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Overview of Edge Computing in the Agricultural Internet of Things: Key Technologies, Applications, Challenges

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ABSTRACT The application of the Internet of Things in agricultural development usually occurs via a monitoring network that consists of a large number of sensor nodes, thus gradually transforming agriculture from a human-oriented and single-machine-centric production model to an information- and software-centric production model. Due to the large area coverage of agriculture and the variety of production objects, if all farmland perception information is gathered into the cloud server, the server will exert greater pressure on the network, which reduces the speed of response to event processing. This problem may be perfectly solved by the recent emergence of Edge computing, which can share the load of the cloud server and reduce the delay. Edge computing has prospects in agricultural applications, such as pest identification, safety traceability of agricultural products, unmanned agricultural machinery, agricultural technology promotion, and intelligent management. The application of the Agricultural Internet of Things integrates artificial intelligence, the Internet of Things, and blockchain and Virtual/Augmented Reality technologies. This paper primarily reviews the application of Edge computing in the Agricultural Internet of Things and investigates the combination of Edge computing and Artificial Intelligence, blockchain and Virtual/Augmented reality technology. The challenges of Edge computing task allocation, data processing, privacy protection and security, and service stability in agriculture are reviewed. The future development direction of Edge computing in the Agricultural Internet of Things is predicted.

INDEX TERMS The Agricultural Internet of Things, artificial intelligence, blockchain, edge computing, smart agriculture, virtual/augmented reality.

I. INTRODUCTION

Agriculture is the foundation of human survival and plays a fundamental role. It is vital to the stability and the development of society. However, with the emergence of three factors that restrict agricultural development: (i) population aging and migration (also known as urbanization) have led to a gradual decline of rural labor; (ii) industrial buildings and residential buildings are gradually eroding agricultural land, resulting in a reduction in agricultural land [1]; (iii) increased climate change will also continue to change crop growth conditions such as temperature, precipitation and soil moisture in unpredictable ways [2]. The challenges that agriculture faces are increasingly severe. In order to meet the challenges, people must be seize the opportunity of the third revolution in the information technology industry, for example, Internet of Things (IoT), big data, artificial intelligence *et al.*. They can bring fundamental changes to agriculture. The Agricultural Internet of Things (Agricultural IoT) not only solves the problems of increasing food demand, environmental pollution caused by excessive use of pesticides and fertilizers, and the safety of agricultural products [3], but also reduces labor costs [4], greatly promoting the continuous development of agriculture in the direction of high quality and high output. However, the widespread use of the Agricultural IoT has led to the explosive growth of sensors and the increasing number of data. The large amount of data increases the load on the cloud server, which reduces the response speed.

The emergence of the Edge computing models can solve the problem of cloud server load. The classical Edge computing models include: the Cloudlet introduced by Satyanarayanan solves the latency problem of accessing the cloud

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by using computing resources available in the local network; the Fog computing introduced by Cisco enables applications to run directly on the edge of the network through billions of smart connected devices; the Mobile Edge computing introduced by the European Telecommunications Standards Institute (ETSI) allows mobile users to utilize computing services from base stations. Through the emergence of three classical Edge computing models, we can find a new trend: some calculations that take place in the cloud are gradually moving to the edge [5]. Similarly, the data generated by the Agricultural IoT is also increasing, resulting in increased load on the cloud server. In order to share the offload of the cloud server, the computation that occurs in the cloud is offloaded to the edge segment for execution. In addition, the real-time requirements of some applications of the Agricultural Internet of Things are high. The edge server is close to the data source, so it provides intelligent services nearby and shortens the response time. Although the Edge computing is favorable for agricultural development, but Edge computing applied to agriculture has little literature, so we combine with a lot of related literature and present a review of the application of Edge computing in the Agricultural IoT, which inspires more people to develop the Agricultural IoT under Edge computing in the future.

This paper reviews the concept and research status of the Edge computing and Agricultural IoT. In addition, we describe in detail the research status of Edge computing in the application of pest identification and crop classification, agricultural product safety traceability, unmanned agricultural machinery, agricultural product promotion, etc., which mainly involves artificial intelligence, blockchain and virtual/augmented reality technology. In the end, the literature also mentions the challenges and opportunities of the combination of Edge computing and Agricultural IoT, and provides direction for the development of Edge computing and Agricultural IoT.

The organizational structure of this paper is as follows. In Section II, it mainly introduces the concept of Edge computing and Agricultural IoT in detail; the necessity of combining Edge computing with the Agricultural IoT is discussed in Section II; then in Section III, the application of Agricultural IoT combined with Edge computing is reviewed; in Section IV, Edge computing combined Agricultural IoT meets the challenges; finally, the paper is concluded and a vision of their future is described in Section V.

II. BACKGROUND

This section mainly introduces the concept, structure, and research status of Edge computing and Agricultural IoT. The aim of this section is to provide the reader with a solid foundation of the research subject.

A. EDGE CPMPUTING

1) DEFINITION AND DEVELOPMENT OF EDGE COMPUTING

With the rapid development of the IoT, billions of smart devices are installed each year. It is estimated that more than 70 billion smart devices will be installed by 2020. The access of a large number of devices has led to an increase in the amount of data to be processed. We face the challenge of processing and analyzing those data, especially if it needs to be processed in real time. Simply using a cloud server is not able to provide real-time response while handling such a large data set. Edge computing is proposed for solving the problem of data explosion and network delay. The research fields of Edge computing include Fog computing [6], Cloudlet [7, 8] and Mobile Edge computing (MEC) [9, 10]. Although Edge computing has been proposed for a long time, there is no uniform and strict definition. Satyanarayanan [11] defines it as, "Edge computing is a new computing model that deploys computing and storage resources (such as Cloudlets, fog nodes) to networks closer to mobile devices or sensors." Its system architecture is shown in Fig. 1, which is divided into three layers: terminal device, edge node and cloud center. As we all know, 5G is becoming more and more popular, and edge computing is one of the core technologies in the 5G era, but its architecture is open and can also be deployed and applied to 4G LTE networks. Operators will smoothly evolve on the existing network structure, and finally achieve full coverage of the computing power of low-level network nodes, and continue to improve edge computing capabilities.

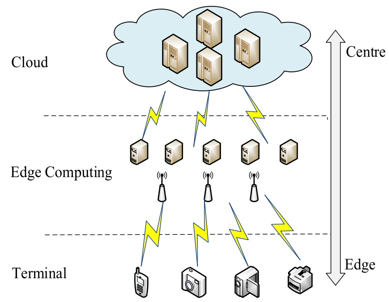

FIGURE 1. The system architecture.

