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REVIEW ARTICLE

Comprehensive Review of IoT-based Smart Agriculture: Technologies, Applications and Barriers

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ABSTRACT

The integration of Internet of Things (IoT) into agriculture is increasingly transforming conventional farming practices into intelligent, connected, and data-driven systems, offering opportunities to enhance productivity, and resource-use-efficiency and promote sustainable food security. This study presents a comprehensive systematic literature review of IoT-based smart agriculture, following the Preferred Reporting Items for Systematic Review and Meta-Analysis (PRISMA 2020) framework. A total of 203 peer-reviewed publications between 2020-2024 were systematically reviewed to examine three interconnected dimensions; IoT technologies, agricultural applications, and implementation barriers. The technological analysis covers sensing technologies, embedded controllers, communication protocols, and computing architectures with particular attention to programmable logic controllers (PLCs), ESP32, microcontrollers, and Raspberry Pi platforms, wireless sensor networks, long range wide area network (LoRaWAN), NB-IoT, Zigbee, and cloud, edge, and hybrid computing architectures in supporting data processing, intelligent analytics, and real-time decision-making approaches. Practical applications-oriented analysis identifies enormous contributions in crop monitoring, precision farming, livestock management, irrigation automation, soil health monitoring, and pest and disease management. Across these domains, we then reviewed the improving performance of IoT technologies, including crop yield increases of up to 78%, water-use efficiency of up to 64% in crop-monitoring applications, water-use efficiency improvements of approximately 21-48% in smart irrigation systems, and pesticide-use reductions of 43-82% in selected pest and disease management applications. Despite these benefits, their widespread adoption remains constrained by high-initial and maintenance costs, inadequate rural connectivity and digital infrastructure, limited technical expertise and energy, interoperability limitations, concerns of data security and privacy challenges. In response to these challenges, we examined an emerging approach, including low-cost open-source platforms, resilient and self-healing hardware architecture, energy-efficient communication protocols, solar-powered systems, ruggedized sensing devices, localized edge intelligence, and hybrid networking and computing architectures. Furthermore, we presented an integrated agricultural IoT framework that connects data acquisition, communication, computing, data visualization, and system management to illustrate how technological components can be coordinated within agricultural ecosystem. Overall, this study consolidate integrated synthesis of recent IoT developments, critically examines the relationships between technological capabilities and implementation challenges, providing a comprehensive evidence base for researchers, technology developers, policymakers, and agricultural practitioners. Its findings offer strategic insights for advancing scalable, cost-effective, and sustainable IoT-enabled agricultural systems and strengthening their contribution to long-term food security.

Keywords: Wireless-Sensor-Networks ▪ Agricultural IoT ▪ Internet of Things ▪ Optimization ▪ Edge computing ▪ LoRaWAN ▪ Challenges ▪ Food security ▪ Interoperability

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1. INTRODUCTION

Sustainable agriculture is vital for ensuring long-lasting and eco-friendly food production, promoting a viable economy. It's instrumental in preserving natural resources, mitigating biodiversity loss, and lowering greenhouse gas emissions [1]. By aligning current agricultural practices with future needs, it utilizes techniques such as crop rotation, nutrient management, pest control, recycling, and water harvesting to promote environmental health. The negative impacts of agricultural waste, chemical use, and greenhouse gas emissions emphasize the need for smart farming to safeguard environmental health. Agriculture remains a crucial contributor to Ethiopia's economy. According to recent survey reports, agriculture contributes around 34% of Ethiopia's GDP. It also contributes nearly 76% of Ethiopia's population engagement, especially in rural areas where farming is often the primary livelihood source [2][3]. The environmental status, demand size, and energy are the three factors mainly influencing sustainable agriculture. The environmental aspect focuses on soil health, water conservation, and biodiversity preservation to sustain productivity and minimize ecological harm [3]. As global populations increase, so does the demand for food, which strains natural resources [4]. Moreover, energy is crucial in sustainable agriculture, which focuses on reducing energy inputs by improving energy efficiency via lower-energy technology [5]. Global food demand is increasing due to a projected population nearing 10 billion by 2050 [6]. Although numerous review articles have been scrutinized individual aspects of Agricultural IoT, such as sensing technologies, communication protocols, smart irrigation, precision farming, or artificial intelligence, there remains a lack of a comprehensive and up-to-date systematic review that integrates the entire Agricultural IoT ecosystem. Existing reviews generally provide limited comparative analyses of enabling technologies, insufficient synthesis of implementation barriers, fragmented coverage of agricultural application domains, and little integration of technological advances with sustainability and food security objectives. Furthermore, recent developments in Edge AI, LPWAN, hybrid cloud-edge computing, and intelligent IoT platforms have not been comprehensively synthesized within a PRISMA-based systematic review. To address these gaps, this study systematically reviews 203 peer-reviewed publications published between 2020-2024, providing an integrated analysis of IoT technologies, applications, implementation challenges, reported performance outcomes, and proposing a unified Agricultural IoT framework to guide future research and practical deployment.

Therefore, emphasis should be given to integrate smart technologies with sustainable practices to bolster productivity. Nowadays, the integration of IoT solutions offer a renovative approach by facilitating data-driven decision-making and real-time monitoring, crucial to improve productivity [7]. IoT is a network of interconnected devices communicating with each other through machine-to-machine (M2M) interactions using both wired and wireless connectivity [8]. While agricultural IoT refers to a network where various farm components; including animals, crops, machinery, agricultural tools, are connected to the internet through diverse technologies [9] which facilitates identification, tracking, and monitoring of agricultural processes. The systematic architecture of IoT, illustrating how its components integrate to create, a data-driven agricultural ecosystem is structured across multiple layers: - the perception, network, data processing, and user interface layers, each enrolling a distinct task as shown in Fig 1.

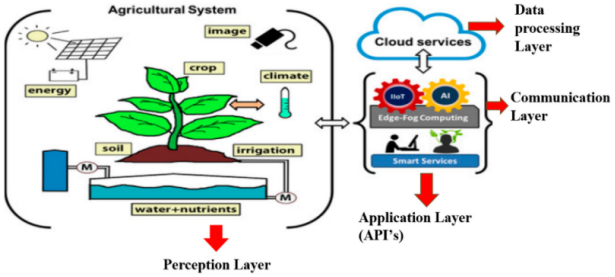


Figure 1. Schematic Layers of agricultural IoT Framework

Perception Layer: consists of diverse sensors and devices that capture agricultural parametric data, such as soil moisture, nutrient, and crop health. Sensors, cameras, GPSs, and drones equipped with imaging technologies provide valuable data that enhance smart farms [10]. Transport Layer: is responsible for transmitting collected data to central processing units via communication protocols like Wireless Sensor Networks (WSN), Low Power Wide Area Networks (LPWAN), 4G/5G networks and IoT Gateways leveraging key resources. LPWAN is particularly suitable for long-range data transmission, and efficient energy [11]. Data Processing Layer: fetches data-processing closer to its source, which reduces latency and conserves bandwidth with resources like cloud platforms and edge computing. Edge devices like gateways handle initial data filtering, and analysis, ensuring that only essential information is transmitted to cloud platforms for further processing [12]. User Interface Layer: provides user-facing interfaces, enabling farmers to access insights and control systems through resources such as Agricultural Management Systems, web interfaces, and mobile apps. It provides dashboards, alerts, and recommendations from real-time data analysis, enabling data-driven decision and also boost productivity [13].

This review primarily offers valuable insights for practition-ers, researchers, and policymakers. The intellectual contribu-tion of this review extends beyond summarizing the existing literature. First, it provides a comprehensive PRISMA-based synthesis of the entire Agricultural IoT ecosystem by inte-grating enabling technologies, computing architectures, com-munication protocols, application domains, implementation barriers, sustainability, and food security within a unified ana-lytical framework. Second, it performs comparative analyses of major IoT technologies, highlighting their trade-offs, deployment suitability, and technological trends across diverse agricultural environments. Third, it synthesizes evidence from 203 recent peer-reviewed studies (2020–2024) to identify emerging research directions and unresolved challenges. Finally, this study outlines integrated Agricultural IoT framework that conceptually links sensing, communication, computing, data analytics, visualization, and system management, thereby providing a structured foundation for future research, technology development, and practical implementation.

2. MATERIALS AND METHODS

2.1 Review Design and Reporting Standards

This study adopts a systematic literature review (SLR) methodology following the PRISMA 2020 guidelines to ensure methodological rigor, transparency, and reproducibility. The review protocol defines the search strategy, eligibility criteria, screening stages and quality assessment procedures prior to study selection. The overall study identification and selection process is summarized using a PRISMA flow diagram (Fig. 2), which presents a consistent and traceable flow of records from identification to final inclusion. This study employs a systematic review approach to comprehensively examine agricultural IoT and its role in enhancing sustainable agriculture and food security. This section outlines the methodology used to collect the necessary data and information.

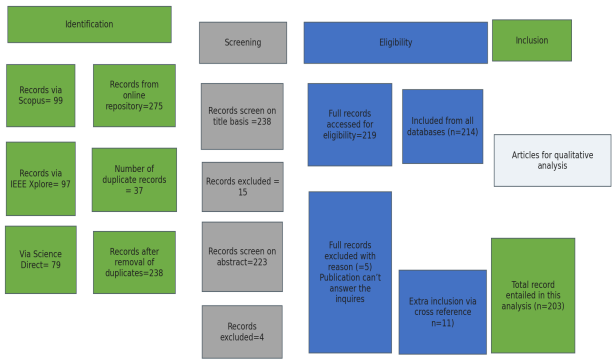


Figure 2. PRISMA framework Landscape for Agricultural IoT review

This study adopted a systematic literature review (SLR) methodology in accordance with the PRISMA 2020 guidelines to ensure transparency, methodological rigor, and reproducibility. A predefined review protocol was used to guide the literature search, duplicate removal, screening, eligibility assessment, data extraction, and qualitative synthesis. Records were identified from Scopus, IEEE Xplore, ScienceDirect, and relevant online repositories. After duplicate removal, the remaining records were screened based on title and abstract, followed by full-text assessment according to the predefined eligibility criteria. Additional relevant studies identified through cross-referencing of eligible publications were assessed separately and incorporated where they satisfied the inclusion criteria. The complete identification and selection process is presented in the revised PRISMA flow diagram (Fig. 2), which provides a transparent and traceable account of the records considered at each stage and the reasons for exclusion. Following the final eligibility assessment, 203 studies were retained for qualitative analysis. To enhance the transparency and reproducibility of this systematic review, the review protocol was predefined following the PRISMA 2020 guidelines. The literature search, study selection, eligibility assessment, data extraction, and evidence synthesis procedures were conducted according to a standardized protocol. The complete search strategy, Boolean search strings, database selection, screening workflow, and study selection process are explicitly described to enable replication by future researchers.

