] who emphasized the role of sensor based soil monitoring in optimizing plant nutrition. GeoCrop, on the other hand, captures the relevance of remote sensing and vegetation indices, essential for yield estimation and precision spraying. These areas indicate how agricultural research is evolving toward predictive, data-driven models that consider environmental variables, making farming more resilient and sustainable in the face of climate change. Together, these five clusters reflect a comprehensive and interconnected ecosystem of modern agricultural innovation.

3.4. Keyword novelty

Table 3 shown novelty keyword and Fig. 5 shown the visualization illustrates a co-occurrence network of keywords in the field of AI and IoT-based precision agriculture, where "precision agriculture" forms the central hub. Closely associated terms such as "machine learning," "remote sensing," "smart agriculture," "deep learning," "unmanned aerial vehicles (UAVs)," and "Internet of Things" appear as highly connected nodes, indicating their strong interrelationship and significance in recent literature. The color gradient, based on the average year of publication, shows that topics like "vegetation index," "article," and "machine-learning" are relatively newer, whereas foundational topics such as "remote sensing" and "crops" have been consistently researched since earlier periods.

Table 3. Novelty keyword

No.	Keyword	Description
1	Vegetation index	Used to assess plant health via remote sensing, e.g., NDVI for crop monitoring.
2	Article	Represents research publications; highlights publication trends or methodology focus.
3	Fertilizers	Focuses on nutrient management, especially in precision agriculture using VRT or AI tools.
4	Crop yield	Estimates agricultural output; now often predicted using ML and sensor technologies.
5	Machine-learning	ML techniques applied in agriculture, distinct from broader 'machine learning' concept.
6	Smart agriculture	Refers to tech-driven farming methods integrating IoT, sensors, and AI for optimization.
7	Irrigation	Water management systems powered by AI to improve efficiency and sustainability.

