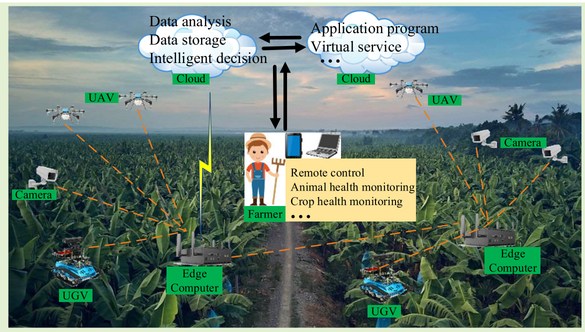
A Review of RGB Image-Based Internet of Things in Smart Agriculture

Xiaomin Li, *Member, IEEE*, Bingfa Hou, Rihong Zhang, and Yongxin Liu, *Member, IEEE*

***Abstract*—Agriculture is an important pillar of world development, and smart agriculture is an emerging paradigm in current practices. RGB Images contain rich information and play an increasingly important role in various scenes of smart agriculture. Image sensing, transmission, and other key aspects rely on agricultural Internet of Things (IoT) infrastructure. However, images contain substantial amounts of data, which poses new challenges to traditional IoT frameworks. In this article, using smart agriculture as the background, the research status of RGB image-based applications in agricultural IoT is reviewed from different perspectives. First, a new RGB image-based IoT framework based on cloud edge computing is proposed. The driving technologies of RGB image information collections, transmissions, and applications are summarized. Then, based on the previous research, an agricultural image IoT application case is presented. Finally, the challenges of RGB image-based agricultural IoT applications are discussed.**



***Index Terms*—Image compression, Internet of Things (IoT), RGB image, smart agriculture, wireless network.**

I. Introduction

AGRICULTURE is a vital pillar of human development and an important component of the global economy. However, with the current global climate deterioration and decreasing arable land and natural farming resources, the populations in underdeveloped regions are rapidly increasing [1], while the major agricultural countries, such as European countries, the United States, China, and Japan, have aging populations (i.e., reduced and aging farming workforce). What is more, under the influence of many factors such as the Russia–Ukraine war and the COVID-19 epidemic, the global food crisis has intensified, which poses new challenges to agricultural production, and it mainly affects food production, transportation, and the entire supply chain [2].

Therefore, an urgent need to improve agricultural systems to be highly resource-efficient systems that are both profitable, environmentally sustainable, and less manpower-dependent [3]. The development of biotechnology and the rapid integration of information technology and agriculture have given rise to the fields of smart agriculture. Among them, smart agriculture has become the most important new paradigm of modern agriculture. Smart agriculture relies on modern information technology and advanced equipment conditions, integrates computer technology, the Internet of Things (IoT) technology, automation technology, 3S (GIS, GPS, RS) technology, and so on [4], and integrates accurate sensing, intelligent control, and intelligent management in the production process to achieve higher resource utilization and labor productivity.

Smart agriculture is based on information, with the IoT [5] being the key driving paradigm. Since the proposal of the concept of the IoT, it has undergone rapid development and gradually has been applied in many fields [6], [7], [8]. In the agricultural field, IoT monitoring through integration with traditional agricultural production technologies has been widely used in farm planting, livestock farms, aquaculture farms, orchards, or other agricultural practices [9]. Traditional agricultural IoT systems realize real-time collection and visual analysis of air temperature and humidity, soil moisture,

Manuscript received 10 April 2023; revised 9 July 2023; accepted 20 August 2023. Date of publication 1 September 2023; date of current version 16 October 2023. This work was supported in part by the Featured Innovation Projects of Guangdong Province of China under Grant 2021KTSCX049 and in part by the Natural Science Foundation of Guangdong Province of China under Grant 2019A1515011346. The associate editor coordinating the review of this article and approving it for publication was Prof. Nitaigour Premchand Mahalik. *(Xiaomin Li and Bingfa Hou are co-first authors.) (Corresponding author: Rihong Zhang.)*

Xiaomin Li, Bingfa Hou, and Rihong Zhang are with the School of Mechanical and Electrical Engineering, Zhongkai University of Agriculture and Engineering, Guangzhou 510225, China (e-mail: xiaocao0624@163.com; houbingfa53@163.com; zhangrihong@zhku.edu.cn).

Yongxin Liu is with the Department of Mathematics, Embry-Riddle Aeronautical University, Daytona Beach, FL 32117, USA (e-mail: LIUY11@erau.edu).

Digital Object Identifier 10.1109/JSEN.2023.3309774

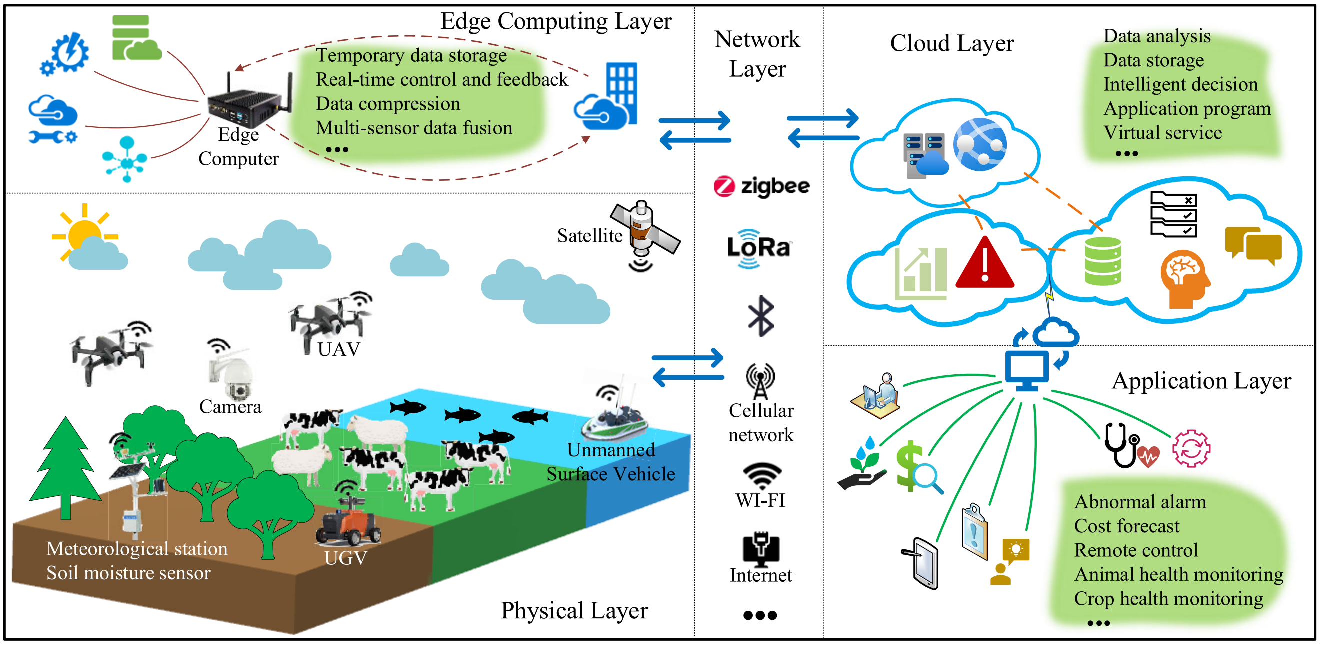


Fig. 1. New agricultural image IoT framework based on cloud edge intelligence.

light, related gas content, and other data through various sensors, thereby realizing agricultural applications such as precision irrigation [10], [11], soil nutrient management [12], pH measurement [13], [14], [15], and greenhouse temperature control [16], [17].