From the development trend since 2010, the attention of Edge computing continues to rise, as shown in Fig. 2 (Some data quoted from [12]). Especially since 2016, the attention of Edge computing has increased rapidly. Shi *et al.* derived five typical scenarios for the application of Edge computing: cloud offload, video analytics, collaborative edge, smart home, smart city [13]. Sun *et al.* proposed a real-time fault detection algorithm based on Edge computing and cloud computing for the video monitoring system, which effectively improved the average repair time [14]. In [15], in order to meet the demand of smart home, a system based on Edge computing was designed to predict the demand for household electricity. The system can provide better quality of service and enhance the scalability of the system. In [16], Higashino *et al.* proposed a large-scale spatio-temporal information collection mechanism based on Edge computing and IoT to mitigate disasters and build a safe and intelligent city.

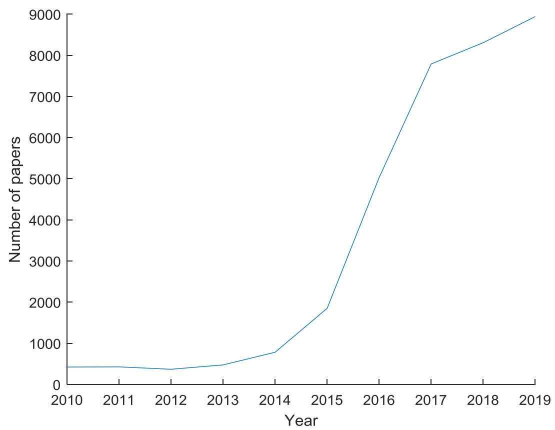

FIGURE 2. Number of papers retrieved by "Edge computing" on Google Scholar.

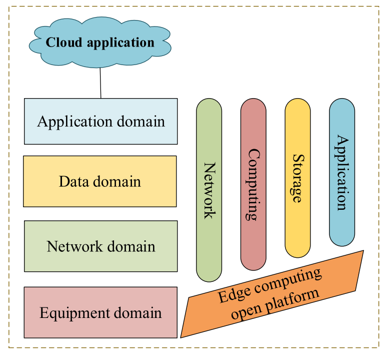

FIGURE 3. The hierarchical deployment structure for Edge computing.

2) THE HIERARCHY OF EDGE COMPUTING

The Edge Computing Consortium (ECC) defines four areas for Edge computing: equipment domain (Perception and control layer), network domain (Connection and network layer), data domain (Storage and service layer), application domain (Business and intelligence layer). As shown in Fig. 3: these four layers are the computing objects of Edge computing.

Equipment domain: in the equipment domain, Edge computing can directly process the perceived information. For example, intelligent identification can be directly deployed in video collection and audio collection. Network domain: in the network domain, the automatic conversion of each network protocol is realized, and the data format is standardized. At the same time, the Edge computing in the network domain can conduct intelligent management of the "converged network", reduce the redundancy of the network, ensure the security of the network, and further participate in the optimization of the network. Data domain: Edge computing in the data domain makes data management smarter and more flexible. First, Edge computing can analyze the integrity and consistency of the data, and conduct data collation to delete redundant and wrong data in the system. Secondly, Edge computing can maintain efficient coordination with cloud computing and share cloud computing tasks. Application domain: Edge computing in the application domain provides localized business logic and application intelligence. It enables applications to be flexible and fast- responding. Edge computing can provide localized application services independently, when it loses contact with the cloud.

Edge computing is deployed in the above four domains, where it is closer to the user and application scenarios. It enables the device to have intelligent sensing capabilities and it can be equipped with adaptive connection strategies and more optimized deployment strategies. It can solve data heterogeneity and related network synchronization problems in the system, and provide local business logic and application intelligence.

Edge computing is an open and distributed platform that provides network, computing, and storage services at the edge of the network, close to the data end. It meets the demands of intelligent, real-time business, data optimization, and security aspects of agricultural digital transformation. In addition, there are two kinds of edge servers mentioned in this paper: remote edge computing servers located on the edge of wireless network; local edge computing device.

B. AGRICULTURAL INTERNET OF THINGS

1) DEFINITION AND DEVELOPMENT OF AGRICULTURAL IoT

Since the IoT technology is proposed in 1999, it has gradually penetrated into various fields [17], [18]. Agriculture is the focus of attention of people all over the world, and it is naturally also involved. With regard to the concept of Agricultural IoT, different researchers have given different interpretations from different perspectives. For example, Li *et al.* [19] believe that the Agricultural IoT usually refers to the use of relevant sensing devices to perceive information on environmental factors in plants, agricultural production tools, etc., and an informational network for real-time monitoring of agricultural production processes, positioning and management of agricultural production objects based on pre-defined protocols for data transmission. The characteristics of Agricultural IoT are relatively clear, mainly in the aspect comprehensive perception, intelligent processing and timely feedback of agriculture from planting to sales [20]. The emergence of cloud computing and its extended Edge computing models such as fog computing and Mobile Edge computing have made the Agricultural IoT a milestone. It has completely transformed the management and operation of the farm [21].

The Agricultural IoT has made great progress in recent years. Xing *et al.* designed a greenhouse information intelligent monitoring system based on ZigBee wireless sensing technology [22]. Diego *et al.* designed agrometeorological monitoring station based on Bluetooth technology, and the data was sent to the computer through the wireless Bluetooth module [23]. In order to realize the collection, management, visualization and upload of real-time information in paddy fields, Zhang *et al.* proposed a paddy field information monitoring system based on Solar-Powered Panel and GPRS technology [24]. However, both ZigBee and GPRS are short-range wireless technologies and have high operating

