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Research Article

Image Detection System Based on Smart Sensor Network and Ecological Economy in the Context of Fine Agriculture

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In this paper, an in-depth study and analysis of the ecological economy of fine agriculture are carried out using image detection methods of smart sensor networks. The analog signal output from the wireless sensor network is filtered and thresholder to convert into a digital signal to complete the sensor monitoring data preprocessing for digital information analysis. In this paper, with the objectives of good environmental adaptability, low power consumption, low cost, and standardization, the key technologies of wireless sensor networks for fine agriculture are studied, including network structure, networking method, node positioning method, data fusion method, rapid energy self-sufficiency, and energy-saving strategy, and the performance evaluation method of wireless sensor network system, IoT-oriented middleware design method, generic node software and hardware design method, and typical application system. Firstly, a convolutional layer is used instead of a fully connected layer, which makes the network more flexible in terms of input image requirements and enables the calculation of the target rice region. Not only will many complex operations be generated, but it will also limit the generalization ability of the model. Then, by introducing a flexible connection layer based on unit and optimizing the loss function of the network, a crop convolutional neural network (Crop-Net) is finally proposed for training and testing rice images at different growth stages to improve the detection accuracy. In this paper, a network quality of service goal-driven evaluation strategy and evaluation method for agricultural wireless sensor network systems is designed to provide a reference for the establishment of industry standards for wireless sensor network systems for fine agriculture.

1. Introduction

Fine agriculture is modern agriculture based on information and knowledge support, and its main goal is to obtain the environmental factors of crop growth, which largely determine the yield and quality of crops. These factors usually include temperature and humidity of the crop environment, water content, wind speed, direction, etc. For this information, it is often characterized by spatial and temporal variability [1]. The essence of the neural network learning process is the distribution of learning data. Although China's agricultural production has made certain achievements, crop production is increasing year by year; the total amount of vegetables, fruits, and aquatic products is abundant, and the per capita possession is at the world's forefront. However, this mainly relies on excessive inputs of organic compounds such as pesticides and chemical fertilizers, which aggravate environmental pollution and irrational watering of agricultural groundwater, resulting in wasted water resources; this crude agricultural operation not only causes high input of agricultural resources and low production efficiency but also even leads to the destruction of ecological balance. With the rapid economic development and the great achievements of modern science and technology, the traditional agricultural management methods have not adapted to the needs of today's social development, and the state strongly advocates the use of advanced science and technology to carry out modern agricultural construction and promote the transformation and upgrading of the agricultural industry chain [2].

The core of "fine" agriculture is the development of intensive agriculture under advanced technical support. The characteristics of the crops themselves and their growing environment are very different and difficult to control and are constantly changing. In this changing environment, most of our agriculture is still managed traditionally, relying on many human and material resources to carry out "foolproof and homogenized" agricultural production activities.

Therefore, the times require to actively improve the inefficiency of traditional agriculture, which relies mainly on human resources to observe and implement agriculture, and to develop fine agriculture with a high degree of information technology [3]. Through the development of fine agriculture, it is possible to standardize the monitoring and feedback of agricultural planting activities in the early stage of preparation, the middle stage of implementation, and the results of implementation, to fully track the whole process of planting things, to achieve the breakdown of responsibilities, to effectively prevent natural disasters and pests, and to reduce economic losses. Based on the demand for UAV remote sensing technology for crop classification information acquisition and because of the characteristics of UAV remote sensing images with high resolution and the phenomenon of large differences in image features of the same species caused by the rich geometric texture of features brought about by high spatial resolution, this study uses deep learning technology that has made breakthroughs in image processing and speech recognition and explores a method that can quickly and accurately target [4]. If centralization and standardization are not performed, the distribution of training data for each batch will be different. This study uses the breakthroughs in image processing and speech recognition to explore a fast and accurate crop classification method for UAV remote sensing images, which is important for the rapid acquisition of digital information of small and medium scale farmland and precise agricultural management.

