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RESEARCH ARTICLE

A Systematic Literature Review of the IoT in Agriculture–Global Adoption, Innovations, Security, and Privacy Challenges

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ABSTRACT Over the past decade, an abundance of research has been conducted in the area of agricultural technology and innovations. The Internet of Things (IoT) has demonstrated its ability to connect numerous agricultural equipment, sensors, and specialists, boosting agricultural procedures in off-the-grid regions. Agriculture has experienced considerable improvements in production, cost reductions, service accessibility, and operational efficiency. With an emphasis on security, developments and trends in the sector, and technological implementation, this research paper offers an up-to-date analysis of existing and projected IoT applications in agriculture. In this article, enabling technologies, agricultural applications based on cutting-edge machine learning models, and services are all examined in relation to the development of IoT deployment in tackling diverse agricultural concerns. In the IoT-based agriculture system, potential challenges and limitations are also addressed. In its conclusion, this research provides an extensive review of the various aspects of IoT in agriculture, with the goal of empowering future researchers enthusiastic to make contributions to and advancement in their quest for a more in-depth comprehension of this field of study. A total of 96 papers were chosen for the selection from 2018 to 2023, and each was categorized using predetermined standards. The research's results have been thoroughly examined, providing an overview of IoT in agriculture.

INDEX TERMS Systematic literature review (SLR), IoT, smart agriculture, crop disease identifications, sensors, communication technologies, applications, machine learning, deep learning, security, blockchain.

I. INTRODUCTION

The Internet of Things (IoT) has been implemented in a variety of applications, including smart agriculture [1], smart factories [2], personal gadgets [3], smart cities and homes [4], [5], smart health systems [6], connected transportation [7], and smart unmanned aircraft [8]. The Internet of Things enables real-world objects to interact with one another, exchange data, and make decisions collaboratively. Using its underlying technologies, such as communication technologies, Internet protocols, applications, and sensor networks, the IoT transforms conventional objects into intelligent ones.

Agriculture serves as the backbone of survival for mankind since it is the primary source of grains for food and other basic resources. The development of the nation's economy is significantly impacted by it. Additionally, it offers individuals numerous and plentiful opportunities for employment. The long-term stability of the country's economy depends on the expansion of the agriculture sector. However, a lot of farmers keep cultivating their land using outdated techniques, which causes an insufficient yield of agricultural products.

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Even when technology was employed and human labor was substituted by automatic machinery, the yield increased [9]. Significant developments have been achieved over the evolution of humanity to maximize agricultural productivity with minimal assets and worker demands. Nonetheless, the rapid increase in population has never enabled both supply and demand to be equated during all of these eras.The rapidly expanding global population is projected to reach approximately 10 billion by 2060, a 25% increase from today's figure, according to the united nations survey [10]. Nonetheless, due to population growth, consumer demand for edible grains has increased dramatically in recent years. Unluckily, the consumption of grain is indirectly linked to population expansion. Consequently, the worldwide production of food will need to be increased in the forthcoming years.To satisfy the demands of this larger, more urban, and wealthier population, agricultural production needs to quadruple by 2050 [11]. More specifically, the present annual wheat output of 2.2 billion tons should be increased as needs grow to almost 3.0 billion tons, and yearly livestock production should increase by over 225 million tons in order to meet the consumption of 500 million tons [12].The IoT has currently established a big influence on the agricultural sector, with an enormous variety of sensors employed to accomplish different smart agriculture purposes. A significant amount of research has been conducted in the agricultural field with Internet of Things technologies for implementing smart agricultural solutions. Every year, the number of IoT applications rises dramatically. By investigating numerous challenges and obstacles in farming, the IoT has contributed to a big shift in the field of agriculture [13]. With the advent of technological advances, it is now predicted that farmers and technological experts will leverage IoT to overcome challenges that farmers face, such as water shortages, managing costs, and productivity challenges. All of these concerns have been addressed by cutting-edge IoT technologies, which have provided solutions to boost production while decreasing costs [14].The worldwide smart farming sector is predicted to grow to \$21 billion by 2030, up from \$6.5 billion in 2019 [15]. Smart agriculture is expected to become a significant internet of things domain in countries that export agricultural products. Internet of Things applications for smart agriculture have recently been introduced employing wireless sensor networks (WSNs), including irrigation sensor networks [16], soil farming precision [17], frost event prediction [18], smart agriculture precision [19].Research carried out on wireless sensors Networks allow users to gather data from sensors and transmit it to central servers [20]. Data received by sensors provides insight into various environmental variables, allowing the entire system to be effectively monitored. Monitoring weather conditions or yields of crops is not just one consideration for crop evaluation; instead, it includes numerous additional factors that impact crop productivity, such as land and field management, crop and soil monitoring, motion of a not-wanted object, attacks by wild creatures, and thefts, among others [21], [22]. Furthermore, IoT enables a well-planned use of limited resources, ensuring that optimal utilization of IoT increases productivity.

There are six significant challenges to developing an environmentally friendly IoT-based agriculture system: hardware, analytics of data, repair and maintenance, connectivity, infrastructure, security of data, and privacy. The most significant hardware issues are around the selection of sensors and distance for IoT devices. As a result, there are several sensor categories that may be utilized in IoT applications (for example, pressure sensors, temperature sensors, chemical sensors,proximity sensors, humidity sensors, water quality sensors, gas sensors, and so on) [23]. The analytics of data issue entails applying predictive algorithms and machine learning (e.g., deep learning methods) to IoT data in order to achieve a nutritional solution for smart agriculture [24]. The repair and maintenance issue requires frequent sensor checks for each IoT device, which can be easily harmed in the agricultural field.The connectivity issues are related to the variety of wireless technologies (e.g., 4G, 5G, Zigbee, WiFi, LoRa, and 6LowPan) that are capable of connecting sensors spread across a vast region in agriculture [25]. The infrastructure issues are related to the setting up and implementation of IoT network architecture employing cutting-edge technologies such as fog computing, cloud computing, virtualization of networks, and more [26]. The key challenge in the development of environmentally friendly IoT-based agriculture is not physical backing; it's more about ensuring both security and privacy. Through the widespread implementation of IoT-based agriculture, an attacker might notice new ways to breach the system (for example, through a fake data injection attack), generating significant security and privacy concerns and advocating for secure sharing of information in the smart agricultural field [27].The taxonomy of the IoT based agriculture system is depicted in Fig.1.

The aim of the proposed study is to publish the results of a systematic literature review (SLR) in the field of IoT in agriculture. On this subject, numerous research studies have recently been published. The state-of-the-art research is gathered, examined, and summarized in this SLR. This SLR has been carried out to gather and integrate recent practical studies with scientific panoramas so that other scientists and practitioners can find directions for implementing IoT in agriculture. This SLR research is the most comprehensive that has been carried out based on the potential of IoT applications in agricultural systems. The major contributions of this study are outlined below:

- According to our research investigation, this is the first survey that offers extensive comparisons of the IoT-based applications for agriculture based on research that has been previously published.
- The foreseeable future of smart agriculture is addressed in this study, along with its magnificent potential to change people's lifestyles by delivering food with high yields. Analyzing the most recent global state-of-the-art developments in IoT-based agriculture and also

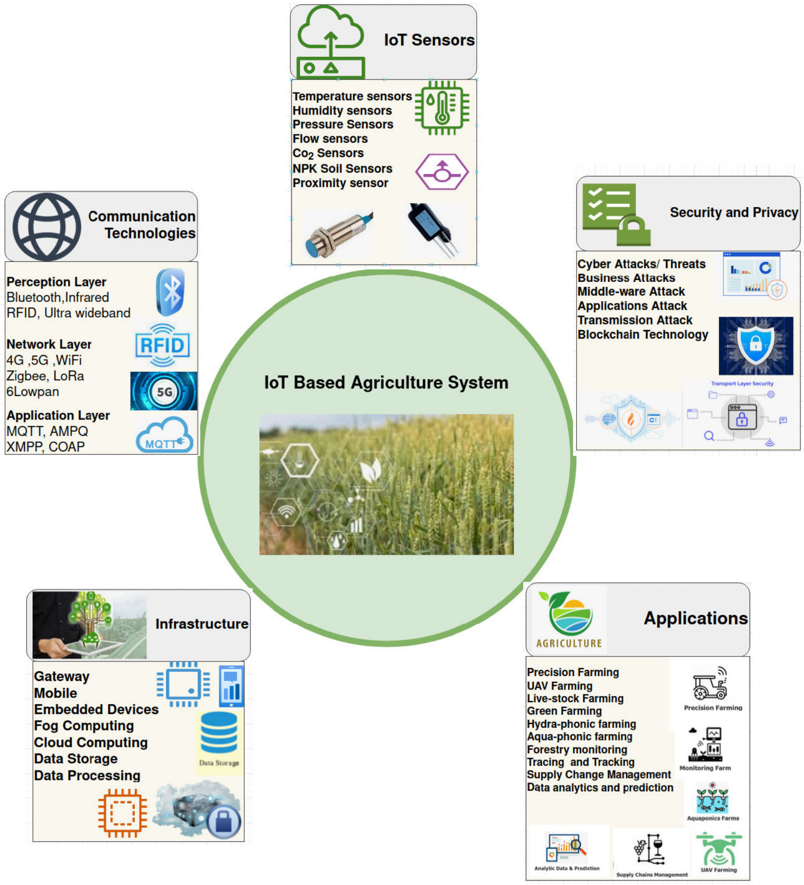

FIGURE 1. Taxonomy internet of things based agriculture system.

highlighting the requirements for effectively implementing these innovative technologies.

- The paper discusses commercially available agriculture-based IoT sensors and devices, communication technologies, and infrastructure for the agriculture-based Internet of Things.
- The paper highlights risk models, security and privacy challenges, and blockchain-based Agriculture IoT security solutions in depth, focusing on IoT-based agriculture applications as well as future research directions for smart agriculture systems.

Overall, these contributions offer a comprehensive and forward-looking analysis of IoT-based applications in agriculture, covering technological advancements, implementation requirements, security challenges, and future research directions. This holistic perspective distinguishes it from existing surveys by providing novel insights and addressing key aspects that may have been overlooked in previous literature. This paper is organised as follows: Section II discusses research methodology with relevant research questions, search strategy, inclusion and exclusion criteria, screening and selection, and quality assessment. Section III highlights the recent developments and trends in IoT-based smart agriculture systems. Section IV describes the architecture of an IoT based agriculture system. Section IV-B describes the communication technologies of an IoT based agriculture system. Section V discusses security and privacy challenges and solutions for smart agriculture. Section VI discusses state of the art machine learning models for smart agriculture systems applications. Section VII discusses Research open challenges and future research directions Finally, Section VIII concludes the paper.

II. RESEARCH METHODOLOGY

A systematic literature review (SLR) is a methodical and structured way of finding, assessing, and interpreting prior research that is pertinent to a certain research question in software engineering, according to [28] and [29]. The literature has suggested a number of strategies for conducting an SLR. This systematic review was carried out in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses reporting checklist [30]. The research includes the development of Research Objectives, Research Questions with motivation, a detailed Search String strategy, screening of the searched results, Data extraction, and evaluation, as illustrated in Fig.2

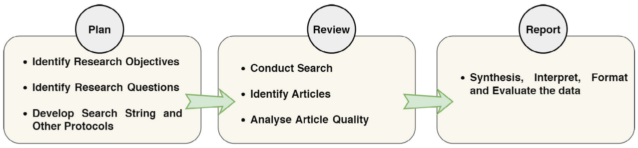

FIGURE 2. Key steps for systematical literature review [28].

A. RESEARCH OBJECTIVE

The main objective of this SLR is to examine and summarise the state of the art in the subject of smart agriculture. In order to accomplish this, prominent research objectives (ROs) have been established to direct the review procedure and serve a well-structured framework for analysis and interpretation. To address important elements of smart agriculture, the following research goals have been established that have been listed in Table 1:

TABLE 1. Table of research objectives for IoT based agriculture SLR.

Number	Objectives
RO1	To assess the effectiveness and utilisation of IoT sensors in smart agriculture
RO2	To evaluate the communication technologies employed in IoT-based smart agriculture systems.
RO3	To investigate the security and privacy considerations in IoT-based smart agriculture.
RO4	To analyse the applications and Deep learning models widely used in smart agriculture.

B. RESEARCH QUESTIONS

Creating research questions is essential to carrying out a systematic literature review. Research questions provide the review with a distinct and focused direction, directing everything from study selection to data analysis. Reviewers can limit the scope of the review and make sure that only relevant articles are included by developing clearly stated research questions. The following Table 2 shows the research questions (RQs) that have been created for the study. These research topics allow for the categorization of current IoT research in agriculture and the identification of potential future study fields.

C. SEARCH STRING

The second phase of the SLR focuses on the primary goal of finding relevant research related to the research topics. This is achieved by gathering published papers that align with the specific research areas using a carefully designed search string. During the initial search, keywords were used to narrow down the focus to IoT applications in agriculture. However, the pilot search also included IoT communication protocols, agricultural sensors, and IoT security and privacy measures to ensure comprehensive coverage. To gather information, a thorough internet research approach was adopted, utilizing various search engines and digital libraries, as mentioned in Table 3. In the search

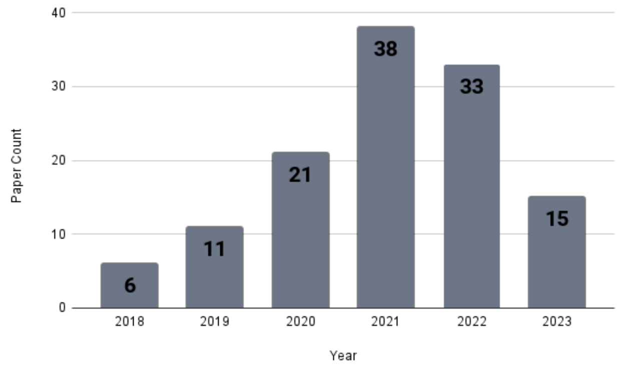

FIGURE 3. Count of articles as per time line.

for relevant and representative papers, a unified searching methodology was employed. The main databases of scientific publications, including IEEE, Scopus, and MDPI, were utilized for the search. The selected time-frame for inclusion of publications in this SLR spanned from May 2018 to May 2023. By employing this comprehensive search strategy, the aim is to capture the most up-to-date and relevant literature in the field.

D. IDENTIFYING RELEVANT ARTICLES

Once the initial search was complete, it became clear that not all of the papers returned were directly related to the research's objectives. It was required to carefully evaluate their actual importance as a result. The first round of screening consisted of choosing articles based on their titles, which allowed us to omit papers that were considered irrelevant to the research topic, as mentioned in Table 4.

After the initial search, screenings were carried out in four stages. First, duplicate research papers are discarded. There were **1776** papers after that stage. The duplicate and unrelated papers were eliminated based on their titles. After the process, **241** papers remained. Thirdly, papers were screened based on abstracts that contained an extensive amount of information relevant to the paper and were retained for further analysis. After this stage, there were still **124** articles on the list. Finally, during the full-text search stage, papers that did not address the research topics were discarded. The research was carefully evaluated to establish whether or not it was experimentally validated. The **96** papers reached a conclusion after this stage was completed, as presented in Table 5. Fig. 3 shows the results of a particular search string for publications published between 2018 and 2023, and Fig.4 shows the ratio of papers published in conferences and journals, while Fig.5 displays the number of publications published by each search domain.

E. QUALITY ASSESSMENT

Quality assessment plays a pivotal role in the systematic literature review process, and thus, a questionnaire was developed to evaluate the quality of the chosen papers. The

TABLE 2. Table of research questions for IoT based agriculture SLR.