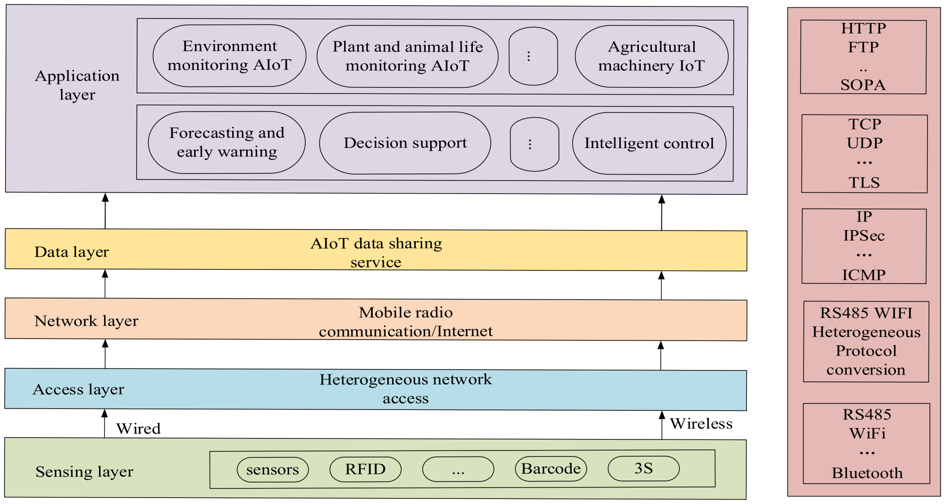

FIGURE 4. **The agricultural IoT architecture (AIoT in the picture represents the Agricultural IoT).**

costs. Therefore, a wide area network monitoring system combining NB-IoT and LoRa is designed in [25]. By studying the development of farmland monitoring systems, we find that the development of Agricultural IoT is not only reflected in the rapid growth of the types and quantities of agricultural sensors, but also in combination with emerging technologies.

2) ARCHITECTURE OF AGRICULTURAL IoT

At the beginning of development, Agricultural IoT mainly focused on the application of the single entity, which leads to the scalability, scalability and interoperability of the entire system gradually fail to meet the growing demand of the agricultural production. Later, the new hierarchical structure model of Agricultural IoT was proposed, based on the specific needs of agricultural production and marketing, combined with the principles of safety, reusability and expansion of IoT systems and practical experience. As shown in Fig. 4, the model is divided into five layers from top to bottom, including the sensing layer, the transport layer, the application layer, etc. The communication protocols and data are transmitted between the layers using different communication protocols.

The sensing layer of the Agricultural IoT consists of various sensor uses Wi-Fi, GPRS, and ZigBee technologies to transmit data, and transmits the collected data to the access layer of the Agricultural IoT system structure; the access layer is mainly composed of hardware gateways and built-in software middleware. The middleware can effectively shield the complexity of the underlying heterogeneous sensing network and provide a unified abstract management interface to provide a foundation for the rapid establishment of Agricultural IoT business applications; the network layer transmits data to the upper layer through Internet Protocol, mobile communication network protocols; the Agricultural IoT data sharing layer is equivalent to a huge data pool, which realizes the integrated sharing of various types of monitoring data. The layer mainly uses transmission protocols such as TCP and UDP; the application layer obtains data from the data sharing layer through protocols such as HTTP, FTP and other protocols and constructs a corresponding Agricultural IoT system. Compared with the traditional three-layer and four-layer IoT architecture, the functions of each layer in the five-layer Agricultural IoT architecture are clearer and more independent, which is beneficial to the network load balancing between servers at different levels, and can reduce the communication burden of the enterprise network.

C. THE NECESSITY OF COMBINING EDGE COMPUTING WITH AGRICULTURAL IoT

Based on the combination of IoT and cloud, the Agricultural IoT system has simple device access and rapid system setup. However, due to the centralized processing of data by the cloud computing model, it is difficult to solve the following problems when the device and data are exploding. (1) Excessive resource cost: the sensors continuously collect various sensor data, and the data is usually stable or rarely changed. Uploading all the data to the cloud for processing will consume a lot of network resources and cloud resources. (2) Real-time performance is difficult to guarantee: data processing and decision-making are all in the cloud, and the processing is not timely. (3) Excessive reliance on the network: when the network is unstable, it cannot process data and control devices in time. (4) Data security and privacy protection: all sensor data and control data need to be transmitted through the network, and there are risks such as information eavesdropping, tampering, fraud and illegal operation of equipment.

These problems will increase the cost of Agricultural IoT systems (network flow, storage, and computational costs), reduce stability and availability of system, and make it difficult to automate production control, especially in large-scale, factory-planted, and aquaculture. In addition, non-standard and self-resource limitations of sensors and control devices (including computing, storage capabilities, etc.) bring obstacles to device access and linkage control. Therefore, it is necessary to study and solve the above problems to develop smart agriculture and promote precision agriculture.

Edge computing provides intelligent services at the edge of the networks which are close to thing or data source, enabling each edge of the IoT to have data collection, analysis, computing, and intelligent processing capabilities to process data, filter data, and analyze data nearby. In addition, local decision-making and processing can meet key requirements of network capabilities and resource constraints, security and privacy challenges. Therefore, we introduce Edge computing into the Agricultural IoT system to improve the standardization, stability, and availability of the agricultural IoT system.

III. RESEARCH STATUS OF EDGE COMPUTING IN AGRICULTURAL IoT

This section introduces the concepts of Artificial Intelligence (AI), blockchain and Virtual Reality /Augmented Reality and their research status in agriculture. The most important concept is to summarize the research status of Edge computing and Agricultural IoT application technology.

A. RESEARCH ON ARTIFICIAL INTELLIGENCE IN AGRICULTURE BASED ON EDGE COMPUTING

Since the breakthrough in deep learning in 2001, AI has entered a new era and is gradually infiltrating the modern agricultural field and injecting new vitality and a new impetus into the development of modern agriculture. In addition, the rapid development of mobile computing technology and the IoT has generated billions of bytes of data at the edge of the network. Driven by this trend, AI must be pushed to the edge of the network to fully release the potential of edge big data. This situation caused the emergence of Edge computing, which is an emerging paradigm that pushes computing tasks and services from the core of the network to the edge of the network. AI computing is becoming increasingly complex, and an increasing amount of data is needed. As a result, edge intelligence (EI) is generated as an interdisciplinary subject of AI and Edge computing [26]. Edge intelligence leverages the available data and resources of end devices, edge nodes, and cloud centers to optimize the total training and reasoning performance of the deep learning model. In 2–5 years later, the Edge computing technologies and machine learning will be in the mainstream [27]. AI has a place in Agricultural IoT application technology and is primarily employed in video analysis, unmanned agricultural machinery, pest identification, and plant species identification. Therefore, the research of edge intelligence is one of the most important components of future research topics.

1) ARTIFICIAL INTELLIGENCE

AI is a branch of computer science. Research in this area includes robotics, language recognition, image recognition, natural language processing, and expert systems. The AI mentioned in this paper primarily involves image processing; its main applications in agriculture are pest and disease identification, crop species identification, and unmanned agricultural machinery.

