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Review Article

Internet of Things in Agriculture: A Systematic Review of Technological Innovations, Implementation Challenges, and Future Trends

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Abstract

The Internet of Things (IoT) has reshaped traditional farming practices, providing unprecedented opportunities to overcome the increasing threats to world food security, resource scarcity, and climate unpredictability. The present paper provides an overall review of IoT applications in agriculture based on the latest research. The review summarizes the findings of various studies to examine the technological basis, deployment architectures, and applications of IoT-enabled smart farming systems. Applications of particular importance include precision irrigation, soil health monitoring, crop disease monitoring, livestock management, and supply chain optimization. The analysis shows that some major trends include the deployment of multimodal data fusion architectures based on the discontinuation of unimodal sensing, the application of artificial intelligence to predictive analytics, and the development of edge-to-cloud computing models. The main challenges are limited connectivity in rural locations, unreliable power supply, data vulnerability to attacks, and the high initial deployment costs. The paper concludes with strategic suggestions for future research and development. These include providing context-specific solutions to suit resource-limited conditions, adopting standardization and interoperability measures, and developing security measures that can facilitate the sustainable use of IoT technologies in global agriculture.

Categories: Agricultural technology (machinery, remote sensing), Sustainable climate smart agriculture

Keywords: internet of things, data fusion, edge computing, food security, smart agriculture, precision farming, disease monitoring, artificial intelligence

Introduction And Background

The global agricultural system is experiencing unprecedented challenges at the convergence of demographic pressure, climate variability, and resource scarcity. The human population is expanding significantly, which requires food production to increase considerably [1]. This is further complicated by the fact that arable land is decreasing, water scarcity is increasing, weather patterns are becoming unpredictable due to climate change, and there is a necessity to minimize the environmental impact of agriculture [2]. Agricultural activities contribute to about 70% of global freshwater withdrawals, and therefore, water-use efficiency is a major issue, especially in arid and semi-arid areas [1]. Although traditional farming methods have contributed to the survival of civilizations throughout the millennia, they are becoming incapable of addressing these overlapping needs.

Digital agriculture has become a new paradigm in response to these existential threats that harmonize modern information technology and agricultural production [3]. The Internet of Things (IoT) has emerged as one of the primary digital technologies of smart farming among a host of other digital technologies. IoT allows the limitation-free connection between physical objects, sensors, actuators, machinery, and livestock, forming smart systems that are able to detect, analyze, and act on live conditions on the farm [4,5]. IoT technologies provide opportunities to increase productivity, optimize the use of resources, decrease environmental footprint, and increase profitability by converting traditional farms into data-driven enterprises [6,7]. Market projections indicate the strategic value of IoT in agriculture. The global smart farming market is expected to grow from an estimated 6.5 billion in 2019 to 21 billion in 2030 [8]. This trend highlights the growing awareness among farmers, agribusinesses, and policymakers that digital transformation is necessary to achieve sustainable agricultural development.

Digital agriculture emerged as a response to such challenges as global population growth, climate change, water scarcity, loss of arable land, and the necessity to reduce the environmental footprint of agriculture. These factors affect both large-scale, capital-intensive production and small-scale local farming. Households and regions dependent on climate-sensitive agricultural production and lacking access to water, electricity, connectivity, and technical expertise are particularly vulnerable in terms of food security. IoT is one of the key concepts in smart agriculture that unites various sensors, actuators, equipment, and livestock. Multiple papers have been written on the application of IoT in precision farming, irrigation, crop monitoring, the detection of plant pathogens and pests, livestock management, and the traceability of agricultural products. For this reason, this paper discusses technological progress in IoT alongside the conditions for its introduction that determine the degree of its impact in different environments.

Research objectives

The objective of this paper is to present a systematic review of the use of IoT in agriculture based on studies published over the last 15 years. An overview of the research is informed by the following research objectives:

1. To investigate the basics and designs of IoT systems used in agricultural settings.

2. To define and classify the most important applications of IoT technologies in the agricultural value chain.

3. To examine new trends, such as multimodal data fusion, artificial intelligence integration, and the edge computing paradigm.

4. To assess the issues and obstacles to the adoption of IoT, especially in resource-limited settings, and to suggest future research and development strategies.

Review

In the agricultural sector, researchers have suggested various IoT-based technologies that boost output with minimal labor input. Various IoT-based agriculture projects have also been developed by researchers to enhance quality and agricultural productivity. The literature has identified some IoT-based farming methods, which are overviewed in this section. Carnegie Mellon University has been trying to develop a plant nursery utilizing wireless sensor technology [9].

A wireless sensor network (WSN)-based polyhouse monitoring system has been introduced by Song et al. [10], and the system utilizes carbon dioxide, humidity, temperature, and light detector modules. Through the application of GPS technology and the ZigBee protocol, a WSN-based system has been suggested that measures various agricultural parameters [9]. They have developed a real-time rice crop monitoring system to boost productivity [11]. Kumar and Ilango [12] introduced a crop monitoring system that gathers rainfall and temperature data and processes it to reduce the risk of crop loss and improve crop productivity. Rajesh [13] suggested a low-cost solution to monitor different agricultural variables, such as temperature, by applying a microcontroller that can be configured as a weather station based on the Bluetooth protocol. Furthermore, the drawback of this system is that it has a limited communication range and must be connected to smartphones via Bluetooth for constant tracking.

A ZigBee-based smart sensing platform was developed by Shaobo et al. [14] to measure various environmental conditions, such as humidity, temperature, sunlight, and pressure, and monitor various greenhouse parameters. Haefke et al. [15] and Ferentinos et al. [16] suggested the operational and design procedures of WSNs toward a more sophisticated monitoring and control system in greenhouses. Various environmental issues associated with greenhouses have also been addressed, such as the standardization of WSN components, packaging of wireless nodes, and interference from electromagnetic fields. Patil et al. [17] proposed a system that monitors animal health besides identifying prevalent diseases, regardless of whether they are native or non-native, as well as biological attacks and natural causes. In a study by Patil et al. [17] and Vijayan and Suresh [18], a low-cost animal health monitoring system was introduced that quantifies heart rate, body temperature, and posture.

Methodology

The systematic review is based on the protocols of Preferred Reporting Items for Systematic Reviews and Meta-Analyses [19] to ensure methodological rigor and transparency (Figure *1*). The literature search was conducted across major databases such as Scopus, IEEE Xplore, ScienceDirect, and Web of Science and covered the period from January 2010 to January 2026. The choice of this timeframe follows the rapid development of IoT in agriculture, starting with early foundational efforts and extending to recent innovations in AI integration and edge computing.

Searching Strategy

Keywords used in the search strategy included IoT, precision agriculture, smart farming, WSNs, crop monitoring, and precision irrigation in different combinations. The relevance criteria applied to the selected articles included relevance to the field of IoT implementation in agricultural settings, with greater emphasis on empirical studies, systematic reviews, and conceptual frameworks that could help comprehend the technological potential, implementation challenges, or directions for future advancements.

Inclusion and Exclusion Criteria

Inclusion criteria were used to select studies that:

1. Contained original research or extensive reviews of IoT in agriculture.

2. Provided adequate technical information about system architectures or applications.

3. Were published in peer-reviewed journals or conference papers.

4. Were written in English.

Review articles were assessed to provide an overview and synthesis of research trends, whereas primary research studies were evaluated for their specific applications and findings. The excluded articles included those that did not address agricultural IoT applications or lacked sufficient technical or research details. To ensure that the included articles met the systematic review's quality criteria, the selected literature was evaluated in terms of methodological details, clarity of the reported system or experiment, validity or deployment evidence, relevance of the application setting, and clarity of the reported results. Since the included literature varied significantly in design, technology, crop/livestock system, outcome measure, and deployment context, the synthesis did not involve a statistical analysis of pooled data but focused on a narrative integration of findings.

Analysis

The framework of analysis adopted in this review is based on four dimensions:

1. Technological development and design

2. Major applications and their proven efficiency

3. Implementation problems and obstacles

4. Future research directions and avenues for innovation

Moreover, specific quantitative values derived from individual studies are reported separately rather than being pooled to represent the findings of multiple studies. This approach helps reduce the risk of overestimating findings when comparing individual studies.

