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Systematic Review

IoT Solutions with Artificial Intelligence Technologies for Precision Agriculture: Definitions, Applications, Challenges, and Opportunities

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Abstract: The global agricultural sector confronts significant obstacles such as population growth, climate change, and natural disasters, which negatively impact food production and pose a threat to food security. In response to these challenges, the integration of IoT and AI technologies emerges as a promising solution, facilitating data-driven decision-making, optimizing resource allocation, and enhancing monitoring and control systems in agricultural operations to address these challenges and promote sustainable farming practices. This study examines the intersection of IoT and AI in precision agriculture (PA), aiming to provide a comprehensive understanding of their combined impact and mutually reinforcing relationship. Employing a systematic literature review following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 guidelines, we explore the synergies and transformative potential of integrating IoT and AI in agricultural systems. The review also aims to identify present trends, challenges, and opportunities in utilizing IoT and AI in agricultural systems. Diverse forms of agricultural practices are scrutinized to discern the applications of IoT and AI systems. Through a critical analysis of existing literature, this study contributes to a deeper understanding of how the integration of IoT and AI technologies can revolutionize PA, resulting in improved efficiency, sustainability, and productivity in the agricultural sector.

Keywords: precision agriculture; smart agriculture; IoT; artificial intelligence; machine learning; farm automation; smart sensor; bibliometric; review analysis

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1. Introduction

Precision agriculture (PA), an innovative approach to agricultural management, integrates cyber-physical devices and systems to optimize resource utilization and maximize yield [1]. This holistic approach encompasses the management of various resources such as water, land, feed, pesticides, weedicides, fertilizers, energy, and time across diverse agricultural domains, including crop cultivation, livestock farming, fish farming, and aquaponics, while spanning different stages of agriculture from land preparation to harvesting [1].

However, the global agricultural landscape faces many challenges, including population growth, urbanization, competition for resources, climate change, and natural disasters, among others [2]. These challenges impede food production and are anticipated to persist, necessitating collaborative efforts between policymakers and technologists to ensure global food security and peace [3,4].

Recognized as a vital tool for sustainably increasing agricultural production, PA holds promise in meeting projected food demand [1,5–7]. Ongoing research initiatives aim to leverage emerging technologies such as the Internet of Things (IoT) to collect and manage data from agricultural facilities [5,8–13]. The integration of IoT with Artificial Intelligence (AI) for decision-making [14], remote sensing for observation [15], and blockchain technology for data security [16] further enhances agricultural processes, including disease identification, pest control, soil monitoring [17,18], and yield prediction [19,20].

This study investigates the application of AI in IoT systems for agricultural purposes, aiming to provide a comprehensive examination of existing literature on IoT tools utilizing AI techniques to address agricultural issues. The systematic review seeks to identify the current state of research, highlight opportunities and challenges, and propose potential applications.

To facilitate understanding, Section 2 discusses prior literature reviews summarized in Figure 1 and Table 1, their strengths and weaknesses, and justifies the necessity of this study. The methodology employed in this research is outlined in Section 3, accompanied by the rationale behind the decisions. Subsequently, Section 4 presents the obtained results, which are then discussed in Section 5. Finally, Section 6 presents the conclusions drawn from this study. Through this structured approach, the study aims to contribute valuable insights to the burgeoning field of PA.

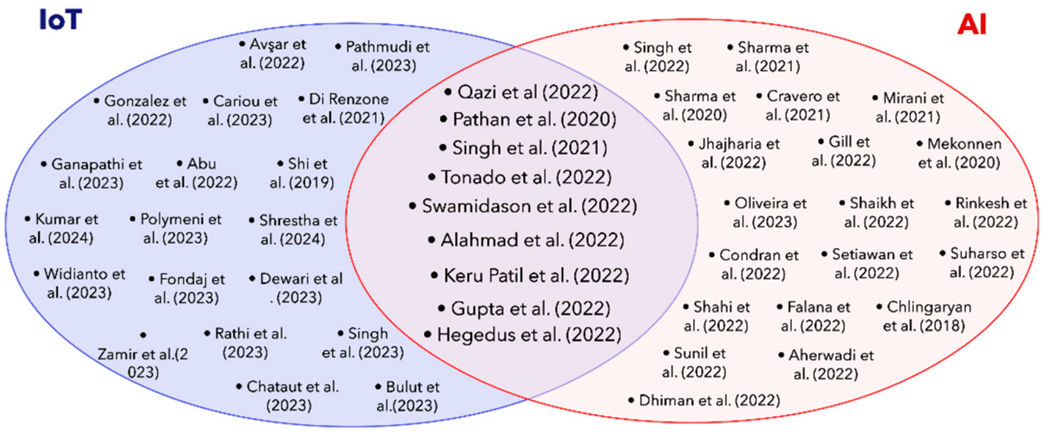

Figure 1. Review studies about AI and IoT applications in agriculture presented in a Venn diagram. **Cited studies for IoT only:** Pathmudi et al. (2023) [7], Avşar et al. (2022) [21], Gonzalez et al. (2022) [22], Cariou et al. (2023) [23], Di Renzone et al. (2021) [24], Ganapathi et al. (2023) [6], Abu et al. (2022) [25], Shi et al. (2019) [26], Kumar et al. (2024) [27], Polymeni et al. (2023) [28], Shrestha et al. (2024) [29], Widianto et al. (2023) [30], Fondaj et al. (2023) [31], Dewari et al. (2023) [32], Zamir et al. (2023) [33], Rathi et al. (2023) [34], Singh et al. (2023) [35], Chataut et al. (2023) [36], and Bulut et al. (2023) [37]. **Cited studies for AI only:** Singh et al. (2022) [38], Sharma et al. (2020) [39], Cravero et al. (2021) [40], Mirani et al. (2021) [41], Jhajharia et al. (2022) [42], Gill et al. (2022) [43], Mekonnen et al. (2020) [44], Oliveira et al. (2023) [45], Shaikh et al. (2020) [46], Rinkesh et al. (2022) [47], Condran et al. (2022) [48], Setiawan et al. (2022) [49], Suharso et al. [50], Shahi et al. (2022) [51], Falana et al. (2022) [52], Chlingaryan et al. (2018) [53], Sunil et al. (2022) [54], Aherwadi et al. (2022) [55], and Dhiman et al. (2022) [56]. **Cited studies for IoT with AI:** Qazi et al.(2022) [57], Pathan et al. (2020) [58], Singh et al. (2021) [59], Tonado et al. (2022) [60], Swamidason et al. (2022) [61], Alahmad et al. (2022) [62], Keru Patil et al. (2022) [63], Gupta et al. (2022) [64], and Baghel et al. (2022) [65].

Table 1. Related work that refers to both IoT and AI, including the cited paper, the acknowledgment of the complementarity of IoT and AI, and the presence of a systematic literature review.

Paper	Complimentarity Investigated	Systematic Review
Qazi et al. (2022) [57]	No	No
Pathan et al. (2020) [58]	No	No
Singh et al. (2021) [59]	No	No
Tonado et al. (2022) [60]	Yes	No
Swamidason et al. (2022) [61]	Yes	No
Alahmad et al. (2022) [62]	Yes	No
Keru Patil et al. (2022) [63]	Yes	No
Baghel et al. (2022) [65]	Yes	No
Gupta et al. (2022) [64]	Yes	No
Hegedus et al. (2023) [66]	Yes	No
This work	Yes	Yes

2. Related Work

PA involves two fundamental technologies: IoT and AI [67,68]. While IoT is utilized for data collection and remote control, AI is applied for prediction and decision-making. These two technologies play a crucial role in ensuring sustainable farming practices [46]. However, it can be observed that review studies that discuss the applications of IoT and AI in agriculture typically examine research works that investigate either one technology independently or both technologies. As illustrated in Figure 1, a Venn diagram depicting how review studies investigate IoT and AI in agriculture is shown. The figure demonstrates the connection between the two technologies and their importance in PA.

2.1. IoT in Agriculture

Numerous studies have been published that examine the application of IoT in agriculture. Some of these studies focus on specific components or systems, such as sensors and wireless sensor networks, while other studies concentrate on specialized applications, such as the monitoring and management of hydroponics or greenhouse systems. Additionally, some studies investigate solutions to challenges such as weather monitoring, pest control, and disease detection.

In protected agriculture, the integration of IoT has led to significant advancements in the efficient use of artificial techniques to modify climatic factors [26]. Kumar et al. [27] highlight the importance of IoT-based monitoring and control strategies in smart agriculture, emphasizing the need for sustainable farming practices. Polymeni et al. [28] also discuss the impact of 6G-IoT technologies on agriculture, focusing on the evolution from Agriculture 4.0 to Agriculture 5.0. Gonzalez et al. [22] investigate the behavior of LoRa systems in a Low-Power Wide-Area Network (LPWAN) in a tropical farming environment, evaluating LoRa performance with the Signal to Noise Ratio (SNR), the Received Packet Ratio (RPR), and Received Signal Strength Indication (RSSI). Shrestha et al. [29] explore the potential of real-time nitrogen sensing and IoT integration in smart agriculture to enhance nitrogen use efficiency. Furthermore, Widianto et al. [30] and Ganapathi et al. [6] delve into the potential of IoT applications in smart agriculture, emphasizing precision farming and crop monitoring.

Moreover, IoT solutions for smart farming are widely discussed by various researchers, such as Fondaj et al. [31], Dewari et al. [32], and Zamir et al. [33]. These studies explore the role of IoT sensor data in predicting agricultural outcomes and optimizing farming practices. Similarly, Rathi et al. [34] review the revolutionizing effects of IoT on agriculture, focusing on precision farming and automated irrigation systems.

In addition, Singh et al. [35] and Chataut et al. [36] offer systematic reviews on IoT applications in various sectors, including agriculture. Bulut et al. [37] present a systematic literature review on IoT in agriculture, highlighting adoption barriers and solutions across different layers of the IoT system architecture. Cariou et al. [23] and Di Renzone et al. [24] also explore IoT for agriculture with a focus on underground data transmission.

Pathmudi et al. [7], Mowla et al. [4], and Avşar et al. [21] examine the use of sensors, controllers, and communication protocols in IoT applications in agriculture and discuss case studies and challenges related to this topic. Ganapathi et al. [6] and Abu et al. [25] explore various applications for sustainable and efficient agriculture, presenting studies on different methods such as drip, greenhouse, and IoT-based monitoring systems, wireless networks, smart agriculture, and PA.

However, it is worth noting that while many of these reviews acknowledge the transformative potential of IoT in agriculture, their emphasis remains solely on IoT technologies, not considering the synergy between IoT and other technologies such as AI.

2.2. AI in Agriculture

AI has numerous applications in agriculture, which vary depending on the specific stages and forms of agriculture under consideration. Studies on the application of AI have explored different aspects of agriculture, such as animal husbandry, crop production, and fish farming, providing an overview of the current state of research in the field [38–43,69].

Many studies have provided a comprehensive overview of the applications of AI in agriculture, such as Mekonnen et al. [44], who investigated the use of various machine learning algorithms for analyzing sensor data in the agricultural domain and conducted a case study using an IoT-based data-driven smart farm prototype. Similarly, Oliveira et al. [45] demonstrated a progression in the field, as evidenced by the increasing number of publications in the past five years. Their analysis revealed the application of over 20 different AI techniques, with machine learning, convolutional neural networks, IoT, big data, robotics, and computer vision being the most commonly utilized technologies.

Shaikh et al. [46] reviewed recent AI techniques applied in soil and irrigation management, weather forecasting, plant growth, disease prediction, and livestock management. They focused on the AI algorithms used and their performance impact. It was reported that deep learning algorithms outperformed conventional machine learning algorithms due to recent technological advances that allow for efficient data processing, powerful computations, and timely decision-making. The use of AI has the potential to improve efficiency, productivity, and sustainability in the industry.

Other research works have explored AI's applications and impact on agriculture from different perspectives and reported various findings. For instance, Rinkesh et al. [47] categorized research works into different areas, such as yield prediction, disease detection, weed detection, species recognition, and crop quality, demonstrating how machine learning technologies can benefit crop production. Condran et al. [48] conducted a systematic review of machine learning applications in PA and identified challenges related to data, such as class imbalance, data sparsity, and high dimensionality.

2.3. Existing Research Gap

Figure 1 demonstrates the diverse approaches taken by previous research studies, indicating either separate investigations of IoT and AI or a combined analysis of both technologies in PA. While the former approach may be suitable for addressing specific aspects, such as IoT device deployment or AI algorithm development, it overlooks the synergistic potential of integrating IoT and AI in agricultural systems.

Table 1 shows review studies that refer to IoT and AI for agriculture. Several studies [60–65] acknowledge the complementary relationship between IoT devices and AI algorithms in agriculture. However, these works often lack systematic reviews, potentially overlooking relevant literature and limiting the scope of analysis. This study aims to fill this gap by systematically examining literature that explores the intersection of IoT and AI in PA, ensuring a comprehensive understanding of their combined impact.

Previous reviews focusing solely on IoT or AI provide valuable insights into individual technologies but fail to capture the holistic view of their integration. By synthesizing literature that combines IoT and AI, this study aims to uncover the synergies and transformative potential of integrating these technologies in PA.

While existing research has extensively explored the applications of IoT and AI in agriculture, there is a notable gap in systematically examining their combined impact on PA. This study seeks to address this gap by conducting a systematic literature review that specifically focuses on the intersection of IoT and AI in agricultural systems. By synthesizing findings from relevant studies, this research aims to provide insights into the complementary nature of these technologies and their potential to revolutionize PA. Through critical analysis and synthesis of existing literature, this study aims to contribute to a more comprehensive understanding of the integrated use of IoT and AI in agricultural systems.

In the following sections, this research delves into various aspects, including definitions, opportunities, challenges, and practical applications, providing an in-depth exploration of the subject matter. By addressing these gaps, this study contributes to a more holistic understanding of the combined effects of IoT and AI in PA.

3. Methodology

This paper presents a comprehensive and reproducible systematic literature review of research works investigating IoT solutions that utilize AI technologies for PA. The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 guideline for reporting systematic reviews [70] was followed to ensure transparency and rigor. The methodology involved three main steps: identification, screening, and inclusion, as depicted in Figure 2.

3.1. Identification

The identification phase is initiated with the development of database queries to retrieve relevant literature from selected databases and websites. Keywords for the query were derived from three main components: IoT, AI, and agriculture, connected with AND operators, as shown in Figure 3. These keywords were then linked with OR operators for each component. Table 2 shows the keywords used for the query components, and Figure 4 shows the complete query constructed. The query was tailored to each selected database or website, with occasional modifications to accommodate specific requirements. Five prominent databases and websites (Scopus, ScienceDirect, IEEE, ACM, and Google Scholar) were queried to ensure comprehensive coverage of scientific literature. The date of each database or website query was recorded for transparency, together with the query modification, as shown in Table A1 in Appendix A.

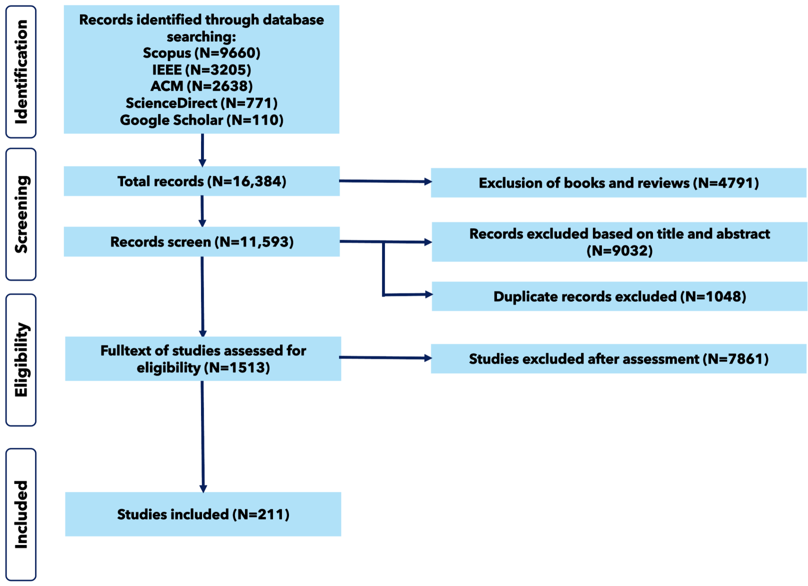

Figure 2. PRISMA process flow: (1) identification—literature is queried and identified from relevant databases and websites, (2) screening—identified literature is screened according to designed exclusion criteria to eliminate irrelevant literature, and (3) inclusion—screened literature that passes the inclusion criteria is included to be reported on.

Table 2. Components of paper identification query (IoT keywords, AI keywords, and agriculture keywords) with corresponding keywords typically used in the literature. The "*" character denotes a wildcard in the keywords.

IoT Keywords	AI Keywords	Agriculture Keywords
internet of things	artificial intelligence	precision agriculture
IoT	artificial-intelligence	agric *
	machine learning	agro *
	machine-learning	fish *
	deep learning	crop *
	deep-learning	farm *
	neural networks	plant *
	neural-networks	animal *
	classif *	
	predict *	
	monitor *	
	forecast *	
	estimat *	
	algorithm *	

Figure 3. Database query components connected with AND boolean operators.

```
(‘‘machine learning’’ OR ‘‘machine-learning’’ OR ‘‘
    deep learning’’ OR ‘‘deep-learning’’ OR‘‘
    artificial intelligence’’ OR ‘‘artificial-
    intelligence’’ OR ‘‘neural networks’’ OR ‘‘neural-
    networks’’ OR ‘‘classif*’’  OR ‘‘predict*’’ OR ‘‘
    monitor*’’  OR ‘‘forecast*’’ OR ‘‘estimat*’’ OR
    ‘‘algorithm*’’)
AND
(‘‘IoT’’ OR ‘‘internet of things’’)
AND
(‘‘precision agriculture’’ OR ‘‘agric*’’ OR ‘‘agro*’’
     OR ‘‘fish*’’ OR ‘‘crop*’’ OR ‘‘farm*’’ OR ‘‘plant
    *’’ OR ‘‘animal*’’)
```

Figure 4. Paper identification query: main components connected with AND boolean operators, and component keywords connected with OR boolean operators. The asterisk (*) characters represent wildcards.

3.2. Screening

The screening process entailed evaluating the titles and abstracts of articles to exclude irrelevant ones based on predetermined exclusion criteria. These criteria included excluding manuscripts not written in English and those that are books, review articles, surveys, and studies not related to agriculture, as summarized in Table 3. After the title and abstract screening, the remaining papers were assessed for inclusion in the review.

Table 3. Exclusion criteria—paper identification and screening rules.

	Criteria
1.	Manuscripts not written in English are excluded.
2.	Books, review studies, and surveys are excluded.
3.	Studies not related to or about agriculture are excluded.

3.3. Inclusion

At the inclusion stage, the remaining papers were thoroughly examined to determine their inclusion based on predetermined criteria shown in Table 4. Studies that utilized IoT hardware/infrastructure for agricultural data collection, monitoring, or control and deployed an AI algorithm were included. Primary research studies on PA using IoT with AI were included.

Table 4. Inclusion criteria—paper selection rules.

	Inclusion Criteria	**Justification**
1.	Studies that utilize IoT hardware/infrastructure for agricultural data collection, monitoring, or control, and deploy an AI algorithm are included.	To ensure conceptual or propositional works without actual IoT and AI/ML implementations are not included.
2.	Primary research studies on precision agriculture using IoT with AI are included.	To ensure relevance to the research objectives, prioritizing empirical evidence, and the review’s scope.

3.4. Bias Risk and Limitations

The study is not without its shortcomings and potential biases. Firstly, the study’s focus on English language publications in journals and conferences may have overlooked relevant studies published in other languages or alternative sources. Secondly, the study did not consider secondary research, reviews, or book chapters, which may have added valuable insights. However, these limitations are thought to have a minimal impact on the overall findings. The review's main focus on research implementing IoT and AI/ML systems means that conceptual or propositional works without implementation have been excluded. While this approach ensures an analysis of practical applications, it may overlook ongoing research that falls outside this scope. Finally, the review's focus on agricultural applications may have inadvertently excluded studies that did not explicitly mention this application. As a result, some relevant research may have been overlooked during the identification and selection process. To mitigate these biases, efforts were made to search multiple databases and websites comprehensively, use predefined inclusion criteria, and transparently report the methodology.

3.5. Data Analysis Plan

The data analysis plan involved synthesizing and analyzing data extracted from selected papers to address the research questions in Table 5. The data synthesis included thematic analysis to identify common themes, patterns, and trends across the literature. Additionally, quantitative synthesis techniques were employed to aggregate and analyze numerical data, such as publication frequencies or characteristics of included studies. The analytical approach was transparently reported to ensure reproducibility and rigor in the data analysis process.

Overall, the methodology outlined above ensured a systematic and transparent approach to conducting the literature review, with measures in place to mitigate potential biases and enhance the study's methodological rigor.

Table 5. Research questions categorized into three groups: statistical questions (SQs), general questions (GQs), and focused questions (FQs).

Ref.	Research Questions
SQ1.	In which databases are the studies published?
SQ2.	What is the number of publications per year?
SQ3.	What are the types (journal or conference) of publications of the studies?
SQ4.	In which countries are the institutions from which the studies were published?
GQ1.	Which forms of agriculture are referred to in the studies?
GQ2.	Which IoT components are referred to in the studies?
GQ3.	Which agricultural challenges are addressed in the studies?
GQ4.	What kinds of data are collected or used in the studies?
GQ5.	Which AI/ML algorithms are used in the studies?
FQ1.	What IoT strengths and weaknesses affect AI/ML positively or negatively in the studies?
FQ2.	What AI/ML strengths and weaknesses affect IoT positively or negatively in the studies?

4. Results

4.1. Overview of Findings

This section presents a comprehensive summary of the key findings and trends uncovered in the systematic review, in response to the statistical questions shown in Table 5.

4.1.1. Sources and Publications

At the end of the inclusion stage, 203 publications were selected for reporting, shown in Table A2 in Appendix B. **In response to research question SQ1 shown in Table 5, Figure 5a shows the distribution of the manuscripts according to retrieval sources.** The studies included in this review include publications from all of the five sources that were queried, namely Scopus, ACM, IEEE, Google Scholar, and ScienceDirect. The pie chart in Figure 5a shows the distribution of papers across these sources. Since Scopus and Google Scholar hold publications from diverse sources, including ACM, IEEE, and ScienceDirect, duplicate publications were credited to the original sources (ACM, IEEE, or ScienceDirect).

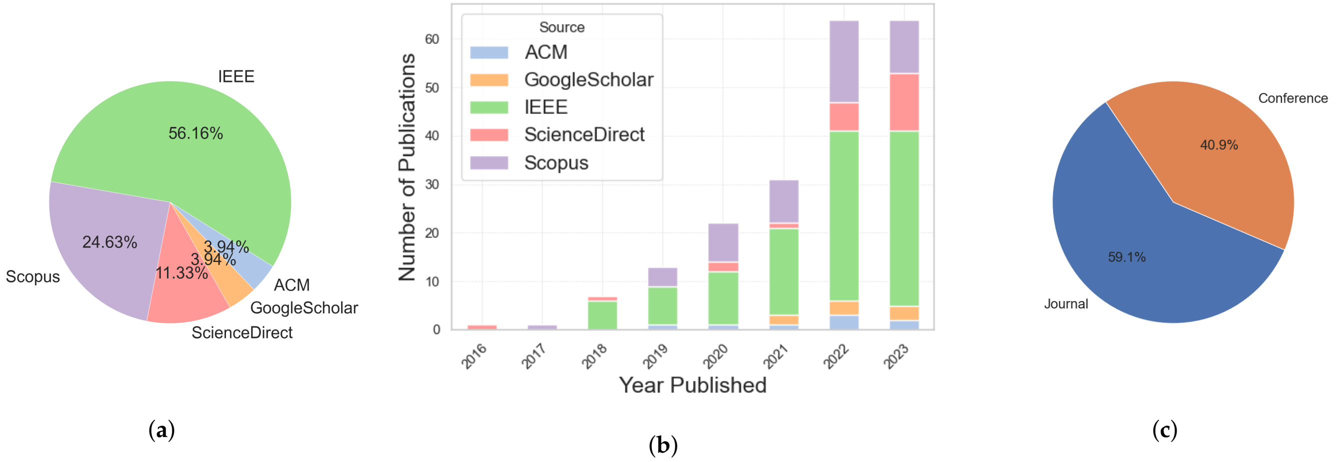

Figure 5. (**a**) Distribution of included papers from sources: a pie chart illustrating the proportion of included papers sourced from queried sources (Scopus, ACM, IEEE, Google Scholar, and ScienceDirect). (**b**) Distribution of papers year of publication and source: a stacked bar chart depicting the number of included papers published each year, categorized by the sources (Scopus, ACM, IEEE, Google Scholar, and ScienceDirect). (**c**) Distribution of papers by publication type: a pie chart showing the distribution of included papers between journals and conference proceedings, providing insights into the publication landscape.

Figure 5a shows that more than one in every two of the included studies was published in IEEE, and close to one in every four was published on Scopus. We also see that ScienceDirect, Google Scholar, and ACM contributed less than one in every five studies.

4.1.2. Trends in Publication over Time

An analysis of the publication year of the 203 included manuscripts reveals an increasing trend in the number of publications over the years, in response to research question SQ2 shown in Table 5. The stacked bar chart in Figure 5b shows the number of papers published from each source per year. Given that the sources were queried before the end of the year 2023, and that many journals and conferences may have yet to publish studies online, there has been an increasing trend consistently observed over the years.

