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MACHINE LEARNING APPLIED TO INDOOR AGRICULTURE: A SYSTEMATIC REVIEW AND TAXONOMY

APRENDIZADO DE MÁQUINA APLICADO À AGRICULTURA *INDOOR*: UMA REVISÃO SISTEMÁTICA E TAXONOMIA

APRENDIZAJE AUTOMÁTICO APLICADO A LA AGRICULTURA INDOOR: UNA REVISIÓN SISTEMÁTICA Y TAXONOMÍA

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ABSTRACT

Characterized by crop cultivation in closed environments, indoor agriculture impacts not only food production but also environmental sustainability, resource optimization, and food security. Innovative strategies, such as the application of machine learning, play a strategic role in addressing the complexities of indoor farming. The analysis of integrated diverse data sources through machine learning (such as temperature, humidity, light, and soil conditions) enables a comprehensive understanding of plant behavior, growth patterns, and system performance. These technologies improve the analysis of agricultural environments, allowing more precise and efficient crop management. Therefore, this article presents a systematic literature review of works related to the application of machine learning in Indoor Agriculture. This research paper analyzes studies published across eight different databases up to the end of 2025. The initial search resulted in over fourteen thousand articles. After applying the inclusion and exclusion criteria, these were reduced to one hundred and fourteen studies selected for full analysis, which led to the selection of seventy final articles to answer the eleven questions proposed in this research paper. This work presents a taxonomy for mapping explored services in indoor agriculture and another for organizing machine learning techniques applied in indoor agriculture research. The results reveal that the selected articles employed sixty-two machine-learning techniques. The analysis identified twenty-seven types of information collected from cultivations, the use of twenty-five different plant species, five types of data collection devices, and five cultivation systems.

KEYWORDS: *Artificial Intelligence. Indoor Agriculture. Indoor Farming. Machine Learning.*

RESUMO

Caracterizada pelo cultivo de plantas em ambientes fechados, a agricultura indoor impacta a produção de alimentos, a sustentabilidade ambiental, a otimização de recursos e a segurança alimentar. Estratégias inovadoras, como o aprendizado de máquina, desempenham papel estratégico no enfrentamento das complexidades do cultivo *indoor.*

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A análise integrada de diversas fontes de dados (como temperatura, umidade, luminosidade e condições do solo) possibilita uma compreensão abrangente do comportamento das plantas, dos padrões de crescimento e do desempenho do sistema, permitindo um manejo das culturas mais preciso e eficiente. Assim, este artigo apresenta uma revisão sistemática da literatura sobre a aplicação do aprendizado de máquina na Agricultura Indoor, analisando estudos publicados em oito bases de dados até o final de 2025. A busca inicial resultou em mais de quatorze mil artigos, reduzidos, após os critérios de inclusão e exclusão, a cento e quatorze estudos selecionados para análise completa, dos quais setenta artigos finais responderam às onze questões propostas. Este trabalho apresenta uma taxonomia para mapear os serviços explorados na agricultura indoor e outra para organizar as técnicas de aprendizado de máquina aplicadas nessa área. Os resultados revelam que os artigos selecionados empregaram sessenta e duas técnicas de aprendizado de máquina. A análise identificou vinte e sete tipos de informações coletadas nos cultivos, o uso de vinte e cinco espécies de plantas diferentes, cinco tipos de dispositivos de coleta de dados e cinco sistemas de cultivo.

PALAVRAS-CHAVE: Inteligência Artificial. Agricultura Indoor. Cultivo Indoor. Aprendizado de Máquina.

RESUMEN

Caracterizada por el cultivo de plantas en ambientes cerrados, la agricultura indoor impacta la producción de alimentos, la sostenibilidad ambiental, la optimización de recursos y la seguridad alimentaria. Estrategias innovadoras, como el aprendizaje automático, desempeñan un papel estratégico para abordar las complejidades del cultivo indoor. El análisis integrado de diversas fuentes de datos (como temperatura, humedad, luz y condiciones del suelo) permite una comprensión integral del comportamiento de las plantas, los patrones de crecimiento y el rendimiento del sistema, permitiendo un manejo de los cultivos más preciso y eficiente. Por lo tanto, este artículo presenta una revisión sistemática de la literatura sobre la aplicación del aprendizaje automático en la Agricultura Indoor, analizando estudios publicados en ocho bases de datos hasta finales de 2025. La búsqueda inicial arrojó más de catorce mil artículos, reducidos, tras los criterios de inclusión y exclusión, a ciento catorce estudios seleccionados para el análisis completo, de los cuales setenta artículos finales respondieron a las once preguntas propuestas. Este trabajo presenta una taxonomía para mapear los servicios explorados en la agricultura indoor y otra para organizar las técnicas de aprendizaje automático aplicadas en esta área. Los resultados revelan que los artículos seleccionados emplearon sesenta y dos técnicas de aprendizaje automático. El análisis identificó veintisiete tipos de información recopilada en los cultivos, el uso de veinticinco especies de plantas diferentes, cinco tipos de dispositivos de recolección de datos y cinco sistemas de cultivo.

PALABRAS CLAVE: *Inteligencia Artificial. Agricultura Indoor. Cultivo Indoor. Aprendizaje Automático.*

INTRODUCTION

It is widely agreed that technological advances accelerate the continuous modernization of agriculture. This transformation primarily relies on embedded computers, innovative sensors (designed for diverse agricultural applications), and more efficient and reliable communication among electronic devices. As a result, agriculture adopts technological resources designed to

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increase yields, from planting to harvesting, through monitoring, recommendations for crop improvements (Fiorentini *et al.*, 2024), and support in cultivation to assist farmers (Chittireddy *et al.*, 2026).

Offering monitoring, recommendations, and support for agriculture, from soil preparation to sales, can be complex. Providing these resources becomes more viable in enclosed spaces such as greenhouses or pavilions, which can be equipped with sensor networks, geolocation, resource mapping, and connectivity. Information generated during crop monitoring is particularly valuable when extended into recommendations for other crops.

Technological advances have increased the productivity and resilience of planted crops. Increased agricultural efficiency has become a strategic priority, since the agricultural sector consumes approximately 70% of available freshwater (Velasco-Muñoz *et al.*, 2018), and population growth is expected to require food production to increase by 35% to 56% between 2010 and 2050 (van Dijk *et al.*, 2021). Rising consumption and intensive agricultural practices thus demand higher efficiency in food production.

As crop-related information becomes increasingly accessible, studies on indoor farming (Mills, 2025; Chen *et al.*, 2025) and machine learning (ML) applied to agriculture (Mali *et al.*, 2025; Gupta *et al.*, 2026) have grown more frequent, as reflected in this review. Studies increasingly employ cameras throughout crops (Khiali *et al.*, 2026; Mamtani, 2025) for image-based production monitoring, and some optimize irrigation by applying the correct volume of water (Morcillo *et al.*, 2024), typically processed on separate computers rather than on the image-capturing devices themselves.

Plant species that typically grow in open fields are increasingly cultivated in protected environments such as greenhouses and pavilions, which create a favorable microclimate that improves pest control, reduces pesticide use, and increases production. Protected cultivation relies on Smart Farming (Karunathilake *et al.*, 2023), applying information and communication technologies (ICT) to agriculture, which, combined with Precision Agriculture, enables data-driven decisions that optimize resource allocation, reduce costs, and minimize environmental impact (Rashid *et al.*, 2025).

Models applied to agriculture improve decision-making by using context data, information characterizing the circumstances of a place, object, person, or entity (Rentz *et al.*, 2024). In agriculture, context typically relies on crop-related information such as irrigation levels, ambient temperature, soil moisture, and humidity.

This article follows a systematic literature review methodology, which, according to Petersen *et al.* (2015), reduces divergence compared to non-systematic reviews. It analyzes the

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literature on machine learning applications in indoor agriculture to answer eleven research questions covering machine learning techniques, data sources, collection devices, cultivation types, crop categories, and research challenges. The final filtering process included 70 studies across eight databases.