2.2 Data Sources and Search Strategy

A comprehensive search was conducted across four major bibliography databases widely used for IoT and agricultural searches: IEEE Xplore, Scopus, ScienceDirect, and Springer. The search covered peer-reviewed publications published between January -2020 and December 2024, reflecting recent advances in IoT-based smart agriculture. The search strategy employed a structured Boolean combination of keywords related to agricultural IoT. This core search string was formulated as "Agricultural IoT," OR "precision farming," OR "Smart agriculture", "sensors" OR "Agricultural technology", OR "Communication tools", OR "Livestock management", OR "Data processing", OR "crop monitoring" or "smart irrigation") AND (Internet of Things) were utilized in various combinations. Databases-specific syntax adjustments and only English language journal articles and conference papers were considered. Accordingly, a total of 203 studies were selected for detailed review, focusing on key areas: technologies used, agricultural applications, and barriers to implementing agricultural IoTs.

2.3 Data Extraction and Analytical Dimensions

For each included study, relevant data were systematically extracted and organized using a three-dimensional analytical framework that guided the synthesis of findings. The framework comprised: first technological dimensions, including IoT architectures, communication technologies (e.g. Lora-WAN, Zigbee, NB-IoT, and Wi-Fi), sensors, actuators, embedded platforms, edge computing, cloud platforms, and AI-driven analytics; second, application domains, covering crop monitoring, smart irrigation, livestock and poultry management, greenhouse farming, aquaculture, and precision agriculture; and third, barriers and challenges, including technical limitations (e.g., energy efficiency, scalability, and interoperability), economic and infrastructural constraints, data security and privacy concerns, and adoption- or policy-related issues. Findings were then grouped and comparatively analyzed to identify technological trends, recurring challenges, research gaps, and emerging opportunities across the reviewed literature. Eligibility criteria were established before the literature search to ensure methodological consistency and minimize selection bias. The eligibility criteria were established before the literature search to ensure methodological consistency and minimize selection bias. The inclusion criteria were designed to capture recent peer-reviewed studies that provide sufficient technical, methodological, or experimental evidence related to Agricultural IoT, while the exclusion criteria removed publications lacking adequate scientific rigor, technical detail, or direct relevance to the objectives of this review. Inclusion criteria targeted recent peer-reviewed studies providing sufficient technical, methodological, or experimental evidence on Agricultural IoT, while exclusion criteria eliminated publications lacking scientific rigor, technical detail, or direct relevance to the review objectives.

2.4 Eligibility Criteria

Studies were included if they:

1. Focused on IoT-based systems or applications in agriculture, including crop production, livestock, irrigation, greenhouse farming or aquaculture

2. Presented empirical results, system architectures, models, frameworks or experimental validations;
3. Addressed at least one of the following: sensing technologies, communications protocols, data processing, automation, sustainability or food security and were published between 2020 and 2024
4. Appeared in peer-reviewed journals or reputable sources

Studies were excluded if they:

1. Were Theses, patents, and short abstracts
2. Were unrelated to IoT or focused solely on conventional (non-IoT) agriculture
3. Lacked sufficient technical or methodological detail
4. Were duplicated across databases and weren't written in English

2.5 Interpretation of Synthesized Quantitative Results

Because the reviewed studies differ substantially in research objectives, agricultural domains, experimental designs, deployment environments, IoT architectures, communication technologies, evaluation metrics, and reported outcome measures, a statistical meta-analysis was not methodologically appropriate. Instead, this review adopted a structured descriptive evidence synthesis approach. Quantitative performance indicators, including crop yield improvement, water-use efficiency, pesticide reduction, energy savings, productivity enhancement, and return on investment, were systematically extracted from the primary studies and comparatively synthesized according to predefined analytical dimensions. These reported values represent descriptive ranges observed across heterogeneous studies and should therefore be interpreted as indicative trends rather than statistically pooled effect sizes, and a generalized benchmark. In this study, it should be noted that all quantitative performance indicators reported in this review (water-use- efficiency, yield improvement, energy savings, RoI, pesticide reduction) are synthesized from the outcomes reported in the reviewed primary studies. These values represent descriptive ranges or representative results observed across heterogenous experimental settings and should not be interpreted as statistically pooled or experimentally validated outcomes of this review. These outcomes are synthesized from heterogeneous studies and should be interpreted as representative ranges rather than generalized benchmark. Additionally, this study didn't perform a formal meta-data-analysis. Consequently, the synthesized quantitative results should not be interpreted as generalized effect sizes or causal estimates but rather as indicative trends observed across the reviewed studies. Third, several reviewed studies rely on an experimental deployment in controlled environments which may capture long term system reliability, maintenance costs and scalability challenges and farmer adoption barriers. Despite these limitations, this study provided a comprehensive comparative synthesis of agricultural IoT technologies, applications, and reported performance outcomes. These findings are therefore best interpreted as evidence-informed directional insights to guide technology selection, system design, and future large-scale empirical validation, rather than definitive performance guarantees. A formal risk-of-bias assessment using clinical evidence appraisal tools (e.g., Cochrane Risk of Bias or GRADE) was not performed because the included studies comprise heterogeneous engineering research, including prototype developments, simulation studies, experimental implementations, communication protocol evaluations, and system architecture papers rather than randomized or controlled intervention studies. Consequently, conventional evidence grading frameworks are not directly applicable. Instead, methodological quality was considered during study selection by including only peer-reviewed publications with sufficient technical and methodological detail. Furthermore, potential sources of heterogeneity, including differences in experimental settings, evaluation metrics, deployment scales, agricultural applications, and performance indicators, are explicitly discussed throughout the synthesis and limitations sections.

3. KEY TECHNOLOGIES USED IN SMART AGRICULTURE

3.1 Agricultural IoT Sensors

Researches steadily demonstrate that sensing technologies enhance efficiency, crop yields, reduce input costs, and indorse sustainable farming enabling real-time data analytics for intervention [14] as detailed in Table 1 below. Environmental Monitoring Sensors- environmental factors such as temperature, humidity, rainfall, and drought play crucial role in determining crop growth and livestock health. Sensors designed for environmental monitoring enable to track crop conditions and predict patterns, allowing for appropriate interventions. Across the reviewed literatures, depending on crop type, climate conditions, and deployment scale studies employing combined temperature and humidity sensing integrated with weather prediction models report crop loss reductions of approximately 32% [15] while the integration of WSN improves energy efficiency by 28% [16]. Light sensors are used to monitor solar radiation and optimize photosynthesis efficiency [17]. Studies suggest that LED lighting can improve crop yields in indoor farming by 20-41. These figures represent aggregated outcomes reported in individual studies.

Soil Monitoring Sensors- multiple reviewed studies indicate that IoT-driven smart irrigation systems report waters consumption reductions ranging from 205 to 41%, while sensor-assisted precision drip irrigation has been associated with crop productivity improvements of approximately 29% compared to traditional practices [16]. Similarly, soil pH and nutrient sensors are reported to improve fertilizer-use-efficiency by up to 35% in controlled deployments [17][18]. These performance gains vary across experimental settings and should be interpreted as indicative trends rather than universal outcomes.

Crop health and pest detection sensors- Early detection of crop diseases and pests are essential for preventing agricultural losses and reduces pesticide reliance. Reviewed studies demonstrate that multispectral and spectral sensing systems can detect crop stress nearly 5-10 days earlier than visual inspection, with reported disease classification accuracies reaching up to 95% under controlled conditions. camera -

