Annals of Telecommunications (2024) 79:35–59
https://doi.org/10.1007/s12243-023-00997-0

Computing paradigms for smart farming in the era of drones: a systematic review

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Received: 16 June 2023 / Accepted: 22 October 2023 / Published online: 18 November 2023

Abstract
In the current era of agricultural robotization, it is necessary to use a suitable automated data collection system for constant plant, animal, and machine monitoring. In this context, cloud computing (CC) is a well-established paradigm for building service-centric farming applications. However, the huge amount of data has put an important burden on data centers and network bandwidth and pointed out issues that cloud-based applications face such as large latency, bottlenecks because of central processing, compromised security, and lack of offline processing. Fog computing (FC), edge computing (EC), and mobile edge computing (MEC) (or flying edge computing FEC) are gaining exponential attention and becoming attractive solutions to bring CC processes within reach of users and address computation-intensive offloading and latency issues. These paradigms from cloud to mobile edge computing are already forming a unique ecosystem with different architectures, storage, and processing capabilities. The heterogeneity of this ecosystem comes with certain limitations and challenges. This paper carries out a systematic review of the latest high-quality literature and aims to identify similarities, differences, and the main use cases in the mentioned computing paradigms, particularly when using drones. Our expectation from this work is to become a good reference for researchers and help them address hot topics and challenging issues related to this scope.

Keywords Smart agriculture · Cloud computing · Edge computing · Fog computing · UAV · Flying edge computing

1 Introduction

Today, we are witnessing climate change, a health pandemic, and a political conflict which have a major impact on food security. According to FAO (Food and Agriculture Organization), the world needs to increase food production by almost 50% by 2050 [4]. To meet this demand, farmers, scientists, and agricultural industries are exploring new modern technologies such as the Internet of Things (IoT), artificial intelligence (AI), cloud computing (CC), edge computing (EC), flying edge computing (FEC), big data, and unmanned aerial vehicles (UAVs). The ecosystem that emerged from this combination is now called smart farming, smart agriculture, or also precision agriculture, which is all about collecting the right data at the right time so that the use of resources can be optimized by considering the requirements of every inch of farmland [16] Today's trends and statistics point out a considerable evolution towards the robotization of the agricultural sector. According to CISCO [1], more than 70 billion devices will be connected by the end of 2025.

According to Polaris Market Research Analysis [2], the global agriculture drones market was valued at USD 1.26 billion in 2021 and is expected to grow at a CAGR (compound annual growth rate) of 29.1% during 2018–2030.

The adoption of these technologies has made agriculture more industrialized and technological, bringing multiple benefits such as increased quantity and quality products, reduced labor costs, and reduced resource consumption.

However, the massive use of connected objects and digital services induces a huge amount of data from farms. Ensuring the best processing, protection, and traceability of this data has become an issue for both farmers and companies in the agricultural sector. For that purpose, prominent metaverse (Facebook, Microsoft, Google, Apple, and Amazon) are using massive Cloud Datacenters (CDCs) to provide effective user services to process this data in a proficient and trustworthy manner.

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In the majority of cases, data from farms is analyzed, processed, and stored in secure clouds. The main advantage of this is to make them accessible from any part of the globe. But, processing and memorizing this massive volume of data at local nodes have been deemed critical challenges, especially when using artificial intelligence (AI) based systems to extract and exploit valuable information. In fact, the centralized processing mode of cloud computing has limited bandwidth, high latency, and high power consumption.

Eventually, the goal of having massive storage capacity with efficient scalability has recently been the driving force behind new emerging research efforts dealing with edge, fog, and flying edge computing paradigms. Fog nodes, in an effort to alleviate processing at the data center level, perform light user requests without having to send them to the cloud while edge nodes provide an innovative service to completely execute user requests at the nearest level to the user. As the research in fog, edge, and flying edge computing is purposefully growing, there is a need to assess the existing research related to these emerging paradigms to find out the possible future directions and research opportunities related to this field.

This work presents a fresh manifesto on modern computing paradigms to identify further opportunities and future directions for emerging paradigms compared with the cloud computing paradigm. It expands our previous work [3] by discussing recent valuable works based on flying edge computing as well as the resulting challenges. Our contribution further includes, through a systematic review methodology, a synthetic taxonomy on the advantages and limits of each architecture.

The remainder of this paper is organized as follows: The background on computing concepts is presented in Section 2 including smart farming, Internet of Drones concepts, and a detailed comparison between the discussed computing paradigms. Section 3 draws the review methodology conducted in this survey. Section 4 describes a systematic literature review of novel research works related to the mentioned architectures to sum up, in Section 5, with a synthetic overview of related open issues. Finally, Section 6, concludes the ongoing work.

2 Background on computing paradigms

Before delving into the main parts of this paper, a general overview that summarizes the different paradigms mentioned will be given. Each paradigm will be carefully discussed concisely for clarity and consistency. The reason for discussing these paradigms is to provide an overview that will guide the understanding of the research objectives of this paper, mainly the information life cycle and each paradigm architecture. The computing technologies in an IoT environment may offer services for end-users, which can improve the system's overall performance with higher throughput in real time. The developing rate of IoT-based smart devices or sensors requires mobility with extensive geographical distribution, which is only possible nowadays through computing technologies [5].

2.1 Smart agriculture

Smart agriculture is an emerging concept that emphasizes the use of advanced technologies such as IoT and AI to improve productivity. It is based on digital tools to collect and analyze various real-time information in order to better understand and analyze the physiological crops needs and to develop decision support tools for the user. The whole picture is as follows: sensors and/or drones with sensing capacities are deployed over the field to monitor specific parameters such as soil moisture, soil fertility, air temperature, smoke, crop growth factors, movement of livestock, and presence of pests. All these collected data are valuable resources for use in data-driven services and decision support systems (DSS) in agricultural platforms and will be then processed in powerful servers to extract and analyze valuable information for a better use of resources and an increasing production [6].

Precision farming can be viewed as comprising four stages: data acquisition, interpretation, analysis, and control. To successfully deploy and run a smart agriculture system, the farmer needs to implement various cutting-edge technologies across these stages to experience perceived benefits. To achieve these goals, we may face several challenges. For example, we should consider setting up a communication network that can integrate a limited number of sensing nodes across a large area of farmland. This will require third-party network provisioning or setting up a private network consisting of access points and uplinks to a private backhaul network, which channels all the data traffic to centralized monitoring software or an analytics head-end system.

While data plays a central role in smart agriculture, data management is an ongoing challenge for many farmers and agribusinesses alike. Even a small farm gathers and stores tons of data to inform related operations and marketing decisions. To overcome this challenge, a smart approach to data processing, management, and storage must be deployed. That is why the agriculture industry is rapidly adopting the big data concept as a key solution for a successful precision agriculture system.

2.2 Internet of Drones (IoD)/UAVs overview

We strongly believe that IoT is a key technology in smart farming, through the use of multi-functional devices such as ground robots and drones. The Internet of Drones (IoD) has recently gained momentum due to its high flexibility in various complex scenarios. In fact, thanks to technical and practical advantages such as high maneuverability and wireless expansion capabilities, UAVs are successfully used in various application areas such as agriculture, search and rescue missions, surveillance systems, and many other civil utilization. These flying robots, in a wide range of applications, are used as first responder because of their fast, cost-effective, and safe deployment capabilities [7]. Further, with improved technology and installations like three-dimensional projects, UAVs are playing the pivotal part of airborne base stations in almost all emerging networks. Thus, the use of drones is expected to improve the performance parameters of various network architectures, such as reliability, connectivity, throughput, and latency.

Because of their involvement in a wide range of daily operations, UAVs have become the best candidates to achieve meaningful results in precision farming [9]. Due to these capabilities, UAVs can be used throughout the life cycle of crops in similar functions as soil health examinations [30], colony [10], factory counting [11], crop health monitoring [13], irrigation [39], spraying fertilizers and pesticides [14], and estimating crop yield. With precise and accurate sensors, drones can determine water stress, low crop nutrients, and poor soil health. By implementing a drone program, farming can become more economically and environmentally efficient by targeting the areas that need the most care. This drone-based technology has become a point of interest for all concerned agriculture professionals, including farmers, agronomists, crop insurance companies, and researchers.

Nevertheless, the adoption of drone networks brings also several issues related to the inherent unreliability of the wireless medium, battery life, and high mobility, which can lead to frequent topology changes. This explains the really large amount of workshops generated in the recent literature on correlated topics. Here, we briefly cite some challenges of remote farming using UAVs in the literature:

- **Deployment and path planning:** Initially, drones should be deployed in such a manner to best cover the farming field. Then, once deployed, these drones should carry out their functions in a cooperative manner and delegate surveillance and data collection tasks to each other to optimize the number of drones used for a given application.
- **Communication:** Drones are generally used to monitor farming areas, to connect sensors, and to collect valuable data. This task requires the establishment of air-air and air-ground exchanges which are carried over wireless links that are most often fluctuating, unstable, and subject to ambient interference.
- **Real-time requirement:** Depending on the targeted farming application, drones can be called upon to provide instantaneous and real-time response times. This aspect represents a challenge in the sense that it requires advanced processing and transmission capabilities.

2.3 Cloud computing overview

The US National Institute of Standards and Technology (NIST) defines "Cloud Computing" as a model for enabling convenient, on-demand network access to a shared pool of configurable computing resources (e.g. networks, servers, applications, and services) that can be rapidly provisioned and released with minimal management effort or service provider interaction.

On another hand, a successful IoT system requires high performance, reliability, efficiency, and scalability. Here, we came up with the idea of merging cloud computing and the Internet of Things, and this allows systems to be automated in a cost-effective way that supports real-time control and data monitoring. These two technologies are considered the real motivators that are driving the agricultural industry to transition to smart agriculture to improve operational efficiency and productivity.

As the cloud is mainly formed by centralized servers also called data centers, it is, generally, quick to deploy, inexpensive to maintain, and practical when data need to be centrally controlled. The main advantage of the cloud is that the stored data can be accessed from anywhere in the world. The cloud can also handle a very large number of analyses at the same time and can manage very complex neural networks thanks to very high computing power.

However, when dealing with a massive amount of data, these cloud nodes are mostly constrained by their high failure rate, security risks, and access delay. Data processing at the central level causes considerable time delays that affect the overall system quality of service (QoS), especially regarding the response time requirement for latency-sensitive applications and intermittent Internet connectivity [18]. On the same perspective, according to IDC forecasts [64], 50% of the Internet of Things with more than 50 billion terminals will face network bandwidth limitations, and 40% of data will need to be analyzed, processed, and cached at the edge of the network. The size of the edge computing market will exceed trillions, and it will become an emerging market that is evenly matched with cloud computing.