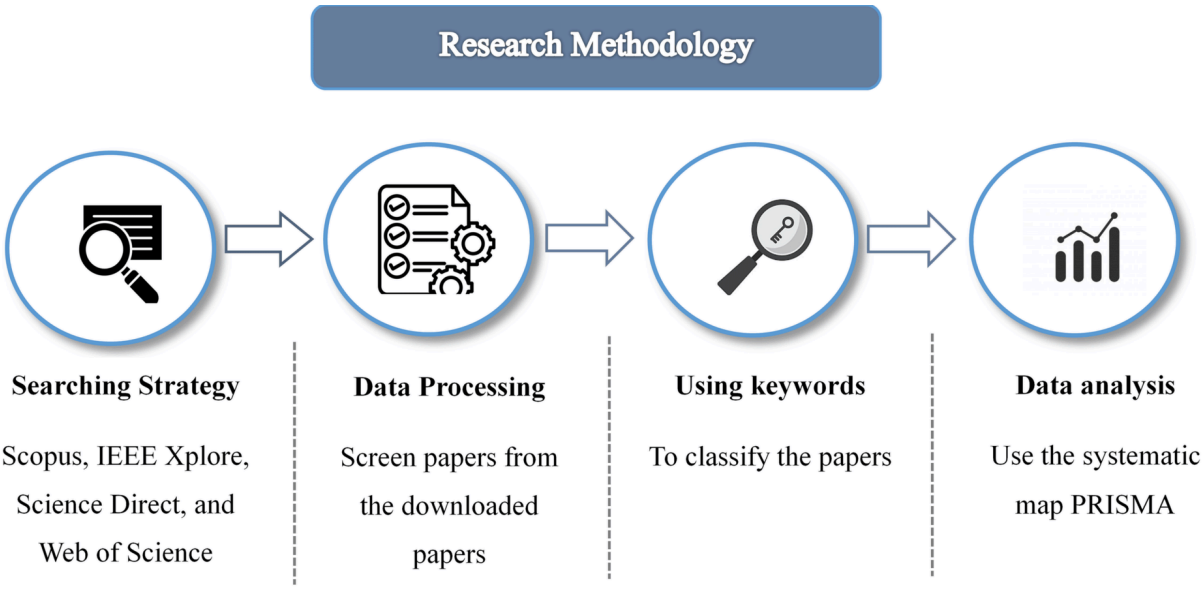


FIGURE 1: Schematic representation of research methodology

PRISMA, Preferred Reporting Items for Systematic Reviews and Meta-Analyses

Internet of Things

Definition and Conceptual Framework

IoT describes a network of interrelated physical objects that are equipped with sensors, software, and other technologies that are able to gather, share, and act on information [4,20]. In agriculture, IoT is applied to establish smart farms, where physical resources, such as soil, crops, livestock, water, and machinery, are nodes of a distributed sensing and actuation network [21,22].

Agricultural IoT is conceptualized as a layered architecture with four basic layers [23,24]. The perception layer involves the physical sensors and actuators that are used in the field. These include soil moisture, temperature, and humidity sensors, cameras, spectral sensors, and automated irrigation valves or robotic systems. The network layer is an infrastructure that offers connectivity between field devices and processing systems to allow data transmission. The communication technologies used can be both short-range, such as ZigBee, Wi-Fi, and Bluetooth Low Energy, and long-range, such as Long-Range Wide Area Network (LoRaWAN), Sigfox, and cellular networks (4G/5G) [25].

The middleware layer processes and stores data, which is often used for real-time analytics via cloud computing platforms or edge computing nodes. The application layer provides actionable insights to end users in the form of dashboards, mobile applications, or automated control systems and allows informed decision-making and targeted interventions [26]. This layered architecture underpins the central operation of agricultural IoT, which involves closed-loop control systems that monitor the relationships between environmental factors, process raw data to support decision-making, and provide appropriate responses without constant human oversight [27].

Enabling Technologies

The development of IoT in agriculture has been facilitated by the growth of various technology sectors. WSNs are platforms for field data management, as nodes are deployed in agricultural areas to track spatial variations in soil status, crop health, and microclimatic parameters [28]. Modern sensor platforms are becoming more sophisticated, such as multispectral sensors used to compute vegetation indices, electrochemical sensors used to analyze soil nutrients, and acoustic sensors used to detect pests [29,30].

Communication technologies have been developed to meet the demands of agricultural environments, which are characterized by large geographical coverage, remote sites, and difficult terrain. Low-power wide-area network technologies, especially LoRaWAN, have become prominent due to their capabilities of supporting battery-powered sensors over distances of over 10 km while maintaining low operational costs [31]. New cellular infrastructure, such as 5G, can provide more bandwidth for applications that require real-time video or high-resolution images [8]. Cloud computing systems offer scalable computing and data storage infrastructure, allowing farmers to use analytics without investing heavily in hosted computing infrastructure [22]. Nevertheless, the use of cloud connectivity has led to the development of edge computing systems, which run computing procedures at the edge so that service access remains intact even when the network is unavailable [32].

Machine learning and AI have become part of agricultural IoT systems and allow advanced analytics to convert raw sensor data into actionable information. Applications of machine learning include the automated detection of crop diseases based on image analysis [33,34], yield prediction based on multimodal sensor measurements [35], and optimization of irrigation scheduling using reinforcement learning algorithms [36].

The structure of IoT is based on three layers, namely, the perception layer (sensing), the network layer (data transfer), and the application layer (data storage and manipulation). Although significant progress has been made, IoT is still evolving and attempting to achieve its final form, as reflected in various reviews [5,37,38] (Figure *2*).

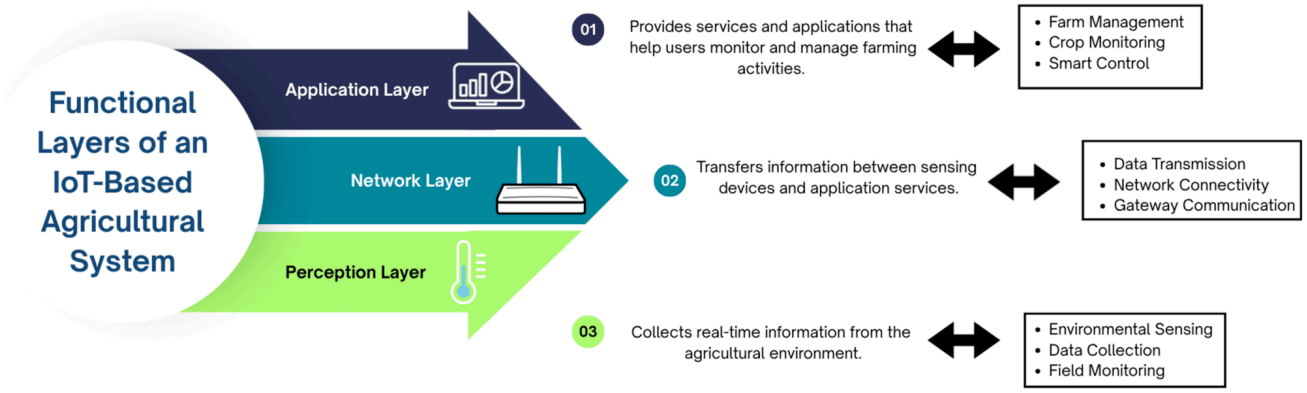


FIGURE 2: Functional layers of an IoT-based agriculture system

IoT, Internet of Things

Layer 1: The Perception Layer

In the perception layer, we find technologies such as WSN, Radio-Frequency Identification (RFID), and, more recently, Near Field Communication. Some overlap exists between WSN and RFID technologies because semi-passive or active RFID tags can be considered wireless nodes with limited computational and storage capabilities. Typically, a wireless sensor node consists of a processing module, usually a low-power microcontroller unit, one or more sensor modules (embedded or external analogue or digital sensing devices), and a radio-frequency communication module, usually supporting a low-power wireless communication technology (Figure *3*).