Table 1. Agricultural Sensor Technology and their Applications

Sensor Type	Range	Communication Technology	Use in Agriculture	Ref
Soil sensor	Moisture: 0–100%, Temperature: -40°C to 60°C	LoRaWAN, Zigbee, Bluetooth, Wi-Fi, RS-485, Modbus	Measure soil moisture, temperature, pH, and nutrient levels	[15]
Temperature Sensor	-50°C to 150°C	Bluetooth, Zigbee, LoRaWAN, Wi-Fi, NB-IoT, RS-485	Regulates irrigation, &heating systems to maintain optimal crop conditions.	[15]
Moisture Sensor	0–100% (Relative Humidity)	Zigbee, Wi-Fi, LoRaWAN, NB-IoT, RS-485	Helps optimize farm by supplying water only when needed to conserve water.	[15]
Humidity Sensor	0–100% RH (Relative Humidity)	Zigbee, LoRaWAN, Bluetooth, Wi-Fi, NB-IoT	Monitors greenhouse conditions to manage humidity for plant health.	[15]
pH Sensor	0–14 pH	LoRaWAN, Zigbee, RS-485, NB-IoT	Ensures soil pH level for optimal crop growth and nutrient absorption.	[17]
Nutrient Sensor	0–200 ppm for N, P & K (varies with the sensor)	LoRaWAN, Zigbee, Wi-Fi, NB-IoT	maintain the balance of nutrients for crops to avoid deficiency or excesses.	[18]
Light Sensor	0–200,000 lux	Zigbee, Bluetooth, Wi-Fi, LoRaWAN	Used for monitoring sunlight exposure and adjusting artificial lighting in greenhouses.	[19]
CO2 Sensor	0–5000 ppm	Zigbee, Bluetooth, Wi-Fi, RS-485, LoRaWAN	Controls ventilation systems in greenhouses to optimize photosynthesis.	[20]
Proximity Sensor	Ultrasonic: 2cm to 4m; GPS 2-10m	Bluetooth, Zigbee, LoRaWAN, Wi-Fi	Livestock tracking, machinery control, crop mapping, geofencing using GPS and RFID.	[21]
Wind Speed Sensor	0.3–75 m/s (varies with type)	LoRaWAN, Zigbee, Wi-Fi, RS-485	manage irrigation systems and preventing crop damage during strong winds.	[22]
Rainfall Sensor	0–500 mm/hour	LoRaWAN, Zigbee, Wi-Fi	Assists in managing irrigation schedules	[23]
Leaf Wetness Sensor	10–100m	Zigbee, LoRaWAN, Bluetooth	Helps disease risk monitoring and pest management	[24]
Camera Sensor	Resolution& range-dependent.	Wi-Fi, Ethernet, 4G/5G, NB-IoT	Monitors crop health, growth, and pest detection	[25]
Water Quality Sensor	Conductivity: 0–2000 μS/cm, Turbidity: 0–1000 NTU, pH: 0–14	LoRaWAN, Zigbee, RS-485, NB-IoT	Essential for aquaculture and irrigation management	[26]
Ultrasonic Sensor	2 cm–4 meters	Bluetooth, Zigbee, RS-485, Wi-Fi	Used in automated machinery for obstacle avoidance	[27]
LiDAR	power and environment matters. 0.1–200m	Ethernet, Wi-Fi, RS-232, CAN bus	Provides detailed topographical and vegetative data for precision agriculture	[28]
Pest detect sensor	Depends on topology and distance	LoRaWAN, Zigbee, Wi-Fi	Monitoring insect pests in fields and reduce crop damage	[29]
Livestock sensor	0–30m (for RFID), 0–2m (for wearable sensors)	GPS, RFID, LoRaWAN, Zigbee, Bluetooth, NB-IoT	Tracking livestock location, health monitoring	[30]

based pest detection systems integrated with machine learning models have reported pesticide-use reductions of nearly 40%, while IoT-driven pest outbreak prediction frameworks report improvements of about 32% in integrated pest management efficiency [20][21]. These values reflect report outcomes from individual studies and are context-dependent. IoT-based pest outbreak prediction model which analyze temperature, humidity, and pest movement data, have also improved the efficiency of integrated pest management (IPM) tasks by 32% [20] [21]. Livestock Monitoring Sensors- Across the surveyed literatures, IoT enabled livestock monitoring systems report milk production increases of approximately 16% in diary applications, reductions in livestock loss through GPS-based tracking of around 26%, and feed efficiency improvements of roughly 21% when smart feeding systems are employed [30]. These outcomes are synthesized from heterogeneous studies and should be interpreted as representative ranges rather than generalized benchmark.

3.2 Controllers

Research demonstrate that IoT controllers improve agricultural efficiency, cut costs and promote sustainability which they serve as central processing units for optimizing operations [31]. Platforms like microcontrollers, PLCs, and ESP8266 empower cost-effective automation, while more powerful controllers such as raspberry Pi and beagle-bone handle complex and data-driven tasks. Emerging solutions like Azure Sphere enhance security and processing capabilities for advanced agricultural applications, while Particle Photon and giant board provide robust connectivity, supporting seamless operations [32].

From the reviewed data, we evaluated 12 IoT controller platforms across 26 smart agriculture projects, presenting adoption trends, and platform preferences as in Table 2. The raspberry Pi is the most dominant platform, utilized in 22 out of 26 reviewed smart agriculture due to its affordability, GPIO flexibility and Linux support [31][39][39], livestock [32][40]

Table 2. Controller platforms utilized in smart agriculture (2020 up to 2024)

Project titles	Beagle Bone Black/ pi	ESP32	Intel Edison	Particle Photon	Giant Board	Edge Controller	Azure Sphere	PLC	WSN	Emb. controller	Intel NUC	Single board controller	Ref.
Smart Irrigation System Using IoT	✓	✓	✓	×	×	×	×	×	×	✓	✓	✓	[31]
IoT-based livestock monitoring	×	✓	×	✓	×	×	×	✓	✓	✓	×	✓	[32]
Precision Agriculture with IoT Sensors	✓	✓	×	×	✓	×	×	×	×	✓	✓	✓	[33]
IoT-based Crop yield optimization	×	✓	✓	×	×	×	×	✓	✓	✓	✓	×	[34]
IoT-based Crop monitoring system	✓	×	✓	×	×	✓	×	✓	×	✓	✓	×	[35]
Google Coral for pest detection	✓	×	×	×	×	×	×	×	×	✓	✓	×	[36]
Precision livestock farming	✓	✓	×	×	×	×	×	×	×	✓	✓	✓	[37]
IoT-enabled soil moisture monitoring	✓	✓	×	×	×	✓	×	×	×	✓	✓	×	[38]
Raspberry Pi for smart irrigation	✓	✓	✓	×	×	✓	×	×	×	✓	✓	×	[39]
IoT-based livestock monitoring	✓	✓	✓	×	×	✓	×	×	✓	✓	✓	×	[40]
IoT for smart irrigation and fertilization	✓	×	✓	×	✓	✓	×	✓	×	✓	✓	×	[41]
Arduino for livestock monitoring	✓	×	✓	×	×	✓	×	×	×	✓	✓	×	[42]
Smart Farming with AWS IoT	✓	×	✓	×	×	✓	×	×	×	✓	✓	×	[43]
Microsoft Azure FarmBeats	✓	✓	×	×	×	×	×	×	×	✓	✓	✓	[44]
IoT-Based Farm Equipment Monitoring	✓	✓	v	×	×	×	✓	×	✓	✓	✓	×	[45]
Google cloud for crop prediction	✓	✓	×	×	×	×	×	×	×	✓	✓	✓	[46]
Drone-based crop monitoring	✓	✓	✓	×	×	✓	×	×	✓	✓	✓	✓	[47]
Smart Beekeeping	×	✓	×	✓	×	×	×	×	✓	✓	×	✓	[48]
Automated greenhouse control system	✓	✓	✓	×	×	✓	×	✓	×	✓	✓	×	[49]
IoT for Agricultural Waste Management	✓	✓	×	×	×	×	×	×	×	✓	✓	×	[50]
Automated crop management system	✓	×	✓	×	✓	✓	×	×	×	✓	✓	×	[51]
IoT-based agricultural climate control	✓	✓	✓	×	×	×	×	×	×	✓	✓	✓	[52]
IoT for pest detection in agriculture	✓	×	×	×	×	×	×	×	×	✓	✓	×	[53]
IoT for Agricultural energy management	✓	✓	×	×	×	✓	×	×	×	✓	✓	✓	[54]
Precision Agriculture with IoT Sensors	✓	✓	×	×	✓	×	×	×	×	✓	✓	×	[55]
Smart Pest Repellent	✓	✓	×	✓	×	✓	×	×	✓	✓	×	×	[56]

and crop [33][55] monitoring. Similarly, ESP32 was another highly preferred platform, appearing in 18 out of 26 projects. Its low-power operation and wireless capabilities (WiFi/BLE) made it the top choice for soil moisture monitoring [38] and climate control systems [52]. Its energy efficiency and compatibility with IoT sensors operability further solidified its role in distributed agricultural monitoring. Moreover, AI-integrated edge controller, like google coral [36][53] which its edge TPU accelerator enables real time ML-based early crop pest identification. We also investigated that the NVidia Jetson often called as edge controller in studies [33][47] has been widespread in drone-based crop monitoring and precision farming leveraging its GPU capable for advanced image processing.

In this study, we reviewed that smart Irrigation [31][39] believed as overcoming the scarcity of global water resources heavily relied on Raspberry Pi and ESP32, as they offer a cost-effective and programmable solution for real time threshold investigation and automatic valve control while Smart irrigation that has been using microcontrollers have reduced water consumption by up to 48% [41], maintaining crop health while ESP32 controllers have improved energy efficiency in greenhouse automation, reducing by 30% of power consumption [54]. Data-driven edge controller has enhanced real time pest detection by 89%, while led 35% water use efficiency in soil moisture management and its disease predication model has shown 82% performance [37]. Livestock monitoring [32], [40] favored WSNs and particle photon and due to their low-power operation and long-range connectivity (LoRa/GSM), crucial for tracking animals in remote areas. PLC-based au-

tomatic livestock monitoring feeding systems have reduced feed waste by 19% [32]. ESP32 and Particle Photon were also often used for tracking livestock, enabling remote monitoring of health, location, and productivity [32][40][42]. Pest Detection literatures [36], [53] increasingly adopted edge controllers, Intel NUC and google coral for their ability to run ML-model efficiently, enabling real-time insect identification pest management with real-time IoT data [36][53].

3.3 Communications Technologies

In this study, we also find that communication technology the key enhancer of IoT ecosystem, playing a crucial role in catalyzing smart agriculture so that essential for empowering seamless data exchange, allowing farmers to effectively monitor soil, crops, and livestock conditions [57]. Considering mainly lower power and wireless constraints we reviewed, commonly used communication technologies in agricultural IoT. Existing IoT communication solutions are categorized based on their protocol, spectrum, and topology [58]. These protocols enable devices within smart agricultural system to interact, exchange information and make decisions to monitor farm condition, thereby enhancing yields and productivity [59]. The common low-power communication protocols used in smart agriculture also be further classified into short-range and long-range categories based on the communication range [58].

- Short-range [60]: - Bluetooth, Zigbee, NFC, Wi-Fi, Z-Wave, RF Module, MQTT Broker.
- Long-range [61]: - LoRaWAN, NB-IoT, Sigfox, Satellite, Cellular (4G/5G) and Ethernet.

The values indicate that short-range communication technologies, such as Bluetooth, Zigbee, and NFC, have a transmission distance of less than 20 meters, high energy efficiency, and low data rates. These protocols are often employed in sensor networks, where low power consumption is crucial. In contrast, long-range communication technologies, such as LoRaWAN, NB-IoT, and Sigfox, have transmission distances of up to several tens of kilometers, consume more energy, and are typically used for backhaul device-to-device communications [62][63] as reviewed in Table 3.

