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SURVEY

Smart Farming Technologies: A Methodological Overview and Analysis

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ABSTRACT This paper presents a comprehensive examination of smart farming solutions through a systematic review of literature available in various digital repositories. Methodologically, we categorize the devices and technologies utilized in these solutions into sensors, actuators, gateways, power supplies, networking, data storage, data processing, and information delivery. Through this analysis, we identify the most commonly employed devices and technologies in smart farming solutions and discuss their utilization within the proposed categories. By synthesizing the gathered information, we offer insights into the current landscape of smart farming, accompanied by recommendations for the selection of devices and technologies tailored to each category. This research contributes to the understanding of smart farming technology and aids stakeholders in making informed decisions regarding the implementation of such solutions.

INDEX TERMS Smart farming, Internet of Things, IoT, LoRaWAN, network, sensors, WiFi, wireless communication.

I. INTRODUCTION

The Internet of Things (IoT) is a global network of smart objects capable of self-organization, information exchange, and responding to environmental changes [1]. These elements, also known as "smart things", range from sensors and devices to machinery and household appliances. The evolution of the IoT has been divided into three main phases. The first phase, spanning from 2002 to 2009, was characterized by an initial slow development, with a limited number of publications. During this period, attention towards IoT began to take shape, marked by the introduction of key reports, such as the one from the International Telecommunication Union in 2005. The next phase, covering from 2009 to 2015, is known as the development phase. During this time, several countries, including the European Union and China, launched specific action plans for IoT, providing strategic guidance for its development and implementation in various application fields. Finally, the phase of accelerated growth, which unfolded between 2015 and 2019, was characterized by a notable increase in research across various fields such as medicine, agriculture, industry, smart cities, among others, and the publication of works related to IoT. During this period, the number of publications grew rapidly, reflecting a growing interest and advancement in the field of IoT [2].

IoT's significance lies in its transformative capacity to revolutionize interaction with the real world. By enabling real-time data collection and analysis, IoT facilitates faster and more accurate decision-making, ultimately enhancing operational efficiency, reducing costs, and generating new business opportunities. As mentioned earlier, IoT finds applications in diverse areas, including:

- **Smart mobility:** IoT is used for traffic management, vehicle tracking, intelligent transportation systems, route optimization, intelligent parking lots, among other things.
- **Smart grid:** IoT is used for efficient energy management, real-time monitoring of electricity consumption,

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integration of renewable energies, optimization of energy distribution, etc.

- **Smart Home:** In this field, IoT is used for home automation, control of connected devices, energy management, security and surveillance, as well as comfort and energy efficiency.
- **Public Safety and Environment Monitoring:** IoT is used for pollutant detection, air and water quality monitoring, early warning systems, natural disaster management, etc.
- **Medicine and healthcare:** IoT is used for connected medical devices, remote patient monitoring, drug management, real-time health monitoring, etc.
- **Industry 4.0:** IoT is used for process monitoring and optimization, predictive maintenance of machinery, supply chain management, quality control and much more.
- **Breeding:** IoT technologies are harnessed for comprehensive livestock management and monitoring of animal health. [3].

Among these various applications, one area where IoT is being used extensively is in smart farming. In smart farming, the importance of IoT lies in its ability to gather real-time data from connected sensors and actuators. This enables informed decision-making, resource optimization, and task automation, leading to more sustainable and productive farming practices. For instance, a study referenced in [4], highlights how IoT integration in smart agriculture can provide key benefits that improve the efficiency, productivity, and sustainability of farming operations. In addition, IoT enables an intelligent, data-driven management approach in agriculture that helps farmers make informed decisions. As a result, they can optimize their farming and harvesting practices, significantly improving their bottom line.

Despite the evident benefits that modern agricultural technologies could bring to the farming sector, their widespread application is hindered by a significant barrier—the lack of knowledge among farmers. As highlighted by various studies, agriculture is a vital component of many economies, yet prevailing conditions among farmers often include deficiencies in education, technology, and financial resources [5]. Traditional agricultural practices, such as manual labor-intensive tasks like tilling, sowing, and harvesting, are still common in many regions, standing in stark contrast to modern methods employing mechanized equipment and hybrid seeds [5]. The challenges in implementing smart farming solutions, as identified in the literature, encompass factors such as undefined standards, issues related to coverage and connectivity, high investments, resistance to the use of new technology, and a shortage of trained manpower [6]. Moreover, the adoption of smart farming is impeded by the absence of models offering guidance on the necessary components for IoT-based monitoring systems [7]. Another significant obstacle is the prevailing lack of education among most farmers living in rural areas, resulting in a lack of knowledge and understanding regarding IoT technologies and their potential applications [8]. To overcome these challenges and unlock the full potential of modern agricultural practices, efforts must be directed toward educating farmers on IoT technologies and demonstrating how these innovations can enhance efficiency, productivity, and revenue on their farms [8].

Common literature examinations show there is a primary interest in addressing challenges and improving efficiency in specific scenarios, such as greenhouse agriculture. For example, [9] emphasizes the automatic reconfiguration of control systems as a fundamental characteristic of their personal scenario. Their goal is to enhance the efficiency of agricultural practices, ensuring optimal conditions for crop growth while minimizing resource wastage. On the other hand, [10] aims to improve efficiency and cost-effectiveness by addressing limitations in current IoT applications, and proposing wireless sensor networks to overcome communication challenges.

This systematic review encompasses various smart farming systems and architectures designed to aid farmers in identifying optimal components for tailored solutions to address specific needs. Our study examines complete solutions, recognizing that each component and its associated technology can affect crop growth in distinct ways. Moreover, our investigation focuses on evaluating the most recent infrastructure components utilized within the realm of smart agriculture and delineates their advantages. By synthesizing scientific literature on Smart Farming and conducting systematic analysis, we have identified pertinent criteria for selecting specific technologies.

The research framework of this study is delineated as follows. Section II describes the research methodology used to understand smart farming solutions by finding research papers on the field. Then, Section III describes and classifies architectural components, encompassing sensor types, automated actuators, gateways, power supplies, networking, data storage, data processing, and information delivery. Building upon this foundation, Section IV analyzes trends among smart farming components from the classification done in the previous section. In Section V, highlights are placed on variables for assessment when choosing a component based on the classification outlined in this paper. Finally, Section VI wraps up with the conclusions of this study.

II. RESEARCH METHODOLOGY

This research paper adopts a structured approach combining research action and a systematic review to understand the technologies utilized in smart farming solutions and the associated data in the domain. The study aims to shed light and provide a thorough analysis of the technologies used for the implementation of complete ground-level architectures and systems, and the advancements they offer.

Following a semi-cyclic research method, the paper is developed in the following three phases: the Plan Phase, the Perform Review Phase, and the Report Results Phase. In the Plan Phase, search parameters and digital repositories are defined to gather comprehensive information. The Perform Review Phase focuses on adapting search strings, collecting preliminary results, and selecting relevant papers. Lastly, the Report Results Phase addresses the findings during the research methodology described before leading to an analysis and discussion of this information.

A. PLAN PHASE

This phase is established to define the tools that will get the necessary information to start the research process. As a first step in this process, the following research questions were formulated:

- What are the most used characteristics in real-world smart farming applications?
- What are the most common components and data treatment solutions for smart farming?

These questions synthesize the necessary ideas for this paper to be a literature review covering the best smart farming architectures, their components, software, and data treatment.

To address the research question, we first established the keywords for conducting a systematic search of relevant literature. The chosen keywords included "smart farming," "IoT," "sensors," "network," and "wireless." These terms, along with appropriate connectors, formed the basis for our initial search. However, the initial search yielded an overwhelming number of results, reflecting the extensive array of devices and mechanisms associated with smart farming solutions.

To refine our search and align the results more closely with our research questions, we excluded certain terms such as "aerial," "CNN," "survey," and "protocol." These exclusions were made to focus on papers that provide comprehensive insights into ground-level architectures rather than isolated studies of individual components. Additionally, excluding terms like "aerial" helped filter out large IoT devices such as drones and robots, which were not the primary focus of our investigation.

These keywords were used in several scientific databases i.e., IEEE Xplore, Science Direct, and ACM Digital Library. The search queries are shown in Table 1.

B. PERFORM REVIEW PHASE

In the previous stage, particular search strings were determined, and in this phase, they were utilized to explore the aforementioned digital databases. Through these investigations, our focus was directed towards recent solutions proposed after 2018. The rationale behind this emphasis lies in the rapid pace of technological advancement, where innovations quickly make older solutions less effective within five years. Thus, prioritizing recent research allows us to analyze the latest developments and stay updated with the forefront of technology in the field.

After the search of previous works, an application called "Rayyan" was utilized for the classification process, whereby the .bib files attained from each digital repository were compiled. These files contain all the papers that match

TABLE 1. IEEE Xplore Digital Library, ScienceDirect and ACM Digital Library search results.

IEEE Xplore Digital Library	
Search String	**Results**
("All Metadata":"smart farming") AND ("All Metadata":iot) AND ("All Metadata":sensors) AND ("All Metadata":network) AND ("All Metadata":wireless) NOT ("All Metadata":aereal) NOT ("All Metadata":CNN) NOT ("All Metadata":Survey) NOT ("All Metadata":"protocol")	92
Science Direct	
Search String	**Results**
("smart farming") AND (iot) AND (sensors) AND (network) AND (wireless) NOT (aereal) NOT (CNN) NOT (Survey) NOT ("protocol")	45
ACM Digital Library	
Search String	**Results**
[All: "smart farming"]AND[All: iot]AND[All: sensors]AND[All: network]AND[All: wireless]AND NOT[All: aereal]AND NOT[All: cnn]AND NOT[All: survey]AND NOT[All: "protocol"]AND[E-Publication Date: (01/01/2018TO12/31/2023)]	17

the search criteria within a specific database. With the assistance of Rayyan's functionality, the relevant data of each paper was highlighted, including the title, abstract, and keywords, among others, which facilitated the classification protocol.

