



A Systematic Review on Edge Computing for Smart Agriculture: Practical Applications and their Future Directions

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Abstract

Edge computing is revolutionizing smart agriculture by enabling real-time data processing closer to the source of information, leading to faster responses and optimized farming practices. Instead of relying solely on centralized cloud computing, edge devices analyze data locally, allowing for quicker decisions on issues such as irrigation, fertilization, and pest control. This leads to increased efficiency, reduced latency, and improved resource management in farming operations. As a result, edge computing transforms smart agriculture into a decentralized, responsive ecosystem where farmers can monitor, adapt, and react to environmental changes and crop health issues very quickly. The integration of edge computing into smart agriculture is rapidly transforming the industry. From this review, we will discuss the essence of edge computing towards sustainable agriculture by explaining how edge-related techniques help to speed the sensor controls and data communication, how edge-powered hardware/firmware boost the information accessibility and how modern developments in edge technology improve overall performance in smart agriculture. This review also covers the key modern developments in sensing and automation, Edge-AI frameworks, on-device computational power, and connectivity innovations that are collectively propelling this agricultural revolution.

Keywords: Artificial Intelligence; Edge computing; Internet of Things; Smart sensors; Smart agricultur

1. Introduction

Smart agriculture leverages cutting-edge technologies, including Internet of Things (IoT) devices, wireless communication networks, and advanced sensors, to monitor critical agricultural parameters [1]. Combining these technologies together for different agriculture applications is usually difficult mainly due to the computational complexities within these systems. Thus, cloud computing came into picture to solve this. But in traditional cloud computing, data from sensors and devices needs to travel to a centralized cloud server for processing and then back to the farm for action. This introduces latency, which can be critical in agriculture where conditions change rapidly (e.g., in mushroom cultivations) [2]. Many agricultural areas lack robust and consistent internet connectivity, making cloud-dependent systems unreliable [3]. The emergence of edge computing has revolutionized smart agricultural means and ways, presenting innovative solutions for the challenges faced by modern farming practices [4]. Edge computing is considered as a technological paradigm that brings computational power closer to data sources such as farm fields or greenhouses [5]. The deployment of sophisticated Edge-AI frameworks and analytics, powered by increasingly potent on-device computational hardware, allows for complex tasks such as pest detection and yield prediction to be performed in the field, minimizing latency and reliance on the cloud.

Edge computing is considered to be one of the evolving technologies that have the potential to bring transformation in the agricultural sector, enabling real-time data processing and decision-making. Edge computing refers to the paradigm of decentralized data processing, whereby computation and analytics are embedded in the data source rather than relying on a distant, centralized cloud infrastructure [6]. By integrating sensors, IoT devices, [7] and computing nodes, edge computing offers a potentially tractable model, where traditional cloud-based solutions may face connectivity and latency challenges [8]. This approach facilitates real-time analysis of crop, soil, and environmental data, allowing fast adjustments to irrigation, fertilization, and pest control [9]. Edge computing optimizes resource use by reducing latency and bandwidth dependence in data communication. It also enhances sustainability and resilience in resource-constrained environments, such as in areas with limited connectivity [10]. The integration of Edge AI further enhances these capabilities, allowing for intelligent automation, predictive analytics, and improved resource management, ultimately reducing operational costs.

This paper uses PRISMA systematic reviewing technique. Literature was collected from different academic databases, such as IEEE Xplore, ACM Digital Library, Springer and Scopus. Search fields like title, abstract and keywords were used for filtering. Literature from the past ten years was considered with a timeline from 2015 to 2025. Both “smart agriculture” and “edge computing” strings were considered as the two major search strings in all of these databases and for further tuning minor search strings like “precision agriculture”, “smart sensors”, “artificial intelligence” and “internet of things” were used.

Below shows the four research questions (RQs) we considered as the basis to choose the required literature for conducting this study.

RQ1: What edge technologies and edge-related architectures are used in smart agriculture? This question aims to

obtain a detailed overview of current ways of using edge computing in different agricultural sectors. This question also covers the overall technical specifications and background knowledge of this review.