Number	Research Questions	Motivation
RQ1	What are the most recent developments and trends in IoT-based smart agriculture systems?	To keep up with the most recent innovations and trends in IoT-based smart agriculture systems to guide your fieldwork and research.
RQ2	What are the different layers of the Internet of Things architecture used in smart agriculture systems?	Recognize the various IoT architecture layers that smart agriculture systems utilize to improve data sharing and decision-making.
RQ3	What are the leading sensor technologies used for data collection and monitoring in agricultural fields?	Identify the most appropriate sensor technologies for data collection and monitoring in agricultural fields in order to direct sensor choice and application.
RQ4	What communication protocols and application layer protocols are frequently used in IoT-based smart agriculture?	To Assess the most popular application layers and communication protocols in IoT-based smart agriculture.
RQ5	What are the major security & privacy concerns in IoT architecture based on smart agriculture?	Enhance the security of IoT-driven agricultural environments to handle privacy threats and guarantee efficient privacy protection measures by gaining knowledge about commonly used security methods in smart agriculture.
RQ6	What are the state-of-the-art ML models and techniques in smart agriculture applications?	To Investigate cutting-edge machine learning models and methods in smart agriculture applications to guide improvements in agricultural performance and decision-making.

TABLE 3. Selection of search strings for different libraries.

Databases	Search String
IEEE, MDPI, Scopus	*(Agriculture Internet of Things OR IoT) AND (Smart Agriculture OR Precision Agriculture) OR (IoT agricultural devices OR IoT agriculture sensors) OR (IoT agricultural protocols OR IoT Communication Protocols) OR (IoT agricultural infrastructure) OR (IoT based agriculture applications OR smart agriculture applications OR Machine learning models for smart agriculture applications)OR(IoT based agricultural security & Privacy challenges OR IoT security concerns) OR (Blockchain based secured smart agriculture)*

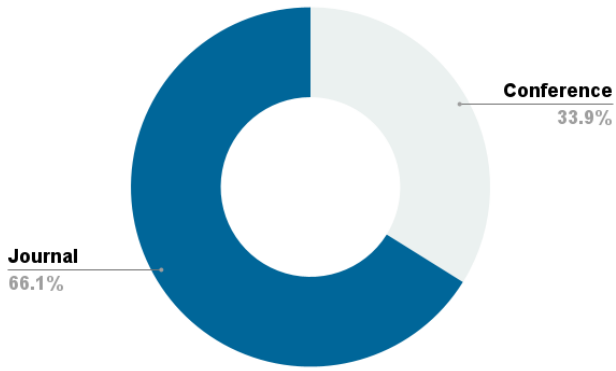

FIGURE 4. Ratio of articles: Journals vs. Conferences.

TABLE 4. Result of search strings from different libraries.

Databases	IEEE	MDPI	Scopus	Total Count
Paper Count	336	202	1273	1811

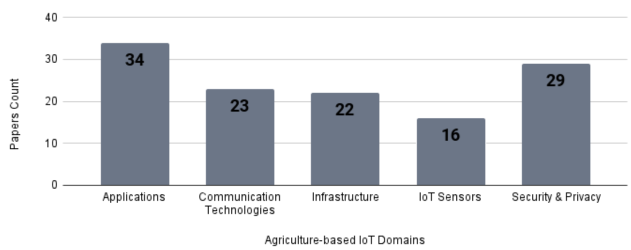

FIGURE 5. Count of articles from agriculture-based IoT domain.

TABLE 5. Count of articles after screening results.

Result of Screening Stages	Paper Count
Remove Duplicates	1776
Title based Search	241
Abstract based search	124
Full text based search	96
Finalized	**96**

questionnaire comprises several questions designed to assign scores for quality assessment. These inquiries encompass:

(a) Assessing the study's contribution regarding the exploration of IoT's potential in agriculture A score of 1 is allotted for "Yes" responses and 0 for "No" responses.

(b) Evaluating whether the study offers a clear solution to agricultural challenges using IoT The scoring system incorporates 1 for "Yes," 0.5 for "Partially," and 0 for "No."

(c) Examining whether the study's outcomes are empirically validated A score of 1 is assigned to "Yes" responses and 0 to "No" responses.

(d) Examining whether the study effectively bridge the domains of agriculture, IoT technology, and relevant disciplines The scoring system incorporates 1 for "Yes," 0.5 for "Partially," and 0 for "No

By scoring these questions, the selected papers' quality assessment is classified, ensuring the inclusion of high-quality studies in the SLR analysis.

III. RECENT DEVELOPMENTS AND TRENDS IN IOT-BASED SMART AGRICULTURE SYSTEMS

By incorporating cutting-edge technology like the IoT, data analytics, and automation with conventional agricultural practices, smart agriculture, sometimes called precision agriculture, has completely transformed the farming sector. Smart agriculture systems based on the IoT have been increasingly popular in recent years because of their potential to increase productivity, cut down on resource waste, and increase crop yields [31]. The most recent innovations and trends in IoT-based smart agriculture systems will be examined in this SLR, emphasizing six major ones: water management/irrigation management, soil management, weather management, nutrient management, waste management, and crop management,as illustrated in Fig.6.

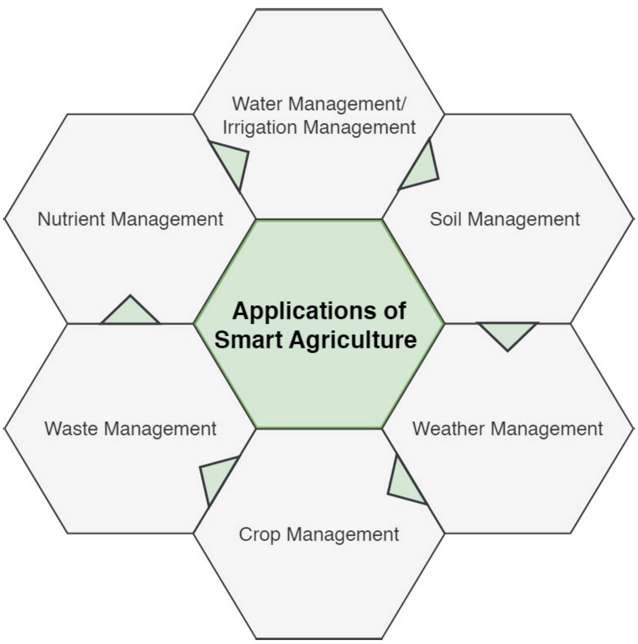

FIGURE 6. Applications of IoT based smart agriculture.

- **Water Management /Irrigation Management:** Agriculture is becoming increasingly concerned about the limited supply of water. Therefore, effective water management is essential. Smart irrigation systems that are IoT-based have become a significant solution. These systems optimize irrigation schedules using sensors, weather predictions, and data analytics, lowering water use and boosting agricultural yields. Recent innovations include incorporating artificial intelligence (AI) algorithms to forecast soil moisture levels, real-time water quality monitoring, and automated control systems that modify irrigation based on plant needs [32]. Farmers may now manage irrigation from anywhere thanks to standard features like remote monitoring and management via mobile application.
- **Soil Management:** Agriculture depends heavily on maintaining healthy soil. Real-time soil monitoring using IoT technologies makes measuring variables, including moisture content, pH levels, and nutrient levels possible [33]. Data is gathered by soil sensors, which are then analyzed to produce valuable insights. A recent trend is combining IoT-based soil management systems with machine learning algorithms to provide individualized suggestions for soil adaptation and fertilization. These systems encourage sustainable farming practices by maximizing nutrient utilization and lowering the chance of over fertilization.
- **Weather Management:** The weather is crucial to agriculture, and IoT has improved the accuracy and accessibility of weather monitoring. Real-time information on temperature, humidity, wind speed, and rainfall is provided by IoT-based weather stations that are equipped with a variety of sensors [34]. Through mobile apps and online platforms, farmers have access to this data, enabling them to make educated choices regarding pest management, planting, and harvesting. Predictive analytics and meteorological data have recently been combined to assess climate threats and predict weather trends. This allows farmers to adjust to shifting weather patterns and reduce crop losses.
- **Nutrient Management:** Crop health and production improvement depend on effective nutrient management. The Internet of things may continuously monitor nutrient levels in the soil and plants. Farmers may improve their fertilization plans while minimizing waste and environmental effects with sensors and data analytics [35]. Smart drones and autonomous vehicles are two recent advancements in IoT-based fertilizer management that allow exact fertilizer application. These technologies help reduce resource waste and environmental damage by enabling site-specific fertilizer delivery.
- **Waste Management:** Keeping agricultural waste to a minimum benefits both the environment and the economy. Smart agriculture technologies driven by the Internet of Things aid farmers in maximizing resource use and minimizing waste. IoT sensors have been used recently to track waste produced during manufacturing and keep an eye on post-harvest storage conditions. Systems for intelligent sorting and recycling have also been created to effectively handle agricultural trash [36]. These developments lessen agriculture's environmental impact and support sustainable farming methods.
- **Crop Management:** Smart agriculture is leading the way with IoT-based crop management systems. These systems use sensors to monitor crop health, development, and pest infestations. The use of multi-spectral cameras on drones to take high-resolution photos of

crops is a recent discovery [37]. Then, preemptive interventions are made possible by AI-powered picture analysis algorithms that spot early indications of illness or stress [38]. IoT-based agricultural management systems also frequently connect to equipment for automated harvesting and precise planting. These developments save labor expenses while improving crop quality and output overall.

IoT-based smart agriculture systems are constantly changing due to new trends and advancements in many areas of agricultural management. With the help of IoT technology, farmers can now make data-driven decisions, increase resource efficiency, and implement sustainable farming methods in water, soil, weather, nutrients, waste, and crop management. In addition to boosting agricultural output, these developments are also helping to preserve natural resources and lessen their harmful effects on the environment [39]. The future of smart agriculture appears bright, with even more breakthroughs on the horizon as IoT technology develops.

IV. DIFFERENT LAYERS OF THE INTERNET OF THINGS ARCHITECTURE USED IN SMART AGRICULTURE SYSTEMS

To guarantee the highest level of reliability, considering the extensive variety of agricultural systems, it is essential to manage numerous pieces of agricultural equipment and sensors that are connected to the Internet in a heterogeneous way. An adaptive, multilayered framework is therefore essential. Each framework, which builds on IoT protocol stacks ranging from three to five layers, provides various advantages. Although the three-layer (perception, network, and application) stack has a simplified structure, the four-layer stack provides additional services,and the five-layer framework has the greatest potential for agriculture. Precision farming, resource optimization, and environmental monitoring depend on higher levels of data interpretation and interoperability, which makes the five-layer IoT protocol stack the best option for agricultural IoT applications given the complexity of agricultural operations and the wide range of sensors and devices involved. The five-layer IoT-based agriculture proposal proposes an organized structure with each of the layers carrying out a specific task [40]. According to Fig.7, the five layers include perception, communication network, platform (processing), application, and business layers. Hardware such as sensors, actuators, and controllers are included in the device layer, which is also referred to as the perception layer. The communication network layer is in charge of connecting to servers, other smart IoT sensors and devices, and network equipment. In addition, the processing and sending of sensor data enables effective use of its strengths. Networks (such as RFID, Bluetooth, NFC, WiFi, 5G, and LAN) are used to send sensor data from the layer of perception to the platform (processing) layer.The data processing (middle-ware) layer stores, analyzes, and processes gigabytes of data while also providing service support, formulations, cloud computing, and middle-ware technologies. It is able to manage and support numerous lower-layer services, such as alerts, retrieval of data, big data processing, cloud computing, and data analyses for IoT-based agriculture applications via cloud platform services like Amazon Web Services, Microsoft Azure, Google Cloud, and others. The application layer is responsible for offering application-specific services to the user. This layer includes devices such as monitoring equipment, geolocation devices, surveillance systems, crop diagnostic systems, and so on [41].The business layer manages all aspects of the IoT-based agriculture system, which include apps, security, business and profit models, and user privacy. Each feature introduces new security and privacy concerns. As such, security and privacy issues are classified accordingly based on their prevalence in each layer [42].

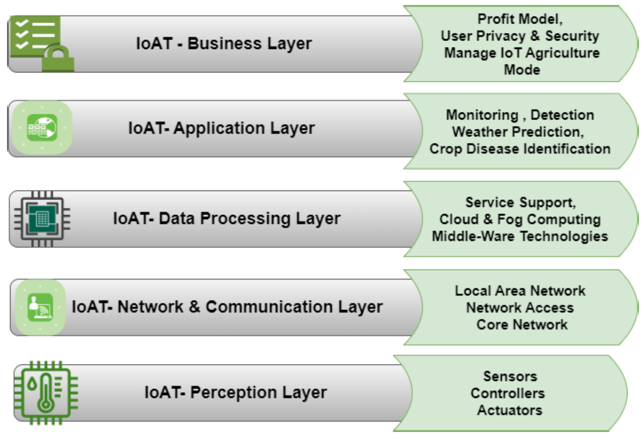

FIGURE 7. Five layer architecture for an IoT-based agriculture system.

A. LEADING SENSOR TECHNOLOGIES USED FOR DATA COLLECTION AND MONITORING IN AGRICULTURAL FIELDS

In agriculture and IoT infrastructure, the perception layer is the physical layer that collects data from the world using sensors, imaging devices, and other technological equipment. These peripherals are in charge of gathering data on moisture in the soil, relative humidity, temperature, quality of the air, water levels at ground level, and other parameters that are essential to monitoring and controlling agricultural procedures [43]. The perception layer is the fundamental component of an agricultural IoT system because it acquires data from the field in real time. The data is then sent to the higher levels of the system to be processed, evaluated, and applied to make decisions. Farmers and agricultural experts may decide alternatives about cultivation, fertilisation, pest control, and other vital aspects of farming when they have access to timely and reliable data about the agricultural environment. The following is a list of some devices and sensors that are frequently used in the perception layer for agricultural purposes:

1) **Micro controller ESP8266:** The ESP8266 is an autonomous system on chip (SOC) connected with TCP and IP that enables the micro-controller to establish a connection to a Wi-Fi network.The ESP8266 may enable or block all Wi-Fi network functions from other application processors.
2) **Micro controller Arduino Mega:** The Arduino Mega is an AT-mega-based micro-controller board with 16 analog pins, 54 digital input and output pins, a crystal oscillator running at 16 MHZ,a USB port for communication, an ICSP header, a barrel jack for power, and a reset push button.
3) **The nRF24L01 radio transceiver module:** The Rf24L01 module is a 2.4 GHz wireless single chip with a baseband protocol engine. The wide range of In order to implement smart farming, a 1100 m long transceiver module that works in the ISM frequency band is necessary.It is in charge of transmitting agricultural data to the layer of application. IPv4 and IPv6 versions are available to offer technological features such as network layer communication. The IPv6 protocol was developed in response to the growing number of addressing devices. In this scenario, the WiFi module ESP8266 communicates with the network layer using IPv4 at 2.400 - 2.4835 GHz. A serial peripheral interface was used to adapt and control this wireless transceiver module.
4) **Soil moisture sensors:** These devices measure the amount of water that is already present in the ground, thereby assisting farmers in determining when and how much water to use for irrigation.
5) **Temperature and humidity sensors:**Monitor the environmental conditions to gain an understanding of the relationship between climate and the growth of crops.
6) **Air quality sensors:**Detect pollutants or gases that may impact the health of plants or the air quality in the surrounding area.
7) **Groundwater level sensors:** These devices are used to measure the levels of groundwater, which is essential for the management of water resources and the prevention of over-extraction.
8) **Weather stations:** These stations are responsible for collecting a wide variety of data pertaining to the weather, such as humidity, wind speed, temperature, and amount of rainfall.
9) **Remote sensing devices:** These are sensors that can be based on drones or satellites that take images and multidimensional data. These sensors are used to evaluate the health of crops and find early indicators of stress or disease.
10) **Light sensors:** These sensor help farmers optimise planting places by measuring the intensity of sunshine and regulating artificially generated light in artificial environments such as greenhouses
11) **Wind sensors:** Keep track of the wind's direction and speed, which can affect the way crops are pollinated, how quickly water evaporates, and how far pesticide spraying drifts.
12) **pH sensors:** These devices measure the level of acidity or alkalinity of the soil and provide information about how this impacts the amount of nutrients that are available to plants.
13) **Nutrient sensors:** These devices monitor key elements such as nitrogen, phosphorus, and potassium in the soil, enabling more exact fertiliser techniques.
14) **Leaf wetness sensors:**These sensors identify the presence of moisture or water retention on plant leaves, which is crucial for preventing diseases and estimating the optimal time to spray herbicides on plants.
15) **Crop health sensors:** A variety of sensors or imaging technologies are used to measure the health of crops by examining chlorophyll stages, leaf colour, or other environmental stress or disease signs.
16) **Water flow sensors:** Track water flow in irrigation systems to identify leakage and improve the distribution of water.
17) **Evaporotranspiration (ET):** Measure the rate of water loss from the soil due to evaporation and plant transpiration. This helps with irrigation schedules.
18) **Tensiometers:** Determine the soil moisture tension, which signifies the force needed by plants to draw water from the soil and facilitates decisions on irrigation.
19) **Water level sensors:** Ensure that there is sufficient water for irrigation by monitoring the water level in reservoirs, tanks, or other sources of water.
20) **Soil compaction sensors:** Determine the degree to which the soil is compacted, which can have an effect on the growth of plant roots and the overall health of the crop.
21) **Weather radar or satellite sensors:**They should be used to provide more comprehensive weather data and forecasts in order to better guide agricultural decision-making.
22) **Carbon dioxide (CO2) sensors:** Optimise plant development and photosynthesis by measuring the amounts of carbon dioxide in greenhouses and other controlled environments.
23) **NPK sensors:** The levels of nitrogen, phosphorus, and potassium in the soil are measured and monitored with the assistance of NPK sensors, which are utilized in the agricultural industry. With this insight, farmers have the ability to make intelligent choices regarding fertilization, leading to improved plant growth and increased agricultural yields.

The data that these sensors and devices receive is often sent wirelessly to a central data processing system, where it is analysed, displayed, and used to start automated actions or make suggestions for farmers. Farmers can use the data from

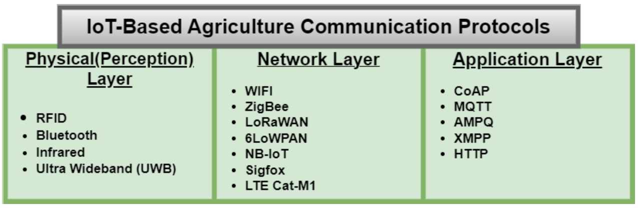

FIGURE 8. Layer-wise communication protocol taxonomy.

these sensors to make data-driven choices and use precision agriculture techniques to boost productivity and sustainability. Selected publications have been summarized in Table 6 in order to evaluate the essential sensor technologies of IoT in agriculture.

B. COMMUNICATION PROTOCOLS AND APPLICATION LAYER PROTOCOLS ARE FREQUENTLY USED IN IOT-BASED SMART AGRICULTURE

Various protocols have been adopted by the IoT network to transmit data, and these protocols are essential in deciding how things communicate during data transmission. These protocols are a set of syntax and logical principles that control how the machine's network operates when exchanging data. The widespread use of several sensors that are challenging to transform into the standard addressing format makes setting up an IoT network complicated, even though common Internet protocols (IPs) fall short in ensuring efficient data transmission. This constraint makes it difficult to set up adequately functional nodes [44]. Since IoT nodes significantly depend on a continuous power supply, particular memory characteristics, and channel throughput capacity, efficient resource management is crucial to overcoming these difficulties. The addition of a data sink to the network is required in the setting of WSNs. This procedure entails gathering data from numerous nodes and sending it to the sink for additional processing. The significance of opting for an adequate data transmission technology is highlighted by the effective placement of sensors and sinks, which can considerably improve the ability to transmit data and the efficiency of an IoT network [45].

Security and privacy are two essential characteristics that such a technique ensures by restricting different sensors from exchanging the same data [46]. It also requires preserving energy, which is an essential priority in IoT applications. Protocols for communicating with the agriculture-based IoT can be classified into three main classifications that are related to the perception, network, and application levels of the IoAT architecture, as presented in Fig.8. Table IV-D summarizes the properties of the protocols used in IoAT at the perception and network layers. This research further illustrates the adaptability and potential advantages of these protocols across various sectors by providing agriculture-based IoT indications of how each protocol might be implemented in the agricultural sector.

1) PERCEPTION LAYER PROTOCOLS FOR AGRICULTURE IOT

Perception layer protocols typically use the IEEE 802.15.4 standard, which is well-known for its simplicity, low cost, and low power consumption.This standard enables wireless communication at a significantly lower data rate and was designed specifically for Internet of Things devices with little bandwidth [47]. It specifies the PHY (physical) and MAC (media access control) layers for an extensive variety of devices, such as fixed, portable, and mobile devices with low power consumption. The IEEE 802.15.4 standard implements a wide-band physical layer using the Direct Sequence Spread Spectrum (DSSS) approach.Three frequency bands are used to govern devices operating on the physical layer: (a) the 915 MHz band, which is licensed in the US; (b) the 868 MHz band, which is licensed in Europe; and (c) the 2.4 GHz ISM band, which is an unlicensed but frequently used band. There are 27 broadcast channels accessible across these three bands. The IEEE 802.15.4 physical layer covers a variety of low-level functions, such as sending and receiving data, signal strength, monitoring,channel energy sensing, clear channel analysis, and more. whereas the IEEE 802.15.4 data link MAC layer is in charge of tasks such as establishing the Personal Area Network (PAN), enabling GTS data transmission,implementing Carrier Sense Multiple Access with Collision Avoidance (CSMA-CA) for channel allocation, establishing reliable links between peer entities, managing control repeater transmissions, and ensuring repeater synchronization. IEEE 802.15.4 is compatible with and well-suited for several IoT protocols, including ZigBee, LoRA,Bluetooth, and LowPan [48]. Agriculture systems frequently use perception layer protocols to reliably and efficiently acquire data from sensors in the fields.

- **Bluetooth:** Bluetooth is a form of wireless communication involving radio signals at ultra-high frequencies (UHF) to assist in communication over short distances. Bluetooth enables wireless communication between numerous agricultural IoT devices [49]. Bluetooth allows connections between devices up to 100 meters apart by using the 2.4 GHz radio frequency. It secures data transfer using authentication and encryption techniques, and its key benefits are its low cost and power efficiency. Bluetooth is more suited for local communication within the farm or a particular location because of its constrained range.
- **RFID (Radio-Frequency Identification):** RFID is a technology that grants every object in the data it records a special identification number. RFID tags can be used in agriculture IoT to track and monitor a variety of assets, including livestock, products, and agriculture machinery. RFID tags exist in a variety of sizes and shapes, with passive tags being less expensive than active tags. These tags may provide crucial information about the tagged objects, like moisture content, temperature, humidity, and other pertinent details. Real-time asset tracking and environmental monitoring are two areas where RFID technology is extremely beneficial [50].

- **Infrared:** Infrared communication is an inexpensive and low-cost technique for wirelessly sending small amounts of data. It appears in agriculture and IoT, such as in thermometers and cameras that monitor temperature and ambient conditions [51]. Infrared technology is widely utilized in remote controls and simple electronics, with data transmitted using protocols such as NEC and RC5. It is appropriate for short-distance communication within a narrow area.
- **Ultra-Wideband (UWB):**The wireless protocol known as ultra-wideband is intended for close-proximity communications between devices. UWB, which operates at a greater frequency range of 3.1 to 10.6 GHz, allows for accurate measurements of distance between transmitters. This high degree of precision is obtained by transmitting billions of radio pulses over a wide frequency band. In the IoT for agriculture, UWB can be employed in applications such as asset tracking and precision farming that require precise positioning and location tracking [52].

In conclusion, the perception layer protocols for the agriculture IoT include Bluetooth for short-range communication, RFID for asset tracking and environmental monitoring, Infrared for simple data transmission, and Ultra-Wideband for applications requiring accurate location and positioning. Each protocol serves a distinct function, enhancing the effectiveness and automation of agricultural activities.

2) NETWORK LAYER PROTOCOLS FOR AGRICULTURE IOT

In agriculture IoT, the network layer encompasses essential technologies such as gateways, networks of access points, and routing devices that are accountable for internet protocol (IP) addresses and other networking operations. A variety of protocols are implemented at this level, including WiFi and Zigbee, which are becoming the most ubiquitous for agricultural IoT. Furthermore, LoRaWAN and 6LoWPAN are employed to simplify communication with sensor networks that are wireless [53]. Remote data transfer and connectivity can be accomplished using conventional cellular wireless technologies such as GPRS or 3/4/5G.

- **WiFi:** The IEEE 802.11-based WiFi standard spans a broad spectrum of frequencies, from 5 GHz to 2.2 GHz. WiFi can communicate over a distance of 20 to 100 meters with data transfer speeds ranging from 1 Mb/s to 7 Gb/s. Since WiFi connects remote monitoring and control devices efficiently and securely, it has become commonly used in IoT-based agriculture systems in order to connect and monitor various assets such as irrigation systems, weather stations, and agricultural machines [54]. This enables farmers to access real-time data, manage equipment from a distance, and streamline agricultural practices for increased effectiveness and productivity.
- **LoRaWAN:** LoRaWAN is a low-power, long-range wireless network based on long-range chirp spread spectrum (CSS) modulation and is optimal for IoT applications. It is implemented in a variety of sectors, including agriculture, smart cities, metering, logistics, and others. LoRaWAN enables efficient as well as reliable communication, dealing with significant challenges including energy management, the preservation of natural resources, and disaster prevention [55].
- **Zigbee:** Zigbee is a well-known standard for transmitting data between agricultural devices. Zigbee, which operates on the 2.4 GHz frequency band, has a wider communication range than Bluetooth. It employs a mesh network topology, comprising components such as end devices, network routers, and processing gateways. The numerous advantages of Zigbee include low power consumption, rapid transfer rates, and high network throughput [56].
- **6LoWPAN:** 6LoWPAN, also known as IPv6 over Low-Power Wireless Personal Area Networks, is a low-power wireless mesh network that gives each node a distinct IPv6 address. This makes it possible to connect directly to the internet using open, standardized protocols. With the help of 6LoWPAN, the IoT ecosystem is accessible to even the smallest devices with minimal computational power [57]. Standard IPv6 packets are sent through IEEE 802.15.4-based networks using encapsulation and header compression techniques. 6LoWPAN enables seamless sensor communication with middleware platforms and network routers for agricultural sensors, enabling them to connect to IP networks.
- **NB-IoT(Narrowband IoT):** NB-IoT is a wireless communication technology intended primarily for low-power, wide-area IoT applications [58]. It works on authorized wireless bands, which provide greater connectivity and penetration, making it appropriate for agriculture internet of things implementations in distant and rural locations. NB-IoT is employed in applications such as soil moisture monitoring, precision farming, and smart drip irrigation systems.
- **LTE-M (Long-Term Evolution for Machines):** LTE-M is a wireless connection technology intended exclusively for IoT devices. It has faster data rates and lower latency than NB-IoT, making it suited for real-time data transfer applications [59]. In agriculture IoT, LTE-M is used to track livestock, monitor equipment, and manage storage on enormous farms and plantations for cultivation [60].
- **Sigfox:** Sigfox is a low-power, wide-area network technology that allows IoT devices to communicate across vast distances. It is appropriate for IoT applications in agriculture that need cheap and energy-efficient connectivity. Sigfox technology is capable of helping track assets, monitor conditions in the environment, and deploy smart drip irrigation systems.

- **LTE Cat-M1:** LTE Cat-M1 is a low-power, wide-area wireless communication technology that improves IoT device coverage and battery life [115]. It is well-suited for agriculture IoT applications that require dependable, long-range communication, such as asset tracking, soil monitoring, and remote equipment management.

These network communication technologies provide a diverse set of possibilities for agricultural IoT infrastructure, adhering to a variety of connectivity requirements, power consumption, and geographical regions. Each technology has its own distinct capabilities, allowing farmers and agricultural enterprises to develop efficient and integrated IoT solutions for increased production and efficiency.

3) APPLICATION LAYER PROTOCOLS FOR AGRICULTURE IOT

Table 8 comprises fundamental technical characteristics to accompany the application layer protocols that are frequently used in IoT-based agriculture applications. These protocols are essential for ensuring connectivity among agricultural equipment and enabling effective data exchange and control. A variety of application communication protocols are being designed in order to meet the diverse requirements of IoT applications for agriculture as the IoT keeps evolving [116].

- **Constrained Application Protocol (CoAP):** CoAP is intended for IoT communication demands that are responsive to traffic congestion-induced efficiency decline. It runs as a low-bit-rate web transport protocol, making it ideal for devices that have limited computational capability and memory [117]. User Datagram Protocol (UDP) is the framework upon which CoAP has been established for transport, resulting in minimal overhead and utilization of resources. It leverages a request-response paradigm, rendering it suitable for a variety of IoT applications in agriculture. The benefits of the star topology of this protocol include low power consumption, low cost, easy deployment, and security.
- **Message Queue Telemetry Transport (MQTT):** The publish-subscribe mechanism has been implemented by the asynchronous MQTT protocol to enable seamless communication between machines. It integrates embedded network infrastructure into middleware systems and applications, which makes it appropriate for IoT implementations with limited resources and low-bandwidth networked devices. When limited memory use, low cost, and low-power devices are required, MQTT performs exceptionally well [118]. It is adequate for telemetry-style messaging from IoT devices to the server because it has a high latency or constrained bandwidth for the transmission of data.
- **Extensible Messaging and Presence Protocol (XMPP):** In an IoT context, XMPP is mainly employed for the exchange of messages. XMPP utilizes the publish-subscribe technique, which is more suited for IoT applications than the request-response technique of CoAP. XMPP has been an endorsed internet protocol that corresponds to the IETF (Internet Engineering Task Force) standards for cross-messaging, telepresence, and video and audio calling, regardless of the existence of modern protocols such as MQTT. The dependability and flexibility of XMPP enable the development of further IoT applications [119].
- **Advanced Message Queuing Protocol (AMQP):** AMQP has been developed with the demands of the industry in mind, offering message routing, queueing, switching, privacy, security, and trustworthiness. The publish-subscribe mechanism employed by AMQP, which is like XMPP, ensures effective message delivery with at-least-once, at-most-once, or just-once definitions. The store-and-forward aspect of AMQP, which ensures accuracy and reliability, is one of its most significant advantages [120]. However, it may cause network disruptions. Transmission Control Protocol (TCP) is the backbone feature of AMQP for secure data transfer and reception.
- **Hypertext Transfer Protocol (HTTP):** HTTP is a commonly employed application protocol for browsing the web, but it is also utilized in IoT for agriculture. It allows web-based apps and IoT devices to communicate, enabling farmers to acquire data and operate machinery for agriculture through internet interfaces. HTTP is extremely advantageous for handling IoT gateways, cloud-based data storage, and agricultural remote monitoring systems [121].