Since Yann LeCun published Gradient-based learning applied to document recognition in 1998 [28], deep learning has been developed for more than 20 years. Represented by the well-known Convolutional Neural Network (CNN), deep learning has achieved leapfrog development in recent years due to the following four classic CNNs: AlexNet [29], VGG [30], GoogleNet [31] and ResNet [32]. Zhang *et al.* improved the GoogleNet model structure and Cifar10 model structure and applied an improved model to training of corn leaf pest identification, which improved the optimal recognition accuracy by 0.4% and 1.7% respectively [33]. Too *et al.* [34] directly tuned the VGG16, Inception-V4, ResNet, and DenseNet networks and applied them to train and test insect images from 14 plants in the PlantVillage image set. They compared the experimental results by using different iterations and attained the optimal recognition accuracy of 99.75%. Goh *et al.* constructed an optimal Convolutional Neural Network to complete the classification task based on plant mutants and improve the classification success rate [35]. Research on the accuracy of pest and disease identification is very mature but few studies examine the running time of the model. In this paper, the author proposes the idea of using Edge computing to reduce the running time of the model.

According to the introduction of [26], the author summarizes the framework of edge intelligence, which includes the edge-based mode, device-based mode, edge-device mode, and edge-cloud mode, as shown in Fig. 5. In Fig. 5(a), the terminal devices receive the data and send data to the edge server. DNN model reasoning is performed on the edge server, and the forecast results are returned to the device. As shown in Fig. 5(b), the edge server sends the DNN model to the mobile device and locally performs model reasoning. As shown in Fig. 5(c), the device divides the DNN model into multiple parts. The device executes the DNN model to a specific layer and sends the intermediate data to the edge server. The edge server will execute the remaining layers, and the predicted result is sent to the mobile device. The device in Fig. 5(d) is responsible for input data collection, and the DNN model is executed in cooperation with the cloud through the edge. Due to the development of deep learning, the commonly employed models of DNN (such as AlexNet and GoogleNet) have reached millions of neurons. All neurons are concentrated in mobile devices or edge servers; thus, the hardware requirements are very high. Their concentration in the cloud server will cause delays; thus, use of the edge-cloud mode is common.

2) RESEARCH STATUS OF EDGE INTELLIGENCE

In this section, we review the relevant literature on the combination of AI and Edge computing techniques. The role of edge nodes in AI is summarized in Table 1.

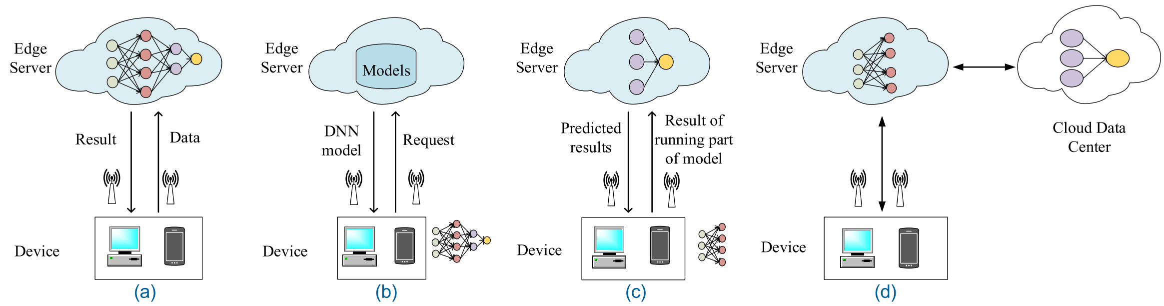

FIGURE 5. Edge Intelligence inference modes: (a)Edge-based mode (b)Device-based mode (c) Edge-device mode (d) Edge-cloud mode.

TABLE 1. Overview of the role of edge computing in artificial intelligence.

Role	References	Approach	Summary
Execution of part of the program	[37], [38]	Fine-grained partitioning procedure	Relieved changes to the program
	[39]	DNN programs are mapped to edge servers and data centers	Cost is reduced by more than 20 times
	[40]	Layer-level compression	Reduced communication costs
	[41]	Partition video tasks	Shorted execution time by 90%
Pretreatment	[42]	Transferred the trained model to the edge server	Increased efficiency
	[43]	Compressed based on parameter obsolescence	Shorted response time and reduced communication costs
	[44]	Built network retraining on the edge server	Improved fault tolerance
Caching of model	[45], [46]	Added a cache model to the edge device	Reduced latency

a: EXECUTION OF PART OF THE PROGRAM

To solve the problems of insufficient processing capability and limited resources of terminal equipment, the industry introduced computational offloading in Mobile Edge Computing [36]. In the application of plant diseases and pests identification, the role of the edge server is to execute part of the program, which uses computing offload technology. At the same time we also need to consider the division of CNN or DNN procedures. MAUI is a system, which enables fine-grained energy-aware offload of mobile code to the infrastructure [37]. It maximizes the potential for energy savings through fine-grained code while minimizing changes to applications. It allows part of the program to be executed locally on the smart phone and others to be run remotely in the infrastructure. Second, MAUI provides a method for each application. But MAUI needs to perform an analysis step for each individual application, while performing DNN partitioning requires prediction. The Neurosurgeon lightweight scheduler proposed by Kang *et al.*, makes decisions based on the DNN topology without any real-time analysis [38]. It selects the best partition point, optimizes end-to-end latency, and performs DNN division between mobile and cloud. The new computing paradigm reduces the computation required by the data center, thus shortening the query service time and improving the query throughput. The deep network layer is partitioned to respectively run on mobile devices and the cloud. Compared to [38], the deep network is further divided into cloud, fog computing devices and users' mobile devices. Decommissioning procedures takes up some time, but their overall time is much shorter than the time they spend executing in the cloud center or terminal alone. Teerapittayanon *et al.* [39] for adapting to the cloud-edge-terminal distributed hierarchy, proposed a distributed depth neural network (DDNNs) based on distributed hierarchy. DNN is divided into various parts by Cloud Exit, Edge Exit and Local Exit, and then it is mapped into a distributed computing hierarchy. The structure takes advantage of the geographical diversity of sensors, which not only reduces communication costs but also improves the accuracy of target recognition. DeepX [40] divides the entire DNN or CNN into multiple parts and executes them on each local device. Its advantage is that it uses runtime layer compression (RLC), which no longer focuses on the training phase of deep learning and the compression of the entire model, but provides the memory consumed in the reasoning phase and the hierarchical compression of the computation runtime. Meanwhile, deep architecture decomposition (DAD) can effectively identify the units of the depth model quickly, decompose them, and allocate the blocks to local and remote processors. But DeepX cannot operate Recurrent Neural Networks (RNN) at present. The deep network layer is partitioned to respectively run on mobile devices and the cloud. Sun *et al.* [41] proposed mVideo to make full use of resources on collaborative edges and cloud nodes. The video stream processing platform is provided with a mechanism to partition video analysis tasks according to the available resources of mobile edge nodes. At the edge node, a lightweight DNN model is used to preprocess the video data, and the results are uploaded to the cloud node for further analysis. Its advantage is that the collected video data covers a large area and reduces communication costs. Overall, the execution time is reduced by 90%.

