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Integration of IoT Sensors and AI–ML for Intelligent Real-Time Farm Management

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ABSTRACT

Efficient farm management of agricultural practices, including crop monitoring, livestock management, resource utilization, and yield prediction is critical for increased efficiency, sustainability, and productivity in agriculture. Current farm management practices often rely on manual observations and conventional data analysis methods, resulting in inefficiencies and inaccuracies. Recent developments in sensing technology (Internet of Things: IoT) and artificial intelligence/machine learning (AI-ML) algorithms have exciting prospects for transforming agricultural operations through real-time insights and decision support. This paper explores real-time sensors and AI-ML techniques in farm-level management, aiming to optimize crop monitoring, livestock management, resource utilization, and yield prediction. The key components of an IoT ecosystem are sensors, actuators, data communication networks, and cloud platforms. Further, it analyzes diverse communication options like cellular networks, satellite connectivity, and low-power wide-area networks (LPWANs), evaluating their suitability for various agricultural applications. This investigation demonstrates the practical benefits for farmers in crop monitoring, irrigation optimization, livestock management, and real-time decision support. Emerging trends like AI-ML techniques integration, precision agriculture applications, and autonomous farming systems hold immense promise for further revolutionizing the field. Studies show that integrating real-time sensor data with AI-ML models can improve precision agriculture, resource allocation, and production processes. This technology can increase yields with reduced resource loss and environmental impacts. Future directions include the refinement of AI algorithms, data source integration, and user-friendly platforms for widespread adoption. This overview explores the potential of IoT in transforming agriculture, highlighting trends like artificial intelligence integration, precision farming, and autonomous farming systems for a sustainable future.

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1. Introduction

The global population is expected to reach 9.7 billion by 2050, up from 7.3 billion today. To meet the increased demand for food, farmers are turning to hi-tech methods to grow crops, which help increase efficiency and reduce the use of natural resources. This advanced agriculture is guided by continuous improvements in digital tools such as Internet of Things (IoT). The IoT is a revolutionary paradigm that refers to the inter-networking between different physical devices, vehicles, appliances, and other objects embedded with sensors, software, and network connectivity, allowing them to collect, store, and exchange data [1, 2]. The core concept of IoT is to enable these "smart" devices to communicate with each other and central systems, creating an intelligent ecosystem that enhances efficiency, convenience, and overall quality of life. At its essence, IoT is about connecting everyday objects with the help of the internet and enabling them to send and receive data [3]. These objects range from daily used simple household items like refrigerators and thermostats to more complex industrial machinery and healthcare devices. The connectivity and data exchange facilitated by IoT enable these devices to operate in a more coordinated and intelligent manner, often with minimal human intervention. Key components of IoT include sensors, actuators, communication protocols, and cloud computing [4-6]. Sensors are integral to IoT devices as they collect and store data such as temperature, humidity, motion, or light from the environment. On the other hand, actuators, allow devices to perform different actions based on the collected data. Communication protocols define how the devices exchange information, ensuring interoperability in a diverse IoT landscape. Cloud computing plays a crucial role in processing and storing the massive amounts of data collected by IoT devices [7-9].

One of the key advantages of IoT is its potential to enhance efficiency across wide range of sectors. In industrial settings, IoT can be applied to monitor and optimize manufacturing processes, track inventory, and predict equipment maintenance requirements [10-12]. Smart sensors can provide the real-time data on soil conditions and crop health in digital agriculture, enabling precision farming practices [13, 14]. In healthcare, with the help of IoT devices monitoring patients remotely, collecting vital signs, and facilitating timely intervention become possible [15]. The smart home concept is a popular manifestation of IoT in everyday life. Home appliances, lighting systems, security cameras, and thermostats can be interconnected to create an intelligent and automated living environment [16-18]. Users can remotely monitor and control these devices through smartphone apps and web-based operation systems, contributing to energy conservation and increased reliability. However, the widespread adoption of IoT also raises concerns about data privacy, security, and ownership. The constant data exchange between devices creates potential vulnerabilities that malicious actors could exploit. Ensuring robust security measures and establishing clear guidelines for data protection are crucial aspects of the ongoing development and deployment of IoT technologies [19-21]. The Internet of Things (IoT) is expected to play a crucial role in developing smart cities, autonomous vehicles, and interconnected industries. Careful consideration of ethical and regulatory aspects is necessary to ensure responsible and secure implementation of this transformative technology. IoT offers unprecedented possibilities for innovation and efficiency. This chapter focuses on exploring the transformative potential of IoT in revolutionizing real-time farm management, highlighting its growing importance in modern agriculture, examining communication systems, quantifying benefits for farmers, and unveiling future scope.

1.1. Literature Gap and Research Rationale

Existing reviews discuss IoT-enabled sensing, precision agriculture, cloud platforms, and AI/ML applications, but these themes are often presented separately or as lists of technologies. For farm-management decisions, practical value depends on how sensing, connectivity, computing location, predictive models, and control actions operate as one system. A further gap is the limited side-by-side explanation of when a technology is suitable, what operational constraints affect it, and how performance should be assessed. This review addresses that gap by connecting the data pathway—from field measurement to a recommendation or actuation—with agricultural use cases, communication options, model selection, and deployment constraints.

1.2. Novelty and Contribution of the Present Review

The contribution of this review is a system-level synthesis of IoT and AI/ML for intelligent farm management rather than the proposal of a new algorithm or the reporting of a new field experiment. It (i) organizes the main

components into an end-to-end architecture linking sensors, gateways, communication networks, edge/cloud computing, AI/ML analytics, farmer interfaces, and actuators; (ii) compares communication technologies and model families against practical selection criteria; (iii) distinguishes monitoring, prediction, decision support, and closed-loop control; and (iv) identifies the performance measures that should be reported when claims of real-time operation, accuracy, or resource savings are made.

1.3. Review Approach and Analytical Assumptions

This manuscript is a narrative technical review based on the studies cited in the manuscript and the technology categories discussed in the following sections; it is not a systematic review or meta-analysis. No new field measurements, controlled experiments, or pooled performance estimates were generated. Accordingly, the comparative tables below are engineering-oriented selection guides. Communication range, latency, power demand, sensor accuracy, and model performance depend on device configuration, deployment environment, data quality, network loading, crop, and task; numerical values should be treated as indicative rather than guaranteed field results. The main assumptions are that (a) sensors are installed and maintained according to manufacturer guidance; (b) calibration and quality checks precede operational use; (c) connectivity may be intermittent; (d) safety-critical actions require local safeguards and/or human oversight; and (e) AI/ML models are useful only when training data represent target farm conditions and performance is independently validated.

1.4. Review Questions

The review is organized around four questions: (1) how should IoT–AI/ML components be connected; (2) which sensors, communication technologies, and computing arrangements suit different agricultural tasks; (3) how should AI/ML methods be selected and evaluated; and (4) what technical, operational, and adoption constraints limit reliable deployment?