4.1.3. Journals versus Conferences

The distribution of publications by type demonstrates a fair balance between journal articles (120 publications accounting for about 60%) and conference papers (83 publications accounting for about 40%). **The pie chart in Figure 5c visualizes the proportion of publications either from journals or conferences, in response to research question SQ3 shown in Table 5.**

4.1.4. Global Contribution

The distribution of authors' institutions across countries reflects a diverse representation from all continents. India is the leading contributor with 72 papers, followed by China with 19 papers, Taiwan with 16 papers, and the USA with 10 papers. Notably, 24 countries contributed one paper, while 11 countries contributed exactly two papers. It is important to note that when multiple authors of a publication are from institutions in the same country, the contribution was counted as one for the country. Conversely, when the authors' institutions are in different countries, each of the institutions' countries earned a count. **Figures 6 and 7 provide visual representations of the geographical distribution of publications in response to research question SQ4 shown in Table 5.**

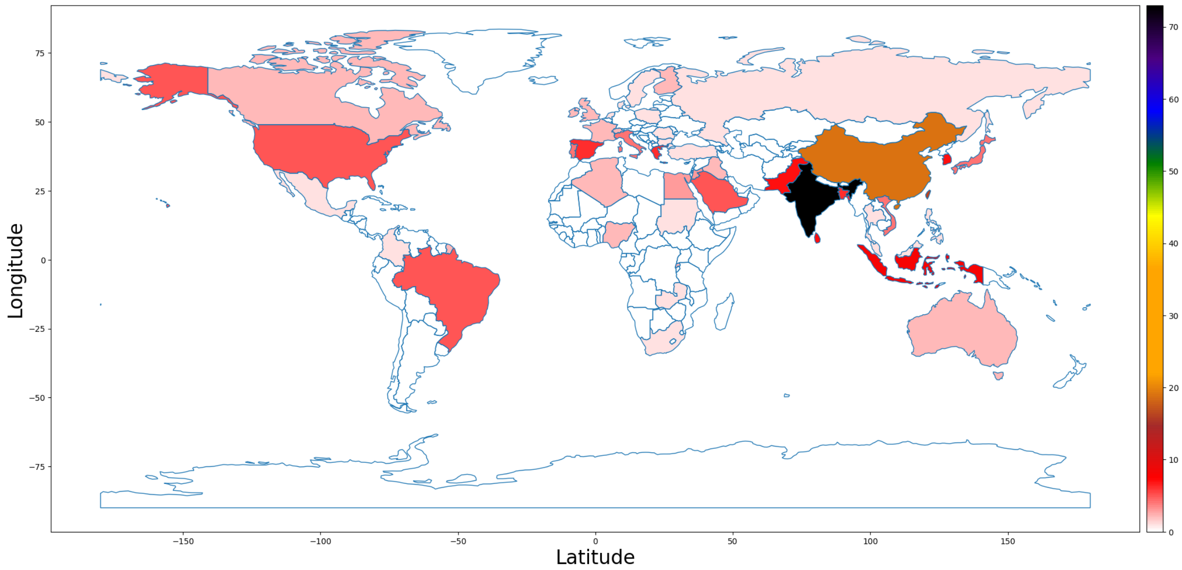

Figure 6. Global contribution—number of papers by country: a geographical map showing the number of included papers from authors' institutions across various countries, highlighting the global distribution of contributions.

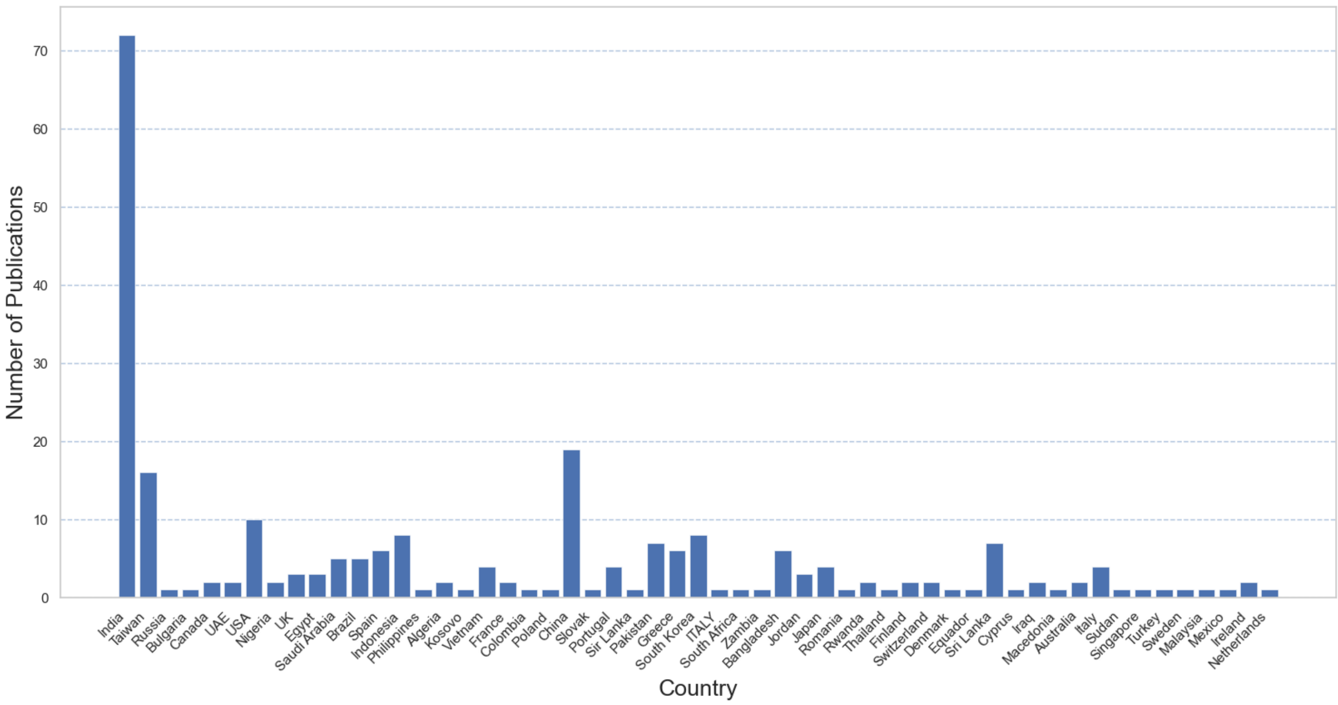

Figure 7. Contributing countries: a bar chart showing the countries of institutions contributing to the literature of the included papers, showcasing the diversity of global research.

4.1.5. Number of Pages, Sources, and Types

As part of the synthesis of the studies included, the type of publication (either journal or conference) and the number of pages per publication were recorded. The box plot in Figure 8 and the grouped bar chart in Figure 9 provide insights into the distribution of pages across different sources and types. While the number of pages of a publication may be considered a measure of its length, it is worth noting that different journals or conferences have varying page specifications that can affect how much literature fits onto a page.

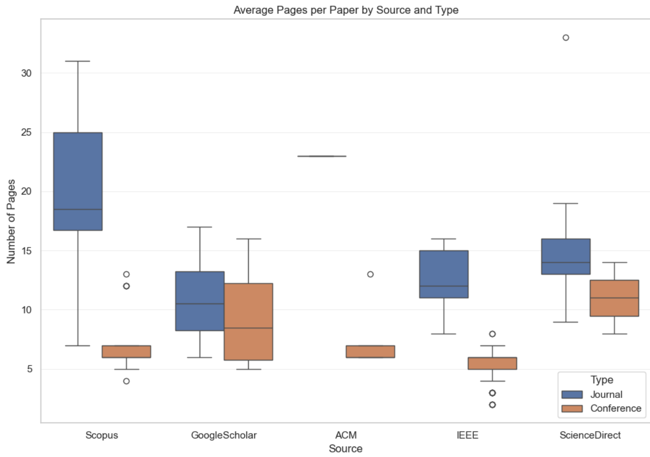

Figure 8. Length of included papers—source and type perspective: a box plot revealing the distribution of the number of pages in included papers, dissected by both source (Scopus, ACM, IEEE, Google Scholar, or ScienceDirect) and type (journal or conference).

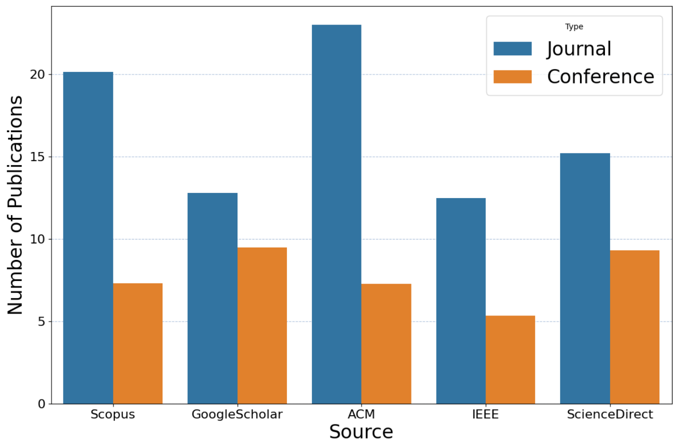

Figure 9. Comparative analysis of publications by source and type: a grouped bar chart providing a comparative analysis of the number of publications grouped by source (Scopus, ACM, IEEE, Google Scholar, or ScienceDirect) and type (journal or conference).

The box plot in Figure 8 shows that journal publications generally have more pages than conference publications for all five sources. The figure also indicates that the range of the number of conference pages does not overlap with that of journals (excluding outliers) for all sources except Google Scholar and ScienceDirect. Figure 9 also reveals that all five sources publish more journals than conferences.

4.1.6. Keyword Insights

The word cloud in Figure 10 visually represents the recurring themes and predominant topics found within the analyzed publications. This intuitive display not only condenses complex information into easily digestible visuals, but also serves as a valuable tool for quickly grasping the core concepts and prevalent subjects disseminated across the body of research.

In summary, this section provides a comprehensive overview of the study's findings, encapsulating the sources, temporal trends, publication types, global contribution, and insights into the length of the included papers. Subsequently, we will delve deeper into the definitions identified in the included studies, after which we will address the general (GQs) and focused (FQs) research questions.

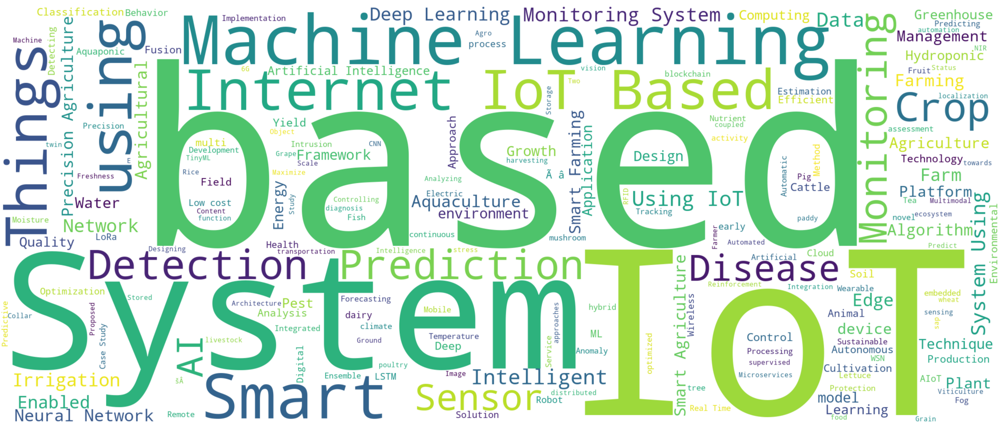

Figure 10. Keywords shaping the discourse: a word cloud representing the recurring themes and concepts derived from the keywords of included papers, offering insights into the focal points of literature on IoT and AI in PA.

4.2. Definitions Identified in the Literature

Clear and precise language is of paramount importance in any research field. Definitions play a crucial role in fostering clear communication, avoiding misinterpretation, and enhancing the overall rigor of scholarly endeavors. The significance of well-defined terms is particularly apparent in interdisciplinary studies, where diverse fields converge, giving rise to various technical terminologies. In our examination of the convergence of IoT technologies, AI/ML, and PA, the need for clear and precise definitions becomes particularly evident.

Here, we present the definitions identified in the literature, categorizing them according to key thematic areas of our research, specifically, AI/ML-related definitions, IoT-related definitions, and definitions pertinent to agriculture. Tables 6–8 contain these definitions, respectively. This aims to provide readers with a reference point, facilitating a nuanced understanding of the terminology employed in the discourse surrounding this body of knowledge. By offering this collection of definitions, we ensure that the terminology does not hinder, but rather enhances comprehension of the subject matter. This reflects our dedication to scholarly precision and invites readers to join us in exploring the intricate language that underpins this interdisciplinary domain.

Table 6. AI/ML-related definitions emphasized in the studies.

Paper	Terminology	Definition
[71–73]	Machine Learning (ML)	ML is the scientific technique wherein computers autonomously learn and improve by processing data from real-world interactions. It involves adaptive mechanisms, enabling learning from examples and experiences, showcasing technology's ability to automate analytical model construction within.
[74–76]	Artificial Neural Network (ANN)	ANN is a class of neural networks designed for systematic tractability and characterized by their mathematical analyzability. These statistical learning algorithms take inspiration from biological neural networks and find applications in diverse tasks, spanning from straightforward classification to advanced functions like speech recognition and computer vision.
[77–80]	K-Nearest Neighbor (KNN)	KNN is a non-parametric supervised learning algorithm. It represents each sample by its K-nearest neighbors, utilizing distance metrics like Euclidean or Manhattan. The algorithm predicts the output based on the most comparable sets, determined by the nearest specified k-value, in a feature space.

Table 6. *Cont.*

Paper	Terminology	Definition
[77,78,81]	Decision Tree Classifier	DTC is a non-parametric, supervised learning algorithm for classification and regression. It utilizes a hierarchical tree structure, where nodes represent features, decision nodes denote logic for data division, and leaf nodes indicate outcomes. It aids decision-making by creating paths leading to class labels or regression values, predicting outcomes by traversing nodes based on feature metrics, as seen in agriculture for crop selection.
[75,77,79,81,82]	Random Forest Classifier (RFC)	The RFC is a supervised learning technique, which enhances decision tree classifier performance through ensemble learning. It combines multiple decision trees independently built using bootstrap resampling, ensuring dataset independence for each tree. Employing a majority vote mechanism, the algorithm delivers robust classification, improving accuracy and generalizability, and mitigating overfitting.
[78,80,82–84]	Support Vector Machine (SVM)	SVM is a supervised machine learning algorithm. It employs a hyperplane to separate classes, with the kernel function transforming data. SVM maps data into a higher-dimensional space, finding a hyperplane that maximizes the separation between data points. The algorithm involves dividing data into training and validation sets, aiming to identify support vectors and margins for effective classification.
[74,75]	Support Vector Regression (SVR)	SVR is a machine learning technique tailored for predicting continuous values by identifying a hyperplane that minimizes the margin between predicted and actual values, accommodating some error. The hyperplane is a linear function of input features that minimizes the distance between itself and predicted values.
[77,85]	XGBoost (XGB)	XGBoost, an ensemble algorithm, employs gradient-boosting decision trees to sequentially train individual trees, each correcting the errors of the previous one. The model aggregates their classifications for a final prediction. It enhances the traditional gradient-boosted decision trees with improvements in loss function, regularization, and column sampling, optimizing predictions through a gradient descent algorithm.
[86]	Ensemble	Ensemble learning constitutes a machine learning paradigm wherein multiple learners undergo training to collectively address a shared problem. Predominantly employed in supervised learning contexts, numerous scholarly investigations affirm that ensemble learning yields superior predictive performance compared to the individual learning algorithms comprising it.

Table 7. IoT definitions emphasized in the studies.

Paper	Terminology	Definition
[71,72,87–90]	Internet of Things (IoT)	IoT refers to a vast network of interconnected physical devices that collect and exchange data using various protocols. Characterized as any entity capable of sensing and affecting the physical environment, IoT incorporates sensors and actuators with unique identification, enabling ubiquitous information sharing and control. In practical terms, IoT involves the integration of components, such as sensors and smart devices, which facilitate remote management in a wide range of applications, from agriculture to weather monitoring.
[91]	Message Queuing Telemetry Transport (MQTT)	A reliable messaging standard for IoT, MQTT ensures the delivery of messages to intended recipients, even in unreliable network connections. It facilitates bidirectional communication between clients and servers.
[91]	Hypertext Transfer Protocol (HTTP)	HTTP is a standardized protocol for web communication enabling interaction between user devices, including smartphones, tablets, or personal computers, allowing access to APIs and facilitating real-time data transfer.
[92]	Arduino IDE	An open-source platform for developing IoT projects, Arduino offers a wide range of libraries and tutorials, making it accessible for beginners to initiate IoT projects.

Table 7. *Cont.*

Paper	Terminology	Definition
[85]	Radio Frequency Identification (RFID)	RFID is a contactless technology that automates the identification of objects, animals, and individuals through a transponder, commonly referred to as a tag. Particularly relevant in perishable food supply chain traceability systems, this technology employs tags to store data. RFID readers subsequently capture tag data, facilitating its transfer to backend databases, allowing remote access for monitoring object parameters.
[93,94]	Smart farming	Smart Farming constitutes a network of devices equipped with sensors and actuators, such as temperature, humidity, and soil moisture sensors, and motors and variable-rate sprayers. These devices collectively generate time-series data, which are subsequently transmitted to a remote application. The application optimizes agricultural processes by analyzing and utilizing the reported data.
[79,95]	LoRaWAN	LoRaWAN provides a long-range communication system with low power consumption. This technology employs chirp spread spectrum modulation, which involves a sinusoidal signal with linear variation across a specified bandwidth, producing a chirp. The advantages of this modulation technique include prolonged battery life and extended-range transmission, albeit at the cost of a reduced data rate.
[79]	Arduino UNO	The Arduino UNO is an open-source microcontroller board based on the Microchip Atmeg 328P microcontroller and developed by Arduino.cc. This board features a range of digital and analog input/output pins that can be interfaced with various expansion boards and circuits.
[96]	ESP32	ESP32 is a series of low-cost, low-power microcontrollers with Wi-Fi and Bluetooth capabilities and a highly integrated structure, powered by a dual-core Tensilica Xtensa LX6 microprocessor.
[97]	Raspberry Pi	Raspberry Pi 4B is an open development platform with strong processor performance and supports for edge computing. Additionally, it supports high-level language programming, which can reduce development costs.

Table 8. Definitions pertinent to agriculture emphasized in the studies.

Paper	Terminology	Definition
[72,82,98–103]	Precision Agriculture	Precision agriculture (PA) employs advanced data technology for optimal crop production. It involves precise crop identification, performance monitoring, machinery use, and variable application of fertilizers, herbicides, and insecticides. PA is a science and tech-driven farm management approach enhancing crop production efficiency.
[93,104]	Greenhouse	A greenhouse is a controlled environment facilitating enhanced and year-round crop yields. Its enclosed structure protects plants from adverse weather, allowing cultivation of various crops, including exotic species. This indoor farm, constructed with transparent materials, maintains a monitored micro-climate, ensuring optimal conditions for plant growth while preventing insect attacks and agricultural damage, thereby reducing human–animal conflicts.
[98,105]	Irrigation	Irrigation is the artificial method of distributing water to farm fields to facilitate the cultivation and growth of crops.
[106,107]	Aquaculture	Aquaculture is the comprehensive practice involving the cultivation and nurturing of aquatic organisms, including fish, crabs, plants, and algae. It encompasses a range of activities, knowledge, and methodologies for the breeding and cultivation of aquatic plants and various animal species.
[90,108,109]	Hydroponics	Hydroponics is a soil-less cultivation method where plants thrive in a nutrient-rich water solution, allowing for agricultural practices in regions with inadequate soil conditions.

Table 8. *Cont.*

Paper	Terminology	Definition
[110,111]	Aquaponics	Aquaponics is an integrated food production technique combining aquaculture (cultivating aquatic animals in a designated water tank) and hydroponics (cultivating soil-less plants with water). In this system, nutrient-rich water, containing bacteria for waste conversion, is supplied to hydroponic plants. Aquaculture involves breeding aquatic plants and animals through diverse methodologies and techniques.
[112]	Relative Humidity	Relative humidity is the proportion of moisture in the air compared to its saturation capacity at a specific temperature. This occurs as water exists in the atmosphere as imperceptible water vapor, commonly referred to as humidity.
[113]	Climate	Climate refers to the prolonged average of weather conditions. It encompasses various meteorological factors including temperature, humidity, rainfall, sunlight duration, air pressure, and wind.
[79,114]	Soil Fertility	Soil fertility denotes the concentration of essential nutrients crucial for plant growth within the soil. The growth of plants is intricately tied to the soil fertility status.

5. Discussion

In this section, we discuss agricultural applications, IoT components, AI/ML algorithms, the impact of IoT and AI/ML, both their strengths and weaknesses, and future directions.

5.1. Agricultural Applications

Here, we focus on agricultural applications, specifically, crop production, animal husbandry, aquaculture, hydroponics, aquaponics, and other variants of agricultural practices.

5.1.1. Forms of Agriculture

In response to research question GQ1 shown in Table 5, the synthesis reveals a diverse landscape of research, identifying various forms of agriculture, as shown in Figure 11.

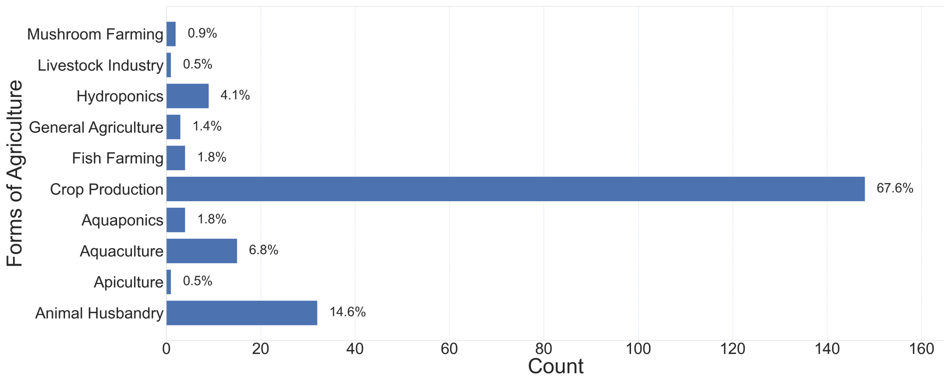

Figure 11. Forms of agriculture. bar chart showing the forms of agriculture found in the synthesis.

Crop Production

Crop production stands out as the most extensively explored domain within the intersection of IoT and AI/ML. The literature reveals a broad spectrum of applications ranging from predictive modeling for yield optimization to disease detection and irrigation management. A notable trend is the integration of advanced technologies like machine learning algorithms, deep neural networks, and edge computing into PA. This implies a concerted effort toward leveraging data-driven insights for sustainable and efficient crop production.

Some studies [115–117] focus on the prediction of crop yield using machine learning techniques. These models often incorporate diverse data sources, including climate data, soil conditions, and historical yield data. This suggests a move towards comprehensive, data-driven decision-making in agriculture. IoT-enabled smart irrigation systems [118–120] are another significant trend in crop production. These systems utilize sensors to monitor soil moisture levels and climate conditions, enabling precise and automated irrigation. This not only contributes to water conservation, but also enhances crop yield and quality.

Many studies have investigated other aspects of crop production, including disease prediction [100,104,116,121], yield prediction [122], pest control [71,123], and crop quality assessment/improvement [124]. However, there remain research gaps for future studies. Future research should investigate cost-effective and farmer-friendly technologies with attention to socio-cultural concerns to enhance their adoption, especially by smallholder farmers. There is also a research gap with crop-specific environment-specific solutions; for instance, disease detection systems built for tea plants may not be applicable to cacao or coffee plant disease detection, and a solar-powered plant monitoring system developed for temperate areas may not work well in other places around the world because of poor sunlight or battery intolerance for extreme atmospheric temperature. Future research should seek to address crop-specific and/or environment-specific challenges for optimum resource utilization and yield enhancement.

Animal Husbandry

Animal husbandry, although a smaller category compared to crop production, demonstrates a growing interest in using IoT and AI/ML for the welfare and productivity of livestock. Key themes include health monitoring, behavior analysis, and tracking systems.

The development of health monitoring systems for livestock [125–127] using wearable devices and sensors is a prominent area of research. These systems aim to provide real-time health status information, enabling early detection of diseases and ensuring timely intervention. IoT-based tracking systems for cattle and pigs [110,115,126] are contributing to efficient herd/swine management. This involves monitoring the location, activity, and behavior of animals, which is crucial for disease detection/control, breeding programs, and overall farm productivity.

While these works provide insights into livestock monitoring, a research gap exists in terms of the holistic integration of animal welfare, health, and productivity, and the scalability of these systems to accommodate large-scale farming operations. Another research gap is the limited focus on the ethical considerations and societal implications of implementing IoT and AI/ML in animal husbandry. Additionally, more attention needs to be given to the development of user-friendly and non-invasive technologies to ensure widespread adoption by farmers.

Aquaculture

The literature shows that aquaculture is another domain which reflects a keen interest in optimizing water quality, monitoring fish health, and enhancing overall aquaculture management by utilizing IoT and AI/ML.

Digital twin-based intelligent fish farming [128] and two-mode underwater smart sensor objects [129] exemplify the innovative use of IoT and AI/ML in aquaculture. These technologies contribute to real-time monitoring, early disease detection, and efficient resource management.

Despite advancements, a research gap is evident concerning the environmental impact of deploying IoT devices in aquatic ecosystems. These environmental factors include, but are not limited to, chemical pollution and radiation exposure. Additionally, there is room for more studies addressing the socio-economic aspects of adopting these technologies in diverse global aquaculture settings. Furthermore, more studies focusing on IoT and AI/ML for aquaculture will provide diverse perspectives for a holistic discussion, which are currently not available because of the limited number of studies.

Hydroponics and Aquaponics

Hydroponics and aquaponics represent interesting areas, for example, of soil-less cultivation methods, which are characterized by precise nutrient management and offer potential solutions for sustainable urban agriculture. Studies such as [92,130] highlight the role of IoT in monitoring and controlling hydroponic systems. The use of machine learning for nutrient control and disease prediction in hydroponics [131,132] is particularly noteworthy. However, research gaps include the need for more standardized protocols for integrating IoT devices into hydroponic and aquaponic systems. Additionally, there is room for studies examining the scalability and economic feasibility of these technologies for broader adoption.

Other forms of Agriculture

While other forms of agriculture (fish farming, mushroom farming, apiculture, and general agriculture), as shown in Figure 11, have fewer representations in the literature, they signify emerging areas of interest. General agriculture applications span across diverse practices, indicating the versatility of IoT and AI/ML solutions. For instance, studies like [133,134] address the challenges that transcend particular forms of agriculture with IoT and AI/ML.

Fish farming and livestock industries show growth potential, with studies focusing on aspects like predictive modeling for fish disease [135]. Mushroom farming [66,136] and apiculture [137], although less explored, showcase the applicability of these technologies in diverse agricultural domains.

The limited number of studies categorized under general agriculture [119,138] suggests a need for more research that transcends specific forms of agriculture. Further research could explore cross-disciplinary approaches that integrate multiple forms of agriculture, addressing overarching challenges in the agriculture sector. Mushroom farming and apiculture also have a limited number of studies; there is a need for interdisciplinary studies, socio-economic evaluations, and scalable implementations to facilitate the widespread adoption of these technologies in diverse agricultural practices.

5.1.2. Stages of Agriculture

Growth Stage

The growth stage of agriculture is crucial for maximizing crop yield and ensuring optimal plant health. Figure 12 shows the distribution of agricultural stages, and Figure 13 shows the stages of agriculture across the forms of agriculture found in the synthesis. A significant portion of the synthesized literature focuses on employing IoT and AI/ML techniques to enhance various aspects of crop growth management. These include precision irrigation systems [139], soil nutrient analysis [140], pest monitoring and control [141], and disease detection [104]. However, there remains a notable research gap in addressing the specific needs of different crops and environmental conditions. While some studies concentrate on specific crops such as tea plants [100] or grapevines [139], there is a lack of comprehensive research covering a wide range of crops and cultivation methods.