Recently, due to the further development of modern agriculture and the rapid rise of deep learning, RGB images and image processing techniques have begun to be heavily integrated into agricultural IoT, such as farmland environment analysis [18], target recognition [19], [20], [21], [22], pest control [23], crop growth analysis [24], [25], crop disease control [26], fruit detection [27], [28], [29], and livestock health analysis [30]. The introduction of image data into agricultural IoT applications not only allows the intuitive analysis of the growth status of animals and plants but also provides a more scientific decision-making theoretical basis for agricultural production management.

Image data can be used to extract important information for smart agriculture applications, but the sensing, transmission, and processing of image data must rely on existing IoT frameworks and technologies. Although some effective results have been achieved in agricultural image IoT research [31], [32], [33], [34], image data have the features of a large amount of data, information density, and other factors, and traditional agricultural IoT technologies face many problems in sensing; data validation; the validity, flexibility, and efficiency of data [35]; transmission speed; storage cost; power consumption; and other aspects. To strengthen the role of IoT technologies in agricultural applications, in this article, a summary of the current situation of image research in the agricultural IoT is presented. A new agricultural IoT framework suitable for image processing and transmission is designed, and the driving technologies of image information collection, transmission, application, and so on are analyzed. A case study is presented to illustrate the application of agricultural image IoT based on recent research, and the problems and challenges of agricultural image IoT are discussed.

This article is organized as follows. In Section II, an edge intelligence-based IoT framework for agricultural images is proposed. In Section III, the driving technologies of agricultural IoT are analyzed with the image as the core, and key issues, such as image sensors and image data transmission methods, are discussed. Some common image data compression techniques are introduced in Section IV, while a categorized overview of typical application scenarios of images in agricultural IoT is presented in Section V. In Section VI, an application case of agricultural image IoT based on edge intelligence is introduced based on previous work. The main challenges are analyzed in Section VII from different perspectives. Finally, this article is summarized in Section VIII.

II. Agricultural Image IoT Framework Based on Cloud Edge Intelligence

In this work, a new agricultural image IoT framework based on edge intelligence is proposed, which combines traditional agricultural IoT technologies, artificial intelligence, cloud computing, edge computing, unmanned aerial vehicle (UAV), unmanned ground vehicle (UGV), and other components. The framework structure is shown in Fig. 1 and includes the physical, edge computing, network, cloud, and application layers.

A. Physical Layer

The physical layer is a key component of information collection and the foundation of the entire agricultural IoT system. It uses sensor technology to obtain real-time agricultural environmental information and image data on crop growth or livestock conditions through various environmental monitoring sensors and camera systems. In particular, the camera system is the most important part for getting RGB images. In addition, mobile devices, such as UGVs and UAVs, are adopted as sensor platforms to solve the problem of the limited range of fixed sensors, making the IoT more flexible, mobility, and scalability [36].

B. Edge Computing Layer

Relevant studies have confirmed that edge computing is an effective auxiliary means to the traditional IoT [37]. Edge computing devices are often deployed near sensors and can process and analyze data directly in the field. This proximity processing capability allows edge computing to quickly respond to and process large amounts of data, enabling real-time control of agricultural equipment. At the same time, edge computing can also be used to temporarily store data, avoid transferring large amounts of data to the cloud server center, reduce network transmission pressure and cloud server data load, and improve the efficiency of the entire system. In addition, multisensor data fusion at the edge computing layer enables more accurate agricultural support decisions. By integrating and analyzing data from multiple sensors, more comprehensive and accurate agricultural information can be obtained, which can be used for agricultural decision-making.

C. Network Layer

The network layer mainly includes the Internet, mobile communication networks, and wired/wireless LANs. Its role is to effectively connect each layer to achieve the transmission of data, results, and other information. Specifically, the network layer provides the carrier for agricultural image data communication, allowing the images and other data to be transmitted efficiently, reliably, and safely. This enables the fusion and interaction among the different layers and the devices [38].

D. Cloud Layer

The cloud directly connects to the edge computing layer and application layer by network system and provides different offline services such as image data storage, processing, mining, building deep-learning model, and predictions. This enables centralized management, analysis, and operations for different applications.

E. Application Layer

The application layer is supported by the cloud providing functionality based on cloud data processing and computation of image and other agricultural data. Such functionality includes auxiliary decision-making expert systems, animal and plant health monitoring, disaster early warning, remote management, intelligent control, and cost and income forecasting.

III. Agricultural Image-Centric IoT Technologies

In this Section, the driving technologies of agricultural IoT are analyzed with the image as the core, and key issues such as image sensors, image signal processor and image data transmission methods are discussed, so as to improve readers' understanding and application of image technology in agricultural IoT.

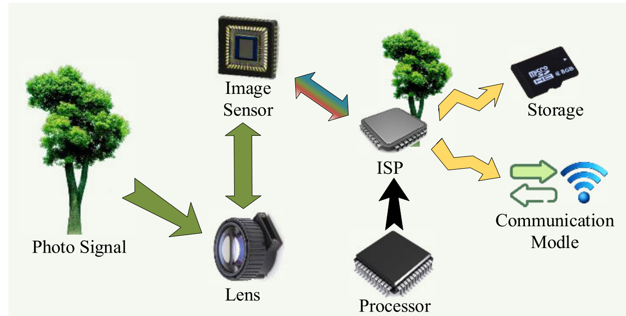


Fig. 2. Image-sensing node framework.

TABLE I
COMPARISON BETWEEN CMOS AND CCD [45]

	CMOS	CCD
Noise	High	Low
Dark current (pA/m2)	10-100	10
Image quality	Moderate	High
Power consumption	1W≤	1-10W
Cost	\$1-\$20	\$2-\$40

A. Image-Sensing Node Framework

Image-sensing node consists of an image sensor, ISPs, control processors, communication modules, power, and storage, as shown in Fig. 2. The image sensor captures optical signals and processes them into digital signals [39]. Users can define parameters such as exposure time and white balance through the control processer to the ISP. The ISP processes the raw image data from the image sensor to produce a natural color image that matches the perceived quality of human eyes. After a corresponding control processor command, the image is stored in memory or transmitted to edge computers through the communication module. Image-sensing nodes can be classified into static and mobile nodes based on their application scenario and deployment mode. Typically, static nodes are used in farms or breeding environments with low cost and no requirement for configuration flexibility. Mobile nodes are usually combined with unmanned vehicle technologies such as UAV and UGV, which have high mobility and can acquire images of specified targets.

With the development of computer vision technology, IoT systems based on machine vision-based perception have emerged. However, the mainstream machine common algorithms [40] have extremely high-performance requirements and the vulgaris image-sensing nodes can no longer meet the use requirements. To solve this problem, many researchers use high-performance processors as the core of image-sensing nodes [41], [42], [43]. However, the improvement of processor performance is usually accompanied by increased power consumption requirements [34].