Ultimately, the protocol involved a meticulous manual approach. This entailed scrutinizing the titles and abstracts of papers gathered from diverse digital databases. Each paper was evaluated individually based on its abstract to determine its suitability for the research. The goal of the process was to identify any words or phrases that could help determine the relevance and usefulness of the papers for answering the proposed research questions. If the information related to the topic was not found, and terms were also missing, papers were discarded. In this manner, the remaining papers underwent individual assessment to determine their alignment with the research topic. A representation of the discard protocol used is shown in Figure 1.

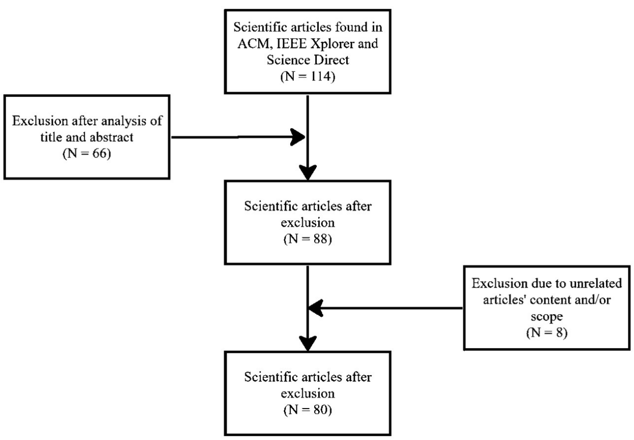

FIGURE 1. Paper reduction process.

This process encountered several challenges and complexities, necessitating resolution through virtual meetings among the responsible team members. During these sessions, a democratic approach was employed to evaluate the papers, with each member presenting their arguments for or against inclusion. Through this collaborative process, conflicts were addressed, and consensus was reached regarding the classification of the papers, ensuring a thorough and cohesive selection process.

C. REPORT RESULTS

During this final phase, all the gathered findings and outcomes were meticulously documented and organized. These valuable insights served as the foundation for the subsequent section, which constitutes the core of this research paper. Moreover, the additional findings were subjected to in-depth analysis and discussion, to identify prominent trends and patterns regarding the utilization of technological components in smart farming, regarding solutions for crops too. By carefully examining and interpreting these results, this study seeks to cover a diverse range of technologies employed for analyzing the types of data that hold relevance in this domain.

III. SMART FARMING SOLUTIONS

In recent years, the integration of technology in agriculture has paved the way for revolutionary approaches to farming practices. One such advancement is smart farming, a paradigm that leverages cutting-edge technologies to enhance efficiency, sustainability, and productivity in agricultural operations. Primarily, smart farming empowers farmers to meticulously monitor and control diverse environmental parameters, such as soil moisture content, ambient temperature and humidity, and other influential factors, by employing strategically deployed sensor technologies. This granular level of environmental control unlocks significant potential for enhancing the efficacy and sustainability of agricultural production practices.

Smart Farming implementation involves several key components, which collectively form a sophisticated ecosystem. Key components include sensor types, gateways, power supply, data storage, data analysis and processing, and information delivery, which lands in the Internet of Things (IoT), sensor networks, wireless connectivity, and even machine learning technologies. Each of them plays a crucial role in creating a comprehensive system.

The subsequent analysis, within the context of previous research, delves into the literature to understand the advancements, challenges, and best practices, providing a comprehensive overview of the state-of-the-art in smart farming technology. Our aim with this exploration is to shed light on the diverse facets of smart farming technology. By dissecting and evaluating each component, we strive to contribute valuable insights to the ongoing discourse surrounding the optimization of agricultural practices through technological innovation.

For a detailed review of practical applications and successful case studies in the implementation of Smart Farming technologies, it is recommended to refer to Section VI: Real-World Applications.

A. TYPES OF SENSORS

Smart Farming has established itself as a revolutionary approach in agriculture, leveraging technology to enhance crop production and optimize resource management. At the heart of this transformation lies the incorporation of sensors, which act as the eyes and ears of smart farming operations. These devices collect real-time data on various environmental parameters, providing farmers with a comprehensive understanding of their fields and crops. Sensors collect data about the agricultural environment. This data is used to feed smart farming systems, which can help farmers make more informed decisions about crop management. Among the different type of sensors for smart farming, the most commons are those created to measure air temperature, air humidity, soil temperature, soil moisture, ambient light, air quality, water level, combustible gas, pH, combustible gas, among others. For example, by monitoring soil moisture, air temperature, air humidity, water level, light intensity, and combustible gas, the scientific article referred to in [11] ensures optimal conditions for crop growth and resource management. Table 2 presents a concise overview of the sensors employed in the reviewed articles. The table is structured as follows: the left column contains the list of the type of sensors, while the right column shows the scientific articles in which these sensors are used or mentioned.

B. AUTOMATED ACTUATORS

Some smart farming solutions also implement automated actuators like relays, UAV, water pump, among others, to optimize resource utilization and crop health. For example, the [12] mentions systems that use relays to control lighting in the greenhouses and water pumps for automated irrigation. In addition, it is mentioned that UAVs can be used for crop monitoring and early detection of diseases or pests. Table 3 presents a concise overview of the actuators and devices employed in the reviewed articles. The table is structured as follows: the left column contains a list of all automated actuators, while the right column shows the scientific article reviewed in which these electronic devices are used or mentioned.

C. GATEWAYS AND EDGE DEVICES

Gateways serve as intermediaries connecting the end devices (such as sensors or actuators) to the network, whether private or public (e.g., the Internet). They facilitate the transmission of data from sensors to servers or from servers to actuators [13]. It's crucial to differentiate between end devices and gateways when considering smart farming architectures. End devices, including Arduino, ESP32, NodeMCU, P89V51RD2 micro-controller, ESP8266, Arm Cortex-A Board, and Libelium, are responsible for collecting data from the field or controlling agricultural processes

TABLE 2. Different type of sensors used in previous works.

Type of Sensors	Article Scientific Reviewed
Soil temperature	[8], [9], [10], [11], [12], [16], [20], [21], [24], [31], [38], [39], [40], [44], [45], [46], [51], [52], [63], [66], [68], [69], [70], [73], [76], [80], [82], [83], [85]
Soil moisture	[8], [9], [11], [14], [15], [16], [17], [18], [19], [20], [21], [24], [28], [29], [30], [35], [39], [40], [42], [44], [45], [46], [48], [49], [50], [52], [53], [54], [55], [58], [60], [61], [63], [64], [65], [66], [68], [70], [73], [74], [76], [77], [80], [82], [83], [85], [86], [87]
Ambient light	[9], [14], [17], [18], [19], [23], [24], [31], [35], [36], [38], [39], [52], [57], [58], [65], [66], [68], [71], [73], [80], [87], [88]
Air quality	[8], [9], [19], [23], [39], [46], [71]
Ultrasonic	[47], [50], [60], [63], [71], [77]
PIR (Motion)	[46], [47], [71], [74], [77]
Humidity (DHT11)	[8], [9], [10], [11], [12], [16], [17], [19], [20], [21], [23], [24], [28], [29], [38], [39], [40], [42], [45], [46], [47], [48], [49], [50], [51], [55], [61], [65], [71], [73], [74], [75], [76], [77], [79], [80], [82], [85], [86], [87], [88]
Sound	[20]
Air temperature	[8], [14], [15], [17], [19], [20], [21], [23], [28], [29], [30], [31], [32], [35], [36], [42], [47], [48], [49], [54], [55], [56], [57], [58], [59], [60], [61], [62], [64], [65], [66], [67], [68], [69], [70], [71], [77], [79], [88]
Air humidity	[14], [17], [18], [20], [21], [23], [24], [30], [31], [32], [35], [36], [42], [46], [50], [51], [54], [56], [57], [58], [59], [60], [61], [62], [64], [65], [67], [68], [69], [70], [71], [85], [87], [88]
Water level	[17], [20], [38], [47], [67], [69], [70], [71], [74], [85]
Combustible Gas	[42], [47], [75]
Ldr	[20], [23], [24], [47], [65], [75]
Atmospheric pressure	[9], [14], [16], [17], [19], [35], [39], [46], [58], [59], [64], [66], [76], [82]
Leaf moisture	[35]
Precipitation	[4], [15], [17], [26], [35], [59], [64], [66], [69], [70]
Soil oxygen	[35]
Wind speed	[17], [26], [35], [64], [66], [69], [70]
Wind direction	[15], [26], [35], [66], [69], [70]
AO3	[15], [25], [26], [44], [53], [63], [66]
Dew point	[36]
Mist pump	[31]
Smog	[46], [56]
Electrical conductivity	[58]
Soil NPK	[58]
pH	[40], [45], [58], [86]
Optical	[58]
Leaf wetness	[58]
Speed of wind	[58]
Flame	[77]

directly. On the other hand, gateways, exemplified by Raspberry Pi act as communication hubs, aggregating data from multiple end devices and transmitting it to the network.

When selecting the appropriate gateway device for a smart farming architecture, various factors must be considered, including the number of connecting devices and communication protocols. The chosen gateway plays an important role in smart farming systems, necessitating the ability to seamlessly integrate new technologies without introducing conflicts in information or communication. Smooth and efficient system expansion relies on this capability.

TABLE 3. Electronic actuators and devices used in previous works.