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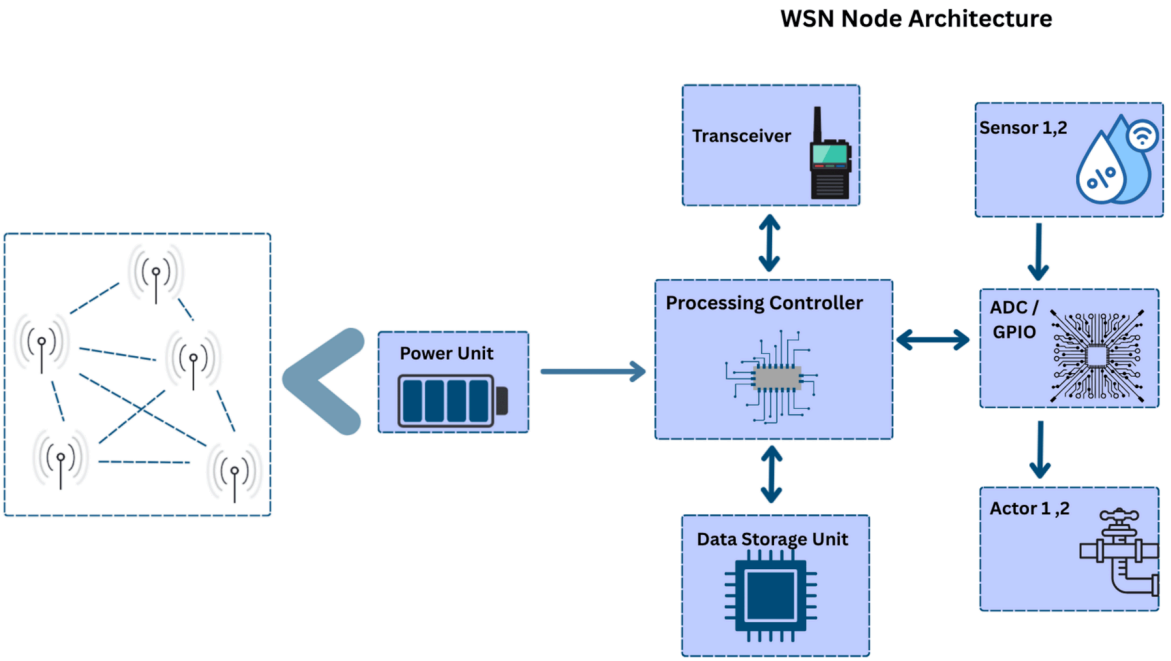


FIGURE 3: The architecture of a typical wireless node

ADC, Analog-to-Digital Converter; GPIO, General Purpose Input/Output; WSN, Wireless Sensor Network

In addition to monitoring and controlling the production process, monitoring, identification, and tracking of agricultural and livestock products after harvest are necessary. In numerous papers concerning the monitoring and control of temperature and humidity in storage and logistics buildings, WSNs are discussed. RFID technology is considered the first and simplest instance of interconnected 'Things'. RFID tags contain data in the form of the Electronic Product Code, and RFID readers trigger, read, and manipulate a large number of tags. By offering object identification, tracking, and data storage on active or passive tags (without the need for an embedded power supply), RFID technology plays an important role in the agricultural domain. Typical user scenarios include product or livestock monitoring, supply chain and quality control tracking, and lifecycle assessment of agricultural products [39].

Layer 2: The Network Layer

At the second layer of IoT, wireless sensor nodes interacting with physical objects and/or their environment communicate with their neighboring nodes or a gateway, building networks through which data are usually forwarded toward remote infrastructure for storage, further analysis, processing, and dissemination of valuable knowledge that can be extracted [5]. When it comes to wireless communications, a large body of scientific literature has been developed on sensor networks, addressing several problems, such as energy efficiency, networking features, scalability, and robustness [4].

Layer 3: The Application Layer

The third layer of IoT is the application layer. It is of high importance and, in many ways, is what facilitates the realization of IoT. The application layer faces several issues that need to be resolved, such as the identification of devices as unique entities. Identifying and addressing billions of devices around the globe will provide direct, Internet-like access to and control over them through the future Internet. Important features of the addressing schema are uniqueness, reliability, persistence, and scalability [5]. IPv6, with its Internet mobility aspects, could alleviate some device identification problems and is expected to play a vital role in this field [38]. However, the heterogeneity of wireless nodes and different types of data, combined with concurrently running operations and the confluence of data from various nodes,

exacerbates the problem even further [40]. Metadata and context-aware addressing, supplementary to IPv6, are expected to contribute significantly to addressing the above-mentioned challenges [41]. Plenty of studies have focused on the standardization of core IoT technologies [42,43]. The classical WSN (Wireless Sensor-Actor Network) paradigm, which involves distributed smart devices sensing and transferring data to a sink and/or driving one or more actuators, represents one step towards the interoperability of devices and objects. Other aspects of IoT include technologies that facilitate intercommunication between devices and/or end users and platforms, as well as software, hardware abstractions, and programming tools on top of which developers and providers can develop and offer new applications and services [4,43,44]. The IoT paradigm is based on the following principles: "Anything communicates, anything is identified, and anything interacts."

Evolution of agricultural IoT research

Scientometric studies reveal that there are specific stages in the development of agricultural IoT research [37,45]. The years 2010-2015 were marked by fundamental research that developed the principles and demonstrated proof-of-concept systems. The early studies were dedicated to the implementation of WSNs for environmental monitoring, with a priority on hardware development and simple connectivity [46,47].

The years 2016 to 2019 saw the fastest growth in research output due to the reduction in sensor prices and the development of cloud systems. Research at this stage began to focus more on integrated systems involving several sensor types and automated actuation [48,49]. The first machine learning applications started to emerge, but they were devoted to different classification problems, such as disease detection [50-53].

Since 2020, studies have shifted towards more complex, integrated solutions involving multimodal data fusion and edge-to-cloud architecture with advanced AI models [32]. New directions include blockchain integration for supply chain traceability [3], digital twins for farm simulation [22], and virtualization of IoT in adaptive sensor networks [32]. This trend indicates that agricultural IoT has evolved from isolated sensing systems into comprehensive digital agriculture environments (Figure *4*).

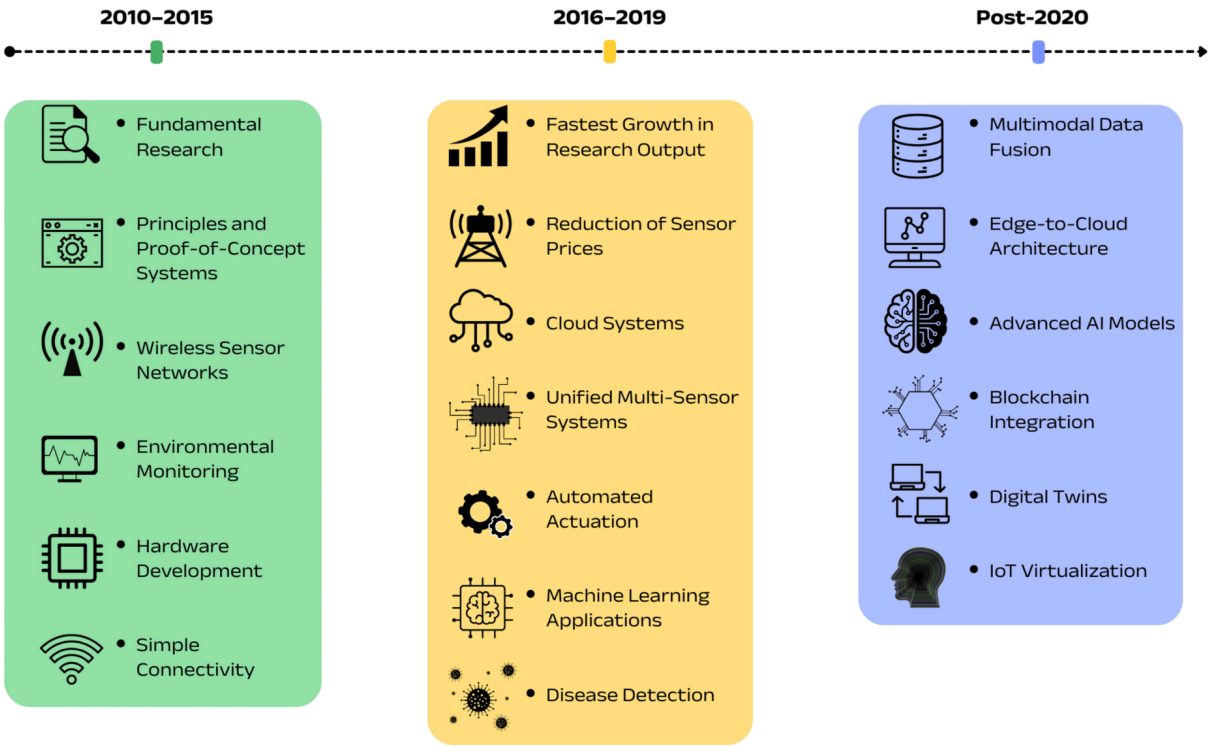


FIGURE 4: Evolution of IoT in agricultural research

IoT, Internet of Things

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Applications of IoT in agriculture

IoT has become a revolutionary technology in modern agricultural practices and offers diverse applications in agriculture.

Crop Health

IoT sensing and machine learning-based image analysis have transformed crop health monitoring. Multispectral and hyperspectral sensors can be installed on ground-based platforms, unmanned aerial vehicles, or satellites to collect reflectance signatures that indicate plant physiological status before the emergence of visible symptoms [29,54]. Vegetation indices, such as the normalized difference vegetation index, are quantitative indicators of photosynthetic activity that can be used to detect water stress, nutrient deficiency, and disease infections at an early stage [54].