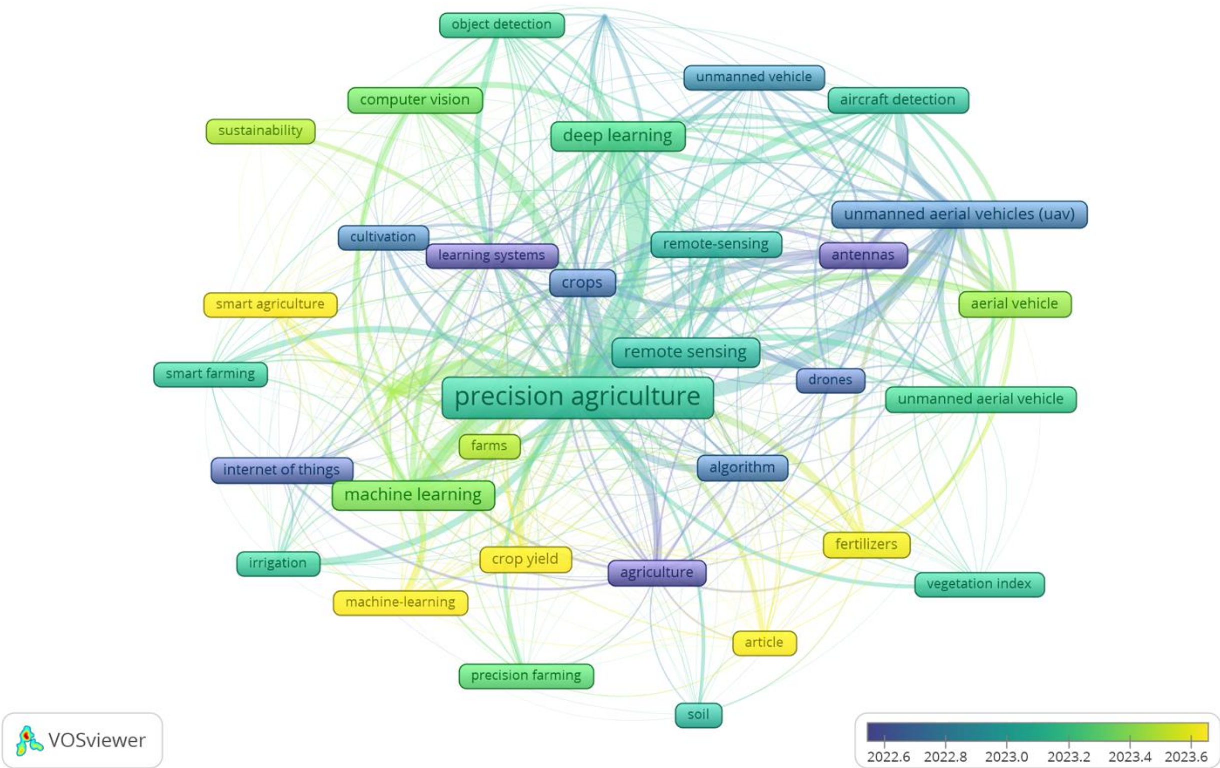

Fig. 5. Co-occurrence network of author keywords related to AI and IoT in precision agriculture (2021–2024), highlighting key thematic clusters and temporal trends

The emergence of keywords such as "vegetation index" and "crop yield" signifies a growing emphasis on data-driven methods for monitoring plant health and predicting productivity in agricultural systems. Vegetation indices, such as NDVI (Normalized Difference Vegetation Index), have become fundamental tools in remote sensing applications to assess crop vigor, detect stress, and estimate biomass. Recent studies demonstrate how integrating satellite-based vegetation indices with AI models significantly improves yield forecasting accuracy [36]. Crop yield prediction, once largely reliant on manual observation and historical data, is now enhanced through precision mapping and sensor technologies. This shift reflects the broader transition from descriptive to predictive analytics in agrotechnology.

The keywords "machine-learning" and "smart agriculture" highlight the evolution of agricultural practices toward intelligent and automated systems. Machine-learning algorithms are being applied to vast agricultural datasets to identify patterns, optimize resource allocation, and detect diseases or anomalies in real time. For instance, convolutional neural networks (CNNs) have been used to classify crop diseases with high accuracy using image data [37]. Smart agriculture, which encompasses IoT, robotics, and cloud computing, enables more sustainable and efficient farming. This concept aligns with research by Verma S [38] which underscores the role of sensor-integrated platforms and ML models in real-time farm management and autonomous decision-making.

In addition, the keywords "fertilizers" and "irrigation" reflect precision input management as a major research frontier within sustainable agriculture. Recent studies are exploring AI-supported irrigation scheduling and fertilizer application to reduce environmental impact and resource waste [39]. Variable rate technology (VRT) powered by machine learning enables farmers to apply fertilizers based on soil nutrient maps and crop needs. Similarly, AI-assisted irrigation systems adapt water usage based on weather predictions, soil moisture data, and plant requirements. These developments not only boost efficiency but also support global goals for climate-resilient agriculture and food security.

4. CONCLUSION

This bibliometric study provides a comprehensive overview of global research trends on the integration of Artificial Intelligence (AI) and the Internet of Things (IoT) in precision agriculture between 2021 and 2024. Using VOS viewer, the analysis identified five key thematic clusters Agri Tech Intelligence, Agri Vision AI, Sky Farm, Root Data, and Geo Crop which reflect the interdisciplinary and rapidly evolving nature of this research domain. The findings show a consistent rise in scholarly interest, particularly in technologies related to smart irrigation, remote sensing, machine learning, and crop monitoring.

However, the geographic distribution of research remains uneven, with limited contributions from regions such as Sub-Saharan Africa and Southeast Asia. Future research should prioritize these underrepresented areas by promoting regional collaboration, increasing open-access data sharing, and supporting inclusive capacity-building initiatives. There is also a need for longitudinal studies that assess the long-term socio-economic and environmental impact of AIoT adoption in different agricultural contexts, including smallholder and climate-vulnerable farms.

Support effective integration of AI and IoT in agriculture, policymakers should invest in infrastructure for rural connectivity, subsidize low-cost IoT devices, and develop national guidelines for data privacy and interoperability. Agricultural practitioners can begin by adopting modular AIoT systems tailored to local needs, such as soil moisture sensors or drone-based field surveys. Furthermore, education and training programs must be developed to equip farmers, technicians, and extension agents with the digital skills needed to operate and maintain these technologies sustainably. In conclusion, this study not only maps the current state of AIoT research in agriculture but also provides a strategic foundation for guiding future research, policy, and practice. By addressing gaps in geographic inclusion and translating technological advancements into accessible tools, stakeholders can accelerate the transformation toward a more equitable and resilient agricultural future.