b: PRETREATMENT

The role of the edge server in the application of farm intelligent monitoring systems and unmanned agricultural machines is pre-processing. In the large-scale video stream analysis, the edge preprocessing is used to make a preliminary judgment of the object, so as to reduce the communication time and the load in the cloud center. The architecture of edge-enhanced video analysis system proposed by M.Ali is composed of camera terminal, edge node, cloudlet and cloud center [42]. The CNN model is trained and the generated model is saved in the cloud. The saved model is then transferred and distributed on cloudlets and cloud resources for object inference. In this paper, edge resources are used for the basic processing stage, which improves efficiency. But the authors did not experiment with the extensibility of the architecture. Edge preprocessing also includes compressing deep neural networks on edge devices. Model compression was introduced to overcome the difficulty of large computation and large memory consumption in the terminal of the model. In 2015, Han's Deep compression model compression method was reviewed [43]. Cropping, weight sharing, quantization, and coding were applied to model compression and good results are achieved. Hardy *et al.* proposed a novel algorithm for updating and compressing models on the server [44]. It is flexible to perform distributed deep learning on edge devices through adaptive compression. In addition, the edge node also plays the role of a supervisor, which contains a test data set to calculate the accuracy of the central model. Finally, we found that compressing images in a system that sends images from edge nodes to cloud nodes can reduce communication bandwidth. But the introduction of compression technology also increases the computational overhead of compression and decompression. In general, transmitting smaller images may result in better performance overall, but higher compression rates may negatively affect prediction accuracy. Chandakkar *et al.* [45] proposed to update or train DNNs on edge devices to provide personalized services. How to deploy updates / training on mobile devices is our challenge. Moreover, simply from the experiment of updating the DNN, it is a hot research topic to study the catastrophic forgetting after construction in the next few years to maximize the data performance.

c: EDGE CACHING

Drolia *et al.* [46] were inspired by the web cache and proposed to add a cache module to the edge device. The advantage of caching on the edge server is that the images obtained by the terminals in the same area of the edge device service often have similarities. By caching the characteristics of these objects, these queries do not need to be submitted to the cloud, which can greatly reduce the delay of users. The challenge is that when the distribution of the query graph changes drastically, the Distribution Estimator in the edge device cannot quickly respond to the change. Later, they proposed Precog [47], which has the same application scenario, and it caches the models from the edge in the terminal device. This is a technology of edge and terminal device collaboration. When an object feature point query is missing on the terminal device, the image of the query is uploaded to the edge, and Markov Estimator in the edge records the query and sends the updated object probability distribution to the terminal device along with the query result. Precog has the same strengths and weaknesses as Cacher.

In general, the program division is aimed at specific neural networks. Two or more edge servers can be used, and the combination of splitting and preprocessing and edge caching can make use of the specific structure of NN, thus providing more opportunities for optimization.

B. APPLICATION OF EDGE COMPUTING IN TRACEABILITY OF AGRICULTURAL PRODUCTS

An increasing number of people are eating organic agricultural products. However, due to the lack of common credit certificates in the market, people are not assured of the purchase of organic agricultural products. Therefore, tracing agricultural products is especially important. Wang *et al.* [48] and Zhang *et al.* [49] use an RFID-based meat traceability system, which traces from the customer to the manufacturer. It connects to the ONS server of the RFID system via the Internet and obtains the PML server of the IP address for each product-related point to obtain detailed information about product circulation; Lahbabi *et al.* proposed a traceability system that can share product certification information in real time [50]. Yun *et al.* described the research progress of key technologies in agricultural product traceability systems [51]. Azram *et al.* proposed a food document traceability model that is based on a software product line [52]. In the above centralized supply chain traceability system, members of the supply chain rely on an information provider to store, transmit, and share all information.

The centralized system approach poses problems because it is a monopoly, asymmetric and opaque information system approach. This can lead to trust issues among players in the supply chain, including fraud, manipulation and tampering [53]. The blockchain, which is the underlying technology of digital currency, securely records transaction information for all currencies in a decentralized distributed ledger. The decentralization of the blockchain and the high transparency ensure that the traceability of stored data cannot be tampered with [54]. Many new distributed applications have been implemented based on blockchain technology. Many of these applications focus on the automation and digitization of financial sector processes. Automating processes can save money and increase transparency. Therefore, blockchain technology can potentially make a significant contribution to the efficiency and competitiveness of world agriculture.

1) BLOCKCHAIN

In 2008, Satoshi Nakamoto proposed the concept of blockchain. Blockchain refers to the technical solution of collectively maintaining a reliable ledger via decentralization and distrust [55]–[57]. The infrastructure model of blockchain technology include a data layer, network layer, consensus layer, incentive layer, contract layer and application layer.

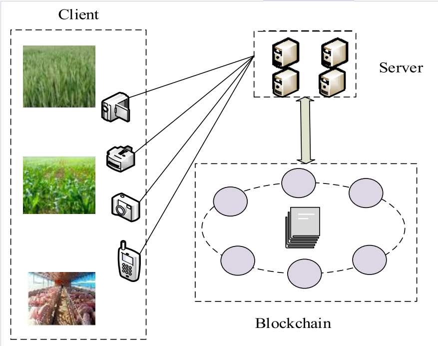

FIGURE 6. Structure diagram of food safety traceability system based on blockchain.

The centralized management of agricultural products and the tampering of data are solved by blockchain technology. Lucena *et al.* [58] proposed a method for measuring the grain quality using blockchains and smart contracts. They proposed an implementation of a practical case that increased the value of genetically modified (GM) exports of Brazilian grain exporters by 15%. To study how to promote value transfer by converting African farmers' assets, such as livestock, farmland and agricultural products, into small-scale agriculture, Chinaka [59] and Schneider [60] proposed a product traceability system that is based on a prototype blockchain to improve the transparency and automation of the agricultural sector. Holmberg and Aquist [61] investigated a solution that is based on blockchain traceability in the dairy industry. These studies apply the concept of blockchain to product traceability but lack a framework of blockchain application. The structure diagram of a blockchain-based food safety traceability system proposed by Wang *et al.* [62] and Li and Wang [63] is shown in Fig 6. Based on this description, we determine that the application of blockchain in Agricultural IoT is increasing.