In this study, our analysis of smart agricultural communication technologies reveals that optimal selection depends on the specific farm requirement; data speed, energy efficiency, and coverage range. This analysis reveals distinct trade-offs between coverage, energy efficiency, and data throughput. Therefore, Satellite IoT serves remote areas despite latency/cost constraints, while wired solutions (Ethernet, MQTT) provide reliable high-speed connectivity for fixed installations [67-69]. For wide-area coverage (2-50km), LPWAN technologies (LoRaWAN, Sigfox) enable ultra-low-power soil/weather monitoring with limited data rates, whereas NB-IoT and cellular (4G/5G) balance moderate power use with better bandwidth for smart farming projects [81-84].

Short-range solutions like BLE and Zigbee (10-100m) excel in low-power, localized applications (livestock tracking, greenhouse monitoring), while Wi-Fi supports high-bandwidth needs (farm automation, drones) at higher energy costs [57-62]. The findings underscore the need for context-specific technology selection, and adopting hybrid networks where a tiered approach combining long and short-range solutions can maximize scalability and efficiency of smart agriculture.

3.4 Computing Technologies

The evolution of computing technologies has been leapfrogging farm practices. In this study, we explore the storage and computing technologies specifically utilize for smartening agricultures such as cloud, edge and hybrid computing [70]. Cloud computing providers such as AWS, Microsoft Azure, and Google Cloud play a pivotal role by supporting real-time data processing for applications like irrigation optimization, crop health monitoring, etc. that enhancing decision-making capabilities [71]. Despite its benefits, the reliance on cloud computing has challenges such as latency, high bandwidth costs and data security, particularly in remote farming areas where internet connectivity is often limited. To address these challenges, edge and hybrid computing models are gaining popularity. Edge computing, in particular, has emerged as a solution that enables localized data processing directly from IoT devices which reduces cloud dependency for real-time decisions and enhances system responsiveness [72][73].

Moreover, the increasing adoption of regulatory frameworks, such as the General Data Protection Regulation (GDPR), the Brazilian General Data Protection Law (LGPD), and the Protection of Personal Information Act (POPIA), has significantly influenced how storage and computing systems elevates the deployment of AgIoT [74]. These regulations emphasize the importance of data security and advocate for localized data processing, ensuring that sensitive agricultural data is handled responsibly and in compliance with local laws [75]. Research demonstrates Edge computing devices such as google coral and NVidia Jetson Nano addresses the limitations of traditional cloud computing by bringing computational resources closer to IoT devices, thus real-time decision-making. This is particularly beneficial in applications such as pest detection, soil quality assessment, on-site processing of large datasets, including sensor data and images, thereby minimizing dependency on centralized cloud infrastructures. In areas with intermittent or no internet access, edge computing proves highly advantageous [76]. This study also finds the importance of hybrid computing, where real-time data processing of aerial imagery is crucial for immediate decision-making and particularly effective in environments with unreliable connectivity, as they allow for local processing of data when possible [77].

In this study, we reviewed the comprehensive overviews of computing technology utilization trends in Agricultural IoT, emphasizing the dominance of cloud platforms like AWS (used in smart irrigation, livestock farming, and decision support), Microsoft Azure (prominent in crop monitoring), and Google Cloud (leveraged for crop prediction and pest detection) as in table 4. Edge and embedded devices, such as NVIDIA Jetson Nano (for drone-based monitoring), Raspberry Pi (cost-effective for irrigation and livestock tracking), and Google Coral (specialized in pest detection), play crucial roles in real-time processing. IoT frameworks like NoSQL databases (for unstructured sensor data), IBM Watson

Table 3. Typical communication technology utilized in smart agricultural (2020-2024)

Technology	Transmission Range	Power	Network	Data Rate	Frequency	Application	Ref
	Short-range communication						
Bluetooth Low Energy (BLE)	10–100 m	Very Low	PAN	1–2 Mbps	2.4GHz (Bluetooth 5.0)	Livestock tracking, handheld sensors	[57]
Zigbee (IEEE)	10–100 m (indoor)	Low	PAN	20-250 kbps	2.4GHz	Smart greenhouses, soil monitoring	[58]
Z-Wave	30–100m (indoor)	Low	Home Area Network	100 kbps	869-908MHz	Home/ Greenhouse automation	[59]
Wi-Fi	50–100 m (indoor)	High	LAN	54Mb–10 Gbps	2.4-5GHz	Farm automation, drone data	[60]
Near Field Comm. (NFC)	<10 cm (near field)	Ultra-Low	Shirt range commun.	106-424 kbps	13.56MHz	Livestock ID, payment systems	[61]
RF Modules	100 m–1 km	Low-Medium	Point-to-point	9.6– 115 kbps	433 MHz, 868 MHz, 915 MHz	Remote sensor, simple telemetry, irrigation	[62]
	Long-range communication						
LoRaWAN	2–15 km (rural)	Ultra-Low	WAN	0.3–50 kbps	868 MHz 915 MHz	Large farms, soil/ weather monitoring	[63]
NB-IoT (Narrowband IoT)	10-35km	Low-Medium	Cellular Network	20-250 kbps	800 MHz, 900 MHz	Govt. smart farming, irrigation projects	[64]
Sigfox	10–50 km (rural)	Ultra-Low	Cellular Network	100 bps	868 MHz, 902 MHz	Low-cost sensor networks	[65]
Cellular (4G/5G)	1–10 km (5G: <1 km)	High	Cellular Network	4G: 100 Mbps, 5G: 10+ Gbps	700MHz – 2.7 GHz (4G); 100 GHz (5G)	Real-time drone/video analytics	[66]
	Satellite communication						
Satellite (IoT)	Global	High		Variable (10–500 kbps)		Remote/desert farming	[67]
Ethernet	100 m (per segment)	Low (PoE)	LAN	10 Mbps–100 Gbps	-	Farm office/control centers	[68]
MQTT Broker	Depends on network (Wi-Fi/Cellular)	Low (if using LP-WAN)	Protocol for IoT	Depends network protocol	Depends network protocol	Cloud-based farm management	[69]

IoT (AI-driven analytics), and Siemens MindSphere/EdgeX Foundry are gaining traction. Hybrid approaches, combining cloud and edge computing (e.g., Azure IoT Edge, AWS Greengrass), optimize real-time decision-making but face trade-offs: cloud platforms excel in scalability and AI training, while edge devices reduce latency but struggle with computational limits. Emerging trends include the need for interoperability (avoiding vendor lock-in via open-source solutions like EdgeX Foundry), energy-efficient edge AI, and underutilized technologies like blockchain for supply chain transparency. Future research should explore 5G/LPWAN for rural connectivity and improved hybrid architectures to balance performance and scalability in smart farming.

4. APPLICATIONS TOWARD SMART AGRICULTURE

The adoption of smart agriculture through IoT technologies have been demonstrating substantial values in sustainable agriculture. Key applications include crop monitoring, precision farming, livestock management, automated irrigation, and pest and disease control, all of which leverage real-time data for optimized decision-making. In terms of sustainability, IoT-enabled agriculture resources optimizable by reducing water consumption by up to 51% [107] and minimizing excessive fertilizers and pesticides, promoting eco-friendly farming [108]. Smart sensors contribute to soil health management by providing moisture level, nutrient content, and pH balance data, ensuring long-term soil fertility and preventing degradation. From a food security perspective, IoT technologies help increase crop yields, with productivity improvements ranging 7% to 46% [109], depending on deployment.

4.1 Crop monitoring

IoT technologies have significantly altered crop monitoring, offering data-driven strategies that enhance productivity, and resource efficiency. The widespread adoption of IoT is expected to enhance crop monitoring, data analysis, and automation, making advanced farm solutions, allowing precise management of seeds, fertilizers, and pesticides to enhance yield efficiency. Crop health and yield predictions rely on spectral reflectance. Advanced automation integrates data collection, processing, and decision-making, enabling efficient farm management, including yield tracking, weather forecasting, soil nutrient monitoring, and field mapping [110]. The focus areas of IoT in crop monitoring include real-time data collection, enabling continuous monitoring of crop health and environmental factors. Efforts to improve scalability with the deployment of cost-effective, energy-efficient sensors and communication technologies like LoRaWAN and NB-IoT making IoT solutions more accessible to smallholder farmers [111]. We conducted a comprehensive review to assess the impact of IoT technology on crop monitoring using key

Table 4. Computing technologies utilized in smart agriculture (2020 up to 2024)