2.4 Fog computing overview

The fog computing architecture comprises various components, including gateways, routers, and cloud services used to distribute computing resources between data devices and the cloud or any other data center in a distributed computing process.

This computing approach was first introduced by Flavio Bonomi at CISCO in 2012. According to [23], fog computing is a highly virtualized platform that provides computing, storage, and networking services between end nodes and traditional cloud computing data centers, typically located at the backhaul network, but not exclusively. The basic idea behind fog is to bring the cloud down to the scale of the farm so that the user's computation demand is served at their proximity rather than performed in the distant cloud. Moreover, fog computing is primarily introduced for applications that need real-time processing with low latency since the data generated by the terminals is pre-processed in decentralized mini-computing centers beforehand, rather than being directly uploaded to the cloud.

The fog nodes are context-aware and support common data management and communication services. The heterogeneity of fog servers comprises shared locations with hierarchically structured blocks. They can be organized in clusters, either vertically to support isolation or horizontally to support federation or relative to fog nodes' latency distance to the smart end devices.

Fog computing can also be used to develop low latency networks between analytic endpoints and devices, which can lead to reduced bandwidth requirements compared to cloud computing. However, fog computing is dependent on multiple links for transferring data from the physical asset chain to the digital layer, which can be potential points of network failure.

Moreover, this type of infrastructure is still rare and especially reserved for large industrialized farms because it requires greater investment in network and IT architecture [57]. Fog also requires graphic computers to be installed on the farm. The maintenance of an infrastructure like fog is more restrictive because not all interventions can be managed remotely.

2.5 Edge computing overview

The emerging paradigm of edge computing (EC) employs novel techniques to address the challenges of ultra-low latency, high data rates, broad bandwidth, and optimal user experience. The EC architecture processes data closer to the source, often on the same device that collects and analyzes the data, enabling fast and seamless results. The proximity to the data source offers significant business advantages, with the biggest benefit being the ability to control critical processes in real time. EC also supports decentralized data storage and processing, eliminating bandwidth limitations and network outages that could adversely affect important business decisions.

Similar to fog computing, edge computing does not require huge bandwidth. Only the analysis results are sent to a cloud-hosted on the Internet. This approach is interesting because it addresses Internet connection problems in certain rural areas (persistence of white areas). However, unlike fog computing, edge computing does not require the installation of a graphic computer on the farm since the edge nodes already have computational capacities. Moreover, devices that use edge computing can provide near real-time analytics that can help optimize performance and increase uptime. These technologies are experiencing strong growth, particularly for facial recognition applications associated with mask-wearing detection or temperature measurement.

However, the deployment cost of EC is higher than that of conventional sensors/cameras since the edge nodes are already equipped with computers and use more advanced technology. Additionally, edge nodes equipped with edge computing technology cannot process the same data stream as a computer (fog) or supercomputers (cloud) due to their limited capabilities. EC is also less scalable compared to fog computing and supports little interoperability. This could make IoT devices incompatible with certain cloud services and operating systems. In addition to these disadvantages, edge computing does not support resource pooling, and maintenance is more cumbersome than in conventional computing as certain problems may require physical maintenance on the farm.

2.6 Flying edge computing overview

Flying edge computing (FEC) has emerged as a promising solution for meeting the quality of service (QoS) requirements of the Internet of Things (IoT) and mobile devices, which often have limited resources in terms of processing cycles and power. In fact, with the advent of drones, these flying robots are used to form flying edge platforms, also called mobile edge computing (MEC) solutions. Such platforms have been employed, on the one hand, to improve the intensive computation and offloading bottlenecks between end nodes and centralized data servers and, on the other hand, to offload processing restrictions of simple fixed sensors [22].

This FEC paradigm can be presented as a server-edge network supported by a cloud computing backend layer close to IoT and mobile device networks.

Flying edge computing aims to extend flying cloud computing for real-time IoT applications. The edge layer distributes the computational load by processing data locally to the edge device level without cloud intervention. Therefore, switching data processing and storage to the edge layer can significantly reduce latency.

Hybrid solutions can be modeled hierarchically, where more computationally intensive tasks are executed in the gateway (the fog) and less computationally intensive tasks are executed in the end devices (fog/edge/flying edge). The collected and processed data is still delivered to the cloud, where it is made available to the user. As illustrated in Fig. 1, hybrid solutions are conceptually modeled with regard to a hierarchical view.

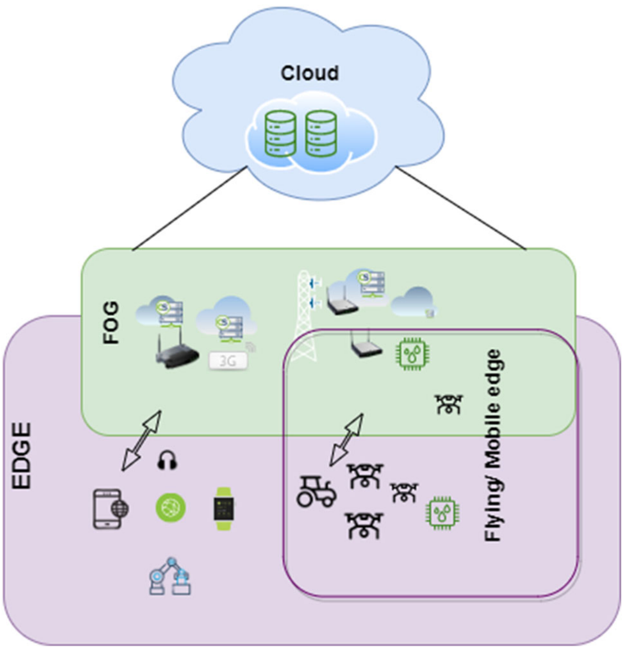

Fig. 1 Hierarchical view of computing

2.7 Differences and similarities of computing paradigms

Unlike the cloud, FC, EC, and FEC share common features relative to the way they bring the intelligence services closer to the users and how they offer customers with lower latency services while making sure, on the one hand, that highly delay-tolerant applications would achieve the required QoS and, on the other hand, lowering the overall network load [48]. That is why it is not trivial to assess the main differences. This subsection attempts to look into similar common features and differences between the above paradigms, which can be summarized in Table 1.

First, we are trying to synthesize information to provide a general comparison between edge computing and flying edge computing, since they are very close:

- Edge computing involves processing and analysis of data on fixed devices located at the edge of the network, while mobile edge computing involves processing and analysis of data on mobile devices (UAVs, tractors, robots, mobile actuators,...) that can move to different locations. Flying edge computing is a specific type of MEC using UAVs.
- Edge computing is suitable for applications that require low latency, real-time processing, and reduced network bandwidth, while flying edge computing is more useful for applications that require real-time data processing and analytics in remote or hard-to-reach locations such as forest fire detection and wildlife monitoring.
- Edge computing typically involves deploying computing resources on fixed and powerful devices such as gateways or edge servers, while flying edge computing implements computing programs on drones with regard to their hardware capabilities.
- Compared to fixed edge servers, the performance of flying edge nodes is strongly constrained by their available energy which requires continuous monitoring of the available resources before tackling a given task and even seeing the implementation of energy-saving solutions to extend their lifetime.
- To cover large geographical areas, flying edge nodes is practically better and cheaper than deploying the high number of fixed edge servers, as connecting these edge servers is challenging because of unreliable and fluctuating communications.
- When using UAVs, the network is much more fault-tolerant, since the tasks initially allocated to the failed drone can be easily redistributed to the other available drones. This fault tolerance is more difficult to manage with fixed nodes because it requires human intervention to repair or change the faulty node.

A focus on the flying edge concept compared with traditional edge and cloud computing is represented in Fig. 2.

Overall, the different computing techniques exhibit the same view of providing QoS to customers, but each one has a separate set of features that makes it original.

Notably, the fog paradigm is designated the most effective and reliable system to better handle the security and privacy challenges encountered.

However, some features of the variants of the edge paradigm, such as decentralization, mobility, fast data processing and analysis, and bandwidth-free constraints, have made it a promising solution to real-time IoT applications.

Particularly, for farming applications requiring UAV remote sensing, the FEC offers several features facilitating the deployment and efficient functioning of such applications. Along with high mobility and scalability, UAVs can offer many potential opportunities in terms of enabling services such as pervasive connectivity, aerial intelligence, self-maintenance capabilities for communications, and sensor deployment. Therefore, UAVs are, generally, used for several roles such as airborne base station subsystem (BSS), data collectors, relay nodes, edge and cloud computing servers, and power suppliers to support IoT applications. These features are likely to extend network coverage and provide diversified and flexible intelligence facilities for new potentialities in modern IoT applications. Among the most relevant benefits of FEC are as follows:

Table 1 Main differences between cloud, fog, edge and flying edge computing

Attribute	The computing technique			
	CC	FC	EC	FEC
Network architecture	Centralized	Centralized/decentralized	Decentralized	Decentralized
Service architecture	Client–server	SOA/microservices	Microservices	Micro/nano-services
Focus	Infrastructure level	Infrastructure level	IoT level	No communications infrastructure needed
Handling multiple IoT applications	Supported	Supported	Not supported	Not supported
Latency	High	Medium	Low	Ultra low
Scalability	High	Average	Limited	Limited
Mobility	Not supported	Offered	Supported	Supported
Energy	High	Low	Low	Very low
Bandwidth cost	High	Average	Low	Low
Storage and computation capacity	High	Varying	Limited	Limited
Access security	Open to all users	Restricted access	Distributed and restricted access	Distributed and restricted access
Data privacy	Third party	Institutional access	Institutional access	Institutional access
Data analysis	Less time-sensitive data processing	Real-time, decides to process locally or send to cloud	Real-time instant decision-making	Real-time instant decision-making
Data attack	High probability	Low probability	Very low probability	Very low probability
Failure risk	Medium	Low	Low	High
Communication	Wired Internet	Wired intranet	Wired/wireless intranet	Wired/wireless intranet
Interoperability	At the Internet	Close to the edge	At the edge	At the edge
No. of nodes	Few	Large	Very large	Very large

- Scalability: The system can be rapidly expanded in terms of coverage area, number of sensor devices, number of drones in operation, and services provided.
- Flexibility: The system is flexible enough to adapt to changes, required services, or monitored areas.
- Fast deployment: The mobile and autonomous aspect of UAVs makes the flying edge easily deployed in remote areas to facilitate IoT services. It is a turnkey system that can be used where there is no communication infrastructure.
- Power effectiveness: As hosted computing services are provided by flying robots (UAVs) which are easily recharged, this scheme is considered to have extremely high-performance efficiency for IoT nodes.
- Communication possibilities: UAVs can potentially adopt many recent cellular and non-cellular wireless communication networks to control the UAV and to enhance the coverage and latency services. The most prominent communication protocols that can be used with UAVs are IEEE 802.11 (Wi-Fi), IEEE 802.16 (WiMax), IEEE 802.15.4 (LRWPAN), cellular networks (3G/4G), IEEE 802.15.1 (Bluetooth), LoRaWAN (LoRa), SigFox, and narrowband IoT (NB-IoT). Typically, the choice of communication protocol depends on the desired achievable throughput, power consumption, range, implementation cost, reliability, delay, and security.