Disease Monitoring

Pest and disease detection applications are based on computer vision algorithms that detect typical symptoms in photographs taken by field-deployed cameras or drones [54]. Convolutional neural networks (CNNs), among deep learning models, have attained over 90% accuracy in diagnosing common crop diseases, such as powdery mildew, leaf rust, and bacterial blight [33,34].

Early identification allows timely intervention, thereby limiting pesticide use and enhancing the effectiveness of disease control. Pheromone traps are automated systems that use camera sensors and machine learning to identify pests in real time by combining pheromone attractants with cameras [48]. In cases where pest pressure exceeds economic thresholds, these systems can send alerts or turn on automated control systems, allowing specific and timely action to be taken. This minimizes crop damage and pesticide use.

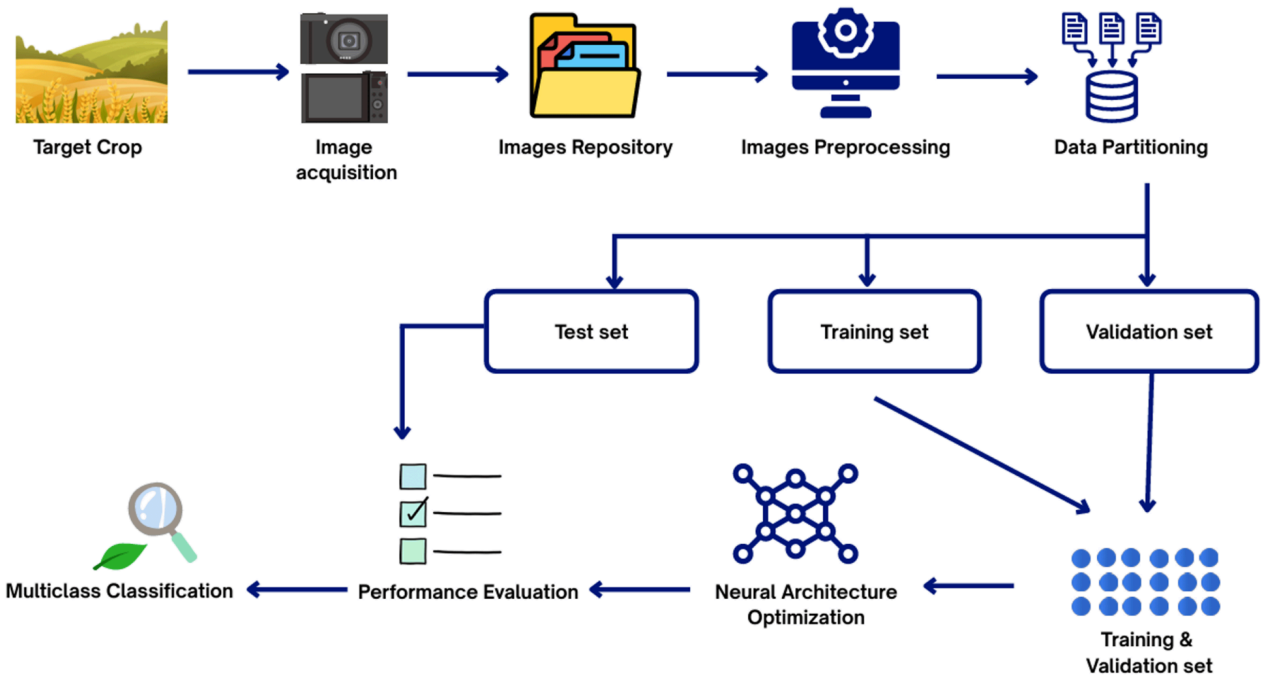


FIGURE 5: Computer vision-based methods for plant disease detection

One of the most critical applications of deep learning, machine learning, and computer vision in the agriculture sector is the detection and classification of crop diseases [49,50] (Figure *5*). The goal is to create algorithms and techniques that can analyze images of leaves or other plant parts and automatically identify and classify plant diseases in agriculture. This can aid farmers in managing diseases. Following a detailed and critical study of numerous recent machine learning- and deep learning-based approaches developed for plant disease detection and classification in the literature, the author has

summarized a few key challenges in crop disease detection and classification, allowing the research community to investigate the causes that may have a significant impact on real-time systems for plant identification and diagnosis. Factors and issues that may affect disease identification and classification have been summarized in studies [51,52].

Pest Monitoring

Gao et al. [53] proposed an agricultural model for wheat. They captured various images of the crop using IoT and drones and uploaded them to the cloud data center to determine the conditions favorable for pests in the field, as shown in Figure *5*, due to climate change. In this architecture, the sensors record data in real time about the crop as it progresses. The field is quite large, and providing a constant power supply to the sensors is difficult; for this, the researchers installed a solar system to power the sensors, and pictures taken by the drones flying overhead are uploaded to the cloud, where they can be processed using spectrum analysis technology to assess the field environment and crop. Because of the flight mode, the flight time of the drones has been extended, and changes in the crop caused by pests or diseases are monitored in the data center using the pictures.

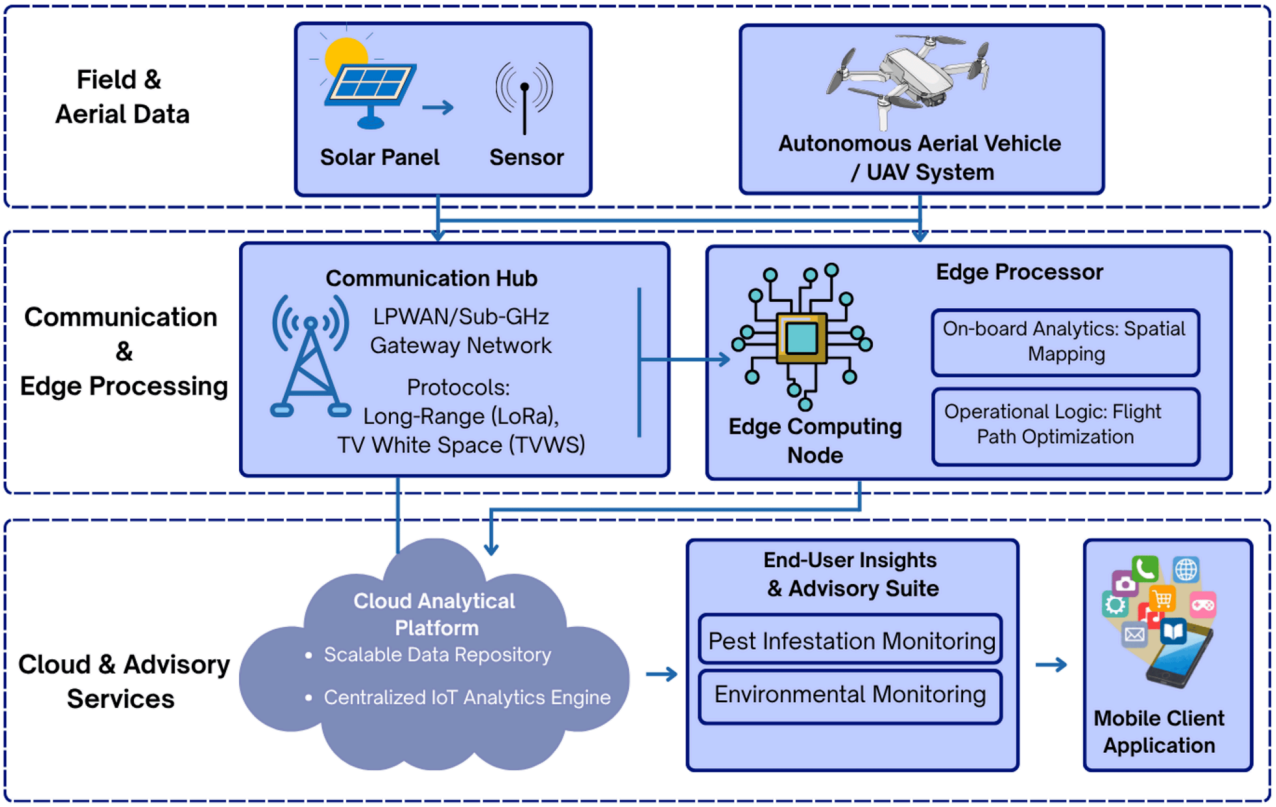


FIGURE 6: Overview of IoT in crop pest prediction system

LPWAN, Low-Power Wide-Area Network; UAV, Unmanned Aerial Vehicle; IoT, Internet of Things

A fuzzy-inference-based crop pest prediction system was proposed by Sharma et al. [54]. Several rice, sugarcane, and millet pests and related diseases were identified based on various weather parameters. The layered architecture is proposed in Figure *6* [53,54]. 5G-LTE is used to create a virtual network connection for the measured parameters, including temperature, humidity, atmospheric pressure, and rainfall. The proposed system predicts rice pest occurrence based on a fuzzy logic-based mechanism.