Agricultural IoT Projects	Amazon Web Services	Microsoft Azure	NoSQL database	Google Cloud	NVIDIA Jetson Nano	Arduino	IBM Watson IoT	Siemens MindSphee	EdgeX Foundry	Google Coral	Raspberry Pi	Ref.
IoT-Based Crop Yield Optimization	×	×	×	×	×	×	✓	✓	×	✓	×	[70]
IoT-based Smart Irrigation System	×	✓	×	✓	✓	×	×	×	×	×	×	[71]
NVIDIA Jetson Nano for Drone-Based Crop Monitoring	×	✓	×	×	✓	×	×	×	×	×	×	[72]
IoT-Based Crop Monitoring System	×	×	×	×	✓	×	✓	✓	×	✓	×	[73]
Smart Farming with IoT and AI	×	✓	×	×	×	×	✓	×	×	✓	×	[74]
Google Coral for Pest Detection	×	×	×	×	×	×	×	×	×	✓	×	[75]
Precision Livestock Farming system	✓	×	✓	×	×	×	×	×	×	×	✓	[76]
IoT-Enabled Soil Moisture Monitoring	✓	×	×	✓	×	✓	×	×	×	×	×	[77]
Raspberry Pi for Smart Irrigation	×	×	×	×	×	✓	×	×	×	×	✓	[78]
IoT for Soil Health Monitoring	×	✓	×	×	×	×	✓	×	×	×	×	[79]
IoT-Based Livestock Monitoring	×	×	×	×	×	×	×	✓	×	×	✓	[80]
IoT for Smart Irrigation and Fertilization	×	×	×	×	×	×	×	×	✓	×	×	[81]
Arduino for Livestock Monitoring	×	×	×	×	×	✓	×	×	×	×	×	[82]
Smart Farming with AWS IoT	✓	×	×	×	×	×	×	×	×	×	×	[83]
IoT-Based Farm Equipment Monitoring	×	×	×	×	×	×	×	×	✓	×	✓	[84]
Google Cloud for Crop Prediction	×	×	×	✓	×	×	×	×	×	×	×	[85]
IBM Watson IoT for Greenhouse Automation	×	×	×	×	×	×	✓	×	×	×	×	[86]
IoT for Agricultural Waste Management	×	×	×	×	×	×	×	×	×	✓	×	[87]
Remote Crop Monitoring with Edge Computing	×	✓	×	×	×	×	×	×	×	×	✓	[88]
Automated Crop Management System	×	×	×	×	×	×	×	×	✓	×	×	[89]
Siemens MindSphere for Farm Analytics	×	×	×	×	×	×	×	✓	×	×	×	[90]
IoT-Based Agricultural Climate Control	×	×	×	✓	×	×	×	×	×	×	×	[91]
Google Coral for Pest Detection	×	×	×	×	×	×	×	×	×	✓	×	[92]
IoT for Pest Detection in Agriculture	×	×	×	✓	✓	×	×	×	×	×	×	[93]
Raspberry Pi for Smart Irrigation	×	×	×	×	×	×	×	×	×	×	✓	[94]
Arduino for Livestock Monitoring	×	×	×	×	×	✓	×	×	×	×	×	[95]
Smart Water Management in Agriculture	×	×	×	×	×	×	×	×	✓	×	✓	[96]
AWS Greengrass for Smart Farming	✓	×	×	×	×	×	×	×	×	×	×	[97]
IoT for Crop Disease Prediction	×	×	×	×	✓	×	✓	×	×	×	×	[98]
Microsoft Azure IoT Edge for Crop Monitoring	×	×	×	×	×	×	✓	×	×	×	×	[99]
IoT-Based Fertilizer Optimization	×	✓	×	×	×	×	×	×	×	✓	×	[100]
Google Cloud IoT Core with Edge AI	×	×	×	✓	×	×	×	×	×	✓	×	[101]
IBM Edge Application for Farm Automation	×	×	×	×	×	×	✓	×	×	×	×	[102]
Siemens MindSphere with EdgeX Foundry	×	×	×	×	×	×	×	✓	✓	×	×	[103]
IoT for Agricultural Water Quality Monitoring	×	×	×	×	×	×	×	✓	×	×	×	[104]
IoT for Agricultural Energy Management	×	✓	×	×	×	×	×	×	×	×	✓	[105]
IoT-Based Farm-to-Table Tracking	×	✓	×	×	✓	×	×	×	×	×	✓	[106]

metrics, deployed IoT technology, scale, yield increase (%), water usage reduction (%), pesticide use reduction (%), data accuracy (%), and ROI (%). Primarily we studied the yield increase (%), representing the improvement of crop productivity attributed to IoT integration. Another critical variable was the water usage reduction (%) via leveraging optimized irrigation systems enabled by IoT devices, studies shown that many farms have been able to significantly reduce their water consumption. We also examined data accuracy (%) was another important aspect of our study which refers to the level of accuracy achieved in data collection and analysis that ensures better decision-making in crop management, from nutrient application to harvest timing. Lastly, we reviewed from the view of return of investment (RoI, %) which measures the economic benefit gained from implementing agricultural IoTs with respect to cost.

In this study, our comprehensive review analyzed the impact of 36 IoT projects on crop monitoring based on key performance metrics, yield increase, water usage reduction, data accuracy, and return on investment (ROI) as shown table 5. The findings indicate that agricultural IoT reveals significant performance metrics such as water usage reduction, data accuracy, yield increase, and return on investment (ROI). LoRaWAN and NB-IoT emerge as dominant technologies in large-scale deployments, particularly for crops like corn, wheat, and tomatoes, where they achieve high water sav-

Table 5. Comprehensive review of economic impacts of IoT in Crop Monitoring (2020 up to 2024)

Crop Type	Deployed IoT Technology	Deployment Scale	Water Usage Reduction (%)	Data Accuracy (%)	Yield Increase (%)	ROI (%)	Ref.
Rice	Zigbee	Small	16	89	12	58	[110]
Soybeans	Zigbee	Medium	14	84	7	36	[111]
Barley	Wi-Fi	Large	17	76.5	33	13	[112]
Tomatoes	LoRaWAN	Medium	21	91	15	38	[113]
Grapes	LoRaWAN	Small	15	85	3.7	30	[114]
Tomatoes	NB-IoT	Large	20	71	16	58	[115]
Corn	LoRaWAN	Medium	24	93	20	42	[116]
Soybeans	Zigbee	Small	18	78.2	15	34	[117]
Cotton	Wi-Fi	Medium	61	57	18	37	[118]
Barley	LoRaWAN	Large	23	92	1.75	52	[119]
Grapes	Wi-Fi	Medium	16	81	12.1	31	[120]
Barley	Zigbee	Large	54	89	20	44	[121]
Lettuce	Wi-Fi	Medium	22	78.92	18	11	[122]
Spinach	NB-IoT	Small	39	88	46	34	[123]
Peas	LoRaWAN	Large	15	92	20	43	[124]
Apples	Zigbee	Medium	26	90	22	44	[125]
Spinach	NB-IoT	Small	6	88	16	34	[126]
Corn	NB-IoT	Large	25	72.8	20	53	[127]
Wheat	LoRaWAN	Large	51	62	9.2	21	[128]
Grapes	NB-IoT	Medium	16	91	21	42	[129]
Potatoes	Wi-Fi	Large	22	51	19	37	[130]
Lettuce	Zigbee	Medium	83	87	18	33	[131]
Wheat	LoRaWAN	Large	31	92	7	14	[132]
Wheat	NB-IoT	Large	9	81.5	21	48	[133]
Corn	LoRaWAN	Large	28	95	44	50	[134]
Rice	NB-IoT	Medium	27	91	12	49	[135]
Cotton	LoRaWAN	Large	32	68	26	35	[136]
Grapes	NB-IoT	Medium	51	80	21	56	[137]
Barley	Zigbee	Large	24	91	20	44	[138]
Lettuce	Wi-Fi	Medium	12	77.8	8	41	[139]
Potatoes	NB-IoT	Medium	23	92	61	76	[140]
Tomatoes	LoRaWAN	Large	64	74	78	58	[141]
Grapes	NB-IoT	Medium	25	54.67	21	45	[142]
Wheat	NB-IoT	Large	30	94	3.9	22	[143]
Peppers	Zigbee	Small	24	79	41	49	[144]
Grapes	LoRaWAN	Large	30	94	25	58	[145]

ings (20–64%) and notable yield improvements (16–78%) while these long-range, low-power networks are well-suited for expansive fields, offering reliable connectivity with data accuracy often exceeding 90% [119][127]. Meanwhile, Zigbee and Wi-Fi are more common in small-to-medium-scale deployments (e.g., rice, soybeans, lettuce), where they deliver moderate efficiency gains (12–26% water reduction) [118][122][131].

A key observation is the trade-off between scalability and ROI. While NB-IoT and LoRaWAN deployments in large farms show strong ROI (up to 58–76%)[170][141], some Wi-Fi-based systems (e.g., barley, lettuce) exhibit lower profitability (11–37%)[112][122], possibly due to network performance and higher infrastructure costs. Conversely, small-scale Zigbee systems (e.g., peppers, spinach) demonstrate surprisingly high yield increases (41–46%), suggesting that IoT adoption in controlled environments (greenhouses, small plots) may offer disproportionate benefits [125][144]. Data accuracy varies widely (54.67–95%), with NB-IoT and LoRaWAN generally outperforming Wi-Fi, particularly in large-scale applications. However, outliers like cotton (57–68% accuracy with LoRaWAN/ Wi-Fi) indicate that crop-specific factors (e.g., dense foliage, irrigation methods) may impact sensor reliability. Yield improvements also differ significantly, with potatoes (61%) [140] and tomatoes (78%) [141] showing the highest gains, likely due to precise irrigation and nutrient management. In this study, as the key insights and future directions we identified that technology selection, crop specificity, data accuracy and RoI consideration were the main factors must be considered in smartening agriculture.

4.2 Precision Farming

Real-time environmental monitoring- One of the foundational applications of IoT in precision farming is real-time environmental monitoring. IoT systems utilize a network of sensors (soil moisture, temperature, humidity, and light) that continuously track the conditions of the farm. Studies have shown that by using WSNs and edge computing, IoT devices can transmit real-time environmental data to a central server, allowing farmers to monitor conditions remotely. Recent studies reveal the role of weather stations, microclimate monitoring, and soil sensors in creating a comprehensive environmental profile of farmlands. Smart soil moisture sensors optimize irrigation systems by providing accurate readings of moisture content, thus preventing water wastage and ensuring the right amount of water. Nowadays, this sensor has become increasingly critical as water scarcity becomes a pressing issue in agriculture [146][147]. Optimizing resource usage- The integration of IoT into precision farming is particularly impactful in the optimization of resources such as water, fertilizers, and energy. By collecting data from various IoT devices, farmers can employ precision irrigation, fertilizer application, and energy management systems to improve productivity while minimizing waste. Researches have ex-

plored how IoT-based planting systems equipped with GPS and sensor technology can automate the planting process. These systems adjust planting depth, spacing, and seed quantity based on the real-time conditions of the field. Precision planting not only improves crop yields but also reduces the competition between plants for resources, leading to healthier crops [147][148].