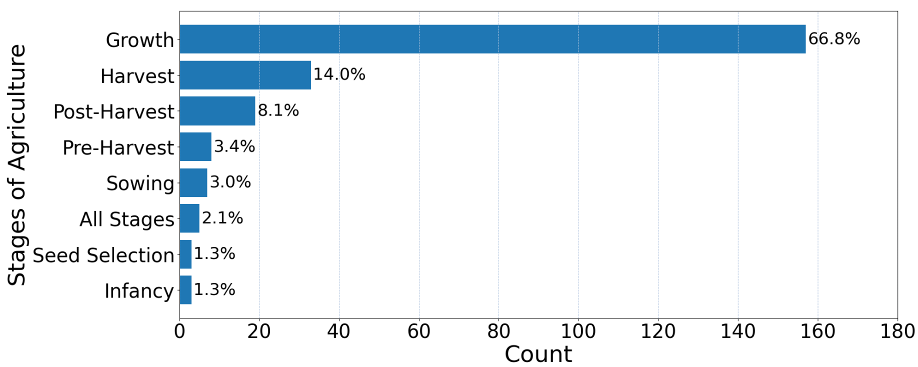

Figure 12. Distribution of agricultural stages.

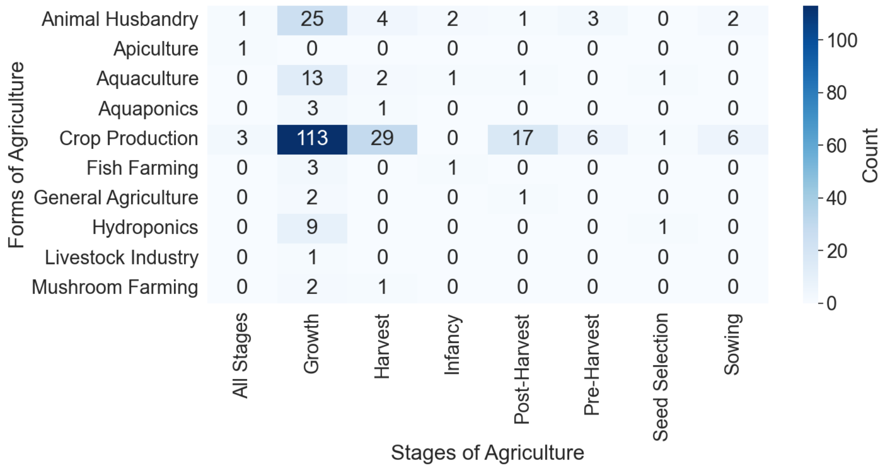

Figure 13. Stages of agriculture across the forms of agriculture.

Moreover, while many solutions focus on monitoring and data collection during the growth stage, there is a need for more studies that leverage AI/ML algorithms for proactive decision-making and intervention. For instance, predictive models for optimal planting times, fertilizer application rates, and crop rotation strategies could significantly benefit farmers during the growth stage.

Harvest Stage

Efficient harvesting is critical for maximizing crop yield and minimizing losses. However, the literature synthesis reveals a relatively smaller number of studies addressing the harvest stage compared to the growth stage. While some research, such as [139], focuses on predicting harvest times based on IoT data and AI algorithms, there is a notable lack of comprehensive solutions for optimizing harvesting processes across different crops and farming environments.

One potential research gap lies in the development of automated harvesting systems tailored to specific crops. While some studies explore autonomous harvesting robots for crops like soybeans [142] or pitayas [118], there is room for further research into the scalability and adaptability of such systems to various agricultural contexts.

Post-harvest Stage

The post-harvest stage of agriculture encompasses activities such as processing, storage, and distribution of harvested crops. While several studies in the synthesized literature focus on post-harvest technologies, such as [85]'s RFID-based traceability system or [143]'s IoT-based smart farming solution, there remains a need for more comprehensive approaches.

One significant research gap pertains to the development of intelligent sorting and grading systems for harvested produce. While some studies, such as [142], mention machine learning algorithms for quality assessment, there is limited research on integrating these systems into large-scale processing facilities to optimize sorting efficiency and reduce food waste.

There is potential for IoT and AI/ML technologies to improve supply chain logistics and cold chain management in the post-harvest stage. Solutions that provide real-time tracking of perishable goods [144] and predictive analytics for demand forecasting could help streamline distribution processes and minimize losses.

Furthermore, there is a need for more crop-specific and geography-specific research on post-harvest handling and storage techniques to prolong the shelf life of harvested produce. Solutions integrating IoT sensors for real-time monitoring of temperature, humidity, and gas levels in storage facilities could help mitigate post-harvest losses and maintain product quality.

Pre-harvest Stage

The pre-harvest stage involves preparatory activities such as land preparation, planting, and crop maintenance before harvesting. While there are fewer studies focused explicitly on the pre-harvest stage [77,145–148] compared to the growth and post-harvest stages, several key areas warrant attention.

One notable research gap is the lack of comprehensive solutions for pest and disease prediction and management during the pre-harvest stage. While some studies, such as [148], mention object detection algorithms for pest tracking, there is a need for more advanced predictive models that can anticipate pest outbreaks based on environmental conditions and crop health data.

Research into sustainable farming practices and resource management techniques could help optimize crop yield and minimize environmental impact during the pre-harvest stage. Solutions integrating IoT sensors for soil moisture monitoring [120] and AI/ML algorithms for optimal irrigation scheduling could contribute to more efficient water usage and nutrient management.

Sowing Stage

The sowing stage marks the beginning of the agricultural cycle and involves activities such as seed selection, planting, and early crop establishment. Since fewer studies explicitly address the sowing stage, there are significant opportunities for innovation.

One research gap in the sowing stage pertains to the development of precision planting technologies that optimize seed placement and spacing for different crops and soil conditions. While some studies, such as [108], mention IoT-based systems for seed selection and planting, there is a need for more research into advanced planting techniques, such as variable rate seeding and seed treatment technologies.

Additionally, there is potential for leveraging AI/ML algorithms to enhance decision-making during the sowing stage, such as predicting optimal planting times based on weather forecasts and soil conditions. Solutions that integrate IoT sensors with predictive models for seed germination and early plant growth could help farmers optimize planting strategies and improve crop establishment.

Seed Selection Stage

The seed selection stage is fundamental to ensuring crop success and involves choosing high-quality seeds with desirable traits for planting. While this stage is often overlooked in the synthesized literature, there are emerging technologies that could revolutionize seed selection processes. One potential research area is the development of AI-driven seed sorting and quality assessment systems that can analyze seed characteristics such as size, shape, and genetic composition. Solutions integrating machine learning algorithms with non-destructive imaging techniques could help streamline seed selection processes and ensure uniform crop establishment. Combining both IoT sensors and data analytics to track seed performance and monitor crop development throughout the growing season will provide real-time insights into seed viability, germination rates, and early plant growth, which can help farmers make informed decisions and optimize crop yield.

Infancy Stage

The infancy stage of agriculture refers to the initial stages of crop or livestock development, where plants are germinating or animals are in the early stages of growth. While this stage is essential for establishing a healthy crop or livestock population, there is limited research focusing specifically on infancy-stage technologies.

One significant research gap is the lack of comprehensive solutions for monitoring and managing crop or livestock health during the infancy stage. While some studies, such as [104], mention AI-driven systems for disease detection, there is a need for more research into early warning systems that can identify health issues, with a special focus on the infancy stage, before they escalate.

Using IoT technologies, moreover, to monitor environmental conditions and optimize growth parameters during the infancy stage will be a good solution. Integrating sensors for monitoring temperature, humidity, air quality, soil parameters, and animal body parameters and behavior could help create optimal conditions for crop germination and animal development, ultimately improving overall productivity.

All Stages

While many studies focus on specific stages of agriculture, there is growing recognition of the importance of integrated approaches that are stage-agnostic or address the entire agricultural cycle by using IoT and AI/ML technologies.

One research area with significant potential is the development of digital twins or comprehensive modeling frameworks that simulate agricultural systems and optimize resource allocation and management strategies. By integrating real-time data from IoT sensors with predictive analytics and simulation models, farmers can make more informed decisions and improve overall farm productivity.

There is a need for more research into scalable and interoperable IoT platforms that can integrate data from diverse sources and enable seamless communication between different agricultural systems. Solutions that leverage standards-based protocols and open architectures could help overcome interoperability challenges and facilitate the adoption of IoT technologies across the agricultural sector.

In conclusion, the synthesized literature highlights various opportunities and challenges across different stages of agriculture, from seed selection to post-harvest processing. While there has been significant progress with IoT and AI/ML technologies to enhance specific aspects of agricultural production, there remain several research gaps and opportunities for innovation.

Key areas for future research include the development of integrated solutions that address the entire agricultural cycle, from pre-harvest planning to post-harvest management. Additionally, there is a need for more comprehensive approaches that consider the specific needs of different stages of agriculture for specific forms of agriculture, farming environments, and stakeholders. By bridging these research gaps and fostering interdisciplinary collaboration between researchers, practitioners, and policymakers, we can unlock the full potential of IoT and AI/ML technologies to create more sustainable, efficient, and resilient agricultural systems.

5.1.3. Agricultural Practices and Challenges Addressed

In response to research question GQ3 shown in Table 5, agricultural practices and challenges identified by the synthesis include a wide array of issues that are vital for the sustenance and advancement of global food security and agricultural productivity. The diverse range of topics covered highlights the multidimensional nature of modern agriculture and the pressing need for innovative solutions to address emerging challenges. In this section, we delve into key themes, examining works addressing similar agricultural practices and challenges while identifying unaddressed research gaps.

Automation and Monitoring in Agriculture

Automation and monitoring technologies have garnered significant attention in recent years, offering promising solutions to enhance efficiency and productivity in agricultural practices [109,149,150]. These technologies, ranging from autonomous mobile platforms to sensor fusion systems, hold immense potential to revolutionize traditional farming methods by enabling real-time data collection, analysis, and decision-making.

One observation is the challenge of integrating these advanced technologies into existing farming systems, particularly among smallholder farmers who may lack the resources or technical expertise [111]. Another observation is the high initial cost of implementing automation and monitoring systems, which may limit adoption among resource-constrained farmers [134,151]. Additionally, there are concerns about data privacy and ownership, especially when utilizing IoT devices that collect sensitive agricultural data [84,151].

There is an opportunity to develop inclusive and user-friendly technologies tailored to the needs of smallholder farmers, incorporating participatory design principles to ensure usability and relevance [152,153]. Research efforts should focus on developing cost-effective automation and monitoring solutions that leverage low-cost hardware and open-source software platforms [144,151,154–156]. Addressing data privacy concerns requires the development of robust policy and governance frameworks that safeguard farmers' rights and ensure responsible data stewardship [85,151].

Soil Health and Nutrient Management

Soil degradation and nutrient depletion pose significant challenges to agricultural productivity. Maintaining soil health and managing nutrient levels are fundamental aspects of sustainable agriculture [108,114]. The trend of soil degradation and nutrient loss due to intensive farming practices, erosion, and deforestation is alarming [114,157]. There are significant knowledge gaps about the long-term impacts of soil degradation on ecosystem services, biodiversity, and human health [157]. Research efforts should prioritize ecosystem-based approaches to soil health management, integrating agroecological principles and indigenous knowledge systems. Long-term monitoring studies are needed to assess the effectiveness of soil conservation practices and nutrient management strategies in mitigating soil degradation. Understanding farmers' decision-making processes and behavioral drivers can inform the design of targeted interventions to promote sustainable soil management practices.

Crop Disease Detection and Management

Effective disease detection and management strategies are crucial for mitigating crop losses and ensuring food security [158]. Advances in AI-powered IoT devices and predictive analytics have shown promise in early disease detection and prevention [119,145,159]. However, many smallholder farmers lack access to affordable and reliable disease monitoring tools and extension services, hindering timely disease detection and response [152]. Similarly, there is an abundance of agricultural data available from remote sensing, satellite imagery, and weather forecasts, yet these data sources are underutilized for disease surveillance and forecasting [83,128,160].

Developing early warning systems for crop diseases using machine learning algorithms and remote sensing data can enable proactive disease management and reduce crop losses. Research efforts should focus on integrating disparate data sources and developing interoperable platforms for sharing disease surveillance data among stakeholders, including farmers, researchers, and policymakers.

Water Management and Irrigation Efficiency

Water scarcity and inefficient irrigation practices present significant challenges to agricultural sustainability [150,161–164]. Precision irrigation systems and AI algorithms offer potential solutions to optimize water usage and improve crop yield. However, inadequate water governance frameworks and competing water demands from urbanization, industry, and ecosystem services exacerbate challenges in agricultural water management [150,158].

Developing climate-resilient irrigation strategies that incorporate weather forecasting, soil moisture monitoring, and crop water requirements [83,165] can enhance water use efficiency and resilience to climate variability. Addressing social equity considerations in water allocation and irrigation planning may ensure equitable access to water resources and minimizing conflicts among water users [166].

Pest Control and Integrated Pest Management

Pest infestations pose a constant threat to crop production and food security [141,167]. IoT-based pest monitoring systems and predictive models can aid in early detection and intervention. One observation is the increasing prevalence of pesticide-resistant pests due to over-reliance on chemical pesticides, necessitating the development of integrated pest management (IPM) strategies [141]. Chemical pesticides harm target pests and disrupt beneficial insect populations, leading to imbalances in ecosystems and secondary pest outbreaks [168]. Successful pest management requires active engagement and collaboration among farmers, researchers, extension agents, and policymakers to implement IPM practices at the landscape level [168].

Research efforts should prioritize biological control methods such as natural enemies, biopesticides, and pheromone-based traps as sustainable alternatives to chemical pesticides [141]. Long-term ecological monitoring studies can elucidate the ecological impacts of pesticide use on non-target organisms and ecosystem services, informing the development of ecologically-based pest management strategies [168]. Understanding farmers' perceptions and behavioral incentives regarding pest management can inform the design of targeted extension programs and policy interventions to promote IPM adoption [141].

Smart Farming and Digital Agriculture

The adoption of smart farming technologies holds promise for optimizing agricultural processes and reducing resource inputs [96,98]. However, the digital divide and disparities in access to technology hinder widespread adoption, particularly among small-scale farmers. The unequal access to digital agriculture technologies, with marginalized farming communities often lacking the infrastructure, training, and support needed to adopt and benefit from these innovations [82,152,169]. Effective knowledge transfer mechanisms are essential for bridging the gap between technological innovation and on-the-ground application. Yet, extension services and training programs often fail to reach smallholder farmers in remote areas [152]. Data ownership, privacy, and governance questions remain unresolved, with concerns about corporate control of agricultural data and the exclusion of smallholder farmers from decision-making processes [170].

Engaging farmers as active participants in the co-design and co-development of digital agriculture technologies can ensure that solutions are contextually appropriate, user-friendly, and socially inclusive. Investing in capacity-building programs that provide training in digital literacy, data management, and technology adoption can empower smallholder farmers to harness the benefits of digital agriculture. Developing innovative policy frameworks that promote data sovereignty, open access to agricultural data, and equitable distribution of benefits can foster a more inclusive and democratic digital agriculture ecosystem [170].

In conclusion, while significant progress has been made in addressing various agricultural practices and challenges, several research gaps remain unaddressed. These include the need for interdisciplinary studies that consider the socio-economic, environmental, and ethical dimensions of agricultural innovation and the imperative to prioritize inclusivity and equity in technology adoption. Future research efforts should aim to bridge these gaps and develop holistic and focused solutions that promote sustainable and resilient agricultural systems.

5.2. IoT Components

IoT systems typically comprise of several components, each with specific functions. **In response to research question GQ2 shown in Table 5, Figure 14 shows IoT components found in the synthesis. We discuss the IoT components in four groups: (1) monitoring and control components, (2) computation components, (3) communication components, and (4) reporting components.**

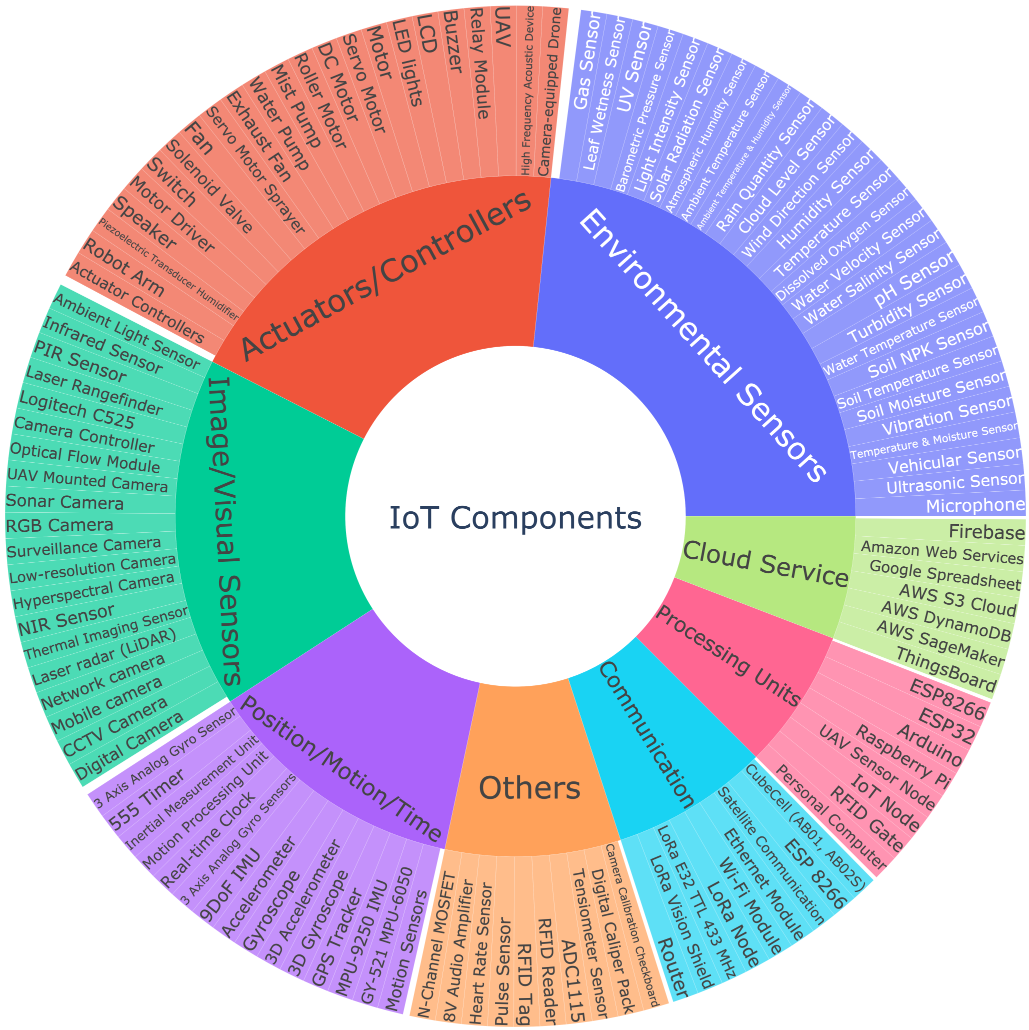

Figure 14. IoT Components found in the synthesis.

5.2.1. Monitoring and Control Components

The Monitoring and Control Components (MCC) in agriculture represent a cornerstone of modern farming practices, offering opportunities for optimization, sustainability, and resilience. This discussion delves deeper into research opportunities surrounding MCC configurations, with a focus on integratability and configurability, non-destructive monitoring, natural event-inspired controls, long-term environmental effects, and simulation systems for AI/ML development.

Integratable and configurable components within MCC systems present a promising avenue for innovation [171]. Designing components that can be easily modified to remove, add, or replace with others not only enhances system flexibility, but also enables cost-effective customization to meet the specific needs of different agricultural contexts. Future research could explore modular sensor designs, standardized interfaces, and plug-and-play functionality to streamline component integration and enhance system scalability.

Non-destructive and non-intrusive monitoring technologies offer significant advantages in agricultural applications, particularly in remote sensing and animal welfare monitoring [127,144]. For instance, remote soil parameter monitoring using satellite imagery or IoT sensors eliminates the need for invasive soil sampling, reducing labor costs and minimizing environmental disruption. Similarly, non-contact animal body parameter monitoring, such as thermal imaging or RFID-based tracking, enables real-time health monitoring without causing stress or discomfort to the animals. Further research could focus on advancing remote sensing technologies, improving data accuracy and resolution, and integrating multimodal sensing approaches for comprehensive monitoring.

Controls that mimic natural events present an intriguing concept for enhancing agricultural sustainability and ecosystem resilience [172,173]. For example, IoT irrigation systems could emulate natural rainfall patterns by delivering water in a manner that replicates the cooling effect of rainwater and promotes soil health while minimizing water wastage. Investigating the feasibility and effectiveness of such nature-inspired control strategies requires interdisciplinary collaboration between agronomists, engineers, and environmental scientists. Future research directions may involve the development of adaptive control algorithms based on environmental feedback and predictive modeling of natural processes.

Long-term environmental and ecological effects of MCC interventions warrant thorough investigation to ensure sustainable agricultural practices [174]. Excessive disease control measures, for instance, may inadvertently disrupt natural ecosystem balances and compromise plant immunity over time. Longitudinal studies are needed to assess the ecological impacts of MCC technologies on soil health, biodiversity, and ecosystem services. Furthermore, integrated modeling approaches, such as life cycle assessments and ecosystem services valuation, can provide insights into the broader environmental implications of MCC interventions and guide decision-making towards more sustainable farming practices.

Simulation systems offer a valuable tool for accelerating the development and testing of IoT systems powered by AI/ML algorithms [175,176]. By simulating various environmental scenarios and deployment conditions, researchers can generate synthetic data to train and validate AI/ML models without the need for extensive field trials. Simulation-based approaches not only reduce time and cost constraints but also enable researchers to explore a wider range of scenarios and optimize system performance before real-world deployment. Future research may focus on developing advanced simulation frameworks tailored to agricultural applications, integrating realistic environmental models and sensor data generation capabilities to facilitate AI/ML model development and optimization.

In conclusion, research opportunities abound in advancing MCC technologies towards greater integrability, non-destructive monitoring, nature-inspired controls, environmental sustainability, and simulation-based AI/ML development. Addressing these challenges requires interdisciplinary collaboration, innovative engineering solutions, and a holistic understanding of agricultural systems and environmental dynamics. By embracing these opportunities, researchers can contribute to the development of more efficient, sustainable, and resilient agricultural practices to meet the growing demands of global food security and environmental stewardship.

5.2.2. Computation Components

In the synthesis, a spectrum of computation components was identified across various studies, pivotal in facilitating the implementation of intelligent systems for PA. Grouping works based on similar computation components provides valuable insights into trends and advancements in this domain. Table 9 illustrates the computation components utilized in research, encompassing microcontroller boards, single-chip computers, Graphics Processing Units (GPUs)/Tensor Processing Units (TPUs), conventional computers, and cloud services.

Microcontroller boards, often used as edge devices, such as Arduino Uno, ESP8266, ESP32, and ATMega, emerged prominently in several studies. These microcontrollers find applicability in deployment closest to the point of observation or control, namely, in proximity to sensors and actuators. Certain studies employ these microcontrollers for executing AI/ML models or substantial computations. For instance, Ref. [177] employed the Arduino Portenta H7 board in their investigation of a smart sensor for energy-saving in IoT PA. Similarly, studies by [131,178–183] utilized Raspberry Pi and [94,106,134,158,184,185] employed Arduino. The authors of [186] proposed SEPARATE, a tightly coupled IoT infrastructure for deploying AI algorithms in smart agriculture environments, leveraging edge computing to enhance efficiency and responsiveness. These microcontrollers furnish a cost-effective and flexible platform for data acquisition, processing, and control in agricultural applications. Edge computing emerges as a promising approach for processing data nearer to the source, thereby reducing latency and bandwidth requirements.

Single-chip computers, commonly deployed as fog computing, are also prevalent in many synthesized studies. Despite the myriad advantages of microcontroller boards, they often furnish limited computation and storage resources. These single-chip computers provide greater computation and storage resources, albeit at a higher monetary cost and/or physical footprint, rendering them suitable for central devices that aggregate resources for multiple microcontroller units. For example, Ref. [187] utilized ESP8266 NodeMCU for developing an IoT and ML-based optimized smart irrigation system. Similarly, studies by [73,74,81,188,189] employed ESP8266 and [92,96,136,166,190,191] utilized ESP32. Deploying AI/ML models in the fog positions the processing near the edge but with fewer resources compared to the cloud.

Table 9. Computation components found in the literature.

	Components
Microcontroller Board	Arduino Uno, Arduino Portenta H7, Raspberry Pi, Raspberry Pi Zero W, Raspberry Pi 3, Raspberry Pi 4, ATmega328p, ARM Cortex-M4, STM32F103-ARM, ATSAMD51, ATmega16, NodeMCU, ATMega328pb, ATmega1281, Wio Terminal
Single-chip Computer	ESP32, ESP8266, NVIDIA Jetson Nano, NVIDIA Jetson AGX Orin, Jetson Nano, ASUS Mini PC PB60G
GPU/TPU	NVIDIA GeForce (RTX 2060 SUPER, RTX 2080, GTX 1070), NVIDIA K80, NVIDIA Titan, Google Coral Edge TPU
Computer	Personal Computer, Server, High-Performance Computing Server, Industrial PC, Host Computer
Cloud Service	Firebase, Amazon Web Services (SageMaker), Heroku, Google Cloud Platform, Google Colab, Google Sheets, MATLAB ThingSpeak, Azure IoT, Alibaba Cloud, Blynk, Dropbox, Cenote platform, Adafruit IO

Personal computers and servers are also recurrently encountered in the literature, either on-site or remotely. These computing devices, bolstered by GPUs and TPUs, extend computational capabilities, as evidenced in numerous studies. However, the setup and maintenance of such systems demand a diverse range of expertise, limiting their accessibility to all researchers. Cloud servers and platforms are extensively harnessed in the literature for data storage, processing, and analysis in IoT-enabled agriculture, offering scalability, accessibility, and computational prowess for real-time decision-making and analytics for farmers and stakeholders.

In conclusion, the synthesis of the literature underscores the diverse computation components employed in IoT-enabled agriculture, encompassing microcontrollers, cloud servers, edge computing, and machine learning algorithms. These components collectively drive the development of intelligent farming systems, empowering farmers to make informed decisions, optimize resource utilization, and enhance agricultural sustainability. Future research endeavors should focus on fortifying the robustness of edge devices for computation, considering their deployment in harsh environmental conditions. Additionally, there is a need for the development of more miniaturized and cost-effective edge and fog devices, alongside augmenting the computational and storage resources available on these devices.

5.2.3. Communication Components

The synthesis reveals a diverse range of communication components utilized across various studies. These components play a pivotal role in enabling data transmission, connectivity, and networking in agricultural IoT systems. Grouping works based on similar communication components provides insights into the prevalent trends and technologies shaping the implementation of intelligent farming solutions.

Wi-Fi Modules

A significant number of studies have utilized Wi-Fi modules, such as ESP8266 and ESP32, for wireless communication in agricultural IoT applications. Wi-Fi modules offer reliable connectivity and facilitate data exchange between sensors, actuators, and central processing units. For example, the authors of [83,192] utilized ESP8266 Wi-Fi modules in their smart farming systems, enabling remote monitoring and control of agricultural processes. Wi-Fi modules have gained popularity due to their ease of integration, cost-effectiveness, and compatibility with existing infrastructure. Moreover, Wi-Fi technology provides sufficient bandwidth for transmitting data from sensors deployed across vast agricultural fields.