Precision Irrigation Management

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Water scarcity is also one of the most acute issues in global agriculture, and irrigation is estimated to consume about 70% of freshwater extraction globally [2]. Precision irrigation systems with IoT offer a solution to this issue, as they provide water at the appropriate time and place in accordance with the actual water requirements of crops, provide real-time monitoring of soil moisture, and forecast weather. The basis of precision irrigation is soil moisture monitoring, and sensors are placed at various levels to measure the vertical distribution of soil water content [55]. Tensiometers, time-domain reflectometry, and capacitance sensors are commonly used, and each has different trade-offs based on accuracy, cost, and installation requirements [56].

Modern systems combine soil moisture measurements with estimated evapotranspiration using local weather stations or satellite measurements to predict irrigation schedules and crop water demand [6]. The actuation of closed-loop systems is through automated irrigation control. Studies have shown water savings of 30% to 50% compared with traditional irrigation techniques, along with reductions in energy use and nutrient leaching [26]. Case studies on grape production have demonstrated that deficit irrigation guided by IoT can enhance fruit quality at a lower water usage of 40% [57].

Soil Health and Nutrient Management

The monitoring of soil health is not limited to moisture content but also includes complex physical, chemical, and biological properties that define the level of soil fertility and productivity. IoT sensors have been developed to monitor critical soil parameters such as temperature, pH, electrical conductivity (as a salinity proxy), and the concentrations of macronutrients such as nitrogen, phosphorus, and potassium [58,59].

Real-time monitoring of soil nutrients allows the accurate application of fertilizers, which is currently not the case, since most applications are carried out uniformly without considering spatial differences in soil properties that determine soil fertility [60]. It has been proven that fertilizer use can be reduced by 15-25% with the help of IoT-based nutrient control without reducing crop yield. This reduction has significant environmental benefits, such as reduced nutrient runoff into waterways and reduced greenhouse gas emissions from fertilizer production and application [61].

Monitoring soil salinity has received special attention in irrigated areas, where soil salinity poses a threat to long-term productivity. IoT-based salinity mapping makes it possible to detect problem areas early and adopt specific leaching strategies to control the salt balance [30,61]. Integration with irrigation systems permits automated leaching measures to eliminate excess salts with negligible water consumption.

Livestock Monitoring and Management

IoT applications are not limited to crop production; they also include livestock management, where sensors allow the continuous monitoring of the health, behavior, and welfare of animals. Physiological parameters such as body temperature, heart rate, and activity patterns are monitored using wearable sensors placed on ear tags, collars, or rumen boluses [6,62]. Real-time health monitoring allows the early diagnosis of diseases, thereby saving lives, reducing treatment costs, and enhancing animal welfare. It has been proven that IoT-based health monitoring is capable of identifying bovine respiratory disease 2-3 days before clinical manifestations of the disease, providing an opportunity for timely intervention and improved treatment outcomes [63].

Through activity sensors, reproductive management applications can identify estrus with more than 90% accuracy, providing breeders with better timing for breeding and eliminating the need for hormonal synchronization programs. Precision feeding systems combine weight sensors with automated feed delivery to improve feed efficiency and minimize waste [64,65] (Figure *7*). These systems regulate rations according to the needs of specific animal species, enhance growth rates, reduce feed consumption, and minimize environmental impacts caused by manure production. Livestock IoT applications also involve instrumenting and analyzing beehives [66,67]. Wireless sensors have been used in animal tracking and behavioral analysis [68,69], as well as in odor and hazardous gas monitoring [70].

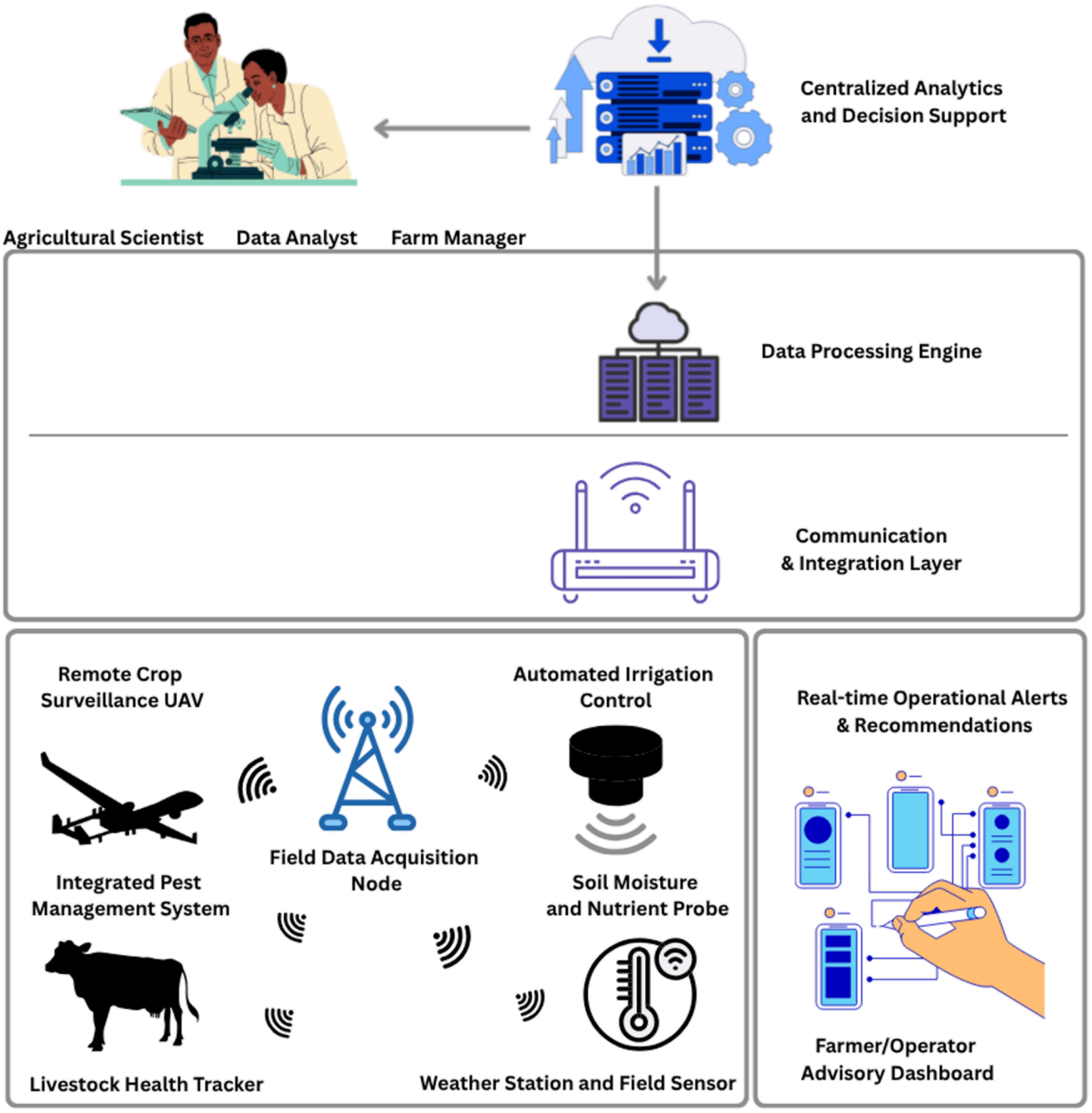


FIGURE 7: Field monitoring of livestock using IoT

IoT, Internet of Things; UAV, Unmanned Aerial Vehicle

Supply Chain and Post-Harvest Management

The IoT applications in agricultural supply chains are relevant to the post-harvest stage, which is the most critical because of the deterioration of quality and food loss. Cold chain monitoring systems are used to monitor the temperature and humidity of cargo during storage and transportation and ensure that they conform to quality requirements, providing the opportunity to react quickly to deviations [7]. Blockchain technology has become an addition to supply chain traceability methodology, forming unalterable lists of the origin and processing of goods [52,53].