2. Importance of IoT in Agriculture

IoT has emerged as a transformative force in various industries, including agriculture. Integration of IoT technologies in agriculture can revolutionize traditional farming practices, enhance productivity, and address challenges related to resource management [13, 14, 22]. IoT enables precision farming by providing real-time soil conditions, crop health, and weather patterns data. Smart sensors in the field collect information about moisture levels, nutrient content, soil and canopy temperatures, evapotranspiration rates, and pest populations (Fig. **1**). This data is critically important for farmers in decision making in irrigation scheduling, fertilization, and pest management, helps to optimize the resource use, and improve crop yields. IoT devices, such as drones equipped with sensors and cameras, can monitor large agricultural fields efficiently [23].

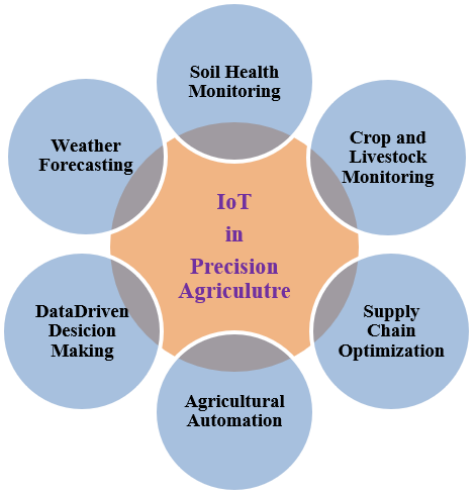


Figure 1: Applications of IoT-based farm management systems in precision agriculture.

These devices can capture high-resolution images and collect data on crop health, identifying hotspots that require attention. Farmers can then take targeted actions, including adjusting irrigation rates in specific zones or site-specific chemical applications [24]. In livestock farming, IoT devices like smart collars or tags can be used to monitor the health and behavior of animals. These devices can track parameters such as body temperature, gas concentrations, activity levels, and feeding patterns. Early detection of health issues allows for timely intervention, which reduces the risk of disease outbreaks and helps to the overall animal welfare. IoT-enabled machinery and equipment contribute to automation in agriculture. Tractors, planters, and harvesters equipped with different sensors and GPS technology can operate precisely and efficiently. This saves labor and ensures that farming tasks are carried out with optimal accuracy, reducing resource wastage. IoT facilitates better management of the agricultural supply chain and provides visibility and transparency by monitoring the storage conditions of harvested crops while tracking the transportation of goods. This leads to improved logistics, reduced spoilage, and enhanced overall supply chain efficiency. IoT sensors can gather real-time weather data, helping farmers make informed decisions about their operations. Accurate weather forecasts enable better planning for planting, harvesting, and other critical activities.

Additionally, IoT contributes to risk management by providing early warnings about extreme weather events and helps farmers to take preventive measures. By optimizing the resources utilization such as water, fertilizers, and pesticides, IoT promotes sustainable farming practices. Farmers can apply inputs more judiciously based on actual needs, reducing environmental impact and contributing to long-term agricultural sustainability. The data collected through IoT devices in agriculture can be analyzed for valuable insights. These insights can inform future decision-making, helping farmers adapt to changing conditions, improve crop varieties, and enhance farm management strategies. In conclusion, the adoption of IoT in agriculture holds immense potential to transform traditional farming into a more efficient, sustainable, and data-driven industry. Farmers can overcome different challenges, increase productivity, and contribute to the global effort to ensure food security by harnessing the power of interconnected devices and smart technologies.

3. Evolution of Farm Management Systems

Farm Management Systems (FMS) have evolved significantly over the years, driven by technological advancements, changes in agricultural practices, and the need for increased efficiency and sustainability. Evolution can be traced through distinct phases, each marked by integrating new technologies and expanding capabilities. In the early days of agriculture, farm management relied heavily on manual record-keeping and traditional methods. Farm managers maintained handwritten logs and records to track activities such as planting schedules, crop yields, and livestock data. This approach was labor-intensive and limited in data analysis and decision support. The advent of computers in the 1970s brought about a significant shift in farm management. Early Farm Management Information Systems (FMIS) began to emerge, enabling farmers to automate specific database-management. These systems often ran on mainframe computers and focused on primary data storage and retrieval [25]. With the widespread adoption of personal computers in the 1980s and 1990s, farm management systems became more accessible to individual farmers [26-28]. Software applications were developed for financial, inventory, and crop rotation planning. However, these systems were often standalone and lacked integration.

The integration of Geographic Information Systems (GIS) and Global Positioning System (GPS) technologies marked a significant advancement. With the advancement in prescription mapping technologies, farmers could now map and analyze spatial data for precise field management. GPS-guided equipment allowed for accurate planting, harvesting, and resource application, increasing efficiency and reducing resource loss. The widespread internet connectivity and the development of cloud computing technologies further transformed farm management. Cloud-based FMS enable real-time data access and collaboration. Farmers could manage their operations remotely, accessing critical information through web interfaces and mobile apps [29, 30]. The Internet of Things (IoT) has profoundly impacted farm management. Smart sensors and devices deployed in fields and on equipment collect real-time data on soil conditions, weather, crop health, and machinery performance. This data is analyzed to provide actionable insights, contributing to precision farming practices. The current phase of evolution involves the integration of advanced data analytics and artificial intelligence (AI) into FMS. Machine

learning algorithms analyze large datasets to provide predictive insights, helping farmers make informed decisions about crop management, resource allocation, and risk assessment [31, 32]. The evolution of FMS reflects a continuous effort to leverage technological advancements to enhance efficiency, sustainability, and decision-making in agriculture. As technology advances, FMS will further integrate cutting-edge technologies to meet the evolving needs of modern farming practices.

The foundation of IoT-based FMS lies in deploying various sensors that collect data from the agricultural environment. These sensors are crucial in monitoring and gathering information for informed decision-making (Table **1**).

Table 1: Key types of sensors commonly used in agriculture.

Sensors in Agriculture	Application	Examples
1. Soil Moisture Sensors	Soil moisture monitoring to optimize irrigation schedules	1.TEROS-10 2.TEROS-12
2. Weather Sensors	Collect temperature, precipitation, humidity, and wind speed. This information aids in crop planning, disease prediction, and overall farm management.	1.ATMOS-14 2.ATMOS-41
3. Crop Health Sensors	Include imaging devices and spectral sensors important for early detection of diseases and nutrient deficiencies,	1.GreenSeeker 2.CropSpec.
4. GPS and Navigation Sensors	Enable precision agriculture by providing accurate location data for farm equipment	1.CANAMEK RTK 2.TeeJet Matrix 430
5. Livestock Monitoring Sensors	Include RFID tags, GPS trackers, and health sensors for monitoring the well-being and behavior of livestock.	1.Kestrel DROP
6. Environmental Sensors	Measure factors such as air quality, light intensity, and atmospheric pressure for optimizing plant growth and animal well-being	TREMS-5
7. Machinery Sensors	Monitor the performance and status of farm machinery, including fuel levels, engine health, and usage patterns.	1.Pressure sensors 2.LiDAR
8. Water Quality Sensors	Assess the quality of water sources, ensuring that irrigation water meets the necessary standards.	1.Walchem 2.Horiba