LoRa (Long-Range) Modules

Several studies have employed LoRa modules for long-range communication in agricultural IoT deployments. LoRa technology offers low-power, long-distance data transmission capabilities, making it suitable for remote monitoring and control in rural areas. Authors utilized LoRa modules for applications such as climate change prediction [188], smart gardening [79,193], water quality monitoring [184], edge-computing flow meter reading [155], and soil moisture monitoring [167]. LoRa modules enable reliable communication over extended distances, overcoming challenges posed by limited cellular coverage in remote agricultural regions. Additionally, LoRa-based solutions are cost-effective and scalable, making them ideal for large-scale deployment in PA.

GSM/GPRS Modules

GSM/GPRS modules have been widely utilized for cellular communication in agricultural IoT systems. These modules enable remote monitoring and control via cellular networks, even in areas with limited Wi-Fi coverage. Authors [191,194] leveraged GSM modules for applications such as crop yield prediction and smart irrigation management. GSM/GPRS technology provides ubiquitous coverage and reliable connectivity, allowing farmers to remotely monitor field conditions and optimize resource usage. Furthermore, GSM-based solutions offer real-time data transmission, enabling timely decision-making and interventions in agricultural operations.

Bluetooth Modules

Bluetooth modules have found applications in short-range communication within agricultural IoT networks. These modules facilitate wireless connectivity between sensors, actuators, and mobile devices, enabling data exchange and control in close proximity. Authors [82,168] utilized Bluetooth Low Energy (BLE) modules for applications such as visual sensor nodes and climate data monitoring. Bluetooth technology offers low-power consumption and compatibility with mobile devices, making it suitable for IoT applications requiring local connectivity and interoperability.

ZigBee Modules

ZigBee modules have been deployed for low-power, short-range communication in agricultural sensor networks. These modules are well-suited for applications requiring energy-efficient wireless connectivity, such as environmental monitoring and precision agriculture. Authors such as [137,163] utilized ZigBee modules for farmland monitoring and bee health monitoring. ZigBee technology enables robust communication in challenging agricultural environments, where factors such as interference and power constraints may affect wireless connectivity. Additionally, ZigBee-based solutions offer mesh networking capabilities, enhancing reliability and coverage in large-scale deployments.

NB-IoT Modules

NB-IoT modules have emerged as a promising communication technology for agricultural IoT applications. These modules offer low-power, wide-area coverage, making them suitable for remote monitoring and control in agriculture. Authors [97] utilized NB-IoT modules for AIoT platform design, enabling efficient connectivity and data exchange in smart agricultural systems. NB-IoT technology provides enhanced coverage and penetration compared to traditional cellular networks, allowing farmers to monitor field conditions in remote or underground locations. Moreover, NB-IoT-based solutions offer long battery life and support for massive IoT deployments, facilitating scalability and cost-effectiveness.

The synthesis of the literature highlights the diverse range of communication components utilized in IoT-enabled agriculture, each offering unique advantages in terms of range, power consumption, and scalability. The selection of communication technologies depends on factors such as deployment environment, coverage requirements, and power constraints, with each solution tailored to meet the specific needs of modern farming practices.

5.2.4. Reporting Components

In recent years, reporting tools such as the Blynk app, ThingSpeak platform, Google Colab, and Google Sheets have played pivotal roles in facilitating data visualization, analysis, and collaboration in agricultural IoT projects. These tools offer various features that enable researchers and practitioners to monitor, analyze, and share data efficiently, thereby enhancing decision-making processes and improving agricultural practices.

Several studies have utilized the Blynk app [194,195] to develop user-friendly interfaces for monitoring and controlling IoT devices in agriculture. The Blynk app provides a customizable dashboard that allows users to visualize sensor data in real time and remotely control connected devices, such as irrigation systems or environmental sensors. This capability enables farmers to monitor critical parameters, such as soil moisture levels or temperature, and take timely actions to optimize crop growth and resource utilization.

Similarly, the ThingSpeak platform [81,196] has emerged as a popular choice for IoT data logging and visualization in agricultural applications. With its cloud-based infrastructure and built-in MATLAB analytics, ThingSpeak enables researchers to collect, store, and analyze sensor data efficiently. Additionally, its integration with MATLAB allows for advanced data processing and visualization, making it a powerful tool for conducting predictive analytics and deriving actionable insights from agricultural IoT data.

Moreover, Google Colab [197,198] has gained traction as a collaborative platform for machine learning and data analysis tasks. Leveraging its integration with Google Drive and Jupyter Notebooks, Google Colab provides researchers with a flexible and scalable environment for running machine learning algorithms and experimenting with large datasets. This capability has been particularly valuable for developing predictive models and optimizing agricultural processes, such as crop yield prediction and disease detection.

Furthermore, Google Sheets [115,195] has been utilized for data management and collaboration in agricultural IoT projects. Its familiar spreadsheet interface and cloud-based storage make it accessible for researchers and stakeholders to organize, analyze, and share agricultural data seamlessly. Additionally, Google Sheet's integration with other Google services, such as Google Forms and Google Apps Script, enables automated data collection and workflow automation, streamlining data management tasks in agricultural research projects.

Overall, reporting tools such as the Blynk app, ThingSpeak platform, Google Colab, and Google Sheets play crucial roles in enhancing the effectiveness and efficiency of agricultural IoT projects. By providing intuitive interfaces, powerful analytics capabilities, and seamless collaboration features, these tools empower researchers and practitioners to harness the full potential of IoT technologies for sustainable agriculture and food production.

In conclusion, integrating reporting tools into agricultural IoT projects facilitates data visualization, analysis, and collaboration, thereby enabling stakeholders to make informed decisions and optimize agricultural processes. Moving forward, continued advancements in reporting tools and their integration with IoT technologies hold promise for addressing the complex challenges facing modern agriculture and promoting sustainable food systems.

5.3. AI/ML Algorithms

5.3.1. Types of Algorithms Used

In response to research question GQ5 shown in Table 5, Figure 15 shows various AI/ML algorithms utilized, ranging from classification to neural networks, image recognition models, regression models, and ensemble methods.

Machine learning algorithms and neural networks are integral aspects utilized for various tasks such as crop disease detection, yield prediction, and environmental monitoring. Authors such as [199,200] applied machine learning techniques for the early diagnosis of bovine respiratory disease and prediction of pesticide amounts and diseases in fruits, respectively. These algorithms enable predictive analytics and decision support systems, empowering farmers to optimize resource allocation and enhance crop productivity.

Machine Learning Methods

Supervised learning techniques, for instance, classification, characterized by their ability to learn from data and make predictions or decisions, have garnered significant attention in PA. In terms of crop production, Ref. [102] used random forest to classify rice growth stages, while [119] utilized classification models, namely SVM and KNN, to predict plant diseases. Both models show good results for each task. In addition, Ref. [89] utilized SVM and decision tree to detect the health of heart rate, body temperature, and the condition of cows. Authors [82], on the other hand, utilized random forest and SVM for classification and ensemble methods to enhance crop productivity in the presence of weeds.

Ensemble learning methods are powerful tools for analyzing agricultural data and extracting actionable insights. Ensemble learning techniques, such as random forest and Gradient Boosting, combine multiple base learners to improve predictive performance [201]. These algorithms have been successfully applied in tasks like crop disease classification and yield forecasting, where the aggregation of multiple models enhances robustness and accuracy.

Regression techniques are pivotal in analyzing agricultural data and making predictions about crop yields, soil characteristics, and weather patterns. Linear regression models, including Multiple Linear Regression, establish relationships between input variables such as weather parameters, soil moisture, and crop yields [202]. By fitting a linear equation to the data, these models provide insights into the factors influencing crop productivity and aid decision-making processes. Support Vector Regression (SVR) algorithms, a variant of SVMs, are adept at capturing non-linear relationships and have been applied to tasks such as soil moisture prediction and water management [82]. SVR maps input data to a high-dimensional feature space, enabling the identification of complex patterns and the generation of accurate predictions. Gaussian Process Regression, known for providing probabilistic predictions, is employed for tasks such as crop yield estimation and disease risk assessment [140]. By modeling uncertainty, Gaussian Process Regression enables farmers to make informed decisions under uncertain conditions and mitigate risks associated with agricultural production.

Unsupervised learning techniques, including K-means clustering, are employed for soil type classification and anomaly detection [157]. K-means clustering partitions datasets into distinct clusters based on similarity, facilitating the identification of soil variability within fields or anomalous conditions requiring attention.

Reinforcement learning algorithms, though less prevalent, hold promise for optimizing agricultural operations such as aquaculture monitoring [128]. This algorithm learns optimal decision-making policies through trial and error, interacting with the environment and receiving feedback to maximize rewards or minimize costs.

Deep Learning

Deep learning approaches, particularly convolutional neural networks (CNNs), have revolutionized image-based analysis in PA [203]. CNNs leverage hierarchical layers of convolutional filters to extract intricate features from agricultural images, enabling precise identification of pests, diseases, and nutrient deficiencies. Other deep learning architectures, including recurrent neural networks (RNNs) and Long Short-Term Memory (LSTM) networks, are also utilized for tasks like time-series forecasting and crop yield prediction [113,204]. Another work utilizes a hybrid of the neural network method and machine learning methods for detecting animal intrusion [189].

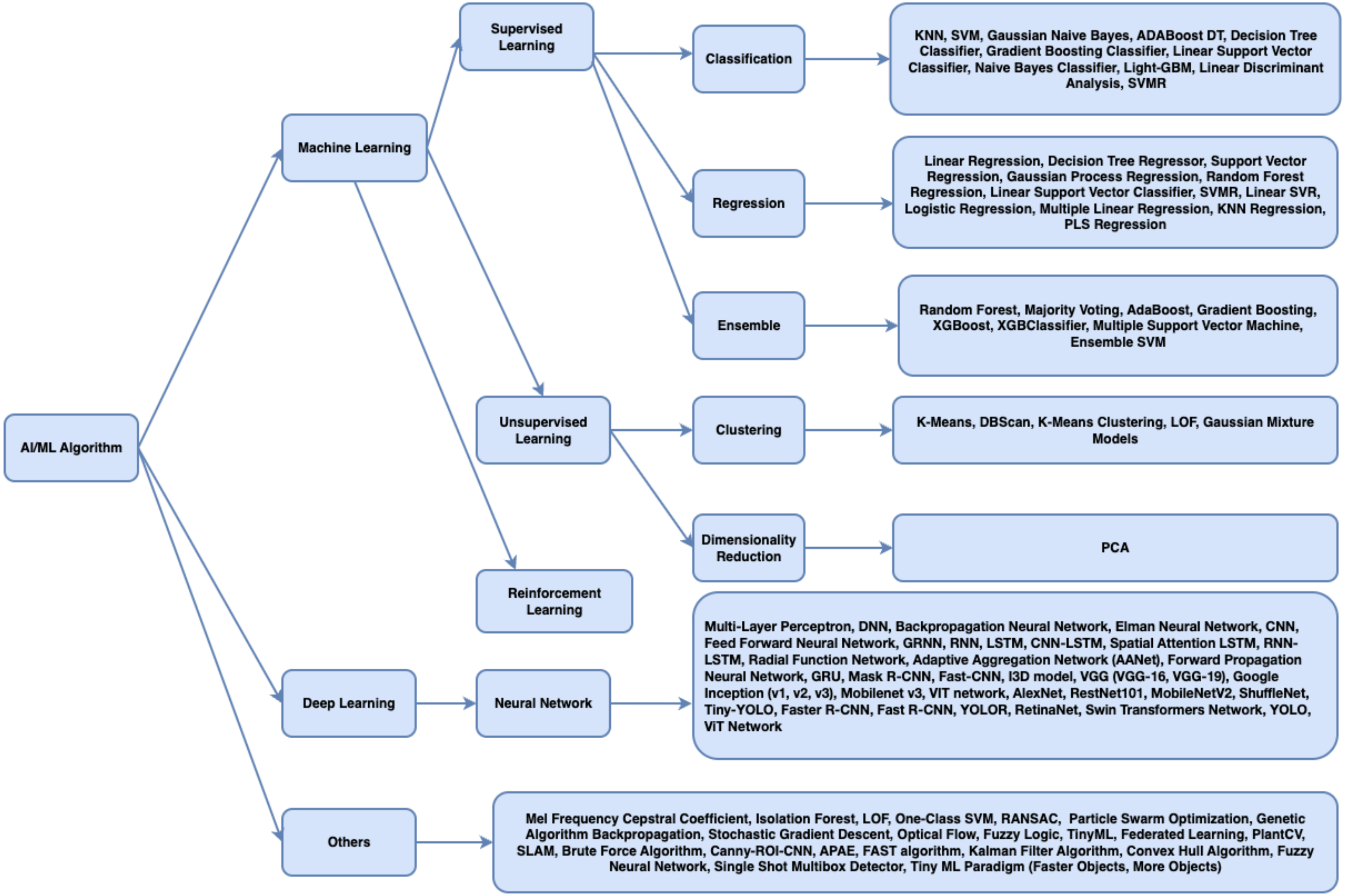

Figure 15. AI/ML algorithms found in the synthesis.

Some works use other algorithms, such as Ref. [205], which utilized MFCC to extract the spectogram of voice features and used a CNN to classify it. The PSO algorithm [206] demonstrated a good performance for optimizing the site selection of agricultural IoT nodes, reducing the wireless transmission loss and improving the communication quality. The Kalman filter algorithm [93] has a strong ability to handle the noisy environment with uncertainty and enable the monitoring of nodes with distinct physical characteristics. TinyML [177] deployed a machine learning model capable of detecting fruit presence with capabilities as an energy-efficient model.

In conclusion, adopting advanced algorithms in PA holds immense potential for optimizing agricultural practices, increasing productivity, and ensuring environmental sustainability. Machine learning algorithms and deep learning architectures are pivotal in processing and analyzing agricultural data, enabling farmers to make informed decisions and optimize resource allocation. As technology continues to evolve, leveraging a diverse range of algorithms tailored to the specific needs of PA will be essential for driving innovation and addressing the challenges facing the agricultural sector.

5.3.2. Kinds of Data Used

PA, driven by technological innovations, relies on a diverse array of data types to optimize farming practices and maximize crop yield. In this review, **we explore the various kinds of data utilized in PA and their applications in response to research question GQ4 shown in Table 5.** The synthesis reveals that six kinds of data were used, with varying frequencies: tabular data, time series data, and image data were the most used, while scalar data, statistical data, and audio data were the least used, as shown in Figure 16. Depending on the objectives of the research, different data types were employed. As the most prevalent, tabular data was used in instances including weather data, animal biometric data, atmospheric parameters [151], and soil data. Table 10 provides an overview of the data types with their descriptions and usage examples.

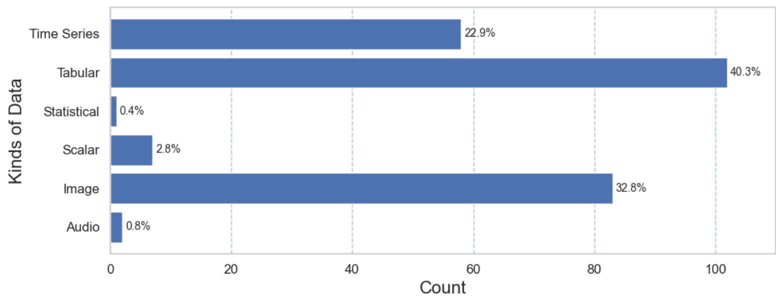

Figure 16. Bar chart showing the kinds of data found in the synthesis.

Tabular Data

Tabular data form the backbone of PA research, providing structured information essential for informed decision-making. With numerous papers leveraging tabular data, researchers analyze various agricultural parameters, including soil characteristics, weather patterns, and crop performance metrics. For instance, studies by [84,178] utilize tabular data to model and predict crop pest infestation levels and detect faults in plant leaf-turgor pressure wireless sensor networks, respectively. Additionally, Ref. [140] employs tabular data to develop an IoT-based soil nutrient analyzer, enabling farmers to monitor soil health and optimize fertilization strategies.

Time Series Data

Time series data, capturing sequential observations over time intervals, enable researchers to analyze temporal trends and patterns crucial for agricultural management. Leveraging time series data, studies such as those by [169,207] forecast environmental parameters like temperature and water availability to optimize irrigation scheduling and enhance crop productivity. Furthermore, Ref. [157] utilizes time series data for anomaly detection in smart aquaculture systems, identifying irregularities in water quality parameters to prevent fish disease outbreaks and improve farm productivity.

Scalar Data

Scalar data, representing single numerical values without temporal context, contribute valuable insights into specific agricultural parameters. While less prevalent, scalar data finds utility in monitoring essential variables such as nutrient concentrations, temperature readings, and rainfall levels. For example, Ref. [208] employs scalar data to measure soil volumetric water content using LoRa RSSI and UAV technologies, enabling the real-time monitoring of soil moisture levels for optimal irrigation management. Similarly, Ref. [132] utilizes scalar data to control nutrient concentrations in hydroponic systems, optimizing nutrient delivery to enhance plant growth and yield.

Image Data

Image data emerge as a powerful tool in PA, facilitating the visual monitoring of crops, livestock, and environmental conditions. With numerous papers leveraging image data, researchers deploy advanced imaging techniques and machine learning algorithms for crop disease detection, pest monitoring, and livestock management. Notable examples include studies by [209,210], which utilize image data for online identification of tea diseases and monitoring active fire locations in agricultural areas, respectively. Additionally, Ref. [143] employs image data to continuously monitor insect pests in mango orchards, enabling early pest detection and intervention to minimize crop damage.

Statistical Data

Statistical data underpin the quantitative analysis of agricultural phenomena in PA research, providing valuable insights into data distributions, trends, and correlations. With examples like [186], which employs statistical methods to analyze agricultural IoT data for deploying AI algorithms, and [211], which utilizes statistical approaches for temperature forecasting in stored grain, statistical data play a crucial role in deriving meaningful insights from agricultural datasets.

Table 10. Kinds of data found in the synthesis, with descriptions and usage examples.

Kind of Data	Description	Usage Examples
Tabular Data	Structured data organized in rows and columns, commonly found in databases or spreadsheets.	Soil health monitoring [134,191,212] Crop yield prediction [108,122,194] Water quality monitoring [213]
Time Series Data	Sequential data points ordered over time, such as weather or environmental observations.	Anomaly detection [157] Soil parameter prediction [178,214] Pest incidence forecast [141] Animal disease detection [215]
Scalar Data	Single numerical values, representing a single quantity or attribute.	Smart greenhouse farming [93] Crop irrigation [216]
Image Data	Multidimensional arrays of pixel values, used to represent visual information in the form of images.	Weed detection [217], disease prediction [71,185,218,219], and flow meter reading [155] Insect monitoring by image classification [180] Crop water status estimation [220]
Statistical Data	Data resulting from statistical processes are often used for analysis and inference.	Detection and monitoring of burning residue of paddy crops [221]
Audio Data	Representations of sound, typically in the form of waveforms.	Audio recording for raven detection [222] Audio clip for pig farm solution [205]

Audio Data

Though relatively less common, audio data hold promise in PA applications such as livestock monitoring and pest detection. Studies by [127,205] utilize audio data for piglet crushing mitigation and analyzing pig behavior, respectively, showcasing the utility of sound-based sensors in animal husbandry and welfare.

In conclusion, integrating diverse data types in PA research underscores the interdisciplinary nature of modern farming practices. By harnessing the power of tabular, time series, scalar, image, statistical, and audio data, researchers can gain valuable insights to optimize agricultural systems for sustainable and efficient food production.

5.3.3. Evaluation Methods Used

Evaluation methods are essential for gauging the effectiveness and performance of algorithms and systems developed for PA. These methods offer valuable insights into proposed solutions' accuracy, reliability, and suitability in addressing agricultural challenges. Here, we delve into various evaluation methods employed in the synthesized research, including accuracy, error/loss-related metrics, precision, recall, F-score, correlation-related measures, confusion matrix analysis, time complexity analysis, specificity, ROC score, and AUC.

The comprehensive evaluation of PA solutions involves considering various factors such as model accuracy, robustness, computational efficiency, and practical applicability in real-world agricultural settings. By employing these evaluation methods, researchers can ascertain the effectiveness and reliability of algorithms and systems designed to optimize agricultural production, resource management, and environmental sustainability. Figure 17 provides an overview of the key evaluation methods discussed in this literature review.

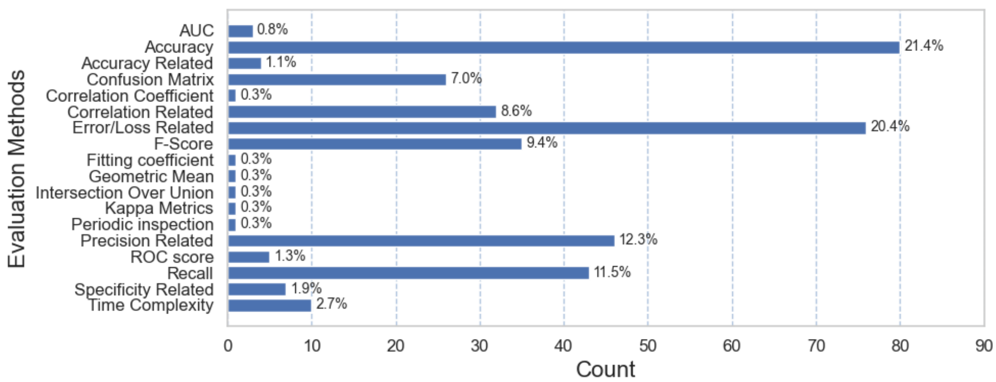

Figure 17. Bar chart showing the AI/ML evaluation methods found in the synthesis.

Accuracy

Accuracy measures the correctness of predictions made by a model or system compared to the ground truth. In PA, accuracy evaluation ensures the reliability of systems in tasks such as crop disease detection, yield prediction, and soil nutrient analysis. For instance, Ref. [194] developed a next-generation device for crop yield prediction using IoT and machine learning, evaluating its accuracy in predicting crop yields based on environmental factors and farming practices. Similarly, Ref. [178] proposed a blockchain and machine learning-based IoT framework to improve contract farming, assessing the system's accuracy in matching farmers with appropriate contracts.

Error/Loss-Related Metrics

Error or loss-related metrics, such as Mean Squared Error (MSE) or Root Mean Square Error (RMSE), quantify the deviation between predicted and actual values. These metrics are essential for evaluating regression models in PA applications like crop yield prediction and environmental parameter forecasting. For example, Ref. [124] analyzed the performance of a farm system for continuous crop quality assessment using machine learning and deep learning techniques, measuring error-related metrics to assess the system's predictive accuracy [124]. Additionally, Ref. [200] proposed an IoT deep learning-based prediction system for estimating the number of pesticides and diseases in fruits, evaluating the model's performance using error/loss-related metrics to ensure accurate predictions.

Precision and Recall

Precision and recall are key metrics for evaluating classification models in PA, especially in pest detection and disease classification tasks. Precision measures the proportion of correctly classified positive instances among all instances classified as positive, while recall measures the proportion of correctly classified positive instances among all actual positive instances. For instance, Ref. [113] developed an IoT-based climate prediction system using LSTM algorithms for smart farming, assessing the precision and recall of the model in predicting climate conditions for optimal agricultural management. Similarly, Ref. [121] evaluated the performance of a smart sensor system for plant disease prediction using LSTM networks, analyzing precision and recall to gauge the system's effectiveness in disease detection.

F-Score

The F-score, also known as the F1-score, is the harmonic mean of precision and recall, providing a balanced measure of a model's performance in classification tasks. It is particularly useful in situations where both precision and recall are important. In PA, F-score evaluation ensures robustness in disease detection, pest monitoring, and crop classification. For example, Ref. [123] proposed IoFT-FIS, an internet of farm things-based prediction for crop pest infestation using optimized fuzzy inference, evaluating the F-score to assess the system's overall performance. Additionally, Ref. [154] developed an IoT-based ideal fish farm, assessing the F-score to evaluate the system's effectiveness in fish health monitoring and disease prevention.

Correlation-Related Measures

Correlation-related measures assess the relationship between variables in PA applications, such as the correlation between environmental parameters and crop yield or the correlation between IoT sensor readings and soil moisture levels. For example, Ref. [131] designed a smart aquaponic system for enhancing farmer revenue, evaluating the correlation between water quality parameters and aquaponic system performance to optimize fish and plant health. Furthermore, Ref. [223] employed hybrid optimization models to classify root diseases in IoT-based systems, analyzing correlation-related measures to understand the relationship between disease incidence and environmental factors [131].

Confusion Matrix Analysis

Confusion matrix analysis provides a detailed breakdown of a classification model's performance by quantifying true positives, true negatives, false positives, and false negatives. It is instrumental in evaluating classification accuracy and identifying model strengths and weaknesses. In PA, confusion matrix analysis is commonly used to assess disease detection, pest monitoring, and crop classification systems. For instance, Ref. [145] developed an ensemble classification and IoT-based pattern recognition system for crop disease monitoring, utilizing confusion matrix analysis to evaluate the system's performance in classifying different disease types. Similarly, Ref. [185] implemented E-Agrigo, an IoT-based smart agriculture system, and conducted confusion matrix analysis to assess the accuracy of crop classification and pest detection.

Time Complexity

Time complexity analysis evaluates the computational efficiency of algorithms and systems, especially in real time or resource-constrained environments. In PA, time complexity analysis ensures that computational tasks, such as data processing and analysis, can efficiently support timely decision-making. For example, Ref. [74] analyzed and predicted tractor ride comfort through supervised machine learning, considering time complexity to ensure that the prediction model can be deployed in real time for optimizing tractor ride comfort during agricultural operations. Additionally, Ref. [169] proposed an optimal environment control mechanism based on OCF connectivity for efficient energy consumption in greenhouses, considering time complexity to design algorithms capable of managing environmental parameters in real time.

Specificity-Related Measures

Specificity measures the proportion of correctly classified negative instances among all instances classified as negative. It complements precision and recall by providing insights into a model's ability to identify true negative instances accurately. In PA, specificity-related measures are crucial for weed detection and pest monitoring, where accurately identifying non-infested areas is as important as detecting infested ones. For example, Ref. [106] developed an IoT-based weed detection system using hybrid leader-based optimization models, assessing specificity-related measures to evaluate the system's performance in distinguishing between weed-infested and weed-free areas.

ROC Score and AUC

Receiver Operating Characteristic (ROC) curve analysis and Area Under the Curve (AUC) evaluation are commonly used in PA to assess the performance of classification models, particularly in tasks involving binary classification, such as disease detection and pest monitoring. ROC curves visualize the trade-off between the true positive rate (sensitivity) and false positive rate (1-specificity) at various threshold settings. At the same time, AUC quantifies the model's overall performance in distinguishing between positive and negative instances. For instance, Ref. [201] estimated the growth probability of ochratoxin A in wine production using AI-powered IoT devices, employing ROC score analysis and AUC evaluation to assess the predictive model's performance. Similarly, Ref. [159] developed an IoFT-FIS platform for predicting crop pest infestation, utilizing ROC score and AUC metrics to evaluate the system's ability to differentiate between infested and non-infested areas.