A. Main contributions

This study provides a comprehensive analysis of Machine Learning applications in Indoor Agriculture through a systematic literature review covering publications up to December 2025. The main contributions of this work are as follows:

- A systematic review focused exclusively on the intersection between Machine Learning and Indoor Agriculture, covering studies indexed in eight scientific databases.
- A taxonomy of application domains that organizes how Machine Learning has been employed in indoor agriculture, including prediction, analysis, productivity improvement, and automatic detection.
- A taxonomy of Machine Learning techniques that categorizes and compares the algorithms adopted by existing studies.
- An analysis of data acquisition strategies, including sensors, imaging systems, microcontrollers, and environmental variables used for model development.
- An investigation of cultivated species, cultivation systems, and data types adopted in Machine Learning applications.
- The identification of current research challenges, limitations, and future research opportunities, including context-aware systems, dataset interoperability, and knowledge transfer between cultivation environments.

THEORETICAL FRAMEWORK

The systematic review process did not identify any prior study focused specifically on indoor agriculture and machine learning; the related works cited here instead concern agriculture and machine learning more broadly. One study addresses Industry 4.0 (Martinho, 2022), covering technologies such as remote sensing, machine learning, big data, deep learning, thermal imaging, and UAVs, while another applies deep learning and satellite imagery to large-scale agriculture (Victor *et al.*, 2025).

Four studies addressed objectives similar to those of this review (Hassan *et al.*, 2021; Saleem *et al.*, 2021; Farjon *et al.*, 2023; Boros *et al.*, 2025), while two others explored sensors

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and communication technologies applied to agriculture more broadly: Wu *et al.* (2017) examined IoT, sensor technologies, and cloud computing for smart agriculture, and Ojha *et al.* (2015) reviewed wireless sensor networks (WSNs), which reduced the need for extensive cabling in agricultural data collection.

Hassan *et al.* (2021) reviewed control strategies combining IoT, AI, machine learning, and remote sensing for disease detection, irrigation, and nutrient management, highlighting gains in crop yield and soil fertility. Saleem *et al.* (2021) examined machine learning and deep learning in agricultural robotics, finding that deep learning models such as RCNN and ResNet-18 outperformed traditional techniques in plant disease detection, crop/weed discrimination, and land cover classification.

Farjon *et al.* (2023) reviewed deep learning methods for object counting in agriculture, noting improvements in yield estimation, disease prevention, and stress detection. Boros *et al.* (2025) analyzed 291 studies (from nearly 45,000 records) on the transition from traditional to integrated, sustainable agricultural practices, concluding that policy support and education remain essential alongside technological innovation.

Avila and Barbosa (2025) conducted a systematic review of smart environments in digital agriculture, showing that IoT, AI, sensor networks, and big data analytics can enhance productivity and sustainability, though high implementation costs, security concerns, and a shortage of qualified professionals still limit large-scale adoption.

Machine learning serves multiple purposes in agriculture, including improving production outcomes, detecting pests, and extracting information from images and other data sources. This review identifies the most used sensors, databases, research gaps, publication trends, and key challenges in the field. It differs from existing studies in the following aspects:

1. It extends the focus beyond any specific application area that includes indoor agriculture, aiming to encompass and identify diverse areas where indoor agriculture and machine learning are applied.

2. It examines machine learning techniques, offering a comprehensive understanding of the analytical methodologies employed in cultivations.

3. It explores the devices and approaches developed for data acquisition.

4. It encompasses an exhaustive search process conducted across eight academic databases to ensure general exploration.

5. It proposes two taxonomies, one for organizing research objectives in indoor agriculture and machine learning, and another for categorizing the machine learning techniques used in the

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field. These taxonomies aid systematic organization and research categorization, fostering better communication and collaboration among experts.

METHODOLOGY

This review's methodology connects data collection, publication venues, application domains, publication years, applied technologies, and development approaches across journals, conferences, and workshops. The review steps include:

- Elaboration of research questions;
- Definition of the search process;
- Establishment of filtering criteria;
- Application of the criteria to select relevant studies.

A. Research questions

Table 1 presents the eleven research questions, organized into one general question (GQ), eight specific questions (SQ), and two statistical questions (STQ). The GQ addresses how studies use machine learning in indoor agriculture; the SQs cover challenges, technologies, techniques, data, and other resources; and the STQs characterize publication trends through December 2025 and the global distribution of authors.

Table 1. Research Questions

Type	Questions
General Question	General Question
GQ	How are the studies using machine learning in indoor farming?
Specific Questions	Specific Questions
SQ1	What are the machine learning techniques used?
SQ2	Which data do the studies use?
SQ3	Does the study use a strategy of database fusion to improve the performance of machine learning?
SQ4	Does the article use context information?
SQ5	What are the devices used for data collection?
SQ6	What plant crops are grown in the studies?
SQ7	Which cultures are considered in the studies?

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SQ8	What are the challenges in applying machine learning to indoor agriculture?
Statistical Questions	Statistical Questions
STQ1	How many publications occur per year and database?
STQ2	What is the geographical distribution of reviewed studies?

B. Development of the research process

The search process includes three stages: (1) defining the search string, (2) selecting databases and understanding their search mechanisms, and (3) retrieving results from the selected databases.

This study adopts a systematic filtering process to structure the review and ensure transparency, reproducibility, and methodological rigor. The filtering process illustrated in Fig. 1 shows the flow of filters applied in the systematic review, including identification, screening, eligibility, and inclusion stages. Each step applies explicit criteria for study selection, supporting consistency in inclusion and exclusion decisions while reducing potential bias.

The first stage follows the search process proposed by Petersen *et al.* (2015), which identifies key terms and their most relevant synonyms. This study defines machine learning and indoor agriculture as the primary terms.

Secondary terms, synonyms or closely related expressions, support the search string. The primary term "machine learning" relates to expressions such as artificial intelligence, neural networks, and deep learning, which studies often use interchangeably.

The term "indoor agriculture" includes related expressions such as urban agriculture, indoor farming, indoor farm, and vertical farming, as well as cultivation environments involving soil, pots, and PVC structures. Table 2 presents the complete set of search terms.

Table 2. Terms used in the search string

Main Terms	**Secondary Terms**
Machine Learning	“Artificial intelligence” OR “neural networks” OR “deep learning”
Indoor Agriculture	“urban agriculture” OR “indoor farming” OR “indoor farm” OR “vertical farming”

After defining terms and synonyms, the search process generated the following search string:

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((“machine learning” OR “artificial intelligence” OR “neural networks” OR “deep learning”) AND (“indoor agriculture” OR “urban agriculture” OR “indoor farming” OR “indoor farm” OR “vertical farming”))

The search string was then applied across eight databases relevant to the research domain, each requiring specific parameter adjustments: ACM Digital Library, IEEE Xplore, ScienceDirect, SpringerLink, Scopus, MDPI, Taylor & Francis, and Wiley.

These databases were chosen to ensure comprehensive interdisciplinary coverage, indexing high-quality publications across computer science, engineering, and agricultural sciences, from computing-focused sources (ACM, IEEE Xplore) to broader technological and applied-science collections (ScienceDirect, SpringerLink, Wiley, Scopus) and agriculture-oriented open-access venues (MDPI, Taylor & Francis).

Database-specific procedures were followed: ACM Digital Library and IEEE Xplore used their advanced search fields; ScienceDirect applied the query to titles, abstracts, and keywords; and SpringerLink excluded "Preview Only" documents and applied "Computer Science" and "Life Sciences" subject filters sequentially.

Scopus was filtered to journal articles, conference papers, conference reviews, and review articles; Wiley used the "articles" filter; Taylor & Francis relied solely on the query string; and MDPI filtered for "articles" and "conference papers."

C. Definition of the criteria for filtering the results

The studies obtained through the research in the databases were subject to Inclusion Criteria (IC) and Exclusion Criteria (EC). The IC are as follows:

IC 1: The study must be published in a journal, conference, or workshop.

IC 2: The study must be a full paper.

IC 3: The study must contain terms related to the search string.

IC 4: The study must be written in English.

IC 5: The study must be published by December 2025.

The complete list of EC is the following:

EC 1: The study consists of a literature review or systematic review.