4.3 Livestock management

Between 2020 and 2024, wearable sensors track vital health parameters, enabling early disease detection and timely interventions, reducing morbidity and mortality [183&194]. GPS and RFID systems enhance livestock tracking, while geofencing improves herd management in extensive grazing. Environmental sensors optimize barn conditions, boosting welfare and resource efficiency. Automated feeding systems enhance nutrition, minimize waste, and cut costs. Energy-efficient devices and communication protocols like LPWAN and LoRaWAN improve accessibility in feeding, milking, and cleaning, reducing labor costs 185/188 that enhance real-time monitoring and strengthens livestock health and resilience.

In this study, our review analysis confirms that IoT advancements are renovating livestock management through measurable improvements in productivity, health monitoring, and resource efficiency as shown in table 6. In dairy cattle [149][1163], wearable health sensors like accelerometers and rumen monitors have achieved a 15-20% ROI, delivering a 15-20% increase in milk yield (2.5-3.5 L/day per cow), 92% accuracy in early disease detection, and optimized feed intake through real-time monitoring. For sheep [150][164] and goats[152][153], smart collars with GPS/RFID and Zigbee-based movement sensors show an 8-32% ROI, providing 88-95% predator detection accuracy (reducing lamb mortality by 25%), 32% ROI in disease tracking for goat herds, and 15% improvement in reproductive success through behavior analytics. Poultry [151][155] operations utilizing Wi-Fi-enabled smart coops and automated feed systems report 18-25% ROI, with 25% higher egg production through environmental control, 18% reduction in feed waste, and 15% lower mortality rates from early disease alerts. In pig farming [154][168], automated smart feeding systems yield 20-24% ROI by improving feed efficiency by 20-24% and supporting 1.2 kg/day growth rates through optimized nutrition.

Aquaculture [193] has benefited from underwater IoT sensors monitoring pH and oxygen levels, achieving 28-48% ROI through 48% returns in automated fish feeding and 30% faster growth rates via real-time water quality adjustments. Beekeeping innovations include smart hive monitors that deliver 10-30% ROI by increasing honey yield by 30% and preventing colony collapse through early disease detection. For horses [157] and beef cattle [164], wearable GPS trackers and RFID tags show remarkable ROI ranges (3-54%), with racehorses achieving 54% ROI through injury prevention analytics and beef cattle improving grazing efficiency by 3-15%.

4.4 Irrigation Automation

The UN Convention to Combat Desertification (UNCCD) warns that by 2030, 168 countries will face severe desertification, and nearly half of the global population already resides in areas with high water scarcity [171]. This review explores the impact of IoT technologies on precision irrigation that optimize water conservation. These components work together to monitor soil conditions and optimize water distribution, allowing farmers to remotely manage irrigation ecosystem [172]. Enhancing water conservation and efficiency- A-IoT enables precise irrigation, ensuring that water use efficiency, preventing overuse and minimizing wastage [173]. Various studies demonstrate that modern smart irrigation integrate multiple IoT components to achieve significant improvements in water efficiency and crop productivity. These systems employ sensor networks utilizing soil moisture sensors (capacitive, tensiometric) with $\pm$2-5% accuracy, in conjunction with microclimate sensors that measure evapotranspiration, temperature, and humidity [174]. The communication infrastructure typically incorporates protocols like LoRaWAN and NB-IoT, which have been shown to reduce energy consumption by 60% compared to traditional cellular networks while maintaining 5-15 km coverage ranges [175]. Advanced control systems leverage cloud platforms (AWS IoT, ThingSpeak) and ML-algorithms to enable predictive irrigation, with studies demonstrating 25-40% reductions in water usage [176]. This empirical study show water use efficiency of 21-48% gains compared to conventional irrigation, along with 15-30% crop yield increase achieved through optimized watering schedules [177]. The economic benefits are equally compelling, with labor cost reductions of 30-50% through automation and system payback periods typically ranging from 12-36 months in commercial deployment [178]. We also reviewed that IoT-based irrigation reduces excessive energy consumption in traditional systems by optimizing pump operations and enabling smart irrigation scheduling. It integrates automated valve control, real-time monitoring, and demand-based load adjustments to enhance efficiency.

4.5 Soil health monitoring

In this study, we swotted agricultural IoT for soil health monitoring has evolved from conceptual pilots to field-ready solutions, demonstrating 18–51% resource savings and 14–32% yield gains. Electrochemical sensors have emerged as a reliable solution for measuring pH and macronutrients (Nitrogen, Phosphorus, Potassium) with $\pm$5% accuracy, which are complemented by capacitive moisture sensors that monitor volumetric water content with $\pm$3% error [179] as shown in Fig.3. For organic matter assessment, spectroscopic sensors utilizing near-infrared (NIR) and mid-infrared (MIR) wavelengths provide non-destructive organic carbon estimation [180], offering users critical data for sustainable soil management. The effectiveness of soil monitoring system depends heavily on communication infrastructure. LoRaWAN dominates rural applications due its long-range (10-15 km) and low-power aptitudes, making it ideal for extensive farms while NB-IoT has become preferred for high-resolution data transmission due to its superior bandwidth [181].

The widespread adoption of IoT in soil health monitoring offers several key benefits that not only improve agricultural productivity but also promote environmental sustainability and economic viability. We reviewed that recent implementations demonstrate that precision nutrient management has achieved 28% reductions in fertilizer use through NPK-sensor-guided applications [182], while IoT-driven pH balanc-

Table 6. Comprehensive review of IoT-based livestock management and outcome (2020 up to 2024)

Livestock	IoT Technology	Application	ROI (%)	Key Metrics	Ref.
Dairy Cattle	Wearable health sensors	Health monitoring, milk yield optimizer	15	Milk yield (liters/day), health alert accuracy (%), feed intake	[149]
Sheep	Smart collars	Grazing management, predator detection	12	Grazing hours/day, predator detection accuracy (%)	[150]
Poultry	Wi-Fi	Feed Monitoring	18	Egg production rate (%), feed-to-weight ratio, mortality rate (%)	[151]
Goats	Zigbee	Movement Detection	15	Disease detection rate (%), reproductive success (%),	[152]
Goats	RFID and biosensors	Disease detection, herd management	8	Disease detection rate (%), fertility rate (%), grazing patterns	[153]
Pigs	Smart feeding	Feed optimization, growth monitoring	20	Feed-to-weight ratio (%), growth rate (kg/day), mortality rate	[154]
Poultry	Smart coop monitor	Environmental monitor, egg production	25	Egg production rate (%), mortality rate (%), feed efficiency (%)	[155]
Buffalo	Water quality sensors, GPS trackers	Water usage efficiency, grazing optimization	22	Grazing distance (km/day), water intake (liters/day)	[156]
Horses	Wearable trackers	Performance monitoring, injury prevention	14	Heart rate (bpm), recovery time (minutes), gait efficiency (%)	[157]
Bees	Smart hive monitors	Honey production, hive health management	31	Hive temperature (°C), honey yield (kg/hive), colony activity (%)	[158]
Aquaculture	Underwater sensors, smart buoys	Water monitoring, feeding automation	28	pH levels, dissolved oxygen (mg/L), fish growth rate (g/week)	[159]
Horses	Wearable trackers	Performance monitoring, injury prevention	54	Heart rate (bpm), recovery time (minutes), gait efficiency (%)	[160]
Bees	Smart hive monitors	Honey production, hive health management	30	Hive temperature (°C), honey yield (kg/hive), colony activity (%)	[161]
Aquaculture	Underwater sensors, smart buoys	Water monitoring, feeding automation	28	pH levels, dissolved oxygen (mg/L), fish growth rate (g/week)	[162]
Dairy Cattle	Wearable health sensors	Milk yield optimization, health monitoring	20	Milk yield (liters/day), feed intake accuracy (%), health alerts	[163]
Beef Cattle	GPS and RFID tags	Grazing optimization, herd tracking	3	Grazing efficiency (%), location accuracy, disease detection rate	[164]
Sheep	Smart collars	Predator detection, behavior tracking	15	Predator detection accuracy (%), survival rates (%), grazing hrs	[165]
Poultry	Smart coop monitor	Environmental control, egg production	19	Feed-to-weight ratio, mortal rate (%), Egg production rate (%),	[166]
Goats	RFID, health monitor	health management, disease tracking	32	Disease detection rate (%), reproductive success (%), feed	[167]
Pigs	Automated feeding systems	Feed optimization, weight monitoring	24	Growth rate (kg/day), feed efficiency (%), health rate	[168]
Bees	Smart hive monitors	Honey production, hive health tracking	10	Honey yield (kg/hive), hive activity levels (%), temperature (°C)	[169]
Aquaculture	IoT buoys, underwater sensors	Water quality, feeding automation	48	pH levels, oxygen concentration (mg/L), fish growth rate (g/week)	[170]

ing has boosted wheat yields by 26% in multiple studies [183]. Water conservation efforts have been particularly successful, with soil moisture-based systems reducing water waste by 34-49% [184] and salt accumulation alerts preventing 19% crop losses in arid regions [185]. Perhaps most impressively, the integration of IoT with remote sensing now enables 90% accurate quantification of soil organic carbon [226], supporting global carbon sequestration efforts. Case studies from diverse agricultural regions demonstrate the adaptability of these technologies. In California almond farms, LoRaWAN

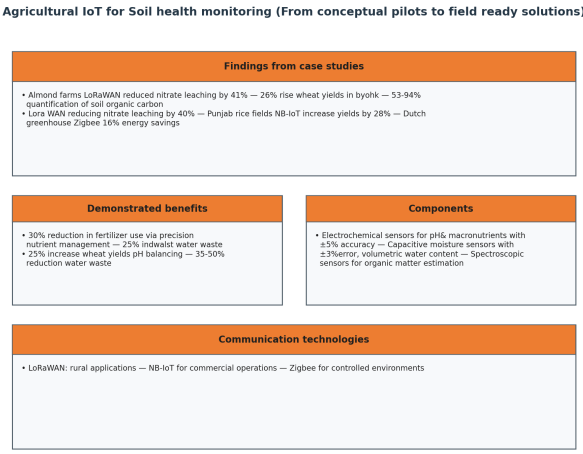


Figure 3. Illustrative key finding of practical IoT based soil health monitoring applications

combined with multispectral imaging reduced nitrate leaching by 40% [187]. Punjab's rice fields saw 28% higher yields after implementing NB-IoT pH monitoring systems [188]. Dutch greenhouse operations achieved 16% energy savings through Zigbee networks paired with edge computing [189].