Various usage scenarios, device capacity, and network constraints all play an essential part in determining the application layer protocol that is used in the agriculture IoT. Farmers and agricultural enterprises may develop complex and effective IoT systems to increase production, optimize utilization of resources, and boost sustainability overall by utilizing these communication protocols.

C. DATA PROCESSING LAYER

The Data Processing Layer plays an essential role in IoT-based agriculture by transforming contemporary farming techniques. This layer enables the smooth gathering of significant agricultural data by integrating numerous IoT devices, such as sensors, drones, and weather stations. The data gathered includes, among other things, data on soil moisture, temperature, humidity, crop health, and machinery condition. The data is preprocessed after gathering to guarantee correctness and consistency, and then it is stored in databases [122]. The rapid analysis enabled by real-time data processing enables farmers to make decisions quickly in response to rapidly altering environmental circumstances.In order to extract useful insights from the gathered data, data analytics is a crucial part of this layer. By using statistical analysis and machine learning algorithms, patterns and trends may be identified. These patterns and trends can then be utilized to build prediction models for better agricultural yields, disease detection, and irrigation plan optimization [123].

TABLE 6. IoT-based agriculture technologies classification and quality assessment.

Classification							Quality Assessment					
Sr.	Ref.	Years	Pub. Source	Research Methods	Sensors	Protocols-Network	Major Focus	a	b	c	d	Score
1.	[61]	2023	Journal	Proposed Framework	Soil sensors	ZIGBEE, wireless sensor network	Integrated soil sensor data and machine learning for an automated system predicting strawberry quality based on soil conditions	1	0.5	1	0.5	3
2.	[62]	2023	Journal	Proposed Protocol	Soil, temperature, NPK, water content, photosynthetic radiation, soil water conditions, soil oxygen level	RPL (Routing Protocol for Low Power and Lossy Networks)	Used cluster-tree structure and dragonfly algorithm for energy-efficient, secure routing protocol enhancing network longevity	1	0.5	1	0.5	3
3.	[63]	2023	Journal	Study	Temperature sensor, soil pH sensor, nitrogen sensor, phosphorus sensor, potassium sensor, and camera	MQTT	Investigated the feasibility of constructing a repeatable, predictive, and verified growth factor model for plants using edge computing and machine learning	1	0.5	1	1	3.5
4.	[64]	2023	Journal	Method	LoRaWAN end-devices	Lorawan, LoRa	Finding the optimal number and position of gateways aided LoRaWAN networks in performing better and using less energy.	1	0.5	0	0.5	2
5.	[65]	2023	Journal	Scheme	Ground sensors	LoRa	Developed a two-tiered TinyML-based decision support system suitable for the requirements of every plantation zone	1	0.5	0	0.5	2
6.	[66]	2023	Conference	Proposed framework	Air temperature sensor, air humidity sensor, solar radiation sensor, soil temperature sensor, wind speed sensor, rainfall sensor	LoRa	Demonstrated a three-tiered smart agricultural framework based on LoRa that makes use of cloud computing and fog technology for data aggregation and decision-making	1	0.5	0	0.5	2
7.	[67]	2023	Journal	Solution	Soil moisture sensors, temperature sensors, humidity sensors	MQTT	Devised an effective system for managing and coordinating community use of high-quality seeds and water resources	1	1	1	0.5	3.5
8.	[68]	2022	Conference	Model	Optical sensors, Electrochemical sensors, Moisture sensors, Motion sensors	WiFi	Created a model demonstrating how AI algorithms in decision systems can enhance precision farming and boost agricultural yield	1	0	0.5	1	2.5
9.	[69]	2022	Journal	Research Study	MultiSPEC 4c, eBee fixed wing platform, GreenSeeker	WiFi, Bluetooth	Examined the correlation between data from airborne and ground sensors, and suggested a photogrammetric framework for effective multispectral data processing	1	0.5	1	0.5	3
10.	[70]	2022	Conference	Survey	Acoustic, Optical, Ultrasonic, Mass flow, Weedseeker, Wind speed, LiDAR, Telematics, Leaf wetness, pH, and Optoelectronic	ZigBee, Bluetooth Low Energy (BLE), LoRaWAN, NB-IoT	Outlined the most recent advancements and challenges in wireless sensors and networks for precision agriculture	1	0.5	0	0.5	2
11.	[71]	2022	Journal	Solution	CCS811, SHT31, BH1750, Soil pH Sensor, ZMPT101B AC Voltage Sensor Module, SCT-013-030 Non-invasive AC Current Sensor	WiFi, ESP8266	Developed a low-cost multisensorial IoT solution for smart greenhouse management that can provide farmers with historical data and real-time information	1	0.5	0	0.5	2

TABLE 6. ***(Continued.)*** **IoT-based agriculture technologies classification and quality assessment.**

12.	[72]	2022	Journal	Platform	Humidity, Soil Humdity with Hygromemter, HD USB camera	LORA, Wifi	Established a cutting-edge solution capable of managing the collection, analysis, forecasting, and detection of heterogeneous data in strawberry farming	1	0.5	1	1	3.5
13.	[73]	2022	Journal	Framework	Temperature and humidity Sensor, Soil Moisture, RFID, Cameras	MQTT, IPFS, Blockchain	A smart Edge-IoT platform was developed to collect, process, store, and secure data from cameras and sensors in a smart agriculture system	1	0.5	0	0.5	2
14.	[74]	2022	Conference	Review	WSNs , RFID	Zigbee, LPWA, Bluetooth, Wi-Fi	Provided a comprehensive review of the challenges and trends in using cloud computing for IoT in climate-smart agriculture	1	0.5	0	0.5	2
15.	[75]	2022	Conference	Solution	Soil moisture sensor, Temperature sensor, Wind velocity sensor, Soil gas sensor, Sunshine sensor	Morse code, GSM, Cloud service	Enhanced agriculture in low- and middle-income countries with the use of cloud computing and IoT technologies	1	0.5	0	0.5	2
16.	[57]	2022	Journal	Proposed Framework	Capacitive Soil Moisture V2.0, DS18B20 Temp Probe, DHT11 Temp & Humidity, GYML8511 UV Light Module	MQTT	Developed an edge computing model using hybrid ML for real-time soil moisture estimation and rain-based water management	1	0.5	0	0.5	2
17.	[76]	2022	Journal	Platform	Capacitive soil moisture Sensor V1.2, DS18B20, BME280, SW-18010-P, GYML8511	LoRaWAN	Created a platform and put into use a flexible IoT-based infrastructure that can offer large-scale agriculture farms real-time data collecting and analytics	1	0.5	1	0.5	3
18.	[77]	2022	Journal	Solution	Soil moisture sensors, DHT11, Water meter sensor	Bluetooth Wi-Fi (ThingSpeak) HTTP	Suggested a revolutionary smart IoT node that gathers, stores, analyses, and visualises data for smart farming applications using a mobile phone and a basic embedded device connected through Bluetooth	1	0.5	0	0.5	2
19.	[78]	2022	Conference	Solution	Temperature sensor (W1209)	Bluetooth (HC-05)	Build an affordable, practical storage space that farmers can use to keep their crops in the field while having smartphone control over it	0.5	0.5	0	0.5	1.5
20.	[79]	2022	Conference	Platform	A photovoltaic transducer, HTS221	Bluetooth Low Energy (BLE)	Illustrated the sensor platform's usability and dependability in a rural setting with vines	1	0.5	1	0.5	3
21.	[80]	2022	Conference	Proposed framework	Temperature, humidity, PH, acoustic, soil moisture sensors	6LoWPAN with low-power and lossy routing (LPLR)	Used a unique routing and encryption technique to enhance the performance and lifetime of energy harvesting wireless sensor networks (EHWSNs) for smart agriculture	1	0.5	0	0.5	2
22.	[81]	2022	Journal	Solution	ATMOS 41, BME680, PYTOS 31, SIL 411, FloraPulse, TEROS 12, TEROS 21, Soilwatch 10	Lorawan	Established an integrated network of sensors for soil, plants, and the atmosphere that communicate wirelessly using the LoRaWAN protocol, as well as a platform for real-time data collection to assess the water condition of vines	1	0.5	1	1	3.5

TABLE 6. *(Continued.)* IoT-based agriculture technologies classification and quality assessment.

23.	[82]	2022	Journal	Proposed Design	RFID tags, RFID readers	MQTT	Suggested a clever, inexpensive, and secure design that can interface with a cloud server enabling data analysis and collect data from harvesting	1	0.5	0	0.5	2
24.	[83]	2021	Journal	Solution	Soil sensor, DHT11 sensor , PIR sensor, Fire sensor, Ultrasonic HC-SR04 sensor, AC sensor	ZigBee, Wi-Fi, MQTT	Proposed an all-encompassing and cost-effective smart agriculture solution that makes use of solar energy, a cloud-based IoT platform, fuzzy logic control, and wireless sensors and actuators	1	1	1	1	4
25.	[84]	2021	Journal	Proposed Framework	LM35 temperature sensor	ThingSpeak	Validated a model for assessing IoT sensor data quality to control uncertainties in smart agriculture	1	0.5	1	0.5	3
26.	[85]	2021	Journal	Framework	Atmospheric pressure sensor (MPX4115A). Humidity sensor, temperature sensor, SOil Moisture, GPS MAPIR	ZigBee, 802.15.4 IEEE	A low-cost smart agriculture system was designed and tested to provide useful knowledge and solutions for increasing crop productivity and quality	1	0.5	1	1	3.5
27.	[86]	2021	Journal	Review	EC-5, 5TE, Hydro Probe2, MP406, GreenTag, PXRF, biosensors, aptamers, graphene electrodes, MIKROE gas sensors, Pogo II VWC	802.15.4, ZigBee, 6LowPAN, ISA100.11a, BLE, LoRa/LoRaWAN, WiFi,GSM, GPRS, EDGE, HSDPA/HSUPA, LTE, WRAN, Z-wave, RFID, NFC, ANT+, Sigfox	An overview of the benefits and challenges of using smart sensing with edge computing in precision agriculture for heavy metal monitoring and soil assessment was offered, as well as some potential solutions	1	0.5	0.5	1	3
28.	[87]	2021	Conference	Platform	Phenocams, Weather station, External sensors	WiFi	GreenDaP was presented as a system that was established and set up to track the development of ripening and weather conditions in the Aosta Valley	1	1	1	0.5	3.5
29.	[88]	2021	Journal	Evaluation	Hydro climatological sensors	GPRS, LoRa	In rural areas, edge computing has been investigated using an LSTM model for frost prediction to bridge the gap between AI and IoT	1	0.5	1	0.5	3
30.	[89]	2021	Journal	Authentication Scheme	Terrestrial wireless sensor nodes (TWSN), wireless underground sensor nodes (WUSN)	AES	Offered an effective mutual authentication and key agreement mechanism for accessing sensor data in a multi-gateway environment by agriculture experts using smart cards, passwords, and biometrics	1	0.5	1	0.5	3
31.	[90]	2021	Conference	Review	Soil sensors, Water sensors, Weather sensors, Plant sensors, Animal sensors	WSN,LoRaWAN,NB-IoT, SigFox, Cellular networks	A thorough review of the computing environment for IoT-based applications in smart agriculture and recommendations for future research avenues	1	0.5	0	0.5	2
32.	[91]	2021	Journal	Architecture	Humidity, Soil Moisture, Temperature, UV Ray Intentsity, Arduino Uno nodes	ZigBee	Proposed a time-sensitive cloud/fog computing architecture that is low-cost, scalable, and latency-adjustable for olive grove applications	1	0.5	0.5	1	3

TABLE 6. *(Continued.)* **IoT-based agriculture technologies classification and quality assessment.**

33.	[92]	2021	Journal	Novel Mechanism	DHT11, LEDs, buzz	IEEE 802.15.4 (Zigbee), 801.15.1 (Bluetooth), IEEE 802.11 (Wi-Fi), IEEE 802.16 (WiMAX), cellular	Proposed and assessed the concept of Flying Edge computing, a UAV-based platform that serves as an edge node for remote IoT applications	1	0.5	0	0.5	2
34.	[93]	2021	Conference	Proposed Framework	Soil sensor, Humidity sensor, Temperature sensor, Leaf wetness sensor	NA	Developed and implemented an IoT-based EF that can gather real-time data from sensors and produce management suggestions for cotton crops	0.5	0	0.5	0.5	1.5
35.	[94]	2021	Journal	System Architecture	Soil temperature, soil moisture, air temperature sensors	LPWAN	Developed a WSAN architecture combining smart IoT base stations with localised processing that can function under the particular restrictions of rural farms in Southeast Asia	1	0.5	0	0.5	2
36.	[95]	2021	Conference	Proposed mechanism	Air temperature sensors, light intensity sensors	6LoWPAN, RPL	Used a residual energy and rank-based dynamic clustering strategy to extend the lifetime of 6LoWPAN networks	1	0.5	1	0.5	3
37.	[96]	2021	Journal	Theoretical model and analysis	NA	LoRa	Investigated on how to set up the drone's flight path and the separation between the sensors and the drone to ensure a specific chance of gathering sensor data	1	1	1	1	4
38.	[97]	2021	Journal	Survey	Location-based sensors, Electrochemical sensors, Temperature and humidity sensors, Optical sensors, Bluetooth Smart or Bluetooth Low Energy (BLE) sensors	Bluetooth Smart or Bluetooth Low Energy (BLE)	Investigated the possible advantages, prerequisites, and difficulties of deploying UAVs equipped with Bluetooth Smart technology for smart farming	1	0.5	0	0.5	2
39.	[49]	2021	Conference	Review	NA	RFID, NFC, LTE, LoRa, Z-Wave, ZigBee, Bluetooth, BLE, SigFox, NB-IoT, CoAP, MQTT, AMQP, HTTP, REST2	Offered a critical assessment of the technological requirements, benefits, and drawbacks of various wireless communication technologies for IoT and their applicability to precision agriculture	1	0.5	0	0.5	2
40.	[98]	2021	Conference	Solution	Plant height sensor, Soil moisture sensor, Fertilizer distribution sensor	Serial communication 4G data communication WSN (thingspeak)	A solution and put into practise an embedded Internet of Things system that links sensors and Arduino devices in a peer-to-peer network for agricultural data	0.5	0.5	0	0.5	1.5
41.	[99]	2021	Journal	Framework	Temperature sensor, gas sensor, IoT camera	Bluetooth, ZigBee, WIFI, and Universal Serial Bus	Provided an effective and scalable framework for UAV-based and genetic algorithm-based data aggregation and distribution that protects user privacy	1	0.5	0	0.5	2
42.	[100]	2020	Journal	Proposed System	Soil Moisture sensor, Temperature, Motion, Humidity,PIR	IEEE 802.15,4e, IEEE 902.11ah, LoRaWAN, SIGFOX, Cellular	Created and tested a real-time autonomous watering system using wireless sensor networks and IoT to control and monitor the farm	1	0.5	0	0.5	2

TABLE 6. *(Continued.)* IoT-based agriculture technologies classification and quality assessment.