The combination of IoT sensors with blockchain platforms provides the option of registering temperature, location, and handling occurrences automatically, which helps build transparency that contributes to food safety, quality assurance, and consumer confidence. Smart storage systems are environments that integrate environmental monitoring, automated fumigation control, and aeration to preserve the quality of grain stored over a long period [71]. Such systems are able to identify the early stages of spoilage or pest attacks that can be addressed by preventive measures that will minimize the post-harvest losses that are being experienced at 10-20% in most developing nations [72]. Today's farming is increasingly mechanized. Hence, standardization systems at every stage of the product from grower to consumer must be introduced to ensure food safety and quality (Figure *8*).

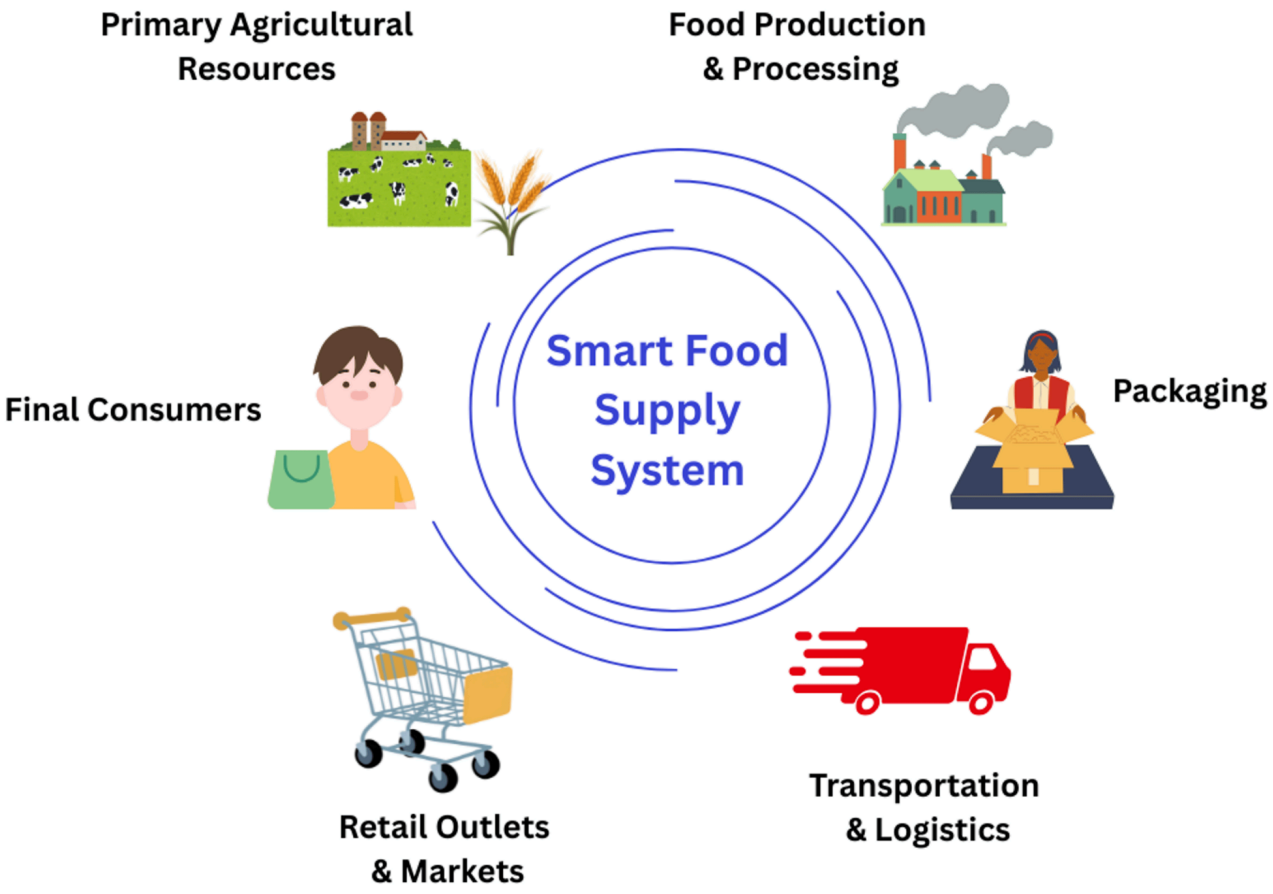


FIGURE 8: Schematic illustration of the Food Supply Chain from the production phase until the final consumer

RFID is the most common IoT technology found in the food supply chain. Agricultural products can be traced with the help of RFID tags, which are enhanced barcodes. Within the framework of the IoT paradigm, recent studies have shown that two or more types of sensors can be used to provide additional information about a product's state when it is recorded using RFID [73,74]. Complete systems involve automated and intelligent schemes, with automatic reasoning based on measured phenomena and AI [75]. Other studies present approaches to organizing a complete food supply chain information management system [75] or designing such a system in a way that maximizes economic profit [76]. RFID has been a common practice on many farms for animal identification and tracking for years. Furthermore, it has been applied to the food chain for traceability control. The use of sensors in tags allows for cold chain monitoring of perishable food products and supports new applications in environmental monitoring, irrigation, specialty crops, and farm machinery.

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Controlled Environment Agriculture

Greenhouse cultivation is more intensive and thus often demands more precise monitoring and control (Figure *9*). Some studies have been limited to local and remote monitoring. Data are most commonly stored and presented in different graphical representations [77,78]. Besides high-precision monitoring, there have been studies showing systems that use meta-processing procedures, with data transferred from remote infrastructures via the Internet. Such systems use well-evaluated equations or crop and climate models to generate assessments of the climate and crop status, enabling the grower to make improved decisions or receive early warnings [79,80].

There have also been studies involving the control of one or more of the actuators in the greenhouse, such as climate control or irrigation control, known as Wireless Sensor-Actor Networks [81]. There are two ways of controlling the operation remotely. The first is manual control by the farmer. In these cases, the system administrator, based on the suggestions made by a Decision Support System/Expert System, chooses to control the machinery. The applications of this monitoring and control category include integrated pest management [82], remote monitoring, warning, and control in open fields [80,83], and controlled-environment agriculture [81,84]. There are also numerous studies on the complete automation of this process, in which the control signals resulting from the processing of the sensed data are directly sent to the actuators, which follow a closed-loop control [85-87].

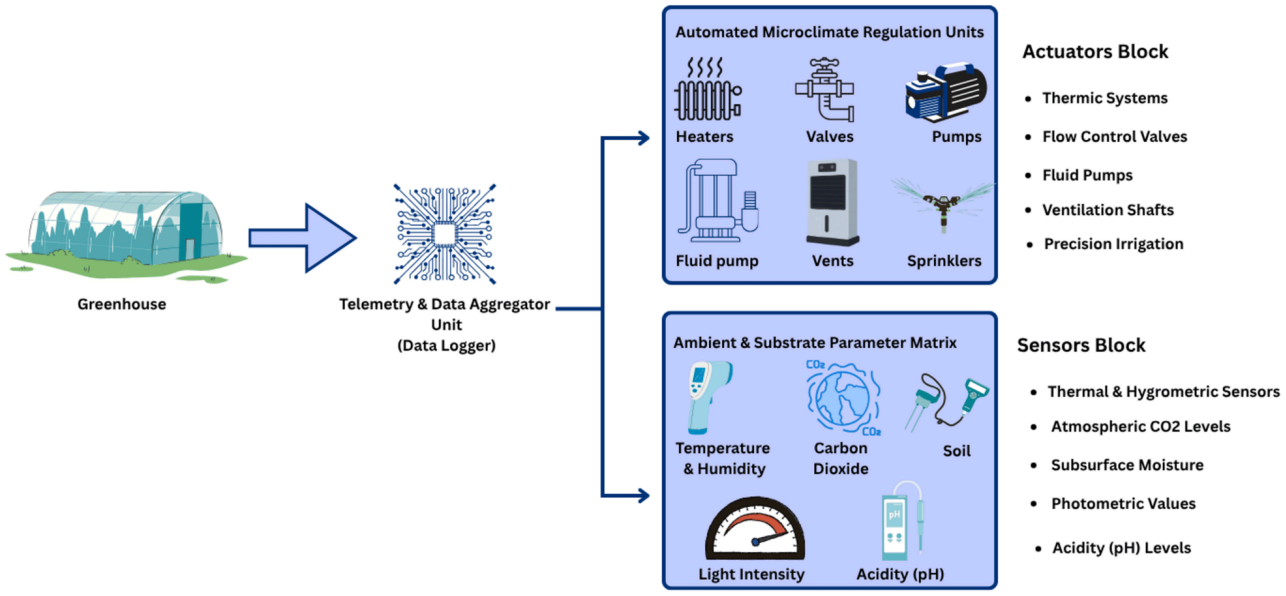


FIGURE 9: Smart greenhouse architecture diagram

Emerging technologies and architectures

Multimodal Data Fusion

The rise in the complexity of agricultural IoT systems has stimulated the emergence of multimodal data fusion methods, which combine information from various types of sensors to produce detailed insights into agricultural systems [32]. There are three levels of data fusion: data-level fusion, which involves the fusion of raw sensor measurements prior to processing; feature-level fusion, which involves the fusion of extracted features across modalities; and decision-level fusion, which involves the fusion of the results of independent analysis systems [32].