Author Contribution
All authors contributed.

REFERENCES

[1] K. Elhattab and S. Elatar, "Survey of IoT and AI applications: future challenges and opportunities in agriculture," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 36, no. 3, pp. 1655-1663, Dec. 2024, doi: https://doi.org/10.11591/ijeecs.v36.i3.pp1655-1663.

[2] A. M. Somaya and A. Younes, "Agriculture: the next machine-learning frontier," *Harnessing Automation and Machine Learning for Resource Recovery and Value Creation: From Waste to Value*, pp. 363-380, Jan. 2025, doi: https://doi.org/10.1016/B978-0-443-27374-2.00014-5.

[3] A. Parashar, J. Mabrouki, and J. Sharma, "AI and Smart Technologies for Smart Agriculture Environment," *Studies in Big Data*, vol. 143, pp. 95-107, 2024, doi: https://doi.org/10.1007/978-3-031-50860-8_6.

[4] P. Singh, S. Singh, and R. S. Dubey, "Climate Change Impacts on Agriculture: Crop Productivity and Food Security," *Climate Change and Sustainable Development*, pp. 61-86, Jan. 2023, doi: https://doi.org/10.1201/9781003205548-4.

[5] J. L. Ares-Sainz, A. Arias, N. Matovic, L. Ladu, G. Feijoo, and M. T. Moreira, "Key governance and sustainability indicators for certification systems: Bridging certification and policy frameworks in the bioeconomy," *Sustain Prod Consum*, vol. 56, pp. 156-181, Jun. 2025, doi: https://doi.org/10.1016/j.spc.2025.03.017.

[6] I. Chowdhuri and S. C. Pal, "Challenges and potential pathways towards sustainable agriculture crop production: A systematic review to achieve sustainable development goals (SDGs)," *Soil Tillage Res*, vol. 248, p. 106442, May 2025, doi: https://doi.org/10.1016/j.still.2024.106442.

[7] F. Assimakopoulos, C. Vassilakis, D. Margaris, K. Kotis, and D. Spiliotopoulos, "AI and Related Technologies in the Fields of Smart Agriculture: A Review," *Information (Switzerland)*, vol. 16, no. 2, Feb. 2025, doi: https://doi.org/10.3390/info16020100.

[8] A. M. Somaya and A. Younes, "Agriculture: the next machine-learning frontier," *Harnessing Automation and Machine Learning for Resource Recovery and Value Creation: From Waste to Value,* pp. 363-380, Jan. 2025, doi: https://doi.org/10.1016/B978-0-443-27374-2.00014-5.

[9] L. Kambizi and C. Bvenura, "The Future of Undervalued Indigenous Crops: A Brief Overview," *Food Security and Nutrition: Utilizing Undervalued Food Plants*, pp. 1-3, Jan. 2024, doi: https://doi.org/10.1201/9781003469766-1.

[10] M. Janni, E. Maestri, M. Gullì, M. Marmiroli, and N. Marmiroli, "Plant responses to climate change, how global warming may impact on food security: a critical review," *Front Plant Sci*, vol. 14, 2023, doi: https://doi.org/10.3389/fpls.2023.1297569.

[11] S. K. Sharma, A. K. Sharma, S. Sharma, K. Shukla, and I. Ishaan, "IoT-based smart agriculture," *Convergence of Cloud Computing, AI, and Agricultural Science*, pp. 137-151, Aug. 2023, doi: https://doi.org/10.4018/979-8-3693-0200-2.ch007.

[12] K. Elhattab and S. Elatar, "Survey of IoT and AI applications: future challenges and opportunities in agriculture," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 36, no. 3, pp. 1655-1663, Dec. 2024, doi: https://doi.org/10.11591/ijeecs.v36.i3.pp1655-1663.

[13] S. M. Shankaregowda, R. R. Koppala, and R. Bhardwaj, "Advancing smart agriculture through AIoT integration for sustainable farming solutions," *AIoT and Smart Sensing: A Comprehensive Guide to the Next Generation of Smart Devices*, pp. 95-110, Jan. 2025, doi: https://doi.org/10.1201/9781032618173-8.