43.	[101]	2020	Conference	Survey	temperature, humidity, wind, air pressure, soil pH, moisture, chlorophyll, ZigBee sensors, LoRa sensors, wireless cameras	ZigBee and LoRa3, Wi-Fi, Bluetooth, cellular networks	Summarized the ways in which IoT technology might help farmers and the agricultural sector improve and raise crop harvest quantity and quality	1	0.5	0	0.5	2
44.	[102]	2020	Journal	Design and Development	Soil moisture sensor, Soil temperature sensor, Light intensity sensor, DHT11 sensor	ESP8266 Wi-Fi module	Developed a method for assessing the precision and dependability of data gathered, transferred, and retrieved remotely via an IoT system	1	0.5	1	0.5	2
45.	[103]	2020	Journal	Proposal	Temperature and humidity Sensor, Soil Moisture	WIFI IEEE 802.11	The evaluation of remote sensing drones' suitability to carry out gateway activities for WSN in PA provided guidance regarding selecting the appropriate drone parameters for successful data transfer	1	0.5	0	0.5	2
46.	[104]	2020	Conference	System	DHT 22, GY-GPS6MV2, GY-68 Pressure Sensor BMP180, MQ-2 Gas Sensor Module	LoRaWAN	Developed a system for predicting the environment for each time using prototype equipment for measuring the environment and the installation area's weather information	1	0.5	0	0.5	2
47.	[105]	2020	Conference	Solution	Ag/AgCl electrodes, temperature, humidity, solar radiation sensors	lightweight ZigBee-based version of the IEEE 802.15.4 standard	Build and implement a lightweight, ZigBee-based system that is optimised for measuring and evaluating plant action potentials	1	0.5	0	0.5	2
48.	[106]	2020	Conference	solution	pH, Soil moisture, Air temp & humidity, Light luminosity, Gas, RTC module, ESP8266 WiFi	MQTT	Used heterogeneous, reasonably priced sensors to construct a MQTT-based smart farming system	1	0.5	0	0.5	2
49.	[107]	2020	Journal	Proposed Framework	WSAN	LoRaWA, DASH7	Demonstrated a cloud-based middleware solution for intelligent farm management using data from precision farming facilities	1	0.5	0	0.5	2
50.	[108]	2019	Conference	Design and Develpment	Smart biosensors, Smart sensors, Wireless sensors	ZigBee, IEEE 802.15.4,Bluetooth 5, and WSN	Emphasized the traits and qualities of the developed WSNs and their sophisticated sensors for a variety of applications	1	0.5	0	0.5	2
51.	[109]	2019	Journal	Poposed Protocol	Soil Temperature, NPK, Water Content, Photosynthetic Radiation, Soil Water Condition and soil oxygen level Sensors	RPL	Established a cluster-tree-based routing protocol (CTSRD) for IoT networks that considers power effectiveness and security	1	0.5	0	0.5	2
52.	[110]	2019	Journal	Platform	E + E Elektronik EE160, B&C Electronics 2731312-31/3-017T, B&C Electronics SZ 1093, Omron K8AK-LS1, ARAD SF 15, Gems FT110 G3/8, SP110	MQTT and CoAP, NGSI, REST and JSON	Developed an adaptable platform that can handle the demands of soil less culture in greenhouses with complete re circulation and moderately salinized water	1	1	1	1	4
53.	[111]	2019	Conference	Solution	DHT11	LoRa, GPRS	Created and tested a portable LoRaWAN gateway that can enhance the precision and effectiveness of smart agriculture systems	1	0.5	0	0.5	2

TABLE 6. *(Continued.)* **IoT-based agriculture technologies classification and quality assessment.**

54.	[112]	2019	Conference	solution	Light Detecting Resistor (LDR), Soil Moisture Sensor by Spark Fun, CC3200 by Texas Instrument	MQTT	Developed a smart agricultural system that can advise farmers about correct field management and maintain an ideal environment for crop growth	1	0.5	0	0.5	2
55.	[113]	2018	Journal	Survay	location sensors, optical sensors, mechanical sensors, electrochemical sensors, airflow sensors, RFID systems, and UAV sensors	Communications-enabled devices, Bluetooth, ZigBee, Z-Wave, passive and active RFID systems, LoRa, Sigfox, NB-IoT, Wi-Fi, cellular networks	Describe the agricultural IoT ecosystem, how IoT applications are classified, the importance of IoT and DA in agriculture, as well as the benefits, limitations, unresolved challenges, and probable future directions of IoT in agriculture	1	0.5	0	1	2.5
56.	[114]	2018	Conference	IoT node	Soil moisture, water supply temperature, ambient temperature and humidity, wind speed, wind direction sensors	NFC, BLE, ZigBee	Offered new technological advancements and commercial assistance for China's next-generation smart agriculture system	1	0.5	1	1	3.5

The transformed data is then utilized to create decision support systems that provide farmers with actionable advice, enabling more effective resource management and crop management.Automation and control of agricultural activities also become possible through the data processing layer [41]. Farmers are able to manage irrigation, track the behavior of livestock, and improve the efficiency of machinery by feeding the findings back into IoT devices and control systems. However, data security and privacy have become crucial because of the rise in the processing of sensitive agricultural data. In order to ensure that the potential advantages of IoT-based agriculture are achieved while preserving farmers' sensitive data, the implementation of strong security measures provides safety from unauthorized access and data breaches.

D. APPLICATION LAYER

The data and insights from the Data Processing Layer are converted into useful and approachable applications in IoT-based agriculture at the Application Layer. This layer entails developing of software solutions that provide farmers and agricultural stakeholders with useful information, real-time monitoring capabilities, and decision-making tools to help them maximize farm operations. These programs are accessible to farmers on a variety of devices since they may be accessed through web interfaces, mobile apps, or specific platforms. Renowned IoT-based farm apps encompass an enormous range of features [124]. Several applications are focused on precision farming, offering farmers specific information about soil conditions, weather forecasts, and crop health. These programs frequently provide functions like crop disease monitoring, automatic irrigation scheduling, and customized fertilization advice depending on the requirements of each crop. Applications for precision farming seek to increase yields while reducing resource waste, helping to promote environmentally friendly and sustainable agriculture [125].

Monitoring and managing livestock is a different group of applications that is quite common. Farmers can monitor the health and behavior of their animals, spot sickness early, and improve feeding and breeding procedures thanks to IoT-based solutions. These programs boost livestock agricultural production overall, lower veterinary expenses, and improve animal wellbeing.

E. BUSINESS LAYER

The effective integration and application of the internet of things in the farming and agricultural sectors is greatly impacted by the Business layer of IoT in agriculture. It entails developing strong business models, generating distinct value propositions, and carrying out in-depth market research to comprehend the requirements of farmers and stakeholders. The Business Layer promotes the adoption of IoT solutions in agriculture by creating the appropriate business models, such as pay-per-use or subscription-based pricing, and delivering attractive value propositions that highlight enhanced crop yields, resource efficiency, and cost savings [126]. The development of a strong IoT ecosystem for agriculture is further enabled by creating strong connections and establishing partnerships with technology providers, data analytics companies, and equipment manufacturers. To make sure that IoT solutions adhere to standard practices and data protection rules, the Business Layer also handles significant regulatory and compliance aspects [127]. Farmers may successfully install IoT technology on their farms by engaging individuals and providing them with the technical support and continuous help they need. IoT solutions could adapt to changing market needs and evolving technology by developing a scalable and adaptable business strategy, permitting the agricultural sector to take advantage of IoT's opportunities for expansion, sustainability, and increased efficiency in farming methods.

TABLE 7. Summary of agriculture-based IoT perception and network layer protocols.

Layer	IoT Protocols	Standard	Frequency	Data-Rate	Transmission Range	Cost	Topology	Power Consumption
Perception	RFID	ISO, IEC	13.56 MHz	106-424 Kbps	20 cm	Low	Ring	Very Low
Perception	Ultra-Wideband	802.15.4	3.1–10.6 GHz	53–480 Mbps	10 m	Low	Radio Tech	Low
Perception-Network	Infrared	Not Standardized	850-900 nm	14.4 Kbps	1 m	Low	LAN	Low
Perception-Network	Bluetooth	802.15.1	2.4 GHz	1-24 Mbps	8-10 m	Low	Star	Medium
Perception-Network	ZigBee	802.15.4	868/915 MHz, 2.4 GHz	20–250 Kbps	10–20 m	Low	Star, Tree, Mesh	Low
Network	Wi-Fi	802.11a, b, g, n	2.4 GHz	2–54 Mbps	20-100 m	Low	Star	High
Network	6LoWPAN	802.15.4	2.4 GHz	250 kbit/s	10–100 m	Low	Star	Low
Network	LoRaWAN	802.15.4g	133/868/915 MHz	0.3–50 Kbps	3–4 km	Low	Star	Very Low
Network	NB-IoT	3GPP standardized	LTE Licensed band	50 Kbps	up to 10 km	Low	Star	Very Low
Network	LTE-M	3GPP standardized	LTE Licensed band	300 Kbps-1 Mbps	more than 10 km	Low	Star	Moderate
Network	Sigfox	Not Standardized	868/915 MHz	100 bps - 1000 bps	1-3 km	Low	Star	Very Low
Network	LTE-Cat-M1	3GPP standardized	LTE Licensed band	200 Kbps-1 Mbps	5-10 km	Low	Star	Moderate

TABLE 8. Summary of characteristics of IoT application layer protocols.

Protocols	Architecture	Standards	Header/Message	Encoding Format
MQTT	Client-Server, Broker	IETF, Eclipse foundations	4-Byte/Small	Binary
AMQP	Publishers-Subscribers, Broker	OASIS AMQP TC	Undefined, large	primitive, or a described format code
COAP	Client-Broker	OASIS, Eclipse foundations	2-Byte/Small	Binary
XMPP	Client-Server	IETF, open standard	1023-Bytes	Binary
HTTP	Client-Server	IETF, with HTTP/1.1, HTTP/2 and HTTP/3	4-Kbytes to 8-Kbytes	UTF-8, Base64 and Gzip

V. MAJOR SECURITY & PRIVACY CONCERNS IN IOT ARCHITECTURE BASED ON SMART AGRICULTURE

According to modern agricultural studies, more than 90% of the total IoT sensor communications throughout the field of agriculture are carried out without adequate encryption. According to this concerning estimate, around 57% of smart devices deployed in agriculture are affected by vulnerabilities in security that might expose confidential data [128]. The disruption of agricultural systems caused by these breaches of security goes beyond that; there is also an imminent threat to the security of individuals.In the agricultural environment, cyberattacks may have broad implications, especially for the lives of individuals. A cybersecurity breach has a tendency to become devastating, particularly in instances endangering individuals. The swift development and broader implementation of the Internet of Things in agriculture, especially in emergency situations such as infectious diseases, has heightened security and ethical issues. Ensuring the confidentiality of crucial and sensitive data related to agriculture transforms into a harder challenge. Several different kinds of attacks, hazards, and threats might be targeting multi-layers of the IoT framework, demanding tight security and privacy standards in the field of agriculture [129]. It is essential to apply techniques like cryptographic and non-cryptographic algorithms to efficiently identify and prevent invasions. There are also plenty of malware attacks that can threaten the security of data, authenticity, reliability, and accessibility that have been identified as consequences for IoT systems. In accordance with the aforementioned security-related issues, the agricultural operation emphasizes key management, detection of intrusions, authenticating measures, and controlling access in its existing security strategy. This preventive approach is critical for guaranteeing the confidentiality of agricultural data and the continuous trustworthiness of IoT devices in the agricultural sector. The Table 9 highlights the latest research on IoT-based agriculture security challenges and effective solutions.

A. MULTI-LAYERED SECURITY THREATS / ATTACKS

An IoT-based agriculture system has plenty of security challenges, including data collection, storage, processing, and transmission via Internet access, as well as malicious application and business data activity [130]. In a multi-layered framework, Fig.9 depicts vulnerabilities in security in the IoT-based agricultural system. Security flaws are often inadvertently or unexpectedly detected. Agriculture surroundings may be accessed by animals, farm workers, and machine equipment, all of which might generate issues. A significant number of security risks are extremely widespread; however, several are specific to individuals who work in challenging environments such as IoT-based agriculture.

1) PERCEPTION LAYER THREATS

This is mostly around tangible devices, including sensors and actuators. Physical equipment may malfunction as a result of malicious or unintentional actions by people, computer viruses, malware, or cyberattacks. IoT-based agriculture applications employ a diverse set of sensors and technology, which introduces a number of security threats, such as the ones listed below:

- **Signal Jamming/Radio Jamming:** Signal jamming, mainly radio jamming, causes an enormous risk to agriculture by halting critical systems that include remote imagery for monitoring crops,GPS for precision agriculture, and communication devices for cooperation. As a result of this disruption, location may not be precise, data gathering may be interrupted, communication may be disrupted, and there may even be the possibility of damage or loss [131]. Signal jamming may result in financial consequences, inefficiency in operation, and security risks in the agricultural sector, which is more dependent on cutting-edge technology such as unmanned agricultural machinery. To protect agricultural operations and sustain production, mitigation solutions include reliability in navigation and communication systems, signal monitoring, adherence to regulations, and precautions for physical security.
- **Spooling:** Spooling, which stands for "Simultaneous Peripheral Operations On-Line," is a crucial procedure in the field of agriculture that facilitates the seamless control of information exchange and jobs. Spooling is the temporary storage of data within a queue or buffer until it is processed by agricultural equipment or computer systems, including planting guidelines, irrigation timetables, or harvest data. This approach enables the seamless synchronization of many operations, eliminating devices from waiting endlessly since data is processed [132]. It allows tractors, for example, to keep cultivating or harvesting when data concerning the soil is investigated and adjusted in the meantime. Spooling is essential for increasing the efficiency of contemporary agricultural practices since it helps to reduce downtime and makes sure that equipment is used effectively in accordance with real-time data inputs.
- **Node Capturing/ Node Outage:** Node capture or node outage is a significant threat in agricultural networks of sensors and IoT implementations [133]. Numerous sensors or data-gathering sensors scattered over farming land to track different indicators such as moisture in the soil, temperature, and the condition of crops are referred to as nodes. When these nodes are deliberately manipulated or taken away, data gathering is disrupted, and the reliability of agricultural tasks and decision-making processes may be threatened. Node outage, on the other hand, refers to the temporary or permanent failure of these nodes owing to technical faults or environmental variables, resulting in gaps in data collection and reducing the efficacy of precision agricultural operations. Both node capture and node outages can result in inefficient resource management, lower agricultural yields, and financial losses.
- **Routing Attacks:** An attacker generates network packets that are used to deceive different devices by altering or concealing the source address.Agriculture routing hacks include the malicious modification of networked data channels. The security of agricultural operations may be jeopardized as such attacks, which might result in inaccurate data routing, disrupt vital activities [134]. It is critical to put adequate safety precautions in place to prevent such attacks.
- **Threat to NDP Protocol:** Numerous attacks may be attempted against the Network Dynamic Data Exchange (NDP) protocol, which is frequently employed in agricultural monitoring networks. Unauthorized parties' monitoring may threaten the security of essential agricultural data. Implementing robust security methods like authentication, encryption, and detection of breaches, as well as frequent monitoring and modifications, is crucial to guaranteeing the authenticity of the NDP protocol [135].
- **Data Transit Attacks:** In the agricultural sector, data transit attacks encompass a wide range of fraudulent activities aimed at disrupting the reliability, privacy, or accessibility of data once it is transmitted over the internet [136]. Monitoring confidential data related to agriculture during transit is a prime instance of a breach that could lead to stolen information or spying. Additionally, interference with data in transit might cause data to be inaccurate, which could lead to agricultural alternatives that are inadequately informed. To ensure the safe and reliable transfer of crucial

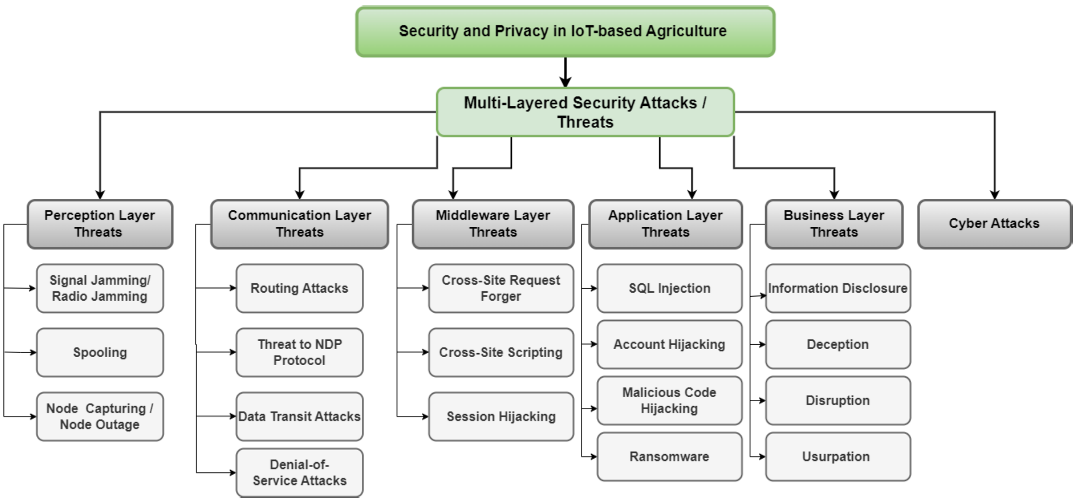

FIGURE 9. Taxonomy of multi-layered security and privacy concerns in IoT based agriculture.

data in agriculture, powerful encryption technologies, secure communication protocols, and extensive network security measures are required.