B. Image Sensor Types

As shown in Table I, there are two types of image sensors currently used in agriculture for capturing RGB images: one is complementary metal–oxide–semiconductor (CMOS) image

TABLE II
COMPARISON OF SOME CMOS IMAGE SENSORS

CMOS image sensor	Manufacturer	Optical Format	Pixel Size	Active Pixels	Power Consumption
SC450AI[51]	Smartsens	1/1.8"	2.9μm	2704 × 1536	N/A
SC301IoT[52]	Smartsens	1/2.8"	2.5μm	2052 × 1540	N/A
AR0134CS[53]	ON Semiconductor	1/3"	3.75μm	1280 × 960	<400mW
AR0130CS[54]	ON Semiconductor	1/3"	3.75μm	1280 × 960	<270mW
IMX335LQN[55]	SONY	1/2.8"	2.0μm	2704 × 2104	N/A
IMX415-AAQR[56]	SONY	1/2.8"	1.45μm	3864 × 2228	N/A
OS02H10[57]	Omnivision	1/2.8"	2.9μm	1920 × 1080	<110mW
OV9756[58]	Omnivision	1/3"	3.75μm	1280 × 960	<166mW
OV12895[59]	Omnivision	1/2.3"	1.55μm	3840 × 2160	<300mW
YACF5D0C9SHC[60]	SK Hynix	1/5"	1.12μm	2592 × 1944	<136mW
Hi-0521[61]	SK Hynix	1/2.8"	2.0μm	2592 × 1944	N/A
PV3109K[62]	Pixelplus	1/4"	2.8μm	1288 × 728	N/A
V4209K[63]	Pixelplus	1/2.9"	2.8μm	1924 × 1084	N/A

TABLE III
COMPARISON OF SOME REPRESENTATIVE INTEGRATED CIRCUITS

Processor	Manufacturer	Top Performance	Max Input clock	Power Consumption
TMS320DM816x[64]	TI	1080p@60fps	165MHz	N/A
TMS320DM6446[65]	TI	720p@30fps	54MHz	N/A
GK7205[66]	GOKE	4M@18fps	81MHz	900mW
GK7102C[67]	GOKE	1080p@15fps	81MHz	550mW
GK7202[68]	GOKE	1080P@30fps	81MHz	N/A
XS5030[69]	CHIPUP	8M@30fps	N/A	N/A
XS5032[70]	CHIPUP	8M@15fps	N/A	N/A
XS5013[71]	CHIPUP	1080P@60fps	148.5MHz	N/A
AP0100CS[72]	ON Semiconductor	720p@60fps	30MHz	185mW
AP0101CS[73]	ON Semiconductor	960p@45fps	30MHz	130mW
XC6130[74]	X-chip	1080P@30fps	27MHz	100mW
XC7022[75]	X-chip	1080P@30fps	27MHz	N/A
FH8556[76]	Fullhan	8M@15fps	N/A	1000mW

sensors and charge-coupled device (CCD) image sensors [44]. Image sensors are the most important part of image-sensing nodes, but they can consume a significant amount of power when working for extended periods. Therefore, selecting appropriate image sensors for image IoT systems is an important task.

Compared with CMOS sensors, CCD has the advantages of good image quality and high light sensitivity [46]. However, CMOS is more commonly used due to its lower manufacturing cost, leading to more research and optimization on sensors using this technology [47], [48]. Consequently, the imaging quality gap between CMOS and CCD is narrowing rapidly. Moreover, because of their advantages of low power consumption and small size [46], CMOS-based sensors are more suitable for agricultural IoT applications. Also, the models and performance of some CMOS image sensors are shown in Table II.

C. Image Signal Processors

In the process of camera imaging, ISP is responsible for processing the raw signal data from the image sensor [49]. Its main functions include linear correction, noise reduction, bad pixel removal, white balance, and automatic exposure control [50], restoring the details of the light field under different lighting conditions. In addition, the ISP has many other important functions. The first is the overall operating response speed of the camera, such as startup speed, focusing speed, and shooting interval. The efficient operation of the image processor is necessary to process a large amount of data quickly and accurately, thereby improving the camera's operation response speed. The second is the camera's battery life. Optimizing the workflow of the image processor can reduce power consumption and extend battery life.

To a large extent, the performance of the ISP determines the image quality and processing speed of a camera. Table III

TABLE IV
COMPARISON OF IMAGE FORMAT

Name	Lossy / Lossless	Color Depth(bits)	Refs.
RAW	lossless	12, 14 (Single Channel)	[78]
GIF	lossless	8	[79]
BMP	lossless	1, 4, 8, 16, 24, 32	[79]
JPEG	lossy	8 (grayscale), 12, 24	[80]
JPEG 2000	both	8 or 16(grayscale), color up to 48	[81]
PNG	lossless	16, 24, 32	[82]
TIFF	lossless	1, 2, 4, 8, 16, 24, 32	[81]

shows some representative ISPs and compares their computing power and power consumption.

D. Digital Image Formats

Digital image format refers to the format of digital image storage files. Digital images can be stored in different file formats, each with its own compression methods, storage capacities, color performance, image quality, and file size [77].

Each image format has its unique characteristics, some offer better image quality and contain more information but take up more storage space, and some have a higher compression rate and take up less space but sacrifice image quality. Choosing which format to use depends on the specific characteristics of the format in question. Table IV provides a comparison of some image formats' respective parameters.

E. Image Data Transmission Methods

Common IoT image data transmission networks can be categorized into wired and wireless transmission networks. In wired networks, data transmission technologies mainly utilize physical media such as network cables and different buses to transmit information. In wireless networks, transmission technologies mainly include Wi-Fi, Zigbee, Bluetooth, cellular networks, and LoRa [83], [84], [85]. Table V shows the major wireless transmission modes and the performance, with the costs based on hardware prices obtained from major manufacturers.

After comparing several common data transmission methods, it can be observed that wired transmission methods have advantages such as higher stability, strong robustness to interference, and high transmission rates. However, they also have higher requirements for terrain layout, climate conditions, power supply, construction and maintenance costs, as well as poor expandability. On the other hand, wireless transmission methods offer simple deployment, quick installation, low maintenance cost, and high scalability. Compared with wired methods, wireless transmission methods have lower stability and transmission rates and need to solve problems such as intercluster interference [87]. In addition, 3G/4G/5G have the advantage of wireless communication and high transmission rates, but their operation and maintenance costs are also relatively high.

IV. IMAGE DATA COMPRESSION TECHNOLOGIES

Image compression can reduce the size of image data, thereby decreasing the resource consumption of the IoT system in terms of bandwidth and energy required for image transmission. There are two types of image data compression methods: traditional coding compression and machine-/deep-learning compression methods. Some image compression algorithms are listed in Fig. 3. Depending on the compression rates, they can be further divided into lossless compression and lossy compression. Lossless compression, such as the one supported by the PNG file format, enables complete image restoration without any loss of information and can generally achieve compression ratios in the range of 2:1–5:1 [88]. In agricultural applications, lossy compression is the primary method used, which improves the compression ratio by eliminating redundant information without significantly affecting the subjective content of the image [80], [89].

A. Traditional Image Compression Methods

The most commonly used lossy compression algorithms include JPEG [80], which uses discrete cosine transform (DCT) for image quantization and entropy coding. Due to the quantization and block processing of the DCT coefficients, blocky artifacts are often encountered in highly compressed JPEG images because of the lack of global multiscale consideration. To address these problems, researchers have introduced a new orthogonal transform in the form of the JPEG2000 [89] compression protocol. JPEG2000 expresses images using the wavelet transform, which converts the 2-D image into a 1-D vector that is then multiplied by a matrix of linear transformation coefficients and a vector of image expression coefficients (e.g., DCT or wavelet coefficients). JPEG2000 uses 15% less space than the original JPEG algorithm. In 2010, Google released WebP, a superior image compression format that supports both lossy and lossless compression. In 2014, Bellard [90], a French programmer, created Better Portable Graphics (BPG), which uses techniques from image coding formats to achieve better compression ratios. Unlike JPEG, which sacrifices image quality for compression, BPG is based on high-efficiency video coding intracoding technology, which further eliminates spatial clutter using pixel spatial correlation.