In conclusion, the evaluation methods discussed in this literature review are pivotal in assessing the effectiveness, reliability, and suitability of PA solutions. By employing a combination of accuracy, error/loss-related metrics, precision, recall, F-score, correlation-related measures, confusion matrix analysis, time complexity analysis, specificity-related measures, ROC score, and AUC evaluation, researchers can comprehensively evaluate the performance of algorithms and systems designed to address various agricultural challenges. Moreover, these evaluation methods facilitate the development of robust and efficient solutions for optimizing agricultural production, resource management, and environmental sustainability.

5.4. IoT-AI/ML Complementarity

IoT is currently expanding its influence in various fields. Often, the impact of IoT helps farmers because the combination of IoT and ML provides a convenient effect to users, in this case, farmers. Here we examine **the impact of IoT strengths/weaknesses on AI/ML in response to research question FQ1 shown in Table 5. We subsequently examine the impact of AI/ML strengths/weaknesses on IoT in response to research question FQ2 shown in Table 5.**

5.4.1. Impact of IoT Weaknesses on AI/ML Models

IoT systems, such as those reliant on Wi-Fi connections [162], may encounter challenges due to the need for continuous power and network availability [74]. Moreover, the complexity of IoT setups can exacerbate issues related to data transmission [74], while external factors like weather conditions or equipment malfunction may introduce discrepancies or missing values in IoT datasets [81,102]. Therefore, robust methodologies are essential to address missing values and ensure the reliability of ML algorithms despite intermittent connectivity issues in IoT deployments, as AI/ML models heavily rely on IoT data.

Another difficulty encountered is that the development of IoT-based systems requires a long operation time to collect large volumes of data [197]. However, this data collection is vital for the future performance of ML. System complexity and long processing time are among the obstacles that should receive wider attention in IoT development.

IoT systems often confront resource constraints, which diminish their capacity to accommodate intricate AI/ML models effectively. Due to constraints in processing power and memory, IoT devices frequently prioritize model size over performance [177,224].

Furthermore, the communication protocols employed by IoT devices are typically not in real time, thereby hindering the ability of AI/ML models operating on these devices to furnish prompt predictions [107].

Physical degradation and environmental factors pose formidable challenges for IoT deployments. IoT devices are susceptible to wear and tear, as well as weather conditions, which can lead to malfunctions and breakdowns. Consequently, AI/ML models reliant on IoT-generated data may also experience interruptions or inaccuracies in their predictions [79].

Moreover, the remote administration of IoT physical components presents logistical challenges. Unlike virtual resources, IoT devices cannot be effortlessly modified or managed remotely. This limitation can impede the smooth operation of AI/ML models on IoT platforms, occasionally necessitating physical intervention for maintenance or updates [204,225].

Future research could explore innovative solutions to mitigate the impact of IoT weaknesses on AI/ML models. Investigating techniques to optimize AI/ML algorithms for resource-constrained IoT environments could enhance model performance without compromising on device constraints. Research focusing on developing real-time communication protocols tailored to IoT devices could enable AI/ML models to deliver timely predictions, even in dynamic environments. Exploring advanced predictive maintenance strategies to proactively address IoT device failures and degradation could enhance the reliability and longevity of AI/ML deployments in IoT ecosystems. Lastly, investigating methods for remote administration and management of IoT physical components to streamline maintenance processes and ensure seamless operation of AI/ML models represents another promising avenue for future research.

5.4.2. Impact of IoT Strengths on AI/ML Models

The advent of IoT has significantly impacted AI modeling by enabling the generation of large volumes of data in a short period. This data abundance, facilitated by IoT devices, plays a crucial role in enhancing the AI modeling process [105]. Furthermore, IoT devices can be strategically deployed close to the objects or environments under control or monitoring, thereby enhancing data accuracy and the ability to influence/control the environment [80,102,125]. Unlike traditional data collection methods, IoT devices do not require frequent changes in response to fluctuating physical or environmental conditions, allowing for continuous data collection for AI/ML and control in extreme conditions [83,141]. Moreover, IoT's ability to operate on minimal power, often utilizing sources like solar panels and batteries, ensures that AI systems running on IoT infrastructure also consume low power [165,226].

In addition to the aforementioned strengths, the quality of data collected by IoT devices is critical for enhancing the accuracy of AI systems. Utilizing high-quality yet affordable sensor elements, such as camera sensors, is essential to achieve accurate system performance [227]. Moreover, efficient data transmission infrastructure is imperative to support real-time data transmission, thereby facilitating ML tasks [82]. Combining efficient IoT devices with proper infrastructure utilization can significantly enhance the efficiency of ML tasks within a learning context. To address power consumption challenges associated with multiple devices, innovative solutions such as Edge TPU Co-processor technology have been developed, enabling high-performance ML operations with minimal energy consumption [147].

Future research in the intersection of IoT and AI/ML could focus on developing advanced methodologies to optimize energy efficiency in IoT devices while maintaining high-performance AI/ML operations. This could involve exploring novel techniques for power management, such as dynamic voltage and frequency scaling, to dynamically adjust power consumption based on workload demands. Additionally, studies on the development of intelligent algorithms for adaptive power management in IoT environments could lead to more efficient and environmentally friendly AI/ML deployments.

5.4.3. Impact of AI/ML Weaknesses on IoT

The integration of AI/ML with IoT introduces several challenges that impact the effectiveness of both technologies. One significant issue arises from the trade-off between AI/ML performance and the constraints of IoT infrastructure. Due to the limited resources of IoT devices, smaller AI/ML models may underperform, compromising the accuracy of predictions [177,224]. Additionally, the requirement for large datasets in AI/ML training poses a burden on IoT devices tasked with generating substantial volumes of data, potentially straining their resources and efficiency.

The inherent latency in AI/ML model predictions conflicts with the real-time responsiveness expected from IoT devices, hindering their ability to provide immediate feedback or actions based on AI insights. Moreover, the dynamic nature of AI/ML models necessitates retraining when conditions change, which may require IoT devices to be recalled for updates, leading to operational disruptions and logistical challenges. These weaknesses underscore the need for innovative solutions to optimize the integration of AI/ML with IoT, ensuring seamless performance and responsiveness in dynamic environments.

AI/ML serves as a pivotal tool in furnishing predictions or detections, enabling machines to autonomously execute tasks. However, the iterative learning process occasionally yields suboptimal outcomes. As elucidated in [128], ML outcomes may occasionally befuddle themselves, distinguishing between normal and aberrant results. Consequently, the yielded results often fail to meet expectations, reflected in the modest accuracy rates. The repercussions of inaccurate learning manifest as hardware designated to execute tasks based on learned outputs become ensnared in confusion, thus subverting optimal performance.

Deficient AI/ML models may inadvertently extend computation times, as expounded in [77,216]. Prolonged computations persist until yielding satisfactory outcomes. One contributing factor to this protracted computation lies in the extensive volume of data necessitating processing.

Future research could explore novel approaches to address the challenges from the integration of AI/ML with IoT, to enhance the synergy between these technologies. Investigations into the development of lightweight AI/ML models tailored for IoT devices could mitigate performance trade-offs while maximizing efficiency. Additionally, research efforts focused on optimizing data generation and transmission protocols within IoT networks could alleviate the burden on devices and improve real-time responsiveness. Furthermore, exploring adaptive AI/ML algorithms capable of dynamically adjusting to changing conditions without necessitating frequent retraining could enhance the adaptability and resilience of IoT systems. Overall, interdisciplinary collaborations and innovative methodologies are essential to unlock the full potential of AI/ML-enabled IoT applications and propel advancements in diverse domains ranging from healthcare to smart cities.

5.4.4. Impact of AI/ML Strengths on IoT

The integration of AI/ML with IoT presents a symbiotic relationship that holds immense potential for revolutionizing various domains. AI/ML's adeptness in error and outlier detection complements IoT's data generation capabilities, ensuring the reliability and accuracy of information collected from IoT devices [84]. AI/ML's proficiency in trend analysis facilitates the imputation of missing or erroneous data, enriching the completeness of IoT datasets and enhancing their utility [228]. Techniques such as data augmentation and transfer learning further optimize AI/ML performance, potentially reducing the burden on IoT devices to generate excessive amounts of data [187,220]. Additionally, the non-physical nature of AI/ML models enables seamless modification and duplication across multiple devices, streamlining deployment and management within IoT ecosystems [118,229].

In agricultural contexts, the fusion of IoT and AI/ML has yielded transformative outcomes, empowering farmers with real-time insights and automation capabilities [150]. ML algorithms serve as guiding beacons for instructing IoT systems in orchestrating automated processes, enabling dynamic field monitoring and task optimization [192]. Notably, ML's ability to handle lightweight data offers a promising avenue for IoT systems with limited data collection capabilities, thereby conserving power and optimizing system performance [78]. Through techniques like data augmentation and fusion, ML enhances data accuracy and completeness, contributing to more effective IoT operations [146,230]. Furthermore, advancements in TinyML technology offer energy-efficient solutions by reducing the size and power consumption of ML models [94,224]. Additionally, predictive models leveraging LSTM in ML aid in optimizing sensor workload and conserving power [193]. These innovations underscore the transformative potential of integrating AI/ML with IoT, heralding a new era of efficiency and sustainability in various applications.

5.5. Identified Research Opportunities/Future Work

The combination of IoT technologies with AI/ML in the realm of PA has sparked a wealth of research endeavors. In this section, we discuss research opportunities for future work. PA, characterized by the integration of IoT solutions with AI/ML technologies, has garnered significant attention, as evidenced by this comprehensive literature review. The discussion below delineates key opportunities identified in the combination of Agriculture, IoT, and AI/ML.

5.5.1. Agriculture Opportunities

The reviewed literature highlights various opportunities for advancing agricultural practices. Authors [75,204,231,232] emphasize the potential for enhancing crop-specific interventions, such as implementing dynamic nutrient delivery, as suggested by [204], and incorporating additional parameters influencing crops, as proposed by [231]. Additionally, expanding IoT applications along the coffee value chain, as recommended by [75], introduces possibilities for traceability and disease control. Moreover, the inclusion of biosensors [232] and 24 h tracking of animals [126] exemplifies the opportunities for livestock monitoring, emphasizing the potential for real-time insights and improved animal welfare.

The diverse applications extend to optimizing storage conditions [233], enhancing beekeeping practices [147], and streamlining pest detection in aquaculture [107]. The latter aligns with [106]'s emphasis on refining and validating aquaculture models and integrating robotics for more efficient systems.

AI/ML for Crop Monitoring and Management

AI/ML applications in crop monitoring and management, particularly the use of deep learning architectures [220,234], present exciting possibilities. The ability of CNNs to process vast amounts of image data for disease detection and yield prediction underscores their potential. Nevertheless, challenges in model interpretability and generalizability across different crops and regions are apparent. Addressing the interpretability challenge in deep learning models for agriculture is a critical research gap. Future studies should focus on developing models that not only deliver accurate predictions but also provide insights into decision-making processes for end-users.

Smart Irrigation Systems

IoT-enabled smart irrigation systems represent a paradigm shift in water resource management [165,235]. The integration of historical weather data with real-time IoT inputs in autonomous systems holds promise for sustainable irrigation practices. However, scalability issues and the energy consumption of these systems demand careful consideration. Investigating the scalability of autonomous irrigation systems and developing energy-efficient models is a pressing research need. Future studies should focus on creating adaptive systems capable of scaling from small farms to large agricultural landscapes while minimizing energy consumption.

Cattle Monitoring and Health Management

The deployment of IoT devices in cattle monitoring [234] offers insights into the health and behavior of livestock. The use of advanced classifiers showcases the potential for early disease detection. However, challenges persist in ensuring the accuracy of these classifiers across diverse cattle breeds and environmental conditions. The generalization of cattle activity classifiers across different breeds and environmental contexts is a research gap. Future studies should explore the development of adaptable models that cater to the diversity inherent in global livestock management.

5.5.2. IoT Opportunities

The integration of IoT technologies in agriculture presents transformative opportunities [210,220,234]. Authors [119,124,213] advocate for the use of low-power sensors, aerial images from drones, and advanced clustering algorithms to enrich data collection, improve system scalability, and enhance decision-making accuracy. The versatility of IoT applications is demonstrated by its deployment in diverse agricultural stages [75] and various forms of agriculture, such as crop production [103,108,145,180], fish farming [107], aquaculture [88,157,236], and beekeeping [137,147]. The authors recommend evaluating the system's efficacy against scenarios with missing data, providing robust insights into real-world challenges.

Challenges in IoT Integration

Despite progress, significant challenges remain in achieving seamless interoperability among diverse sensor networks. There is a notable research gap in developing standardized protocols for IoT devices across diverse agricultural landscapes. Future investigations should emphasize creating interoperable frameworks, fostering a more cohesive and interconnected IoT ecosystem.

Sensor Fusion and Fast Terrain Sampling

Optimizing IoT node deployment through fast terrain sampling and sensor fusion methodologies [206] is crucial for PA. The use of optimization algorithms offers insight into addressing transmission losses in real-world terrains. However, the development of standardized frameworks for sensor fusion remains a challenge. A research gap exists in creating standardized frameworks for sensor fusion. Future investigations should focus on developing adaptable models that account for diverse terrains and environmental conditions.

Autonomous IoT Systems

The advent of autonomous IoT systems [235] in agriculture raises intriguing possibilities for data-driven decision-making. However, concerns regarding the reliability and security of autonomous systems in dynamic agricultural environments need thorough exploration. A notable research gap concerns the security and reliability of autonomous IoT systems. Future studies should explore developing robust security measures and mechanisms to ensure the resilience of autonomous agricultural systems against cyber threats.

5.5.3. AI/ML Opportunities

The convergence of agriculture with AI and ML technologies offers opportunities for predictive analytics, optimization, and intelligent decision-making. According to several authors, incorporating Generative Adversarial Networks (GANs), hyperparameter optimization, and deep learning techniques can lead to improvements in image conversion, model refinement, and the identification of more efficient learning parameters [93,95,129,146]. It is crucial to continually improve models, which involves updating them after deployment, using meta-heuristic-optimized techniques, and incorporating evolutionary algorithms for hyperparameter optimization [95,146,177].

Hybrid Deep Learning Models

The development of hybrid deep learning models, which combine CNNs with LSTM, demonstrates a comprehensive approach to crop monitoring [220]. However, challenges in addressing diverse environmental conditions and extending the model to other crops warrant attention. Adapting hybrid deep learning models to various environmental conditions and crops/animals is a significant research gap. Future studies should explore methods to improve the generalizability of these models across different agricultural settings.

Decision Tree Analysis for Beehive Monitoring

The application of decision tree analysis in beehive monitoring [137] demonstrates the versatility of AI in diverse agricultural domains. However, the potential biases in decision trees and their sensitivity to input variations require thorough examination. A research gap exists in understanding the biases and sensitivities of decision tree models in agriculture. Future investigations should focus on developing methods to address these issues and enhance the reliability of decision tree-based analyses.

Leader-based Optimization in Weed Detection

The introduction of leader-based optimization in weed detection [217] signifies a tailored approach to addressing specific agricultural challenges. Yet, the scalability and adaptability of these models to different weed types and environmental conditions necessitate further investigation. A research gap lies in assessing the scalability and adaptability of leader-based optimization models in diverse agricultural contexts. Future studies should explore ways to enhance the versatility of these models for widespread applicability.

5.5.4. Future Directions

Scalability and Interoperability

Scaling IoT and AI/ML solutions for PA [129,204] remains a focal point for future research. Developing scalable models that can seamlessly integrate with existing agricultural practices while ensuring interoperability is pivotal for widespread adoption. Future research should prioritize the development of scalable and interoperable frameworks for IoT and AI/ML solutions. Collaborative efforts between researchers, industry stakeholders, and policymakers are necessary to create standardized protocols.

Citizen-Centric Participation

The integration of citizen-centric features in PA frameworks, as exemplified by [204], introduces a new dimension of community involvement. Exploring ways to enhance community participation in decision-making processes and leveraging collective intelligence can be a promising avenue. Future studies should delve deeper into citizen-centric features, exploring methods to enhance community participation in agricultural decision-making. Collaborative research initiatives involving communities can provide valuable insights for designing inclusive agricultural frameworks.

Environmental Impact Assessment

While the benefits of IoT and AI/ML in agriculture are evident, a comprehensive assessment of their environmental impact is crucial [204]. Future research should delve into the energy consumption, waste generation, and long-term ecological effects of large-scale IoT solutions in agriculture. Future research endeavors should prioritize conducting comprehensive environmental impact assessments of IoT and AI/ML applications in agriculture. This includes evaluating energy consumption, waste management, and ecological consequences to ensure sustainable technology deployment.

Cross-Domain Integration

Exploring the potential for cross-domain integration in agriculture is a promising area for future exploration [204]. Insights gained from precision crop monitoring could be extrapolated to livestock management and other agricultural domains, fostering a holistic and synergistic approach to smart agriculture. Future research should focus on cross-domain integration, exploring ways to leverage insights gained from one domain to enhance practices in another. Collaborative research initiatives across diverse agricultural domains can pave the way for holistic smart agriculture.

6. Conclusions

The integration of IoT and AI/ML in PA has been found to have transformative potential, as indicated by the current research. Moreover, the study identifies research gaps in the standardization of protocols for integrating IoT devices into agricultural systems, the economic feasibility of these technologies, and the scalability for broader adoption. By emphasizing the need for interdisciplinary studies, socio-economic evaluations, and scalable implementations, the research advocates for holistic solutions that transcend specific forms of agriculture to foster the widespread adoption of IoT and AI technologies in farming practices.

Despite the numerous and comprehensive studies that have been conducted by researchers in the past, there is a lack of focus on the effects that IoT solutions and AI/ML technologies have on each other in the context of agriculture. Although some studies have explored the use of IoT and AI/ML in agricultural settings, there was a noticeable gap in the research that systematically examines the combined impact of these technologies on precision agriculture. This study addresses this research gap by conducting a systematic literature review that focuses on the intersection of IoT and AI in agricultural systems. Despite the study's limitations of considering only English language publications in journals and conferences, by systematically analyzing and synthesizing the findings from relevant studies, this research provides valuable insights into the complementary nature of IoT and AI/ML and their potential to transform precision agriculture.

Exploring IoT and AI applications across all stages of agriculture, from seed selection to post-harvest processing, underscores the potential for end-to-end monitoring and decision support systems to revolutionize farming practices. The development of digital twins and comprehensive modeling frameworks that integrate real-time data with predictive analytics holds promise for optimizing resource allocation, enhancing decision-making, and improving overall productivity.

While significant strides have been made, it is essential to address the identified research gaps and opportunities to ensure the sustainable and widespread adoption of these technologies. Future research work should focus on developing scalable and interoperable frameworks for IoT and AI solutions in PA, investigating robust data security measures and privacy protocols, researching predictive maintenance strategies, and exploring the fusion of data from multiple sensors, data types, and sources to improve decision-making processes.

In conclusion, this study emphasizes the transformative impact of IoT and AI technologies in PA, offering innovative solutions to address challenges such as population growth, resource competition, climate change, and food security. By bridging research gaps, fostering interdisciplinary collaboration, and promoting the adoption of standardized IoT platforms, the agricultural sector can unlock the full potential of IoT and AI technologies to create sustainable, efficient, and resilient farming systems.

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Abbreviations

The following abbreviations are used in this manuscript:

ACM	Association for Computing Machinery
AI	Artificial Intelligence
AUC	Area Under Curve
APAE	Analytical Prediction Algorithm using Estimations
BLE	Bluetooth Low Energy
CNN	Convolutional Neural Network
DNN	Deep Neural Network
DOAJ	Directory of Open Access Journals
FQ	Focused Question
GRNN	General Regression Neural Network
GSM	Global System for Mobile Communications
GPRS	General Packet Radio Service
GPUs	Graphics Processing Units
IEEE	Institute of Electrical and Electronics Engineers
IoT	Internet of Things
IPM	Integrated Pest Management
KNN	K-Nearest Neighbor
LD	Linear dichroism
LOF	Local Outlier Factor
LoRa	Long-Range
LSTM	Long Short-Term Memory
MCC	Monitoring and Control Components
MDPI	Multidisciplinary Digital Publishing Institute
MFCC	Mel-Frequency Cepstrum Coefficients
ML	Machine Learning
MSE	Mean Squared Error
PA	Precision Agriculture
PCA	Principal Component Analysis
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
PSO	Particle Swarm Optimization
R-CNN	Region-Based CNN
RFID	Radio Frequency Identification
RMSE	Root Mean Square Error
RNN	Recurrent Neural Network
ROC	Receiver Operating Characteristic
RSSI	Received Signal Strength Indicator
SLAM	Simultaneous Localization and Mapping
SQ	Statistical Question
SVM	Support Vector Machine
SVMR	Support Vector Machine Regression
TLA	Three-Letter acronym
TPUs	Tensor Processing Units
UAV	Unmanned Aerial Vehicle

Appendix A. Paper Identification

Databases/Websites and Queries

Table A1. Records of paper identification queries. For each database/Website, the query used, reason for modification, and date of query are provided.

Database	Query	Reason for Modification
Scopus Queried: 17 November 2023	ALL ((“machine learning” OR “machine-learning” OR “deep learning” OR “deep-learning” OR “artificial intelligence” OR “artificial-intelligence” OR “neural networks” OR “neural-networks” OR “classif* ” OR “predict*” OR “monitor*” OR “forecast*” OR “estimat*” OR “algorithm*”) AND (“IoT” OR “internet of things”) AND (“precision agriculture” OR “agric*” OR “agro*” OR “fish*” OR “crop*” OR “farm*” OR “plants” OR “animal*”)) [1]	No major modification to query.
ACM Queried: 22 November 2023	(“machine learning” OR “machine-learning” OR “deep learning” OR “deep-learning” OR “artificial intelligence” OR “artificial-intelligence” OR “neural networks” OR “neural-networks” OR “classif*” OR “predict*” OR “monitor*” OR “forecast*” OR “estimat*” OR “algorithm*”) AND (“IoT” OR “internet of things”) AND (“precision agriculture” OR “agric*” OR “agro*” OR “fish*” OR “crop*” OR “farm*” OR “plants” OR “animal*”) [1]	No major modification to query.
IEEE Queried: 17 November 2023	(“machine learning” OR “machine-learning” OR “deep learning” OR “deep-learning” OR “artificial intelligence” OR “artificial-intelligence” OR “neural networks” OR “neural-networks” OR “classif*” OR “predict*” OR “monitor” OR “forecast*”OR “estimate“ OR ”estimation“ OR “algorithm”) AND (“IoT” OR “internet of things”) AND (“precision agriculture” OR “agric*” OR “agro*” OR “fish*” OR “crop*” OR “farm*” OR “plants” OR “animal*”) [1]	Total number of query wildcards limited to 9.
ScienceDirect Queried: 17 November 2023	(“machine learning” AND (“IoT” OR “internet of things”) AND (“agriculture” OR “fish” OR “crop” OR “farm” OR “plants” OR “animal”)) OR (“deep learning” AND (“IoT” OR “internet of things”) AND (“agriculture” OR “fish” OR “crop” OR “farm” OR “plants” OR “animal”)) OR (“artificial intelligence” AND (“IoT” OR “internet of things”) AND (“agriculture” OR “fish” OR “crop” OR “farm” OR “plants” OR “animal”)) OR (“neural networks” AND (“IoT” OR “internet of things”) AND (“agriculture” OR “fish” OR “crop” OR “farm” OR “plants” OR “animal”)) OR (“classification” AND (“IoT” OR “internet of things”) AND (“agriculture” OR “fish” OR “crop” OR “farm” OR “plants” OR “animal”)) OR ("prediction" AND ("IoT" OR "internet of things") AND ("agriculture" OR "fish" OR "crop" OR "farm" OR "plants" OR "animal")) OR ("monitor" AND ("IoT" OR "internet of things") AND ("agriculture" OR "fish" OR "crop" OR "farm" OR "plants" OR "animal"))	Allows fewer boolean connectors (max 8 per field). Wildcards ‘*’ are not supported. As a result, all wildcards were removed.
GoogleScholar Queried: 17 November 2023	allintitle: (“machine learning” OR “machine-learning” OR “deep learning” OR “deep-learning” OR“artificial intelligence” OR “artificial-intelligence” OR “neural networks” OR “neural-networks” OR “classif*” OR “predict*” OR “monitor*” OR “forecast*” OR “estimat*” OR “algorithm*”) AND (“IoT” OR “internet of things”) AND (“precision agriculture” OR “agric*” OR “agro*” OR “fish*” OR “crop*” OR “farm*” OR “plants” OR “animal*”) [1]	Search options include title-search or search everywhere. Searching everywhere returned too many results, so title-search was used.

[1] The asterisk (*) characters represent wildcards.

Appendix B. Paper Inclusion

List of Included Papers

Table A2. Included papers. List of studies that passed the inclusion and reported on.