- **Denial-of-Service (DoS) Attacks:** A DoS attack prevents consumers from incorporating devices or other resources on the network. Through overwhelming intended devices or resources on the network and numerous excessive requests, this activity is carried out in order to make it challenging or unattainable for a variety of consumers to communicate [137]. An agricultural operation frequently includes a significant number of interconnected nodes and categories; consequently, identical kinds of attacks are feasible in the environment of smart agriculture. Such attacks can merely affect the routine functioning of various units within a single farming operation; however, they may also serve to interfere with legal cyber services across various areas.

2) COMMUNICATION LAYER THREATS

The communication layer security flaws in smart agriculture are comparable to those discovered in various IoT applications when taking into account the architecture and usage of the technology. For instance, compared to other protocols, WiFi encryption is more susceptible to password cracking. There are some basic security issues at the communication layer mentioned below:

3) MIDDLE-WARE LAYER THREATS

The security risks and threats related to the computing and software solutions that facilitate data transfer and processing among agricultural devices and sensors and higher-level applications are referred to as the middle layer of threats in agriculture. The security and integrity of agricultural operations may be threatened by these risks, which additionally comprise hacking of data, control of access flaws, gateway discrepancies, and the possibility of data theft. A few of these are listed here.

- **Cross-Site Request Forger:** On IoT equipment that implements RESTful APIs, that sort of attack appears to be more prevalent. The end-user is deceived by replying to an insecure application without recognizing it because of the CSRF method [138]. The web-based user interface of the IoT layer is at risk of CSRF attacks if its configurations are not adequate.
- **Cross-Site Scripting:** An XSS attack potentially attacks RESTful applications for the Internet of Things through inserting side scripting into websites to bypass accessibility restrictions [139]. These kinds of attacks are made possible through the websites of cloud-connected IoT apps.
- **Session Hijacking:** This form of attack is widespread among RESTful-based Internet of Things technologies. Since several IoT gadgets retain session connectivity at the website user interface sessions can be hacked enabling a hacker to hack into session data [140].

4) APPLICATION LAYER THREATS

According to the increased scalability and adaptation of cloud computing, application companies are getting increasingly interested in hosting applications there. This layer serves as the intuitive interface for IoT-based agricultural devices connected to users with the middle-ware. The kinds of potential attacks on this outermost layer include:

- **SQL Injection:** A SQL injection vulnerability has been identified in an agricultural management system. When a hacker injects an erroneous SQL query into a web server database. A resilient SQL injection attack might compromise or alter agriculture information, providing a substantial threat to IoT devices, notably those used in agriculture [141].

- **Account Hijacking:** Various IoT products employ inadequate security or transmit data in plain text over the Internet. When a packet gets captured once a consumer has been verified authorized, a hacker is capable of hijacking an account [142]. The most significant cause of this attack's starting point, as reported in various cases, is outdated operating systems with insecure patches.
- **Malicious Hijacking:**Installing malicious software that conducts unlawful operations with the intent to trigger network disruption [142].
- **Ransomware:**Encrypts significant data and intends to make a significant payment to retrieve it. This threat has the potential to initially appear on one machine and spread across the network [143]. Hackers can encrypt sensitive data and hold the code for decryption as a token for cash.

5) BUSINESS LAYER THREATS

This layer fosters the agricultural services supplier's enterprise logic and facilitates every aspect of the organization's process, comprising surveillance, supervisors, and growth. It is also in charge of processing data related to agriculture for findings. Threats on this layer are currently being investigated, but the damage they cause is more significant as they include critical agricultural information. Potential violations include disclosure of data, deception, disruption, and usurpation.

- **Information Disclosure:** Unauthorized manipulation of confidential information, such as production records, threatens the security of the IoT-based agriculture system. A hacker might use previously described techniques, for example, session hijacking and CSRF, to obtain illegal access to confidential data [144].
- **Deception:** Disrupted data threatens the integrity of data, which may result in serious consequences. Sinkholes and attackers in the middle can both issue deceptive data. Nearly fifty-eight percent of companies do not have a system in place to rectify erroneous information [145].
- **Disruption:** When accurate functions or accessibility to agriculture information are disrupted, the reliability of the system endures, which can have fatal repercussions [145]. A denial-of-service (DoS) attack is a kind of cyberattack that attempts to destroy data.
- **Usurpation:** Unauthorized entrance to particular sections of the system via attacks such as sinkhole, replay, and code injection threatens the integrity of agricultural IoT equipment [146].

6) CYBER ATTACKS

Considering the increasing popularity of next-generation smart agriculture, attackers may attack equipment that interconnects both physical and digital environments to access confidential data online. IoT-connected devices offer especially susceptible access points for attackers, and agricultural data might be stolen. A recent analysis of IoT-based agricultural devices found that 83% of them are using insecure operating systems [147]. Farmers who use these devices might be more vulnerable to attackers who leak critical agricultural data. As demonstrated in Fig.10, 98% of all communications between IoT devices are not encrypted, making 57% of these devices vulnerable to attackers and revealing sensitive data on the network. With the proliferation of connected devices, cyberattacks are expected to become more frequent and severe [148].

B. BLOCKCHAIN-BASED AGRICULTURE IOT SECURITY SOLUTIONS

In the IoT-based agriculture system, security threats depend on the vulnerabilities that are available at several levels, including applications and interfaces, network components, software, firmware, and physical equipment. In order to achieve a certain security level, mitigation strategies for security threats address the vulnerabilities of this interaction at several layers. These countermeasures are more complicated as a result of the various deployment protocols.Blockchain technology is anticipated to have a significant impact on how agriculture-based IoT systems are managed, controlled, and, most critically, secured. The expectation has been made by both the business and scientific communities. This section explains how blockchain can be a crucial enabling technology for offering realistic security solutions to the complex IoT security issues that exist today.

A blockchain is a distributed, decentralized, and unchangeable ledger that keeps track of assets and transactions over a network of peer-to-peer devices. It is composed of a series of time-stamped and authorized data blocks that are encrypted by elliptic curve encryption (ECC) and SHA-256 hashing. This innovation improves trust and transparency by cutting out the requirement for centralized authorities and empowering users to directly share and verify data. The block data basically consists of a hash of the previous block and a list of all transactions. The blockchain offers a cross-border decentralized trust around the world and maintains an extensive record of all transactions. Centralized authority and services, as well as trusted third parties (TTP), are susceptible to disruption, compromise, and hacking [149]. Even if they are trustworthy right now, they might act inappropriately or have corrupt tendencies in the future. Each transaction in the shared public ledger of the blockchain is confirmed by an overall consensus of mining nodes that play a role in verifying and validating transactions. Miners on the bitcoin network [150] verify the block by computing a hash with leading zeros to reach the desired level of difficulty. Block data is immutable, which means that it can never be deleted or changed once transactions have been authenticated and approved by consensus. Blockchain networks can be built in two different ways: (1) permission-ed (or private) networks that are only accessible to a select number of users, or (2) permission-less (or public) networks that allow anybody to join. Block chains with permissions offer greater privacy and improved access control.

A generic blockchain architecture framework is shown in the Fig.11. The architectural framework is mostly made up of the header of the block and the block body, which comprises a collection of transactions. One feature in the block header that can be utilized for tracking software and protocol updates is the version code. Time stamps, block sizes, and transaction counts are also included in the header. The hash value of the most recent block appears in the Merkle root field. For effective data verification, Merkle tree hashing is frequently employed in distributed systems and P2P networks. The first counter value generates the hash with leading zeros, and the nonce field is utilized for the proof-of-work procedure. In order to maintain a block time of around 10 minutes for Bitcoin [151] and 17.5 seconds for Ethereum [152], the difficulty target, which defines the number of leading zeros, is employed. The level of difficulty is modified frequently and improves (with additional leading zeros) as computer processing power advances with time. The block time is predetermined by design to take into consideration how long it takes for blocks to propagate to all miners and for each to agree on a block.Bitcoin is one of the first programs created using blockchain technology, which has subsequently evolved into the basis for several modern cryptocurrencies. With the unveiling of smart contracts in July 2015, Ethereum broadened the possibilities for blockchain technology. These programmable agreements, first proposed by Nick Szabo in 1994, comprise self-executing contracts that can be written in Solidity, a programming language identical to JavaScript, and carried out on the blockchain of Ethereum using Ethereum Virtual Machines (EVM) [153]. In addition to having its own cryptocurrency, Ether, Ethereum also uses a blockchain state to facilitate the execution of smart contracts. Accounts, addresses, codes, and electronic balances are all attributes of smart contracts.

Ethereum's EVM storage can be expensive; however, for large-scale storage requirements, decentralized data stores like IPFS, BitTorrent, or Swarm may be employed for maintaining pertinent data hashes. The management, control, and security of IoT-based agriculture devices are all anticipated to benefit significantly from blockchain technology that is based on smart contracts. The core features of blockchain technology that are listed below can be very advantageous for IoT primarily and IoT security specifically.

- **Address Space:** Blockchain uses a 160-bit address space, as compared to IPv6, which uses a 128-bit address space [169]. A public key obtained using the ECDSA (Elliptic Curve Digital Signature Algorithm) is hashed into a 20-byte (160-bit) address on the blockchain. With a very low probability of address collision and a 160-bit address space, blockchain can generate addresses for roughly $1.46 * 10^{48}$ IoT devices, ensuring secure and globally unique identifiers without the need for centralized oversight like IANA's management of IPv4 and IPv6 addresses. In addition, blockchain provides 4.3 billion more addresses than IPv6, resulting in a better option for the Internet of Things, especially for devices with restricted resources that cannot support an IPv6 stack [170].
- **Data Integrity and Authentication:** Data communicated by IoT devices connected to the blockchain network will always be cryptographically proofed and signed by the authentic sender, who has a unique public key and GUID, ensuring the security and authenticity of the data that is transmitted. The blockchain distributed ledger also records all transactions performed on or by an IoT device and enables their secure tracking [171].
- **Authorization, Authentication, and Privacy:** Blockchain smart contracts provide decentralized authentication logic and rules for IoT device single-party and multi-party authentication. Additionally, blockchain offers a more efficient way of authorizing access rules for connected IoT devices than more traditional authorization protocols like OAuth 2.0, Role-Based Access Management (RBAC), OpenID, LWM2M, and OMA DM, which are frequently used in IoT device authorization, authentication, and management. Smart contracts also guarantee data privacy by defining access guidelines, constraints, and time limits, enabling certain people, organizations, and even devices to own, control, or access data both while it is in use and while it is in transfer [172]. Additionally, these smart contracts can specify who has the power to reset IoT devices, create new key pairs, initiate updates, upgrade IoT software or hardware, and patch IoT software or hardware.
- **Secure Communications:** Conventional IoT networking and communication protocols, including HTTP, CoAP, MQTT,RPL, and 6LoWPAN, have security features that are integrated and demand the use of additional, complicated protocols like DTLS, TLS, and IPSec. These resource-intensive security techniques depend on centralized authority over keys. While omitting centralized authentication processes and streamlining security strategies, blockchain offers distinct GUIDs and pairs of keys for IoT devices. This makes it possible to apply security methods that are less intrusive and better suited for IoT devices [173].
- **Administration and Identification of Things:** The implementation of identity and access management (IAM) for IoT offers a variety of technical issues that require effective, secure solutions. The fluctuating ownership and identification relationships between IoT devices are a major concern. Ownership of the device changes over its lifespan, from the company that makes it to the vendor, reseller, and ultimately the end user [174]. End-user ownership may alter due to selling, retirement, or negotiation. Maintaining the characteristics and interconnections of IoT devices adds a further layer of complexity. These characteristics

TABLE 9. Security challenges and solutions in IoT-based agriculture.

1	[154]	2023	Journal	Physical data capture, Spoofing, session hijacking	Physical layer	Enhancing the security and privacy of data shared among IoT devices for precision agriculture by implementing elliptic curve cryptography.
2	[155]	2023	Journal	Information security	Physical,Network, Application layers	A blockchain-fog computing-SDN system improves security and effectiveness in data collecting, processing, and transmission.
3	[156]	2023	Conference	Authentication and secure communication	Application layer	Precision farming using blockchain and IoT requires safe, immutable, and accurate crop and environmental data.
4.	[157]	2023	Conference	Data Integrity,Device Authentication, Data Security	Physical, Network layers	Implement strong security measures to protect data, maintain integrity, and deter illegal access while reducing resource usage.
5.	[158]	2022	Journal	Optimize fog computing system routing	Network, Application layer	This framework improves precision agriculture using fog systems, ML, and secure IoT resource management with intelligent routing. .
6.	[159]	2022	Conference	Privacy, authorization and authentication	Application layer	An IoT and Blockchain solution is proposed for improved security and productivity in smart agriculture.
7.	[160]	2022	Journal	Insecure interfaces, DDos attacks , and Cyberattacks	Transport Network, Application layer	Cluster key management, deep learning, and a web interface improve precision agricultural security and usefulness.
8.	[143]	2022	Journal	Cyber-attacks and malware attacks	Application Layer	In IoT-based agriculture, a three-phase DMD-DWT-GAN system integrating DWT and a tiny CNN provides precise malware identification.
9.	[161]	2021	Conference	Potential vulnerabilities and threats	Physical, Transport layer	Precision agriculture infrastructure threat modeling using STRIDE detects security problems for each class, improving cybersecurity.
10.	[162]	2021	Conference	Duplication and unauthorized access	Physical, Network layer	To prevent IoAT device duplication and improve security, hardware security using PUF-based authentication is being developed.
11.	[163]	2021	Journal	Cyber threats and DDoS attacks	Application layer	The study compares CNN, DNN, and RNN for Agriculture 4.0 DDoS detection using the CIC-DDoS2019 and TON-IoT datasets.
12.	[164]	2021	Conference	Cyber threats and attacks	Communication, Application Layers	A LoRaWAN soil sensor with HSM and four levels of cybersecurity defense provides strong data security, integrity, and attack resilience.