The effectiveness of IoT-based FMS lies in the seamless integration of sensor data in real-time. Sensors continuously collect data from the agricultural environment, generating streams of information related to soil conditions, weather patterns, crop health, and more. Sensor networks are equipped with different communication systems, allowing them to transmit data to a centralized hub or cloud-based platform. Common communication protocols include MQTT or HTTP [6, 33]. The collected data is aggregated and organized for further analysis. This may involve combining data from multiple sensors to comprehensively view the farm's conditions. The aggregated data is sent to cloud-based servers and stored securely. Cloud platforms offer the scalability and processing power needed for analyzing large datasets. Advanced analytics and machine learning algorithms process the data in real-time. This analysis provides actionable insights, such as predicting crop diseases, optimizing irrigation schedules, or identifying areas for improvement. The analysis results are presented to farmers through user-friendly interfaces, including dashboards and mobile applications. This empowers farmers to make data-driven decisions regarding resource allocation, crop management, and overall farm strategy [34, 35]. FMS can be programmed to generate warnings and notifications based on predefined thresholds. For example, farmers may receive alerts about extreme weather conditions, potential pest outbreaks, or equipment malfunctions, enabling timely intervention. In addition to real-time insights, historical data is stored for trend analysis and long-term planning. This historical perspective aids farmers in adapting strategies based on seasonal variations and changing conditions.

By integrating sensor networks and real-time data analysis, IoT-based FMS empowers farmers with the information needed to optimize agricultural practices, increase productivity, and promote sustainable farming methods (Fig. **2**).

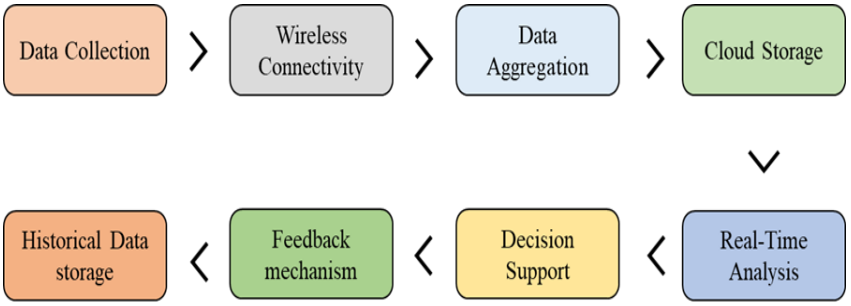


Figure 2: Workflow of IoT-based farm management systems.

4. Key Components of IoT-based Farm Management Systems

4.1. Data Analytics

Raw sensor data often requires preprocessing to clean and filter out noise. To ensure consistency and comparability, sensor data may undergo normalization and scaling processes. This is particularly important when dealing with data from different types of sensors. Temporal analysis involves examining how data changes over time, helping identify trends and patterns. Spatial analysis considers the geographical distribution of sensor data, providing insights into variations across the multiple farm locations [36, 37]. Relevant features are extracted from the sensor data to focus on specific aspects of interest. This step simplifies the dataset and enhances the efficiency of subsequent analysis. Integration of data from various sensors may be necessary for a holistic understanding of the farm environment. Data fusion combines information from different sources to create a comprehensive dataset. Streaming analytics processes data in real-time as it arrives, enabling immediate responses to changing conditions. This is particularly crucial for time-sensitive decisions in agriculture. Descriptive analytics involves summarizing and visualizing data to provide an overview of current conditions. Graphs, charts, and maps help farmers interpret information easily. Future predictions can be done by predictive analytics using historical data and statistical algorithms. This capability is instrumental in anticipating crop diseases, pest outbreaks, or weather patterns [32, 38, 39].

4.2. Machine Learning Algorithms for Predictive Analysis

Machine learning (ML) plays a vital role in predictive analysis within IoT-based FMS. These algorithms leverage historical sensor data to make predictions and optimize decision-making (Table **2**).

Table 2: Key machine-learning techniques used in agriculture.

Machine Learning Techniques	Key Details
1. Regression Analysis	Regression models predict numerical values, such as crop yields or soil moisture levels. Farmers can use regression analysis to estimate outcomes based on historical data [40].
2. Classification Algorithms	Classification algorithms are employed to categorize data into distinct classes. In agriculture, this can be used to classify crop diseases, identify weed species, or categorize soil types [41].
3. Cluster Analysis	Cluster analysis groups similar data points together. In agriculture, this can help identify homogeneous zones within a field, guiding precision farming practices [42].
4. Time Series Analysis	Time series analysis is crucial for understanding how variables change over time. This is valuable in predicting seasonal patterns, crop growth cycles, and climate trends [43].
5. Decision Trees	Decision trees are used to make decisions based on a set of conditions. In agriculture, they can be applied to determine optimal planting times, fertilizer application rates, or irrigation schedules [44].
6. Neural Networks	Neural networks, particularly deep learning models, can handle complex patterns in large datasets. They find applications in image recognition for crop health assessment and other sophisticated tasks [45].

7. Ensemble Methods	Ensemble methods combine multiple models to improve predictive accuracy. Techniques like Random Forests or Gradient Boosting are effective in agriculture for tasks like yield prediction [46].
8. Anomaly Detection	Anomaly detection algorithms identify unusual patterns in data, signaling potential issues. This is valuable for early detection of crop diseases, pest infestations, or equipment malfunctions [47].
9. Reinforcement Learning	Reinforce learning models learn by interacting with the environment. In agriculture, they can optimize decisions over time, such as adjusting irrigation schedules based on real-time sensor data [48].

By employing these machine learning algorithms, IoT-based FMS can provide farmers with predictive insights, enabling them to make informed decisions for crop management, resource optimization, and risk mitigation. The combination of data analytics and machine learning enhances the overall efficiency and sustainability of modern agricultural practices.

4.3. Communication Technologies

4.3.1. Wireless Communication in Farming

Bluetooth and Wi-Fi technologies are commonly employed for short-range communication, facilitating connectivity between sensors, machinery, and control devices for local data exchange. Different cellular networks, including 4G and emerging 5G technologies, are able to cover wide-area, allowing farmers to connect IoT devices across expansive agricultural landscapes and manage farm operations remotely in real-time [49, 50]. Low Power Wide Area Network (LPWAN) technologies, such as LoRaWAN and Sigfox, offer low-power, long-range communication, ideal for connecting sensors in remote areas with minimal energy consumption [51, 52]. Satellite communication becomes crucial in areas with limited terrestrial network coverage, enabling connectivity and control even in remote and isolated farm parts. Mesh networks, consisting of interconnected devices, provide a decentralized and resilient approach, particularly useful in large farms where maintaining a direct connection to a central hub may be challenging. Narrowband IoT (NB-IoT), a cellular communication standard, is designed to connect low-power devices efficiently. It is suitable for long-duration deployment of sensors and devices in agriculture [53]. Zigbee and Z-Wave, wireless communication protocols, find applications in low-power, short-range connectivity for smart devices and sensors within specific farm areas[54, 55]. Additionally, Edge Computing, involving data processing closer to the source, reduces the need for extensive data transmission, making it beneficial for scenarios where low-latency communication is crucial, such as real-time monitoring of machinery in agriculture.