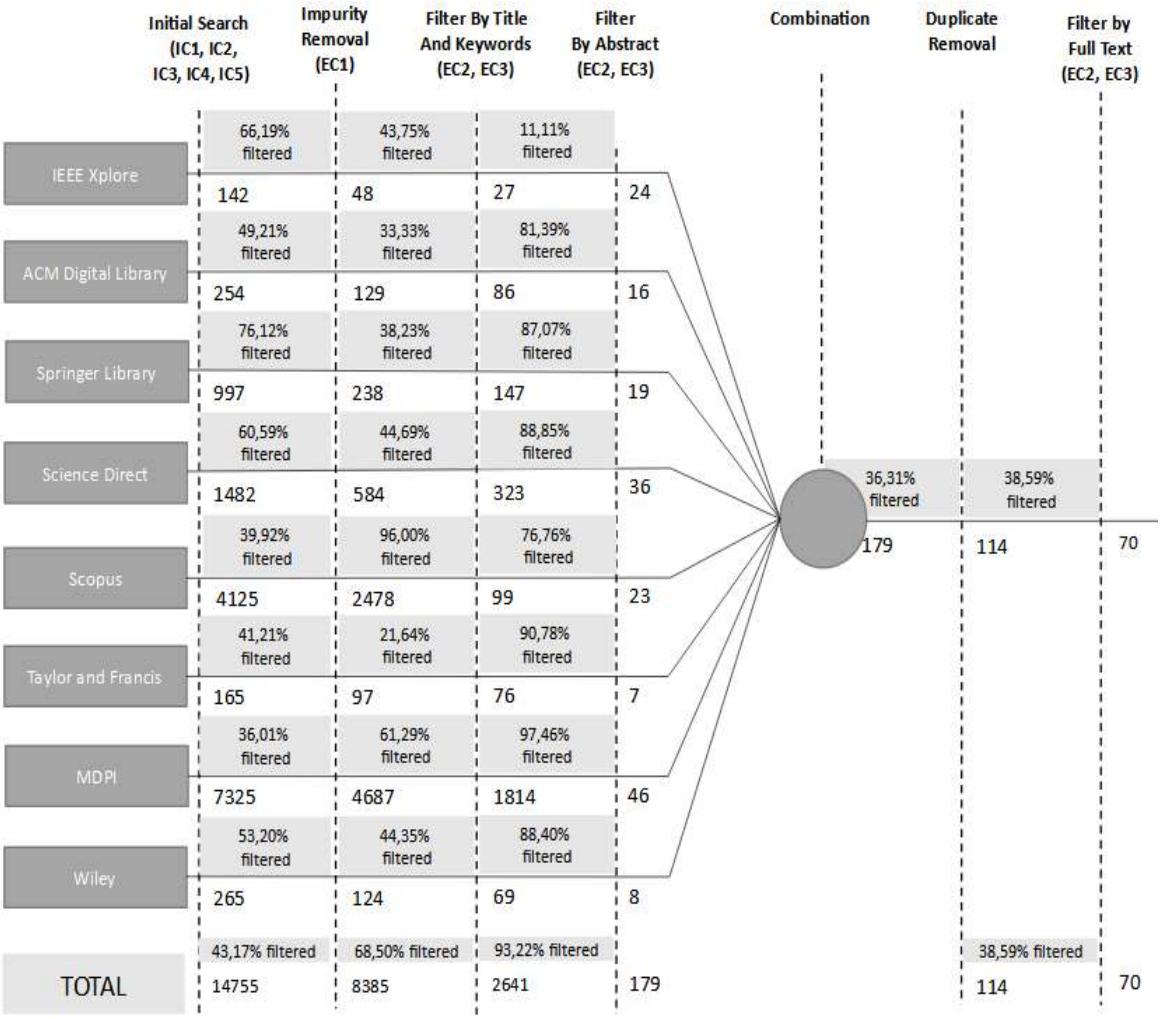
EC 2: The study does not focus on indoor farming.

EC 3: The study does not present a machine-learning application.

The inclusion and exclusion criteria helped obtain studies that best fit the review scope while eliminating discrepancies. Fig. 1 illustrates the filtering process and the percentage of articles removed at each stage.

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Fig. 1. Flow of filters applied in the systematic review, illustrating the identification, screening, eligibility, and inclusion stages of the study selection process



After applying the search string and the first five inclusion criteria, filtering proceeded by removing studies per the first exclusion criterion, then refining the selection through title and keyword analysis, abstract reading, and finally removal of duplicate articles.

At the end of the filtering process, each article was read entirely, in accordance with the last two exclusion criteria (EC 2 and EC 3). IEEE Xplore was the database that resulted in the fewest studies in the initial search. However, this database was more assertive, considering the percentage of articles found in the initial search and their merging after reading the abstract.

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Four databases showed similar results in the initial search (142 to 265 studies) and in filtering percentages. MDPI and Scopus alone provided more than 99.8% of the filtered results, generating more articles overall despite producing fewer relevant articles for the proposed theme.

Table 3 presents the final list of seventy studies, organized chronologically with their ID, reference, H-Index (marked N.A. when unavailable, typically for recent conference papers), and classification by image/data use and publication venue. These article IDs recur throughout the figures and tables that follow.

Table 3. List of filtered studies

ID	Reference	H-Index	Image	Data	Venue
A01	(Mehra *et al.*, 2018)	188	No	Yes	Journal
A02	(Yang *et al.*, 2018)	92	No	Yes	Journal
A03	(Vadivel *et al.*, 2019)	10	No	Yes	Conference
A04	(Tasrif Anubhove *et al.*, 2020)	1	Yes	No	Conference
A05	(Lauguico *et al.*, 2020)	11	Yes	No	Conference
A06	(Wickramaarachchi *et al.*, 2020)	26	No	Yes	Conference
A07	(Mya *et al.*, 2021)	6	No	Yes	Conference
A08	(Ghandar *et al.*, 2021)	204	No	Yes	Journal
A09	(Sharma *et al.*, 2021)	14	No	Yes	Conference
A10	(Amir *et al.*, 2021)	204	No	Yes	Journal
A11	(Chowdhury *et al.*, 2021)	14	Yes	No	Journal
A12	(Martini *et al.*, 2021)	219	No	Yes	Journal
A13	(Büyüközkan *et al.*, 2021)	148	No	Yes	Journal
A14	(Chang *et al.*, 2021)	187	Yes	No	Journal
A15	(Liu *et al.*, 2022)	188	No	Yes	Journal
A16	(Hwang *et al.*, 2022)	52	Yes	No	Journal
A17	(Hamidon and Ahamed, 2022)	219	Yes	No	Journal
A18	(Li *et al.*, 2022)	188	Yes	No	Journal
A19	(Ajagekar and You, 2022)	86	No	Yes	Conference
A20	(Dhal *et al.*, 2022)	11	No	Yes	Journal
A21	(Franchetti and Pirri, 2022)	187	Yes	No	Journal
A22	(Wang *et al.*, 2022)	282	Yes	No	Journal
A23	(Soheli *et al.*, 2022)	75	No	Yes	Journal
A24	(Zhang and Chen, 2022)	98	No	Yes	Journal
A25	(Cui *et al.*, 2022)	44	No	Yes	Journal
A26	(Devi Thangavel *et al.*, 2023)	81	No	Yes	Journal
A27	(Abbasi *et al.*, 2023)	18	Yes	No	Journal
A28	(Rajendiran and Rethnaraj, 2023)	24	No	Yes	Journal
A29	(Parsa *et al.*, 2023)	108	Yes	No	Journal
A30	(Mohmed *et al.*, 2023)	282	No	Yes	Journal
A31	(Prasad *et al.*, 2023)	51	No	Yes	Conference
A32	(Moorthi *et al.*, 2023)	13	No	Yes	Conference
A33	(García-Vázquez *et al.*, 2023)	101	No	Yes	Journal