IoT agriculture is to combine wireless communication and sensing technology to realize real-time monitoring of environmental parameters in the agricultural field and to complete the adjustment and processing of the agricultural environment through a remote terminal platform. The promotion of IoT technology in agriculture has solved many problems in traditional agriculture, using advanced equipment and technology, saving a lot of costs, and the development of IoT agriculture is of practical significance to promote economic growth and agricultural modernization. This paper builds an IoT-based agricultural environmental parameter monitoring system based on IoT communication and fully considers the practicality of the system, describes the overall architecture of the system and the design of its subsystems, and realizes the automation and intelligence of the agricultural production environment. The real-time monitoring of agricultural ecological environment parameters completes the scientific and refined management of crops and improves the efficiency of agricultural production.

2. Related Works

It is difficult to realize large-scale agricultural field management due to the difficulty of early line and pipeline deployment. With the flourishing development of sensors, computer networks, wireless communication technology, and remote sensing technology, developed countries led by the United States and the Netherlands, have started to vigorously promote the digital management of agricultural information [5]. The United States, as a largely agricultural country, has an adoption rate of up to 80% for agricultural technology. In addition, the United States has built AGNET, a large agricultural computer network system with remote sensing technology as the core, which provides many information resources for the modern management of agricultural information in the U.S. Gupta et al. developed a wireless sensor network greenhouse monitoring system to monitor the temperature and humidity information of greenhouses [6]. It is a commonly used disease detection method under the traditional method. Nie and Yang designed an automatic irrigation system based on an Arduino microcontroller, which contains a water flow sensor and water pressure sensor, and the water in the pipe can turn on when the set humidity is reached to complete the automatic watering of orchards [7]. The experimental results showed that this method achieved good results in the corn leaf database. Udutalapally et al. proposed a method to distinguish wheat pest leaves based on imaging hyperspectral technology from the perspective of optics, constructed a spectral ratio fingerprint feature based on the relative change of spectra, preferentially selected several image-based geometric and texture features in a targeted manner, and achieved very promising recognition ability for wheat in the experiments [8].

In the field of crop growth period identification, the current crop growth detection based on traditional methods, in addition to observation under manual experience, still mainly relies on spectral features for analysis on the one hand and remote sensing images for detection of a large range of crops on the other hand [9]. Firstly, the detection means relying on spectral analysis is more complicated than direct image capture, less real-time, and prone to the problem that crops in different growth periods present the same spectral characteristics. In addition, although the detection method based on remote sensing images is suitable for the detection of large crops, it is susceptible to the influence of weather, and usually, the image acquisition system is more complicated if remote sensing satellite image data are used, and the detection accuracy has a lot of room for improvement. Giraldo et al. extracted five principal components in the full visible-near infrared spectrum of sugarcane and used a multiple linear regression model to enhance a variety of modeling methods to detect the spectral images of sugarcane leaf reflections to determine the sugarcane growth [10]. Guillén et al. used a color gamut segmentation-based image detection method to detect three types of growth periods of rice using thermal infrared images, but usually, the growth periods of rice can be divided into at least eight periods, and this detection method is not suitable for multiple types of crop growth detection [11].