4.3.2. Connectivity Solutions for Remote Areas

Connectivity in remote agricultural areas is challenging, but IoT-based Farm Management Systems (FMS) offer solutions. Satellite Internet, mesh networks, and signal repeaters provide reliable connectivity and expand communication range. Combining multiple options like cellular, satellite, and LPWAN ensures redundancy. Solar-powered solutions address power needs in off-grid locations. FMS can store offline data and synchronize when a connection is available. Establishing localized communication hubs reduces the need for direct connections to the central hub. These solutions enable farmers to optimize decision-making and enhance agricultural practices with real-time data.

5. Benefits of IoT in Farm Management

5.1. Precision Agriculture

Precision Agriculture shows a dynamic shift in farming practices, empowered by IoT-based FMS. IoT-based FMS introduced advanced technologies to optimize resource utilization, enhance crop yield, and improve overall agricultural efficiency.

5.1.1. Optimized Resource Utilization

The efficient use of resources is crucial in modern agriculture, and IoT-based Farm Management Systems (FMS) play a key role in enabling precision farming practices to achieve this goal. One important application is Precision Irrigation, which involves the use of soil moisture sensors and real-time weather data to precisely regulate irrigation. This ensures that crops receive the right amount of water at the right time, preventing issues such as over-irrigation or water scarcity. The result is improved water-use efficiency, leading to economic benefits for farmers and a reduction in the environmental impact associated with excessive water usage.

Another important application is Variable Rate chemical applications, made possible through FMS equipped with sensors and GPS technology. This technology allows farmers to analyze soil nutrient levels and crop requirements, enabling them to apply fertilizers in varying amounts across different zones of a field [56]. By adopting this targeted approach, farmers minimize fertilizer waste, optimize nutrient uptake by crops, and contribute to sustainable agriculture practices. Smart Pest Management is also a significant aspect of precision agriculture, utilizing sensors and imaging devices to monitor crop health and detect signs of pest infestations [57]. This allows for the precise and timely application of pesticides only in affected areas, thereby reducing the overall use of chemicals and minimizing environmental impact. Automated Machinery Control is integral to precision agriculture, involving the use of IoT-enabled machinery equipped with GPS and sensors [58]. These machines can operate autonomously or with minimal human intervention, following predefined paths and adjusting operations based on real-time data. This leads to precise planting, harvesting, and other farming activities, further optimizing resource utilization. Lastly, Data-Driven Decision Support is crucial for optimized resource utilization in agriculture [59]. The data collected by sensors on soil conditions, weather patterns, and crop health provides farmers with valuable insights. FMS analyzes this data to generate recommendations for optimal farming practices, helping farmers make informed decisions on resource allocation and management.

5.1.2. Improved Crop Yield and Quality

Improved crop yield and quality are essential goals in modern agriculture. The integration of IoT-based FMS enables a comprehensive approach to achieving these objectives. Predictive analytics for crop yield is a key component, where machine learning algorithms analyze historical data, weather patterns, and other factors to predict future crop yields [60]. Farmers can use these predictions to plan harvest schedules, optimize storage, and make informed marketing decisions, contributing to overall operational efficiency. Remote monitoring of crop health is also crucial, involving continuous surveillance of crops through sensors and imaging devices. Early detection of diseases, nutrient deficiencies, or other issues allows farmers to take prompt corrective actions, leading to healthier crops and increased yields. Quality monitoring and traceability ensure that crops meet predefined quality standards throughout the production process. IoT-based FMS tracks the quality of agricultural production from planting to harvesting and even in storage conditions [61]. Climate resilience is addressed through precision agriculture practices, where FMS continuously monitors weather patterns and analyzes historical data to determine optimal planting times, suitable crop varieties, and strategies to mitigate climate-related risks. Efficient crop rotation and planning are facilitated by FMS, assisting farmers in planning rotations and optimizing field layouts based on historical data and soil conditions. This strategic approach contributes to soil health, reduces the risk of disease buildup, and enhances overall crop productivity. Integration with market demands is achieved through precision agriculture, as supported by IoT-based FMS. Farmers can align their production with market demands by understanding consumer preferences and market trends, allowing them to adjust planting and harvesting strategies and ultimately improve economic returns.

5.2. Real-Time Monitoring

5.2.1. Crop Condition Monitoring

Monitoring Crop Conditions is a fundamental aspect of precision agriculture, and various IoT technologies play a vital role in providing real-time insights for informed decision-making [49, 62]. Soil Health Monitoring involves the use of sensors that continuously measure parameters such as moisture levels, temperature, and nutrient content [63-65]. This real-time data allows farmers to receive immediate feedback on soil conditions, enabling precise irrigation and fertilizer application tailored to the specific needs of the crops. Weather Monitoring is

facilitated by IoT-connected weather stations (Fig. **3a**) that provide crucial real-time data, including temperature, precipitation humidity, and wind speed [66, 67]. This information is essential for planning agricultural activities, predicting disease outbreaks, adapting to changing weather conditions, and ensuring optimal crop management.

Crop Health Imaging utilizes ground (canopy physiology sensing system [CPSS, Fig. **3b**)]) or aerial (drone imagery) imaging sensors to capture thermal/RGB images of crops. Image analysis algorithms then identify patterns associated with nutrient deficiencies, and crop health, enabling early detection of diseases, or pest infestations, thereby supporting proactive intervention [68, 69]. Remote Sensing, using satellites and aerial sensors, enhances the monitoring of large agricultural areas in real time. This technology allows farmers to assess crop conditions and identify areas that may require specific attention, contributing to efficient resource allocation. Smart Irrigation Monitoring involves sensors embedded in irrigation systems that provide real-time water usage, pressure, and distribution data. This capability enables farmers to monitor and control irrigation remotely, ensuring that crops receive the required amount of water at the right time, thereby promoting water-use efficiency [70-72]. Crop Growth Metrics are tracked through IoT devices such as smart cameras and sensors. This real-time monitoring allows farmers to assess the developmental stages of crops, aiding in timely decision-making related to activities like harvesting. In conclusion, the integration of these advanced monitoring technologies in precision agriculture provides farmers with a comprehensive understanding of crop conditions, enabling them to implement precise and timely interventions for optimized agricultural practices [13, 73].