2) THE RESEARCH STATUS

Although the blockchain solves the problem in which data is easily falsified, the scalability of the blockchain is small and the memory is insufficient. The problem was solved by the combination of blockchain and edge computing technology. In table 2 an overview of the combination of edge computing and blockchain applications. Liu *et al.* proposed new electric vehicles cloud and edge (EVCE) as a typical application scenario of the Internet of Things, which also involves the transmission and transaction of information and energy [64]. At the same time, using the blockchain to connect the strong and weak electricity can provide EVCE with transparency and traceability security guarantees. Xu *et al.* proposed a product traceability system that is based on blockchain and Edge computing technology [65]. The role of the blockchain is to prevent malicious tampering by third parties. The edge server performs a difficult hash calculation with the blockchain node and returns the result to the blockchain node for verification. If the blockchain node does not have sufficient internal storage space, it can offload the entire blockchain to the edge server and store only relatively new blocks (referred to as storage offload) in the internal storage. The disadvantage is to consider the computing power of the edge nodes. In this regard, Stanciu proposed that the deployment of computing on the edge nodes requires smaller Dockers containers. The three-layer edge model was mentioned in [66]. It consists of physical devices and processes, edge nodes and cloud services. The blockchain is deployed on the top layer to ensure transaction security and to be properly verified. Edge computing solves the inconvenience caused by blockchain computing applications due to limited computing power and available energy consumption of Agricultural IoT terminal equipment. But the paper does not take into account the problem of the efficiency of identity verification and the vulnerability of the connection between the edge node and the terminal. In [67], a distributed trusted authentication system combining edge computing and blockchain is proposed. The system is composed of three parts: physical network layer, blockchain edge layer and blockchain network layer. Edge computing is applied in the edge nodes of the blockchain to provide name resolution and edge identity authentication services based on smart contracts. In addition, the edge computing cache strategy is proposed to improve the hit rate and reduce the delay.

TABLE 2. Overview of the combination of edge computing and applications of blockchain.

Reference	Description
[64]	Implemented data processing and analysis during collaborative operations
[65]	Performed more complex hash calculations
[66]	Edge computing is applied in the edge nodes of the blockchain
[70], [71]	Managed local networks, packaged data formats, and provided computing power

However, as the application of blockchain technology becomes more mature, the increase in data has caused inventory inflation [68]. The problem of insufficient storage arises when the blockchain is only applied to the digital currency, to which the application scenario of the blockchain is not limited. For example, in [54], transaction information involves files, videos, and audio, which generates higher requirements for blockchain storage capabilities. However, the high demand for storage of blockchain data is not conducive to the development of blockchain. By combining IPFS [69] and blockchain, a decentralized identity management solution is proposed. According to [70] and [71], the working principle of the agricultural product traceability system, which is based on blockchain technology and combines Edge Computing and the IPFS mechanism, is shown in Fig. 7: Edge Computing is used to manage local networks, package data formats, and provide computing power. Data is transmitted from the intelligent terminal to the edge node through the edge gateway, and files with large memory, such as photos and videos, are stored via the IPFS mechanism. The content hash value returned after the storage is transmitted to the edge node through the

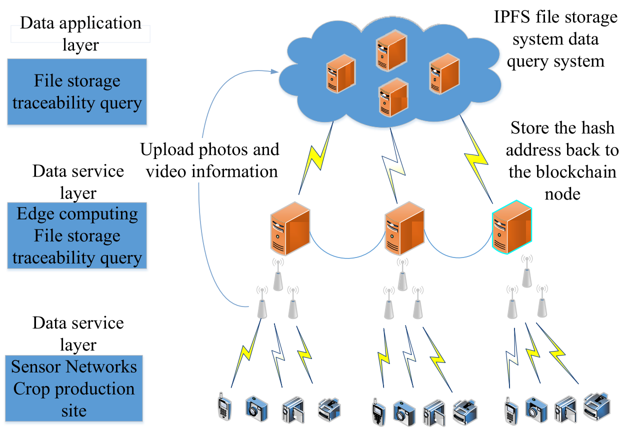

FIGURE 7. Agricultural product traceability architecture based on edge calculation, blockchain and IPFS.

cloud server. The value is packaged in the JSON format with the previous data, and the packaged data is stored in the blockchain in the form of a transaction. Once the transaction is completed, the data stored in the blockchain cannot be tampered with, and the data is queried in real time based on the hash value after the transaction. In the security traceability architecture of blockchain products based on edge computing, edge nodes only play the role of data processing. The security of data transmission and the efficiency of identity authentication are not considered. All in all, by building a decentralized system, blockchain can provide infrastructure support for the IoT and help solve the ubiquitous security issues in the IoT. At the same time, the IoT provides a large number of landing scenarios for the blockchain.

C. STUDY ON THE COMBINATION OF VR/AR AND EDGE COMPUTING IN AGRICULTURE

Virtual Reality and Augmented Reality have been the focus of the industry's attention since 2016. Users have higher and higher requirements for real-time performance. Scholars have found that the actual physical or network distance between the client and the cloud is too large to limit the response speed of VR / AR. At the same time, the growth rate of bandwidth resources in the cloud lags far behind the growth rate of data, which ultimately leads to cloud computing being unable to meet the higher VR / AR computing requirements of bandwidth. The idea is to combine edge computing with VR/AR.

Compared with former cloud computing, Edge computing can better support AR/VR computing scenarios: (1) Cisco noted that global devices will generate 600ZB data in 2020 in the Global Cloud Index [72], 90% of which is temporary data similar to AR/VR scenarios. A large amount of temporary data can be stored at the edge nodes to alleviate the pressure on the cloud bandwidth. (2) High delay, strong jitter and low data transmission rate caused by the unstable links and routes in the complex network environment affect the responsiveness of cloud services [73]. The edge-side is closer to the user-side in both geographical distance and network distance, which ensures lower latency and reduces network jitter, which renders edge calculation more useful and responsiveness stronger [11]. (3) The images involved in AR computing, such as face data, belong to the user's private data. These data is stored at the edge, which reduces the possibility of privacy leakage.