Like edge computing, MEC shortens the distance between where data is produced, collected, and analyzed in the cloud. Processing that is typically offloaded to the data center is now done virtually by mobile edge clouds, which collect, store, and process information from nearby wireless devices within the cloud network. Being close to the device and bypassing the user enables significant performance improvements, including higher bandwidth, lower latency, and faster response times and decision-making. Cloud, fog, and edge have limitations regarding computing capacity, coverage range, storage resources, and latency. Using a single computing paradigm is not enough to fulfill the diverse requirements of a huge number of traditional and heterogeneous IoT devices. It depends on the use case, but a user might be faced with computation-sensitive and latency-sensitive applications at the same time. In this case, the user would require the services provided by both cloud and edge or fog [17]. This is where a federation between computing paradigms can play a key role in resolving such issues.

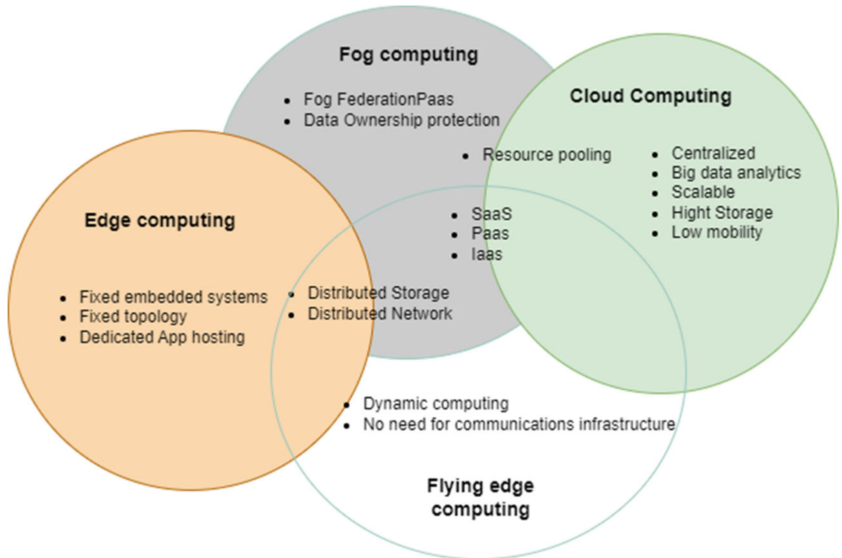

Fig. 2 Similarities and differences between computing techniques

Each of these paradigms has its unique features and applications. For instance, cloud computing is widely used in the deployment of web applications and data storage. Edge computing is employed in real-time applications such as autonomous vehicles, industrial automation, and smart homes. Fog computing is used in applications that require decentralized computing, such as precision agriculture. Flying edge computing, on the other hand, is a relatively new concept that combines edge computing with UAVs. It is mainly used for real-time data processing and analytics in remote or hard-to-reach locations, such as environmental monitoring, wildlife conservation, and disaster management.

A comparative overview of these computing techniques with details about the pros and cons of each one is given in Table 2.

3 Review methodology

Over the past few years, several works have been proposed in the field of smart farming. The academic community has extensively analyzed this rich literature from multiple perspectives and with specific objectives in mind. In this review, our primary goal is to identify specific smart agriculture use cases that rely on a combination of cloud, fog, edge, and flying edge architectures. Our contributions in this work include (i) presenting a representative list of application domains based on the required computing architecture, (ii) investigating relevant works based on a multi-layered architecture with a focus on main contributions/achieved objectives and components of the proposed solutions, and (iii) providing a comparative summary of the pros and cons of each computing architecture based on the latest results listed in this review. Finally, we also discuss the impending challenges and open issues in computing paradigms-based smart agricultural applications. To create a review that meets publication requirements and specific considerations associated with each step, we followed various standards and guidelines suggested for literature reviews, such as those in [15, 19, 54], and we adopted the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) methodology to systematically review the existing literature on smart farming with IoT in the era of drones. Figure 3 shows the workflow and the basic steps of our review process which include (1) designing the review, (2) conducting the review, (3) analyzing, and (4) writing up the review.

Hereafter, we explain one by one the key steps followed to carry out this survey with relative details concerning the number, the quality, and the filtering of the references used.

3.1 Designing the review

Faced with a plethora of literature on digital precision agriculture, it was necessary to restrict our field of study to a specific and targeted topic.

The development of wireless technologies and the drone market motivated us to address the prospects for the advent of these key components in modern agricultural applications. Through the keywords used in our research, we found well-ranked surveys that we decided to include in this paper.

For example, in the review [19], the authors identify the main devices, platforms, network protocols, and data processing technologies for IoT-based smart farming applications. This work reports an increasing trend towards the integration of complementary technologies that rely on cloud and big data computing for processing large amounts of data, with a particular use of artificial intelligence and image processing techniques. As this study was focused on the sensing

Table 2 The comparison of cloud computing and other computing paradigms

	Architecture	Pros	Cons
CC	· Centralized computing model	· Scalable	· Long latency/response time
	· Accessed through the Internet	· Cost-effective	·*limitedbandwidth*
	· Large-scale data storage and processing on remote servers	· Based on an Internet-driven global network on robust TCP/IP protocol	· Security vulnerabilities
			· No offline mode
			· Bottlenecks if many devices send data simultaneously
FC	· Coined by Cisco	· Real-time data analysis	· Data must pass through many links to approach the fog node
	· Extending cloud to the edge of the networks	· Fast	· Single point of failure
	· Hybrid computing model between cloud and edge computing	· Sensitive data remain inside the network	
	· Any device with computing capability, storage, and network connectivity can be a fog node	· Saves storage and network costs	
		· More scalable than mist and edge	
		· Operations can be managed by the IT team	
		· Fog node can be deployed in protected, private, public, or hybrid mode	
EC	· Decentralized computing model	· More secure than FC and CC due to the proximity	· Less scalable than fog and cloud
	· Limited peripheral layers	· Fast	· Requires more node energy
	· Pushes the intelligence, processing power, and communication of an edge gateway of appliances directly into devices like programmable automation controllers (PACs)	· Not dependent on the Internet	· No cloud awareness
			· Not usable in hard conditions or where sensor nodes are fluctuating
FEC	· Can work with no communications infrastructure	· Completely secure	· Most devices are constrained by their size and battery usage
	· A flying node acts like a computing and communication machine	· Works offline and no need to any communications infrastructure	
	· Involves deploying computing resources and data processing capabilities on UAVs, which can fly to remote or inaccessible areas to collect and process data	· Saves power	
		· Scalable	
		· Provides real-time data analysis and decision-making capabilities in remote or hard-to-reach locations	

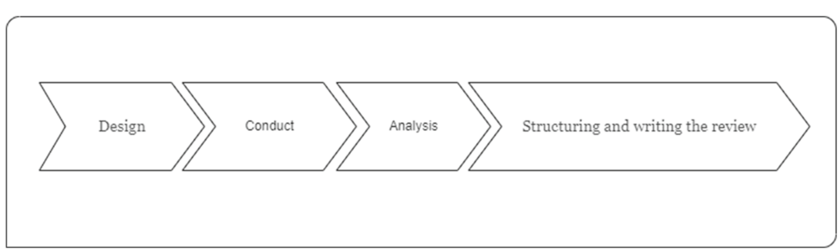

Fig. 3 The review process of our work

and the data collection layer without a specific concern on multi-layered computing solutions, our work may extend this review by including the analysis of computing paradigms' usage in smart agriculture as a way to deal with challenges associated with traditional centralized cloud solutions such as high communication latency, lack of support for real-time reaction to detected events, and large bandwidths.

The paper [64] presents a review of the application of EC in the Agricultural Internet of Things and investigates the combination of EC with AI, blockchain, and virtual/augmented reality technologies. The challenges of edge computing task allocation, data processing, privacy protection, and service stability in agriculture are reviewed, but their study was limited to edge computing, and no comparison was made between edge and other computing paradigms.

The authors in the survey [20] provide an extensive review of the use of smart technologies in agriculture based on relevant research works. They elaborate an extensive state-of-the-art of new technologies for smart agriculture including, the Internet of Things, cloud computing, machine learning, and artificial intelligence. Moreover, this survey discusses the components used in different architecture models and briefly explores the communication protocols used to interact from one layer to another. Finally, the challenges of smart agriculture and future research directions are briefly pointed out in this article, with a particular concern on climate impact. However, the paper does not provide any comparative analysis of the architectural design of the reviewed solutions and does not include fog-based solutions.

This survey [18] is a systematic review of cloud, fog, and edge computing applications and architecture components from research articles published between 2015 and 2021. The study carried out reports a high focus on applying the cloud-fog-edge combinations in order to get the benefits of a truly connected and smart farming concept. We intend to augment such a study with more fresh papers and introduce the flying edge paradigm as a trendy advanced solution capable of solving many of the challenges raised.

In the paper [21], the authors review the latest research on IoT and UAV technology applied in precision agriculture. Besides an overview of the main principles of the "intelligent" perspective in the process of cultivation so-called "Agri-Food 4.0," the authors present the role of UAV technology in smart agriculture by analyzing the applications of UAVs in various scenarios and their utility in complex agricultural environments. Moreover, a brief description of their AREThOU5A project is outlined where emerging developments in the field of Internet of Things (IoT), low-power wide-access radio technologies, energy harvesting, and machine learning are exploited to promote rational use of water resources in agriculture. This review, however, does not address either the architectural design or the data computing concern of the reviewed solutions. Also, an in-depth comparative analysis is also still required.