Electronic Devices	Scientific Article Reviewed
Camera	[16], [39], [42], [44], [56], [65], [82], [83]
Buzzer	[16], [21], [44], [46], [71], [75]
Relay	[16], [17], [18], [28], [30], [44], [70], [71], [81], [88]
Flashlight	[44], [53]
Water pump	[10], [15], [16], [17], [18], [21], [28], [30], [38], [46], [47], [49], [52], [53], [58], [61], [62], [64], [70], [71], [78], [81], [88]
UAV	[83]

Moreover, the effectiveness of gateways relies on their compatibility with the chosen data management framework. They should adeptly support the architecture's data delivery and reception methods, thereby guaranteeing efficient and cohesive data management across the entire smart farming infrastructure.

Many studies leverage cost-effective, open-source tools to fabricate end devices and gateways. Arduino, ESP32, NodeMCU, P89V51RD2 micro-controller, ESP8266, Arm Cortex-A Board, and Libelium emerge as popular choices for end devices in smart farming, harnessing their capabilities to read sensor data and execute predefined responses [13]. Raspberry Pi serves as gateway nodes in certain setups, particularly those employing a 6LoWPAN-based WSN configuration [14]. In this context, the gateways facilitate the aggregation of data from end devices and ensure seamless communication with network servers.

The use of both end devices and gateways shows a trend in utilizing cost-effective, open-source solutions for the development of smart farming applications. These devices are widely recognized for their versatility and scalability, catering to the diverse needs of agricultural technologies. Table 4 highlights the popularity of these devices within smart farming applications, showcasing their adaptability to varying requirements. Moreover, the table reveals distinctive areas of specialization for each device, reflecting the nuanced considerations made by designers to tailor smart farming solutions to specific priorities and applications.

D. POWER SUPPLY

Smart farming requires installed devices nearby crops. These devices need a reliable and efficient power supply to operate. Due to the expansive nature of agricultural crops, the provision of continuous electrical power via traditional electrical cables is not feasible. Considering this scenario, the importance of portable electrical power sources choice becomes crucial. Table 5 shows battery types discussed in the reviewed articles. Some of the most used power supplies include AA, AAA, 9V and lithium-ion type batteries (LiPo and LiFePO4 mainly), but some solutions also use solar panels and external or internal/on-device power supply units.

TABLE 4. Gateways and edge devices used in previous works.

Networking device	Scientific Article Reviewed
Arduino	[4], [9], [16], [17], [20], [21], [25], [27], [30], [36], [37], [38], [39], [40], [43], [47], [50], [51], [60], [61], [62], [65], [70], [75], [76], [77], [78], [81], [82], [84]
Raspberry PI	[14], [16], [20], [22], [23], [34], [42], [56], [57], [58], [59], [60], [61], [63], [64], [65], [66], [68], [69], [71], [72], [73], [74]], [80]
ESP32	[9], [11], [12], [18], [28], [53], [54]
Arm Cortex-A Board	[44], [67]
P89V51RD2 micro-controller	[45]
ESP8266	[16], [18], [20], [21], [29], [30], [46], [49], [52], [65], [71], [89]
Libelium	[32]

TABLE 5. Power supply solutions used in previous works.

Power Supply	Scientific Article Reviewed
Battery, Pill	[29], [27], [47], [33], [49], [50], [54], [40], [16], [56], [57], [58], [59], [21], [42], [61], [62], [73], [63], [30], [17], [64], [15], [65], [22], [66], [67], [23], [68], [69], [18], [70], [20], [71], [72], [10], [43], [37], [9], [39], [80], [81], [82], [83]
Computer, Laptop	[25], [45], [53], [40], [16], [56], [57], [58], [59], [21], [42], [61], [62], [73], [63], [30], [17], [64], [15], [67], [23], [68], [69], [70], [20], [71], [76]
Power Supply Unit	[44], [40], [16], [56], [57], [58], [59], [21], [42], [61], [62], [73], [63], [30], [17], [64], [15], [66], [67], [23], [68], [69], [70], [20], [71]
Solar panel, solar energy, solar radiation	[27], [47], [33], [48], [49], [40], [42], [73], [17], [18], [70], [20], [72], [74], [43], [35], [9], [8]
Power line	[54], [75], [76], [4], [88]
AA battery	[21]
LiPO, LiFePO4 batteries	[28], [20]
AA battery	[89]
9V battery	[70]
Not mentioned	[46], [34], [14], [53], [55], [40], [60], [61], [62], [73], [63], [64], [65], [22], [66], [23], [68], [69], [20], [71], [72], [12], [11], [38], [77], [36], [78], [84], [85], [86], [87]

Just a small part of covered literature refers to power supplies as specified batteries, solar panels, and fuel cells. For example, in [15] an autonomous gardening rover (quadrotor UAV) with plant recognition was built using neural networks. They relied on a 12V, 7Ah battery to power the rover, which could run for about 2 hours (autonomy time). They plead that solar panels could be used to extend and fill the battery life once it lacks, however there was no basic explanation at all comprising energy plans or their structure.

Problem solvers frequently prioritize practicality over addressing specific issues when prototyping solutions. Non-commercial solutions often lack sophistication in their assembly. This is evident in the selection of power supplies, where researchers commonly treat their solution systems as modules attached to or hosted within local, non-portable hardware (such as computers or controllers directly plugged into wall outlets), rather than opting for commonly specified batteries or power supply units (PSUs). This tendency may be attributed to projects not yet reaching the production stage.

For instance, in [16] a 12 V PSU was used to power a Raspberry Pi 3 (processor), an Arduino UNO R3, a Node MCU ESP8266 (controllers) and some periferics (fans, sensors, cameras, etc), which served for composing a system for data transmission and processing for an "Agri-IoT" framework. In contrast, [17] and [18] employed solar panels for energy supply in their proposed irrigation systems. These panels were built for sensor nodes to be deployed in remote areas and thus reduce maintenance. One of these, charges 12 V, 7 Ah rechargeable batteries with a 10 W, 12 V poly-crystalline solar panel.

Now, in an IoT-based crops system, [19] utilized a LiFePO4 battery to power the sensors and actuators. They found that this battery type offers a longer lifespan and higher energy density compared to lead-acid batteries. In contrast, [20] outlined the necessity of a LiPO battery for constructing a flexible mobile multi-sensor unit using open-source hardware platforms.

Additionally, literature demonstrates that solutions rely on the physical principle of relays, meaning they typically require both an AC connection and a DC battery connection to achieve integral system functionality (four AAA batteries in this scenario). In [21], a pair of relays were used for air pumping and cooling fan control in a stable automated monitoring and environmental control system for laboratory-scale cultivation.

Nowadays, advanced smart farming solutions feature smart/industrial machines, with robots capable of tasks such as planting, harvesting, spraying, and weeding. Regarding high-speed information transfer, [22] discusses machines and robots requiring robust and enduring power supplies not only for movement and operation but also for efficient data sharing. Recent projects aim to enhance productivity, manage data, and improve decision-making processes while tackling challenges [23]. For actuators to execute real-world daily tasks, data loads must be processed swiftly to enable the system to demonstrate real-time operations effectively. Nevertheless, in most scenarios, even the most sophisticated rovers or drones cannot surpass farmers in all-day tasks. Achieving a compelling balance between performance and battery life for a device remains a challenge that must be addressed and thoroughly tested.

E. NETWORKING

Communication protocols at the medium access control, network, and application layers have been designed aiming to optimize data rate and allow large amounts of information to be transmitted efficiently, over reliable connections with minimal transmission errors [24]. Communication technology is key to ensuring compatibility, security, scalability, and efficiency, enabling the seamless integration of various devices and technologies to optimize agricultural processes.

The efficient implementation of a smart farming solution requires flexibility in arranging sensors placed across varied distances within the smart agriculture system. These sensors, positioned both near and far from each other as well as from the central gateway, correspond to the diverse spatial zones covered by monitored crops. The number of sensors deployed relies not only upon the physical area but also on the specific parameters considered in crop analysis. Consequently, the communication infrastructure must support a range of data types and hardware, enabling their seamless integration into a unified gateway. The continuous transmission of crop status updates is an important aspect of the significance of a reliable communication system. Finally, as agricultural architecture evolves, scalability becomes critical. The communication framework should facilitate the integration of new devices, offering an efficient and user-friendly connectivity solution for the farmer.

In short, the acquisition of communication technology is important it can fulfill requirements on three metrics: energy efficiency, coverage, and scalability [13].

Several solutions have employed distinct communication technologies tailored to specific needs. For instance, in [25] and [26], a Wi-Fi model facilitates data transmission to the cloud for subsequent analysis. Conversely, the solution proposed in [27] utilizes Zigbee due to its capacity to interconnect numerous nodes (up to hundreds) and transmit over considerable distances of up to 120 meters in line of sight. Another solution employs LoRaWAN as its primary communication technology, leveraging its wide coverage, extensive range, low power consumption, cost-effectiveness, and satisfactory transmission rate, particularly suitable for telemetry data [28].

Table 6 contains a list of communication papers and the papers in which they are used respectively.

According to the results, the most used technologies in the architectures are Wi-Fi, and Bluetooth, which are traditional protocols, this can be related to the fact that they have been in the market for a long time and can be widely accessible, contrary to new technologies that may take time to find their way to a bigger audience. But it can also be noted that the protocol's range is diverse, showcasing the variability of the conditions between the solutions of smart farming, therefore a different type of protocol is chosen to fulfill its necessities.

F. DATA STORAGE

Cloud-based smart farming solutions platforms are one of the most used options to store and process the data collected from sensors and devices. A smart hydroponics system that automates the growing process of the crops using Bayesian Network (BN) model [15], uses Google Firebase as cloud storage service. Similarly, using Google Sheets (a web-based spreadsheet app from the Google Docs Editor suite), [16] delivers data gathered from the analog channel of an Arduino UNO controller through the Node MCU ESP8266 controller. Cloud-based data storage offers advantages such as scalability, accessibility, and security.

TABLE 6. Gateways and edge devices used in previous works.