Ref.	Agricultural Concern [1]	IoT Components [2]	AI/ML Algorithms [3]
1. [151]	Crop Production Greenhouse Farming/High Cost of Labor and Energy Consumption Growth/Smart Farming	DHT11 Ambient Temperature and Humidity Sensor, Soil Moisture Sensor (SKU: 12251) Arduino Uno, Cloud Server SIM900 Wireless Broadband Router	SVC, KNN, Logistic Regression Tabular, Scalar Precision, Recall, Accuracy, F1-score
2. [81]	Crop Production Farmer Assistance/Analyzing the Parameters Suitable to Crop Growth Post-Harvest/Periodic Inspection	DHT22 Temperature and Moisture Sensor, Soil Sensor Arduino UNO, ESP8266, Thingspeak ESP8266 Wi-Fi Module	Random Forest, Decision Tree, KNN Tabular, Time Series, Scalar Accuracy
3. [91]	Aquaculture, Fish Farming Twin-based Intelligent Fish Farming/Automated Fish Feeding, Environment and Health Monitoring Infancy, Growth/Fish Farming	Sonar Camera, RGB Camera, Water Temperature Sensors, Water pH Sensor, Water Salinity Sensor, Water Velocity Sensor, Dissolved Oxygen Sensor Cloud Server	Mask R-CNN, YOLOv4, Multi-layer Perceptron, Principal Component Analysis (PCA), Adaptive Aggregation Network (AANet), Fast-Segmentation Convolutional Neural Network (Fast-CNN), Long Short-Term Memory (LSTM) Network, DB-Scan, I3D model, Optical flow Tabular, Image Algorithm Evaluation
4. [221]	Crop Production detecting and Monitoring Burning Eesidue of Paddy Crops/Monitoring the Burning Residue of Paddy Crops, and Water Quality Monitoring in Real Time Growth/Other	Unmanned Aerial Vehicle Cloud Server	Convolutional Neural Network Image, Real Time, Statistical Precision, Recall, Accuracy
5. [77]	Animal Husbandry Health Status Classification for cows/The Combination Information From Microenvironments, Macroenvironment and Cow's Information in Supporting of the Classification Pre-harvest/Others	Temperature Sensor, Humidity Sensor, Animal Identification Device, Wind Direction Sensor, Cloud Level Sensor, Rain Quantity Sensor AWS Glue Workflow, S3 Bucket, SageMaker	Random Forest, Convolutional Neural Network, XGBoost Tabular, Time Series, Scalar Accuracy, Precision, Recall, F1 score

Table A2. *Cont.*

Ref.	Agricultural Concern [1]	IoT Components [2]	AI/ML Algorithms [3]
6.	Crop Production, Animal Husbandry	SV 38 V MEMS Triaxial Seat-Pad Accelerometers, SV 151 MEMS Accelerometer, SV 106 a Six-Channel Human Vibration Meter, SV 958 Four-Channel Sound, Vibration Analyzer	Linear Regression, Decision Tree Regressor, Support Vector Regression, Gaussian Process Regression, Artificial Neural Network
[74]	Analyzing and Predicting Tractor Ride Comfort. Real-Time Monitoring and Fleet Management Applications/Improve Tractor Ride Comfort in Real Field Applications in Developing Countries, Comfort Optimization, Limited Access to Credit, Inadequate Infrastructure, Lack of Knowledge and Skills, Feeding a Growing Global Population	ESP8266 Microcontroller, Cloud Server	Tabular, Time Series
	Sowing, Growth, Harvest, Post-Harvest/Agricultural Machinery	RJ 45 port	R-square, Root Mean Square Error, MAE, Training Time
7.	Crop Production	UAV-Mounted Camera, LCD	GL-CNN
[101]	Growth Prediction of Palm Tree plantings/Monitoring Growth and Predict the Plantings of Palm Tree By	Raspberry Pi, GPU	Tabular, Time Series, Image
	Growth/Periodic Inspection	USB	MAE, Accuracy, Precision, Recall, F1-Score
8.	Crop Production	DHT22/AM2302 Temperature and Relative Humidity Sensor, MHZ-19 CO_2 Sensor	Multi-Layer Perceptron, Multiple Linear Regression
[196]	Moisture Content and Carbon Monitoring in Real Time to Predict the Quality of Corn grain/Monitoring and Obtain the Equilibrium in Real Time	ESP8266 D1 Mini-Module, ThingSpeak	Tabular
	Post-Harvest/Periodic Inspection	Wi-Fi Module	R, R^2, MAE
9.	Aquaculture	RTD PT100 Temperature Sensor, SEN 0161 pH Sensor, SEN 0189 Turbidity Sensor	Deep Reinforcement Learning, Artificial Neural Network
[128]	Aquaculture Monitoring System/Providing Efficiency in Accuracy of the Data Generated by the System and Reliability of Data That Can Be Accessed in Real Time	Arduino Uno R3, Firebase	Tabular
	Post-Harvest/Aquaculture Monitoring	Wi-Fi Module	MAPE, Accuracy, Precision, Recall, F1-Score
10.	Crop Production	DLPNIRNANOEVM NIR Sensor	Support Vector Machine, XGBoost, Deep Neural Network
[197]	Real-Time Monitoring of Gluten Levels and Quality Control in Flour Production/Accurately Classifying Wheat Flour Using Near-Infrared Spectroscopy (NIRS) Technology	Raspberry Pi 4, NVIDIA GeForce RTX 2060 SUPER Graphic Card, AWS DynamoDB, AWS sagemaker	Tabular, Time Series, Scalar
	Post-Harvest/Others		Accuracy, F2-score, Training Time

Table A2. *Cont.*

Ref.	Agricultural Concern [1]	IoT Components [2]	AI/ML Algorithms [3]
11. [78]	Crop Production Ad-hoc Network Ecosystem for Precision Agriculture/Low Latency Infrastructure in a Highly Sparse Network Growth/Other	pH Sensor, Rainfall Sensor, Soil Moisture Sensor, Temperature Sensor, UAV Sensor Nodes, Vehicular Sensor Cloud Server	Decision Tree, KNN, SVM, Naive Bayes, Majority Voting Tabular F1-score
12. [204]	Crop Production Smart Monitoring and Controlling of greenhouse/Predictions for the Environmental Conditions of the Innovative Greenhouse Growth/Greenhouse	Temperature Sensor, Humidity Sensor, AM2305 Temperature and Humidity Sensor, AM2315 Sensor, Buzzer 5Vdc, Relay 5vdc, Water Flow Sensor, Mist Pump, Exhaust Fan, Roller Motor, Misting Fan Web Server, Node-Red Cloud Server D1 Mini Pro	LSTM Tabular, Time Series, Scalar
13. [102]	Crop Production Rice Growth Stage Classification /The Transition of Life Cycle of Paddy Rice Is Challenging to Determine Manually Growth/Periodic Inspection	Soil Sensor, Weather Station, Surveillance Camera Raspberry Pi, Amazon S3 cloud, AWS Cloud Server, Google Colab Pro	Random Forest Tabular, Time Series Confusion Matrix, Accuracy, F1-Score
14. [129]	Aquaculture Underwater Smart Sensor Object/Monitor the Fish in Real Time to Assess the Wellness of the Fish Harvesting/Health Monitoring	Go Pro Stereo Camera, Sonar Camera, Calibration Checkboard NVIDIA GeForce RTX 3090 GPU, Cloud Server	Mask RCNN, Gaussian Mixture Modeling, KNN Regression, CNN Image Confusion Matrix
15. [231]	Crop Production Utilizing Precision Agriculture in Predicting Apple Disease/ Growth, Harvest/Precision Agriculture	DHT22 Temperature, MTS420 Sensor and Humidity Sensor MTS420 Sensor Board IRIS 2.4 GHz Module	Linear Regression Tabular

Table A2. *Cont.*

Ref.	Agricultural Concern [1]	IoT Components [2]	AI/ML Algorithms [3]
16. [216]	Crop Production Banana Irrigation and Scheduling System/Water Optimization and Predict the Environmental Status of Crop Field Growth/Irrigation	F-28 Soil Moisture, HPT675 Water Level Sensor, THERM200 Soil Temperature Sensor, HTM2500LF Humidity Temperature Transducer, SHT11 Soil Moisture, Digital Inclinometer Raspberry Pi M2M (ZigBee)	KNN, Reinforcement Learning Tabular, Scalar Spearman Correlation, Coefficient of Determination (R^2), Root Mean Square Error (RMSE)
17. [156]	Animal Husbandry Dairy Cows Localization and Activity detection/The Activity Sensors to Monitor Several Events in Real Time, Increasing Productivity of Farms, Continuous Control of Animals and Production Systems Growth/Precision Livestock Farming	MPU-9250 IMU, RFID Tag, RFID Reader ESP32 MCU, STM32F103-ARM microcontroller Wi-Fi 802.11 Transceiver, RFID Antenna	Gaussian Mixture Model Kinds of Data Accuracy, Precision, Sensitivity, Specificity
18. [125]	Animal Husbandry Cattle Health Monitoring Systems/Predict Cattle Health in Real Time Growth/Cattle monitoring	DHT22 AM2302, DHT11, DHT12, GY-521 MPU-6050 MPU6050, Module 3 Axis Analog Gyro Sensors, SON1205 Heart Rate Sensor Cloud Server, Web Server, Mobile Node	LightGBM (Light-Gradient-Boosting Decision Tree) Tabular, Time Series R-Squared, Absolute Loss, Squared Loss, Root-Mean-Square-Loss
19. [122]	Crop Production Crop and Yield Forecasting/Predict Crop and Yield Productivity Growth, Harvesting/Yield prediction	Relay, Water Pump, Temperature Sensor Microprocessor, Firebase Wi-Fi Module	Random Forest Tabular Accuracy
20. [115]	Animal Husbandry Livestock Monitoring/Disease Prevention and Control Growth/Periodic Health and Activity Monitoring, Reproduction Management	DS18B20 Dallas Body Temperature Sensor, Pulse Sensor, ADXL345 3-Axis Accelerometer ESP-8266 Node MCU, Google Sheets ESP-8266 Wi-Fi Module	Logistic Regression Tabular Accuracy, Precision, F1-Score

Table A2. *Cont.*

Ref.	Agricultural Concern [1]	IoT Components [2]	AI/ML Algorithms [3]
21. [237]	Crop Production Rice Blast detection/Detecting and Managing Rice Blast Disease in Rice Crops Growth, Harvest/Periodic Inspection	Temperature Sensor, Humidity Sensor, Rain Sensor, Pressure Sensor, CO Sensor Cloud Server	Unspecified Image Training Accuracy, Validation Accuracy
22. [213]	Crop Production Water Quality Monitoring System/The Lack of Continuous Monitoring of Quality of Groundwater Growth/Irrigation	pH Sensor, Temperature Sensor (DS18B20), Electric Conductivity Sensor, ADC1115 ESP8266 NodeMCU 1.0, Cloud Server Gateway, ESP8266 Wi-Fi Module	DNN Classifier, Multi-Layer Perceptron Tabular Accuracy
23. [238]	Crop Production Crop Monitoring and management/Forecast the Appropriate Crops Growth, Harvest/Irrigation	DHT11 Humidity Sensor, Soil Sensor, Active Buzzer, IR Sensor, Relay, Water Pump ESP32 MCU, Firebase, Web Server ESP32 Wi-Fi Module	Random Forest, Neural Network, CNN Image Algorithm Evaluation
24. [198]	Aquaculture Assessment and Prediction of nitrite/Manually Assessment of Nitrite Growth/Aquaculture	Servo Motor, LCD, WebcamWater Pump, DC Motor Cloud Server, Raspberry Pi 3, Google Colab Platform Wi-Fi Router, Wi-Fi Module	Decision Tree, ANN (Feed-Forward Neural Network) Tabular Accuracy
25. [113]	Crop Production IoT-Based Climate prediction/Management of Farmers Agricultural Land by Producing Climate Type and Crop Planning Growth/Climate prediction	DHT11 Temperature and Humidity Sensor, Rain Gauge, LDR, Anemometer, ESP32 Microcontroller, Database Server, Cloud Server	LSTM Tabular Root Mean Square Error, R^2, Loss
26. [177]	Crop Production Smart Sensor for Energy saving/Smart Intelligent Sensor for Fruit Harvesting and Fertilizer Harvesting/Precision Agriculture	Low-Resolution Camera, Lora Vision Shield Cloud Server, Arduino Portenta H7 Microcontroller LoRaWan Communication Module, Laird RG1868 Gateway	Tiny Ml Paradigm (Faster Objects, More Objects) Image Accuracy

Table A2. *Cont.*

Ref.	Agricultural Concern [1]	IoT Components [2]	AI/ML Algorithms [3]
27. [148]	Animal Husbandry Track locust intrusion/Preventing and Tracking Locust Intrusion in Real Time Detection Pre-Harvest/Pest Management	555 Timer, N-Channel MOSFET, 8V Audio Amplifier, High Frequency Acoustic Device, CCTV Camera Arduino Atmega	YOLO v5 Image Precision, Recall, Mean Average Precision
28. [239]	Crop Production Prediction of Growth, Harvest Day, and Quality of Lettuce Crops in a Hydroponic Environment /Establishment of Suitable Growth Models for Greenhouse Applications Post-Harvest Stage /Greenhouse	GYJ-0154 Motor Driver, KM-37A535 Motor, MDU-1049 Motor Driver, LM2596 DC-DC Converter, PB-1300-3AR3 AC-DC Adapter, Temperature Sensor, Humidity Sensor, CO_2 Sensor, Light Intensity Sensor ATmega328p, Raspberry Pi 3 Model B, CC2530 ZigBee Module, Wi-Fi Module	Fuzzy Logic, Neural Network, Neural Fuzzy Tabular, Image Root Mean Square Error, R^2
29. [75]	Crop Production Smart Farming System for Coffee farms/Fully Implemented and Validated for Smart Farming Pre-Harvest, Growth/Periodic Inspection	pH Sensor, Ambient Temperature Sensor, Temperature Sensor Raspberry Pi 3 Model B, Cloud Server Gateway	Tree Regressor, ANN, XGBoost, Support Vector Regression, Random Forest Kinds of Data Pearson Correlation, Root Mean Square Error, MAE, Relative Squared Error (RSE)
30. [147]	Crop Production, Animal Husbandry Varroosis Detection/Constantly Monitor Beehives and Analyze the Video Data Stream in Real Time Pre-Harvest/Pesticide	ArduCam OV5647 5Mpx Camera Raspberry Pi, Google Coral USB Accelerator GSM Modem	CNN Image F1-Score, Confusion Matrix, Precision, Sensitivity
31. [232]	Animal Husbandry Predicting Mutton Sheep stress/Enhancing the Quality of Prediction Relationship Between Environmental Factors and Stress Growth/Periodic Inspection	DHT22 Ambient and rElative Humidity Sensor, RC-4HC Ambient Temperature and Relative Humidity Sensor, JY901B 9 Axis Accelerometer Gyroscope Sensor, DT-178A Vibration Sensor	GRNN, Backpropagation Neural Network, Elman Neural Network Tabular Fitting Coefficient, Absolute Errors, Relative Error

Table A2. *Cont.*

Ref.	Agricultural Concern [1]	IoT Components [2]	AI/ML Algorithms [3]
32.	Crop Production	Laser Radar (LIDAR), 9-Degrees-of-Freedom Inertial Measurement Unit (9DoF IMU), RGB Camera	CNN
[240]	Wearable Edge AI Technology to Monitor and Analyze Ecological Environments for Various Agricultural purposes/Applying Machine Learning Tools in a Wearable Edge AI	Raspberry Pi Zero W, Raspberry Pi 3B, Raspberry Pi 3B+, Jetson Nano (5 W Mode), Jetson Nano (20 W mode)	Image
	Growth/Monitoring		Precision, Recall, F1-score
33.	Crop Production	DHT11 Temperature Sensor, HX711 24-bit ADC Converter, LoRa E32 TTL 433 MHz, Photo-Resistor, IC 74HC151, IC 74HC595	Linear Regression
[188]	Wireless Sensor Networks and Machine Learning for Climate Change prediction/Accurate Predictions of Future Sand Movement in Specific Region and Adapting Climate Condition	ESP8266 Node MCU, ATmega 328P-AU MCU, Web Server	Tabular, Time Series
	Growth/Periodic Inspection	ESP8266 Node Wi-Fi Module	MAE
34.	Crop Production	Relay, Water Pump, Soil Moisture Sensor, NKP Sensor	Random Forest, LGBM, KNN, Decision tree, XGBoost, CNN (VGG-16)
[146]	Multimodal Precision Farming System/ Lack of Access to Basic Farming-Related Information, Such as Fertilizer Doses	Node MCU, Arduino IDE, Firebase, Web Server	Tabular, Image
	Pre-Harvest, Growth/Fertilizer		Precision, Recall, Accuracy, F1-Score
35.	Crop Production	Soil pH Sensor, Soil Moisture Sensor, Soil NPK Sensor, DHT11 Ambient Temperature and Humidity Sensor, Color Sensor (GY- 31 TCS3200)	Random Forest, CNN, Decision Tree
[195]	A Virtual Assistant to Maximise Crop Yield/Decision Support System Aided With Recommendation	Arduino UNO, NodeMCU ESP8266, Google Sheets	Image, Time Series
	Growth/Monitoring	NodeMCU ESP8266 Wi-Fi Module	Accuracy, Precision, Recall, F1-Score, Confusion Matrix
36.	Crop Production	DHT-22 Temperature and Humidity Sensor, MQ-135 Voltage Sensor, LDR Luminous Intensity Sensor	ANN (Forward Propagation Neural Network)
[144]	Low-Cost Viticulture Stress Framework/Remote Real-Time Monitoring and Detect Viticulture Stress	Firebase	Tabular
	Post-Harvest/Periodic Inspection	ESP-WROOM-32 Module	Accuracy, Precision, Recall, F1-Score

Table A2. *Cont.*

Ref.	Agricultural Concern [1]	IoT Components [2]	AI/ML Algorithms [3]
37.	Crop Production	Temperature and Air Humidity Sensor, Temperature and Leaf Moisture Sensor, Soil Moisture Sensor, Resistive Soil Moisture Sensors, Pyranometer and UV (Preferably UVA or UVB) Sensor, Leaf Wetness and Digital Caliper Pack	Support Vector Classification, CNN
[241]	Low-Cost Viticulture Stress Framework /Managing Stress Factors Affecting Table Grape Varieties	Vity-Stress Concentrator, MCU	Image
	Growth/Vine Stress Monitoring	BLE Wi-Fi Transponder, USB 3G/4G Dongle	
38.	Crop Production	Water Level Sensor, pH Sensor, Temperature and Humidity Sensor, Ground Temperature and Moisture Sensor, Solar Radiation Sensor, Conductivity Sensor, Wind Direction Sensor, Wind Speed Sensor	Support Vector Machine, Linear Regression, Random Forest, ANN
[242]	Acer Mono Sap Integration Management Based on Energy Harvesting Electric/Monitoring and Optimizing Sap Collection Processes in Acer Mono Trees	External Server	Tabular
	Harvest/Sap Integration Management	Network Module, Gateway	Precision, Recall, Accuracy
39.	Crop Production	RFID Gate, ALR-9900+ RFID Reader, RFID Tag	XGBoost
[85]	Enhance the Efficiency and Effectiveness of RFID-Based Traceability Systems for Perishable Food/Food Safety and Quality Standards in the Food Industry	Web Server	Tabular
	Post-Harvest/Perishable Food Handling	Linear Antenna ALR-9610-AL	Accuracy, Precision, Recall, F1-score
40.	Crop Production	MicroNIR PAT-W Sensor, MicroNIR PAT-U Sensors, Electric Motor, Screw Conveyor	PLS (Partial Least Squares) Regression
[233]	Analytical Approach for Common Wheat/Predicting the Issues About the Product Characteristics and Loss of Final Product	Cloud Server	Tabular
	Post-Harvest/Other		R^2, Root Mean Square Error

Table A2. *Cont.*

Ref.	Agricultural Concern [1]	IoT Components [2]	AI/ML Algorithms [3]
41. [243]	Crop Production Feed Chain in Olive Pitting, Slicing and Stuffing Machines/The Minimum Error of Traditional Systems Are Impossible to Remove Post-Harvest/Other	LED, Camera, Magnetic Sensor Dropbox, CM1K chip, Industrial PC	CNN, Backpropagation Neural Network Image Confusion Matrix
42. [93]	Crop Production Distributed Misbehavior Detection in Smart greenhouse-/Misbehavior Detection Approach to Detect Misbehaving Sensing Nodes Growth/Smart Green House	Temperature Sensor, Soil Moisture Sensor, Variable Rate Sprayer Arduino Uno Wireless Module	Kalman Filter Algorithm Scalar ROC, AUROC
43 Other [244]	Crop Production Precision Agriculture, Open Field Agriculture/High Installation and Maintenance Cost Growth/Irrigation	ATMOS 41, GS3 (Soil Temperature, Conductivity and Dielectric Permittivity) Sensor Cenote Platform Gateway	Fuzzy Rule Base Tabular
44. [218]	Crop Production Detection of Sigatoka Disease in Plantain Growth, Harvest/Other	Raspberry Pi Camera Module Rev 1.3, DS18B20 One Wire Temperature Sensor, YL-38 Soil Moisture Sensor, AM2301 Humidity Sensor Raspberry Pi 3, ThingSpeak Platform	ANN-Multi lAyer Perceptron Image Confusion Matrix
45. [71]	Crop Production, Animal Husbandry Automated Pest Monitoring for Fall Armyworm/Manual Pest Inspection Growth/Pesticides	DHT11 Moisture and Temperature Sensor, Pi Camera Module, IR Break Beam, Davis Anemometer Raspberry Pi 3 Model B+, Arduino Uno Quectel EC25 Mini PCIe 4G/LTE Module	Inception v3 Image Accuracy

Table A2. *Cont.*

Ref.	Agricultural Concern [1]	IoT Components [2]	AI/ML Algorithms [3]
46. [126]	Animal Husbandry Monitoring Individual Pigs Without Human Inspection Growth/Periodic Inspection	Intel RealSense Camera Embedded GPU	TinyYOLO With Image Processing Techniques (GMM, Binarization With Othsu, and Connected Component) Image Pixel-Level Accuracy
47. [245]	Animal Husbandry Precision Livestock Farming/Remotely Provide Accurate Feeding Information Growth/Feed Management	Ambient Temperature Sensor, Humidity Sensor, Ammonia Sensor, Carbon Dioxide Sensor, Hydrogen Sulfide Sensor, Entrance Monitoring Sensor, Exit Monitoring Sensor, RFID Identity Recognizer Core Processor Wireless Transmision Module	Unspecified Tabular, Time Series Unspecified
48. [87]	Crop Production, Animal Husbandry Cloud-Integrated Farming /Increasing the Crop Yield Without Human Intervention Growth/	DHT22 Temperature and Humidity Sensor, Barometric Pressure Sensor, Ambient Light Sensor, Dual-Axis Accelerometer Sensor MTS420 Sensor Board Zigbee Module, IRIS Mote, Gateway	Convex Hull Algorithm Image Periodic Inspection
49. [72]	Crop Production Precision Agriculture Using Iot and Machine Learning/Predict the Apple Scab as the Common Disease for Apple Crop Growth/Irrigation, Pest Management	Monitoring/Control Components Computation Components Communication Components	Linear Regression Tabular Algorithm Evaluation
50. [124]	Crop Production Continous Assessment of Crop Quality/Combining Monitoring and Automated Actions During Crop Growth Growth/Periodic Inspection	Temperature Sensor, Wind Sensor, Rain Sensor, Electrical Conductivity Sensor, Humidity Sensor, Radiation Sensor, Carbon Dioxide Sensor, Direction Sensor, and Wind Speed Sensor, RGB Camera	Random Forest Tabular Mean Squared Error (MSE)
51. [246]	Crop Production Crop Growth and Disease Monitoring/Lack of Access to Information About Crop Health Growth, Harvest/Disease Monitoring	Soil Moisture Sensor, Humidity Sensor Node MCU, Firebase Cloud Firestore, Heroku	Google Inception v2 Image Accuracy

Table A2. *Cont.*

Ref.	Agricultural Concern [1]	IoT Components [2]	AI/ML Algorithms [3]
52. [73]	Animal Husbandry Crop Protection Against Animal Intrusion/Crop Loss Sowing, Growth/Periodic Inspection	Pi Camera V2 Module, LED Lights Raspberry Pi 4 ESP8266 Wi-Fi Module	R-CNN, Single Shot Multibox Detection Image Mean Average Precision (MAP)
53. [105]	Crop Production Automatic Irrigation and Crop Monitoring System/Manual Disease Monitoring and Conventional Irrigation Methods Growth, Harvest/Irrigation	DC Motor, Relay Module, DHT11 Temperature and Humidity Sensor, Relay Module, 5V Water Pump ESP8266 NodeMCU	CNN Image
54. [116]	Crop Production Intelligent IoT-Based Combined Crop-Type and Disease Prediction/Predict Crop Yields and Detect Illness in Crops Growth/Periodic Inspection	Soil NPK Sensor, Soil pH Sensor Arduino Uno, Raspberry Pi, Azure IoT hub Wi-Fi Module	SVM, KNN Classifier, Decision Tree Tabular, Image Accuracy, Precision, Recall, F1-Score
55. [194]	Crop Production Soil Dampness Growth/Precision Agriculture	Soil Moisture Sensor, LED Display, Solenoid Valve, Switch, LED Arduino Mega, Personal Computer GSM SIM 800L	ANN, Fuzzy Logic, SVM Tabular MSE, Accuracy (R Squared)
56. [112]	Crop Production Agricultural Crop Recommendation/Provide Tailored Crop Recommendations That Optimize Resource Usage Growth/Crop Management	Soil Moisture Sensor, Raindrop Sensor Arduino UNO R3, ESP8266(NodeMCU) Module, Raspberry Pi ESP8266 Wi-Fi Module	Decision Tree Tabular
57. [247]	Crop Production Watering Intelligently With Distributed Optimization/Applying the Correct Amount of Moisture to the Area Growth/Irrigation	Soil Moisture Sensor, Solenoid Valve Raspberry Pi Zero	Unspecified Time Series Unspecified
58. [248]	Crop Production Autonomous Growth for Space Farming/Human Intervention Growth, Harvest/Periodic Inspection	BME280 Pressure, Humidity and Temperature Sensor, RGB Camera, Hyperspectral Camera (Cubert Ultris 5) NVIDIA Jetson AGX Orin, Raspberry Pi 4 Wi-Fi Module	YOLO v7 Image
59. [224]	Crop Production Tiny Ml-Based System/High Cost of Monitoring Growth, Harvest/Other	LCD Display, DHT22 Temperature and Humidity Sensor (AM2302 or RHT03) ATSAMD51-Based Wio Terminal Realtek RTL8720DN-Powered Bluetooth and Wi-Fi Module	TinyML Kinds of Data

Table A2. *Cont.*

Ref.	Agricultural Concern [1]	IoT Components [2]	AI/ML Algorithms [3]
60. [95]	Crop Production MUlti-Function Control for Smart Sensor/The High Computation Creates Actuation Lag and Reduces Analysis Rate Growth/Other	Smart Sensors Cloud	Federated Learning (Amendable Multi-Function Sensor Control) Tabular Algorithm Evaluation
61. [88]	Aquaculture Planetary Digital Twin/Deploying a Virtual Digital Replica of Aquaculture to Control Essential Water Quality Variables Growth/Precision Agriculture	Temperature Sensor, Dissolved Oxygen Sensor, pH Sensor, Turbidity Sensor, Ammonia Sensor ESP32 MCU, Arduino, Cloud Server SX1276 LoRa tRansceiver Module	Unspecified Time Series Unspecified
62. [97]	Crop Production Front and Rear End Separation Architecture/Lack of Intelligent Processing of Data Growth/Smart Agriculture	Soil NPK Sensor, DHT22 Temperature and Humidity Sensor, Illuminance Sensor, Human Induction Sensor, Raindrop Sensor Raspberry Pi 4B NB-IoT Module	Inception v3, Mobilenet v3, VIT Network Time sEries, Scalar Accuracy
63. [107]	Aquaculture, Fish Farming Fish Farming/Measuring In Real Time of Water Quality Growth/Periodic Inspection	pH Sensor, Electrical Conductivity Sensor, Total Dissolved Solids Sensor, Dissolved Oxygen Sensor Arduino Mega, ESP32, ThingSpeak ESP32 Wi-Fi Module	CNN Image
64. [193]	Crop Production Smart Gardening System/Traditional Approach Relies on Continuous Data From the Field Growth/Periodic Inspection	DHT11 Sensor Raspberry Pi, Arduino UNO, ThinkSpeak Server LoRa Radio RYLR896 Module, LoRa Gateway Wireless Module	LSTM Time Series MSE
65. [150]	Crop Production Optimized Smart Irrigation System/Increase Crop Production and Dealing With Water Distribution Problems Growth/Irrigation	Temperature, and Humidity Sensor (DHT11), Soil Moisture Sensor ESP8266 NodeMCU, ThinkSpeak Cloud NodeMCU Wi-Fi	MLP, Random Forest, SVM, Adaboost, Gradient Boosting, XGBClassifier Tabular Confusion Matrix