This review [8] presents a thorough examination and bibliometric analysis of the use of drones in the agricultural domain. The main objective of the paper is to provide a comprehensive overview of the existing literature on drone applications in agriculture and to identify significant patterns, research areas, and influential contributors in this field. For that purpose, the authors conducted a systematic review of research articles obtained from various databases. They categorized the studies based on their primary focus, such as crop monitoring, pest detection, irrigation management, and yield estimation. The paper highlights the potential advantages of employing drones in agriculture, including enhanced operational efficiency, cost-effectiveness, and environmental sustainability. In addition to the literature review, the authors employed bibliometric techniques to analyze the collected and reviewed articles. They examined citation networks, co-authorship patterns, and keyword co-occurrence to gain insights into the research landscape and identify emerging trends. The findings of this bibliometric analysis showcased the remarkable growth of research in this area, with a substantial increase in the number of publications over time. The analysis also revealed key research topics such as remote sensing, image analysis, and precision agriculture, which have received significant attention within the field. Moreover, the analysis identified influential authors and institutions that have made noteworthy contributions to the advancement of drones in agriculture.

Being aware that integrating UAVs in smart farming faces obstacles related to technology selection and deployment, particularly in data acquisition and image processing and the lack of standardized workflows, the authors of the paper [92] address these challenges by conducting a comprehensive review of recent UAV applications in precision agriculture. They explore common applications, UAV types, data acquisition techniques, and image processing methods to provide a clear understanding of each technology's advantages and limitations. They aim to delve into the theoretical background and related work of UAV, cloud, IoT, big data, and AI approaches in smart farming and precision agriculture. They identified numerous research queries (RQ) for which they gave findings from **the latest** state of the art with a detailed classification.

This paper [19] presents a comprehensive survey on mobile edge computing nodes (ECNs) and identifies some open research questions related to their intrinsic characteristics. In particular, mobile ECNs are classified into four categories, namely aerial, ground vehicular, spatial, and maritime nodes. For each specific group, any mutual basic terms used in the state-of-the-art are described, different types of nodes employed in the group are reviewed, the general network architecture is introduced, the existing methods and algorithms are studied, and the challenges that the group is scrimmaging against are explored. Moreover, the authors provide a deep study of the integrated architectures according to each use case. Finally, the research gaps, that are yet to be filled in the area of mobile ECNs, are discussed along with directions for future research and investigation in this promising area.

Therefore, after a first scan of existing literature reviews and to clearly assess the scope addressed in our contribution, we limited our research question to the role of cloud, fog, edge, and flying edge computing combinations in smart farming, with a particular focus on the latest existing works dating from 2020 to 2023.

Thus, after identifying the research question and considering general review methods, we designed a research strategy for tracking relevant proposals. This included the selection of search terms and suitable databases, as well as the decision on inclusion and exclusion criteria.

Figure 4 shows the designed search strategy from different e-resources. In our study, we used the most popular scientific digital resources to obtain research papers. The articles were fetched from various digital libraries such as Elsevier, IEEE Xplore, Springer, Mdpi, and Google Scholar. The "Search string creation" and "Search keywords selection" have played an essential role in finding useful research papers from the literature.

3.2 Conducting the review

To conduct this review, we added the Zotero plugin to our browser to create a pool of selected articles. **Zotero:** is a free, easy-to-use tool to help us collect, organize, annotate, cite, and share research. It works as a personal research assistant in the browser, offering many interesting features such as automatically collecting citation information from websites, storage of portable document format (PDF), files, images, links, and entire pages, including saved searches and labeling them for better understanding and identification.

After collecting an initial set of articles, we screened the texts to ensure that they met the inclusion criteria. We also performed an analysis of the references in the selected articles to identify other potentially significant articles.

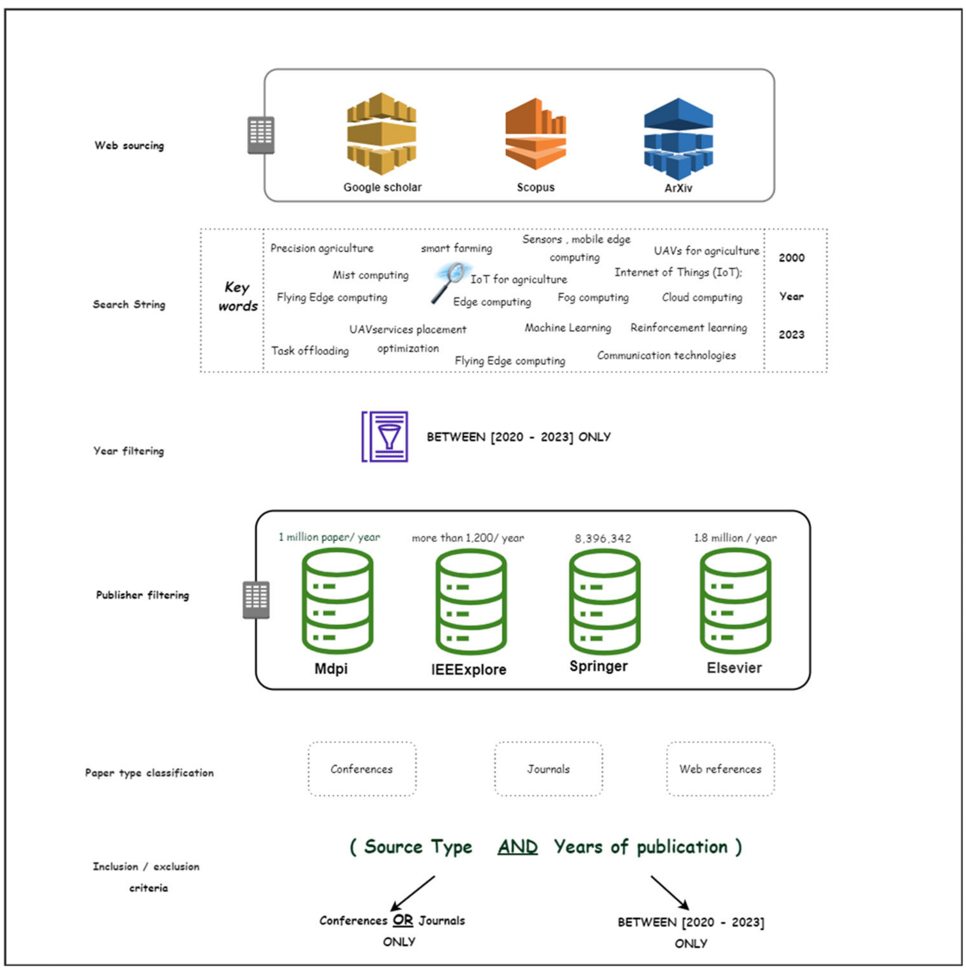

Fig. 4 Stepwise process to select the articles reviewed in this survey

3.3 Analyzing the review

At this stage, it is important to consider how the selected articles will be used for proper analysis. After selecting the final sample, standardized methods should be used to obtain relevant information from each item. This can include descriptive information such as author, year of publication, subject, or type of study, as well as effects and findings. It can also include a conceptualization of a particular idea or theoretical perspective. Importantly, this should be done according to the purpose and research question of the specific review.

In this research, we aim to investigate and provide a review of existing research on cloud, fog, edge, and flying edge computing applications in the agricultural field. To achieve our goal, we adopted an analytical method to determine the type of information that needs to be abstracted to fulfill the purpose of the specific review and analysis. Once this is determined, we can decide on how to document and report this process.

This step allows us to check the eligibility of articles after reading the full text and extracting relevant information. We will assess the quality of each article based on their relevance to the research question, the clarity of the research objectives, the soundness of the methodology, and the validity and reliability of the results. The information extracted from each article will be synthesized and analyzed to draw meaningful conclusions about the current state of research on cloud, fog, edge, and flying edge computing applications in agriculture.

To begin writing, we prioritized clearly describing the process of designing and conducting the literature review, including how we collected, analyzed, synthesized, and reported the literature. We started by exploring and explaining key concepts and paradigms related to smart agriculture, followed by identifying commonalities and differences between computing paradigms. We then reviewed relevant surveys and articles, examining their main contributions and limitations, and identified potential future research directions and areas for contribution. Finally, we discussed notable challenges and potential solutions.

This subsection focuses on trends in computational paradigms in the agricultural context, analyzing the yearly distribution of publications in selected journals and conferences that report on precision agriculture. In order to classify the existing proposals according to our original objective, we analyzed the selected articles and identified an omnipresent use of cloud computing, even in hybrid solutions involving fog and/or edge computing. There is also a notable trend towards the integration of an edge layer, specifically the flying edge, which aligns with economic trends in this direction.

From a scientific contribution perspective, most of the reviewed papers focused on crop monitoring and resource management applications, with little attention paid to aqua farming. The main issues addressed in the selected articles were task offloading, energy consumption, and path planning. However, there were few works that addressed security issues and interference mitigation problems.

Figures 5, 6, 7, 8 and 9 give a detailed overview of the reviewed papers by publishers, by rank, by computing paradigm, by application domain, and by addressed challenges respectively.

4 Literature review

The exploitation of UAVs in the field of precision agriculture, although beneficial and advantageous, brings new challenges and raises numerous issues according to the role of such UAVs (user, MEC server, or relay). Based on recent literature which is full of new contributions, we classify the works identified into eight categories according to the scientific problem targeted by the use of these drones, namely (1) latency and time optimization, (2) path planning, (3) task offloading and scheduling, (4) resource management, (5) networking and wireless communication, (6) security, (7) data processing, and (8) precision and optimized prediction.

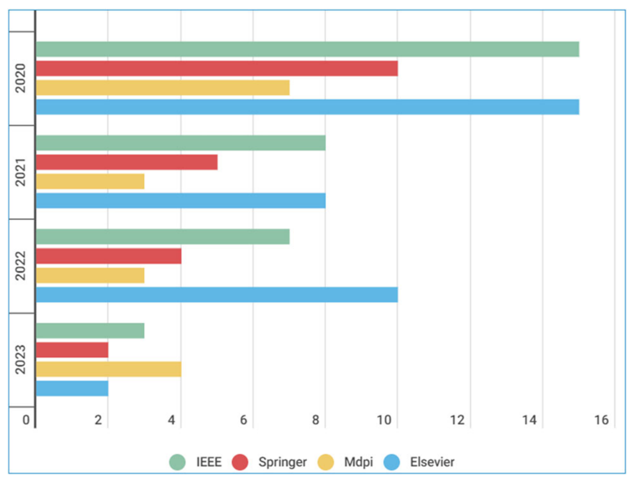

Fig. 5 Distribution of research papers by publishers

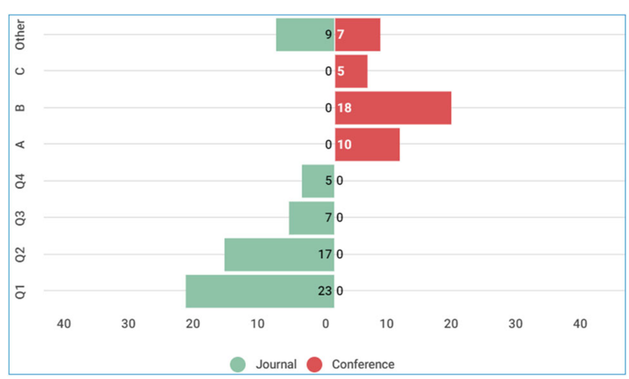

Fig. 6 Distribution of research papers by rank

4.1 Latency and time optimization

The authors in [40] aim to develop a system that can collect, process, and analyze environmental data in real time, enabling timely decision-making and interventions in olive grove management. They specifically focus on latency-sensitive applications, where quick response times are crucial for effective monitoring and control. The proposed architecture leverages both cloud and fog computing paradigms to provide a scalable and flexible solution. Cloud computing offers the necessary computational power and storage capabilities, while fog computing brings computing resources closer to the data sources in the olive groves, reducing latency and enabling real-time data processing. By adjusting the latency dynamically, the architecture ensures that time-sensitive tasks related to environmental monitoring, such as irrigation control, disease detection, or pest management, can be performed efficiently. The system integrates various components, including sensors, data collection devices, fog nodes, cloud resources, and decision support systems, to create an end-to-end solution for time-sensitive environmental monitoring in olive groves.