Communication Protocol	Scientific Article Reviewed
Cellular networks	[29], [30], [33], [36], [53], [81]
Wi-Fi	[4], [9], [15], [16], [18], [20], [21], [25], [26], [29], [30], [33], [36], [40], [42], [46], [47], [48], [50], [51], [52], [53], [54], [55], [56], [57], [58], [59], [60], [61], [62], [65], [66], [70], [71], [72], [73], [74], [75], [78], [84], [88]
LoraWAN	[8], [28], [35], [39], [53], [67], [72], [76], [78], [82], [83], [89]
GSM	[17], [30], [45], [71]
Zigbee	[8], [12], [17], [27], [40], [53], [67], [71], [74], [77]
MQTT	[10], [12], [16], [37], [43], [49], [64], [75], [80], [75]
UHF	[50]
ISM	[50], [67], [73]
GPS	[16], [20], [22], [40], [51], [55], [58], [62], [68], [78]
6LoWPAN	[14], [73]
Radio wave	[53]
Bluetooth	[16], [18], [21], [23], [40], [42], [53], [54], [56], [57], [58], [59], [60], [61], [64], [66], [69], [70], [73], [78], [84]

Additionally, there are also IoT cloud platforms that store and process the data collected from IoT devices. Revisiting [15], the use of ThingSpeak as an IoT cloud platform to store and visualize the sensor data is helpful when building self-sustainable agricultural production through data analytics. Similarly, [29], designed and implemented a connected smart farming system that uses Blynk server as an IoT cloud platform to store and control the sensor data.

Both, "regular" cloud-based and IoT cloud-based data storage offers advantages such as real-time data processing, remote monitoring, and event detection for smart farming solutions.

Another solution found is local storage devices such as SD cards, USB drives, or local computers (relying on HDD or SSD drives) to store the data collected from sensors and devices. In [30], an Android application developed for storing the logs of a smart autonomous gardening rover with plant recognition through neural networks, acquires the data from the on-board sensors directly to the internal device storage (use of SD card can be assumed). Similarly, the design and implementation of a span greenhouse agriculture IoT system in [31] stores the data gathered by the sensor nodes on a local computer. Local data storage offers advantages such as low cost, simplicity, and privacy for smart farming solutions.

Again, everything depends on what the context is and what scope researchers want to have with the information generated. Even though data is the main concern in this subtopic, it is important to understand that most of the times designers will prefer a centralized solution, i.e. a place or service where the smart farming solution can be deployed and the data gathered can be processed as well; hence, it is possible to have almost total control.

Table 7 provides an overview of previous paragraphs. Cloud and local (computer) storage are the most preferred data storage solutions. For sure, a combination of both will provide a secure way to handle data given the high availability and continuous synchronization of information.

TABLE 7. Data Storage solutions used in previous works.

Data Storage	Scientific Article Reviewed
Generic cloud service	[14], [53], [54], [55], [40], [16], [56], [60], [21], [42], [62], [73], [63], [30], [17], [64], [15], [65], [22], [66], [67], [23], [68], [18], [70], [20], [71], [74], [12], [76], [39], [85]
Generic computer storage drive	[45], [16], [56], [57], [58], [59], [60], [21], [42], [61], [62], [73], [63], [30], [17], [64], [15], [65], [66], [67], [23], [68], [69], [70], [20], [71], [72], [9], [36], [80]
ThingSpeak	[26], [25], [47], [48], [34], [21], [15], [18], [38], [78], [81], [4]
IoT Cloud	[46], [16], [21], [73], [64], [65], [23], [18], [77], [82], [83], [88], [8]
Firebase	[51], [21], [15], [10], [43], [89]
MySQL	[33], [62], [71], [11], [37], [84]
Google Drive	[63], [75]
Blynk	[29], [47]
Generic SD card	[44], [20]
Node-RED	[49]
The Things Stack	[28]
Adafruit	[52]
Not mentioned	[50], [61], [64], [15], [65], [69], [72], [35], [86], [87]

G. DATA PROCESSING

Reduced food production often stems from various factors, such as inadequate planning, unpredictable weather conditions, improper harvesting and irrigation techniques, and livestock mismanagement [32]. In addressing these challenges, technology emerges as a crucial factor by harnessing extensive information through sensors and climatic records. This data is instrumental in understanding plant needs and environmental conditions, enabling the precise allocation of resources like water and minerals. Consequently, this enhances the overall health of the system, mitigates challenges faced by farmers, and significantly reduces the reliance on fertilizers and chemicals [32]. These technological advancements, rooted in effective data processing, lead to sustainable practices, minimize waste, and elevate efficiency within the agricultural process.

The current investigation recognizes three primary domains for data processing in smart farming: artificial intelligence (AI) serves as the overarching category, threshold-based data analysis, and manual determination as shown in Table 8. In this context, [33] exemplifies the integration of cloud-based ML algorithms analyzing drone-captured images to identify vine diseases, highlighting ML as an integral component of the broader AI framework. Similarly, [34] leverages AI, specifically a neural network, to predict greenhouse air temperatures. Despite the diverse applications of AI and ML, some farmers persist in employing threshold-based data approaches to set operational conditions [26], while others rely solely on statistical information presented in dashboards derived from collected data, lacking the advanced decision-making capabilities inherent in AI systems [35].

TABLE 8. Gateways and edge devices used in previous works.

Data processing	Scientific Article Reviewed
IA	[4], [8], [9], [15], [16], [17], [21], [22], [23], [30], [33], [34], [38], [42], [43], [52], [54], [57], [58], [59], [60], [61], [63], [64], [65], [66], [68], [69], [70], [72], [73], [74], [82], [83], [84], [85], [86], [87]
Threshold-based data	[15], [16], [25], [26], [28], [30], [42], [44], [45], [46], [47], [49], [51], [53], [56], [63], [70], [71]
Manual control	[11], [15], [35], [36], [37], [39], [49], [51], [56], [61], [65], [75], [78], [80], [81], [88], [89]

Manual interpretation in data processing involves the human-driven analysis and comprehension of information without relying on automated algorithms or computational models. In this context, individuals, often experts or domain specialists, inspect and make sense of raw data, identifying patterns, anomalies, or specific insights that may not be easily discernible through automated means. This hands-on approach allows for a qualitative understanding of the data, drawing on human expertise, intuition, and contextual knowledge to extract meaningful information.

H. INFORMATION DELIVERY

The presentation of monitoring information to farmers or users is an important consideration in smart farming systems. This is because the information can be presented through a variety of channels, such as web platforms, mobile platforms, text messages, desk application, etc. The different channels for presenting information have their own advantages and disadvantages. Web platforms offer a wide range of features and capabilities, but they can be difficult to use for users who are not familiar with technology. Mobile platforms are easier to use and more accessible, but they may have limitations in terms of functionality. Text messages are the simplest and most accessible form of presentation, but they are also the least flexible. The choice of the right channel for presenting information depends on several factors, such as the needs of the farmer or user, the type of information being presented, and the available budget. Table 9 presents a concise overview of the different ways to display information utilized in the reviewed articles. The table is structured as follows: the left column contains a list of all ways to display information, while the right column shows the scientific article reviewed in which these information deliveries are the subject of study.

TABLE 9. Ways to display information used in previous works.

Information Delivery	Scientific Article Reviewed
Mobile app	[4], [8], [22], [26], [29], [30], [37], [40], [43], [46], [47], [49], [51], [53], [54], [55], [57], [58], [62], [74], [75], [83], [84], [85], [88]
Webpage	[8], [9], [10], [11], [15], [16], [17], [18], [20], [23], [25], [38], [40], [46], [47], [52], [53], [60], [62], [64], [71], [76], [77], [78], [80], [83], [85], [86], [88], [89]
Email	[16], [25], [30], [62]
Message	[17], [21], [30], [35], [38], [44], [45], [53], [62], [71]
Desk application	[15], [21], [30], [33], [40], [42], [44], [45], [56], [59], [61], [63], [65], [66], [67], [69], [70], [73]
Thing Speak API	[18], [21], [48], [49], [78]
Cloud Platform	[39], [81]
None	[12], [14], [20], [23], [27], [28], [40], [42], [59], [61], [62], [63], [64], [66], [67], [68], [69], [70], [72], [82], [87]

IV. DISCUSSION

A. SENSORS

Figure 2 clearly demonstrates that a vast majority of authors prefer the implementation of multiple sensors for effective control in smart farms. The Soil Moisture sensor is particularly prominent, with fifty mentions in the reviewed architectures. This indicates the significance of measuring soil moisture to understand plant growth conditions. According to study [9], soil temperature is a crucial factor affecting seed germination, root development, and nutrient availability, all of which are essential for determining the optimal watering times. The use of the Soil Moisture sensor enables more precise and effective irrigation, thus improving the quality and yield of crops, as outlined in [36]. Closely following are two closely related sensors, the Air Temperature sensor, and the Air Humidity sensor, with 42 and 36 appearances, respectively. Their importance lies in the fact that temperature and humidity are critical environmental parameters that directly impact plant growth and health. Temperature influences photosynthesis, respiration, and transpiration, while humidity affects water and nutrient absorption. As per [36], the joint measurement of both variables allows for comprehensive monitoring of environmental conditions, facilitates the identification of plant stress, and enables precise decision-making to adjust irrigation, ventilation, and other factors. With twenty-eight mentions, the Soil Temperature sensor plays a significant role. According to the scientific article cited in [12], monitoring soil temperature is vital for optimizing plant growth, as it affects seed germination, nutrient absorption, and soil microbial activity. With twenty-four mentions, the Ambient Light sensor is crucial for measuring water flow in irrigation systems, key in controlling water supply to the plants, as mentioned in [37]. Beyond the sensors mentioned, Figure 2 presents a wide array of additional tools used by researchers.