[14] N. Gouiza, H. Jebari, and K. Reklaoui, "IoT in Smart Farming: A Review," *Lecture Notes in Networks and Systems*, vol. 930 LNNS, pp. 149-161, 2024, doi: https://doi.org/10.1007/978-3-031-54318-0_13.

[15] F. Fuentes-Peñailillo, K. Gutter, R. Vega, and G. C. Silva, "Transformative Technologies in Digital Agriculture: Leveraging Internet of Things, Remote Sensing, and Artificial Intelligence for Smart Crop Management," *Journal of Sensor and Actuator Networks*, vol. 13, no. 4, Aug. 2024, doi: https://doi.org/10.3390/jsan13040039.

[16] A. Ghilan, Y. El Afou, A. Boulaalam, and N. El Akkad, "Precision Farming Based on Artificial Intelligence Algorithms: Monitoring of Agricultural Fields Based on the Description and Analysis of Data Obtained by Several Sensors," *Lecture Notes in Networks and Systems*, vol. 887 LNNS, pp. 199-209, 2024, doi: https://doi.org/10.1007/978-3-031-74491-4_16.

[17] A. M. Somaya and A. Younes, "Agriculture: the next machine-learning frontier," *Harnessing Automation and Machine Learning for Resource Recovery and Value Creation: From Waste to Value*, pp. 363-380, Jan. 2025, doi: https://doi.org/10.1016/B978-0-443-27374-2.00014-5.

[18] N. Kharraz and I. Szabó, "Cloud-Driven Data Analytics for Growing Plants Indoor," *AgriEngineering*, vol. 7, no. 4, Apr. 2025, doi: https://doi.org/10.3390/agriengineering7040101.

[19] S. S. Shinde, G. M. Kale, S. L. Nalbalwar, and S. B. Deosarkar, "AI for Sustainable Agriculture: Smart Farming Solutions," *2024 3rd International Conference on Artificial Intelligence*, Computational Electronics and Communication System, AICECS 2024, 2024, doi: https://doi.org/10.1109/AICECS63354.2024.10957312.

[20] A. A. Issa, S. Majed, S. A. Ameer, and H. M. Al-Jawahry, "Farming in the Digital Age: Smart Agriculture with AI and IoT," *E3S Web of Conferences*, vol. 477, Jan. 2024, doi: https://doi.org/10.1051/e3sconf/202447700081.

[21] O. El Ghati, O. Alaoui-Fdili, N. Alioua, O. Chahbouni, and W. Bouarifi, "An overview of the applications of AI-powered Visual IoT systems in agriculture," *Proceedings - 2023 IEEE International Conference on Advances in Data-Driven Analytics and Intelligent Systems*, ADACIS 2023, 2023, doi: https://doi.org/10.1109/ADACIS59737.2023.10424223.

[22] A. Subeesh and N. Chauhan, "Deep learning based abiotic crop stress assessment for precision agriculture: A comprehensive review," *J Environ Manage*, vol. 381, p. 125158, May 2025, doi: https://doi.org/10.1016/j.jenvman.2025.125158.

[23] D. Chen and Y. Huang, "Integrating reinforcement learning and large language models for crop production process management optimization and control through a new knowledge-based deep learning paradigm," *Comput Electron Agric*, vol. 232, p. 110028, May 2025, doi: https://doi.org/10.1016/j.compag.2025.110028.

[24] M. Alkhayyal and A. M. Mostafa, "Enhancing LoRaWAN Sensor Networks: A Deep Learning Approach for Performance Optimizing and Energy Efficiency," *Computers, Materials and Continua*, vol. 83, no. 1, pp. 1079-1100, Mar. 2025, doi: https://doi.org/10.32604/cmc.2025.061836.