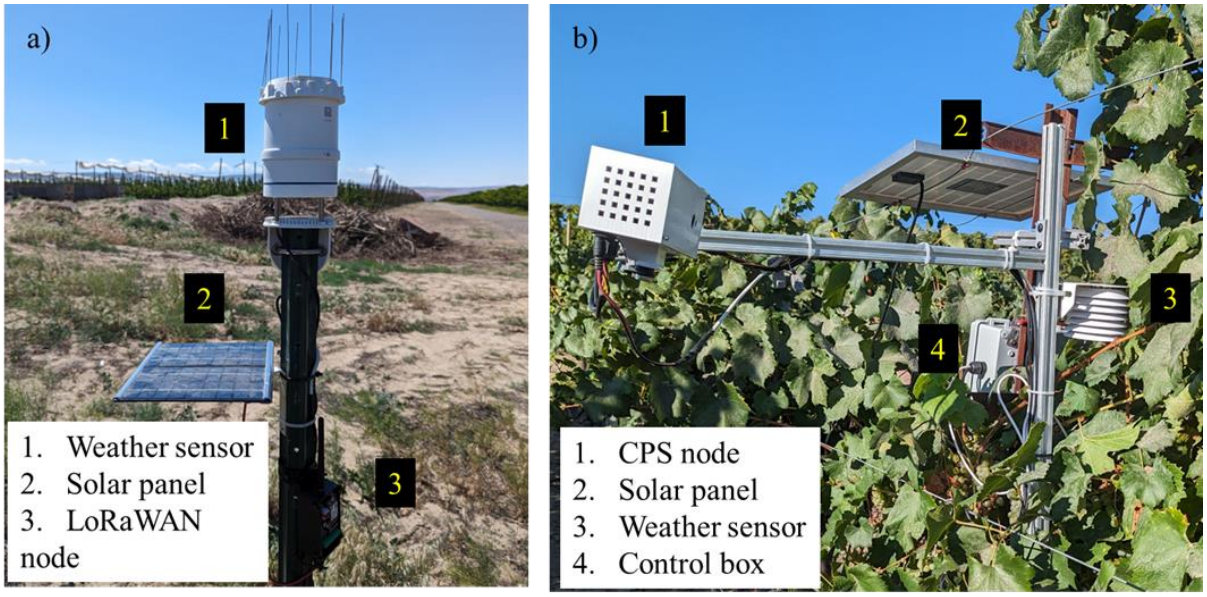


Figure 3: IoT-connected **a**) weather station and, **b**) canopy physiology sensing system (source: Washington State University).

5.2.2. Livestock Health Monitoring

Livestock Health Monitoring has become an integral component of modern agriculture, thanks to innovative IoT technologies that enhance the well-being of animals and overall improve farm management. GPS Tracking is a key feature, with livestock fitted with GPS-enabled devices that allow real-time tracking. This technology proves invaluable for managing grazing patterns, locating animals, and preventing loss or theft, contributing to efficient livestock management practices [74, 75]. Health Monitoring Sensors, such as smart collars or ear tags, continuously collect data on vital signs and behavior. Real-time livestock health monitoring system (Fig. **4**), enables early detection of illnesses, facilitating timely and targeted interventions to ensure the health and welfare of the livestock [76]. Activity Monitoring involves sensors that track the activity levels of livestock, providing insights into their well-being. Changes in behavior, such as reduced activity or unusual patterns, can serve as early indicators of potential health issues, allowing for prompt attention and care. Smart Feeders and Waterers, equipped with IoT technology, record the consumption patterns of livestock [77, 78]. Real-time data on feeding and drinking habits assist farmers in ensuring that animals receive optimal nutrition and hydration, contributing to improved overall animal health. Environmental Conditions are monitored through sensors placed in barns and shelters, providing

real-time insights into factors like temperature and humidity [79, 80]. This information helps farmers create optimal living conditions for their livestock, ensuring their comfort and well-being. Alerts and Notifications are a crucial aspect of Livestock Tracking and Health Monitoring. Farmers receive immediate alerts about anomalies in livestock behavior, health issues, or environmental conditions, allowing for prompt and effective action, ultimately enhancing the overall health and productivity of the livestock.

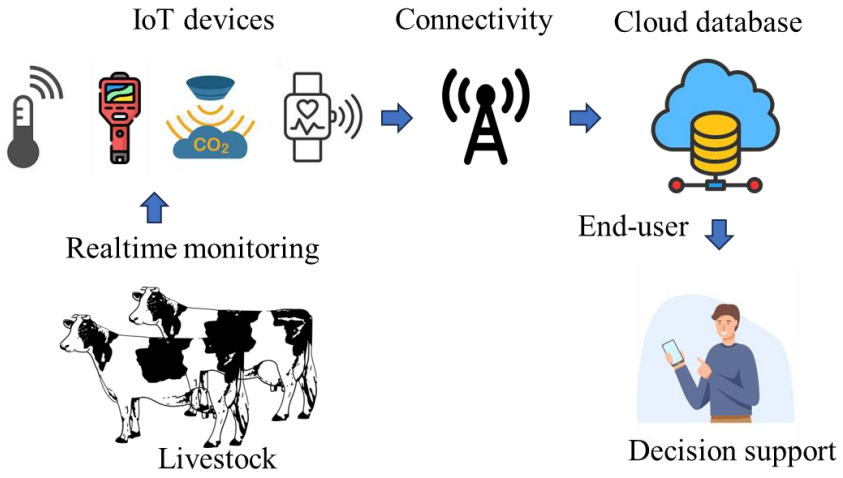


Figure 4: Schematics of IoT-based livestock health monitoring system.

Real-time monitoring in agriculture, facilitated by IoT-based FMS, empowers farmers with actionable insights for proactive decision-making [81]. Whether it's optimizing crop conditions or ensuring the health and well-being of livestock, real-time monitoring contributes to the overall efficiency, productivity, and sustainability of modern farming practices.

6. Challenges and Considerations

6.1. Data Security and Privacy

Robust measures must be in place to safeguard sensitive agricultural data. One crucial aspect is Data Encryption, where strong encryption mechanisms are implemented to secure data transmitted between IoT devices, sensors, and cloud-based platforms. This ensures that confidential information remains protected and inaccessible to unauthorized entities [82, 83]. Access Controls play a vital role in maintaining data integrity by establishing strict regulations on who can view, modify, or access agricultural data within the FMS. This helps prevent unauthorized tampering with critical information. Secure Storage is equally important, and selecting secure storage solutions adhering to industry standards ensures the protection of data repositories, with additional safeguards like encryption at rest. Regular Audits are essential for identifying vulnerabilities and addressing potential threats [84, 85]. Proactive security audits contribute to the ongoing integrity and security of the entire FMS. Moreover, Compliance with Regulations is crucial, requiring farmers to stay informed about data protection regulations and privacy laws relevant to agricultural data. Ensuring compliance with these regulations guarantees the protection of farmers and stakeholders, underscoring the responsible handling of data in the context of precision agriculture [86, 87].

6.2. Infrastructure Requirements

Infrastructure requirements play a vital role in the successful implementation of IoT-based FMS, and several key considerations must be addressed. Network Reliability is foundational, especially in remote agricultural areas, where a stable and robust network infrastructure is essential [88, 89]. The success of the FMS hinges on real-time communication between devices and central systems, emphasizing the need for reliable connectivity. Scalability is another vital aspect that should be integrated into the design of the FMS infrastructure. As farm operations

expand, the system must have the flexibility to accommodate additional sensors, devices, and increased data volume without compromising performance. Addressing Power Supply challenges, particularly in off-grid or remote areas, is crucial [49, 65]. Consideration of alternative power sources, such as solar or wind, for IoT devices ensures continuous operation and sustained data collection. Compatibility and Integration are imperative to maximize efficiency and automation. FMS should seamlessly integrate with existing farm machinery and equipment, fostering cohesive communication. Data Storage Capacity is a critical consideration for handling the growing volume of agricultural data generated by sensors and devices. Adequate planning for data storage, whether through cloud solutions or on-premises infrastructure, is essential to support the expanding data needs of precision agriculture [22, 29]. In summary, ensuring reliable network connectivity, and scalability, addressing power supply challenges, compatibility with existing equipment, and planning for sufficient data storage capacity are integral aspects of establishing a resilient and efficient infrastructure for IoT-based Farm Management Systems.