Precision irrigation has utilized data-level fusion, in which soil moisture, weather, and crop data are blended together to produce unified representations that are used to guide irrigation decisions [60,88]. Crop disease object detection is a popular application of feature-level fusion, in which different spectral, thermal, and visual features derived from imagery

are fused to enhance classification accuracy [33,89]. Decision-level fusion allows the development of resilient systems involving many different independent models that help make final decisions and minimize the effects of errors in any one model [32].

Multimodal fusion has the advantages of higher accuracy due to complementary information, greater robustness due to redundancy, and the ability to capture complex interactions that are not possible in single-modality systems [32]. Its limitations include the multicomponent nature of system integration, higher data-processing demands, and the fact that sophisticated calibration and validation methods may be required.

A multimodal data fusion framework named Rice-Fusion has been proposed for rice disease diagnosis. Diagnosis of rice diseases using a single modality may not be reliable or accurate; thus, the fusion of heterogeneous modalities is crucial for robust and reliable rice disease diagnosis. This brings a new perspective to the field of rice disease diagnosis [35].

Multimodal data fusion and deep learning were applied for comprehensive resistance score regression. Three combination methods involving 3D-CNN and 2D-CNN were used to extract and fuse multimodal information collected by unmanned aerial vehicles, such as spectral, structural, and texture information, for weed resistance assessment. The results of this study show that the successful combination of multimodal data fusion, comprehensive resistance score, and deep learning can lead to a more precise and reliable assessment of weed resistance in agricultural fields [34].

Edge-to-Cloud Computing

The conflict between real-time physical processing requirements and the limitations of agricultural connectivity has led to the development of edge-to-cloud computing systems [90]. These systems utilize edge computing devices located on or near the farm to carry out the initial processing of data, filtering, and local decision-making, while cloud computing is used to store data long-term, carry out advanced analytics, and manage the systems. Edge computing offers various benefits for agricultural IoT. One such benefit is low latency, which allows real-time control responses without requiring a connection to the remote cloud. Bandwidth requirements are also kept to a minimum, since only processed data or alerts are sent to the cloud. Furthermore, edge nodes continue to operate during network outages, which enhances system resilience [28].

Additional functions of cloud platforms, such as scalable storage, advanced analytics based on greater computing resources, and collaboration tools that allow various stakeholders to share data, make them complementary to edge computing [22]. Modern trends in the deployment of advanced agricultural IoT systems are represented by hybrid architectures that allocate processing tasks between the edge and the cloud depending on latency requirements and the nature of the data. One study presents a scalable edge-to-cloud system for precision irrigation services and applications. The system incorporates new and existing services and automates data transfer, thereby enabling precision irrigation and decision-making.

AI Integration

Machine learning has been extensively involved in agricultural IoT systems, which convert raw sensor data into predictive data that allows proactive instead of reactive management. The applications can be applied in various fields, including yield and disease prediction, optimization of irrigation plans, and resource management [35,91]. In particular, CNNs have proven to be highly effective for image-based applications such as disease detection, weed recognition, and fruit counting [34,92].

Time-series forecasting of weather variables, crop developmental stages, and pest population dynamics takes place using recurrent neural networks and long short-term memory (LSTM) models [93]. Reinforcement learning has emerged as a viable method to optimize irrigation and nutrient regulation, and algorithms are able to learn optimal control policies by interacting with simulated or real environments [36]. These strategies are capable of finding non-intuitive strategies that mitigate conflicting goals, such as maximizing yields, conserving resources, and reducing environmental impact.

The efficiency of an LSTM network for crop classification was evaluated in the context of identifying apple and rice cropping areas. The goal was to address the limitations of phenology-based classification thresholds by using LSTM to account for the entire trend of the Normalized Difference Vegetation Index [93].

IoT Virtualization and Digital Twins

IoT virtualization is a new paradigm in which physical sensors are virtualized so they can be reconfigured and shared among applications [32]. Virtualization allows adaptive sensor networks in which the logical behavior of sensing systems is not linked to physical equipment, but sensing resources can be flexibly used to address varying monitoring needs. Digital twins go a step further by developing holistic digital processes of physical agricultural systems that replicate their real-time counterparts [22]. These digital replicas combine information from various sources, such as IoT sensors, satellite images, weather forecasts, and historical data, to recreate the system behavior of a particular system and predict outcomes under various management conditions. Digital twins have been used in agriculture to predict yield responses to various irrigation or fertilizer policies, optimize machines by modeling field operations and minimizing fuel usage and soil compaction, and conduct whole-farm simulations that combine crop, livestock, and financial models to aid in strategic planning.

A digital twin is an artificial potato planted in the field and harvested like a real potato. The 'digital' potato is fitted with a sensor to record the treatment it has received, particularly shocks, blows, speed of rotation, etc. This information can be applied to fine-tune the cutting machine settings to ensure minimal potato damage. The digital potato is then synchronized with a cloud platform to provide smart services such as potato price or field revenue estimation. Digital twins are also used in the development of field robots (phenotyping and crop treatment in vineyards). They simulate robots' autonomous behavior in 3D space using real-time data and mimic the simulated digital twin to control the real-life robot. This results in shorter development lead times, better evaluation of sensor behavior, and a reduction in the number of field experiments needed to evaluate phenotypes or test the effects of crop treatments.

Challenges and barriers to adoption

Connectivity and Infrastructure Constraints

Agro-IoT connectivity in rural areas is one of the main concerns associated with agro-IoT implementation, particularly in developing nations, where telecommunication infrastructure is not as advanced [94]. Farming is typically carried out across geographical areas that are too extensive to be supported by short-range communication technologies, and most farms are too remote to support wired network solutions. LoRaWAN and Narrowband-IoT are solutions to this problem that provide long-range connectivity with low power consumption [31].

The bandwidth of these technologies is low, which constrains high-resolution imagery or video applications. Satellite connectivity has the ability to reach the whole world, but it is more costly and has latency limitations. The problem is not limited to communication; power supply is also an infrastructure concern. Remote sensor nodes tend to rely on batteries, and their provision involves maintenance overheads that depend on the network size [95]. Solar-powered nodes are more autonomous but costlier and more complex. Electrical grids in regions with unstable power supplies must be supplemented with alternative energy sources, even when using gateway nodes and edge computing infrastructure.

Security and Privacy Vulnerabilities

The development of interconnected devices that are present in farm settings creates major challenges in security and privacy [96,97]. IoT devices are usually not well secured, and this provides intruders with loopholes to compromise operations, destroy data, or undermine the integrity of the systems. The problem of data privacy arises from the collection of specific data on farm operations, which can be commercially sensitive [7,51].

The rights and ownership of agricultural data are also controversial topics, and farmers are concerned about how their data are used by technology providers and agribusinesses. Specific security threats to agricultural IoT include false data injection attacks, which may result in automated systems using more water or chemicals, and ransomware attacks that

leave farmers without access to important control systems [98]. The further integration of IoT with farm equipment creates more vectors for cyber-physical attacks that may result in physical damage or safety risks.

Economic Viability and Return on Investment

The economic argument for agricultural IoT relies on various aspects, such as farm acreage, type of crop, availability of existing infrastructure, and local environment [99,100]. Early capital expenses for sensors, gateways, and supporting infrastructure can be high, along with recurring expenses for data connectivity, cloud services, and system maintenance. In the case of smallholder farmers, especially in developing nations, the resources needed to adopt IoT are usually greater than the resources at their disposal [32].

The perceived risk of technology failure and uncertainty of returns can discourage adoption, even when the initial outlay is low. Service-based business models and cooperative ownership models are also emerging as alternative business models to overcome these barriers [101]. Return on investment is a variable concept depending on the application. Irrigation control systems usually provide the quickest paybacks in terms of water and energy conservation, with payback periods of 1-3 years in water-deprived areas [26]. The benefits of disease detection and improved accuracy in pesticide application include reduced chemical expenditures and better yields, but these benefits are less predictable.

Interoperability and Standardization

The agricultural IoT ecosystem is currently plagued by disintegration, with several vendors developing proprietary solutions that are not interoperable with one another [21,102]. Farmers might be trapped in particular technology stacks, with no opportunity to use best-of-breed components or switch providers without replacing the entire system. Some progress has already been made in standardization, particularly in communication protocols, with LoRaWAN and Message Queuing Telemetry Transport being widely adopted [25].