However, traditional image compression algorithms have some inherent defects. For example, they use inaccurate approximations in the coding process, which can lead to compression artifacts such as blur, block effects, and ringing effects [91]. In addition, traditional image compression methods tend to minimize the differences between pixels in the original image, without considering downstream perception tasks such as object detection. Therefore, these methods may be not suitable for image-based agricultural IoT applications, and there is a need for research on more practical image compression methods.

B. Image Compression Based on Machine Learning and Deep Learning

The use of machine learning presents various alternative techniques for image compression, including determining quantization coefficients, removing compression artifacts, and compressing color images. Paek and Ko [92] developed an image compression scheme using K-means, while

TABLE V
COMPARISON OF DIFFERENT WIRELESS COMMUNICATION MODES [83], [84], [85], [86]

Transmission Methods	Theoretical Data Rate	Frequency Band	Effective Range	Cost
Wi-Fi	11–54 Mbps	2.4/5 GHz	15-150 m	≤$ 10
Bluetooth LE	125 Kbps – 1 Mbps	2.4 GHz	5-100 m	≈$ 1
Bluetooth	1-3 Mbps	2.4 GHz	3-30 m	$ 2-5
Zigbee	20-250 Kbps	433/868/915/2400 MHz	30-100 m	≤$ 20
LoRa	50 bps - 300 Kbps	433/868/915 MHz	2-5 km (urban), 15 km (rural)	≤$ 5
Sigfox	100 bps	868/915 MHz	30-50 km (rural) 3-10 km (urban)	≤$2
NB-IoT	250 Kbps	800/900 MHz	10 km≤	≤$ 10
3G	10 Mbps	900 / 1900 / 2100 MHz	2-5 km	N/A
4G	100 Mbps	700 / 800 / 1800 /2100 MHz	1-3 km	N/A
5G	10Gbps	Sub-6GHz	100-300 m	N/A

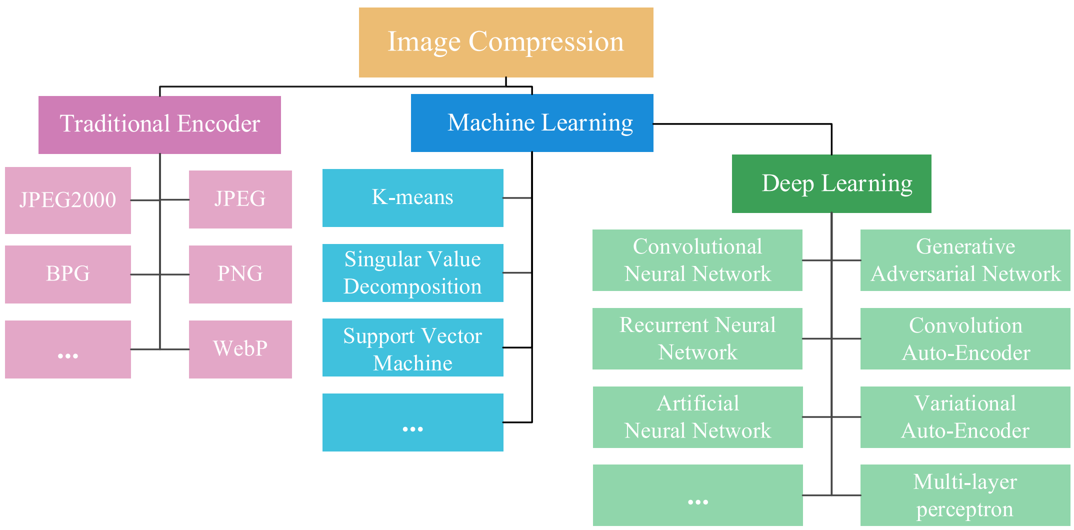


Fig. 3. Commonly used image compression technologies.

Rufai et al. [93] combined singular value decomposition and wavelet difference reduction to achieve a high compression ratio while maintaining good image quality. Support vector machine (SVM) is one of the most representative algorithms in machine learning. In [94], a new image compression algorithm combining SVM and DCT was proposed, which achieved better image quality than JPEG when the compression ratio was greater than 20:1. Li et al. [95] proposed a compression algorithm based on SVM and the second-generation curvelet transform to reduce the block effect.

Deep learning, as a new field of machine-learning research, is considered to have unique advantages for image compression, such as image feature extraction, expression ability, and high-dimensional data processing ability [96]. From the perspective of historical development, the application of deep learning to image compression can be roughly divided into three stages, as shown in Fig. 4, with the initial approaches emerging in the 1980s. Multilayer perceptron (MLP) and simple neural networks were the basis of such compression algorithms from the 1990s to the 2000s. In recent years, significant progress has been made in the research of image compression based on deep learning. From the perspective of algorithm classification, the field includes MLP, CNN [97], RNN [98], convolution autoencoder (CAE) [99], variational autoencoder (VAE) [100], generative adversarial network (GAN) [101], and others. These algorithms are gradually approaching or even exceeding the traditional codecs in compression performance.

MLP can approximate any continuous function with a small enough error [102], which provides a basis for high-dimensional data reduction and compression. The main structure of the MLP consists of densely connected hidden layers, an input layer, and an output layer. Chua and Lin [103] proposed an image compression method based on MLP using the compact expression ability of MLP signals and their conduciveness to high-density parallel computing. Sonehara [104] used an MLP in the structure of an autoencoder, encapsulating transformation, quantization, and entropy coding into independent modules, and realized image compression with bottleneck layers whose dimensions were much smaller than those of the input and output layers. In the field of image compression, random neural networks are often combined with image compression frameworks based on MLP. For example, Gelenbe [108] proposed a feedforward neural network with a codec structure, which combined random neural networks.

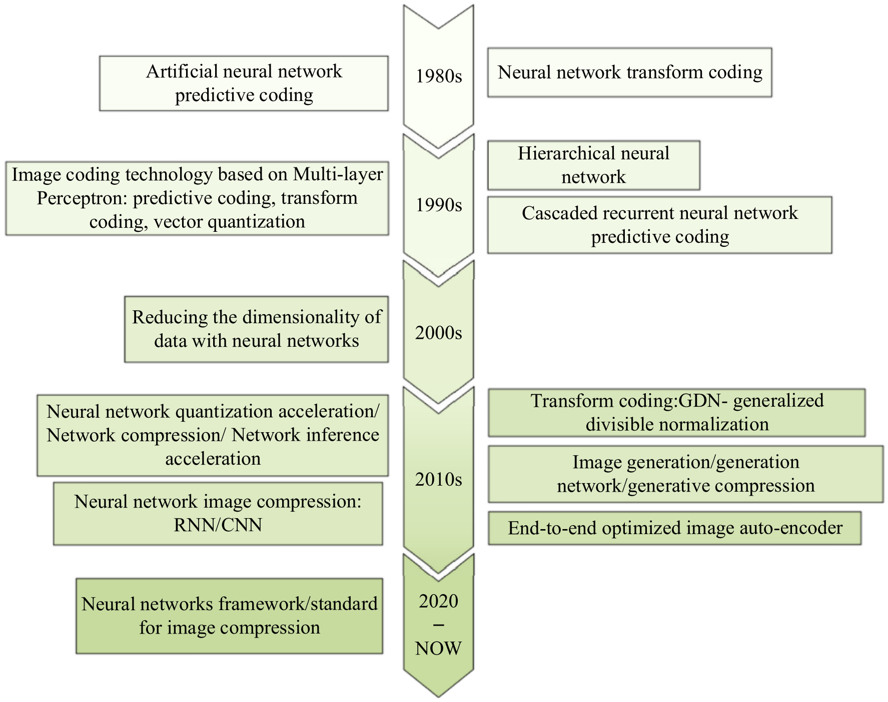


Fig. 4. Development of deep-learning image compression technology [103], [105], [106], [107].