TABLE 9. ***(Continued.)*** **Security challenges and solutions in IoT-based agriculture.**

13.	[165]	2020	Journal	Malicious nodes identification	Network, Application layers	Implement trust-based cloud IoAT detection and prevention technologies to provide security and privacy.
14.	[166]	2020	Journal	Malicious adversaries	Communication layer	Improve IoT agricultural sensor security with cluster heads, SNR-based efficiency, and data security via a linear congruent generator.
15.	[167]	2020	Journal	Data privacy and security	Physical, Application layers	Farmers' data is protected from leaks and variations with blind factors and ElGamal Cryptosystem privacy-preserving data mining.
16.	[168]	2019	Conference	Data integrity, confidentiality, and authenticity	Application layer	IoT blockchain improves agri-tech by protecting sensor data and enabling automated policy checks using smart contracts for transparency.

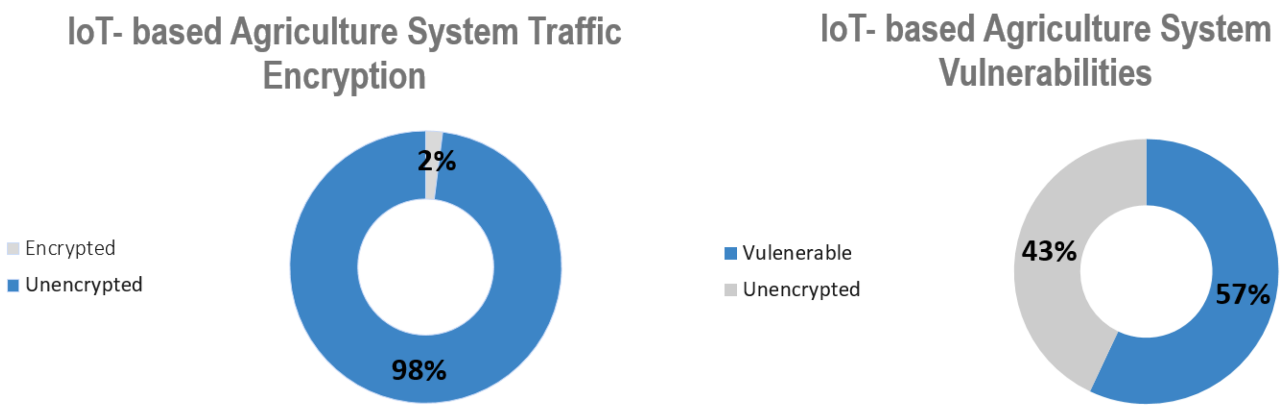

FIGURE 10. **Cyber attacks in IoT based agriculture system.**

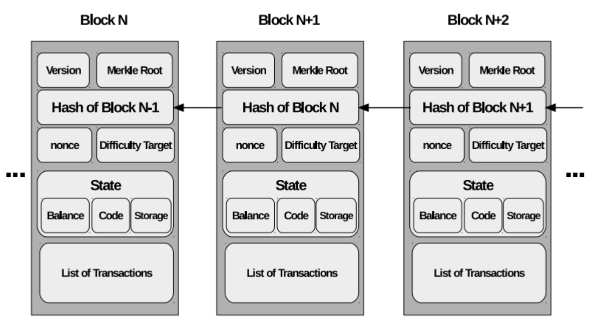

FIGURE 11. **Chained blockchain architectural framework with header and body fields.**

include information on the maker, make, classification, model number, location, and location GPS coordinates. In addition, IoT devices have complex linkages that range from links between devices and people to connections between devices and services. These connections involve a variety of activities, including installation, use, logistics, distributing, upgrading, repairing, and more.

Blockchain technology provides a strong, secure, and cost-effective solution to these problems. It is frequently used to establish reliable and authorized identification enrollment, keep track of possessions, and retrieve valuables. Blockchain-based technologies like TrustChain have been put out to enable trustworthy transactions while maintaining transaction security inside a decentralized system [175]. The capabilities of blockchain are also advantageous for IoT devices. Blockchain technology can be utilized to authorize and give identification to interconnected IoT devices, featuring a wide range of qualities and complex interconnections that may be securely recorded and maintained on the decentralized ledger of the blockchain.

VI. THE STATE-OF-THE-ART ML MODELS AND TECHNIQUES IN SMART AGRICULTURE APPLICATIONS

The world is presently dealing with an unprecedented converge of problems related to food items and agricultural sustainability. Given the continual rise in global population and the introduction of unknown factors due to climate change into conventional farming methods, the demand for innovative and effective agricultural solutions has never been greater. The fusion of cutting-edge technology, notably the IoT and deep learning, has ushered in a new era of agriculture named as "smart agriculture".

It is a difficult challenge to turn raw data into knowledge that can help farmers and agricultural professionals in real-time decision-making. The development of the IoT has completely changed how data is collected in the agricultural sector. A plethora of data on soil moisture levels, temperature, weather patterns, and crop health is continually gathered by IoT sensors implanted in soil, rainfall stations, drones, and cutting-edge agricultural equipment [176]. This constant flow of data has the potential to reveal invaluable information about how the agricultural environment functions.

Smart agriculture, which represents a paradigm shift from conventional agricultural practices, is built around precision agriculture. The key to optimising resource use, improving agricultural productivity, and reducing environmental impact is automation and data-driven decision-making. For analysis and decision-making, deep learning models are utilised in smart agriculture, and the Internet of Things is used for real-time data collection. Deep learning techniques, for instance, may be used to estimate productivity, manage disease and insects, and perform accurate irrigation [177].

The importance of deep learning models in smart agriculture will only increase as we continue to tackle major issues like climate change and food security [178]. Deep learning models provide incomparable levels of accuracy and efficiency, revolutionising the way we address agricultural processes. CNNs,RCNN, ResNet-18 and many more are the few examples of deep learning models that have shown to be particularly effective in tasks like fruit counting, weed/crop discrimination, and land cover classification. These models can analyse enormous volumes of data gathered from several sources, such as IoT devices, drones, and weather stations, and turn this unprocessed data into insights that can be put to use. As a result, crop yields have increased, resource waste has decreased, and agricultural sustainability has increased [179]. This can offer useful information for managing fields and planning crops.As part of our examination of the many dimensions of smart agriculture, we pinpointed particular uses for DL models. The Table 10 provides a concise summary of our findings

A. CONVOLUTIONAL NEURAL NETWORKS

Convolutional Neural Networks (CNNs) have become an effective tool for smart agriculture, offering answers to a range of problems. CNNs are proficient at identifying and classifying plant diseases, differentiating weeds and crops, counting fruits, and classifying land cover [180].

These models can analyze enormous volumes of data gathered from several sources, such as IoT devices, drones, and weather stations, and turn this raw data into valuable insights.

CNNs are a specific kind of deep learning model that is particularly effective for processing grid-like data, such as picture data. They are made to automatically and dynamically learn spatial relationships of features from massive datasets. They are, therefore, beneficial for image analysis jobs, which are frequent in smart agriculture.

For instance, CNNs may be applied to crop image analysis to quickly identify diseases. This enables farmers to take immediate measures to stop the disease's spread and reduce crop loss [181]. Similarly, CNNs can distinguish between crops and weeds based on photos collected in the field. This can aid in creating efficient weeding systems that focus on weeds while ignoring crops [182]. These models may also be used to count the quantity of fruits based on photos captured in fields. This can offer an accurately calculated yield estimate, which is essential for supply chain and logistics planning [183]. The categorization of land cover based on satellite photos may also be done using CNNs [184].

Various agricultural issues, from disease diagnosis to plant recognition, may be addressed using CNN's ability to precisely recognize and localize objects in pictures. However, To fully realize the promise of CNNs in smart agriculture, issues with data collecting and computing resources must be resolved.

B. REGION-BASED CONVOLUTIONAL NEURAL NETWORKS

In smart agriculture, region-based convolutional neural networks (RCNNs) have been used to locate and identify leaf diseases. These models can pinpoint the precise areas in images where a disease is present, which is important in determining the severity of the condition and selecting the best course of treatment. By utilizing RCNNs in smart agriculture, manually monitoring big fields is no longer necessary. This technology also makes it possible to identify illnesses early, reducing the degradation of plant growth.

A typical RCNN starts by producing a list of region proposals, which could include an object of interest. These areas are suggestions based on the features that CNN has learned. The model then assigns each region suggestion to a backdrop or one of the object classes [185]. In the case of smart agriculture, the backdrop may be healthy plant tissue, while the object classes could be various kinds of plant diseases. The flexibility of RCNNs to accommodate different object sizes is one of its main features.

This is significant in smart agriculture, where the extent of the infected region might fluctuate dramatically. RCNNs do this by employing area suggestions with various aspect ratios and sizes, which enables them to recognize objects of various sizes and forms. Plant disease detection is one of the main areas where RCNNs are used in smart agriculture. Early disease detection is essential for successful disease management since plant diseases can have a significant

TABLE 10. Deep learning model's application in smart agriculture.

SR #	Ref.	DL Model	Dataset	Pre-Processing	Results	Major Focus
1.	[88]	LSTM	Data obtained from the developed IoT system	Removing outliers and out-of-range values, normalizing and rescaling the data in the range of [0, 1], and using a moving average	RMSE:0.6173, MAE:0.4136, R2:0.9936	To evaluate the efficiency and power consumption of edge computing systems for a deep learning model that forecasts crop frost using IoT data1
2.	[180]	CNN, FCN, RCNN, SVM, RF, ANN	EPR-based data, CORINE Land-Cover 2006 dataset, ImageNet dataset	Image Segmentation, Feature Extraction, Background Removal, Noise Reduction, Data Augmentation	NA	Provide a comprehensive overview of the performance of machine learning and deep learning models for agricultural operations implemented through robotic platforms, and to identify the research gaps and future directions
3.	[181]	CNN	PlantVillage dataset	Resizing, Cropping, Augmenting	F1-score:0.987	Developed a framework that can automatically detect and classify crop diseases and pests using deep learning and IoT
4.	[182]	CNN	Different datasets; images of nine weed species in maize, potato and sunflower, and images of four weed species in tomato	Image Resizing, Cropping, Augmentation, Normalization, Labeling	Accuracy: 77%–98%	A novel CNN-based modular spot sprayer was developed after reviewing several technologies and prototypes for precision chemical weed management techniques, particularly patch spraying and spot spraying
5.	[183]	FRCNN, CNN	Fruits 360 collected from Kaggle	Resizing, Cropping, Normalizing the images	F1-score:99.2%	Developed an accurate, quick and reliable fruit detection system using CNN
6.	[184]	CNN	Collection of 64 x 64 pixels images representing the four land cover classes, obtained from Sentinel-2 satellite images	Cropping the satellite images into smaller images of the same size as the dataset, normalizing the pixel values to the range [0, 1]	global accuracy of 98% and 91% for the binary- and three-class CNN model respectively	Used CNN to divide the Eastern Economic Corridor (EEC) of Thailand's land cover into four categories: city, crop, forest, and water
7.	[185]	RCNN	PASCAL VOC 2012 dataset, the Microsoft COCO dataset, and the ImageNet dataset	Resizing the image, Normalizing, Data Augmentation, Generating Region Proposals using Selective search, Region Proposal Network, or default bounding boxes	NA	Thoroughly describe the region-based convolutional neural network (R-CNN) and its most recent advancements and to compare their performance in terms of accuracy and speed
8.	[186]	CRNN–RCNN	Banana leaf dataset	Histogram pixel, Localization technique with a median filter for image enhancement and region-based edge normalization for image segmentation	Accuracy: 98%, precision: 97.7%, recall: 97.7%, sensitivity: 98.69%	Developed an integrated system incorporating enhanced image processing algorithms for quicker disease detection in banana leaves
9.	[187]	Faster RCNN	FT_BRC	Resizing, Cropping, Augmenting	mAP: 0.555 (at IoU = 0.5)	Evaluated the effectiveness of Faster RCNN models with various extracted features for weed detection in difficult field situations
10.	[188]	LSTM	Time series data collected from 10 DHT11 sensors attached to 10 Arduino Unos, which measure the temperature and humidity of the atmosphere	Removing missing values and separating the sensor data	According to researchers, the method improves harvest output by about 20%, reduces water use by almost 20%, and lowers labour costs by roughly 55%—60%	LSTM model, cloud computing, and sensor technology were used to track and forecast environmental and soil characteristics, which enhanced the agricultural process
11.	[189]	LSTM	Data from humidity sensor collected by the smart agriculture system	Normalization using the Min Max method and splitting the data into time series form	LSTM: 0.08 RMSE, back-propagation: 0.10 RMSE	Examined how well LSTM and back-propagation performed in predicting air pressure data from the smart agriculture dataset
12.	[190]	CNN-LSTM classifier	PlantVillage dataset	Resizing, Cropping, Normalizing	F1-score:99.17%	Using a CNN-LSTM classifier, which is a suggested hybrid model for plant disease diagnosis using deep learning, illnesses of plants were discovered
13.	[191]	CNN-LSTM	New dataset consisting of a sequence of satellite images and the exact crop yield for the years 2001-2011 covering a total of 948 tehsils	NA	average RMSE: 143.1 kgs/hectare across all the states	Developed a technique to estimate wheat crop production in India using satellite pictures using a deep neural network model that operates directly on raw images without hand-crafted features

TABLE 10. *(Continued.)* **Deep learning model's application in smart agriculture.**