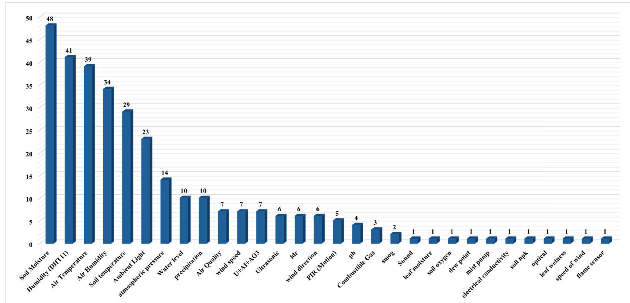

FIGURE 2. Sensors used in the reviewed research.

B. AUTOMATED ACTUATORS

Figure 3 indicates a clear preference among authors for the use of specific actuators and electronic devices in the efficient management of farm resources. The water pump is particularly noteworthy, being mentioned 24 times in the analyzed architectures. According to the research [10], the main benefit of using water pumps for crop irrigation is their ability to optimize water usage. Through continuous monitoring of temperature and humidity, the system can adjust irrigation to specific areas as needed, avoiding over-watering in already moist areas, thereby enhancing water usage efficiency. Relays, cited in 11 instances, play a key role in regulating power supply to devices like water pumps. The study [37] emphasizes that using relays allows for more precise control of electronic devices and improves the system's energy efficiency. Furthermore, as noted in [38], relays enable the automation of processes such as irrigation, adapting to environmental and soil conditions, leading to improved crop efficiency, and reducing the need for human intervention. On the other hand, cameras, mentioned 8 times in the review, are highlighted in [39] for their effectiveness in monitoring the presence of fruits in the field, essential for efficient crop management and informed decision-making in precision agriculture. Figure 3 expands the view on a variety of actuators and electronic devices used by researchers to deepen their analyses.

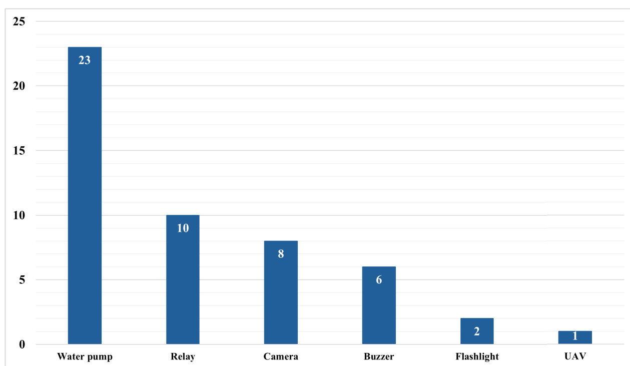

FIGURE 3. Automated actuators used in previous works.

C. GATEWAYS AND EDGE DEVICES

As depicted in Figure 4, given the specified percentages, Raspberry Pi stands out as the most commonly used gateway, being present in 25.3% of the examined architectures.

Among end devices, Arduino has the highest usage percentage at 32.9%, indicating its widespread adoption in smart farming applications. This prevalence suggests that factors such as the extensive community support, flexibility, and user-friendly nature of Arduino have played pivotal roles in end device selection. Arduino's adaptability in interfacing with a diverse array of sensors commonly employed in smart farming further enhances its appeal as an end device, ESP32 and NodeMCU follow with equal usage percentages of 7.7%. this may be due to being chosen for smart farming applications due to their integrated Wi-Fi capabilities, compatibility with various sensors, cost-effectiveness, community support, and flexibility in programming. The percentages for the Arm Cortex-A Board, P89V51RD2 micro-controller, and Libelium are significantly lower compared to other devices. Their inclusion in the spectrum of devices used reflects the diversity in technological choices made by researchers to address specific requirements and challenges in smart farming applications.

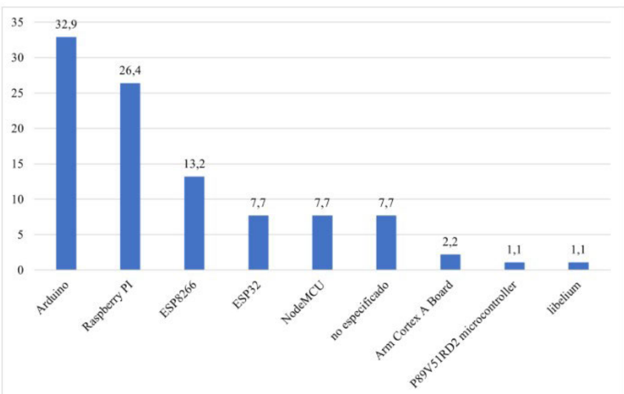

FIGURE 4. Gateways and end devices used in previous works.

Given the predominantly academic nature of the studies reviewed, many smart farming solutions focused on smaller-scale implementations that didn't require extensive gateway infrastructure. Consequently, there is a noticeable lack of emphasis on gateways in the papers examined. This trend underscores the importance of versatile and adaptable end devices like Arduino, ESP32, and NodeMCU, which were frequently utilized to meet the needs of these smaller-scale applications.

D. POWER SUPPLY

The Power Supply Type (PST) classification approach holds significant relevance for researchers, designers, engineers, and farmers in the realm of smart farming. It serves as an initial framework for understanding the diverse array of power supply options, along with their respective advantages and disadvantages, supported by real-world, long-term use cases. This approach helps with the development, design, installation, maintenance, and utilization of proof-of-concept solutions, all of which are aimed at enhancing existing farming methodologies and systems.

Batteries and pills were frequently referenced terms in PST discussions, appearing 45 times. Computers and laptops, which encompass both external and internal power supply units (PSUs) housed within desktop or laptop chassis, were mentioned 28 times. Surprisingly, in 31 instances, there was no mention of how power supply issues were addressed.

The prevalence of terms such as batteries and pills suggest their versatile meanings. These terms encompass various conventional small-scale power storage options, including AA, AAA, 9V, and LiPO / LiFePO4 batteries. They are chosen for their portability and utility, particularly in remote areas where access to grid power and maintenance schedules may be limited.

Some less commonly discussed terms related to power systems technology (PST) include Solar panels, Solar energy, PSUs, and various battery types such as AA, AAA, and 9 V; including LiPo and LiFePO4 varieties. Additionally, references to the Power line, denoting the wall outlet, are infrequently mentioned in this context. It is worth exploring the reasons behind the lesser prevalence of these terms – whether due to their lesser-known status, limited utilization, or reduced significance within the field.

Figure 5 provides a visual representation of the occurrence and distribution of these terms and associated topics, offering valuable insights into their relative importance and interrelationships within the PST domain.

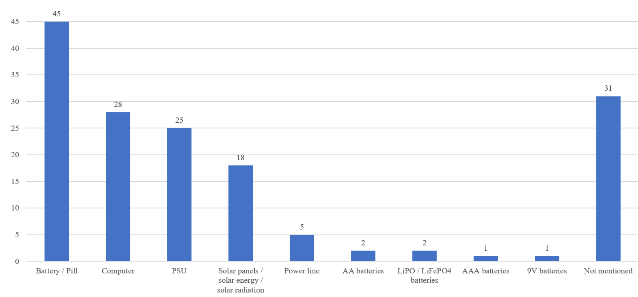

FIGURE 5. Preferred power supply types in smart farming solutions.

While solar energy presents an attractive option for areas lacking access to power lines, its effectiveness hinges on a robust energy storage system for uninterrupted power supply. Unfortunately, this critical aspect often remains inadequately addressed. PSUs face limitations due to their lack of portability and dependency on power lines, which restrict their utility in remote or mobile applications.

Traditional disposable batteries like AA, AAA, and 9 V are plagued by a limited lifespan, rendering them less viable compared to rechargeable alternatives such as LiPo and LiFePO4 batteries. Renowned for their durability and high energy density, these rechargeable options offer a more sustainable solution.

While power lines offer reliability, they are inaccessible in many common farming scenarios. Ultimately, the choice of power supply type depends on various factors, including the specific application, geographical location, power requirements, and associated costs. By addressing the complexities and trade-offs inherent in different power supply options, stakeholders can make more informed decisions to meet their energy needs effectively.

E. NETWORKING

In Figure 6, WiFi emerges as the primary communication protocol in the examined previous works, constituting 44% of the solutions, likely due to its widespread availability and high data transfer rate, particularly in small-scale smart farming applications. The familiarity of WiFi modules among researchers may also contribute to its popularity, facilitating easy wireless communication. However, WiFi's dominance may be influenced by its performance limitations in long-distance transmissions or remote areas. Following Figure 4 bluetooth follows WiFi in popularity, showing good performance for short-range solutions. However, it hasn't been as commonly selected for large-scale and scalable applications.

Overall, the prevalence of WiFi and Bluetooth as the main communication protocols can be attributed to the emphasis on small-scale smart farming applications in the research findings.

Other protocols, including LoRaWAN and Zigbee, account for 12% and 10% of usage, respectively. LoRaWAN exhibits superior adaptability to diverse and challenging environments. Furthermore, they boast long-range capabilities, which are particularly advantageous for large-scale smart farming architectures. Additionally, both LoRaWAN and Zigbee feature low-power characteristics, facilitating efficient data transmission over extended periods. It's worth noting, however, that Zigbee is not renowned for its long-range capabilities. Despite this limitation, its adaptability to various environments and low-power features make Zigbee a viable choice for specific smart farming applications where extended range may not be a critical requirement.

Other protocols, such as MQTT with a lesser percentage, provide a glimpse into the diverse usage cases addressed by the revised solutions. MQTT operates on a publish-subscribe model, facilitating time-sensitive applications that require real-time data processing and export. On the other hand, MQTT offers some architectures a robust solution for applications demanding real-time data processing and communication. Lastly, the protocols remaining encompass a wide spectrum, ranging from cellular networks (GSM), long-range wireless technologies (LoRaWAN, UHF, ISM), short-range communication (Bluetooth, Zigbee), positioning systems (GPS), to data representation and transmission (MQTT, 6LoWPAN).