Nevertheless, data formats, semantic models, and application interfaces remain inconsistent, making it difficult to implement integrated systems capable of combining data from two or more sources. The interoperability issue also extends to data integration with other systems, such as weather services, market information platforms, and government reporting systems [64]. Both open platforms and application programming interfaces are gradually improving connectivity, yet considerable obstacles remain.

Digital Literacy and Capacity Building

Effective adoption of agricultural IoT should be supported by both technology implementation and human resources to manage and operate systems [99,103]. Many farmers are not familiar with digital technologies, and rural areas in many cases lack access to technical support services. Training courses and user interface design have already started to address these difficulties, but substantial gaps remain. Systems designed without considering user needs and capabilities can be discarded even in the cases of proven technical functionality [104].

Extension services, which have been used to provide farmers with technological transfer, are frequently underfunded and do not necessarily have the knowledge of digital agriculture. This is particularly a significant issue in developing nations with lower levels of formal education and less technologically advanced infrastructures [32]. Interventions that involve the use of technology, a long-term capacity building, and peer-learning networks have shown promise in overcoming these barriers.

Discussion and future directions

Synthesis of Findings

This systematic review has discussed the contemporary situation in the area of IoT applications in the agricultural sphere, which shows that it is a rapidly developing field with increasing practical significance. The major results may be summarized in four dimensions: Technological maturity has developed significantly, and sensor technologies,

communication protocols, and analytics platforms have become reliable and affordable enough to allow practical use. The process from research prototyping to commercial products has been speeded up, with more and more integrated solutions being available for particular agricultural applications.

The range of applications has broadened, and IoT technologies now cover the entire agricultural value chain, encompassing field preparation, harvest, and post-harvest management. Precision irrigation and soil monitoring are the most developed applications, but there are new applications of sensor technology in pest management, livestock monitoring, and supply chain traceability. The patterns of adoption differ greatly depending on the region and type of farm. Commercial farms in the developed world have been the earliest to adopt and make use of IoT to streamline their operations and enhance sustainability. Smallholder adoption and uptake are low in developing countries due to economic, infrastructure, and capacity factors. There is a change in research focus from fundamental issues of connectivity and data gathering to integrated system architectures that bring together various sensing modalities, incorporate artificial intelligence, and address the issues of scalability and sustainability.

Across the reviewed literature, agricultural IoT has moved from wireless sensing and monitoring systems to integrated systems of multimodal sensing, AI, edge-to-cloud computing, virtualization, and digital twins. The literature consistently reports precision irrigation, soil monitoring, crop health assessment, livestock monitoring, and supply chain traceability as important application areas, while commonly reported benefits include improved monitoring, targeting, sensing, decision support, and earlier detection. These findings build on earlier reviews of smart agriculture and IoT [6,7,9,21,26,27] but go beyond them by unifying established areas with newer developments in multimodal data fusion, edge-to-cloud architectures, AI, IoT virtualization, and digital twins [32,37], and emphasize the importance of context for technology performance. Rural connectivity, unstable power supply, cybersecurity and data governance, high initial and recurring costs, interoperability, and digital capacity remain key constraints, especially in resource-limited and smallholder settings. Overall, the review offers a framework that connects technology development to applications and adoption in the agricultural value chain. The evidence is largely descriptive and heterogeneous, and therefore the conclusions should be interpreted as a synthesis of the reported findings and not as a pooled estimate of IoT's impact. This nuance is now explicit in the revised methodology and conclusion.

Research Gaps

The literature review shows that there are several areas of research that are important to address in future studies. The absence of multimodal data fusion structures is a major weakness, and most of the literature is devoted to specific sensors or simple combinations [32]. There should be research on systematic methods of fusion to maximize information recovery and address computational requirements.

There are no well-developed real-time decision-support systems that interpret sensor data to provide actionable recommendations. Most of the systems gather and present data without decision support, and farmers have to process multifaceted information to decide what to do [35]. This gap could be overcome through research on user-centered design and decision-support algorithms.

Although resource-constrained environments are significant to global food security, little research has been conducted on them relative to their significance to the world [32]. There is a need to conduct studies that specifically focus on low-cost, low-power, and resilient systems suitable for smallholder settings and to research sustainable business models and deployment strategies.

The literature lacks long-term performance and reliability studies. The majority of reported deployments cover single growing seasons or temporary demonstrations, and there is little information on the longevity of the systems, maintenance levels, or long-term benefits of such systems.

Recommendations for Future Research

Based on the findings of this review, the following recommendations are proposed for future research and development:

Develop Integrated Multimodal Fusion Frameworks: Further studies need to be conducted on systematic methods of data fusion that can support the various sensing modalities of interest in agriculture and address computational complexity. Frameworks need to be reviewed in terms of enhancing the quality of decisions and the robustness of systems.

Invest in Edge-to-Cloud Architectures: The next generation of systems must take advantage of distributed processing power to balance real-time control demands with the analytical potential of cloud systems. Current research directions include processing tasks, lightweight machine learning models that can be deployed at the edge, and architectures that are resilient to disconnection.

Design for Resource-Constrained Contexts: Research needs to be particularly focused on meeting the needs of smallholder farmers and regions with limited infrastructure. This includes ultra-low-power systems, solar-powered autonomous nodes, simplified user interfaces, and other connectivity solutions. Models of shared infrastructure and cost-reduction strategies should be explored.

Address Security and Privacy Holistically: Security considerations must be incorporated during the initial design of the system and not treated as an afterthought. Current research priorities include lightweight encryption that can be implemented on resource-constrained devices, privacy-preserving data aggregation, and system data governance that balances the interests of farmers with system needs.

Develop Standardization and Interoperability Approaches: Semantic interoperability, common data models, and standardized application programming interfaces can be researched to minimize fragmentation and allow integrated systems. Research activities should be complemented by interaction with standards development organizations and industry groups.

Conduct Longitudinal Deployment Studies: The discipline needs data about the long-term performance of systems, user adoption, and sustained economic effects. Multiyear research in different environments would provide information regarding the durability of systems, their maintenance needs, and the development of farming practices.

Implications for Policy and Practice

The implications of this review for policy and practice go beyond the research context. For policymakers, agricultural IoT needs more than technology promotion; it also requires the creation of physical infrastructure, such as rural connectivity, electrical stability, and extension facilities [105,106]. Fragmentation and the safeguarding of farmers' interests can be addressed by investing in interoperability standards and data governance frameworks.

For practitioners such as farmers and agribusinesses, effective adoption of IoT has to be aligned with specific operational situations and a clear understanding of economic returns. Risk reduction through a phased implementation approach that begins with applications familiar to the users, such as irrigation monitoring, and gradually increases in complexity can be achieved through capacity building [56]. The key to sustained adoption is integration with current management practices and consideration of user training.

For technology developers, it is important to understand the limitations and priorities of agricultural users in order to develop the right solutions. Systems with proven ability to operate in the harsh realities of agricultural fields, with user-friendly interfaces and low maintenance requirements, will have higher adoption rates than technically advanced systems with poor operability.

Conclusions

The reviewed evidence suggests that IoT technologies can make significant contributions to more efficient and sustainable agricultural production, as well as livestock and post-harvest management, through enhanced precision and data-driven decision-making. Indeed, the reported findings and evidence mainly relate IoT applications to improved monitoring, more efficient use of water and other resources, early warning of potential crop and livestock issues, and enhanced traceability. Yet, the evidence is largely descriptive and heterogeneous, and the benefits can hardly be

generalized across different production settings because of the high variability in farm characteristics and environmental conditions across different regions. Moreover, connectivity and energy access, cybersecurity and data privacy concerns, costs of implementation and maintenance, interoperability, and digital competence may represent critical barriers to the adoption and continued use of IoT in agricultural production. Future research and development activities in the field should therefore focus on long-term experiments and validation trials in diverse settings while also considering the scope of applications and their cost-benefit, as well as standardized and interoperable solutions, accessible data storage and governance, and advanced analytical capabilities to support adaptive management. This way, the IoT-driven development of agriculture will address the industry's needs in climate change adaptation, water and resource management, and food security while being sensitive to the opportunities and limitations of different agricultural settings.

Additional Information

Author Contributions

All authors have reviewed the final version to be published and agreed to be accountable for all aspects of the work.

Concept and design: Muhammad Usama Intizar, Muhammad Sami Intizar, Aqsa Siddique

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Data Availability Statements

Data sharing is not applicable. This work is theoretical; no datasets were generated or analyzed.

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