1) VIRTUAL/AUGMENTED REALITY TECHNOLOGY

VR and AR are immersive interactive environments that are based on computing information [74]. VR emphasizes the immersion of the virtual world, which emphasizes that people can interact with objects in the virtual world in a natural way. While AR emphasizes the ability to incorporate computer-generated virtual information into real-world scenarios and does not isolate the connection between the observer and the real world [75]. VR and AR differ by the device. The VR device is a closed-type head-mounted display, which is cumbersome and inconvenient. AR equipment is divided into three types: head-mounted, hand-held and space-projected by Bimber and Raskar according to the application scenario [76], which is relatively light.

Recently, the application research of VR/AR technology in agriculture has emerged. According to the study of Cupial [77], AR has many applications in agriculture and will become an important technology in the Agricultural IoT in the future. Fernandez *et al.* [78] developed a tractor assist system that is based on wearable AR technology. When a tractor is working in the field, the parts that have been treated in the field are displayed in the field of view of the driver's AR glasses. Vidal *et al.* reviewed the current status of AR and proposed its new applications in weed science [79]. It includes software for image identification for species identification and quantification of weeds, and selection of herbicides based on weed density. Nigam *et al.* [80] proposed a primitive augmented reality system. They use augmented reality technology to help farmers identify insects and successfully utilize integrated pest management. Generally, farmers are not trained in entomology, and they tend to destroy the insects they find in the field. In fact, not all insects should be eliminated because the prosperity of fields and ecosystems depends on their existence. The authors of the paper proposed an innovative augmented reality application that they intend to help farmers identify insects and use integrated pest management. The system made recommendations for farmers to use pesticides reasonably and reduce pollution.

Another interesting augmented reality application for greenhouses shown in Neto and Doke [81]. This application uses a network of humidity and temperature sensors to sense conditions to develop staphylococcus fungi in tomatoes and warn farmers through their mobile devices. In addition, Liu *et al.* noted the use of AR technology to simulate the growth of plants and livestock, to visualize information and help users manage different agricultural jobs [82]. Janna and Timo [83] proposed the use of drones and AR technology to accurately control the fertilization rate in agriculture.

TABLE 3. The role of edge servers in VR/AR.

Function	Reference	Techniques	Merits	Demerits
	[87]	Data is cached on the user terminal	Improved hit rate by 10%	It has not be verified in edge server
	[88]	Collected user requirements for VR content with UAV	Reduced communication costs	VR devices are difficult to connect with edge
Caching in edge	[89]	Offloaded computing tasks to edge servers	Relieved data center load	There was impact on the fine-grained performance of communication expense
	[90]	Predicted and cached the next video frame on the edge server	Shorted waiting time	Result in wrong prediction when the object dramatically changed
	[91]	Performed AR computing tasks and stored 3D models at the edge server	Enhanced the portability of AR devices	Made computing performance of edge server to be considered
Performing some VR/AR tasks	[92]	Animation is compressed and streamed, and sent to the local edge server for rendering	Reduced rendering costs	Lead to anamorphic animation

A drone is responsible for collecting soil information, and the AR technology guides the user to the generated sample points. In applications in agriculture, a mix of AR and VR technologies are utilized where virtual and actual environments are smoothly combined [84]. Premsankar *et al.* [85] experimentally demonstrated that cloud deployments have higher latency than edges. Edge computing was introduced. Although various studies have investigated edge caching and computing, their use for AR/VR applications has been given minimal attention [86].

2) RESEARCH STATUS

In this section, we learned that the role of edge computing in AR/VR is mainly to store in edge and execute some VR/AR tasks at the edge. In table 3, we summarize the role of edge servers in VR/AR.

In fact, the role of edge computing in VR/AR is mainly edge caching. In edge caching, caching strategies can be divided into proactive and reactive. In proactive caching, the content to be requested is predicted and brought to the cache. In reactive caching, the content obtained is cached and is updated according to user needs. S.Park *et al.* came up with the idea of caching on the client side [87]. The priority cache mentioned in the paper can be used in the edge cache. M. Chen *et al.* studied edge caching in VR networks to reduce backhaul traffic and meet real-time requirements of VR users [88]. In their proposal, a unmanned aerial vehicles (UAVs) is used to collect the VR content requested by the user and transmit it to the small base station and the retrograde cache. Deep learning algorithms is implemented to find the best caching strategy. In J. Chakareski's research, the authors used edge computing to overcome the computing limitations of VR devices by enabling users to offload computing tasks to edge servers [89]. The author's goal is to use the Lyapunov stochastic optimization model to minimize calculation and transmission power consumption, but it is affected by co-channel interference, reliability and delay constraints. M. S. Elbamby *et al.* proposed an proactive caching and computing scheme to meet the high reliability and low latency requirements of VR users [90]. In the paper, information about user actions and game actions is used to pre-calculate and cache the next video frame to minimize latency while multi-connectivity is applied to ensure reliability. Although it is aimed at the application of VR games, it is also applicable the planting of plants in the online VR of the Agricultural IoT. To briefly summarize, the architecture diagram of the edge server playing a role of caching in VR/AR is shown in Figure 8.

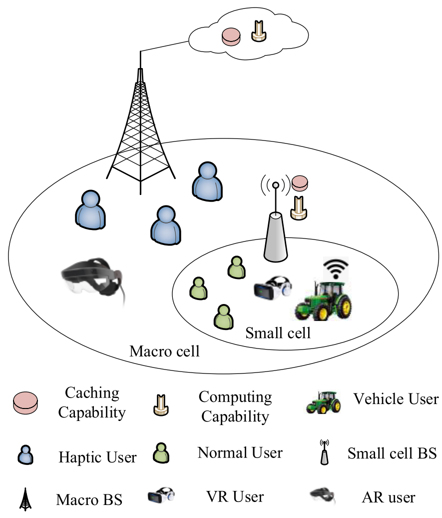

FIGURE 8. Structural diagram of the combination of edge calculation and VR/AR in agriculture.

Edge computing can also perform some parts VR/AR tasks. Yan and Qiao [91] proposed a method for solving the delay and bandwidth for Web AR that primarily deployed the edge server between the clients, assumes AR computing tasks and storage of 3D models, which is closer to the user end and satisfies the user's requirements for real-time performance. First, the cloud node initiates full AR service access. After receiving a user request, it selects the most appropriate edge computing node and redirects the request based on the IP address. Then, according to the calculation task division, an independent AR engine and 3D model database are used to identify the target image. The architecture overcomes the difficulties of poor portability of AR devices, poor pure front-end performance, and high cloud computing costs. In addition, Hou *et al.* [92] proposed rendering on edge servers in order to provide a more lightweight wireless VR / AR experience. The paper lists the advantages and disadvantages of rendering on cloud servers, remote edge servers, and local edge servers: The advantage of cloud server rendering is that it allows users to experience VR / AR when moving or anywhere, but the bandwidth cost is high, and it is easy to cause network delay due to congestion; Remote edge server rendering can also achieve mobility, but its mobility depends on the movement of the mobile device, and there is a delay; Local edge server rendering does not provide mobility or provides very limited mobility but no latency. We can choose the server for rendering according to our needs. Finally, we found that edge computing reduced the response time of VR / AR, shared the computing power of VR / AR terminals and made VR / AR more widely used in agriculture.