Based on this achievement, Cramer et al. [109] used block processing for parallel training in adaptive random neural networks with different compression ratios, to achieve image compression at multiple-bit rates.

In recent years, CNNs have demonstrated their advantages in many fields, including image segmentation [110], [111], [112] and feature detection [113], [114]. Compared with MLP, CNN not only avoids overfitting to a certain extent but also requires fewer parameters through parameter sharing. Yu et al. [115] used a CNN to accelerate hierarchical decomposition and effectively reduce compression traces. Wang et al. [116] designed an efficient reconstruction framework by taking advantage of the powerful learning ability of CNN. However, in end-to-end coding, loss functions that use the gradient descent method require the objective function to be differentiable. The quantization module used in image compression is nondifferentiable, which makes training CNN-based image compression frameworks difficult. To solve this problem, Ballé et al. [117] used uniform noise to approximate the error in estimating quantization so that the entire image compression framework would be differentiable. This was the first work that combined end-to-end image compression and CNN, and the compression performance of this method was comparable to that of JPEG2000. In 2017, Theis et al. [118] designed an autoencoder based on the traditional CNN structure and improved the quantization and entropy rate estimation modules. This model was a pioneering attempt at image compression methods that utilized autoencoders. In 2018, Ballé et al. [119] added the scale hyperpriors to the original framework and modeled the probability distribution of the code more accurately.

Different from CNN, RNNs have a memory ability. In 2016, Toderici et al. [98] used an RNN-variant based on a gated recurrent unit and a residual network, achieving compression performance comparable to that of JPEG. In 2017, the same team [120] proposed an iterative image compression method based on RNN, which led to compression performance at the same level as WebP. On this basis, Minnen et al. [121] added spatial prediction before the RNN, and the compression performance reached that of JPEG2000. In addition, some algorithms combining deep-learning methods with traditional image codecs have been proposed. For example, Jiang et al. [122] proposed a new image compression framework that combines CNN and JPEG codecs. This framework outperforms traditional codecs such as JEPG2000 in compression performance.

With the increasing efficiency of GPUs, GANs have become a popular deep-learning model [123]. In the field of image compression, GANs have been used to improve the subjective quality of generated images. The seminal work was done by Rippel and Bourdev [124], who pioneered GAN-based image compression methods in 2017. This framework introduced the adversarial loss function into the rate–distortion function for end-to-end training. At low bit rates, the subjective evaluation of the reconstructed images greatly exceeded that of traditional compression methods such as JPEG2000, JPEG, and WebP. The main reason is that adversarial learning allows the texture details of the reconstructed images to be more realistic and reduces the blur phenomenon significantly. Over the past three years, innovative GAN-based methods, such as image compression at extreme bit rates [101] and image compression with semantic information [125], have emerged.

In addition to the above image compression methods, image compression methods based on a region of interest have been adopted in some special fields [126], [127], which have particular significance for agricultural image compression.

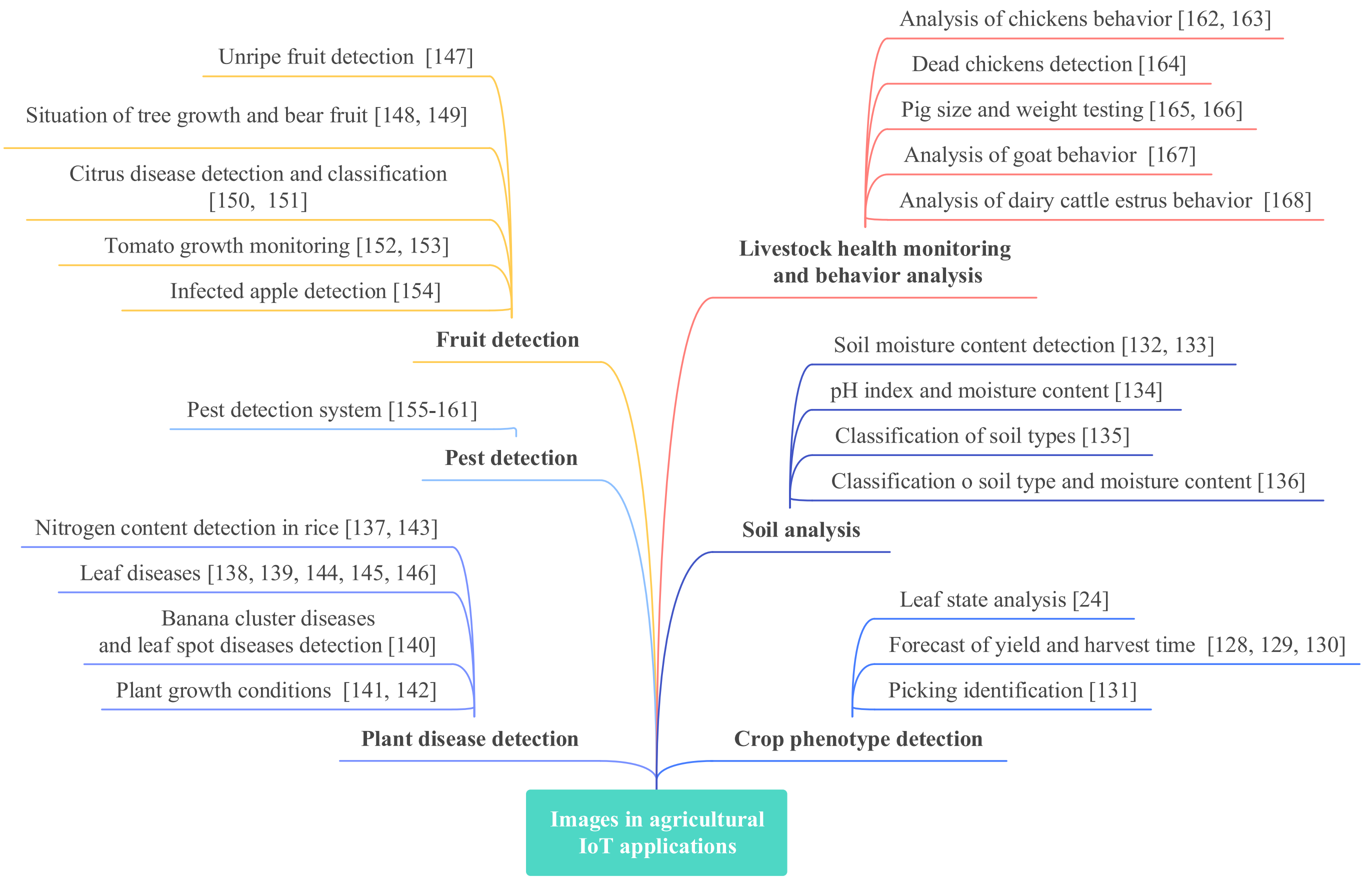


Fig. 5. Typical application of images in agricultural IoT.

In practical applications, low compression ratios can be used for the interesting part of an image to obtain a better image effect, while high compression ratios can be used for the other parts to conserve storage space, to ensure that the important information is not lost, and the data are compressed effectively.