RQ2: What are the practical applications of these edge computing techniques in smart agriculture? This question is used to investigate the current implementations, their benefits.

RQ3: What are the performance trades-offs and adoption barriers reported when deploying edge computer systems in smart agriculture? The purpose of this question is to identify and formulate a set of research gaps

RQ4: Any future considerations or developments to address these issues? This question is used to explore promising technologies that could reshape the agricultural community with future research.

Then, this selected literature was grouped and explored further into 4 subtopics under section 2 which will be discussed next.

2. Concepts around edge computing and smart agriculture

Edge computing in smart agriculture brings data processing closer to the farm. This shift from centralized cloud computing to localized, on-site analysis allows more information to be accessed in a short period of time [11]. Real-time data analysis enables farmers to promptly address crop stress, optimize irrigation, and adjust fertilization strategies, improving yield and resource efficiency. Agricultural edge systems use distributed sensors like temperature, humidity, soil moisture, CO₂ to monitor climate and soil conditions in real time. Such monitoring enables precision control of irrigation, ventilation, and input application by detecting environmental changes locally. Cameras and imaging equipment with various vision capabilities can be utilized for environmental monitoring by recording data on plants and soil. High-resolution images support tasks like weed segmentation, crop counting, and disease detection via on-device vision models [12]. Figure 1 below expresses some promising technologies that should consider developing smart agriculture.

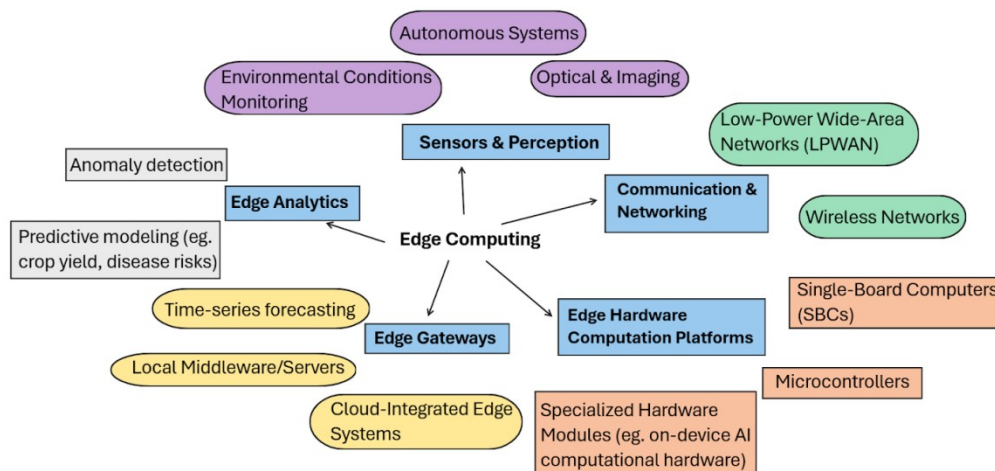


Figure 1: Overview of concepts and techniques related to edge computing in agriculture.

Edge computing does not replace the cloud but complements it. Cloud-edge integration means data and models flow between on-site nodes and remote servers. The cloud is used for heavy analytics, long-term storage, and coordination across farms, while edge handles immediate control. In some smart agriculture systems, edge gateways are used to aggregate sensor data and provide local processing services (a “fog” node) [13]. This may include buffering or running lightweight databases and APIs at the farm.

Other than above techniques, integration of AI in edge computing has enabled real-time data analysis and decision-making at the edge of the network, increasing productivity and sustainability [14] [15]. Under the below sections, we will cover the core technological developments related to edge computing, which can be observed in modern farming.

2.1. Advancements in sensing techniques

The foundation of smart agriculture lies in the proliferation of advanced sensors. Thus, modern edge technology developments have moved beyond simple data collection to real-time, automated interventions. IoT-enabled sensors now monitor a vast array of parameters, including soil moisture, nutrient levels, pH [16]. Edge computing processes this constant stream of data on-site, allowing for immediate automated responses. For instance, an edge gateway can analyze soil moisture data and trigger precision irrigation systems to water specific zones of a field, conserving water and optimizing crop health without relying on a distant cloud server. Similarly, in livestock management, edge devices can analyze behavioral data from wearables to detect early signs of illness and alert farmers for timely intervention [17]. This localized automation is crucial for operational efficiency and resource optimization.