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A34	(Sikati and Nouaze, 2023)	35	Yes	No	Journal
A35	(Wang *et al.*, 2023)	219	Yes	No	Journal
A36	(Maya Olalla *et al.*, 2023)	219	No	Yes	Journal
A37	(Verma *et al.*, 2024)	N.A.	No	Yes	Conference
A38	(Winata *et al.*, 2024)	N.A.	No	Yes	Conference
A39	(Radha and Prasanna, 2024)	N.A.	No	Yes	Conference
A40	(Schneider *et al.*, 2024)	169	Yes	No	Journal
A41	(Kempelis *et al.*, 2024)	60	Yes	Yes	Journal
A42	(Shi *et al.*, 2024a)	91	No	Yes	Journal
A43	(Shi *et al.*, 2024b)	188	Yes	No	Journal
A44	(Khandakar *et al.*, 2024)	94	No	Yes	Journal
A45	(Choi *et al.*, 2024)	92	Yes	No	Journal
A46	(Chowdhury *et al.*, 2024)	91	Yes	No	Journal
A47	(Tripathi *et al.*, 2024)	19	Yes	No	Journal
A48	(Kharraz and Szabó, 2025)	25	No	Yes	Journal
A49	(Lee *et al.*, 2025)	116	Yes	No	Journal
A50	(Isaza *et al.*, 2025)	273	Yes	Yes	Journal
A51	(Liu *et al.*, 2025)	114	Yes	No	Journal
A52	(Glukhikh *et al.*, 2025)	35	Yes	No	Journal
A53	(Peyal *et al.*, 2025)	N.A.	Yes	No	Conference
A54	(Subburayan *et al.*, 2025)	N.A.	No	Yes	Conference
A55	(Bakirov *et al.*, 2025)	49	No	Yes	Journal
A56	(Mulyono *et al.*, 2025)	21	No	Yes	Journal
A57	(Bakir and Gezer, 2025)	70	Yes	No	Journal
A58	(Pattnaik *et al.*, 2025)	19	No	Yes	Journal
A59	(Salian *et al.*, 2025)	N.A.	Yes	Yes	Conference
A60	(Dinesh *et al.*, 2025)	N.A.	No	Yes	Conference
A61	(Kumar *et al.*, 2025)	N.A.	No	Yes	Conference
A62	(Hassan *et al.*, 2025)	15	No	Yes	Journal
A63	(Carbone *et al.*, 2025)	149	Yes	No	Journal
A64	(Chutichaimaytar *et al.*, 2025)	33	Yes	No	Journal
A65	(Kang *et al.*, 2025)	33	Yes	No	Journal
A66	(Rathor *et al.*, 2025)	152	Yes	No	Conference
A67	(Fevgas *et al.*, 2025)	33	Yes	No	Journal
A68	(Karimzadeh *et al.*, 2025)	188	No	Yes	Journal
A69	(Chou and Huang, 2025)	188	Yes	Yes	Journal
A70	(Mansour *et al.*, 2025)	33	No	Yes	Journal

RESULTS AND DISCUSSION

This section presents the results obtained from analyzing the seventy studies selected for the review. The process addressed the research questions by analyzing and considering the selected works.

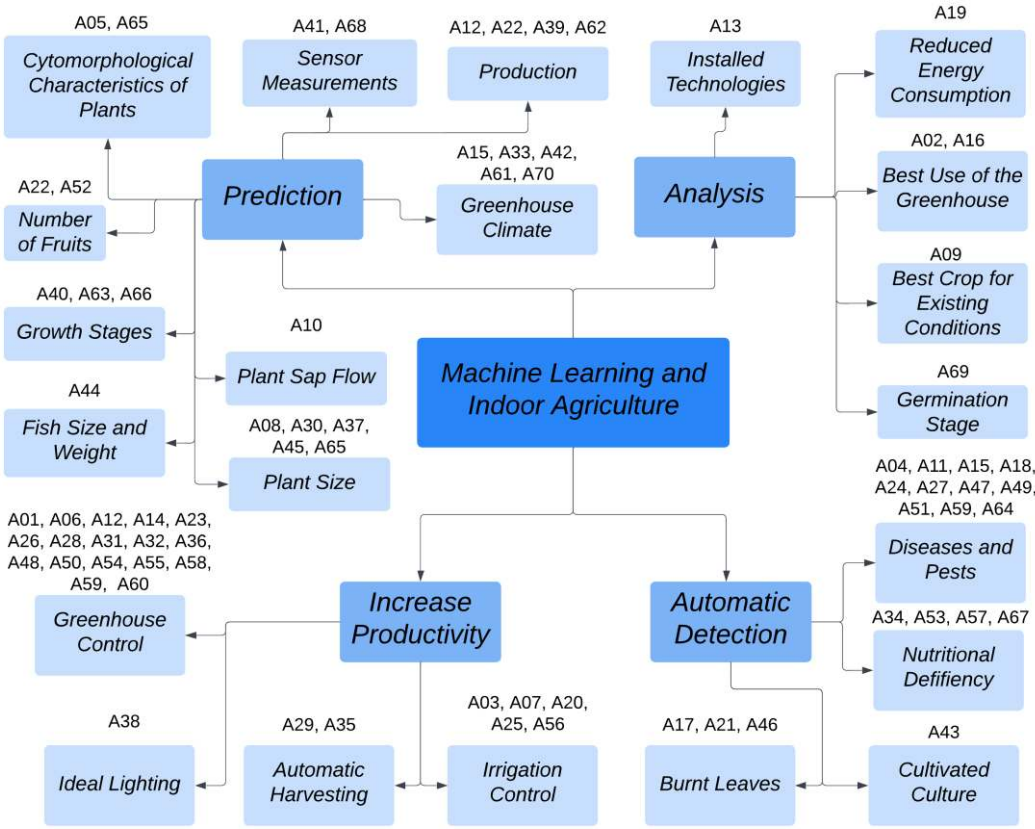
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A. GQ: How are the studies using machine learning in indoor farming?

The selection of seventy studies from the review shows the use of machine learning across various areas and purposes in indoor agriculture. Fig. 2 presents a taxonomy of twenty-one different machine learning uses, organized into four main categories: prediction, analysis, increasing productivity, and automatic detection; the numbers in the figure correspond to the article IDs in Table 3.

Each category includes subcategories at a slightly lower level of abstraction, maintaining a hierarchical relationship with the main category. The "prediction" category, which focuses on forecasting aspects of crop production such as fruit yield, has the most subcategories (nine), while "increased productivity" covers the most studies (twenty-five).

Fig. 2. Taxonomy of study areas in Indoor Agriculture and Machine Learning research



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Studies within "analysis" evaluate crop or environmental conditions to support decision-making, such as reducing energy consumption. "Increased productivity" covers research on cultivation efficiency, most often through greenhouse control systems, while "automatic detection" groups four automated approaches that assist farmers with agricultural tasks.

Machine learning has also been applied to reduce energy consumption inside greenhouses and to predict weather conditions, aiming to improve plant development and enable early disease detection (five studies; see Table 3). García-Vázquez *et al.* (2023) predicted the internal temperature of greenhouses, Yang *et al.* (2018) demonstrated how machine learning improves agricultural land use, and Sharma *et al.* (2021) suggested optimal crops based on greenhouse environments and soil conditions.

Machine learning also supports the detection of tip-burn and other plant diseases (twelve studies; see Table 3). Ghandar *et al.* (2021) predicted weekly plant growth and daily fish growth in aquaponic systems, where water circulates between fish tanks and plant cultivation. Dinesh *et al.* (2025) optimized nutrient management in aquaponics, Verma *et al.* (2024) predicted plant growth under different LED lighting conditions, and Winata *et al.* (2024) designed optimal lighting systems based on cultivation stages.

Fourteen studies focused on crop control: ten applied machine learning indices in greenhouses and four addressed nutrient delivery in irrigation systems (see Table 3). Martini *et al.* (2021) improved crop productivity by reducing cultivation time and increasing plant weight compared to traditional methods; Chang *et al.* (2021), Soheli *et al.* (2022), Cui *et al.* (2022), and Salian *et al.* (2025) also pursued productivity improvements.