4.6 Pest and disease control

Modern agriculture faces unprecedented challenges from pests and diseases, with studies documenting potential yield losses exceeding 40% in staple crops like wheat, rice, and maize. Studies demonstrate that IoT solutions enable earlier detection (typically 5-14 days before visual symptoms appear), reduce pesticide usage by 43-82%, and improve treatment precision through targeted interventions [230/190]. Contemporary IoT systems employ multi-modal sensor arrays to detect biotic stresses with unprecedented accuracy. Multispectral imaging sensors deployed on drones and fixed stations can identify crop stress signatures with 85-92% accuracy, often 5-7 days before human-visible symptoms [191]. Electronic nose (e-nose) arrays have shown particular promise in detecting volatile organic compounds (VOCs) associated with specific pathogens, achieving part-per-billion sensitivity for diseases like potato late blight. For insect pests, acoustic sensors monitoring the 200-800 Hz frequency range can identify chewing insects like corn borers with 78% accuracy [192]. For real-time insect activity monitoring, acoustic sensors provide a cost-effective solution, detecting pest sounds (e.g., chewing, movement) with 78% accuracy and reducing pesticide use by 40%, with the shortest ROI period of just 12 months due to their low deployment costs. At the cutting edge, autonomous laser systems offer unparalleled precision, eliminating target pests with 97% accuracy while slashing chemical reliance by 85%, though their high initial investment results in a longer ROI of 36 months [193]. Emerging nanofluidic delivery systems represent a breakthrough in precision treatment, though they do not directly contribute to pest detection. Instead, they enable 89% reductions in pesticide volumes by releasing targeted doses only when triggered by IoT alerts [194].

In this study, we reviewed that many countries gained from their IoT based pest and disease control investments. To illustrate, China vineyards have demonstrated the economic viability of IoT systems, where a network of 120 nodes per hectare monitoring microclimate conditions achieved 65% reduction in fungicide applications while maintaining 99% disease prevention efficacy. This French case study reported full system payback within 14 months through €220/ha annual savings [195]. In tropical agriculture, Brazilian soybean farms utilizing solar-powered smart traps with edge-based image processing reduced fall armyworm monitoring labor by 76% while achieving 91% species identification accuracy [195]. Dutch greenhouse operation has pushed the boundaries of biological control, combining hyperspectral imaging with automated beneficial insect releases to reduce chemical use by 82% while maintaining pest suppression through ecological balancing [196]. Autonomous laser systems now achieve 97% pest targeting precision while consuming just 5W/target, compared to 50W for conventional electrical zappers, though current effective range remain limited to 15m [197]. Nanofluidic phytohormone delivery devices represent another leap forward, responding to IoT disease alerts within 4-6hr (versus 3-5days for conventional spray) and demonstrating 89% efficacy against bacterial spot in tomato pilot trials [198].

5. BARRIERS TO IMPLEMENTING AGRICULTURAL IOTS

During our review, we also identified challenges faced IoT-based smart agriculture including high initial costs, infrastructure, data and operational barriers [199] as shown in figure 4.

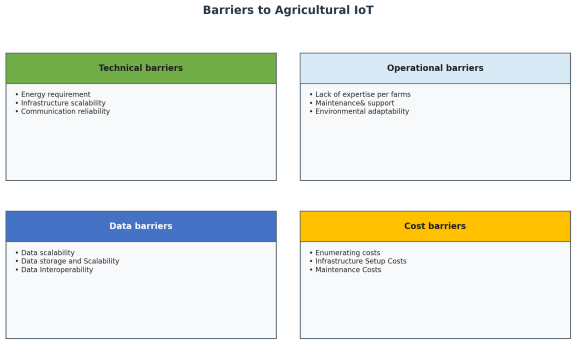


Figure 4. Barriers to Agricultural IoT

Cost barriers: - in this study, we reviewed that costs of modern infrastructures, present financial challenges for wide deployment of agricultural IoT, especially for smallholder farmers. Enumerating cost is a deterrent, as farmers often underestimate expenses related to software subscriptions, training and upgrades. The agricultural IoT technologies like sensors, satellites and actuators are expensive, along with maintenance fees. Ongoing expenses, including technical support, software updates, energy supply and communication networks particularly in off-grid areas also contribute to the financial burden. In this study, we found that one key solution to reduce agricultural-IoT costs is the adoption of low-cost, open-source such as Raspberry Pi and Arduino, relatively affordable. Another major cost factor is also cloud storage and data transmission. By processing data locally with Edge AI, LoRaWAN and Sigfox offer cost-effective connectivity

compared to others [200]. Operational barriers: - a critical challenges in implementing agricultural IoT technologies is the lack of expertise amidst farmers. Many lacks the technical skills to operate complex systems, leading to underutilization or improper integration. We also reviewed maintenance and support remain major hurdles, as the rural areas often lack access to skilled technicians. Another pressing issue is environmental adaptability of agricultural IoT hardware as many technologies aren't designed to withstand harsh farming conditions; extreme weather, dust, and over moisture can degrade performance [201]. hardware durability, energy supply, communication reliability due to poor network and interoperability calibration contribute to device failures, increased operational costs and inefficiencies. Establishing localized networks, AI-driven predictive maintenance and developing, ruggedized, weather resistant hardware solutions easily improve reliability [202].

Data barriers:- as agriculture generates increasing amounts of data from sensors and monitoring systems, its scalability becomes a critical issue. Many existing platforms struggle to process large datasets efficiently, necessitating edge computing and cloud-based solutions. Data storage and management also pose challenges as vast amounts of agricultural data (soil health, weather patterns, crop yields) require secure, scalable storage. Real-time processing is essential for timely agricultural decisions, but latency remains a challenge, especially in remote areas. Standardized protocol (AgGateway's ADAPT, FAO's OADA) are essential to enable cross platform data sharing and analytics [203]. Technical barriers: - energy requirement present a significant hurdle, particularly in off-grid farming regions, where continuous power in unreliable. Solar powered devices, energy efficient sensors and low-power wide area network (LpWAN) were believed mitigate. Hardware scalability is another concern, as deploying and managing numerous sensors and automated machinery across large farms is complex, modular, plug-and-play design can simplify expansion. Finally, communication reliability remains chaos in rural areas with poor network. For energy supply in remote areas, energy harvesting technologies such as solar, wind, and kinetic energy, along with low-power devices using protocols like LoRaWAN or NB-IoT and efficient energy storage. Communication reliability in rural areas can be improved by using hybrid networks combining satellite, cellular, and LPWA technologies [204].

6. DISCUSSION

In this study, we conducted a systematic review to examine the role of Agricultural IoT in promoting sustainable agriculture and food security published between 2020 and 2024, excluding non-peer-reviewed, repetitive, and irrelevant publications. After filtering, 203 studies were selected for review analysis into three main areas: agricultural applications, IoT technologies, and barriers to IoT implementation as drawn in Fig. 5, highlights the distribution of reviewed articles across various fundamental domains of Agricultural IoT. We examined fourteen(14)-articles of Agricultural IoT-controllers, focusing on their role in automating key processes like irrigation, precision farming, and livestock management. It also examined 10 articles on sensors, emphasizing their importance for monitoring environmental and soil conditions. Additionally, 8 articles on communication and 11 on computing technologies highlighted the significance of data transmission and processing in Agricultural IoT, with a need for further improvement in communication protocols and network efficiency. The review covered various IoT applications, including crop monitoring (23 articles), soil health monitoring (21 articles), and livestock management (17 articles), showing widespread adoption for improving productivity.

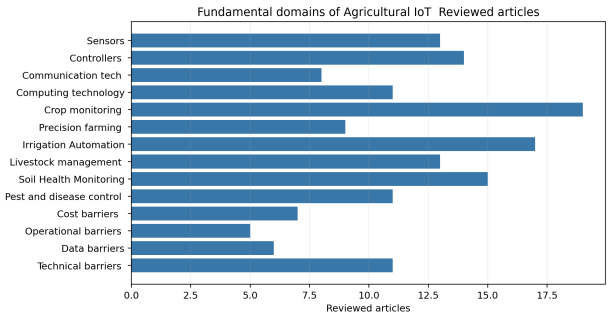


Figure 5. Distribution of reviewed Articles across Fundamental Agricultural IoT domains

Key areas for optimization included irrigation automation and precision farming (both 14 articles). About 15-articles examined pest and disease control, showcasing Agricultural IoT's role in early enhancing crop health and productivity. Moreover, this study also identified several barriers hindering the widespread of Agricultural IoT, particularly for remotely located and small-scale farmers. These include cost factors (7 articles), Technical barriers (11 articles), data barriers (6 articles) and operational barriers (5 articles) were reviewed. To mitigate these barriers, the study examined several approaches. This includes adopting subscription-based service models, customizing open-source platforms, and utilizing solar-powered devices. Additionally, weather-resistant hardware for durability, efficient data management through lightweight compression techniques, is crucial for overcoming bandwidth limitations.

In this study we also identified the adoption level of agricultural IoT controllers in which the data swotted the growing of agricultural IoT due to their automation capacity and smartening data management as shown in figure 6. Among the most widely used controllers, MCUs (Microcontroller Units) and SBCs (Raspberry Pi) stand out. The MCU has shown a notable rise in adoption, particularly from 2021 onward, reaching nearly 50 projects by 2024. The adoption of single-board-computers (SBCs) including the Raspberry Pi, has grown consistently over time, making them one of the most commonly utilized controllers in agricultural applications due to their versatility, and ease of use.