Image compression based on deep learning comprises many different algorithms, each which its characteristics: CNNs are better than traditional image compression transformation in feature extraction and are often used for image feature extraction, while RNNs and GANs are used for image compression. As part of the RNN model family, long short-term memories can process and merge spatial information well and leverage convolution operations, making them more suitable for image compression. GANs perform well when the limits of image compression are reached, improving the quality of reconstructed images and the real-time compression of image data. The improvement of computer vision capabilities and the availability of large training datasets have caused great interest in the application of deep-learning neural networks in image recognition and processing, which is worthy of further exploration.

V. Typical Applications of Agricultural Images IoT

Agricultural IoT and image processing technology as a new technology has a wide range of application prospects and constantly promotes the development of agriculture. It can use cameras and other equipment to collect image data, to provide more information for agriculture. This section will introduce typical applications of images in the agricultural IoT, as shown in Fig. 5, including soil analysis, plant disease detection, and pest detection.

A. Crop Phenotype Detection

Crop phenotyping is a fundamental task in the field of agriculture, involving the use of image processing and machine-learning techniques to identify and describe the characteristics and manifestations of different crops. By accurately identifying and describing crop phenotypes, agricultural researchers can gain a better understanding of crop growth status and yield potential, enabling them to take appropriate measures to improve agricultural production.

Lu et al. [128] proposed a mushroom detection system that utilizes YOLOv3, a popular object detection algorithm, to recognize mushrooms and calculate their size and growth rate. This system allows for estimating the harvest date of mushrooms. Wang et al. [129] improved the YOLOv5 network and developed an iMushroom detection framework that integrates monitoring systems and cloud services. This framework enables yield prediction and quality control of mushrooms. Dias et al. [130] introduced an automatic flower identification algorithm based on DeepLab, an advanced semantic segmentation model. The algorithm focuses on extracting flowers from fruit trees and estimating their quantity, which enables the estimation of fruit yield and weight. Kumar et al. [24] proposed a crop growth monitoring system that utilizes machine vision and machine-learning techniques to identify leaves and analyze their area and age. This system provides valuable information for farmers, offering recommendations for irrigation or fertilization based on the analyzed results. Li et al. [131] designed a bell pepper detection method based on YOLOv4, incorporating attention mechanisms and multiscale prediction. This method enhances the accuracy of identifying bell peppers, supporting the functionality of picking robots in agricultural settings.

B. Soil Analysis

Soil image analysis is one of the applications of the agricultural IoT, providing important information on soil health, optimizing agricultural production, and suggesting planting recommendations. Traditional methods, such as hand excavation and weight comparison, are prone to errors. Image processing technology offers a more reliable alternative.

Several studies have proposed using image analysis to measure soil moisture content. For instance, Jagüey et al. [132] used an embedded camera to take images of soil and distinguished light and dark pixels through gray-level analysis to determine whether the soil was wet or not. Kabilan and Selvi [133] used transduction SVM to analyze the RGB images of soil and determine soil water content to optimize the irrigation system. Bolla et al. [134] used MATLAB for enhancing image contrast, adjusting image size, and transforming color space to determine R, G, and B values, which were then used to calculate soil pH index and water content with these values. Other scholars combined HSV, GLCM, and Gabor Wavelet to analyze soil image and distinguish types of soil [135]. Recently, Kalra et al. [136] developed a web application using color-based image processing to automatically analyze soil images and distinguish between soil type and water content.

C. Plant Disease Detections

Plant disease detection is a key application of images in the agricultural IoT, which can detect diseases that may affect plants in advance and enable effective preventive measures to be taken. Traditional methods of plant disease detection, such as leaf examination and pathogen diagnosis, require professional technicians and consume a lot of time and energy. Therefore, many researchers have proposed the use of image processing technology for plant disease detection.

Some researchers used machine learning to detect plant diseases. In 2017, Thorat et al. [137] captured leaf images using a camera connected to a Raspberry PI, ran SVM on the device to classify common plant diseases, and sent the real-time status of leaf diseases to farmers. In 2019, Devi et al. [138] introduced a disease detection system for bananas that used a camera sensor connected to a Raspberry PI to periodically capture plant images and classify banana sigatoka diseases based on GLCM characteristics using random forest classification technology. In 2021, Mishra et al. [139] proposed an image-based plant disease detection system and developed a sine cosine algorithm-based rider neural network for disease detection.

Other scholars have added color space techniques to image processing. In 2017, Rau et al. [140] obtained rice leaf color using LAB color space technology and established a rice color database for comparison to analyze whether the nitrogen content of plants is normal. In 2018, Tran et al. [141] proposed an image transmission scheme based on sensor nodes and wireless networks. Plant images are collected and transmitted to the cloud, and image processing technology is used to convert the images into binary graphs to analyze the growth state of plants. In 2019, Pavel et al. [142] sent leaf images to a database built by Raspberry PI, transformed RGB images into LAB color space using K-means clustering, and finally used image processing and multiclass SVM to classify diseases. In 2020, Sundari et al. [143] used a Raspberry PI camera to capture leaf images and transmit them to the cloud, where they processed the images with smoothing filters and set thresholds to filter green. The remaining pixels show the infected area of bacterial or fungal infection.

Some scholars have combined detection technology with drone technology to detect plant diseases. In 2018, Kitpo and Inoue [144] proposed an IoT-based UAV system. Field images captured by the UAV are sent to the server, where SVM is used to detect and classify rice disease characteristics, and the UAV's GPS sensor is used to locate infected rice in the field. Xenakis et al. [145] combined the IoT with robots and proposed a plant disease diagnosis support system. They integrate CNN into the robot system for plant disease diagnosis. To solve the problem of low precision and poor robustness of commonly used deep-learning models in the actual application environment, Zhao et al. [146] developed a multicontext fusion network deep-learning system that can extract highly discriminative and robust visual features from crop images and output the crop disease prediction.

D. Fruit Detections

Traditional detection of fruit methods relies on manual experience and operation, which can often be inefficient. Agricultural IoT offers a more accurate, automated, real-time, and data-driven approach to fruit detection, enabling quality detection, yield prediction, automatic picking, and other applications that help farmers improve production efficiency and yield, reduce costs, and increase agricultural and social benefits. Several researchers have conducted studies on fruit detection.

In 2015, Rupanagudi et al. [147] developed a fully automated fruit detection method using wireless webcams and cloud computing to identify immature stage fruit and used Java to develop video processing applications. Behera et al. [148] and Anugraheni et al. [149] proposed methods to monitor fruit tree growth and fruit condition using IoT devices and image processing. Behera collected data through cameras and IoT nodes, transmitted it to Raspberry Pi, and identified fruit using color and morphology processing. Anugraheni distinguished mature and immature cherry tomatoes using color segmentation and counted them using the watershed algorithm. Song et al. [150] and Kumar et al. [151] focused on citrus disease detection and classification. Song used the YOLO to automatically detect citrus canker, while Kumar proposed a deep-learning model called DLVGG19-FSVM. The model captured citrus fruit images from farmland through IoT devices and accurately separated diseased areas and healthy areas using image preprocessing technology, feature extraction technology, and classification technology. Kitpo et al. [152] and Lee et al. [153] focused on tomato growth monitoring. The former used Faster RCNN and K-means to identify tomatoes and extract areas of interest and then used SVM to classify tomato growth after color extraction. The latter used multiple IoT cameras mounted on trusses inside the greenhouse to monitor the growth of tomato flowers and fruit through deep-learning-based flowering and unripe fruit detection. In addition, Jiang et al. [154] designed a neural network with three convolutional layers and two fully connected layers to detect infected apples in images.

E. Pest Detections

Pest detection plays an important role in the agricultural IoT, helping farmers find and deal with pest problems in a timely manner, and avoid crop losses caused by infestation. Compared to traditional inspection methods, agricultural IoT offers a more intelligent and efficient solution.