Within the prediction category, nineteen studies estimated yield, growth, or physiological parameters from sensor and imaging data; for example, Wang *et al.* (2022) estimated yield and fruit count from natural plant growth, Amir *et al.* (2021) predicted tomato sap flow from climate and irrigation data, and Kang *et al.* (2025) correlated computer-vision features with lettuce morphological traits such as leaf area and fresh weight. Others addressed nutrient-deficiency detection, growth-stage and maturity classification, water-stress detection, germination staging, and fish or root monitoring in aquaponic systems (see Table 3 for the complete list of studies and techniques).

Some studies focus on greenhouse optimization (Hwang *et al.*, 2022) or evaluate installed technologies (Büyüközkan *et al.*, 2021). Autonomous harvesting systems appear in Parsa *et al.* (2023) and Wang *et al.* (2023) (strawberry and tomato harvesting, respectively), while Shi *et al.* (2024b) presented automatic crop detection, Chowdhury *et al.* (2024) detected leaf defects, and Tripathi *et al.* (2024) identified plant diseases that may compromise production.

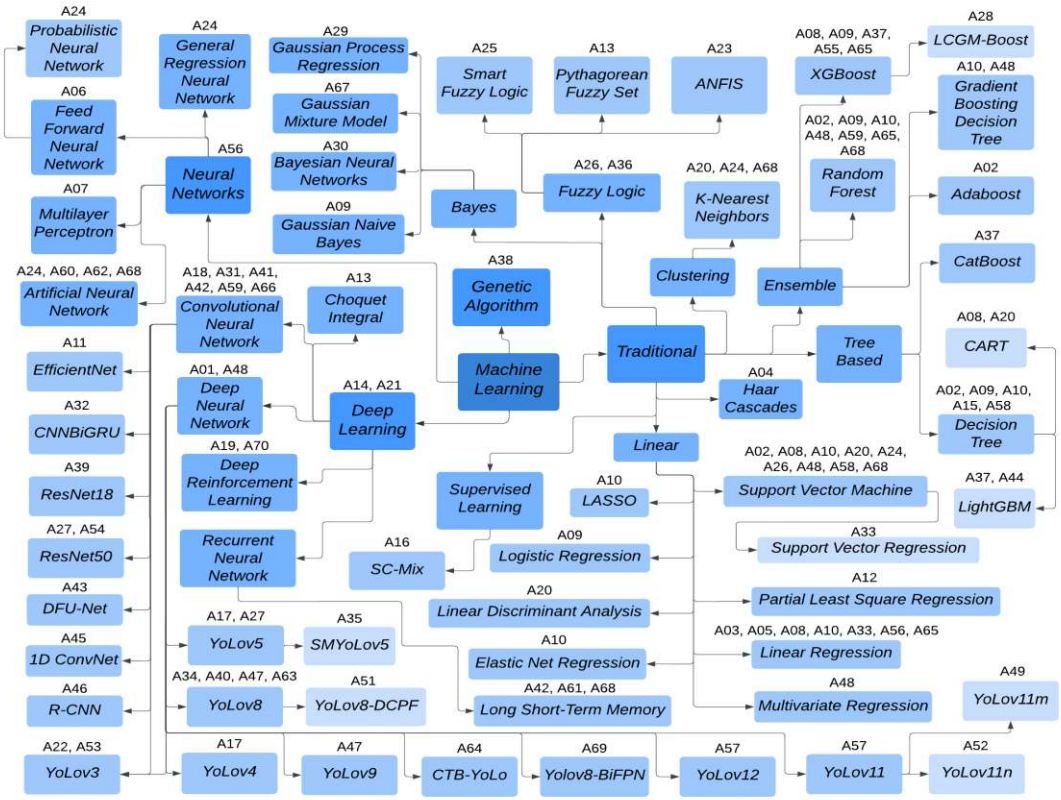
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B. SQ1: What are the machine learning techniques used?

Fig. 3 presents a taxonomy of the sixty-two machine learning techniques identified in this review, organized around three main categories: traditional methods, neural networks, and deep learning. Traditional methods represent the largest group, with subcategories organized by technique structure (tree-based, linear, clustering, ensemble, fuzzy logic, supervised learning, and Bayes). Decision Tree (DT) was the most frequent tree-based algorithm, used directly in five studies, followed by the CART (two studies) and LightGBM (two studies) subcategories (see Table 3 and Fig. 3).

Support Vector Machine (SVM) was the most frequently used technique in the linear category, appearing in ten studies, nine directly and one as Support Vector Regression (SVR) (García-Vázquez *et al.*, 2023).

Fig. 3. Taxonomy of machine learning techniques applied in Indoor Agriculture research



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Linear Regression (LR) also appeared frequently, used in seven studies, while K-Nearest Neighbors (KNN) was the only technique in the clustering subcategory. In the ensemble category, Random Forest (RF) appeared most frequently, followed by XGBoost, used in six studies, five directly and one through an improved version proposed by Rajendiran and Rethnaraj (2023), called Lettuce Crop Growth Monitoring-Boost (LCGM-Boost). In the neural networks category, Wickramaarachchi *et al.* (2020) applied the Feedforward Neural Network subcategory twice, while Zhang and Chen (2022) used its Probabilistic Neural Networks subcategory.

Although deep learning models are technically neural networks with multiple layers, this taxonomy treats them as separate categories to highlight their distinct usage patterns among the reviewed studies. Regarding deep learning algorithms, Deep Neural Networks (DNN) appeared in nineteen studies across thirteen subcategories, two directly, and the rest as YOLO-based variants (YOLOv3 through YOLOv12, including SMYOLOv5, YOLOv8-DCPF, YOLOv8-BiFPN, YOLOv11m, YOLOv11n, and CTB-YOLO; see Table 3 and Fig. 3).

The Convolutional Neural Network (CNN) category appeared in nine subcategories, with the CNN subcategory itself covering four studies and the ResNet50 subcategory covering two.

Some studies applied more than one machine learning technique. Amir *et al.* (2021) applied seven techniques (including Linear Regression, SVM, and Random Forest), and Kharraz and Szabó (2025) applied six (including SVM, Gradient Boosting, and Deep Neural Networks). Sharma *et al.* (2021) and Karimzadeh *et al.* (2025) each applied five techniques, while Ghandar *et al.* (2021) and Salian *et al.* (2025) applied four.

C. SQ2: Which data do the studies use?

Table 4 presents the twenty-seven distinct types of information collected across the selected studies. Crop images or photographs were the most common (47.14%, thirty-three studies), followed by ambient temperature (45.71%, thirty-two studies) and ambient humidity (34.29%, twenty-four studies).

Table 4. List of information used in machine learning

Data	Number of Studies (%)	ID of Studies
Water pH	17 (24.29%)	A01, A03, A07, A08, A09, A10, A12, A20, A28, A36, A44, A54, A56, A58, A60, A62, A68
Water Temperature	8 (11.43%)	A03, A08, A12, A28, A58, A60, A61, A69

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Ambient Temperature	32 (45.71%)	A01, A02, A03, A06, A07, A08, A10, A12, A15, A19, A23, A24, A25, A26, A30, A31, A32, A33, A36, A41, A42, A44, A48, A49, A55, A58, A59, A61, A62, A68, A69, A70
Ambient Humidity	24 (34.29%)	A01, A02, A03, A09, A10, A12, A23, A24, A25, A26, A31, A32, A33, A41, A42, A48, A50, A55, A58, A59, A61, A62, A69, A70
Tank Level	3 (4.29%)	A01, A07, A12
Luminosity	10 (14.29%)	A01, A02, A23, A30, A41, A48, A50, A55, A58, A61
Soil Moisture	15 (21.43%)	A03, A23, A24, A25, A26, A30, A31, A32, A36, A48, A50, A54, A55, A59, A61
CO2	8 (11.43%)	A06, A10, A30, A32, A48, A54, A62, A70
Images	33 (47.14%)	A04, A05, A11, A14, A16, A17, A18, A21, A22, A27, A29, A31, A34, A35, A40, A41, A43, A45, A46, A47, A49, A50, A51, A52, A53, A57, A59, A63, A64, A65, A66, A67, A69
Plant Height	2 (2.86%)	A06, A38
Water EC	10 (14.29%)	A07, A10, A12, A20, A28, A36, A54, A55, A62, A68
Water TDS	1 (1.43%)	A07
Water ORP	2 (2.86%)	A07, A44
Ratio	1 (1.43%)	A08
Soil Composition	3 (4.29%)	A09, A41, A48
Rainfall	1 (1.43%)	A09
Sap Flow	1 (1.43%)	A10
Plant Temperature	1 (1.43%)	A10
Growing Time	1 (1.43%)	A12
Plant Quantity	2 (2.86%)	A12, A39
Economic Data	1 (1.43%)	A13
Leaf Wetness	1 (1.43%)	A15

This review uses the term water consistently to refer to both pure water and nutrient solutions (i.e., water enriched with plant nutrients). This standardization avoids ambiguity when reporting parameters such as pH or temperature.