IV. CHALLENGES

A. DATA PROCESSING

A large amount of data is generated in the agricultural IoT, so edge computing meets challenges related to data processing. In terms of data generation, edge nodes need to have storage plans, which determine whether the data is structured, semi-structured, or unstructured. So the IT team should know how much data and what type of data the edge node will have on the farm in the short or long term. In terms of data storage time, in some cases, the collected data is retained for a long time. However, in some cases, only a part of the data need to be retained or stored for a short period of time. For example, in the image recognition of pests and diseases under edge computing, when edge nodes execute part of the program, the original data can be discarded and only the feature data can be saved. In terms of data transfer, not all collected data must be moved to another platform. In some cases, only a portion of the data needs to be moved, or only data that has been aggregated, cleaned, or transformed in some other way, and may not even need to be moved. Much depends on the processing and analysis after data collection.

B. TASK ASSIGNMENT

In the paper, the Agricultural IoT is mainly end-edge-cloud collaboration that is the terminal, edge nodes and cloud center work together. So assignment of task is directly related to the execution and efficiency of the tasks. Partitioning in the edge environment needs to decompose the application into multiple components according to various state information, such as resources, energy consumption and response delay of the edge node. While the semantics of the original application is preserved, the program components are placed on different edge nodes. The Neurosurgeon proposed by Kang *et al.* [38] refers to the use of Fine-grained Computation Partitioning to partition the DNN model, which is executed at the edge or the cloud. How to design and implement the application partitioning technology in the Edge computing environment enables the proper distribution of application components among multiple heterogeneous edge nodes. Thus, the high performance and reliability of the application is obtained in the Edge computing environment. Some scholars are solving the problem of task allocation. For example, Using Lyapunov optimization theory to design a resource allocation algorithm based on a single slot. The problem of task offloading and resource allocation are transformed into three sub-problems of user local computing resource allocation, power and loan resource allocation, and edge server resource allocation.

C. PRIVACY PROTECTION AND SECURITY

Computing closed to the data source is an effective way to protect privacy and data security. However, in the environment of Edge computing, privacy protection and security face the following challenges: (1) farmers' awareness of privacy and security is weak. The survey shows that wireless connection uses default passwords, which indicates that many users do not protect their personal privacy. In this case, people can easily use a webcam, temperature and humidity sensors and other equipment to spy on a farm's confidential planting and breeding data. Farmers' awareness for privacy and security should be strengthened, and they are encouraged to change their passwords. (2) higher requirements exist for the physical security of edge equipment. Edge devices do not operate in fixed places, such as cloud computing centers. Most of these devices are open to the outside world in an uncontrolled environment and data on edge devices is more valuable than data on IoT terminals; they are more vulnerable. The access control system is added to the edge. In principle, this access control system should be suitable for multi-entity access control between different trust domains. At the same time, various factors such as geographic location and resource ownership should also be considered. (3) effective tools for data privacy and security are lacking. Although many data security methods are available, they are not fully applicable to Edge computing architectures. The network edge is more vulnerable to hacking in a highly dynamic environment. (4) distributed management is more difficult. Each endpoint has a specific vulnerability and should be protected differently. How to manage vast infrastructure is one of the challenges that we face.

D. SERVICE STABILITY

The farms occupy a vast area, so they are all in the wilderness and the signal is poor. Service stability is especially important. Any kind of reliable system has four characteristics: distinguishability, scalability, isolation and reliability. Distinguishability: the rapid development of the IoT has caused the deployment of multiple services at the network edge. However, these services have different priorities. Key services need to be executed before common services are executed. For example, failure judgment and failure alarm of an unmanned harvester have priority over straight driving. Scalability: when certain equipment is worn out, the first problem to be solved is whether the newly purchased equipment can continue the service execution of the original system. We can design a flexible and extended service management layer to solve this problem. Isolation: in a distributed system, shared resources can be managed by different synchronization mechanisms, such as locks or tokens. In the edge system, this problem is more complicated. In the automatic watering system, if the program does not respond, the user can still water. Issues of isolation can be solved by deploying or uninstall the framework and adding access control. Reliability: when the edge device fails, the Edge computing system can inform the user which component is in trouble. Cao *et al.* discovered that the data transmission accuracy of edge equipment is lower in the case of low power and other unreliable conditions [93]. Thus, saving energy is a way to improve reliability.

V. CONCLUSION AND PROSPECTS

Edge computing, as an emerging network architecture, has realized localized services and improved user experience. Edge computing is extensively employed in the retail, financial, and agricultural fields. In this study, we comprehensively discuss the concepts related to Edge computing and Agricultural IoT. We have transformed the research status of Edge computing applications in the agricultural field into the research status of Edge computing combined with AI, blockchain, and VR/AR. For AI, Edge computing can perform data preprocessing and share the computing of the cloud server and storage models. For blockchain technology, Edge computing solves the problems caused by a lack of computing power and available energy consumption for terminal devices to the blockchain. The data stored in the edge server can ensure the reliability and security of the data by using blockchain technology. For VR/AR, Edge computing primarily reduces the response time. Some programs on the terminal can be offloaded to the edge server, which makes VR/AR devices lighter; thus, the scope of use is expanded. We identified and discussed four open research challenges. This study provides information for future researchers to learn about the application of Edge computing in the agricultural field and advances the research to resolve the unaddressed issues. As the two important supports of the digital transformation of the industry, Edge computing and cloud computing will jointly promote the Agricultural IoT to create greater value in the aspects of network, business, application and intelligence.

Most of the current research on edge computing is applied in fields such as smart cities and smart homes. Few scholars have studied the application of edge computing in agriculture. In the next step, we will focus on the difference between the program running under the edge computing and the cloud center, and study the program specifically applicable to the edge computing architecture to ensure the integrity, robustness and accuracy of the program under the edge computing environment. In the future, edge computing will have a broad market in the agricultural field. According to IDC forecasts, 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. The vast market space of edge computing will bring unlimited imagination and new opportunities to agriculture.

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