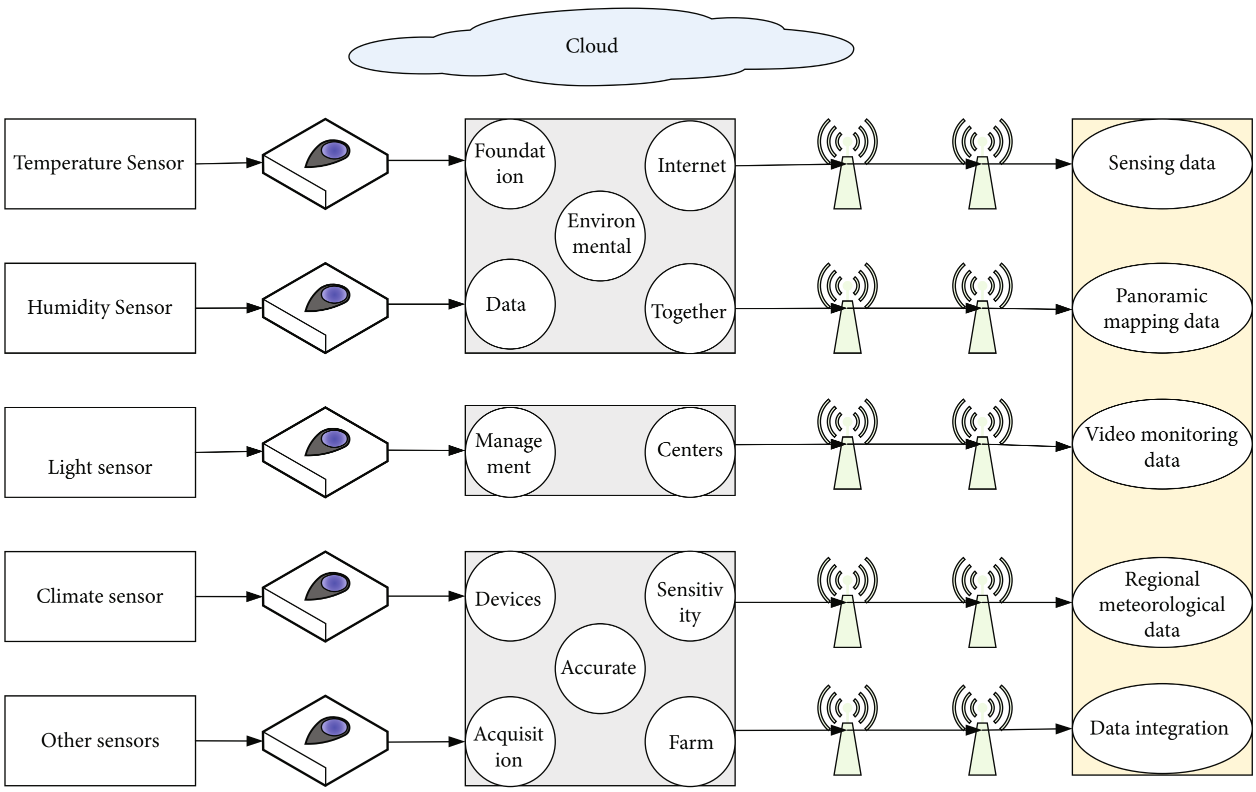

Figure 1: IoT networking architecture.

This kind of traditional method classifies the extracted features through support vector machine, to obtain the final disease identification result. To improve the performance of wireless sensor network, from the concept of data fusion technology, the significance and basic methods of data fusion technology are outlined, and based on the elaborated algorithm basis, a set of data processing algorithms is constructed for this system to improve the system data fusion performance, and the accuracy and implement ability of the algorithm are verified through system simulation experiments. Because of the problems arising in the process of melon cultivation, the construction of a refined management system can achieve accurate real-time monitoring, optimization of the cultivation process, intelligent management, and autonomous decision-making, allowing the overall production and operation process of crops to be visualized, digitalized, and traceable, planting green and nutritious crops, which can effectively improve the production and quality of watermelon, expand the scale of agricultural cultivation, and bring large-scale. The economic benefits of the farmers, more food safety issues can be further implemented, so that people can eat with peace of mind and comfort.

3. Intelligent Sensor Networks for Fine Agroecological and Economic Image Detection Analysis

3.1. Intelligent Sensor Network Design. The core and foundation of the Internet of Things are the Internet, and the emergence of the Internet of Things is an extension of the Internet, but the essence of the Internet of Things is still the Internet [12]. Deployment of collectors, sensors, and other IoT devices in farms can collect and monitor on-site environmental data and equipment data in real-time and bring such data together in farm data storage and management centers, which are then processed and then displayed in mobile devices such as cell phones and tablets in the form of charts. And the mutation of the packet loss rate from 0 to 1 is completed within a short distance. Agricultural information sensing technology is the basis for carrying out refined agriculture, equivalent to nerve endings; the sensitivity of nerve endings is very important for accurate data acquisition and requires the use of sensor devices with high accuracy.