The diverse range of communication protocols illustrated in Figure 6 signifies the absence of a standardized approach within the smart farming community when constructing such architectures. While this flexibility allows for tailoring solutions to specific architectural requirements, it also raises concerns about scalability and compatibility when integrating different systems. The absence of a universally adopted standard may lead to challenges in scalability and interoperability, emphasizing the importance of establishing common frameworks or guidelines within the smart farming domain to ensure seamless integration and scalability across various technological solutions.

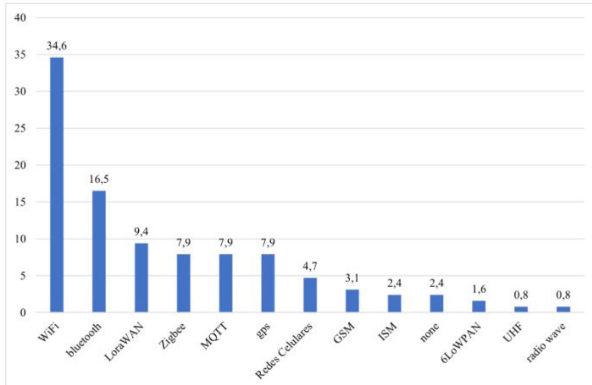

FIGURE 6. Network usage distribution.

F. DATA STORAGE

The choice of data storage depends on several factors, such as data volume, availability, accessibility, security, and cost. Among the data storage solutions observed in the smart farming scenarios studied, Computers and Laptops were the most common (30 occurrences), followed by ThingSpeak (12 occurrences), Cloud (10 occurrences), IoT Cloud (10 occurrences), with an additional 10 occurrences where data storage method was not mentioned. This can likely be attributed to the versatility, ease of use, and affordability of modern computers, along with the specialized features offered by ThingSpeak software for IoT data storage and visualization. Additionally, cloud storage provides scalability, practicality, and security in a cost-effective manner.

While other data storage solutions such as Google Docs Editor suite, Firebase, MySQL, SD cards, Blynk Server, Node-RED, Things Stack Network Server, and Adafruit are less common, they offer unique advantages and disadvantages that may make them suitable for specific scenarios. For example, cloud-based solutions like Google Drive and Firebase offer remote accessibility and collaboration, while on-premises solutions like SD cards and computers provide greater control over data security and privacy. Ultimately, the choice of data storage solution should be carefully considered based on the specific requirements and constraints of each smart farming application; certainly, it often depends on the scalability of the project.

Figure 7 shows that local Computers and Laptops are among the most preferred solutions, being almost 50% of reviewed alternatives. This dominance may be because every farm has its own needs, i.e. they are local non-scalable proposals.

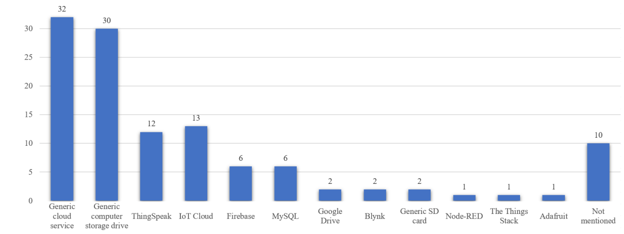

FIGURE 7. Preferred data storage types in smart farming solutions.

G. DATA PROCESSING

In Figure 8, the predominant methods in smart farming applications are collectively identified under the overarching category of artificial intelligence (AI). Within this broader classification, the most prevalent techniques include machine learning (ML), which involves algorithmic approaches responsible for analyzing and interpreting data to autonomously respond to the status of crops or dictate necessary parameters for plant care. The use of AI, encapsulating ML, signifies a growing reliance on automated systems that leverage data-driven insights to optimize agricultural processes.

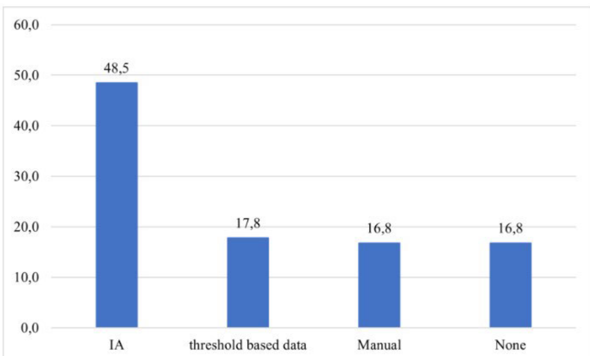

FIGURE 8. Data processing chart.

Some studies have specifically highlighted machine learning as a key component, potentially due to its more recognizable and widely understood term compared to the broader umbrella of artificial intelligence. This preference for emphasizing machine learning could stem from the specificity and clarity associated with ML methodologies, which involve the training of algorithms to learn patterns from data.

The second most adopted approach involves a simpler method of setting predefined limits for variables, triggering specific actions accordingly. While effective in stable environmental conditions, this approach may be limited when faced with diverse datasets, potentially impacting the required care for crops under new conditions.

The third approach incorporates direct human intervention, where analysis and responses from the system are obtained through data display, often in the form of dashboards. Unlike sensor-driven systems, many solutions in this category rely on human decisions for actions like water sprinkling, and alerting farmers through text or audio. While this approach may not optimize resource usage, it does contribute to maintaining control over plant health.

Figure 8 illustrates the distribution of data processing usage in smart farming solutions. This categorization underscores the diversity of priorities among designers, with some favoring sophisticated automated systems, others opting for simplicity and predefined triggers, and some relying on direct human involvement for decision-making. The juxtaposition of these approaches highlights the multifaceted nature of smart farming solutions and the need for a nuanced understanding of the varying degrees of autonomy and control within these systems.

H. INFORMATION DELIVERY

An essential aspect of smart farming solutions is how information is delivered to the user. To illustrate the most used ways to present information to the user, Figure 9 has been developed, based on the scientific articles reviewed.

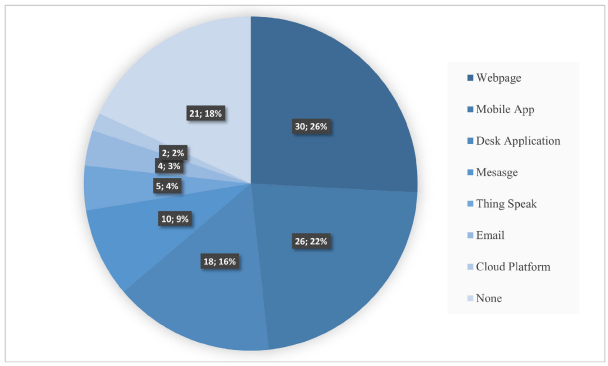

FIGURE 9. Effective methods for presenting information from research reviewed.

Figure 9 shows that 26% of the reviewed articles use a web application to present information to the user, while 22% use a mobile application. On the other hand, 18% do not specify the deployment type, while 16% use a desktop application, 9% use SMS messages, 4% use a Things Speak platform API, 3% use email, and finally, 2% use services provided by cloud platform. The popularity of certain solutions is primarily due to the convenience and accessibility they offer to users. For instance, web and mobile applications account for 48% of the solutions due to the increasing prevalence of mobile applications and the easy way for accessing information from any location. Desktop applications, which represent a smaller percentage than web and mobile applications at 16%, are still used by some users who prefer to work on more traditional platforms. On the other hand, SMS messaging is popular due to its simplicity and wide availability on mobile devices, making it a viable option for data communication in remote agricultural environments.

V. DEVICE SELECTION STRATEGY

A. SENSOR

In the design smart farming architecture, a diverse range of sensors is essential for gathering precise environmental data relevant to crop management decisions. The choice of sensors depends on the specific needs of the smart farming solution, focusing on collecting data vital for effective decision-making regarding crop yields. These sensors must seamlessly transmit data to the gateway without disrupting other sensor functions or communications. To ensure farmers can focus on utilizing collected data rather than troubleshooting hardware issues, selected sensors should be adaptable across different architectures to meet these criteria and facilitate straightforward migration if infrastructure adjustments are required.

Reliable and precise sensors are crucial for high-quality data collection. It is important to maintain consistent precision and close alignment with actual values [9]. The assessment of sensors should include their measurement range and calibration to ensure accurate precision evaluation. Furthermore, sensors must be able to withstand various climatic and environmental conditions to accurately assess farm conditions. It is important to note that different sensor materials may perform differently under freezing or high temperatures, which can impact data accuracy or cause damage [37]. Hence, understanding the environment and the components and materials of the sensors is crucial for an extended architectural life cycle.

B. AUTOMATED ACTUATORS

Selecting automated actuators is vital for Smart Farming infrastructure as they convert control system signals into physical actions. Actuators serve as the backbone for automating critical agricultural processes such as activating irrigation systems, regulating greenhouse ventilation, and facilitating the operation of agricultural implements [10], thereby significantly enhancing operational efficiency within the farm environment.

In the realm of Smart Farming, a diverse array of actuators is employed, encompassing electric actuators and water pumps, among others. Notably, the utilization of water pumps is paramount for optimizing irrigation processes, ensuring precise delivery of water to crops at optimal intervals [12]. Similarly, the deployment of relays for controlling greenhouse lighting contributes to the creation of ideal growth conditions for plants, consequently augmenting both crop yield and quality. The selection criteria for actuators in Smart Farming include considerations such as reliability, durability (with adherence to IP67 standards), energy efficiency, compatibility with sensors and controllers, functionality for specific tasks like irrigation management, and ease of integration into the system.