The experimental results captured the expected behavior and validated the effectiveness of the prototype in dealing with time-sensitive agricultural applications, procuring high throughput (around 95% on average). The fog network effectively handles incoming traffic, and varying time intervals between sensor readings did not significantly impact the mean round-trip time (RTT). The fog devices, also, accurately estimate their traffic load and make targeted adjustments, resulting in successful load balancing within defined bounds. These findings support the claims made in the paper and demonstrate the potential of the system for practical field deployments in agricultural monitoring, but the biggest barrier and main takeaways of such works are the lack of a large-scale olive grove deployment. Limitations related to optimized energy consumption, challenges with nodes' clock synchronization, and constraints regarding overall automation were also reported. These limitations provide insights into areas that could be further explored or improved upon in future research and development efforts.

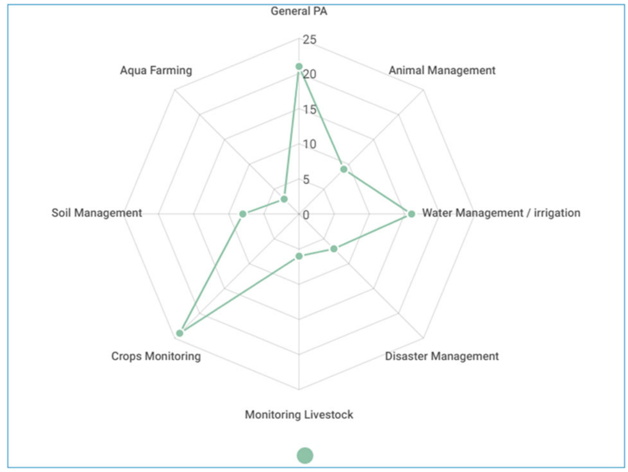

Fig. 8 Distribution of research papers by application domain

The paper [50] discusses the design and implementation of a system for sheep monitoring and tracking based on image processing techniques. The system involves equipping drones with various sensors and cameras to capture data related to the health, behavior, and location of sheep. The collected data is then processed and analyzed to provide valuable real-time insights for farmers. The novelty of this contribution lies in the ability to monitor large cattle over wide areas when ensuring real-time response time and very high precision. The authors of the paper present the hardware and software configuration for developing a drone, and the measurement results showed that the system can reli-

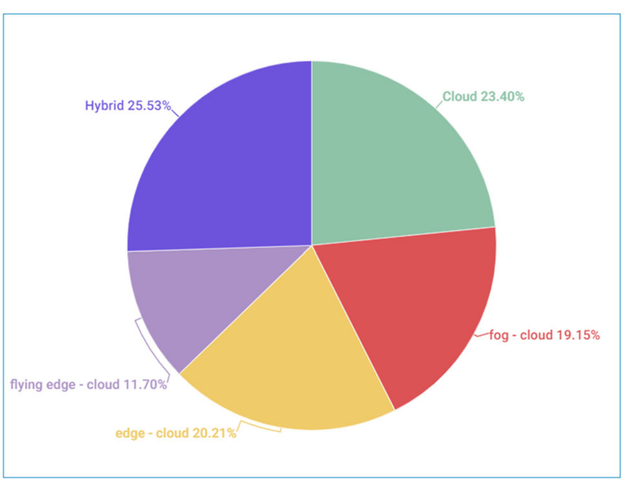

Fig. 7 Distribution of research papers by computing paradigms

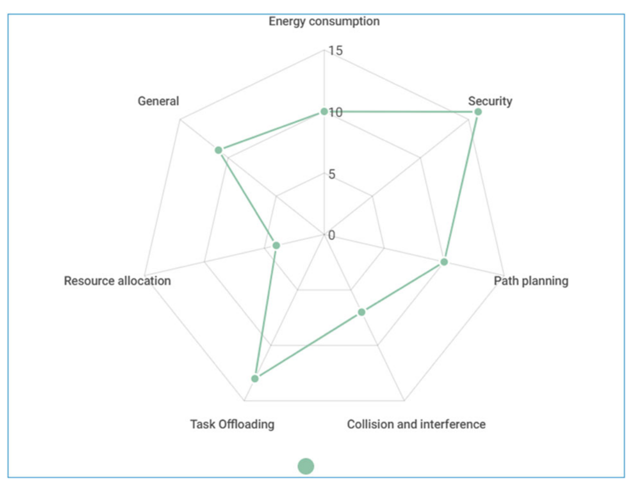

Fig. 9 Distribution of research papers by challenges

ably (with an accuracy of 89–97%) detect sheep on a farm. One of the drawbacks raised by the proposed system was the high power consumption of the onboard companion computer used to run the image processing algorithms. Similarly, a UAV-based convolutional neural network (CNN) for recognizing and counting calves is proposed in [51].

The paper [36] proposes a monitoring system for aquaponics that incorporates IoT technology and edge computing. The main goal of the system, designed with miniaturization, modularization, and low-cost features, is to provide real-time monitoring and control for cultivation-breeding ratio research. The system can realize remote monitoring and intelligent control of parameters needed to keep fish and plants under optimal conditions.

The system is modularized, which means it is composed of different components that work together to achieve overall functionality. It utilizes various IoT devices such as sensors and actuators to collect data from the aquaponics system, including parameters like temperature, pH level, water level, and nutrient concentration. These devices are connected to a central hub or gateway, which acts as an interface between the IoT devices and the edge computing system.

The edge computing component plays a crucial role in the system by processing and analyzing the collected data locally, near the source of data generation. This enables real-time monitoring and control without relying solely on cloud-based processing, which can introduce latency and dependency on internet connectivity. By performing computations at the edge, the system can respond quickly to changes in the aquaponics environment and trigger appropriate actions or adjustments.

The paper highlights the advantages of using edge computing in the context of aquaponics monitoring, including reduced latency, improved reliability, and enhanced scalability. It also discusses the modular nature of the system, which allows for flexible configuration and customization to meet specific requirements and scale the system as needed.

The authors in [16] propose a system that combines cloud computing, flying edge computing, and UAV technology to enable smart agriculture. The goal of such work is to enhance the efficiency of agricultural operations through real-time data collection, analysis, and decision-making. The proposed platform is highly dynamic and flexible, so it can be deployed and can collect data quickly depending on the latency requirement for each use case. Most importantly, it can be used in tough terrains like the desert and hilly areas. A simulation was made to evaluate the performance of this cloud-connected flying edge computing system where multiple configurations, including local and remote IoT service calls, are involved. The response times of the service calls were recorded, and it was found that the flying edge machine exhibited the best response time, benefiting from the energy efficiency of end nodes. Furthermore, the average service lookup times were compared, and it was observed that services provided by the flying machine (UAV) to end nodes had significantly lower lookup times compared to services provided by the cloud through flying machines. This indicates that flying computing machines (UAVs) can offer faster service provision to IoT devices.

4.2 Path planning

The paper [26] illustrates a case study for collaborative UAV-WSN operation in large-scale monitoring for precision agriculture. Key contributions are mainly in the design of optimized trajectories for UAV-enabled field data collection and for in-network data processing that allows efficient use of limited ground sensor network resources. Particularly, the authors propose combined segment and loiter tracking modes, which balance between path length and time spent in the neighborhood of a cluster head. Through multiple hierarchical data processing steps, the authors demonstrate the increasing quality of the extracted information, its timeliness, and lower network-wide latency for decision-making. The authors also mention the use of edge computing, which involves performing some of the processing tasks on the UAVs and WSNs themselves, to reduce the latency and improve the real-time responsiveness of the system.

The potential drawbacks of the proposed system are related to the increased complexity of multi-level data processing, communication, and interoperability constraints between the aerial platform and the ground sensors. The paper does not address potential challenges associated with the use of UAVs and WSNs in precision agriculture, such as privacy concerns, regulatory issues, and the potential for system failure due to adverse weather conditions or other factors. A more thorough discussion of these challenges could help to ensure that the proposed system is practical and feasible in real-world scenarios.

In this paper [27], Qayyum et al. developed a clustering-based trajectory design algorithm that aims to optimize the flight path of a UAV that flies across the fields to collect data, which are further transmitted to fog nodes for processing. The proposed model is based on two phases: the data collection phase where IoT sensors are deployed randomly to form a cluster based on their RSSI and the UAV calculates an optimum trajectory in order to gather data from all clusters and to offload this data to the nearest base station and data scheduling phase where the BS finds the optimally available fog node based on efficiency, response rate, and availability to send workload for processing.

The authors also propose the use of machine learning algorithms, such as k-means clustering, to group farm areas with similar characteristics and optimize the UAV's flight path for data collection.

One potential limitation of this research is that the proposed trajectory design may be sensitive to changes in environmental conditions, such as weather patterns or seasonal variations. Additionally, they do not provide a detailed evaluation of their algorithm's performance in real-world scenarios, which may limit the practical applicability of their approach.

4.3 Task offloading and scheduling

The authors of the paper [95] propose a multi-UAV-assisted mobile edge computing (MEC) system targeting areas with a lack of base stations. In the considered system, multiple UAVs cooperate to provide a service to IoT devices. They formulate a non-linear optimization objective to minimize the energy consumption of a such system featuring a joint UAV deployment and task scheduling optimization algorithm. The UAV numbers, the hovering position of each UAV, and the best strategy for offloading and resource allocation were the principal optimization concerns of their solution. The optimization problem was simplified into two sub-problems based on the idea of a block coordinate descent algorithm and solved using the improved PADE and greedy algorithms. Experimental results demonstrate that the algorithm has positive convergence performance and can accomplish more tasks under the constraint of delay compared to two benchmark state-of-the-art algorithms. This study, however, is limited to the fixed flight height of the UAV and does not include scenarios, such as forests and city centers, with different heights of occlusion and where fixed UAV heights may collide.