6.3. Farmer Adoption and Training

Farmer Adoption and training are pivotal aspects of successfully integrating IoT-based FMS into agricultural practices. To facilitate widespread adoption, it is crucial to prioritize user-friendly interfaces. Designing intuitive interfaces ensures that the FMS is accessible and easy to navigate, allowing farmers to leverage its capabilities without the need for extensive training. Recognizing the diverse technological literacy levels among farmers, comprehensive training programs should be developed [90, 91]. These programs should educate farmers on both the technical aspects and practical applications of the FMS, empowering them with the knowledge needed to maximize its benefits. Addressing Technological Barriers is essential in ensuring inclusive adoption. Recognize the varying degrees of technological literacy among farmers and provide support to those less familiar with digital technologies. Offering assistance in system usage and troubleshooting helps bridge the gap, promoting equal access to the benefits of the FMS [92]. Implementing Demonstration and Pilot Programs is an effective strategy to showcase the advantages of the FMS. These programs allow farmers to experience the system firsthand, gaining insights into its impact on farm efficiency and productivity. Through firsthand experiences, farmers can make decisions regarding the adoption of the technology. Feedback Mechanisms are vital for continuous improvement. Establishing mechanisms to gather insights from farmers using the system ensures that the FMS remains aligned with the evolving needs and preferences of the farming community. Regular feedback allows for adjustments and enhancements, ultimately fostering a collaborative approach to technology development and adoption [49, 93]. In conclusion, prioritizing user-friendly interfaces, comprehensive training programs, addressing technological barriers, implementing demonstration and pilot programs, and establishing feedback mechanisms are key elements in promoting the successful implementation of IoT-based FMS among farmers, ensuring that technology serves as a valuable and accessible tool for enhancing agricultural practices.

Addressing these challenges and considerations is crucial for the successful implementation and widespread adoption of IoT-based Farm Management Systems. By prioritizing data security, ensuring robust infrastructure, and facilitating farmer adoption through training and user-friendly interfaces, agriculture can harness the full potential of IoT-based FMS for sustainable and efficient farming.

7. Future Trends and Innovations

7.1. Integration with Other Technologies

The integration of IoT-based FMS with other advanced technologies is poised to revolutionize agriculture, offering farmers enhanced capabilities and efficiencies. In the realm of AI and Machine Learning, future FMS will witness deeper integration with algorithms, augmenting predictive and prescriptive capabilities. This synergy will provide farmers with more sophisticated insights, empowering them to make informed decisions and optimize their agricultural practices. Blockchain technology is set to play a crucial role in ensuring traceability and transparency within agricultural supply chains. By leveraging blockchain, FMS can securely record and verify transactions related to crop production, processing, and distribution [94, 95]. This not only enhances the integrity of data but also fosters trust among consumers and stakeholders by providing a tamper-proof and transparent

record of the entire supply chain. The emergence of Edge AI is anticipated to become more prevalent in FMS. In this paradigm, AI algorithms are deployed directly on IoT devices or edge computing nodes. This allows for real-time data processing, reducing latency and significantly enhancing the responsiveness of FMS, particularly in critical applications like precision agriculture where timely decisions are crucial.

The integration with digital twin technology is another promising avenue for FMS. This enables farmers to create virtual models of their agricultural assets, such as fields or equipment. Digital twins facilitate simulation, optimization, and scenario analysis, providing a virtual environment for testing different strategies before implementation. This innovative approach allows farmers to fine-tune their agricultural practices, leading to increased efficiency and productivity.

7.2. Emerging IoT Solutions in Agriculture

The emergence of IoT solutions in agriculture continues to reshape the industry, offering innovative approaches to address challenges and enhance efficiency. The deployment of 5G Connectivity stands out as a transformative development, providing low-latency, high-speed connectivity. This is particularly advantageous for real-time monitoring, autonomous machinery, and applications that demand rapid data transmission. The rollout of 5G networks in agriculture is expected to significantly improve the capabilities of IoT-based FMS [96, 97].

Swarm Robotics is gaining prominence in precision agriculture. Multiple small robots, working collaboratively in swarms, can perform tasks such as seeding, weeding, or monitoring in a coordinated manner. This approach improves efficiency along with reduces the need for large, centralized machinery. Swarm robotics represents a promising solution for enhancing precision and flexibility in various agricultural operations [98, 99]. Smart Weeding and Pest Control are areas where IoT-based FMS is making significant strides. Robotic systems equipped with computer vision are incorporated into FMS to enable smart weeding solutions. These systems can identify and selectively remove weeds, reducing the reliance on herbicides and promoting sustainable agricultural practices [100, 101]. Additionally, smart pest control mechanisms utilize AI to target pests with precision, minimizing the use of pesticides and also helping to reduce environmental impact.

Quantum Computing is on the horizon as a cutting-edge technology with potential applications in agriculture. As quantum computing technology matures, its utilization in agriculture is anticipated to grow [102]. Quantum computing's ability to handle complex analysis tasks, such as simulating molecular interactions in soil or optimizing large-scale crop rotation strategies, holds promise for providing more sophisticated decision support within FMS. This could lead to more precise and optimized agricultural practices, contributing to sustainable and efficient farming.

7.3. Potential Impact on Sustainable Farming Practices

Resource-optimized farming stands out as a key area where IoT can contribute. By enabling precise monitoring and control, farmers can minimize water usage, reduce chemical inputs, and optimize energy consumption. This approach promotes eco-friendly agriculture by ensuring that resources are utilized efficiently, leading to reduced environmental impact [22, 49, 103]. Climate-resilient agriculture is another critical aspect. FMS equipped with real-time weather data, predictive analytics, and adaptive strategies empower farmers to proactively respond to climate variations. This proactive approach helps mitigate risks and ensure stable yields despite changing weather patterns, contributing to overall climate resilience in agriculture. Circular Economy in Agriculture is facilitated by IoT-based FMS, supporting the development of circular economy models. This involves efficient recycling of agricultural waste, optimal utilization of by-products, and closed-loop systems that minimize environmental impact [104, 105]. Such practices contribute to sustainable and regenerative farming by ensuring that resources are used cyclically and efficiently.

Data-driven conservation Practices are a direct outcome of using IoT in agriculture. By monitoring soil health, biodiversity, and ecosystem dynamics, farmers can implement conservation strategies that preserve natural resources and promote biodiversity on their farms. This data-driven approach helps to make informed decisions that match with conservation goals. Smart Ecosystem Management represents an evolution in FMS, moving

beyond traditional monitoring of crops and livestock to encompass the overall ecological balance of the farm. Smart sensors and data analytics contribute to holistic ecosystem health and resilience, allowing farmers to manage their entire agricultural ecosystem sustainably [106, 107]. The future of IoT-based Farm Management Systems holds exciting possibilities, with the integration of AI, blockchain, and other emerging technologies. These innovations are poised to revolutionize agriculture, and makes it more sustainable, resilient, and technologically advanced [49, 108, 109]. As these trends unfold, farmers and stakeholders will have powerful tools at their disposal to navigate the complexities of modern farming practices.