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Amir *et al.* (2021) and Martini *et al.* (2021) used the most diverse sets of variables (seven and eight, respectively), including water pH, temperature, humidity, and electrical conductivity (EC), among others.

D. SQ3: Does the study use a strategy of database fusion to improve the performance of machine learning?

Among the seventy studies, none supported the integration of datasets from different crops. All focused on a single dataset, typically for one crop type. Franchetti and Pirri (2022) used datasets from different crops to evaluate their system, though not as a native cross-dataset feature, and Abbasi *et al.* (2023) used three distinct datasets solely for training and testing.

Therefore, incorporating a new dataset requires manual implementation and training. A key challenge in this context involves configuring systems to accept datasets from different crop types. Furthermore, enabling systems to automatically learn from new datasets and provide recommendations for improvements, especially when direct application may pose risks to crops, would represent a significant advancement.

Only two studies supported more than one crop type: Martini *et al.* (2021) (hydroponic and semi-hydroponic) and Vadivel *et al.* (2019) (hydroponic and soil-based, within a greenhouse).

E. SQ4: Does the article use context information?

Context and context histories (Rentz *et al.*, 2024; Lima *et al.*, 2022) appeared in only one study. Martini *et al.* (2021) applied contextual information in a context-aware architecture, with a context history module and a server-side similarity check to avoid storing redundant data.

Only Martini *et al.* (2021) incorporated ubiquitous computing, using greenhouse sensors that collect data automatically every fifteen minutes, an interval suited to environments where climate changes gradually due to controlled elements such as curtains and plastic coverings.

Further research should explore contextual information more broadly, since only one study applied it explicitly. Context-aware prediction (da Rosa *et al.*, 2016) could help models identify crop growth stages and relevant variables; Liu *et al.* (2022), for instance, predicted greenhouse climate up to seventy-two hours ahead for disease detection, but without using context or context-history concepts.

F. SQ5: What are the devices used for data collection?

This review classifies studies by the type of device used to collect crop information and Table 5 presents these devices. Cameras were the most used devices, applied by 45.71% of the

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studies (thirty-two out of seventy) for computer-vision-based analysis. Arduino was used in 12.86% (nine studies) and Raspberry Pi in 8.57% (six studies).

Table 5. List of devices used to collect information

Devices	Number of Studies (%)	ID of Studies
Arduino	9 (12.86%)	A01, A03, A07, A12, A23, A24, A31, A36, A55
Raspberry	6 (8.57%)	A01, A07, A12, A48, A58, A69
ESP8266	3 (4.29%)	A08, A25, A32
Camera	32 (45.71%)	A04, A05, A11, A14, A16, A17, A18, A21, A22, A27, A29, A31, A34, A35, A40, A41, A43, A45, A46, A47, A49, A50, A51, A52, A53, A57, A63, A64, A65, A66, A67, A69
ESP32	5 (7.14%)	A50, A54, A56, A58, A59

A cross-analysis reveals that studies using computer vision techniques tend to rely on Raspberry Pi for its higher processing capability, while environmental-monitoring studies (temperature, humidity, soil conditions) predominantly use Arduino for its efficient sensor integration and low power draw. Hybrid approaches combine both, with Raspberry Pi handling image processing and Arduino managing sensor data acquisition, improving system modularity.

Seventeen studies did not report which devices they used to collect data (see Table 3). In contrast, Cui *et al.* (2022), Mehra *et al.* (2018), and Mya *et al.* (2021) consistently combined Raspberry Pi with Arduino to collect data, a pattern that separates processing and sensing responsibilities: Raspberry Pi typically handles computationally intensive tasks, such as image analysis and machine learning inference, while Arduino manages real-time data acquisition from sensors, enhancing scalability and reducing computational overload on a single device.

Although studies only began adopting the ESP32 in 2025, five had already used it to collect crop data (see Table 3), integrating sensing, processing, and wireless communication within a single device. These studies frequently target Internet of Things (IoT) architectures, where ESP32 enables real-time data transmission and edge processing, a shift toward more compact, cost-effective solutions for distributed monitoring and reduced infrastructure complexity.

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G. SQ6: What plant crops are grown in the studies?

Table 6 presents all crops cultivated in the studies included in this systematic literature review. Tomato and lettuce stand out as the most frequently studied crops. Each of these two crops appeared in fifteen studies, representing 21.43% of the total analyzed.

Table 6. List of plant crops cultivated in the studies

Crops	Number of Studies (%)	ID of Studies
Cucumber	1 (1.43%)	A15
Lettuce	15 (21.43%)	A05, A07, A16, A17, A20, A21, A27, A30, A34, A57, A58, A65, A66, A67, A68
Tuberose Bulbs	1 (1.43%)	A08
Coriander	2 (2.86%)	A03, A64
Tomato	15 (21.43%)	A01, A04, A06, A10, A11, A22, A24, A31, A33, A35, A39, A42, A49, A52, A63
Arugula	1 (1.43%)	A12
Strawberry	4 (5.71%)	A12, A29, A36, A41
Radish	1 (1.43%)	A12
Arabidopsis	1 (1.43%)	A14
Pepper	4 (5.71%)	A25, A40, A42, A56
Basil	1 (1.43%)	A27
Spinach	3 (4.29%)	A27, A50, A53
Parsley	1 (1.43%)	A27
Grape	1 (1.43%)	A31
Apple	1 (1.43%)	A31
Potato	1 (1.43%)	A31
Mushroom	1 (1.43%)	A32
Chinese Cabbage Leaves	1 (1.43%)	A37
Brassica Plants	1 (1.43%)	A38
Cotton	1 (1.43%)	A43
Melon	1 (1.43%)	A43
Pennywort	1 (1.43%)	A46
Cherries	1 (1.43%)	A51
Beetroot	1 (1.43%)	A55
Tarragon	1 (1.43%)	A55

Two studies cultivated four plant types each (Abbasi *et al.* (2023): lettuce, basil, spinach, and parsley; Prasad *et al.* (2023): grapes, tomatoes, apples, and potatoes), while Martini *et al.* (2021) cultivated three (arugula, radish, strawberries). Overall, the studies covered twenty-five different crops.

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H. SQ7: Which cultures are considered in the studies?

Table 7 presents the distribution of crop types across the seventy studies. The studies addressed five cultivation types: hydroponics, semi-hydroponics, soil-based cultivation, aquaponics, and aeroponics.

Table 7. List of crop types in the studies

Crop Type	Number of Studies (%)	ID of Studies
Hydroponics	17 (24.29%)	A01, A03, A06, A07, A12, A13, A16, A17, A46, A47, A53, A56, A57, A58, A62, A64, A68
Soil	32 (45.71%)	A02, A03, A04, A09, A11, A14, A15, A18, A19, A21, A22, A24, A26, A27, A30, A31, A32, A33, A35, A37, A38, A40, A42, A43, A49, A50, A51, A54, A55, A61, A63, A67
Semi-Hydroponics	7 (10.00%)	A10, A25, A29, A36, A41, A52, A65
Aquaponics	6 (8.57%)	A05, A08, A20, A27, A44, A60
Aeroponics	1 (1.43%)	A28

Seven studies did not specify the cultivation type or testing conditions, and two of these (Choi *et al.* (2024) and Mansour *et al.* (2025)) only indicated that their experiments involved different crops, without further methodological detail.