The work in [97] introduces a two-stage end-to-end deep reinforcement learning (DRL)-based smart agricultural system. In stage one, the authors propose ant colony optimization (ACO)-based deep Q-learning network (A-DQN) model for efficiently analyzing tasks such as irrigation scheduling, pest detection, soil monitoring, fire detection, field and soil monitoring, and crop growth monitoring. This ACO-DQN model offloads the task to either edge, fog, or cloud networking devices based on latency, energy consumption, and computing power. With the need for ultra-low latency, the authors create a mathematical model for smart agriculture task scheduling which balances both low latency and low energy consumption for time-critical tasks. They convert this model into a multi-objective optimization problem considering time delay and energy consumption. Then, once the task is offloaded to computing devices, the task of predicting and monitoring various agriculture activities is performed based on DRL models at a second stage. The proposed method is evaluated and compared to traditional deep Q-networks, and the experimental findings demonstrate a marked enhancement in terms of convergence speed, planning success rate, and path accuracy.

The authors in [98] present a novel offloading model based on dynamic programming explicitly tailored for flying fog-based IoT networks based on 5G/6G technologies. The proposed algorithm aims to intelligently determine the optimal task assignment strategy by considering the mobility patterns of drones, the computational capacity of fog nodes, the communication constraints of the IoT devices, and the latency requirements. Extensive simulations and experiments were conducted to test the proposed approach compared to static edge-cloud architecture. The obtained results revealed significant improvements in latency, availability, and the cost of resources.

4.4 Resource management

The authors in [25] developed a novel optimization algorithm that aims to achieve a balance between energy consumption and quality of service (QoS) in a hierarchical fog-cloud computing network. The proposed algorithm minimizes the energy level among all nodes in the network while ensuring that the QoS requirements of all users are met. The proposed solution involves the use of fog nodes (small-scale computing devices located close to end-users) and cloud computing resources to support applications that require low latency and high bandwidth. The authors aim to provide a generic energy-efficient communication framework for hierarchical fog-cloud computing networks that can support a wide range of applications, such as Internet of Things (IoT) applications and smart city services.

As a novelty, the authors also propose the use of the wireless power transfer concept (WPT) to provide energy to the fog nodes and reduce the need for battery replacement or recharging. Obtained results showed that the computing mode selection is the dominant factor affecting the system performance where local computing is considered a better choice for users with relatively poor channel gains while fog/cloud computing is considered a better choice for users with relatively good channel gains. One potential drawback of this research work is that the proposed algorithm may be computationally expensive and require a significant amount of processing power, which could limit its practical applicability in resource-constrained fog nodes. Additionally, the proposed framework may require significant changes to the existing communication infrastructure, which could be challenging to implement and may require significant investment.

An edge-conscious autonomous swarm deployment architecture was adopted by [47] where the authors present an empirically based model for efficient autonomous swarm deployment. They built and deployed a real autonomous UAV swarm to map leaf defoliation in soybeans. Using this deployment, they determined environmental conditions that led to malfunctions, inefficient edge energy usage, and predictions. Based on these findings, they developed a deployment model for UAV swarms that decreases malfunctions and data irregularities by 4.9× and decreases edge energy consumption by 45%, while increasing deployment times by only 4%. In particular, simulations demonstrated that the decentralized decision-making approach enabled UAVs to adapt their deployment based on environmental conditions and obstacles in the field, which resulted in better data collection efficiency compared to a centralized deployment approach. Swarm stability also was proved even in the presence of UAV failures or malfunctions. This deployment model can hold for low-flying UAVs in common agricultural settings, but UAVs that fly at higher altitudes, for instance, may experience different levels of effect from temperature, lighting, and wind.

The paper [99] addresses the energy efficiency and spectral efficiency trade-off problem of UAV-based irrigation systems. The authors propose to adopt massive multiple input, multiple output (M-MIMO) technology as a promising way to ensure wireless communication in future 6G-based networks. They design a network model with a three-layered architecture (cloud-fog-flying edge) and analytically compute the achievable spectral efficiency and the energy efficiency of the studied system. Then, they numerically determine the optimal number of ground base station antennas as well as the optimal number of IoT devices that should be used to ensure the maximum energy efficiency while guaranteeing a high spectral efficiency. The novelty of this proposal stands for the consideration of circuit power (CP) along with the transmit power and throughput to model the UAV-based irrigation system. This feature proved that the maximum ratio (MR) combiner scheme does not require matrix inversions, whereas the multicell minimum mean squared error (M-MMSE) combiner scheme requires the inversion of an MxM-dimensional matrix. The numerical results prove also that the proposed UAV-based irrigation system outperforms conventional systems and demonstrate that the best spectral and energy efficiency trade-off is obtained by using the M-MMSE combiner. However, this research still has some limitations, mainly regarding the high computational complexity of computing the inverse MxM matrix, especially when M is large. This complexity is also affected by the need to estimate the channels and acquire the channel statistics of all IoT devices, which is not trivial when dealing with large-scale fields. Additionally, regarding the massive amount of collected data from such networks, it is essential to deploy real-time control and to develop security methods to protect data from unauthorized access or interception.

4.5 Networking and wireless communication

The authors in [94] present a novel environmentally-aware and energy-efficient multi-drone coordination and networking scheme that features a reinforcement learning (RL)-based location prediction algorithm coupled with a packet forwarding algorithm for drone-to-ground network establishment. They, specifically, address application requirements of connectivity and energy efficiency when considering environmental and energy constraints. The novelty is in the approach of using reinforcement learning (RL) to estimate future drones' trajectories based on their coordination status and their onboard sensor information. Specifically, once the intermediate drone accurately predicts the position of the destination drone, a list of preliminary decisions on where to forward packets are made. The authors consider various drone mobility models such as the Gaussian-Markov model (GMM), mission-based plan model (MBPM), and random way point model (RWPM) within their prediction technique. The proposed packet forwarding algorithm features two drone location-based solutions, i.e., heuristic greedy and learning-based, that can support heterogeneous drone operation requirements under disaster response management scenarios. The proposed scheme is evaluated in a simulation test bed featuring rural and metropolitan areas and compared with numerous state-of-the-art networking algorithms. Results show that the developed solution overcomes obstacles and can achieve 81–90% of network connectivity performance observed under no obstacle conditions. In the presence of obstacles, their scheme improves the network connectivity performance by 14–38% while also providing 23–54% of energy savings in rural areas; the same in metropolitan areas, an average of 25% gain is achieved when compared with baseline obstacle awareness approaches and with 15–76% of energy savings.

The authors of this contribution [49] developed a system using IoT technologies to inspect water quality for livestock development. A drone-mounted LoRa gateway transmits data from sensors to the cloud, while offline storage is available in case of internet access absence. The integration of IoT sensors and the LoRa gateway into a vertical take-off and landing (VTOL) drone enabled effective farm monitoring. The proposed solution also optimizes the drone's flight path using advanced algorithms, reducing mission time and overcoming battery limitations based on the traveling salesman problem (TSP). Overall, this research provides a comprehensive solution for water inspection, farm monitoring, and data collection in agriculture using drones and IoT technologies. The communication link performance was evaluated under various conditions such as spreading factors (SFs), LoRa gateway modes, and drone speeds. This evaluation investigates the Doppler effect at higher flight speeds and determined that LoRa technology performed well at a maximum drone speed of 95 km/h and with a spreading factor of 12 which demonstrated the robustness of LoRa technology.

The paper [93] proposes a system that can capture and transfer thermal data captured by aerial edge intelligence to terrestrial edge intelligence for irrigating dry patches. This data is transmitted by an integrated LoRa transceiver through peer-to-peer long-range communications, which avoids the usage of secondary repeaters and hence helps to create a low latency in long-range edge computing systems in places where cellular communication is not available and reduces the number of drones used for this task, particularly in large farms. Experimentation scenarios are based only on RSSI and spreading factor (SF) results and do not include environmental or weather effects.

The work in [42] introduces a fog-based cooperative framework that leverages the capabilities of neighboring IoT devices to optimize the transmission of monitoring data in a farming context. By considering the traffic load and connectivity of devices and by using distributed machine learning techniques, the framework dynamically predicts the most suitable devices to relay data, reducing network congestion and improving overall system performance. They also, identify the redundant nodes that are collecting the same data and forbid using them in order to efficiently manage network resources and prolong the system life cycle. Additionally, the paper emphasizes the importance of data security in IoT-based smart monitoring systems by incorporating data encryption and authentication techniques in a fog-based chain to protect sensitive agricultural data from unauthorized access and tampering. To evaluate the effectiveness of the proposed framework, the authors conduct simulations and compare the performance with existing approaches. The results were promising and showed the ability of the solution to improve energy efficiency, achieving an average increase of 20% while varying node number and 22% while varying distances from the sink. This work could be extended to maintain cloud integrity from the point of users' perspective in order to deal with a fully secured system.

4.6 Security

The study in [101] focused on layered architectural design, identified security issues, and presented security demands and upcoming prospects. In addition to that, the authors propose a security architectural framework for agriculture 4.0 that combines blockchain technology, fog computing, and software-defined networking. The suggested framework combines Ethereum blockchain and software-defined networking technologies on an open-source IoT platform that prevents erroneous control and information delivery while improving network management. It is then tested with three different cases under a DDoS attack. In this proposal, a first sensor layer is used to acquire meaningful information from the external environment via sensors to take required action against it. Then, a fog layer, made up of multiple fog nodes such as a virtualization node, agricultural sensor data monitor, block-chain client software, and simulated switch, hosts all authentic analysis and latency-sensitive applications. After that, an SDN controller is integrated to help with network monitoring by managing all transactions among network and application devices, allowing it to manage and adjust network flows more efficiently in response to new requirements. It maintains a consistent glimpse of the network from afar, delivering data to fog nodes via one APIs and application via other APIs (MQTT, CoAP...). In addition, the SDN controller employs a blockchain contractor to properly secure flow tables of SDN in the blockchain, hence avoiding rule counterfeit. The solution could be improved by adding an intrusion detection system featuring various deep learning algorithms to prevent the insertion of fake sensor data in the intelligent agricultural field.