[25] N. Sakib Sizan, D. Dey, Md. Abu Layek, M. A. Uddin, and E.-N. Huh, "Evaluating blockchain platforms for IoT applications in Industry 5.0: A comprehensive review," *Blockchain: Research and Applications*, vol. 6, no. 3, p. 100276, Sep. 2025, doi: https://doi.org/10.1016/j.bcra.2025.100276.
[26] N. Ahmed and N. Shakoor, "Advancing agriculture through IoT, Big Data, and AI: A review of smart technologies enabling sustainability," *Smart Agricultural Technology*, vol. 10, p. 100848, Mar. 2025, doi: https://doi.org/10.1016/j.atech.2025.100848.
[27] K. Sharma and S. K. Shivandu, "Integrating artificial intelligence and Internet of Things (IoT) for enhanced crop monitoring and management in precision agriculture," *Sensors International*, vol. 5, p. 100292, Jan. 2024, doi: https://doi.org/10.1016/j.sintl.2024.100292.
[28] K. Obaideen et al., "An overview of smart irrigation systems using IoT," *Energy Nexus*, vol. 7, p. 100124, Sep. 2022, doi: https://doi.org/10.1016/j.nexus.2022.100124.
[29] S. Touil, A. Richa, M. Fizir, J. E. Argente García, and A. F. Skarmeta Gómez, "A review on smart irrigation management strategies and their effect on water savings and crop yield," *Irrigation and Drainage*, vol. 71, no. 5, pp. 1396-1416, Dec. 2022, doi: https://doi.org/10.1002/ird.2735.
[30] F. T. Maestre et al., "Plant species richness and ecosystem multifunctionality in global drylands," *Science* (1979), vol. 335, no. 6065, pp. 214-218, Jan. 2012, doi: https://doi.org/10.1126/science.1215442.
[31] Z. Ahmed, D. Gui, G. Murtaza, L. Yunfei, and S. Ali, "An Overview of Smart Irrigation Management for Improving Water Productivity under Climate Change in Drylands," *Agronomy*, vol. 13, p. 2113, vol. 13, no. 8, p. 2113, Aug. 2023, doi: https://doi.org/10.3390/agronomy13082113.
[32] T. Qin, L. Wang, Y. Zhou, L. Guo, G. Jiang, and L. Zhang, "Digital Technology-and-Services-Driven Sustainable Transformation of Agriculture: Cases of China and the EU," *Agriculture (Switzerland)*, vol. 12, no. 2, p. 297, Feb. 2022, doi: https://doi.org/10.3390/agriculture12020297.
[33] F. Fuentes-Peñailillo, K. Gutter, R. Vega, and G. C. Silva, "Transformative Technologies in Digital Agriculture: Leveraging Internet of Things, Remote Sensing, and Artificial Intelligence for Smart Crop Management," *Journal of Sensor and Actuator Networks*, vol. 13, p. 39, vol. 13, no. 4, p. 39, Jul. 2024, doi: https://doi.org/10.3390/jsan13040039.
[34] C. F. Lacerda, Y. Ampatzidis, A. de Oliveira Costa Neto, and V. Partel, "Cost-efficient high-resolution monitoring for specialty crops using AgI-GAN and AI-driven analytics," *Comput Electron Agric*, vol. 237, p. 110678, Oct. 2025, doi: https://doi.org/10.1016/j.compag.2025.110678.
[35] S. Huda et al., "IoT-Enabled Plant Monitoring System with Power Optimization and Secure Authentication," Computers, *Materials and Continua*, vol. 81, no. 2, pp. 3165-3187, Nov. 2024, doi: https://doi.org/10.32604/cmc.2024.058144.
[36] R. Pushpalatha, T. Roshni, B. Gangadharan, and G. Kutty, "Computer-Aided Crop Yield Forecasting Techniques - Systematic Review Highlighting the Application of AI," *Environmental Modeling and Assessment*, vol. 29, no. 6, pp. 1095-1110, Dec. 2024, doi: https://doi.org/10.1007/s10666-024-09978-6.
[37] K. Bhosle and V. Musande, "Evaluation of CNN model by comparing with convolutional autoencoder and deep neural network for crop classification on hyperspectral imagery," *Geocarto Int*, vol. 37, no. 3, pp. 813-827, 2022, doi: https://doi.org/10.1080/10106049.2020.1740950.
[38] S. Verma, A. Chug, and A. P. Singh, "Application of convolutional neural networks for evaluation of disease severity in tomato plant," *Journal of Discrete Mathematical Sciences and Cryptography*, vol. 23, no. 1, pp. 273-282, Jan. 2020, doi: https://doi.org/10.1080/09720529.2020.1721890.
[39] M. Sultan et al., "Convolutional Neural Networks in Detection of Plant Leaf Diseases: A Review," *Agriculture*, vol. 12, p. 1192, vol. 12, no. 8, p. 1192, Aug. 2022, doi: https://doi.org/10.3390/agriculture12081192.