In the farm environment, IoT networking technology collects and transmits all aspects of information such as field sensing data, panoramic mapping data, video monitoring data, and regional meteorological data to the cloud platform for data integration in a unified manner. As shown in Figure 1, using different protocols and point-to-multipoint ZigBee + GPRS network communication to achieve remote collection of sensor data in smart farming, the crop growth environment can be monitored in real time, and the crop can be reasonably controlled.

Wireless communication technology refers to a communication method to exchange information by using the feature that electromagnetic wave signals can be propagated in the air. We call the communication method on the move mobile communication, and people call wireless communication and mobile communication collectively wireless mobile communication. In this study, considering the measurement

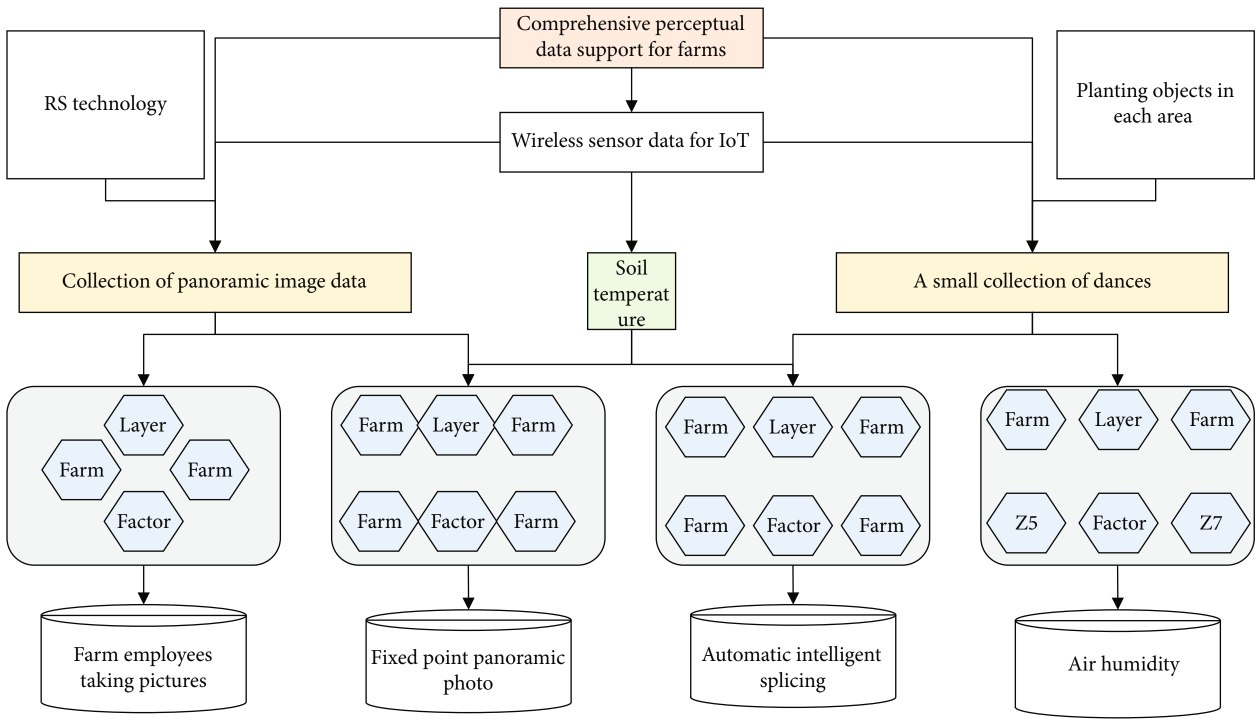

Figure 2: Source of comprehensive farm perception data.

interval of 10 m in the measurement of the sending and receiving distance, the distance *d* with a packet loss rate of 1% measured for the first time is regarded as its transmission range or transmission distance. Line communication technology itself has many advantages. The cost is low, and wireless communication technology does not have to establish physical lines, moreover, a lot of manpower to lay cables, and wireless communication technology is not limited by the industrial environment. The ability to counteract changes in the environment is stronger, fault diagnosis is also easier, and wireless communication technology mainly has long-range communication technology and short-range wireless communication technology.