In this work [12], the authors propose a fog computing framework for intrusion detection of energy-based attacks on UAV-assisted smart farming. The framework aims to enhance the security of smart farming systems, especially those that are assisted by unmanned aerial vehicles (UAVs). The proposed framework uses a hierarchical architecture that includes three levels: the UAV level, the fog level, and the cloud level. At each level, specific techniques are used to detect energy-based attacks, including physical intrusion detection sensors, machine learning-based anomaly detection algorithms, and statistical anomaly detection methods. A fog broker, a key central element that manages interactions between the UAVs and sensors, is utilized for deploying an intrusion detection system (IDS). IDS implements machine learning classification to detect and flag compromised UAVs based on their behaviors as malicious or benign. Flagged UAVs are then penalized through a coin-based system, where the greater number of coins collected allows for a greater amount of charge.

To perform evaluation, various machine learning algorithms, including XGBoost random forest (RF), decision tree (DT), extra tree (ET), stacking, and k-means, were utilized and compared through several metrics such as accuracy, precision, recall, F1 score, root-mean-square error, and R-squared score. Results showed that all algorithms performed well due to hyperparameter optimization, with XGBoost achieving the best performance with 99.77% accuracy, 0.1055 root-mean-square error, and 99.81% R-squared score. The model was configured with realistic values based on existing literature and real-world data. Machine vision-based techniques and extensive deep learning techniques could improve the effectiveness of such systems.

This work [44] presents a novel approach to smart agriculture that combines intelligent decision-making, IoT technologies, and blockchain for improved water consumption and data security. The system utilizes sensors to collect real-time data on temperature, soil moisture, light intensity, and humidity from the environment and the field. This data is stored in an IoT cloud platform for analysis. The system implements intelligent fuzzy logic and blockchain technology to make smart decisions for watering plants. The intelligent fuzzy logic component uses a set of rules to determine the watering requirements of plants based on input variables. Blockchain technology was introduced to ensure data privacy and access control, allowing only trusted devices to interact with the system. Multiple users can remotely monitor and interact with the system through an Android application. The system sends alerts to users regarding watering requirements and can control the water motor on/off. The experimental results demonstrate the scalability, efficiency, and high security of the proposed system. It effectively handles the process of watering plants and provides reliable notifications to users with an overall accuracy of 96.7%.

4.7 Data processing

The work in [43] studies the application of fog-based IoT systems in smart agriculture for processing complex events. The authors, first, explore the challenges faced in traditional cloud-centric architectures and then propose a multi-tier hierarchical fog-based approach that brings computation closer to the data source in agricultural environments. The proposed approach is geolocation and context-aware, in which the new sensor nodes in a network connect to a fog node based on the data type and the Euclidean distance between them. The main objective is to enable real-time decision-making in smart agriculture. Simulation results showed promising performance in different scenarios, with accuracy, precision, and recall consistently above 99%. This indicates that the proposed approach provides reliable and consistent information about the monitored environment. The effectiveness of the complex event processing (CEP) engine, which includes rules and events, was validated through tests in an irrigation scenario, and the tests were successfully completed. The average actuator response time obtained was approximately 7.15 ms on a local network, demonstrating that the CEP engine also meets the application's requirements for the timely activation of irrigation. The proposed approach, however, could be improved with a self-configuration of the nodes regarding the best characteristics to be considered for the choice of the fog node, such as the processing power. Moreover, instead of rule-oriented modeling, the data stream-oriented CEP mechanism which is similar to SQL worth exploring.

The authors in [28] propose an edge-assisted data collection approach for critical events, such as natural disasters or pest outbreaks, in the context of the software-defined wireless sensor network (SDWSN)-based Agricultural Internet of Things (IoT). The main contribution is the development of an effective edge-assisted data collection approach that addresses the challenges of data transmission and storage. The proposed approach involves the use of edge computing and ensures a balance between the main information on an event and the corresponding data volume, which allows the processing and storage of data at the edge of the network, to decrease the data redundancy, reduce the amount of data transmitted to the cloud, and improve the efficiency of data collection in the agricultural IoT. The authors of this work conduct automatic data type selection using mutual information, events categorization, and related data sensing to realize essential event sensing and reduce the cost of data collection. An experimental prototype is designed in an agricultural greenhouse to verify the proposed strategy and compare it with the existing methods.

The findings of this work demonstrate that the proposed strategy provided a larger margin in balancing between data validity, energy consumption, and latency. However, it may increase the deployment cost of edge servers, which could be solved by a cooperative strategy between edges and cloud servers to share computing resources.

MARbLE, a platform for developing and managing swarms, was proposed in [46]. It is a multi-agent reinforcement learning (MARL) approach at the edge of digital agriculture applications. The main contribution of this work is the development of a framework that can enable autonomous and decentralized decision-making in edge computing systems, which may reduce the amount of data that needs to be transmitted to the cloud and improve the efficiency of the overall system. The platform automatically compiles and deploys swarms and continuously updates the reinforcement learning models that govern their actions, which helps developers experiment their solutions with multiple swarm and edge resource configurations both in simulation and with actual in-field runs.

The evaluation focused on a crop scouting workload, and the performance of MARbLE was compared to autonomous and automated approaches in various swarm sizes. The paper presents the results for 8 mission configurations, 4 of which prioritize maximum accuracy, while the other 4 prioritize maximum profit by minimizing labor costs while providing sufficiently accurate maps with shorter missions. The performance of MARbLE was assessed based on the time taken by swarms of different autonomy settings to accomplish the same task. Shorter times were preferred to reduce labor costs and allow more missions to be performed. Although MARbLE simplifies building MARL systems by replacing handcrafted reward functions with Map() and Eval()

functions that are easier to program, it requires, however, available, realistic, and representative traces from the target environment which could be challenging and costly in novel and dynamic environments. Also, the trade-offs in convergence time and learning efficacy could be more explored by implementing learning techniques other than Bayesian optimization.

The paper [96] presents a novel architecture for implementing a digital twin (DT) for a farm that encompasses a variety of fields. The proposed approach incorporates the use of multi-agents, microservices, linked data, and ontologies for an efficient deployment of the digital twin in a cloud-fog-edge infrastructure. The proposed architecture is based on (i) a cloud layer which serves as the primary domain for big data and data analytics, providing data storage and anonymization services for farm data, and machine learning and data analysis support; (ii) fog layer which represents the farm management system providing local data storage and computing services for in-situ farm data analysis; and, finally, (iii) edge layer which includes any agricultural devices hosting sensors, allowing service composition within the smart farming scenario. The use of linked data concepts fosters service discovery while allowing data to be available and reducing redundancy. One of the main benefits of this approach is the ability to adapt and evolve the DT's decision-making services over time by extending the model to new data streams or incorporating new modeling techniques. The Multi-Agent Micro Services (MAMS) architectural style has been crucial to the success of this approach, as it enables seamless integration of agents and microservices. Unlike traditional approaches that rely on proprietary data silos and vertical architectures, the proposed architecture is designed to break down these barriers and promote better data exchange and collaboration. This work could be improved to enable greater interoperability. The authors, also, may explore alternative models than Zadok for a better crop growth stage prediction and evaluation. This could improve the accuracy and precision of their digital twin and could lead to more informed decision-making and better crop management strategies.

4.8 Precision and optimized prediction

Alonso et al. [45] present an intelligent platform oriented to the application of IoT, edge computing, artificial intelligence, and blockchain techniques in smart farming environments, by means of the novel Global Edge Computing Architecture. They designed this platform to monitor the state of dairy cattle and feed grain in real-time, as well as ensure the traceability and sustainability of the different processes involved in production. The collected data is then used to generate real-time alerts and recommendations for farmers. The proposed platform was deployed and evaluated in a real-world dairy farm and reported promising results and important improvements in the reliability of communications between the IoT-Edge layers and the cloud. As the evaluation of this work was only conducted in one real-world dairy farm, this made their contribution somehow specific and may not be generalized to other use cases. Additionally, the paper does not provide a detailed analysis of the cost-effectiveness of the proposed solution, which could be a concern for farmers who are considering adopting the platform.

The paper [52] proposes an approach for detecting Mildew vine diseases based on multispectral images captured by unmanned aerial vehicles (UAVs) and using optimized image registration and deep learning segmentation. The method is based on the combination of the visible and infrared images obtained from two different sensors. A new image registration method was developed to align visible and infrared images, enabling fusion of the information from the two sensors. A convolutional neural network (CNN) approach is then applied to classify each pixel according to different instances, namely, shadow, ground, healthy, and symptom. The authors propose using the drone's onboard computer as an edge computing device to perform these tasks in real time and without the need for an internet connection. The proposed solution was evaluated on a dataset of 1004 images of grapevines with and without diseases, achieving an accuracy of 96.7%. However, one of the limitations of this research is the small size of the training sample which reduced the performance of the deep learning segmentation and the lack of comparative analysis with other learning techniques.

The paper's [33] main contribution is proposing a method for yield estimation in cotton crops by combining a cotton "Boll Area Index" with in-season unmanned aerial multispectral and thermal imagery. The authors demonstrated that the combination of these techniques can provide more accurate yield estimation compared to traditional methods. They also showed that the use of unmanned aerial vehicles (UAVs) can provide a cost-effective and efficient way to collect the necessary data for yield estimation. Additionally, the authors provided recommendations for future research to improve the accuracy and practicality of this method, such as exploring the use of machine learning algorithms for data analysis. The authors have used mobile edge computing as part of their methodology. The proposed method may require specialized equipment and expertise, which may not be readily available to all farmers. The study is also limited to cotton farming and may not be directly applicable to other crops.

In conclusion, the use of flying edge computing in precision agriculture has emerged as a hot topic in recent years. The reviewed literature shows that this paradigm can address many of the challenges faced by traditional cloud-based solutions, including high latency, limited bandwidth, and security concerns. The various works studied here propose different architectures to improve the performance of precision agriculture systems and have demonstrated promising results in terms of accuracy, efficiency, and scalability. Table 3 classifies some research works based on their application domain.

In parallel with this architectural evolution, in the last decade, deep learning (DL) methods have gained increasingly more attention and become the de facto mainstream of machine learning (ML). In most of the farming scenarios, UAV nodes utilize images captured by cameras as their data inputs, i.e., they are computer vision-related tasks. In this way, UAV tasks in precision agriculture that use DL methods, mainly including crop pest and disease detection, crop growth monitoring and yield estimation, and crop type classification, can be divided into three typical and principal computer vision tasks: classification, detection, and segmentation. Table 4 shows a compilation of typical UAV applications in smart farming using ML and DL methods.

The reviewed papers provide evidence that the adoption of flying edge computing in precision agriculture can significantly improve crop yields, reduce operational costs, and increase overall profitability. The potential benefits of this technology have encouraged many researchers to investigate its applications in various agricultural domains, including hydroponics, smart farming, and dairy farming. Table 5 summarizes numerous research works based on the hybrid computing paradigm where cloud, fog, edge, and or flying edge computing are jointly used.