14.	[192]	ResNet-18 model, DCNN	Set of UAV images obtained from a winter wheat field, annotated with six classes: soil, wheat, and four weed species	Cropping 201 × 201 px image patches from the annotated images, augmenting the patches by rotating and mirroring them, and converting the model to 16-bit precision	accuracy: 94%	Used an embedded system, high-resolution weed maps were created from UAV photos in a computationally efficient manner
15.	[193]	ResNet-16, ResNet-28	Soybean yield dataset collected from Iowa State University Extension and Outreach and USDA National Agricultural Statistics Service	Data cleaning, Data normalization, Data partitioning, Data augmentation	lowest RMSE of 3.78 bushels/acre and the highest R2 of 0.92	Examined the effectiveness of decentralised deep residual network-based regression models for soybean yield prediction, such as ResNet-16 and ResNet-28
16.	[194]	K-means, SVM, GA, RF, DCNN, INAR-SSD, FRCNN	Datasets are developed by the researchers	Image segmentation, feature extraction, feature selection, image augmentation, and data normalization	NA	Provided an in-depth analysis of the IoT in popular farming applications, wireless communication protocols, and the role of sensors in precision farming
17.	[195]	DRNN-FCNN	GitHub dataset, which consists of orthomosaic images of different crop growth stages captured by UAVs	Resizing, Noise removal, Data Cleaning, Image Enhancement, Edge Normalization, Smoothening, and Multi-Resolution Segmentation	F-1 score:64.5%	Proposed a crop monitoring system that can employ deep learning models to classify the crop status, find weeds, and detect anomalies while updating the database in real time with data from UAV and IoT sensors
18.	[196]	CNN	PlantVillage Dataset	Resizing, Cropping, Grayscaling, Normalizing	F1-score:0.95	Utilising convolutional neural networks and IoT, the paper's primary goal is to categorise leaf diseases
19.	[197]	CNN with a U-Net architecture	Custom dataset created which is composed of 10,000 UAV images of soybean crops	Resizing the images to 512 × 512 pixels, Data Augmentation techniques such as rotation, flipping, scaling and cropping, Normalizing the pixel values to the range [0, 1], Splitting the dataset into training, validation and test sets	AP:0.87 for pest detection, accuracy:0.94 for pest classification, F1 score: 0.90 for pest localization	Presented a thorough analysis of the usage of unmanned aerial vehicles (UAVs) for agricultural operations and to emphasise the significance of simultaneous localization and mapping (SLAM) for a UAV solution in the greenhouse
20.	[198]	Faster RCNN	A total of 1000 photos of tomato and maize leaves with various diseases were utilised in the training of the model	Labeling the images with bounding boxes and class names, resizing the images, generating CSV files for training, creating label maps, creating configuration files	accuracy:80.4%, mAP (IoU = 0.50:0.95):0.414, mAR (IoU @ 0.5:0.95):0.6016	Created and demonstrated a full IoT-based Smart Greenhouse system that combines monitoring, alerting, cloud storage, automation, and disease prediction
21.	[199]	MobileNet-V2 with SRCNN	PlantVillage dataset	Resizing, Normalization, RGB to grayscale conversion, background removal, image interpolation, and data augmentation	accuracy: 96.12%, validation loss: 0.1607, training loss: 0.1007	Developed and deployed CROPCARE, a real-time smart system that combines mobile vision, IoT, and cloud services for crop disease diagnosis and prevention
22.	[200]	ICNN	Leaf dataset	Resizing, CIELAB conversion, segmentation	F1-score: 99.1%	Developed a smart soil and plant monitoring system that leverages IoT to increase agricultural yield and lessen its negative effects on the environment
23.	[201]	YOLOv3-SPP for fruit detection and ResNet18 for feature extraction	NA	Resizing the images, correcting the detections using thresholding, and extracting the bounding boxes of the fruits	accuracy : 91%-95%	Presented a complete smart harvesting solution that can count fruits from videos, link them to geographical data, and arrange containers in the best possible harvesting locations
24	[202]	Hybrid CNN	PlantVillage dataset	Resizing, Normalizing	F1 score: 0.975	A hybrid convolutional neural network model with feature reduction increased the precision and effectiveness of grape leaf disease detection and classification

impact on crop production and quality. Farmers now have a powerful tool for early disease diagnosis thanks to RCNNs, which can be trained to recognize disease signs from photos of plant leaves or stems [186].Identification of crops and weeds is another crucial field for RCNN applications in smart agriculture. Precision farming techniques, such as the focused application of herbicides, may be guided by precise identification and differentiation of crops and weeds. RCNNs may be applied to field image analysis to locate and identify crops and weeds precisely [187]. Another research [203] proposed ML and DL methods for weed detection and classification in crops, which achieved 90% accuracy with

Random Forest and ConvNeXt on the CottonWeedID15 dataset and 99.5% accuracy with SVM on the early crop weed dataset.

However, RCNNs demand training data and are computationally expensive. This can be difficult in smart agriculture since data collecting can be costly and time-consuming. Despite these difficulties, RCNNs have demonstrated excellent potential in smart agriculture. In the upcoming years, it is anticipated that RCNNs will play a more significant part in smart agriculture due to continued developments in deep learning and the expansion of high-quality agricultural data. They can assist farmers in taking prompt action to reduce crop loss and maintain food security by making it possible to detect illnesses early and accurately. Techniques like Fast R-CNN and Faster RCNN have enhanced the original RCNN. The importance of RCNNs in smart agriculture will only increase as we continue to face major issues like climate change and food security.

C. LONG SHORT-TERM MEMORY

Long Short-Term Memory (LSTM) networks, a recurrent neural network, have shown promise in smart agriculture. Because LSTMs can characterize temporal sequences and their long-range interactions, they are particularly well suited for tasks requiring time-series data, typically seen in agricultural applications. LSTM networks may be used To make wise judgments about irrigation, fertilization, and pest management, for example, to anticipate the environmental conditions of plants based on past data. Additionally, because LSTM networks can process lengthy data sequences, they are appropriate for examining the constant stream of data produced by IoT sensors in smart agriculture [188]

Environmental condition monitoring is one of the main uses of LSTMs in smart agriculture. Data on the environmental circumstances of plants are continually tracked in a smart agriculture system. This time-series data may be analyzed using LSTMs to forecast future environmental conditions [189]. For instance, they may be used to forecast temperature, humidity, and other environmental variables, which are essential for plant development.

In smart agriculture, the domain of pest detection is a crucial application of LSTMs combined with CNNs [190]. The frequency of pests can change over time and is frequently influenced by environmental factors. LSTMs may be utilized to analyze environmental and historical data on pest occurrences to forecast future pest occurrences. This can make it possible for farmers to minimize crop loss and take preventative measures. Crop yield prediction may also be done with LSTMs. Environmental conditions, agricultural methods, and crop variety are only a few variables that might affect crop yield. When combined with other relevant data, LSTMs may be used to analyze past yield data to produce precise predictions [191]. Farmers may be able to organize their marketing and harvesting operations better, increasing their profitability. Their capacity to create complex temporal correlations in data can help with yield prediction, precise pest identification, and better environmental condition monitoring. Issues with data collecting and computing resources must be resolved to fully grasp the potential of LSTMs.

D. RESIDUAL NETWORKS

A type of CNN called residual networks (ResNets) invented the idea of ''skip connections,'' which enables the gradient to be directly back propagated to older layers. The fundamental advantage of a ResNet is its capacity to train 100+ layer networks with impressive accuracy over a wide range of datasets (such as ImageNet). ResNets are particularly helpful in addressing challenging agricultural tasks that need high-level feature extraction and abstraction because they can efficiently train deep networks.

A single residual block in a ResNet comprises a ReLU activation function, batch normalization, and numerous layers of convolutions. ResNets apply to smart agriculture in a variety of contexts. Precision agriculture can also benefit from the usage of ResNets. Utilizing cutting-edge technology to handle agricultural tasks more precisely and effectively is known as precision agriculture. This involves accurate fertilizer and pesticide application, variable rate irrigation, and the best planting and harvesting techniques. To generate insights that help direct precision agricultural practices, ResNets can analyze large amounts of data on weather, soil quality, crop trends, and satellite images.

Plant disease and pest detection is one of the most popular uses of this technology [192]. Plant diseases and pests significantly influence the productivity and quality of crops. By prompting response and minimizing crop loss, early and precise identification of various diseases and pests can increase production. With its deep architectures and skip connections, ResNets can accurately identify numerous plant diseases and pests by extracting detailed information from photos of plant leaves and stems.

Predicting crop yield is another area in which ResNets is used in smart agriculture. An essential component of agricultural planning and management is crop production prediction [193]. For precise yield estimates, ResNets may be used to analyze various data sources, such as meteorological data, soil quality data, and crop patterns.

ResNets have a lot of potential for the subject of smart agriculture. Their capacity to simulate highly complex patterns and correlations in data can result in more accurate production predictions, better disease and pest detection, and effective agricultural management techniques.

VII. RESEARCH OPEN CHALLENGES AND FUTURE RESEARCH DIRECTIONS

There are a number of open research problems and potential areas for further investigation in the field of IoT-based agricultural applications; some of these open challenges and potential areas are mentioned in this section.

1) **Implementation and maintenance:** A notable challenge can be caused by the deployment and continuous

maintenance of IoT-based agricultural systems spanning significant agricultural regions. To make sure that everything runs smoothly and effectively, this challenge requires tackling a variety of technological, logistical, and resource-related challenges. To fully utilize IoT in agriculture, solutions to these challenges must be identified that are realistic.

2) **Cost:** Numerous monetary factors, including preliminary setup costs and continuing operating costs, must be taken into account when deploying IoT in agriculture. Hardware expenses such as IoT devices, sensors, base station infrastructure, and gateways are all included in the setup costs. On the other hand, continuing payments for subscriptions for services like centralized data collection, data interchange, and IoT device management are included in the running costs.
3) **Security:** There is presently no unified benchmark to determine the security resilience of suggested solutions in the environment of IoT-based agriculture systems. In order to examine the level of security in their individual research initiatives, several research groups separately undertake security evaluations, frequently utilizing adversarial analyses. Because of varying underlying assumptions and guiding concepts, these evaluations frequently lack uniformity. The development of a system for estimating the level of security in research activities has become crucial for the IoT-based agriculture security community [128]. For example, a web-based application that delivers findings according to user input may be implemented to establish an agricultural IoT security evaluation system. However, it's crucial to highlight that neither the security analysis of recent agricultural studies nor the use of cryptography techniques in cryptanalysis are included in this work. To accurately gauge the security level of IoT-based agricultural systems, more research must be conducted.
4) **Advancement of communication & network technologies:**Considering the advantages provided by developing cutting-edge communication technologies, potential consumers have agreed to endorse smart agriculture systems [44]. The requirement for rapid and efficient network connections in order to ensure system coordination has been demonstrated by contemporary advances in technology that have led to immense advances in the processing of data. The advancement of 6G networks has been driven by this demand. It is projected that 6G and IoT technologies will combine to establish a panorama of smart agriculture networks in the future, improving device integration, increasing network efficiency, and addressing security issues. Key 6G technology advancements, such as Software-Defined Networking (SDN), Massive Multiple Input, Multiple Output (MIMO), Network Function Virtualization (NFV), Machine-to-Machine (M2M) communication, and millimeter-wave communication, are essential for addressing the aforementioned challenges in order to deliver highly effective smart IoT-based agriculture solutions.
5) **Big data:** The efficient processing of an extensive amount of agricultural data is critical in IoT-based agriculture systems. This data is collected by IoT sensors placed in the agricultural environment, where scenarios and factors fluctuate constantly. Furthermore, as the demand for accurate and reliable assessment of crop conditions advances, sensors and connection points produce an extensive amount of agricultural data in a variety of formats [122]. Processing various and large data quantities can be difficult, potentially impeding timely access, even though continuous access is critical. Any disruptions in accessing data might result in serious effects in major instances, including those impacting vital crops or livestock. Substantial drifts in the capacity of data are expected to decline as algorithms for prediction become more capable of predicting such occurrences. Organizations are likely to participate in both inside and outside education to train young scientists with the ability to overcome these difficulties, according to the Global Institute for Analytics. Businesses will prioritize data updates and shift their focus from managing system procedures to acquiring computations. Furthermore, more firms are likely to investigate the possibility of exploiting their agricultural data resources. There will certainly be significant growth for well-known services and suppliers like Kaggle, Algorithmia, and DataXu, leading to the emergence of booming algorithm economies in the agriculture sector.
6) **Artificial intelligence:** Network security is one of the areas where machine learning and deep learning have become research hotspots. For instance, machine learning-based networks, especially detection of intrusion techniques, are increasing in prevalence and have conceivable applications in IoT-based agriculture systems. In the area of agriculture IoT, deep learning networks, as discussed in the previous section, have been used to evaluate the provision of data, such as crop disease identification, throughout multiple layers of IoT systems for quick identification of potential problems [187]. Considering the growing popularity of deep learning techniques on agricultural servers for tasks such as identifying diseases, it is essential to investigate their effectiveness in guaranteeing system privacy and the security of data.
7) **Blockchain:** The primary focus of blockchain researchers is the optimization of blockchain-based solutions for IoT devices with limited resources. These advancements aim to ensure data integrity and transparency throughout the agricultural process. The study specifically explores the implementation of smart contract technology to streamline agricultural transactions, address interoperability issues, increase

data privacy and ownership rights for landowners and stakeholders, and develop adaptable blockchain frameworks. These strategies are designed to capitalize on the potential advantages of blockchain by addressing the distinctive challenges offered in the agricultural environment, thus improving the security, efficiency, and dependability of IoT applications in agriculture [172].

8) **Agriculture robotic system:** The growing importance of agricultural productivity and effectiveness has drawn attention to the importance of robotics in agriculture, notably in activities such as robot crop cutting,drone-based field monitoring, spray quadcopters, and robot-detecting diseases, where innovations in robotics technology have transformed conventional agricultural practices. Fundamental, flexible, simple, and affordable technological solutions must be prioritized in the forthcoming generations of agricultural automated machines and systems engineering. switching from outdated electrical control devices, sensors, and networking systems to their digital versions may assist these innovations become more prevalent. In contrast to traditional electric motors, which can be complex, large, and expensive, the agriculture robotics market requires simplified and logic-driven technology solutions. The emerging phenomenon of the IoT has the potential to effortlessly incorporate with agricultural technology and equipment in the future years, boosting the efficiency and precision of numerous fields of agriculture.

9) **Unmanned Aerial Vehicles (UAVs) and AI Technologies in Agriculture:** With the expansion of IoT and the advent of communication technologies, the use of drones in agriculture has accelerated significantly. In the future, AI offers a viable way to improve the potential and effectiveness of UAVs in agricultural operations. AI has the potential to transform drone capabilities by empowering them to perform a wide range of essential functions that enhance agricultural practices. A few examples are soil analysis, automated planting, targeted crop spraying, real-time crop health monitoring, precision irrigation, and extensive crop inspection. Furthermore, drones equipped with a variety of sensors, including 3D cameras, thermal imaging, multi-spectral imaging, and optical cameras, make it easier to monitor various crop conditions, disease outbreaks, vegetation density, and soil parameters. AI has the potential to analyze the data collected from these sensors and provide valuable insights such as the need for pesticides, fertilizer distribution, canopy cover mapping, yield forecasts, plant counting, and plant height measurement. It demonstrates the various uses of UAVs in agriculture, including mapping, spraying, harvesting, and sensing, and opens up opportunities for potential advances in this field with the use of AI technology.

10) **Eco-sustainable Technologies:** The primary focus of research in eco-sustainable technologies is assessing the mineral balance of agricultural treatments and examining any potential effects on cutting-edge IoT-based agricultural systems. Furthermore, nanotechnology can be crucial in enhancing the intelligence and adaptability of smart agricultural systems, particularly for IoT devices. To build intelligent and environmentally conscious agricultural systems that rely on IoT sensors for monitoring and improvement purposes, this area presents an immense research gap that has to be addressed.

VIII. CONCLUSION

This review article provides an extensive and systematic analysis of IoT-based agriculture systems, spanning technical advancements, sector developments, device sustainability, applications, communication standards, gaps in research, significant privacy and security concerns, and solutions that are distinctive to IoT in agriculture, as well as state-of-the-art ML models and techniques in smart agriculture applications. It presents an in-depth explanation of IoT technologies and how they might be used in different sectors of agriculture. The report evaluates key findings from previous research and emphasizes the particular security concerns of IoT in agriculture, considering its broad spectrum of applications. Additionally, it emphasizes significant application fields and research opportunities, offering valuable data to researchers and industry experts. The importance of IoT security, including technological developments like blockchain for risk mitigation, is also emphasized in the article.In order to improve the effectiveness and accuracy of automation, modeling, and forecasting systems in agriculture, the debate predicts the rise of hybrid technologies that combine big data analytics, data mining, artificial intelligence, and the Internet of Things.

DECLARATIONS

DATA AVAILABILITY

N/A

CONFLICT OF INTEREST

It is declared by the authors that there is no conflict of interest.

CODE AVAILABILITY

Code can be provided on request.

AUTHORS CONTRIBUTIONS

Tanzeela Shakeel and Muhammad Shmoon worked on the literature review and wrote the initial draft of the article. Asma Naseer floated the idea, supervised the systematic literature review, and contributed to the article write-up. Awais Ahmad verified and analyzed the findings and contributed to the article write-up. Shafiq Ur Rehman improved the article write-up. Volker Gruhn reviewed and supervised the project.

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