Hydroponics, where nutrient-enriched water recirculates through structures such as PVC channels without soil or substrate, was used in seventeen studies (24.29%), with Mehra *et al.* (2018) being the earliest identified in this review.

In the semi-hydroponic cultivation model, plants grow in pots or plastic containers, and the irrigation system does not recirculate water. Instead, the system delivers water and nutrients directly to the substrate.

Soil-based cultivation, the most traditional method in conventional agriculture, appeared in 45.71% of the studies (thirty-two out of seventy). Aquaponics, which follows a similar principle to hydroponics but integrates fish farming (fish raised in a separate tank supply nutrients to the plants through biological waste), appeared in six studies (see Table 7).

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Rajendiran and Rethnaraj (2023) investigated aeroponics, in which plant roots remain suspended in a controlled-humidity environment supplied by a nutrient solution at the base of the system.

I. SQ8: What are the challenges in applying machine learning to indoor agriculture?

Among the seventy studies, a key challenge is developing solutions not restricted to a specific environment, driven by factors such as data diversity, machine learning infrastructure and cost, differing control requirements across crops, and a lack of integration among existing solutions.

The diversity of crop data is a significant challenge: even the same crop under similar conditions may be monitored with different variables (e.g., temperature and humidity versus soil moisture and light), which limits the transferability of models trained on distinct datasets. Each crop also prioritizes different parameters: pH may be critical for lettuce in hydroponics, while electrical conductivity matters more for arugula.

Data-acquisition infrastructure is another key factor. Image-based monitoring typically informs plant health, pest presence, and harvest timing, while sensor-based systems provide continuous environmental and physiological data at higher deployment cost. Real-time acquisition often also depends on reliable connectivity, since many solutions rely on cloud-based architectures.

These challenges contribute to the development of numerous machine learning solutions tailored to specific crops rather than generalized systems. This specialization results from differences in collected data, training requirements, and the variability of outcomes across distinct agricultural contexts.

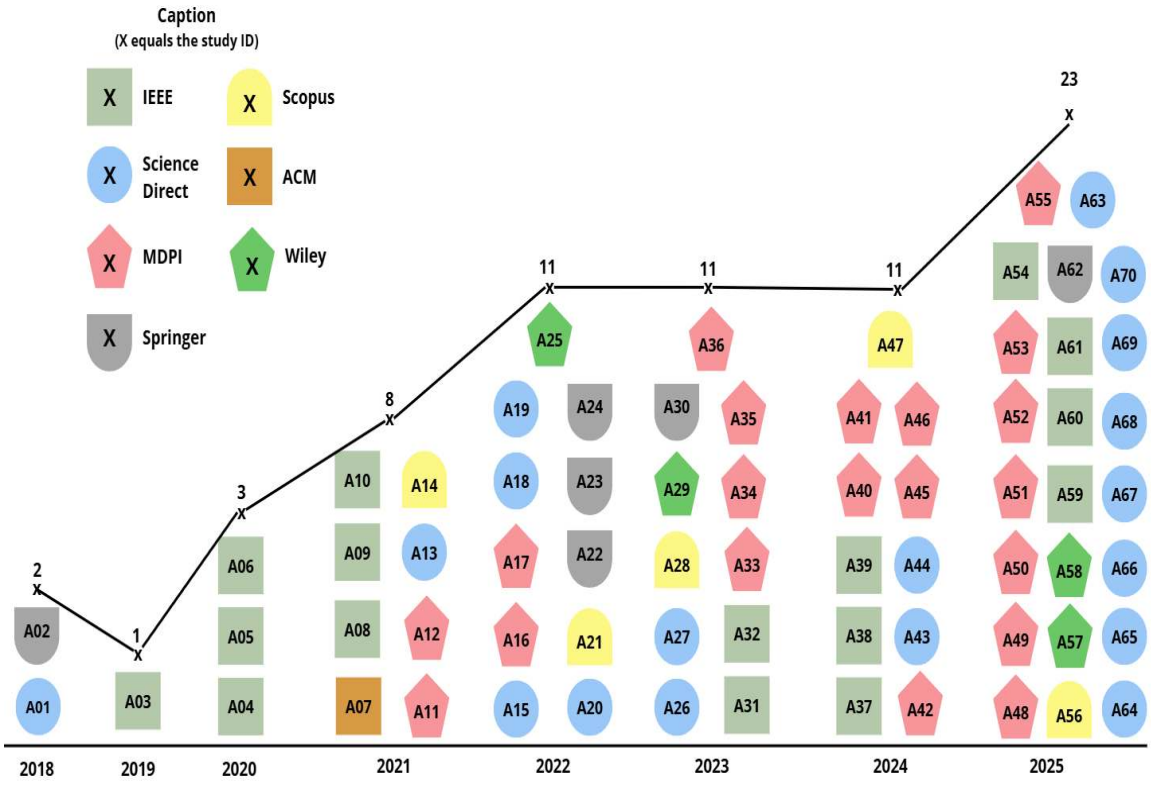
J. STQ1: How many publications occur per year and database?

This review analyzed studies that integrate machine learning with indoor farming without applying an initial time restriction in the search process. However, the filtering stage revealed that studies in this area only began to appear from 2018 onward.

Fig. 4 illustrates the distribution of articles by year and database. Publications increased sharply between 2021 and 2022, remained stable through 2024, and then more than doubled in 2025, indicating growing and still-evolving interest in the field.

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Fig. 4. Publication per year and databases



The database with the highest number of studies was MDPI, with twenty articles (28.57%), followed by ScienceDirect with eighteen (25.71%) and IEEE Xplore with sixteen (22.85%). SpringerLink, Scopus, and Wiley contributed six, five, and four studies, respectively, and the ACM Digital Library contributed one. The Taylor & Francis database yielded no studies after applying the inclusion and exclusion criteria.

The analysis also highlights the journals with the highest number of publications: Computers and Electronics in Agriculture published six of the reviewed studies, and Sensors published five (see Table 3).

K. STQ2: What is the geographical distribution of reviewed studies?

The geographical distribution of the reviewed studies spans thirty-two countries and 338 authors. Fig. 5 ranks these countries by number of author affiliations, with the corresponding flag, count, percentage, and ranking.

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Fig. 5. List of countries where there are affiliations of authors

Flag								
Country	India	China	South Korea	USA	Mexico	United Kingdom	Qatar	Bangladesh
Affiliation	65	54	28	16	15	13	12	11
%	19,23%	15,97%	8,28%	4,73%	4,43%	3,84%	3,55%	3,25%
Classification	1	2	3	4	5	6	7	8
Flag								
Country	Indonesia	Philippines	Brazil	Germany	Turkey	Ecuador	Malaysia	Sri Lanka
Affiliation	9	8	7	7	7	6	6	5
%	2,66%	2,36%	2,07%	2,07%	2,07%	1,77%	1,77%	1,48%
Classification	9	9	11	11	11	14	14	16
Flag								
Country	Japan	Russia	Kazakhstan	Pakistan	Italy	Latvia	Bulgaria	Greece
Affiliation	5	4	4	4	4	4	4	4
%	1,48%	1,18%	1,18%	1,18%	1,18%	1,18%	1,18%	1,18%
Classification	16	18	18	18	18	18	18	18
Flag								
Country	Myanmar	Spain	Ukraine	Netherlands	Canada	Saudi Arabia	Australia	Taiwan
Affiliation	4	4	3	3	2	2	2	2
%	1,18%	1,18%	0,88%	0,88%	0,59%	0,59%	0,59%	0,59%
Classification	18	18	27	27	29	29	29	29
Flag								
Country	Egypt	Guinea	Portugal	Palestine	Thailand	Malta		
Affiliation	2	1	1	1	1	1		
%	0,59%	0,29%	0,29%	0,29%	0,29%	0,29%		
Classification	28	34	34	34	34	34		

India leads in author affiliations (65 authors, 19.23%), followed by China (54, 15.97%) and South Korea (28, 8.28%), reflecting strong research activity in Asia. The United States (4.73%) and several European countries, including the United Kingdom (3.84%), Germany (2.07%), and the Netherlands (0.88%), also contribute, though with comparatively lower representation.