In summary, the reviewed literature underscores the importance of jointly using UAVs and edge computing in precision agriculture and its potential to revolutionize the way we grow crops. This is a promising topic that has attracted the attention of many researchers, and there is still much room for exploration and innovation in this field.

5 Open challenges

Although cloud-fog-edge-based technologies are being widely used in agriculture and offer several advantages, the research and practice of edge intelligence, especially in precision agriculture, are still in an early stage. Below, we list some notable challenges and specific issues that need to be addressed within the scope of this paper.

- **Security:** When agricultural applications deal with CC, data security and privacy, authorization and trust, authentication, secure communication and compliance with regulations are the significant challenges [56]. Smart farms accumulate vast amounts of data generated by different types of data sources, such as sensors, actuators, and edge equipment. Therefore, data stored in the cloud may be leaked, which can lead to serious economic losses to farmers and agribusinesses. Moreover, as smart agriculture is still emerging and has a low level of security features, recent solutions will demand data availability and accuracy as key points to help farmers build robust and efficient systems. Secure proposals may require an architecture that can handle compatibility, heterogeneity, and interoperability with numerous devices and should allow multiple access, in a secure and coordinated way, to avoid data loss and compromise the system efficiency. Papers [44, 48, 56, 60, 62, 101] address this challenge and propose security features such as IDs, cryptography, firewalls, and blockchain technology that may improve smart farm security in different scenarios. In particular, thanks to the peer-to-peer (P2P) network, blockchain technology eliminates the need for a central authority and avoids the single point of failure problem. It was

Table 3 Research papers and their application domain

Computing paradigm	Application domain	Reference	Year
Cloud computing	Crop monitoring	[29]	2020
	Soil management	[30]	2021
	Animal management	[35]	2020
	Water management	[37]	2021
Fog computing	Intrusion detection	[12]	2023
	Irrigation management	[39]	2020
	Animal management	[35]	2021
Edge computing	Aqua farming	[36]	2022
	Environmental disaster management	[31]	2021
	Crop management	[24]	2022
Flying edge computing	Crops monitoring	[33]	2023
	Disaster management	[32]	2022
	Livestock management	[38]	2022

Table 4 ML and DL-based methods for typical UAV applications in smart farming

Application task	Learning method	Data type	Dataset	Performance	References
Counting cattle	CNN	Images	1^{st} dataset of 19,097 images + 2^{nd} dataset of 826 images	Accuracy of 90%	[51]
Complex event processing	CEP	Time series	360 moisture reading + 540 temperature reading	Accuracy of 98%	[43]
UAV intrusion detection	XGBoost, random forest, decision tree, extra tree, stacking, and *k*-means	Network traffic	80 messages	Accuracy of 99.7%	[12]
Data privacy and security	Fuzzy logic	Time series of humidity, temperature, soil moisture and intensity of light	219 entries	accuracy of 96.7%	[44]
Vine disease detection	CNN	Visible and infrared images	105.515 patches of visible images and 98,895 patches of infrared images	Accuracy of 92% at grapevine level and 87% at leaf level	[52]
Risk quantification and task offloading	DRL	Network traffic	100 network simulations	Remaining energy level, uplink delay and convergence time	[55]
Object detection for yield estimation	CNN, RNN	Images	900 images	Accuracy greater than 90%	[53]
Crop type classification	CNN	RGB images	3770 images	Accuracy of 99.25%	[86]
Sensing and yield estimation maps for apple orchads	RCNN (region CNN)	Images	806 pictures (354 for training)	Accuracy of 88.96%	[90]

introduced first for product tracking, as transactions are timestamped and the history is preserved. Added to that, it is adequate when integrated with data-driven applications thanks to its immutability characteristics that provide reliable information. Blockchain is also used as a secure infrastructure to manage UAV work, and it performs well in many areas, especially when talking about swarm of UAVs [63].

- **Mobility:** This challenge arises from the dynamic nature of farming operations, which involve mobile assets such as vehicles, machines, robots, and livestock. Ensuring real-time monitoring, tracking, and management of these assets poses several challenges, such as network latency, unreliable connectivity, bandwidth limitations, centralized dependency, and delayed decision-making arise. To overcome these issues, leveraging fog and edge computing becomes crucial. By deploying edge devices or fog nodes on intermediate layers between mobile assets, data processing and decision-making can occur locally, reducing dependence on the cloud, minimizing latency, and enabling real-time monitoring and management in agricultural environments. These papers [64]–[69] propose fog/edge-based architectures to address the mobility challenge by reducing dependence on cloud infrastructure and facilitating seamless monitoring and management of mobile assets in agricultural environments. Such architectures need, on the other side, an efficient deployment/placement of fog servers and/or edge nodes that maximizes coverage and throughput. While UAV deployment in a three-dimensional space remains an NP-hard optimization problem [34], different optimization heuristics, such as ant colony, particle swarm, and genetic algorithm, are already used to solve this problem with low complexity.
- **Task offloading:** The task offloading challenge in precision agriculture revolves around efficiently distributing computational tasks between different computing resources, such as edge devices, fog nodes, and cloud infrastructure. In fact, precision agriculture heavily relies on sensor data, including information from drones,

Table 5 Review of research works based on hybrid computing paradigm

Ref.	Main contribution	The computing paradigm			
		CC	FC	EC	FEC
Sakthi and Rose [14]	Proposed smart agricultural knowledge support system to provide real-time information about soil and water pollution for better pesticide and fertilizer usage	Cloud applications	Fog node, gateway	Sensors	
Alonso et al. [45]	Presented a platform based on EC, AI, and blockchain techniques in smart farming environments to monitor the state of dairy cattle and feed grain in real time	Cloud applications, APIs	–	Sensors, edge gateway, local data store	–
Montoya-Munoz and Rendon [41]	Proposed a reliability-oriented and fog-based architecture that detects outliers and inferring data in the data collection process	Data centers	Fog controllers	Sensors	–
Tsipis et al. [40]	Developed a latency adjustable cloud/fog computing architecture for accurate, reliable, and almost real-time monitoring olive crops	Cloud servers	Fog servers	–	–
Popescu et al. [26]	Designed optimized trajectories for UAV-enabled field data collection and processing that allows efficient use of limited ground sensor network resources	Cloud servers	Fog gateway	IoT devices, edge gateways	–
Apolo-Apolo et al. [90]	Proposed a cloud-based environment for generating yield estimation maps from apple orchards using UAV images and DL techniques for apple detection	Cloud servers	–	IoT devices, edge gateways	Edge server

satellites, and ground-based sensors, to make informed decisions about crop management, irrigation, pest control, and yield optimization. However, processing and analyzing the huge amount of data generated by these sensors can be computationally intensive and time-consuming. Task offloading aims to alleviate this burden by intelligently distributing tasks from resource-constrained edge devices to more powerful fog nodes or cloud servers, where complex computations can be performed. To that end, several factors need to be considered such as data volume, latency requirements, network bandwidth, energy consumption, and real-time analysis needs. Several recent articles have focused on the task offloading problem from diverse perspectives, particularly in fog and edge computing-based solutions [55, 77, 80, 83, 84, 87–89]. While, some works focus on optimizing the delay, energy consumption, or load balance through fog/edge server placement for enhancing the performance of the real-time control, other efforts are dealing with multi-objective optimization.

- **Path planning:** Path planning in precision agriculture presents significant challenges that researchers need to address [74, 75]. Unlike traditional path-planning scenarios, precision agriculture involves dynamic and ever-changing environments. The complexity arises from the need to navigate UAVs through vast agricultural fields with various obstacles, uneven terrain, and intricate crop patterns. Precision agriculture requires not only capturing data, but also ensuring optimal coverage of the entire field. Path planning algorithms must consider factors such as field boundaries, crop health variations, sensor limitations, and real-time data processing requirements. Additionally, UAVs often operate under time constraints, such as limited daylight hours or specific stages of crop growth, further complicating path planning. Ensuring the efficient allocation of resources, reducing redundant flights, and minimizing energy consumption are additional challenges. The path planning problem in precision agriculture demands the development of intelligent algorithms and techniques that can adapt to the dynamic nature of agricultural environments, optimize data collection efficiency, and enable informed decision-making for farmers. Overcoming these challenges will unlock the full potential of UAVs in precision agriculture, revolutionizing farming practices and enhancing crop yields.
- **Power management:** Smart farms require sensors, actuators, and mobile devices. All of these devices depend on available power resources to collect data, perform processing tasks, communicate, and move. Energy efficiency is then considered a key factor in ensuring the successful completion of tasks in the shortest possible time. Most of the work proposed so far assumes that UAVs are equipped with an unlimited source of energy, based on the assumption that it is always possible to recharge. However, from a practical point of view, the use of the recharging step is not as simple and generally leads to non-negligible delays, to an alternative scenario, and to the development of fault tolerance solutions. Existing research [76]–[78]attempts to address energy efficiency by addressing all these limitations.

All the challenges mentioned above are mainly associated with cloud-based applications. However, the combination of different computing paradigms, such as cloud-fog-edge computing, has the potential to address many of these challenges. In this survey, we have observed that modern hybrid computing in agricultural applications can solve general cloud issues like latency, bandwidth, and networking traffic problems. Moreover, it has been found that most of these applications are low-cost. It is worth mentioning that cloud-fog-edge computing can also address larger problems, such as real-time data processing with low latency and high bandwidth, unnecessary costs, data security, and data protection. Nevertheless, further research is required to understand how to overcome these challenges effectively.

6 Conclusion

This paper presented a comprehensive systematic literature review on the role of modern computing paradigms—namely, cloud, fog, edge, and flying edge computing—in smart agriculture domains. Our analysis covered various aspects such as application domains, research approaches, and architectural modeling. Our findings suggest that these computing techniques, when combined in a complementary way, can significantly aid the digital transformation of the industry in terms of network, business, application, and intelligence. However, data obtained from edge nodes need to be summarized in the cloud for deeper analysis as cloud computing has a significant impact on data availability by providing scalable, on-demand access to computing and storage resources over the internet. Further research is needed to overcome some of the challenges identified in this study and to fully realize the potential of these computing paradigms in the agriculture industry.

Funding This research was conducted under the project PHC-Utique 21G1116 funded by the partnership Hubert Curien "Utique" of the French Ministry of Europe and Foreign Affairs and the Tunisian Ministry of Higher Education and Scientific Research.

Data Availability However, data obtained from edge nodes need to be summarized in the cloud for deeper analysis as cloud computing has a significant impact on data availability by providing scalable, on-demand access to computing and storage resources over the internet.

Declarations

Conflict of interest The authors declare no competing interests.

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