2.2. Advancements in on-device computation power

Many recent studies focus on running ML models on resource-constrained microcontrollers through TinyML techniques such as pruning, quantization, and architecture search. Single-board computers like Raspberry Pi continue to dominate in such in-field computing. The feasibility of sophisticated edge analytics is directly tied to the increasing computational power of on-device processors. The latest generation of edge devices, including specialized agricultural sensors, gateways, and even autonomous tractors, are equipped with powerful multi-core CPUs, GPUs, and dedicated AI accelerators like Tensor Processing Units (TPUs) and Vision Processing Unit (VPUs) [18]. This enhanced processing capability allows for more complex data fusion and analysis at the edge. For example, an edge device can simultaneously process data from soil sensors, weather stations, and drone-mounted multispectral cameras to create a comprehensive, real-time picture of crop health [5]. This on-device power is critical for enabling the autonomous operation of farm machinery, which must make split-second decisions based on its immediate environment. The development of low-power, high-performance processors continues to be a key enabler of more advanced edge computing applications in agriculture.

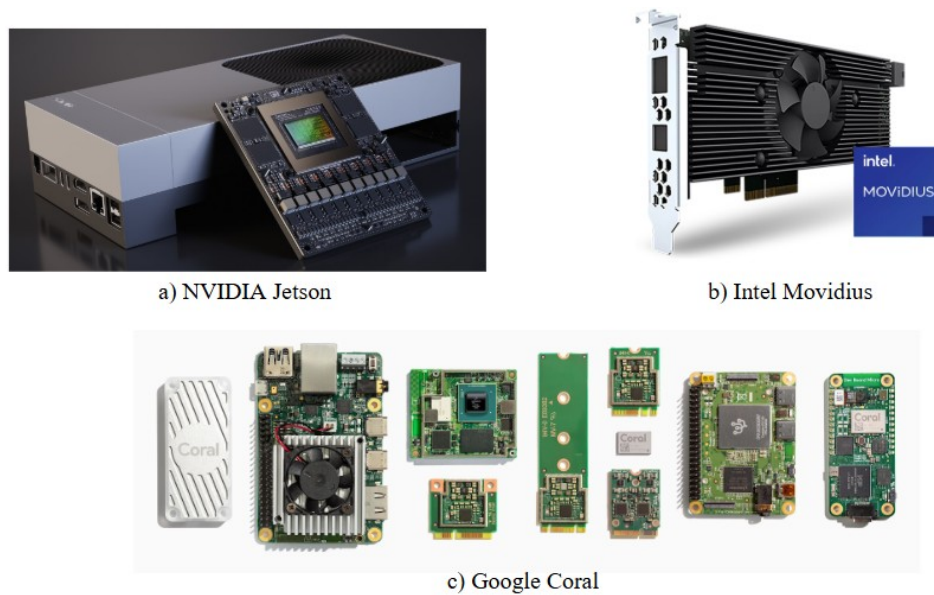


Figure 2: Some famous hardware platforms for AI computation in smart agriculture

2.3. Edge-AI Frameworks

Instead of transmitting vast datasets to the cloud for analysis, lightweight machine learning models are now deployed directly on edge devices. These models can perform complex tasks in real-time, such as identifying pests and diseases from drone or camera imagery, predicting crop yields based on localized data, and optimizing harvest times. Edge-AI frameworks are often deployed as multi-layered designs to balance computational load and for energy distribution [19]. These frameworks also show significant improvements in scaling compared to cloud-based solutions [20].