The manufacturers of wireless sensing have their production standards and specifications in carrying out the production process of their products, and they often make individual customization and production according to the requirements issued by the demanders of the products [13]. Especially in the early stage of producing products, some chip manufacturers output products mainly for the requirements of a small number of customers, so the specifications produced have large differences and cannot be generalized; limiting the chip applicable system way, it is difficult to achieve mutual use and interoperability. Historical data provides a reference for users to fully grasp the system, and middleware provides data query functions. GUI provides historical data query function. In agricultural production, crop growth-related factors are complex and diverse, and the specifications of their applicable sensing devices vary. To interconnect the wireless sensing devices and improve the match with the system, it is required to work according to the wireless sensor network standards and work together to achieve the goal.

According to the main body of system management and implementation, the specific submanagement roles of the system mainly include the company's decision-making and management, farm technicians, farm base managers, and agricultural experts five target users to carry out real-time monitoring of growth, standardized management of planting, and remote guidance and control of melon and fruit production bases. Belonging to this system for the melon fruit planting operation process for personalized customization and specification, in the refinement of the operation of the management system, after real-time dissemination of planting-related instructions, the planting standardization plan in the specific implementation details of management optimization, so that each operation is valued and recorded, planting standards are further standardized [14]. The highest accuracy rate is 89.75%. Among them, the method proposed in this paper has a good detection effect, whether it is for the disease image with blurred texture under the dark light and low contrast state or for the clearer disease image under the bright light and high contrast state.

After the import of data from various interfaces, it is gathered into a data bus containing a large amount of data. These data will be integrated, compared, and analyzed to obtain the essence part and make full use of the data to extract key information, such as temperature sensor data exceeds the standard will carry out production warning and synchronize the release of production instructions to inform the base manager to carry out the corresponding operation, forming a rapid response and efficient problem-solving methods.

The comprehensive perception data source of the farm in this system mainly includes two parts, as shown in Figure 2; one is the collection of crop growth panoramic image data, the farm technicians or administrators take photos through mobile terminals such as mobile phones the farm site in the form of specific images appears and then periodically transmitted back to the platform, to achieve automatic intelligent stitching of multidirectional fixed-point map, to present the environmental conditions of the farm in a panoramic image.

In the perception layer of IoT, the important environmental factors inside and outside the farm, such as soil, atmosphere, water quality, meteorology, and disaster, are monitored, collected, wirelessly transmitted, and reported through RF technology, sensors, cameras, and RS technology to obtain the growth of crops in real time, install tags on the planting objects in each area, record and supervise them, grasp the real-time situation in all aspects, and upload them to the cloud platform [15]. It realizes digital control of field operations such as seed selection and sowing, scientific fertilization, effective irrigation, and reasonable wedding so that the resources of agricultural inputs are utilized precisely and with maximum efficiency.

The videos and images presented by the multichannel data sources can be viewed in real time by the managers and employees of the farm through the public account to see the new situation. Therefore, on the one hand, through the data collection of intuitive panoramic images, on the other hand, using advanced IoT technology to organize and analyze objective data on the growth of crops and growth environment, after a large amount of accumulation and analysis of planting data, a crop growth digital mapping file can be established to provide an objective basis for future inquiries on traceability.

As there are various factors of crop growth index data and growth situation, the construction of IoT needs strict standards to apply to it. Crop sensing data includes information on various types of different measurement units such as temperature, humidity, and nutrient level. Moreover, the problem of different protocols for data transmission exists, and agricultural sensing data also forms the characteristics of wide sources and heterogeneity [16]. There is still a lot of room for improvement for crop disease image detection, especially for many different types of disease crop images. To improve the efficiency of crop sensing, the output of IoT data is a standard format; for these multiple sources of heterogeneous data need to be further fused, to achieve the rapid output of standardized, high-quality data.