Table A2. *Cont.*

Ref.	Agricultural Concern [1]	IoT Components [2]	AI/ML Algorithms [3]
66. [219]	Crop Production Disease Detection /The Disease Can Affect the Vineyard Easily Growth/Periodic Inspection	Air Temperature and Humidity Sensor, Solar Radiation Sensor, Atmospheric Pressure Sensor, Soil Temperature and Humidity Sensor, Leaf Moisture Sensor, Precipitation Sensor, Soil Oxygen Level Sensor, Wind Speed and Direction Sensor Libelium Smart Agriculture Smart Agriculture Extreme Wi-Fi Module, 3G/4G Module	CNN Image Algorithm Evaluation
67. [249]	Animal Husbandry IoT Solutions for Ungulates Attacks/Low Cost Agricultural Field Protection Infancy, Growth/Other	PIR Sensors, Buzzer, Soil Moisture Sensor Cortex- A72 Raspberry Pi 4 B	YOLO v5 Image Accuracy
68. [138]	General Agriculture Anomaly Detection for Electric Energy Consumption/Traditional Detection of Power Anomalies Post-Harvest/Other	Farming Sensors, Actuator Controllers IoT Talk Engine, Data Talk, Altalk	Hybrid CNN and LSTM Tabular, Time Series MAE, MSE, Root Mean Square Error, MAPE
69. [133]	Crop Production IoT-Based Smart Farming/Smart Irrigation Services Based on Water Level Prediction Growth/Irrigation	RS 485 Ultrasonic Water Level Sensor, Water Pump Cloud Server Wi-Fi Module	Linear Regression, Random Forest Tabular, Time Series Precision, Recall, Accuracy, F1-score
70. [192]	Crop Production Smart Farm Android Application/Remote Monitoring Growth/Other	DHT11 Temperature and Humidity Sensor, Soil Moisture Sensor, Driver Module, DC Motor Node MCU, Heroku Cloud Platform, Web Server ESP32 Wi-Fi Module	Random Forest Regression Tabular R^2 Score
71. [79]	Crop Production Environmental Tracking System/Climate Change Lead to Inefficient Crop Production Growth/Other	DHT-22 Sensor, MQ-135 (CO_2 ppm) Sensor, LDR Sensor Arduino Uno, SIM7000E Module LoRa Module	KNN, SVM, Random Forest Tabular Confusion Matrix

Table A2. *Cont.*

Ref.	Agricultural Concern [1]	IoT Components [2]	AI/ML Algorithms [3]
72. [189]	Crop Production Smart Crop Protection Against Animal Interference/Animal Intrusion Growth/Other	Buzzer, LED lights, Pi Camera ESP8266 Node MCU, Raspberry Pi 4, Firebase Cloud ESP8266 Wi-Fi Module	R-CNN, Multiple Support Vector Machine, Linear Regression Image Confusion Matrix
73. [80]	Animal Husbandry Behavior Monitoring System Based on Wearable Inertial Sensors/Early Detection of Health Issues and Timely Intervention Growth/Periodic Inspection	Wearable Inertial Sensor STM32L051 Microcontroller Flash Memory	KNN, SVM Tabular Accuracy, Sensitivity, Precision, F1-Score
74. [225]	Crop Production Onset Disease Detection/Continuous Crop Monitoring Over a Period of Time Growth/Periodic Inspection	Sonoff GK- 200MP2-B IP Camera, Raspberry Pi-Based Camera Controller, Temperature Sensor, Pressure Sensor, Humidity Sensor, Ambient Light Sensor, U.V Light Sensor, Soil Moisture Sensor, Leaf Wetness Sensor Amazon Web Services Cloud, Raspberry Pi Wi-Fi Access Point, SX1262 LoRa Transceiver	CNN Image Accuracy
75. [66]	Mushroom Farming Mushroom Vertical Farming/Growing Crop in Controlled Indoor Environments Growth/Other	Temperature and Humidity Sensor, Commercial Off-the-Shelf Humidifier, RS485 (RGB LED Strip Controller) Jetson Nano, Firebase	Fuzzy Rule Base Time Series
76. [98]	Crop Production Precision Agriculture/Reduce Human Efforts, Water Wastage, and Power Consumption Growth/Irrigation	Temperature and Humidity Sensor (DHT22), Soil Moisture Sensor (SEN0193 v2.0), Rain Drop Sensor, Motor Starter, Solenoid Valve, CH340G NodeMCU-ESP12E ESP-12E Wi-Fi Module	Random Forest Tabular Accuracy
77. [99]	Crop Production Water Showering Mechanism/Low Cost Growth/Other	ADC Converter, DHT11 Sensor, MQ2 Sensor Raspberry Pi	Gradient Boosting, KNN, Gaussian Naive Bayes, Random Forest, XGBoosting, Decision Tree Tabular, Time Series Confusion Matrices

Table A2. *Cont.*

Ref.	Agricultural Concern [1]	IoT Components [2]	AI/ML Algorithms [3]
78. [100]	Crop Production Plant Disease Prediction/Disease Attack and Environmental Conditions Growth/Periodic Inspection	DHT-22 Temperature and Humidity, Rain Sensor Arduino	Multiple Linear Regression Time series Multiple R, R Square, Adjusted R Square, Standard Error
79. [250]	Crop Production Crop Cultivation Using IoT and Computational Intelligence/Traditional Methods in Monitoring Agricultural Fields Growth, Harvest/Periodic Inspection	Soil Moisture Sensor NodeMCU, Cloud Database	CNN Image
80. [251]	Animal Husbandry Egg Production in the Poultry Farm/Real-Time Environmental Impact Growth/Poultry Management	MQ-135 Ammonia Gas Sensor, DHT-22 Ambient Temperature and Humidity Sensor, LDR, Sound Arduino Uno, Server, SD Card Ethernet Shield	Multiple Linear Regression, K-Nearest Neighbor, Naive Bayes, XGBoost, Random Forest Tabular, Time Series Correlation Matrix
81. [252]	Crop Production Remote Crop Disease Detection/Plant Diseases Lead to Reducing the Accessibility of Food Growth/Periodic Inspection	Raspberry Pi Camera NVIDIA Jetson Nano 4GB, Google Drive Wi-Fi Module, RP-Style Antennas	CNN, AlexNet Image Accuracy
82. [114]	Crop Production IoT-Based Context-Aware Fertilizer Recommendation/-Costly, Time-Consuming, and Laborious Nature of Real-Time Soil Fertility Recommendation Growth, Harvest, Post-Harvest/Fertilizer Application	NPK Soil Sensor Cloud Server Gateway, Radio Frequency-433 (RF-433) MHz Module	Logistic Regression, Support Vector Machine, Gaussian Naive Bayes, K-Nearest Neighbor Tabular, Time Series Accuracy, Confusion Matrix
83. [96]	Crop Production Smart Agricultural System/Optimizing Farming Operations, Reducing Cost Growth/Fertilizer Application	DHT11, LDR, Soil Moisture Sensor, Relay Switch Arduino, ESP32, Dual-core Tensilica Xtensa LX6 Microprocessor, AWS IoT, AWS Lambda, AWS DynamoDB, Cloud Firestore Firebase Authentication Wi-Fi Module	Random Forest, Support Vector Machine, Naive Bayes, Logistic Regression, Decision Tree Tabular Accuracy
84. [118]	Crop Production Autonomous Mobile Robot System/Agricultural Population Loss, Community Decline Growth, Harvesting	Light Detection and Ranging (LiDAR) Sensor, Display screen, Robot Arm, Nine-Axis Gyroscope NVIDIA Jetson Nano	YOLO v3-Tiny, SLAM (Simultaneous Localization and Mapping) Image Accuracy

Table A2. *Cont.*

Ref.	Agricultural Concern [1]	IoT Components [2]	AI/ML Algorithms [3]
85. [152]	Crop Production Low-Cost Irrigation System/Low-Cost, Sustainable Irrigation System Growth/Irrigation	DHT22 Sensor Raspberry Pi 3 B+, Arduino NRF24L01 Module	LSTM, GRU Time Series, Tabular MSE, RMS, MAE
86. [83]	Crop Production Weather Monitoring and Rainfall Prediction/Inaccurate And Complicated Weather Forecast System All stages/Periodic Inspection	Rainfall Sensor, Wind Speed Sensor, Barometric Pressure Sensor, Humidity Sensor, Temperature Sensor, Arduino L293D Motor Expansion Module Cloud Server, Controller Unit	Support Vector Machine Time Series Accuracy, Precision, Recall, F1-Score
87. [190]	Crop Production, Hydroponics Hydroponic Intelligent Portable System/Improper Management in Agriculture Growth/Other	ESP32 Camera, DHT11 Sensor, DS18B20 Water Temperature Sensor, pH Sensor, Water Turbidity Sensor ESP32 Microcontroller, Raspberry Pi, Cloud Server Wi-Fi Module	CNN Tabular, Image Algorithm Evaluation
88. [253]	Crop Production IoT-Based Bacillus Number Prediction/Predict the Amount of Bacillus in an Open Farm Field by Using Very Small Dataset Growth/Other	Soil Temperature, Soil Humidity Sensor, pH Sensor, EC Sensor	Multi-Layer Perceptron Tabular MAPE
89. [254]	Crop Production Smart Agriculture Monitoring System/Monitoring and Adjusting Environmental Parameters Growth/Farm monitoring	LDR Sensor, Temperature and Humidity DHT11 Sensor, Ultrasonic Sensor, Soil Moisture Sensor, LCD, Relay, Motor, Servo Motor Raspberry Pi, Arduino UNO Wi-Fi Module	RNN Tabular
90. [222]	Crop Production Smart Raven Deterrent System/High Cost of Drobe-Based Approaches Growth/Periodic Inspection	Presence development board (CXD5602), Electric microphone (100 Hz–10 kHz), Microphone Preamplifier BOB-12758, Speaker Multi-core MCU	CNN Audio Signal Confusion Matrices

Table A2. *Cont.*

Ref.	Agricultural Concern [1]	IoT Components [2]	AI/ML Algorithms [3]
91. [255]	Crop Production Onion Detection/Unscientific Storage Facilities Lead to the Wastage of Onions Post-Harvest/Periodic Inspection	MQ2 Gas Sensor, DHT11 Temperature and Humidity Sensor, LCD ESP8266, Google Colab ESP8266 Wi-Fi Module	CNN Image Precision, Recall, F1-score
92. [256]	Crop Production Smart Farming Robot for Detecting Environmental Condition/Climate Change, Damaging Effect of Insects on Plants Growth, Harvest/Greenhouse	VEML6075 UVA /UVB /UV Index Sensor, SCD30 Sensor, SZDoit Smart Robot, Metal Gearmotor 25Dx65L mm HP, HC-SR04 Obstacle Sensor Raspberry 4.0 SparkFun LoRa Gateway, Arduino Nano 33 BLE Sense	K-Means Tabular WCSS Measure
93. [187]	Aquaculture Home Garden Management/Irrelevant Instructions for Growing the Crops Seed Selection, Growth/Periodic Inspection	DHT11, DHT22 Temperature and Humidity Sensor, Soil Moisture Sensor, Water Level Sensors, Focus Camera Arduino Uno, ESP8266, Web Server, Firebase ESP8266 Wi-Fi Module	Decision Tree Classifier Tabular
94. [108]	Hydroponics Remote Monitored Smart Hydroponics/Fail to Predict the Soil and Water Conditions Correctly Seed Selection, Growth	Temperature and Humidity Sensor, Infrared Sensor, Water Level Sensor, Buzzer, pH Sensor, LCD, Relay, ADC ESP32 NodeMCU, Cloud Storage Bluetooth Module, Wi-Fi Module	Random Forest Tabular Confusion Matrices
95. [92]	Crop Production, Hydroponics AI-Enabled Hydroponics System/Automated Remote Monitoring Growth	ESP32-CAM (OV2640 Camera), TCS34725 RGB Color Sensor, DS18B20 Temperature Sensor, Water-Turbidity Sensor, DFRobot Gravity Analog pH Sensor, Buzzer, Full-Spectrum LED lights, Submersible Water Pump, 5V Dual Channel Relay Module With Optocoupler, 7-Segment LED display ESP32 Microcontroller, ESP32-WROOM DEVKIT, Azure IoT-Hub, Azure DataBricks Wi-Fi Module, Bluetooth Module	Logistic Regression Tabular Accuracy, Recall, Precision, F1-score
96. [199]	Animal Husbandry Early Diagnosis of Bovine Respiratory Disease (BRD)/Early Diagnosis and Prediction of Calves With BRD Growth/Periodic Inspection	Precision Livestock Technology	Gradient-Boosting Classifier, Support Vector Machine Image, Tabular Accuracy

Table A2. *Cont.*

Ref.	Agricultural Concern [1]	IoT Components [2]	AI/ML Algorithms [3]
97. [257]	Crop Production Crop Management Application/Resource Management, Crop Quality Improvement Growth/Periodic Inspection	Temperature Sensor, Humidity Sensor, Soil Moisture Sensor, Light Intensity Sensor, Color Sensor, Pressure Sensor, pH Sensor Controller Unit, Cloud-Based Server Wi-Fi Module	Unspecified Tabular, Time Series Unspecified
98. [161]	Crop Production AI for Irrigation System/Traditional Irrigation System Growth/Irrigation	Soil Moisture Sensor, Water Pump NodeMCU (ESP8266), Raspberry Pi 3B+, Web Server	PLSR (Partial Least Square Regression) Tabular Algorithm Evaluation
99. [139]	Crop Production Grape Leaf Disease Identification System/Low Data Rate of Image Transmission Growth/Other	LoRa Node Arduino UNO Dragino LoRa Shield, Dragino LG01-N Gateway	CNN, Grad-CAM Image Accuracy
100. [258]	Hydroponics Integrated Smart Farming/Conventional Farming Leads to Lower Quality of Products Growth/Other	Ambient Temperature and Humidity Sensor, pH Sensor, Oxidation Reduction Potential (ORP) Sensor, CO_2 Sensor, electrochemical Sensor, Ultrasonic Sensor, Water Flow Sensor, Camera Arduino Uno, Raspberry Pi, Cloud Server	CNN Image Accuracy
101. [259]	Aquaculture Lot for Precision Agriculture/Water Quality Growth/Precision Aquaculture	Dissolved Oxygen (DO) Sensor, pH Sensor, Conductivity Sensor, Temperature Sensor, Actuator Cloud Server LoRa Gateway	LSTM Time Series, Tabular
102. [162]	Crop Production Water Control for Farming Irrigation System/Challenges Growth/Irrigation	Soil Sensor (FC-28), Ambient Temperature and Humidity Sensor (DHT11) Arduino UNO, ESP8266, Blynk Server ESP8266_12E Wi-Fi Module	ANN Tabular Mean Squared Error
103. [160]	Crop Production Classification of Nutrient Deficiencies in Plants/Rice Nutrient Inadequacies, Difficulty in Creating a Comprehensive Database for Crop Disease Growth/Plant application	Camera	CNN, LSTM Image Precision, recall, F1-measured

Table A2. *Cont.*

Ref.	Agricultural Concern [1]	IoT Components [2]	AI/ML Algorithms [3]
104. [260]	Animal Husbandry Livestock Monitoring and Tracking/Poor Maintenance of Cattle Sector Growth/Periodic Inspection	Temperature and Humidity Sensor (DHT11), Body Temperature Sensor (DS18B20), Heart Rate and SpO2 Sensor ESP32 microcontroller ESP8266 Wi-Fi Module	Support Vector Machine (SVM), Decision Tree, Multi-Layer Perceptron Tabular, Time Series Accuracy
105. [166]	Crop Production Vegetable Supply System/Predict Growth Requirement Growth	Temperature and Humidity Sensor ESP32, ESP8266, Raspberry Pi	LSTM Time Series
106. [117]	Crop Production Prediction of Paddy Yield/Errors in the Fertilizing and Planting Processes Growth	Temperature Sensor, NPK Sensor, Humidity Sensor, Wind Speed Sensor, Wind Direction Sensor Node MCU, Arduino, Cloud Server,	GRU Tabular, Time Series F1-Measure
107. [135]	Aquaculture ReMote Aquaculture Monitoring/Lack of Infrastructure and Resources Growth/Periodic Inspection	Ambient Temperature Sensor, Water Temperature Sensor, pH Sensor, Water Level Sensor, Camera, Ammonia Sensor, LCD Display, Relay, 10rpm Motor, Alarm Unit NODEMCU-ESP32 Controller, PC Wi-Fi Module	Canny-ROI-CNN Image Accuracy
108. [261]	Crop Production Horticultural Lighting System/ConventiOnal On–Off Time-Scheduling Methods Growth, Harvest/Periodic Inspection	Spectral Light Sensor (AS-7341), SS-110 Spectroradiometer, LED Light (Q400), Raspberry Pi Camera Module v2, Raspberry Pi 3 B+, Cloud Storage (Google Drive), ThingSpeak Platform, PC Wi-Fi Module	PlantCV Image MAE, MAPE, MSE, Root Mean Square Error
109. [262]	Crop Production AI-Based Storage Monitoring/Poor Maize Storage Monitoring Growth/Periodic Inspection	Ambient Humidity and Temperature Sensor (DHT22), Gas Sensor (MQ135), Light Intensity Sensor (LDR) Arduino Uno, Remote Database, Heroku SIM 800 GSM	VGG-16 Image Accuracy
110. [263]	Crop Production Irrigation Management/Determine The Evapostranspiration From Limited Environmental Conditions Growth/Irrigation	Temperature and Humidity (DHT-2), NodeMCU Node (ESP8266(LX106)) NodeMCU Wi-Fi-Enabled Module	K-Nearest Neighbors (KNNs), Support Vector Machine, Gaussian Naive Bayes, ANN Tabular Confusion Matrices

Table A2. *Cont.*

Ref.	Agricultural Concern [1]	IoT Components [2]	AI/ML Algorithms [3]
111. [183]	Animal Husbandry LoRaWan Cattle Tracking Prototype/Challenges Growth	CubeCell AB01, CubeCell AB02S Raspberry Pi 4, RAK4631 Module LoRa SX1276 Transceiver, LoRa Shield, Nordic nRF52840, LoRaWAN Stack	LSTM Tabular
112. [264]	Animal Husbandry Pest-Dense Area Localization/Limited Communication, Bad Data Transmission Growth	LM393 Voltage Comparator, Atmospheric Humidity Sensor Mega328pb MCU, Backend Server ZigBee Wireless Communication Module (2.4 GHz)	Planarization algorithm Topology Map Unspecified
113. [209]	Crop Production Tea Cultivation/Online Identification Method of Tea Diseases Growth, Harvest/Periodic Inspection	Camera (DS-2DC4423IW-D(C)) Cloud Server (OneNET Cloud Platform), Edge Node FLASH FISH Mobile Wi-Fi, Border Gateway (Universal TL-WDR5620)	Swim Transformers Network Image Accuracy, Confusion Matrix, Precision, Recall, Specificity
114. [236]	Aquaculture Aquacolony/Underwater Feeding Device Growth	Underwater Network Camera (VB-H651V), PoE Hub Personal Computer Ethernet hub	Support Vector Machine Image Accuracy
115. [157]	Aquaculture AnomaLy Detection for Smart aquaculture/Occurrence of Abnormal Conditions in Aquaculture Growth	pH Sensor, Dissolved Oxygen Sensor, Temperature Sensor Computation Components Communication Components	K-Means Clustering, Isolation Forest, Local Outlier Factor (LOF) Time Series Accuracy, Precision, Recall, F1-score
116. [184]	General Agriculture Portable Quality Monitoring System/The Gradient of the Water's Nutrients and pH Level. Growth	LCD, AD5933 Impedance Converter Arduino Uno, ThingSpeak Platform LoRa Shield	KNN Tabular Algorithm Evaluation
117. [201]	Crop Production AI-Powered IoT Devices In Wine Production/Ochratoxin A (Food-Contaminating Mycotoxins) Harvest, Post-harvest	B-L475E-IOT01A Discovery Kit, Capacitive Digital Sensor for Relative Humidity and Temperature (HTS221), 3D accelerometer, 3D Gyroscope (LSM6DSL), Dynamic NFC Tag (M24SR), Real-Time Clock Calendar Antenna M4 Core-Based STM32L4	ANN Tabular, Time Series Accuracy, Confusion Matrix

Table A2. *Cont.*

Ref.	Agricultural Concern [1]	IoT Components [2]	AI/ML Algorithms [3]
118. [103]	Crop Production Agricultural Applications/Challenges Agricultural Stages/Practices	Satellite (Landsat 7 and 8, Sentinel-2), Camera-Equipped Drone Processor	Unspecified Tabular, Time Series, Spectral Images Unspecified
119. [167]	Crop Production Soil Volumetric Water Content measurement/Inconsistency Data Resources Growth/Other	LoRa Antenna, Unmanned Aerial Vehicle (UAV) Host Computer LoRa Antenna	LSTM Time Series R^2, Root Mean Square Error, MAE
120. [265]	Crop Production Automatic Disease Detection and Pesticide Atomizer/Manual Monitoring Crops Growth/Periodic Inspection	Sprayer with Servo Motor, Raspberry Pi Camera Module Rev1.3, IR Sensors, DC Motors, IR Sensors, DC Motors Raspberry Pi 4 Wi-Fi Module	YOLO v3, Inceptionv3, SVM Image Accuracy
121. [149]	Crop Production Autonomous Mobile intelligent/Manual Inspection Growth/Periodic Inspection	Network Camera (Logitech C525), Apple iPhone 11 Camera, Thermal Imaging Sensor (PureThermal 2 With Lepton 3.5), LiDAR (RPLiDAR A1), Robotic Arm System (Open MANIPULATOR-X), Temperature and Humidity Sensor (YUDEN-TECH eYc THS13), Carbon Dioxide Sensor (YUDEN-TECH eYc GS43), JGB37-520 DC Gear Motors, Nine-Axis Sensor (MPU9250), RPLiDAR A1 Lidar ASUS Mini PC PB60G, ESP32 DOIT DEVKIT, Raspberry Pi 4B, 802.11 b/g/n/e/i 2.4 GHz Wi-Fi	CNN, YOLOv4 Image Accuracy
122. [140]	Crop Production Soil Nutrient Analyzer/Lack of Cost-Effective Soil Nutrients Growth/Fertilizer	Color Sensor (TCS34725), RGB LED Light, ESP32-Wroom-32 ESP32 Bluetooth Radio	Gaussian Process Regression Tabular MSE
123. [208]	Animal Husbandry Aquaculture Grid System/Quality Of Aquaculture Product Growth	Water Quality Sensor, Temperature Sensor, Dissolved Oxygen Sensor, pH Sensor ESP32 LoRa Module, 4G Module	Genetic Algorithm Backpropagation Time series MSE, Root Mean Square Error, MAE

Table A2. *Cont.*

Ref.	Agricultural Concern [1]	IoT Components [2]	AI/ML Algorithms [3]
124. [131]	Aquaponics Smart Aquaponics System/Traditional Agriculture Growth	Temperature Sensor, pH Sensor, Turbidity Sensor, Electrical Conductivity (EC) Sensor, Light Intensity Sensor, Temperature Sensor, Carbon Dioxide Level Sensor Atmega328p (Arduino Uno and Arduino Nano) Microcontroller Board, NodeMCU, Raspberry Pi 4, ESP8266 microcontroller Wi-Fi Module	Random Forest Time Series Absolute Mean Error
125. [266]	Crop Production PlanT Growth in a Greenhouse/Inefficiency in Agriculture Sector Growth	Mobile Camera, L298N Motor Driver, HC-SR04 Ultrasonic Sensor, 720-Pixel Web Camera, DHT22 Sensor, Piezoelectric Transducer Humidifier, Soil Moisture Sensor, Water Pump, Ultrasonic Mist Maker, Camera, Cooling Fan NodeMCU, GoogleSheets Wi-Fi Module	YOLO v5 Image
126. [182]	Crop Production Fog -Enabled LoRa/High Power Consumption Growth	Temperature and Humidity Sensor (DHT11) Raspberry Pi 4 (Model B, 8GB RAM), Chirpstack Opensource Long-Range Wide-Area Network (LoRaWAN) Server Dragino PG-1302 (10-Channel LoRa-Integrated Circuit), Dragino Arduino LoRa Shield-Based on Semtech SX1276/SX1278 Chip	Analytical Prediction Algorithm using Estimations Time Series MAE
127. [120]	Crop Production IrrigatiOn Management System/Increase iN the Consumption of Drinking Water Growth/Irrigation	Xiaomi Mi Flora Sensor, DHT11 Moisture Sensor, YF-S201 Flow Meter, Ultrasonic Level Sensor (HC SR04), Electrovalve DA14580 Processor, ESP32-WROOM Bluetooth Low Energy (BLE) Module	XGBoost, Classification and Regression Tree (CART), KNN, Logistic Regression, Linear Discriminant Analysis, Gaussian Naive Bayes Tabular Accuracy
128. [267]	Aquaponics, Aquaculture Growth Estimation Aquaponics/ConveNtional Cultivation Methods Growth, Harvest	Monitoring/Control Components Fog Node, Edge Node Gateway	MASK-R-CNN Image Root Mean Square Error, RMSPE

Table A2. *Cont.*

Ref.	Agricultural Concern [1]	IoT Components [2]	AI/ML Algorithms [3]
129. [268]	Crop Production, Aquaculture Freshwater Aquaculture Management/Maintaining the Aquaculture Environment Growth	Disolved Oxygen Sensor (DFRobot Gravity Model No: DFR1628), pH Sensor (DFRobot Gravity, Model SEN0161), Total Dissolved Solids Sensor, Temperature Sensor (DS18B20), Optical Water Level Sensor, Water Electrical Conductivity Sensor, Oxygen Pumps, Water Pumps, Biofilters, Water Filter, Solenoid Valves, Aerator, Air Diffusor Edge Node, Fog Node	Random Forest, Support Vector Regression, Gradient-Boosting Machine, Linear Regression (LR) Time Series Correlation(R), MAE
130. [227]	Crop Production, Animal Husbandry Estimating Quality of Tea Leaves/Cost-Effective, Manual Labor Harvest/Periodic Inspection	DJI Mavic Mini Light-weight Drone, Drone-Mounted Camera, Mobile Camera, Real-Time Clock ESP8266 Wi-Fi Module	YOLO v5 Image Accuracy, Loss
131. [169]	Crop Production Open Connectivity Foundation for Energy consumption/Uneasily Control Greenhouse Environment Growth/Greenhouse	Temperature Sensor, Humidity Sensor, CO_2 Sensor Raspberry Pi Wi-Fi Module	LSTM Time Series Root Mean Square Error, MAE, R^2
132. [121]	Crop Production Plant Disease Prediction/Crop Loss Due to Plant Diseases Growth/Periodic inspection	Soil Temperature Sensor, Soil Moisture Sensor, Ambient Humidity Sensor (HIH 5030), Ambient Temperature Sensor (MCP 9701A), Leaf Wetness Sensor (Phytos 31:LWS-L12) Thingspeak Platform Wi-Fi Module	LSTM Tabular Accuracy, Precision, Recall, F1-Score
133. [109]	Hydroponics Sensor Fusion-Based Smart Hydroponic/Automation and Monitoring of Environmental Conditions Growth	Water Depth Sensor (EC-3190), Light Intensity Sensor (Light-Dependent Resistor—LDR), Temperature and Humidity Sensor (DHT11), Water Temperature Sensor (MAX6675), pH Sensor (EC201), ESP8266 Wi-Fi Module	Random Forest Tabular