Recent advancements have focused on developing energy-efficient and lightweight AI models suitable for resource-constrained edge devices [21]. Techniques like model pruning and quantization are being employed to reduce the computational footprint of these models without significantly compromising accuracy. Also, some computer vision models, including YOLO variants and lightweight segmentation networks, are widely used in edge-AI frameworks for disease and pest detection, achieving high accuracy and real-time performance [22]. These Edge-AI frameworks empower farmers with immediate, actionable insights, transforming reactive problem-solving into proactive management.

2.4. Connectivity Innovations

Reliable connectivity remains a significant hurdle in many rural and agricultural areas. Modern wireless technologies, particularly Low-Power Wide-Area Networks (LPWAN) and 5G, are directly addressing this challenge and unlocking the full potential of edge computing in smart agriculture. To bridge connectivity gaps, researchers have explored low-power wide-area networks and private 5G [9]. As for some examples, LPWAN protocols like LoRaWAN enable kilometer-scale coverage at 98% packet delivery rates [23].

Thus, LPWAN technologies, such as LoRaWAN and Narrowband Internet of Things (NB-IoT) [24], are ideal for connecting low-bandwidth sensors over long distances with minimal power consumption [25]. This makes them perfect for deploying vast networks of soil, weather, and livestock sensors across large farms, ensuring multi-year battery life and reducing maintenance costs [26]. On the other hand, 5G offers high bandwidth and ultra-low latency, including private 5G networks for large agricultural enterprises, will facilitate a new level of high-performance edge computing, enabling near-instantaneous data transfer and analysis for mission-critical applications [27]. Below table shows a summary of above technological innovations with some benefits and limitations in general

Table 1: Agricultural benefits gain by using modern technological advancements with technical limitation

Innovations	Benefits	Limitations
IoT-enable Sensors / Smart Sensors	Real-time decision making and monitoring.	• High initial cost. • High cost of repair and maintenance.
Light-weight AI frameworks/models	Fast computation and mobility.	• Accuracy vs. computation power tradeoff • Harder to interpret and tune with diverse environment parameters
In-field embedded systems (eg:- microcontrollers, single-board computers etc.)	• Less or sometimes no cost on cloud computations. • Limited exposure to external services, improving privacy and security. • In case of no cloud connectivity, - Offline resilience - Lower operational dependency	Power constraints and limited uptime and continuous processing.

Innovations	Benefits	Limitations
Dedicated AI hardware/accelerators (eg:- GPUs, TPUs, DPUs)	Fast access to AI at the point of need.	High capital cost and cooling requirements
Power-efficient and reliable communication (eg:- LoRaWAN, NB-IoT)	Better interactions and low latency control due to lower bandwidth usage and close integrity.	• Coverage vs. bandwidth tradeoff. • Network management costs

3. Case studies and real-world applications

Edge computing tries to reconstruct agriculture into a data-driven industry, which is capable of addressing food security, environmental resilience, and economic viability in the face of global challenges like climate change and population growth. For example, intelligent irrigation systems which can adjust water delivery based on instantaneous soil moisture and weather data. Autonomous machineries are used to optimize planting and harvesting routes. Sophisticated sensors are used to monitor crop health for early detection of pests and diseases. Hence, edge computing significantly reduces resource usage which leads to lower operational costs for farmers but also lessens the environmental footprint of agricultural activities. Below table shows real-world applications under edge computing which directly relates to farming and other agriculture implementations.

Table 2: Real-world applications of edge computing in the field of agriculture

Category	Technologies Used	Examples
Crop monitoring and Weeds/Pest Detection using Imaging	AI models on edge devices (RetinaNet, MobileNetV3-small, Light-CSPNet, YOLO), model quantization and compression, knowledge distillation, feature-fusion, thermal imaging	[28], [29], [30], [31], [32], [33]
Agricultural Robotics	Offloads segmentation, E5SH systems	[33], [34], [35], [36]
Environmental Monitoring	Edge IoT, smart irrigation, soil management, microclimate control	[37], [38], [41], [42]
Communication	Long-range LPWAN (eg - LoRa, WSN, Zigbee), 5G or MQTT with edge gateway	[35], [43], [44]
AI Integration	AI-enabled microcontrollers, Edge TPUs and VPUs, TinyML	[30], [39], [45], [46], [47]