7.4. Comparative Technical Synthesis for Deployment

An IoT–AI/ML farm-management system should be evaluated as an end-to-end pipeline. The field sensor is only the first component: data quality, communication reliability, processing location, model validation, and the mechanism for communicating or implementing recommendations all affect operational performance. Fig. (**5**) summarizes this architecture.

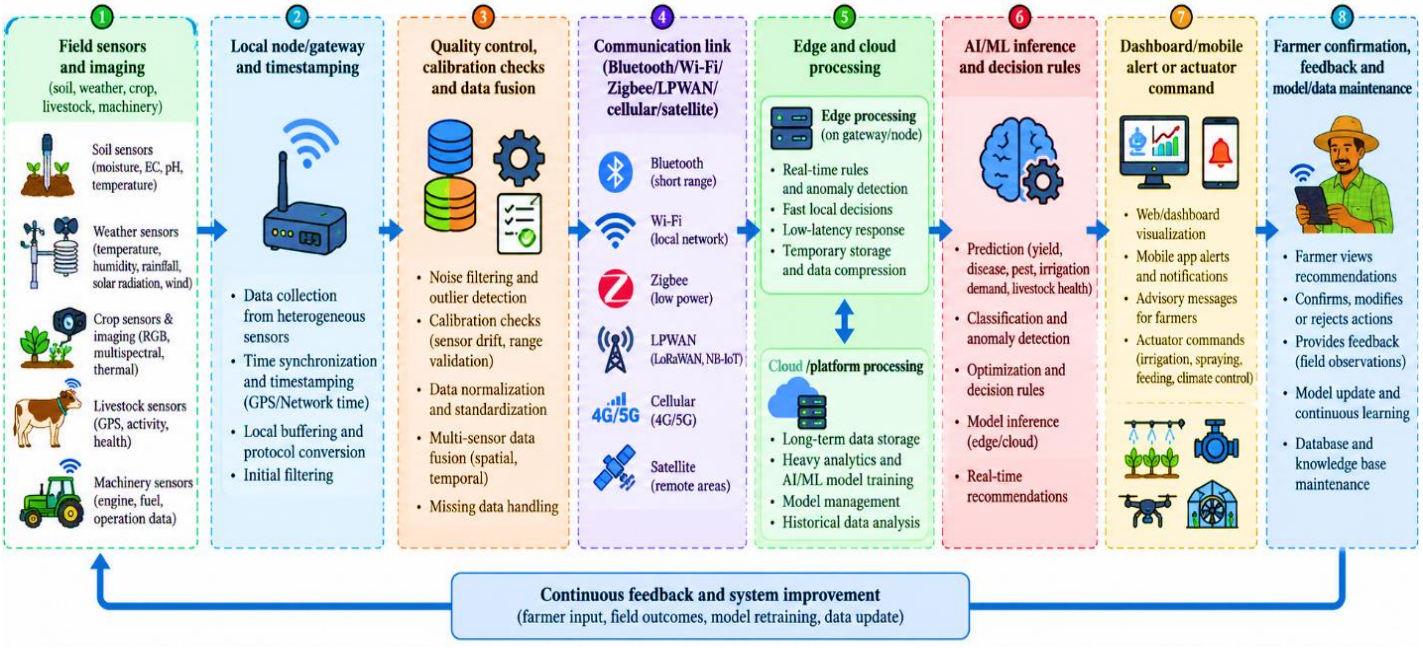


Figure 5: Conceptual end-to-end architecture for IoT–AI/ML-enabled farm management.

The architecture separates data acquisition from decision execution (Table **3**). Local threshold rules or edge inference are preferable when connectivity is unreliable or when delay could cause crop, livestock, or equipment harm. Cloud processing supports long-term storage, cross-field comparisons, model training, and computationally intensive analysis. Hybrid systems can buffer data locally and synchronize when the network becomes available. Closed-loop actuation should include range checks, manual override, fail-safe states, and logs of recommendations and actions.

A sensor category does not have one universal accuracy specification (Table **4**). A new study should name the exact model and cite its datasheet or a validation study before stating numerical accuracy, operating range, or resolution. Calibration frequency should be based on manufacturer recommendations, field drift, and the consequences of an incorrect decision.

These are broad qualitative engineering comparisons (Table **5**), not guaranteed specifications. Actual range, throughput, latency, energy use, and cost should be confirmed from the selected module, operator, local radio environment, and service plan. For quantitative comparisons, report test environment, distance, packet delivery ratio, end-to-end latency distribution, energy per message, and total ownership cost.

Table 3: Sensor categories, quality considerations, and sampling choices.

Sensor/Data Type	Agricultural Use	Accuracy, Calibration and Suitability Considerations	Indicative Sampling Approach
Soil moisture / temperature	Irrigation scheduling, root-zone monitoring	Accuracy depends on soil texture, installation depth, salinity and sensor type; field calibration and representative placement are important.	Minutes to tens of minutes for irrigation decisions; faster sampling may be needed for control.
Weather station (air temperature, RH, rainfall, wind)	Weather-aware irrigation, disease risk, spray-window decisions	Exposure, siting, shielding, sensor drift and maintenance affect data quality; compare against a reference instrument where feasible.	Typically 1–15 min for operational monitoring; event-based logging may be required for rainfall.
Electrical conductivity / pH / nutrient-related sensors	Water/soil quality and nutrient management	Different sensors measure different proxies; ion-selective and optical systems may require calibration and maintenance.	Task-dependent; periodic readings may suffice, with more frequent readings for fertigation control.
RGB / multispectral / thermal imaging	Crop stress, disease/weed screening, canopy and water-stress assessment	Affected by illumination, canopy stage, viewing geometry, image resolution and model domain; ground-truth labels are needed.	Image capture is event- or flight-based; processing time depends on image volume and model complexity.
Livestock wearable / RFID / GPS	Activity, location, identity, health-anomaly screening	Fit, animal species, placement, battery condition and behavior influence reliability; alerts should be checked by trained staff.	Seconds to minutes for activity/location; health trends may require longer aggregation.
Flow, pressure and machinery sensors	Irrigation delivery, pump status, equipment maintenance	Install according to pipe/vehicle geometry; verify zero/span and compare with known operating conditions.	Seconds to minutes for fault detection; slower logging may suit routine usage records.

Table 4: Indicative communication-technology comparison for agricultural deployments.

Technology	Typical Coverage Scale	Data-rate Capability	Power Profile	Potential Agricultural Fit	Main Limitations
Bluetooth / BLE	Personal-area / short range, typically equipment or room scale	Low to moderate; version and mode dependent	Low for BLE	Nearby sensors, tags, phone-to-device setup	Short range and obstruction sensitivity; not generally whole-farm backhaul.
Wi-Fi	Local area; building/yard scale, often tens of metres per access point	Moderate to high	Moderate to high relative to LPWAN	Cameras, gateways, powered farm buildings	Coverage and energy use can limit battery-operated remote nodes.
Zigbee / IEEE 802.15.4	Short-range mesh; links often tens of metres, extended by routing	Low to moderate	Low	Dense sensor networks, greenhouses, barns	Mesh design, interference, and gateway placement affect performance.
LoRaWAN / LPWAN	Long range; several kilometres may be possible in open rural settings	Low data rate; small periodic messages	Very low at end device	Soil moisture, weather summaries, tank/flow status	Not suitable for continuous high-resolution imagery or large files.
NB-IoT / cellular IoT	Wide-area cellular coverage where supported	Low to moderate; service and network dependent	Low at device; coverage conditions matter	Metering, periodic telemetry, managed deployments	Coverage, module/service cost, network availability and latency vary.
4G LTE	Wide-area cellular coverage	Moderate to high	Moderate	Mobile equipment, gateways, image transfer	Coverage and recurring data costs may limit remote use.