Table A2. *Cont.*

Ref.	Agricultural Concern [1]	IoT Components [2]	AI/ML Algorithms [3]
134. [269]	Crop Production Plant Disease Identification/High Cost of Manual Controlling Growth, Harvest/Periodic Inspection	Soil Moisture Sensor (SEN0114), pH Sensor (PHE-45P), Temperature and Humidity Sensor (DHT11), Water Pump ESP8266, Atmega16 Microcontroller, Raspberry Pi 3 ESP8266 Wi-Fi Module, GSM800L Module	Googlenet, Alexnet, VGG-19 Image Accuracy
135. [168]	Crop Production IoT Climate Data/Crop Yield and Cost Growth/Pest Prediction	Ambient Temperature Sensor, Solar Radiation Sensor, Precipitation Sensor, Humidity Sensor, Wind Speed and Direction Sensor Remote Data Server	Unspecified Tabular, Time Series Unspecified
136. [181]	Crop Production Smart Farming/Loss Of Crop Due to Climatic Condition Growth/Monitoring	Ambient Temperature and Humidity (DHT-11), Soil Moisture Sensor (FC-28), Gas Sensor (MQ-135), Light Intensity Sensor (LM-393), 5V-10A Relay Module Raspberry Pi 3, Cloud Server Wi-Fi Module	Logistic Regression, SVM Tabular
137. [134]	Crop Production Monitoring systems/Failure of Crop Production and Lack of Nutrients Growth/Monitoring	Relative Humidity and Temperature Sensor, (DHT11), Soil Moisture Sensor Arduino Uno, ESP8266, Thingspeak platform Wi-Fi Module	Gaussian Naive Bayes, Linear Support Vector Classifier, Decision Tree, Random Forest, Gradient-Boosting Classifier, Logistic Regression, Stochastic Gradient Descent Tabular Accuracy
138. [212]	Crop Production Real-time Application of IoT in Agriculture/Manual Agriculture Growth/Monitoring	Soil Moisture, Ambient Temperature and Humidity Sensor (DHT11), Passive Infrared (PIR) Sensor, Camera, pH Sensors, Relay Raspberry Pi, Blynk Cloud Wi-Fi Module	CNN Tabular, Image
139. [163]	Animal Husbandry, Crop Production Smart Farmland Monitoring and Animal Intrusion Detection/Manula Irrigation and Animal Intrusion Growth, Harvest/Periodic Inspection	Temperature and Humidity Sensor (DHT11), Moisture Sensor (YL-38), NOIR-V2 Camera Module, Passive Infrared (PIR) Sensor Raspberry Pi, Google Cloud Platform ZigBee Module	CNN, SVM, Naive Bayes, KNN Image Accuracy

Table A2. *Cont.*

Ref.	Agricultural Concern [1]	IoT Components [2]	AI/ML Algorithms [3]
140.	Animal Husbandry	Camera, Infrared Sensor, LEDs	Naive Bayes Classifier
[180]	Intelligent Insect Monitoring System/Toxic Products	Raspberry Pi Zero, Cloud Server	Image, Tabular
	Growth, Harvest/Monitoring	GSM Module, Wi-Fi Module	
141.	Crop Production	Temperature Sensors (LM 35 TO-92-3), Soil Moisture Sensors (LM358), Humidity Sensors (DHT11), Light Intensity Sensors (BH1750), Hyperspectral Cameras (HySpex), Water Flow Sensors (YF-S201)	CNN, Ensemble SVM
[145]	Crop Disease Monitoring System/Data Sharing and Automatic Farming	Auduino Uno	Image, Tabular
	Pre-Harvest/Disease Detection	GSM Module, Wi-Fi Module	Precision, Recall, Accuracy, Specificity
142.	Crop Production	Air Temperature Sensor, Air Humidity Sensor, CO_2 Concentration Sensor, Illumination Intensity Sensor, Soil Moisture Sensor, Soil Temperature Sensor, Leaf Wetness Sensor, Soil Humidity Sensor	Logistic Regression
[179]	Predicting Agricultural Pests and Diseases/	Raspberry Pi 3 Model B, Arduino Uno R3, AWS IoT, Amazon Simple Storage Service (S3), Elastic MapReduce (EMR)	Tabular, Time Series
	Growth/Monitoring	ZigBee Module	AUC
143.	Crop Production	Soil Moisture Sensor, Temperature and Humidity Sensor	Fuzzy Logic System
[270]	Plant Monitoring/Quality and Productivity of Plant Development	NodeMCU, Blynk Platform	Time Series
	Agricultural Stages/Practices	Wi-Fi Module	
144.	Animal Husbandry	GPS Tracker Collars Equipped With Pitch and Roll Tilt Sensors	Random Forest, Decision Trees (DTs) using C50, XGBoost, K-Nearest Neighbors (KNNs), Support Vector Machine (SVM), Naive Bayes
[271]	Animal Monitoring-Based IoT/Additional Support of Animal Husbandry Activities	Web Servers	Time Series
	Growth/Animal Monitoring	MiniPC (Gateway)	Confusion Matrix
145.	Crop Production	Ambient Temperature and Humidity Sensor (DHT11), Comparator Chip (LM393), Soil Moisture Sensor (EC-1258), RPi Camera	CNN
[191]	Edge Computing Framework/Poor Crop Health, Soil Infertility, Limited Resources	Arduino Uno (ATmega328P), RPi 3B+, ESP32 MCU Node	Image, Time Series
	Sowing, Growth/Monitoring	ESP32 Wi-Fi Module	Accuracy

Table A2. *Cont.*

Ref.	Agricultural Concern [1]	IoT Components [2]	AI/ML Algorithms [3]
146. [178]	Crop Production Contract Farming/Poor Economic Condition All Stages/Crop monitoring	Sensor Node Raspberry Pi, Cloud Server Wi-Fi Module	Density-Based Spatial Clustering of Applications with Noise (DBSCAN) Tabular, Time Series
147. [214]	Crop Production Prediction of Soil Moisture and Temperature/Environmental Data Acquisition Growth/Periodic Inspection	Soil Temperature and Moisture Sensor (SM3002B), Ambient Temperature and Humidity Sensor (AM3006) STM32F103ZET6 Microcontroller, Alibaba Cloud Transceiver Module (RSM3485), WH-NB75-B5 NB-IoT wireless Module	LSTM Tabular, Time Series Root Mean Square Error, MAPE, R^2
148. [200]	Crop Production Prediction of Amount of Pesticides and Diseases/Harmful Pesticides Post-Harvest/Plant Monitoring	Gas Sensor (MQ135), Moisture Sensor (DHT11), Temperature Sensor, pH Sensor Arduino UNO, Cloud Server (MATLAB ThinkSpeak) Wi-Fi Module (ESP8266)	CNN, SVM Image Accuracy, Precision, Recall
149. [272]	Crop Production Agricultural Field Monitoring/Human Effort Growth, Harvest	Soil Moisture Sensor (LM393), Smoke Sensor (MQ2), Gas Sensor (MQ9), Actuators (Water sprinklers) Arsuino Uno, ESP8266, Cloud Server Wi-Fi Module	CNN Image Accuracy, Precision, Recall, F1-Score
150. [273]	Crop Production Agricultural Environmental Data Collection System/Real-Time Detection of Environment Growth/Periodic Inspection	Fungus Detector, Ambient Temperature and Relative Humidity Sensor, Soil Moisture Sensor, Wind Speed Sensor, Wind Direction Sensor, Sunlight Intensity Sensor ZigBee Module, Wi-Fi Module, GPS Module Microcontroller, Cloud Server	SVMR (Support Vector Machine with Radial Basis Function) Tabular Mean Absolute Error
151. [86]	Crop Production Agricultural Irrigation Prediction/Manually Controlled System Growth/Irrigation	Light Intensity Sensor, Air Sensor, Soil Sensor (RS-485 interface) API Server, Raspberry Pi3 LoRa Module	Linear SVR, SVC, ADABoost DT, Random Forest, XGBoost Tabular, Time Series Mean Absolute Error, Mean Bias Error, Root Mean Square Error

Table A2. *Cont.*

Ref.	Agricultural Concern [1]	IoT Components [2]	AI/ML Algorithms [3]
152. [203]	Crop Production Pest Detection/Prompt Detection of Dangerous Parasite All Stages/Periodic Inspection	Camera Raspberry Pi, Intel Movidius Neural Compute Stick (NCS) LoRa radio	VGG-16, LeNet Image Accuracy, Recall, Precision, F-score
153. [90]	Hydroponics Predictive Control on Lettuce NFT/Unoptimized Manual Control Growth/Optimization	Temperature Sensor, Water Level Sensor, Light Intensity Sensor, Humidity Sensor, Relay, Fan, Lamp, Solenoid Valve Raspberry Pi, Arduino MQTT Module	Deep Neural Network Tabular, Time Series Accuracy
154. [274]	Crop Production Smart Intelligent Advisory Agent/Traditional Cultivation Methods Agricultural Stages/Practices	Soil Moisture Sensors, Digital Humidity and Temperature (DHT11) Sensor, and pH Sensor Server Wi-Fi Module	SVM, CNN, RNN Image, Time Series MSE, R^2
155. [275]	Crop Production Intelligent Animal Repelling System/Loss Production, Ungulate Attack Growth/Others	20 Megapixels Digital Camera RPi 3B+, NVIDIA Jetson Nano, Cloud Server Wi-Fi Module, LoRa Module RN2483A, Xbee Radio Module	YOLO, Tiny-YOLO Image Mean Average Precision, Average Precision, Recall
156. [143]	Crop Production Digital Farming/Crop Cultivation Measurement Crop Cultivation/Others	Soil Moisture Sensor Web Server Wi-Fi Module	LSTM Image Accuracy
157. [111]	Fish Farming, Aquaponics Smart Aquaponics Monitoring/Traditional Agricultural Practices Monitoring/Precision Farming	Temperature Sensor (DHT11), Light Intensity Sensor (BH1750), Soil Moisture Sensor (LM393), Ultrasonic Sensor HC-SR04, Relay Driver Circuit Module, pH Sensor SEN0161 Raspberry Pi, Cloud Server Wi-Fi Module	Mask RCNN Image, Time Series Precision, Recall, F1-Score
158. [205]	Animal Husbandry Piglet Crushing Mitigation/Piglet Mortality All stages	Actuators (Vibration, Shock, Water Drop, Heat, Air Blast), Motor, Camera, Microphone, Temperature Sensor PigTalk Server, GPU (Nvidia GeForce RTX 2080), CPU (Intel Core i7-7800X)	Mel Frequency Cepstral Coefficient, Convolutional Neural Network, Min–Max Scaling Audio Data Accuracy

Table A2. *Cont.*

Ref.	Agricultural Concern [1]	IoT Components [2]	AI/ML Algorithms [3]
159. [164]	Crop Production Smart Plan Irrigation System/Challenges Growth/Irrigation	Soil Temperature and Moisture Sensor, Humidity Sensor, Motor ESP8266, Personal Computer Wi-Fi Module, SPI	Gradient-Boosting Regression Trees Tabular Accuracy
160. [94]	General Agriculture Smart Farming IoT/Not Working Properly in Remote Areas Growth	Sensor Node Arduino Uno, Raspberry Pi, Cloud Server nRF24L01	CNN Image, Tabular
161. [89]	Animal Husbandry Dairy Farming, Cattle Farming/Efficient Cattle Health Monitoring Growth/Poultry Growth Monitoring	Motion Sensors, Gyroscope (GY-25), Accelerometer, Heart Rate Sensor (MAX30100), Body Temperature Sensor (MLX90615) Microcontroller, Raspberry Pi, Cloud Server Wi-Fi Module (WEMOS D1), MQTT Module, Wi-Fi Router	Support Vector Machine, Decision Tree Tabular Accuracy
162. [127]	Animal Husbandry, Livestock Industry Analyzing Pigs' Behavior/Declining and Aging Livestock Population Growth/Recognition and Observation	Environment Air Quality Sensors, Water Flow Sensor, Camera, Microphone	Faster R-CNN Image
163. [110]	Aquaponics, Hydroponics Water Temperature Forecasting/Extreme Water Temperature Growth/Control and Monitoring System	Water Temperature Sensor, Aquarium Water Heater, Aquarium Fan Cooler, Relay Module Server, ESP8266 Microcontroller MQTT Broker	Decision Tree Regressor, AdaBoost Tabular MSE, R Squared
164. [207]	Crop Production Soil Moisture Calibration/Expensive Soil Moisture Sensor Growth, Harvest	Soil Moisture Sensor	Naive Bayes, Support Vector Machine Time Series Confusion Matrix
165. [132]	Hydroponics Hydroponics Nutrient Control System/Manual Hydroponic Farming Growth	Actuator, Water Pump, pH, TDS Sensor, Temperature probe Arduino Leonardo, ESP8266, Server Wi-Fi Module	KNN Tabular Accuracy

Table A2. *Cont.*

Ref.	Agricultural Concern [1]	IoT Components [2]	AI/ML Algorithms [3]
166. [276]	Crop Production IoT-Based Object Detection/Agricultural Damage From the Monkey in the Farm Field Growth	Camera, Buzzer Node, Server Gateway Router	K-Means, FAST Algorithm Image, Tabular Recognition Rate
167. [153]	Crop Production Wireless Sensor Network-Based Autonomous Farming Robot/Dynamic Changes in the Environment Growth	Camera, DHT11 Sensor, Smoke Sensor, Soil Moisture Sensor, LDR Raspberry Pi, MCU (AVR), ESP8266 nRF, Wi-Fi	ANN Image Confusion Matrix
168. [104]	Crop Production Smart Greenhouse Disease Prediction/Plant Disease Detection Growth	Raspberry Pi Camera, DHT11 Humidity and Ambient Temperature Sensor, Soil Moisture Sensor Raspberry Pi, Personal Computer GSM Module	DNN, Fast R-CNN Image, Tabular Accuracy
169. [202]	Crop Production Kiwi Fruit Shelf Life Estimation/Quality Standard Maintenance Post-Harvest/Food Quality Application	MQ2 Gas Sensor, DHT22 Temperature/Humidity Sensor WIO Terminal (ATSAMD51-Based Microcontroller) WIO Terminal	Multiple Linear Regression Time Series
170. [154]	Aquaculture, Fish Farming Fish farm-Based IoT/Cost-Effective Fish Farm Monitoring Growth	pH Sensor (TOL-00163), Ultrasonic Sensors (HC-SR04), IR Optical Sensor (TCRT5000) Arduino UNO, Web Server WEMOS D1 (Wi-Fi Module)	Linear Regression Model Tabular, Time Series Accuracy, ME, MSE, Root Mean Square Error
171. [82]	Crop Production Visual Sensor Nodes/Wireless Sensor Network Pre-Harvest/Monitoring	Raspberry Pi Camera Module v1 Raspberry Pi 3 model B, RabbitMQ Server Bluetooth Low Energy (BLE 4.0)	Random Forest, Support Vector Machine Image Accuracy, Recall, Precision, Specificity, F1-Score
172. [185]	Crop Production E-Agrigo/Conventional Farming Growth, Harvest	Sunlight Intensity Sensor, Soil Moisture Sensor, Soil pH Sensor, Humidity and Temperature Sensor Arduino Arduino Wi-Fi Module	Naive Bayes, SVM Tabular, Image Accuracy
173. [211]	Crop Production Temperature Forecasting/Temperature Monitoring Growth	DS18B20 Digital Temperature Sensor Control Host, Cloud Server	Spatial Attention LSTM Time Series Root Mean Square Error

Table A2. *Cont.*

Ref.	Agricultural Concern [1]	IoT Components [2]	AI/ML Algorithms [3]
174. [76]	Crop Production Plant Monitoring Control System/Leaf Disease Growth/Tomato Crop Plantation Monitoring	Soil Moisture Sensor, Temperature-Humidity Sensor (DHT22), Solenoid Valve ESP8266, Personal Computer Wi-Fi Router, Zigbee Module	ANN (Backpropagation) Image Confusion Matrix
175. [142]	Crop Production Robot Monitoring for Soybean Field Soil Condition/Soil Moisture Growth/Soybean Growth	Ultrasonic Distance Sensor (HC-SR04), Humidity Sensor (BME280), Camera Module, Motor Driver (L298N), Things-Board, Water Pump Raspberry Pi 3B+ MQTT Broker (Hive MQ)	KNN Image Accuracy, Recall, Precision, F1-Score
176. [277]	Crop Production Fruit Quality Detection/Identification and Quality Evaluation Post-Harvest/Food Quality Detection and Management	Humidity Sensor, Light Sensor, Temperature Sensor, Camera, Relay, DC Motors Microcontroller, Computer Wi-Fi Module	CNN Image
177. [278]	Crop Production Ornamental Plant Care/Soil Humidity Monitoring Growth	Atmospheric Temperature and Humidity Sensor (DHT11), Water Pump, Soil Moisture Sensor (YL-38, YL-69), Relay ESP8266 ESP8266 Wi-Fi Module	ANN (Multi-Layer Perceptron), K-Means Tabular
178. [158]	Crop Production Precision Irrigation/Food Security and Climate Change Pre-Harvest/Irrigation	Soil Moisture Sensors, Air Humidity and Temperature Sensor (DHT22), VEML6070 UV Sensor Raspberry Pi 4B, Arduino MEGA 2560 R3 Xbee Zigbee Wireless Adapter	RNN-LSTM Tabular Root Mean Square Error, MSE, MAE, R^2, Correlation Coefficient, Relative Absolute Error, Root Relative Absolute Error
179. [119]	Crop Production Automatic Irrigation of Water and Plant Disease Detection/Lack Higher Crop Productivity Sowing/Water management	Soil Temperature and Moisture Sensor (DHT11), Flow Sensor	SVM, KNN Image Accuracy, F1-Score, Precision, Prediction time, Training time

Table A2. *Cont.*

Ref.	Agricultural Concern [1]	IoT Components [2]	AI/ML Algorithms [3]
180. [84]	Crop Production Precision Irrigation/Sensor Fault Detection in Japanese Plum Leaf-Turgor Growth	Leaf Temperature and Turgor Pressure Sensors MQTT Broker and Client	SVM, Decision Tree, Naive Bayes, Logistic Regression, KNN Tabular, Time Series Accuracy, Precision, Recall, F1-score, AUC, MCC, Kappa
181. [186]	Crop Production Precision Agriculture/Large Datasets of IoT Infrastructures Growth, Harvest	Temperature Sensor High-Performance Computing Server, IoT Device MQTT Broker and Client	CNN-LSTM Tabular, Time Series R^2, Root Mean Square Error, MAE
182. [223]	Crop Production Root Disease Classification/Inability to Accurately Classify Crop Productivity/Root Disease Monitoring	IoT Nodes Cluster Heads	Remora Chicken Swarm Optimization With SqueezeNet (RCSO-Based SqueezeNet) Image Sensitivity, Specificity, Accuracy, Computational Time
183. [141]	Crop Production Pest Incidence Forecasting/Pest Control Growth/Pest Control and Monitoring	Temperature and Humidity Sensor (DHT22), Soil Moisture Sensor (YL-38, YL-69), Light Intensity Sensor (GY-30), and Atmospheric Pressure Sensor (BMP180) Raspberry Pi 4, Arduino Nano, DS3231 Module Grove-LoRa Radio, SX1276 Transceiver	LSTM Tabular, Time Series R^2, MSE
184. [136]	Mushroom Farming Mushroom Farm Automation/Traditional Mushroom Cultivation Growth, Harvest/Toxic Mushroom Classification	Camera Module, AC Bulb ESP32, Raspberry Pi	Naive Bayes, Decision Tree, Logistic Regression, KNN, SVM, Random Forest Image Confusion Matrix
185. [230]	Crop Production Data Fusion in Smart Agriculture/Small Battery Life, Limited Storage, Low Accuracy Growth, Harvest/Soil Moisture, Evapostranspiration	Soil Moisture Sensor, Wetness Sensor, Waterproof Temperature Sensor Arduino Pro Mini, Raspberry Pi Zero Wi-fi Adapter, nRF24l01	Kalman Filter, Weighted Outlier Robust Kalman Filter, SVM Time Series Root Mean Square Error, R^2, MAE, MSE, Prediction Speed, Training Time

Table A2. *Cont.*

Ref.	Agricultural Concern [1]	IoT Components [2]	AI/ML Algorithms [3]
186. [215]	Animal Husbandry Early Lameness Detection/High-Cost, Complex Equipment, Human Observation Infancy/Real-Time Identification	Long Range Pedometer Local PC MQTT Module	Random Forest, KNN Time Series Accuracy
187. [226]	Crop Production, Animal Husbandry Continuous Monitoring of Insect Pest/Mango Cultivation Damaged by Insect and Environmental Condition Pest Monitoring	Raspberry Pi Camera v2.1 Module, SHT20 Temperature–Humidity Sensor, BH1750 Light Intensity Sensor Raspberry Pi Zero W, Cloud Server Raspberry Pi Zero W Wi-Fi Module	TinyYolo, Light-Weight CNN, CNN Image Detection Rate, Precision, Recall, F1-Score
188. [106]	Aquaculture Water Quality Assessment/Real-Time Monitoring Growth/Other	NITRATE (PPM) AquaTest, pH Sensor (HI 98107), AMMONIA (mg/l) GS06 Sensor, Temperature Sensor (LM35), Dissolved Oxygen Sensor (DO-520), TURBIDITY Sensor (2100P), MANGANESE (mg/l) 2 S Water Arduino Uno, ESP8266	Dilated Spatial Temporal CNN Time Series Accuracy, Precision, Recall, Root Mean Square Error, MAPE, MAE, AUC, ROC, Loss
189. [159]	Crop Production Asparagus Cultivation/Asparagus Growth and Monitoring Pest and Disease Growth, Harvest	Raspberry Pi Camera, DHT-22 Temperature, Humidity Sensor, Soil Sensor (Temperature, Humidity, and Electrical Conductivity) Raspberry Pi 3B	YOLO v5, YOLOR, Faster R-CNN, RetinaNet Image, Tabular Precision, Recall, Confusion Matrix
190. [123]	Crop Production, Animal Husbandry Crop Pest Infestation/Identify Crop Diseases Growth	Soil Moisture Sensor, Atmospheric Temperature Sensor, Soil Temperature Sensor, Rainfall Sensor Raspberry Pi 4, CC2650 MCU, Cloud Server 5G-LTE Module	Fuzzy Logic Tabular, Time Series Confusion Matrix, F-measure, MCC, ROC, Accuracy, Train time, Run time

Table A2. *Cont.*

Ref.	Agricultural Concern [1]	IoT Components [2]	AI/ML Algorithms [3]
191. [155]	Crop Production Flow Meter Monitoring/Time-Consuming and Costly Agricultural Stages/Irrigation	Raspberry Pi 8 megapixel RGB Camera Raspberry Pi 4, Cloud Server Raspberry Pi LoRa Node pHAT, External 915 MHz LoRa Antenna	YOLO Image Accuracy
192. [210]	Crop Production Active Fire Locations/Challenges Post-Harvest/Reducing Active Farm Fire	Temperature Sensor, Smoke Sensor (MQ-2), Flame Sensor, IP Camera Raspberry Pi XBee Modules	Convolutional Neural Network, Mobile Net v2, Fuzzy Logic Image Precision, Recall, F1-Score, Accuracy, R^2 Score
193. [220]	Crop Production Water Status in Wheat Crop/Accurate Assessment of Plant Water Sowing, Growth/Irrigation	Temperature and Relative Humidity Sensor (TH10), Wind Speed Sensor (Macsensor, W70S), Soil Moisture Sensor (RS485/Analog), RGB Camera (LM-817, Sony IMX179, 1080P, USB 3.0) Raspberry Pi 3b+, Web Server Wi-Fi Router	CNN, LSTM Tabular, Image Accuracy, Precision, Recall, Intersection Over Union, F-measure
194. [234]	Animal Husbandry Cattle Activity Monitoring/Information Related to Standing Behavior of Cattle Growth/Practices	Motion Processing Unit (MPU6050), GPS Module (Neo 6M), Temperature Sensor Thermistor Microcontroller (ATMEL328) GSM Module (SIM800)	XGBoost, Random Forest Tabular Accuracy, Precision, Sensitivity, Specificity
195. [165]	Crop Production Resource Optimization Sowing, Growth/Control Soil Quality	Soil Moisture Sensor (YL 69), Pressure Sensor (BMP 280), Humidity and Temperature Sensor (DHT11), Wireless Network Node MCU (ESP 8266) Cloud Server	Radial Function Network Time Series Accuracy, Sensitivity
196. [137]	Apiculture Honey Bee Health Monitoring/Protecting the Honey Bees All Stages	Gas Sensors (CO2 TGS4161; O2 SK-25; NO2 MiCS-2710; and Air Contaminants TGS2600 and TGS2602), Temperature MCP9700A Sensor, Humidity 808H5V5 Sensor, Acceleration LIS331DLH Sensor ATmega1281 microcontroller ZigBee Radio Module	Decision Tree Tabular Confusion Matrix, Accuracy

Table A2. *Cont.*

Ref.	Agricultural Concern [1]	IoT Components [2]	AI/ML Algorithms [3]
197. [235]	Crop Production Irrigation System/Food security, Autonomous Irrigation of Crops Site Selection	Tensiometer Sensor, Soil Moisture Sensor, Temperature Sensor, Humidity Sensor Microcontroller Board 6G-Communication Module	ANN Tabular, Time Series Accuracy, Sensitivity, Precision
198. [206]	Crop Production Site Selection/Optimization Site Selection	Laser Rangefinder, Inertial Measurement Unit (IMU), Optical Flow Module STM32H743IIT6 Microprocessor ZigBee Module	Particle Swarm Optimization, K-Means Tabular R-Square
199. [217]	Crop Production Weed Detection/Plant Recognition, Detection Seed Selection, Sowing, Growth/Plant Inspection	Cloud Server	YOLO v5, Kernel Extreme Learning Machine Image Precision, Specificity, Recall, MCC, Accuracy, Geometric Mean

[1] Agricultural Concern: Forms of Agriculture; Agricultural Applications/Challenges; Agricultural Stages/Practices; [2] IoT Components: Monitoring/Control Components; Computation Components; Communication Components; [3] AI/ML Algorithms: Types of Algorithms; Kinds of Data; Algorithm Evaluation.

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