In 2011, Tirelli et al. [155] developed an automated pest detection system that captures images of insect traps and transmits them to a remote host station for image processing and insect counting. However, this method has some problems, such as high power consumption and node signal attenuation, leading to some image transmission errors. In 2017, Rustia and Lin [156] designed a remote greenhouse pest monitoring system based on IoT, using wireless imaging and sensor nodes. Image data from the insect trap are uploaded to the server by the Raspberry Pi for real-time analysis and monitoring. The system successfully solved the problem of image loss caused by excessive transmission distance by automatically switching between Wi-Fi and 4G networks. Brunelli et al. [157] used a similar method to detect apple egg moth. In 2020, Ramalingam et al. [158] proposed a remote insect monitoring method, where the sensing layer sends insect trapping images to the processing layer through the transport layer. They also used the Faster RCNN ResNet object detection framework to automatically identify the insect class. To pinpoint the location of pests, Chen et al. [159] developed an image-based pest identification and location system, which used YOLOv3 to identify lychee stink bug. Stevanoska et al. [160] proposed a pest population detection system that collects image data from multiple cameras placed in the vineyard and uses target recognition technology to determine the number of pests. In addition, some scholars have proposed a pest removal system using the IoT and image processing technology [161]. The system captures image of pests using a camera, processes them to confirm their presence, and generates ultrasonic waves to drive them away from the farmland.

F. Livestock Health Monitoring and Behavior Analysis

Livestock health monitoring and behavior analysis plays a crucial role in the agricultural IoT, as it can predict and prevent disease outbreaks, reduce livestock losses, and prevent the spread of infectious diseases by monitoring livestock behavior, body temperature, diet, and other indicators. Compared with traditional monitoring methods, agricultural IoT technology can provide more accurate and real-time data to help farmers identify and deal with problems in a timely manner.

Machine-learning techniques using poultry big data and camera sensing technology can be used to detect suspected disease symptoms. Carroll et al. [162] and Carpentier et al. [163] used a similar system that uses chicken recognition and abnormal motion detection algorithms to study areas related to chicken health, nutrition, stress levels, behavior, environment, and disease. In order to reduce human–poultry contact, Liu et al. [164] designed and built a new system for removing dead chickens from poultry farms. Cameras are used to remotely monitor the condition of chickens in poultry farms, and the dead chickens are identified and located using YOLOv4.

Pork is one of the world's leading meat sources and is vital to many countries' economies and food supply chains. To ensure stable pork production, some scholars have carried out relevant research. In 2016, Shi et al. [165] proposed a method for estimating pig weight based on binocular vision system. The image acquisition system realizes the automatic identification and image acquisition of the pig and then generates the body contour and reconstructed image of the pig in the image analysis system to calculate the weight of the pig. In 2019, Lee et al. [166] proposed a deep-learning-based computer vision method for automatic monitoring of pig farms. Pigs are detected using TinyYOLOv3, and the size of the pig is calculated using the Gaussian mixture model, binarization with OTSU, and connected component.

In addition, scholars have also studied the behavior of cattle and sheep. Rao et al. [167] proposed a goat monitoring system combining the IoT and machine learning and developed an automatic classification method of goat behavior based on Faster RCNN to automatically identify whether the goat is drinking or eating. Chen [168] analyzed cows' estrus behavior by monitoring their body temperature and activity intensity, combining cameras and image recognition technology to monitor cows' daily behavior, improving the system's accuracy.

VI. Intelligent Agricultural Image IoT Monitoring System: A Case Study

In order to solve the problem of labor shortage in crop farming and improve the level of automation and intelligence, based on the novel agricultural image-based IoT framework with edge intelligence proposed in Section II, our team developed an intelligent agricultural IoT monitoring system. Next, the elements of this system are presented and this case will be introduced from the aspects of system composition, working principle, and system function, as shown in Fig. 6.

We conducted tests of the intelligent agricultural IoT monitoring system in an experimental field located in Baiyun District, Guangzhou City, Guangdong Province (113.44884°E, 23.36374°N). The system comprises: 1) EZVIZ CS-C3W monitoring camera; 2) UAVs and UGVs with Inter RealSense 435i depth camera; 3) TWOWIN T600 edge computer with NVIDIA Jetson AGX Xavier as its core; and 4) remote server fit with Intel Xeon Gold 5218 CPU and NVIDIA TITAN RTX GPU.

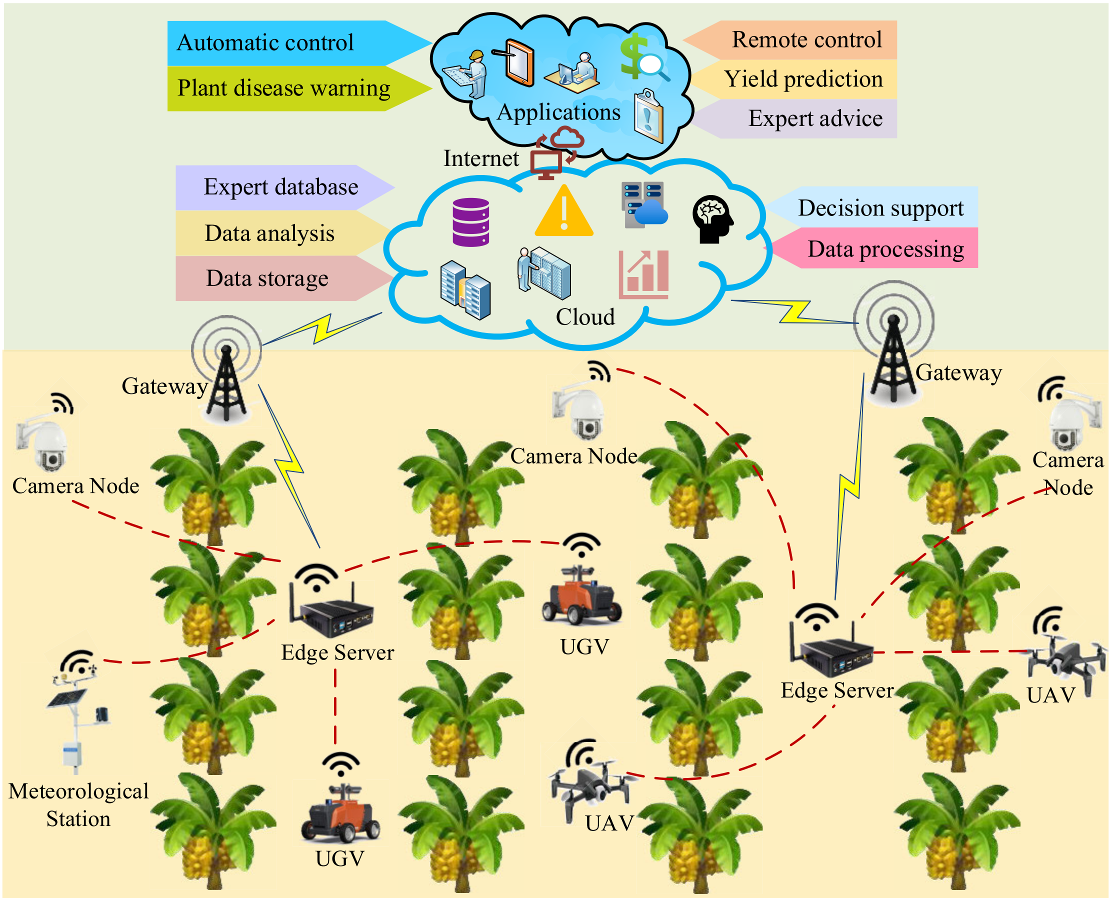


Fig. 6. Case study of the novel agricultural image IoT framework.