5G	Wide-area where deployed; local performance varies	High potential throughput and low latency under suitable conditions	Variable by device/network configuration	High-volume data, robotics and time-sensitive applications	Do not assume ultra-low latency or ubiquitous rural coverage without site testing.
Satellite	Regional to near-global depending on service and terminal	Service-dependent; suitable for backhaul and remote connectivity	Service- and terminal-dependent	Remote farms without terrestrial coverage	Terminal, subscription, power, sky visibility and service latency can be significant.

Table 5: AI/ML method selection by agricultural task and evaluation needs.

Model Family	Typical Agricultural Task	Relative Computational Demand	Data and Training Considerations	Recommended Evaluation
Linear / regularized regression	Yield, water demand, soil moisture trends	Low	Small to moderate structured datasets; relatively interpretable	MAE, RMSE, R^2; validation by season/site
Decision tree / Random Forest / gradient boosting	Yield prediction, risk classification, feature-based recommendations	Low to moderate	Tabular data; interpretability varies	MAE/RMSE for regression; precision, recall, F1, ROC-AUC for classification
Support vector machine	Disease/risk classification and small-to-medium datasets	Moderate; depends on data size and kernel	Feature scaling and parameter tuning are important	F1, balanced accuracy, ROC-AUC; external validation
CNN / deep learning vision models	Disease, weed, fruit, crop-stress and image classification	Moderate to high; GPU often useful for training	Large labelled image sets; represent lighting, crop stage and location variation	Precision, recall, F1, mAP/IoU as appropriate; field-level validation
Time-series models	Weather, soil moisture, irrigation demand and sensor trends	Low to high depending on model	Ordered time-stamped data; avoid temporal leakage	MAE/RMSE, forecast horizon, calibration and baseline comparison
Reinforcement learning / optimization	Adaptive irrigation or control policies	Moderate to high; simulation and safe testing often required	Reliable state/action/reward definition; safeguards and offline/simulation evaluation	Water/energy use, yield or quality constraints, robustness and safety
Anomaly detection	Sensor failure, pump faults, livestock behaviour deviations	Low to high depending on method	Baseline data and representative anomaly labels are helpful	False-alarm rate, detection delay, precision/recall and missed-event rate

The table compares typical trade-offs, not a universal ranking (Table **5**). Model accuracy should not be compared across papers unless the target, dataset, split strategy, class balance, prediction horizon, and metric are comparable. Report a baseline, independent or temporal validation, uncertainty where possible, and performance on farms or seasons not used for training.

7.5. Real-time Performance and Quantitative Reporting

The term “real-time” should be defined relative to the decision being supported. A weather dashboard that updates every 10 minutes and a pump shut-off controller that must react within seconds have different requirements. End-to-end response time includes sensor sampling, local processing, uplink/downlink, queueing, model inference, alert delivery, and actuator response (Table **6**). Edge processing can reduce dependence on the network for urgent rules, while cloud processing supports heavier analytics and long-term model development. A robust evaluation should report median and high-percentile latency (for example, 95th percentile), packet delivery or data-loss rate, system uptime, inference time on actual hardware, energy use, and the time from alert to verified action. Required thresholds must be selected for each use case and validated in field conditions.

Table 6: Suggested quantitative performance indicators for IoT–AI/ML farm-management studies.

Performance Dimension	Metrics to Report	Interpretation and Reporting Guidance
Sensor measurement quality	Bias, MAE/RMSE against a reference, repeatability, drift, calibration interval	Sensor-specific and installation-specific; report datasheet plus field validation.
Communication reliability	Packet delivery ratio, data completeness, outage duration, RSSI/SNR where applicable	Measure across representative distances, seasons, crop canopy and weather conditions.
End-to-end latency	Median, 95th percentile and maximum delay from measurement to alert/action	Define start/end timestamps and include network, inference and actuation.
AI/ML performance	MAE/RMSE/R^2 for regression; precision/recall/F1/AUC for classification; task-specific image metrics	Compare with a baseline and use independent/temporal/site-level validation.
Resource and operational outcomes	Water, fertilizer, pesticide, energy, labour, yield/quality, false alarms and response time	Report baseline, comparison period, sample size, uncertainty and confounding factors.
System cost and resilience	Hardware, connectivity, maintenance, battery life, downtime, cost per hectare/device	Include lifecycle costs, not only initial purchase price.

Because this article is a narrative review and does not generate primary experimental data, it does not report new accuracy scores, latency measurements, or resource-saving percentages. Such values should be quoted only from identifiable studies and with their context. The tables above provide a structured reporting framework and comparative synthesis rather than claiming pooled numerical results. A stronger evidence base would include a study-level table recording application, crop/site, sensor/model, dataset size, validation design, metric, baseline, and reported result for each selected empirical paper.

8. Conclusions

IoT in agriculture involves integrating sensors, devices, and connectivity to collect, store, and analyze data for improved farm management. IoT brings significant benefits to agriculture, including precision farming, real-time monitoring, cost reduction, and data-driven decision-making. Farm management systems have evolved from traditional practices to sophisticated, technology-driven solutions, offering unprecedented insights and control. Components such as sensor networks, data analytics, communication technologies, precision agriculture, and real-time monitoring form the foundation of IoT-based FMS. Challenges include data security, infrastructure requirements, and farmer adoption, which are crucial to address for successful implementation. The future of IoT-based FMS involves integration with AI, blockchain, 5G, swarm robotics, and cloud computing, aiming to enhance efficiency, sustainability, and decision-making in agriculture.

The role of IoT-based FMS in promoting sustainable agriculture cannot be overstated. By promoting precision farming, optimizing resource utilization, and facilitating data-driven conservation practices, technology becomes a catalyst for eco-friendly and regenerative farming. The integration of AI and blockchain ensures traceability, transparency, and trust in the agricultural supply chain, benefiting farmers and building consumer confidence in the sustainability of agricultural practices. In conclusion, the future of agriculture is interconnected with the evolution of IoT-based Farm Management Systems. Embracing these technologies is not just a technological advancement but a commitment to sustainable, efficient, and resilient farming practices that meet the challenges of a rapidly changing world. With the power of IoT, farmers can navigate complexities, optimize operations, and contribute to a more sustainable and productive agricultural future.

A key limitation of this review is that it is narrative rather than systematic and does not produce a pooled estimate of technical performance. The recommendations should therefore be interpreted as a framework for selecting and evaluating systems, not as proof that one communication technology or AI/ML model is universally superior. Future empirical work should validate complete sensor-to-decision pipelines under diverse farm conditions and report reproducible metrics for accuracy, latency, energy, reliability, cost, and resource outcomes.

Conflict of Interest

The authors declare that they have no conflicts of interest.

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