4. Challenges, limitations, and future directions

Edge computing tries to reconstruct agriculture into a data-driven industry, which is capable of addressing food security, environmental resilience, and economic viability in the face of global challenges like climate change and population growth. For example, intelligent irrigation systems which can adjust water delivery based on instantaneous soil moisture and weather data. Autonomous machineries are used to optimize planting and harvesting. Edge computing can enhance smart farming by processing data near sensors, but it faces significant technical and operational hurdles. Especially the cost of smart edge devices. Edge systems require substantial upfront investment in sensors, edge computing hardware (e.g., routers, gateways), communication infrastructure, and integration services. Advanced sensors (e.g., hyper spectral cameras, electrochemical soil analyzers) represent a major cost component, potentially out of reach for small-scale farmers [48]. On the other hand, large-scale farmers will be benefited more significantly from edge deployments due to the ability to amortize high fixed costs over larger areas, making the return on investment (ROI) more attractive where smallholders struggle with this calculus [49]. Affordable edge devices are typically resource-constrained (limited CPU, memory, and energy) and must often operate with intermittent or low-bandwidth connectivity, making it hard to run heavy AI models or stream high-resolution imaging continuously [50]. Rural deployments also raise scalability and security concerns like weak and unstable connectivity. Heterogeneous sensor networks must be managed at scale while protecting data privacy and defending against cyber-attacks [10]. Overcoming the challenges associated with hardware limitations, data scarcity, and algorithmic complexity requires concerted efforts from researchers, industry stakeholders, and policymakers [51]. To address these challenges, emerging approaches include federated or distributed learning (training AI models across many farm devices to avoid central data transfer) and aggressive on-device model optimization (pruning, quantization, knowledge distillation to create lightweight networks) can be used [50].

Hybrid edge–cloud architectures are also being explored, wherein local preprocessing filters and summarizes raw sensing (e.g. UAV or camera imagery) and the cloud performs more complex analytics when connectivity permits [52]. The decentralization of data processing and decision-making enabled by edge computing has the potential to revolutionize many industries [53] [54]. These strategies aim to overcome resource bottlenecks and enhance the scalability, security, and real-time autonomy of precision agriculture systems. The fusion of scientific research and technological innovation holds tremendous promise for the future of precision agriculture and its beneficial influence on agriculture and society as a whole [55]. Below shows a brief overview of these future directions with respective development considerations.

Table 1: An example of a table

Future directions	Development considerations
Federated (or distributed) learning	Tries to improve data generalization by training cross-farm models (yield forecasting, disease classifiers)

Future directions	Development considerations
AI model optimization	In this direction, researchers try to find smaller, faster and more energy-efficient ways of computations.
Event-driven edge AI	Tries to introduce new or optimize current hardware and software systems for fast/rare event tracking like insect movements and sudden pest outbreaks. (eg:- Dynamic Vision Sensors (DVS), Spiking Neural Networks [56])
Hybrid edge–cloud architectures	Focus on providing always-on local intelligence in remote farms using very low power and latency considerations.
Self-sustaining nodes	Tries to implement sensor nodes that harvest renewable energy and use relevance-aware to extend lifetime and support continuous edge AI in remote fields.

5. Conclusion

Edge computing is rapidly emerging around modern agriculture techniques, due to its more efficient, sustainable, and data-driven approach. By bringing computational capabilities closer to the data source, edge computing enables real-time data processing and localized decision-making, minimizing the latency and bandwidth limitations inherent in cloud-centric models. The ability to operate effectively in rural areas with limited internet connectivity further underscores its practical utility, making advanced smart farming accessible to a broader range of agricultural enterprises. Combining sophisticated technologies like IoT, drones, and renewable energy with AI to create automated and real-time systems can be considered as some of the major future edge computing and agriculture research considerations within the community. Moreover, real-time insights provided by edge systems contribute to improve data-driven research applications. In essence, edge computing is pivotal in fostering a more resilient, productive, and environmentally responsible agricultural future.

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