The monitoring camera captures images of banana trees at regular intervals using the data acquisition framework [169]. To reduce the cost of image data transmission and storage, the monitoring camera sends images to the edge computer through the USB, bus for extracting the region of interest, only the fruit portion is extracted to compress the image size. We used the YOLOv4 object detection algorithm to extract banana fruit from the images and removed the unnecessary background information, as shown in Fig. 7.

In the case study, the new IoT system significantly reduces the amount of space occupied by image data. After compressing the image data, the edge computer sends it to a remote server for analyzing the fruit, such as identifying maturity and detecting diseases. The results are then conveyed back to UAVs and UGVs, which drive to the infected plant and take images to further identification of the disease.

Furthermore, the image data can be combined with temperature and humidity data obtained from the meteorological station, which is then used for intelligent analysis in the server, management, and planting advice to the user. This agricultural IoT system is flexible and lightweight due to the integration of UAVs and other technologies. Moreover, edge computing technology has been introduced to effectively reduce the network delay caused by the transmission of large amounts of image data, prevent network congestion, and improve system efficiency.

VII. Challenges and Solutions

Although agricultural IoT technology is gradually being adopted at scale, there are still some problems and challenges that need to be addressed, which are discussed in this section.

A. Impact of Agricultural Images on IoT Systems

On the one hand, the introduction of image nodes enhances the diversity and richness of the entire system's data. However, on the other hand, image nodes pose challenges to traditional agricultural IoT systems, which have to spend additional energy, bandwidth, storage space, and so on to complete the image sensing, transmission, storage, and processing for different tasks. With the advancement of technologies and methods such as software-defined networks, image optimization sensing, collaborative sensing, and intelligent charging, optional solutions have been provided for this challenge.

B. Diversity of Agricultural Image Demands

Agricultural production involves many fields and links, which means different tasks, such as crop identification, pest and disease detection, and land use, among others. Different tasks require practical demands for agricultural image diversity. To complete different agricultural management tasks, different algorithms and models are needed to process and analyze image data. The practical demands mentioned above

Fig. 7. Comparison of image before and after processing in edge servers.

further cause diversity in agricultural image demands and corresponding algorithmic model datasets complexity. Therefore, standardizing the sensing, processing, and analysis of images for the same or similar agricultural tasks may be a possible way to solve this problem.

C. Impact of Agricultural Heterogeneous and Changeable Environments on Image Quality

In agricultural production scenarios, image quality and analysis results are easily affected by environmental changes, including background interference, crop density and height, seasonal changes, terrain, lighting, and differences in target objects. Especially under different lighting conditions, images exhibit different brightness, contrast, and color, while factors, such as crop variety and growth stage, can lead to differences in target object size, shape, and color. Algorithms and strategies for image restoration and repair based on specific agricultural environments and needs bring hope for addressing this challenge.

D. Balance of Costs and Benefits

Agricultural image applications provide data support for intelligent management and control of agricultural production, offering possibilities for increasing agricultural value. However, this can also bring about some cost challenges. On the one hand, equipment, such as image nodes and image servers, typically has higher prices than ordinary IoT devices. On the other hand, these devices are more susceptible to factors, including solar radiation, extreme temperatures, and dust in harsh environments such as farmland, which can damage electronic circuits and result in higher maintenance costs. Therefore, balancing the benefits and costs of introducing image into agricultural information systems is another challenge that needs to be considered. Building cheaper, more reliable, and reusable image equipment and algorithms is one possible solution to this challenge.

In addition, agricultural environments, such as orchards and fields, often involve long-distance propagation, leading to problems such as signal attenuation and transmission delays. In order to overcome the challenges of large space, distributed wireless transmission systems can be adopted. Such a system uses multiple wireless access points or repeaters to extend the network range, and by installing multiple access points in the field, the transmission of wireless signals can be extended so that data and information can be transmitted more efficiently to distant places but also increases the cost. Therefore, considering the balance between costs and benefits, choosing the right location for sensors and network equipment is crucial. Also, select the appropriate network structure and topology to improve the transmission efficiency and stability.

VIII. Conclusion

Image-based IoT applications are becoming an important driving force of smart agriculture and a key component of a new agricultural paradigm. This article reviews related research with images as the core and the relevant agricultural IoT infrastructure, proposes a new agricultural image IoT framework based on cloud edge computing, and introduces image-driven agricultural IoT technology. This article discusses core issues related to image-based agricultural IoT applications, such as image sensors, image-sensing nodes and image transmission methods, and sketched image compression methods and technologies. In addition, this article summarized typical image-based agricultural IoT applications in animal husbandry and crop cultivation. Although image-based agricultural IoT applications have made considerable progress, there are still many challenges to be addressed, particularly in terms of equipment durability, image quality, data acquisition, and processing costs.

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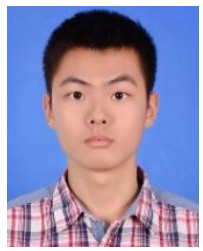
Xiaomin Li (Member, IEEE) received the B.S. degree from Air Force Engineering University, Xi'an, China, in 2004, the M.S. degree from South China Agricultural University, Guangzhou, China, in 2014, and the Ph.D. degree from the South China University of Technology, Guangzhou, in 2018.

He is currently an Associate Professor at the Zhongkai University of Agriculture and Engineering, Guangzhou. Thus far, he has published more than 80 scientific articles. His research interests include cyber-physical systems, smart agriculture, big data, and wireless networks.

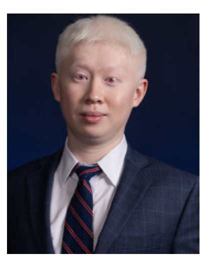


Bingfa Hou was born in Guangdong, China, in 2000. He received the bachelor's degree in mechanical and electronic engineering from the Zhongkai College of Agricultural Engineering, Guangzhou, China, in 2022, where he is currently pursuing the master's degree in agricultural engineering.

His research interests include agricultural Internet of Things technology, machine learning, and image processing.

Rihong Zhang currently serves as an Associate Professor and a Master's Supervisor at the Zhongkai University of Agriculture and Engineering, Guangzhou, China. He has published over 30 academic research articles and obtained 16 utility model patents and ten authorized invention patents. His main research areas include modern electromechanical system design and control, smart agricultural technology and equipment, and planting and harvesting technology and equipment.

Prof. Zhang is a member of the Communist Party of China. He received the Second Prize of the Guangdong Provincial Agricultural Technology Promotion Award in 2015, the Third Prize of the Guangdong Provincial Science and Technology Award in 2017, and the Second Prize of the Guangdong Provincial Agricultural Technology Promotion Award in 2018.



Yongxin (Jack) Liu is currently an Assistant Professor of Data Science at Embry-Riddle Aeronautical University, Daytona Beach, FL, USA. He joined the Security and Optimization for Networked Globe Laboratory (SONG Lab) in 2017. He is the creator of zero-bias deep learning, which is applied in explainable AI and anomaly detection. He is also the creator of the channel separation incremental learning algorithm, which harnesses the catastrophic forgetting issues in deep learning with mathematical assurance and applied in ADS-B signal identification systems. Other than that, his early work in unauthorized drone detection has resulted in two patents and was cited as first reference by the Department of Defense in August 2021. His research focuses on explainable AI for aviation and particularly for signal intelligence.