In this study, we studied ESP8266 and ESP32 have also seen increasing adoption, especially from 2021 onwards offering cost-effective and efficient solutions for wireless communication, making them ideal solutions for smart agriculture [42][44]. Their built-in Wi-Fi capabilities make them attractive options for IoT developers working on agricultural projects that require real-time data transmission and remote monitoring. The adoption of PLCs and Edge controllers has shown significant growth, particularly in 2023 and 2024. This study found that PLCs are increasingly ideal due to reliable

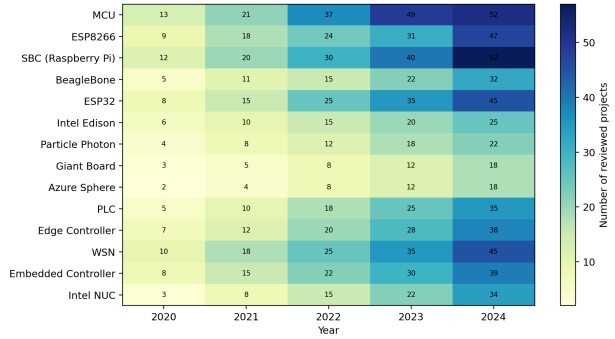


Figure 6. Reviewed data on Controller technology utilized in Smart agriculture (2020-2024)

agricultural automation, ensuring stable performance in harsh environment [46][51]. Several emerging controllers, such as Azure Sphere, Giant Board, and Intel Edison, have started gaining traction, although their adoption remains relatively lower compared to other controllers [47][50][55]. The usage of Azure Sphere has notably increased in 2023 and 2024, reflecting a shift towards secure IoT-based farm solutions that prioritize cybersecurity and data integrity. WSNs have become vital in large-scale agriculture by supporting efficient data collection and communication, with a notable increase in adoption since 2020, peaking in 2024. Subsequently, this study examined recent advancements in IoT communication technologies that underpin smart agricultural systems as illustrated in Fig 7. Accordingly, various communication technologies such as LoRaWAN, SigFox, and Zigbee have made substantial strides with respect to minimum energy consumption, in off-grid environments.

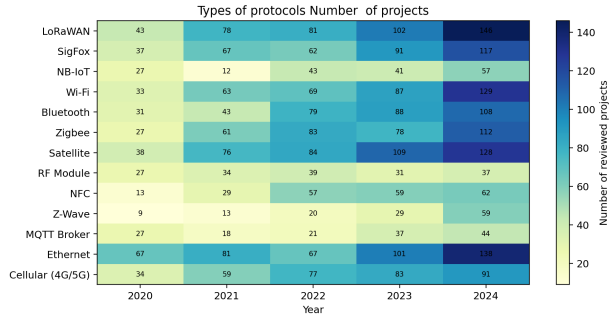


Figure 7. Reviewed data on Communication technology utilized in smart agriculture (2020-2024)

In this study, the five-year trend analysis of IoT communication technologies highlights a dynamic shift in preferences, driven by application needs and technological advancements as shown in figure 2. LoRaWAN emerges as a dominant force, showing a sharp increase in 2024. Its scalability, energy efficiency, and long-range capabilities likely contributed to this rise, making it ideal for agricultural deployments. Similarly, Satellite communication experienced notable spikes in 2020 and 2024, indicating its strategic importance in remote and globally dispersed IoT networks, despite its higher cost and latency. NB-IoT shows steady growth, reflecting increasing adoption in smart cities and metering applications, where emerging technologies like NFC, Z-Wave, and MQTT Broker protocols show gradual increases in usage, but expanding applications in smart home systems, proximity-based services, and lightweight IoT messaging frameworks. In contrast, SigFox shows a declining pattern after 2021. Ethernet retains modest but steady growth, likely due to its continued relevance in fixed infrastructure settings. Finally, Cellular (4G/5G) technologies show clear upward momentum, particularly in 2024, indicating broader adoption in mobile and high-speed use cases, fueled by the global rollout of 5G networks. Wi-Fi and Bluetooth maintain moderate but stable usage throughout the years that their ease of integration in consumer devices keep them relevant, although challenges such as limited range (Bluetooth) and high-power consumption (Wi-Fi) may limit their expansion in large-scale.

6.1 Proposed Comprehensive IoT-based Framework for Smart Agriculture

Within the scope of this study, an IoT based Smart agriculture framework has been proposed as in Fig. 8 below consisting 5-key components, which are system management, data visualization, data acquisition, common platforms and data processing.

The data acquisition component employs a converged a comprising both wired (controller area network-CAN) and wireless (LoRa, ZigBee, Nb-IoT, Bluetooth) communication technologies meanwhile a wide area network-WAN technology, including 4G and emerging 5G networks enhance data transmission speeds, network control, and energy efficiency. The leapfrog of 5G, particularly enables real time agricultural monitoring with high speed connectivity. Computing platforms serve as the backbone for data storage, statistical analysis and decision-making via utilizing i) edge computing, ii) cloud computing and iii) big data analysis. The big data technology enables predictive analysis by identifying patterns within agricultural datasets supporting functions such as agricultural image processing, statistical modelling, simulation and early warning systems. Cloud computing offers scalable software, hardware and infrastructure services reducing storage costs for farmers by managing large datasets (videos, images, and sensor data). However, while cloud platforms enhance decision making through expert driven quantitative analysis challenges such as internet dependency and power constraints limit their reliability in remote farming areas. Edge computing addresses these limitations by processing data locally, reducing latency, improving transmission speeds and enhance data security. It is particularly beneficial for real time agricultural monitoring, where immediate data processing is crucial. Data processing module constitute diverse audio, video text, and image processing tailored diverse techniques to system requirements. The flexibility ensures adaptability across different agricultural applications from crop disease detection to livestock health monitoring. Data visualization which is functional for real time monitoring and control enhances farm management via monitoring (tracking environmental conditions, crop growth soli health and animal wellbeing), controlling (automating pest management, fertilization and greenhouse conditions) and tracking/tracing (livestock and field locations. These functions are managed via centralized controller ensuring seamless integration with system management module. The system management component incorporates sensors, and air vehicles to automate agricultural processes used to collect information about different agricultural variables and this collected information



Figure 8. IoT enriched Smart Agriculture Framework.

were processed through embedded devices to make the proper analysis. This framework lays a strong foundation for smart agriculture contributing to sustainable farming practices, resource efficiency and improved crop yields.

6.2 Theoretical and Practical Implication

The findings of this systematic review extend beyond summarizing Agricultural IoT technologies by providing important theoretical insights into digital agriculture and technology adoption. The observed rapid increase in the adoption of controllers such as Raspberry Pi, ESP32, and edge computing platforms demonstrates that Agricultural IoT is evolving from isolated automation solutions toward integrated cyber-physical agricultural ecosystems. This evolution aligns with the smart farming ecosystems, where sensing, communication, computing, artificial intelligence, cloud platforms, and decision-support systems function as interconnected components that collectively improve agricultural productivity, sustainability, and resilience. From the perspective of the Diffusion of Innovation (DOI) Theory, the increasing adoption of

technologies such as LoRaWAN, NB-IoT, Raspberry Pi, and edge computing can be explained by their relative advantage, compatibility, simplicity, trialability, and observability. Technologies offering long communication range, lower energy consumption, reduced implementation costs, and compatibility with existing agricultural infrastructures are more rapidly adopted than alternatives with higher deployment costs or greater technical complexity. The decline in the adoption of some communication technologies, such as SigFox, also reflects how technological competition and ecosystem maturity influence innovation diffusion within smart agriculture.

The findings of this review are also consistent with the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT). The increasing implementation of Agricultural IoT solutions indicates that farmers and agricultural stakeholders are more likely to adopt technologies when they perceive clear performance benefits, including improved crop productivity, water conservation, labor reduction, and better decision-making. However, the barriers identified in this review including high implementation costs, limited digital skills, unreliable rural communication infrastructure, and insufficient technical support represent significant constraints on perceived ease of use and facilitating conditions, thereby limiting widespread technology adoption, particularly among smallholder farmers. Furthermore, this review supports the Socio-Technical Transition perspective, which argues that technological innovation alone cannot transform agricultural systems. Successful digital transformation requires coordinated changes across technology, infrastructure, institutions, policy, education, and market ecosystems. The reviewed studies consistently indicate that smart agriculture depends on reliable communication infrastructure, affordable computing platforms, cybersecurity, farmer training, extension services, and supportive government policies. Consequently, Agricultural IoT should be viewed as part of a broader digital transformation process rather than merely as a collection of connected sensing devices.

The proposed IoT-based Smart Agriculture Framework reflects this ecosystem-oriented perspective by integrating sensing technologies, communication networks, edge and cloud computing, big-data analytics, artificial intelligence, visualization platforms, and automated control systems into a unified architecture. Unlike many existing studies that focus on individual technologies, the proposed framework illustrates how these components interact to support real-time monitoring, predictive analytics, precision decision-making, and sustainable resource management. This integrated approach contributes to climate-smart agriculture by improving water-use efficiency, reducing unnecessary fertilizer and pesticide application, enhancing livestock management, and strengthening food security. Finally, this review identifies several future research directions. Greater emphasis should be placed on interoperable IoT architectures, Edge AI, federated learning, digital twins, explainable artificial intelligence, cybersecurity, and low-cost solutions specifically designed for resource-constrained farming environments. Future research should also investigate socio-economic factors affecting technology adoption, evaluate long-term field performance under diverse climatic conditions, and develop standardized benchmarking protocols that enable meaningful comparisons across Agricultural IoT studies. Such efforts will accelerate the transition toward scalable, sustainable, and resilient digital agriculture.

7. CONCLUSION

This article has provided an overview of agricultural IoT in smart agriculture, discussing key agricultural IoT technologies, applications and barriers to agricultural IoT deployment in between 2020 and 2024. Employing a rigorous methodological approach, the review synthesizes findings from 203 selected studies with its empirical evidence from the literatures demonstrates that sensing technology, automated system and data driven decision making patronized improve agricultural productivity while optimizing resources. Apart from this, all major components of IoT based Smart agriculture have been contextualized in a clear framework.

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