Latin America and the Middle East show moderate participation (e.g., Mexico, Brazil, and Qatar), while several other countries, including Bangladesh, Indonesia, the Philippines, Australia,

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and Canada, among others, contribute smaller shares, reinforcing the global scope of the field (see Fig. 5 for the complete ranking).

This distribution reveals not only the widespread interest in indoor agriculture but also disparities in research concentration, likely influenced by differences in technological infrastructure, funding availability, and agricultural priorities. The predominance of contributions from Asian countries suggests a strong alignment between research efforts and regional challenges related to population growth, food demand, and resource optimization.

Bibliometrically, MDPI, ScienceDirect, and IEEE Xplore account for most of the selected studies, while Computers and Electronics in Agriculture and Sensors are the leading journals, reflecting a convergence of interdisciplinary research spanning agriculture, engineering, and data science.

Overall, research on machine learning in indoor agriculture is globally distributed and rapidly evolving, though the observed geographical concentration points to opportunities for broader international collaboration, particularly with underrepresented regions.

L. Limitations and threats to the validity of the study

Systematic reviews carry inherent risks to validity, often from decisions made during the review process. To mitigate this, the study selected eight well-established databases relevant to computer science, reducing potential bias from database coverage.

The search strategy combined primary terms ("machine learning" and "indoor agriculture") with at least one of seven secondary terms, aiming to maximize relevant results; future reviews could explore additional terms to capture studies that address similar topics without using these exact keywords.

This review included only English-language articles, which may have excluded relevant non-English studies, and focused exclusively on studies explicitly applying machine learning to indoor agriculture, a clear scope that may have limited interdisciplinary contributions.

The data extraction did not differentiate between sensor models serving the same purpose (e.g., all air-temperature sensors were grouped as "ambient temperature"), which may introduce some bias from varying data quality and precision.

Furthermore, the review considered only studies related to greenhouse environments, excluding those focused on outdoor agriculture. This restriction may have omitted relevant research on machine learning applications that could be transferable to controlled environments.

The filtering process itself may exclude potentially relevant studies. To mitigate this, the review adopted a systematic mapping approach widely recognized in the literature (Petersen *et*

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al., 2015) and incorporated methodological aspects from prior studies (dos Santos *et al.*, 2024; Heckler *et al.*, 2025; Monteiro *et al.*, 2025), enhancing the reliability of the findings compared to traditional narrative reviews.

DISCUSSION

The increasing global population, combined with limited arable land and food shortages, highlights the importance of innovative agricultural solutions. Machine learning applications in indoor agriculture offer significant potential to enhance productivity, enabling higher yields within limited cultivation areas.

This review identified sixty-two machine learning techniques applied to indoor agriculture, covering functions such as pest detection, energy optimization, climate prediction up to seventy-two hours in advance, and automated control of greenhouse conditions and irrigation, demonstrating the versatility of machine learning in addressing complex agricultural challenges.

Despite these advancements, most machine learning models rely on highly specific datasets tailored to a single crop type or environment, limiting their ability to generalize. Models rarely incorporate heterogeneous datasets, restricting their adaptability to broader agricultural scenarios.

The lack of generalized models remains a critical limitation, as only three studies support multiple crop types. This limitation does not arise solely from algorithmic constraints but also from the inherent variability of biological processes across plant species. Differences in growth patterns, nutrient requirements, and environmental responses introduce significant complexity. Moreover, the absence of standardized data sets and variations in sensor configurations, data collection frequency, and environmental conditions further hinder model transferability and reproducibility.

The analysis also identified twenty-one distinct applications of machine learning, with prediction the most prominent category (nine application areas). Automatic detection tasks consistently rely on image-based approaches, particularly camera systems, to identify plant diseases, pests, crop types, and nutritional deficiencies.

Greenhouse control and irrigation management are recurring objectives, though each study adopts different sensor configurations, data types, and control strategies, reinforcing the flexibility of machine learning while highlighting the lack of standardization in system design.

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The review identified twenty-five crop types, with tomatoes and lettuce the most frequently studied. Only a few studies applied machine learning across multiple crops, such as Abbasi *et al.* (2023) and Martini *et al.* (2021), underscoring the need for more generalized approaches.

Economic factors also shape the adoption of machine learning in indoor agriculture. High-performance image-based systems increase implementation costs, limiting adoption in resource-constrained settings, while low-cost sensor-based systems are more accessible but often lack advanced analytical capabilities, a key trade-off for scalability and real-world deployment.

The review also identified five cultivation systems: soil-based cultivation (the most common), hydroponics, semi-hydroponics, aquaponics, and aeroponics, with the last remaining largely unexplored, indicating an opportunity for further investigation.

From a methodological perspective, future research should prioritize: standardized data collection protocols to improve reproducibility; integration of heterogeneous datasets to enhance model generalization; hardware choices that balance computational performance with cost; and modular system architectures that improve scalability across crops and environments.

Bibliometrically, journals accounted for 74.28% of the reviewed studies and conferences for 25.72%, with a marked increase in publications during 2025, reflecting the field's growing consolidation.

Overall, machine learning in indoor agriculture is a rapidly evolving research area with significant potential. Addressing challenges related to data heterogeneity, lack of standardization, limited generalization, and economic constraints remains key to enabling broader adoption and scalability.

FINAL CONSIDERATIONS

This study presented a systematic literature review on the application of machine learning in indoor agriculture. The final dataset included seventy studies selected through a rigorous filtering process that initially retrieved over fourteen thousand articles from eight distinct databases. Each study was analyzed in detail to address eleven research questions. The review examined application domains, crop data types, machine learning techniques, data acquisition devices, cultivation systems, crop types, publication sources, and other relevant aspects. In addition, it identified key challenges and future research directions in this field.

The findings indicate that machine learning in indoor agriculture represents a growing research trend, driven by the ability to create controlled microclimates within greenhouse environments. These conditions reduce exposure to external climate variability and enable more

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precise monitoring and control of crop development. However, most studies focus on specific crops and rely on limited datasets, applying machine learning techniques to narrowly defined problems based on the available data.

Beyond the identified trends, this review highlights important research gaps that deserve further attention. The results show a strong predominance of image-based approaches and deep learning architectures, particularly YOLO-based models, while only a limited number of studies explore context-aware mechanisms or the integration of heterogeneous datasets. In addition, most studies focus on a small set of crops, especially lettuce and tomato, which may limit the generalization of current machine learning solutions to other cultivation environments. These findings indicate opportunities for future research involving context-aware systems, dataset interoperability, transfer learning across different crops, and more generalized machine learning frameworks capable of supporting a broader range of indoor agriculture applications.

Future research should prioritize the development of generalized and proactive models that extend beyond single-crop applications. Integrating heterogeneous datasets from different crops remains a significant challenge, as current approaches typically rely on homogeneous data sources. Expanding dataset diversity may enable systems to generate more robust and transferable insights, including predictions based on previously unseen conditions.

Another promising direction involves the development of adaptive systems capable of continuous or self-updating learning. Such systems could remain aligned with evolving environmental conditions and agricultural practices. However, fully autonomous decision-making raises concerns due to the potential risks associated with incorrect interventions. A more viable approach involves decision-support systems that provide recommendations, allowing agronomists to validate and approve suggested actions before implementation.

Based on the gaps identified in this review, future research should address several key challenges: (i) the creation of standardized and publicly available datasets that integrate environmental, visual, and physiological data, enabling consistent benchmarking; (ii) the development of generalized machine learning models capable of knowledge transfer across crops and cultivation systems; (iii) the design of hybrid architectures that combine edge and cloud computing to balance real-time responsiveness and computational efficiency; and (iv) the establishment of evaluation frameworks that consider not only predictive performance but also economic feasibility, scalability, and energy efficiency. Addressing these challenges will strengthen the methodological foundations of the field and accelerate the transition from experimental research to real-world applications.

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Finally, future reviews may expand this work by incorporating other artificial intelligence techniques and exploring outdoor agricultural scenarios. Further investigations should also examine challenges related to scalability, interoperability, and practical deployment, which remain critical barriers to the widespread adoption of machine learning in agriculture.

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