C. GATEWAYS AND EDGE DEVICES

In the process of selecting options for gateways and end devices in smart farming applications, several key criteria should be carefully considered to ensure the effectiveness and compatibility of the chosen devices with the overall system. Firstly, it is essential to assess the functionality required for the specific smart farming application, whether it involves data collection from sensors, control of actuators, or serving as a communication hub. Compatibility is another critical factor, necessitating alignment between the selected devices and existing infrastructure, including sensors, communication protocols, and data management frameworks [13]. Scalability is paramount to accommodate future expansion or changes in the smart farming system, necessitating devices that can seamlessly integrate new technologies and support increased data volume over time. Evaluation of communication protocols supported by the devices is crucial, with considerations including Wi-Fi, Bluetooth, LoRaWAN, Zigbee, or cellular networks, based on application requirements and environmental conditions [13].

Cost-effectiveness plays a significant role, in balancing initial purchase costs, maintenance expenses, and potential future upgrades against required functionality and performance. Reliability is paramount in harsh agricultural environments, necessitating devices known for their durability, resistance to environmental factors, and long-term stability. Additionally, consideration of community support is essential, with active communities providing valuable resources and assistance for troubleshooting and development [13].

Finally, ease of use is crucial for both developers and end-users, requiring devices with intuitive interfaces, comprehensive documentation, and straightforward setup processes.

D. POWER SUPPLY

Researchers' literature has shown that there is a lack of information regarding power supply choices. Overall, there are not common ways to approve or discard a specific power consumption device other than meeting minimum specifications that a given solution requires. Let us think about how sensors and actuators can function effectively, it is crucial to consider their energy consumption. Wireless sensors typically consume more energy than wired sensors; therefore, the use of an autonomous and sustainable energy source, such as solar energy, is recommended. In that way, [48] and [49] mention the use of solar-powered sensors. These autonomous devices offer greater flexibility and ease of installation compared to wired systems. Nevertheless, despite solving the energy consumption issue, they can be more expensive and complex to install.

Commonly revisited solutions for power provision include various battery types such as standard alkaline batteries (AA, AAA, 9V), lithium-ion batteries (LiPo), and lithium iron phosphate batteries (LiFePO4), as well as power sources like solar panels and direct power lines (wall outlets). Additionally, computer and laptop batteries, as well as power supply units (PSUs) housed within their chassis, are often considered.

It is important to note that any portable power solution typically offers less autonomy compared to on-site power sources. However, rechargeable batteries emerge as the most prevalent choice due to their versatility and ability to sustain operations in remote locations where periodic status checks by maintainers are feasible.

In similar ways, sophisticated technologies like drones or rovers would not be able to perform their activities without large batteries or always-connected power supplies [21]. Every automated solution, especially those designed to operate without human assistance, will require energy for easy assembly. This underscores the importance of exploring further approaches to address this issue. Resolving such a challenge will empower designers and engineers to fully leverage the current purposes aligned with the latest technological innovations. Consequently, a more mature smart farming solutions market will emerge.

E. NETWORKING

The literature has shown different aspects to consider when choosing a network, one of these considerations is the scalability of the smart farming solution and the area that is going to be covered, this can be classified in large-scale architectures, that will cover extensive areas, and short range and small-scale applications, that are designed for compact and localized applications. On the large-scale side, there are protocols like LoRaWAN, that enable nodes to be positioned far from the gateway, but it will not transmit big amounts of data, perfectly fit for smart farming data. On the other hand, the short-range and small-scale solutions, WiFi emerges as a predominant choice due to its widespread availability and high data transfer rate. WiFi modules are familiar to researchers, making them accessible and facilitating wireless communication easily, but there are also protocols like Zigbee that enable low-cost low-power wireless networks.

Other architectures may need real-time data processing, for this matter, protocols are operating at higher layers, such as MQTT, which are suitable for applications demanding real-time data processing and communication.

Lastly, given the importance of energy efficiency in smart farming applications, particularly in remote and resource-constrained environments, prioritize protocols that contribute to reduced power consumption. LoRaWAN and Zigbee, with their low-power characteristics, are suitable choices for applications requiring efficient data transmission over extended periods while conserving energy.

F. DATA STORAGE

In smart farming environments, researchers prioritize data storage solutions that provide transparency, reliability, security, and decentralization [50]. This enables automated and optimized management of agricultural systems. By employing such solutions, researchers can ensure secure storage of agricultural data and efficient access, facilitating seamless communication and decision-making processes within the farming ecosystem. Additionally, decentralized data storage helps mitigate the risk of single points of failure and enhances data resilience, crucial for maintaining uninterrupted operations in agricultural settings. Moreover, automated management systems leverage these storage solutions to streamline agricultural processes, optimizing resource allocation and enhancing overall productivity.

Both local and cloud solutions serve their purposes effectively, each catering to the specific needs of farmers. The choice between them ultimately hinges on the unique requirements of the farmer and their locality. As these prototypes continue to evolve, they are bound to transform into more robust devices. The selection criteria for these solutions will be shaped by various factors including the geographic location of farm crops and the specific needs of end-users. Local solutions tend to mature rapidly due to their close alignment with immediate needs, whereas cloud-synced options provide a more seamless guarantee of data integrity, confidentiality and availability.

G. DATA PROCESSING

The literature has shown three key methods to manage the data generated by the designed solutions, each suited to different scenarios and considerations [26], [33]. For smart farming solutions aiming at maximum efficiency and automation, the adoption of artificial intelligence (AI) is recommended with a focus on machine learning (ML) [33]. ML algorithms can analyze and interpret data autonomously, responding to the status of crops and dictating necessary parameters for plant care. This approach, exemplified by cloud-based ML algorithms analyzing drone-captured images, enables the system to make data-driven decisions, optimizing agricultural processes and reducing reliance on manual intervention. Such systems are particularly suitable for large-scale farming operations where automation can enhance efficiency [33].

In scenarios where environmental conditions are stable and simpler data processing is preferred, the use of threshold-based approaches for setting predefined limits can be effective [26]. This method, highlighted in some studies, triggers specific actions based on predetermined thresholds. While it may lack the adaptability of AI-driven systems, this approach is straightforward and overall useful for small-scale architectures. Consider threshold-based data processing for applications where simplicity and stability are prioritized over complex automated systems [26].

For smart farming solutions that require direct human intervention and decision-making, especially in situations where human expertise is crucial, manual data processing methods should be considered [26]. This approach involves experts or domain specialists inspecting and making sense of raw data, identifying patterns or anomalies that may not be easily discernible through automated means. This hands-on approach allows for qualitative understanding, drawing on human expertise and contextual knowledge [26].

It's important to note that the choice of data management method should also consider implementation costs, particularly in the context of low-cost smart farming architectures analyzed in the literature [26], [33]. AI-driven systems may require significant computational resources for training models, while threshold-based approaches and manual data processing methods may offer more cost-effective alternatives. Additionally, the availability of existing data for AI modeling and the priority of developing web or mobile applications can influence the selection of data management methods [26], [33].

H. INFORMATION DELIVERY

The literature has shown key factors to consider when selecting the appropriate method for presenting information to users in the realm of smart farming. Different ways of presenting information in smart farming can provide usability features such as interactivity, personalization, ease of interpretation, and accessibility [37]. User experience varies depending on the type of data and the solution used, with screen size influencing usability. The availability of real-time information is critical for agile decision making in agriculture.

On the contrary, [12] suggests that different methods of presenting information in smart farming have different time and resource implications. For example, setting up a web system may require more upfront time and resources compared to a mobile application installed directly on devices. Updates in web systems are typically centralized, while mobile applications may require individual updates on each device, making the process more cumbersome. In addition, installation and update requirements are different for web systems, mobile applications, and desktop applications. While web systems are accessible through compatible web browsers, mobile applications must be downloaded and installed on each device. Maintenance also varies, from managing servers and databases for web systems to updating applications in mobile stores.

From an operating system perspective, the development of a web application for crop recommendation in smart farming is important [38]. It affects the compatibility and accessibility of information presentation options, as certain features may vary. Developing specific applications for specific systems offers better performance and advanced functionalities but may entail platform limitations and additional costs. Conversely, universal solutions such as web systems are more accessible, but may lack performance and functionality. The decision depends on factors such as performance, required functionality, accessibility, and development costs, with each approach having its pros and cons in terms of compatibility and accessibility.

Regarding implementation costs, [43] discusses the costs associated with developing, implementing, and maintaining smart agriculture solutions. It mentions the development of a customized web platform, which involves upfront costs for design, programming, testing, and ongoing maintenance costs such as software updates and technical support. Compared to simpler solutions such as cloud services or email, custom development may be more expensive initially, but offers more control and specific functionality. Other factors impacting costs include ongoing technical support and system scalability, with custom solutions potentially requiring more resources but offering greater customization flexibility and advanced functionality.

VI. REAL-WORLD APPLICATIONS

The application of smart farming technologies has proven to be effective in various agricultural contexts. A notable project implemented an IoT-based agricultural monitoring and automation system using low-cost sensor nodes to create a wireless sensor network (WSN) [10]. The farm faced challenges in efficiently managing irrigation and monitoring environmental conditions due to variability in soil moisture and climate, leading to inefficient water use and fluctuations in crop quality. The IoT system enabled real-time collection and transmission of critical data such as temperature and soil moisture to a cloud platform. As a result, decision-making became more precise, reducing water usage by 10% through irrigation automation and canceling unnecessary irrigation when rain was forecasted. This approach enhanced long-term sustainability by reducing reliance on manual and less accurate methods, increasing production efficiency and quality by 12%. In another case, an IoT-based telemetry and control system was implemented in a greenhouse [2]. This system optimized the environmental conditions necessary for plant growth by integrating GPRS sensors, a real-time visualization platform (ThingSpeak), and a mobile application (Blynk) for remote device control. Automation and real-time monitoring led to more efficient resource use, resulting in a 12% reduction in water consumption and a 3% reduction in energy consumption, while simultaneously improving crop production and quality by 9%. These outcomes promote more sustainable agricultural practices and demonstrate the effectiveness of smart technologies in agricultural management. Finally, a study investigated the use of a virtual soil moisture sensor based on deep learning in an olive grove in Pisa, Italy [9]. Through the deployment of sensor nodes and the use of LSTM algorithms, the system provided more accurate soil moisture estimation, optimizing irrigation and reducing water and pesticide consumption. The results indicated a significant improvement in the efficiency and sustainability of traditional farming practices, presenting a more advanced alternative for crop management.

VII. INTEGRATION AND SCALABILITY OF IoT TECHNOLOGIES IN AGRICULTURE

IoT technologies have been successfully integrated into various crop sizes, showing their versatility. In small gardens, humidity and temperature sensors are used to adjust irrigation and optimize water use [81]. In medium-sized plantations, automated irrigation systems and monitoring platforms that integrate climatic data have significantly improved resource efficiency, including water and fertilizers [37]. Large farms employ sensor networks and drones to monitor and manage crop health precisely, enabling more efficient large-scale production [37].

The results and challenges of implementing IoT technologies vary by crop size. Small crops have achieved notable irrigation optimization, but face challenges related to initial investment and maintenance [37]. Medium-sized crops see improved efficiency but struggle with integrating various technologies and training staff [37]. Large crops benefit from enhanced efficiency and cost reduction but face challenges with managing large data volumes and requiring robust infrastructure [37].

To maximize IoT technology efficiency, it is important to adapt solutions to local conditions and specific crop characteristics. This involves customizing irrigation and monitoring systems and designing flexible technological solutions that allow adjustments according to crop size and environmental conditions [81]. Additionally, IoT platforms and cloud-based monitoring systems have proven highly scalable, enabling initial deployment in small areas with gradual expansion as benefits are validated [36].

It is recommended to adopt a step-by-step implementation strategy, starting with basic solutions and expanding as experience is gained or specific crop size settings are defined. Customization and flexible design of technologies are key to their adaptation and scalability. It is also important to consider factors such as existing infrastructure, implementation costs, and the technical capacity of farmers.

VIII. STATISTICAL ANALYSIS OF PERFORMANCE AND EFFICIENCY OF DIFFERENT TECHNOLOGIES

The diverse architectures in smart farming systems present a significant challenge when attempting to perform a direct comparison of their performance and efficiency. Each system is composed of distinct components, ranging from varied power supply methods to different processors and communication protocols. This variation makes it difficult to draw generalized conclusions about which architecture performs best overall.

Many existing studies provide valuable insights but tend to focus on specific aspects of smart farming technologies, such as the implementation of a particular neural network or the efficiency of a certain communication protocol. For example, one study analyzes the role of energy-constrained sensors in a smart farming architecture, particularly how these sensors, like humidity sensors, need to report data frequently to inform irrigation systems. The study demonstrates that by employing a scheduling mechanism based on Deep Reinforcement Learning (DRL), the system can significantly prolong the lifetime of battery-powered sensors, more than doubling their life expectancy compared to non-adaptive methods. This finding underscores the potential of combining data analytics with DRL to enhance the sustainability and efficiency of IoT deployments in smart farming scenarios [72]. Another study focuses on the Firmware Update Over The Air (FUOTA) process for TinyML models within a LoRaWAN agricultural network. It highlights the feasibility and energy efficiency challenges of remotely updating firmware for smart devices used in agriculture. While the study shows that FUOTA is feasible, it also notes that updating large-size firmware over LoRaWAN can be energy-intensive and prone to interference when multiple devices are updated simultaneously. The research suggests future optimization of the FUOTA process to improve energy efficiency and explores the use of hybrid communication technologies, such as combining LoRaWAN for standard data transmission and LTE for firmware updates [82]. Additionally, another paper evaluates a Smart Agriculture Monitoring and Management System that utilizes IoT-enabled devices connected through a LoRaWAN network. The study finds the system effective in controlling crop growth parameters and emphasizes its power efficiency, with deep-sleep modes reducing power consumption by up to 83% for sensors and 86% for actuators compared to active modes. The system is also highlighted for its cost-effectiveness, scalability, and ease of maintenance, making it a promising candidate for widespread adoption in smart agriculture [28].

However, such studies often do not offer a comprehensive analysis of the entire system's performance in a real-world agricultural setting, leaving gaps in our understanding of how different architectures function as a whole.

Given the wide range of factors involved, comparing these technologies across the board is problematic. For instance, while some systems may excel in processing power, they might be less efficient in terms of energy consumption. Others might offer robust communication capabilities but fall short in data processing speed. These differences underline the complexity of evaluating smart farming architectures holistically.

In light of these challenges, future research could benefit from the development of standardized benchmarks and more holistic evaluation methods. Such approaches would provide a more robust foundation for comparing different smart farming architectures, allowing for more meaningful conclusions about their relative performance and efficiency.

IX. EXPERIENCE, AND THE SOCIO-ECONOMIC IMPACT OF SMART FARMING TECHNOLOGIES ON FARMERS AND RURAL COMMUNITIES

Smart farming technologies, encompassing digital sensors, artificial intelligence (AI), and the Internet of Things (IoT), have significantly enhanced farm management and decision-making processes. These technologies provide real-time data and integrated digital solutions, thereby improving farmers' technical efficiency and knowledge. The implementation of these tools offers actionable knowledge and facilitates integrated, real-time decision-making, which is crucial for modern agricultural practices [23]. Additionally, the adoption of user-friendly interfaces, such as mobile and web applications, enables farmers to interact with these technologies more effectively, ensuring improved monitoring and control of farming operations. Non-GUI interfaces, including speech, haptics, and gestures, are particularly beneficial in regions with literacy challenges, further enhancing the overall user experience [42], [88].

With 90% of U.S. farmers now using smartphones to manage their operations, the shift toward digital agriculture is undeniable [90]. These mobile apps have been instrumental in improving decision-making processes, with some estimates suggesting a productivity increase of up to 30% through better data accessibility and resource management [91]. This demonstrates the crucial role that accessible technology plays in modern farming, particularly when considering the socio-economic impact.

The socio-economic impact of smart farming technologies is profound, contributing to increased agricultural efficiency, profitability, and sustainability. For instance, precision agriculture technologies, such as GPS-guided equipment, can reduce costs by up to 25% while simultaneously increasing crop yields by 5% [90]. This optimization of resource utilization, along with reduced labor requirements, has led to significant improvements in farm management practices. Consequently, farms have experienced enhanced productivity, resilience, and environmental performance [23]. Moreover, digital agriculture provides broader socio-economic benefits, such as improved financial management, market competitiveness, and enhanced access to finance, advisory services, insurance, and markets for smallholder farmers. This leads to greater economic stability and improved livelihoods for small-scale producers [42]. Furthermore, the integration of sustainable farming practices through digital and geospatial technologies supports climate change mitigation and biodiversity improvements, thereby contributing to long-term environmental sustainability and societal benefits [23], [68].

Specific technologies have also led to notable increases in production. For example, the use of smart irrigation systems, which are estimated to reach a market size of $1.35 billion by 2025, can reduce water usage by up to 40% while maintaining or even increasing crop yields [90]. Similarly, AI-powered crop monitoring systems have been shown to detect plant diseases with up to 98% accuracy, preventing losses and ensuring higher productivity [90]. These innovations not only support sustainability but also ensure that farms remain competitive in a rapidly evolving agricultural landscape.

However, the adoption of smart farming technologies faces several challenges, including resistance from older farmers, a gap between farmers and technology providers, and the high costs associated with new technologies. Addressing these barriers is crucial for the successful implementation and long-term sustainability of smart farming systems. Overcoming these challenges will ensure that the benefits of digital agriculture can be fully realized, leading to enhanced food security, sustainability, and economic development in rural communities [35], [68].

X. CONCLUSION

The Internet of Things (IoT) has undergone significant evolution, from basic connectivity to incorporating advanced technologies like artificial intelligence and real-time analytics. This evolution has profoundly impacted various sectors, including healthcare, agriculture, manufacturing, and logistics. The transformative capacity of IoT lies in its ability to revolutionize interaction with the physical world, enabling faster decision-making, operational efficiency, cost reduction, and new business opportunities across diverse applications such as smart cities, eHealth, Industry 4.0, and smart homes.

However, despite its potential, the widespread adoption of IoT in smart farming faces challenges, notably the lack of knowledge among farmers. Ongoing conditions, including deficiencies in education, technology, and financial resources, hinder the adoption of modern agricultural technologies. Challenges include undefined standards, issues related to coverage and connectivity, high investments, resistance to the adoption of new technologies, and a shortage of trained manpower. Additionally, the lack of guidance models for IoT-based monitoring systems and the limited education among rural farmers pose additional barriers to adoption.

Once relevant studies were collected and categorized, we proceeded to analyze emerging trends and identify best practices in the field of smart agriculture. This analysis allowed us to shed light on the evolution of smart farming solutions, highlighting technological advancements, challenges, and recommendations for selecting devices and technologies.

Our research revealed that the implementation of smart farming involves a complex interaction among various components, including sensor types, gateways, power supply, data storage, data processing, and information delivery. Each of these elements plays an important role in creating a comprehensive ecosystem that empowers farmers to make informed decisions and optimize their agricultural practices.

This study has provided a detailed insight into emerging technologies in the realm of smart agriculture, emphasizing the importance of IoT as a catalyst for transformation in the agricultural sector. We aim to contribute to the advancement of research in this field by offering valuable guidance for those interested in implementing smart farming solutions and maximizing their impact on the efficiency, sustainability, and productivity of agricultural operations.

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