Steadily promote the standard optimization of the agricultural planting process, realize scientific and reasonable policy development and method implementation, and promote the efficient process of agricultural planting and management, and other issues appear to be highlighted. On this basis, the promotion of changing production and management structures in rural areas and the optimization of agricultural production also require further improvement. There are still many difficulties to be overcome in agricultural production. In the current situation, we need to make good use of modern information technologies such as the Internet and the Internet of Things to dock the real-time supervision and control of agricultural production sites, the supervision and communication of agricultural production links, and the archiving and utilization of agricultural production result data. Realize the fine management of farm breeding and production, improve the quality of products, and increase the profit of farmers.

3.2. Ecological and Economic Image Detection and Analysis.

In the field of crop disease image detection, most of the data we detect comes from the visible-light images taken in the farm field. Due to the characteristics of crops themselves, many farming images have more complex texture feature information. On the other hand, due to the dense planting, the images are easily obscured by the surrounding crop leaves, branches, flowers, and other external objects, which leads to more complex feature information in the images and seriously affects the accuracy of disease image detection by traditional methods using LBP and other such feature operators [17]. Therefore, for the feature extraction operators such as LBP, it is important to improve the feature computation mode to enhance the accuracy of crop image detection in a complex environment for crop disease detection under traditional methods. Therefore, the advantages of LLP and LVP in the field of image feature extraction are combined and further optimized and improved in this paper, and the local line segment vector pattern features are proposed.

Firstly, like the traditional method, LLVP is also calculated by using the relationship between surrounding pixels and the center pixel. First, the location of the center pixel is determined; then, the other pixels in the neighborhood are determined, and each pixel in the neighborhood is compared with the center pixel one by one in a fixed order. When it is smaller than the center pixel, it is 0; otherwise, it is 1. However, instead of relying on a circular neighborhood of radius r, the surrounding pixels are determined by customizing the intersecting line segment L with the sampling point n, in line with LLP. The distance d between the angle a of the intersecting line segments L1 and L2 and the uniformly distributed sampling points can theoretically be chosen arbitrarily. This solves the problem that it is difficult to consider both near and distant features in the process of feature calculation. This allows the feature operator to extract richer image texture information and improve the efficiency of crop image detection under traditional methods.

Therefore, the advantages of LLP and LVP in the field of image feature extraction are fused in this paper, and the local line vector pattern (LLVP) feature is proposed and applied in the field of crop disease detection and identification, and the fused LLVP feature formula is shown as follows:

$$\begin{cases} \gamma(V) = U = \mathrm{LLP}(\gamma), \\ \mathrm{LLVP}(V) = \mathrm{LLP}(\mathrm{U}), \end{cases} \tag{1}$$

where V represents a binary feature vector and denotes a local block transformation function of the feature vector V based on logic operations under binary. A new binarized vector U is obtained by dividing the feature vector in the same spacing order and then by the operation.

Deep learning techniques provide solutions to the big data problems that arise in daily life, but the conditions for building deep learning models are relatively high, mainly in terms of the high demand for the quantity and quality of sample data [18]. In other words, the quality and quantity of samples when building a sample set for deep learning are directly related to one of the important factors of model accuracy. A good sample set can get a better model accuracy through training, while a bad sample set may not be able to converge all the time in the model training, leading to a low accuracy model, which is thus meaningless for solving classification problems. This also shows that the classification method of the convolutional neural network has more advantages in the classification ability of more target types than the traditional detection method based on artificial features combined with the SVM classification idea. Therefore, the effective acquisition of high-quality samples becomes the primary key issue for model training.

The construction of the sample set is based on selected samples of crops from the orthophotos acquired by the original UAV, and the specific operation is to select 60 samples of 2048∗2048 pixels area size and label each class of samples with labels and randomly crop each sample and label together into 64 blocks of 256∗256 size input data, in the case that the number of samples is not very large, the ratio of its sample set division. The recommended ratio of training set: validation set: test set is 6 : 2 : 2, so 36 sheets are randomly selected as the training set, 12 sheets as the validation set, and then the remaining 12 samples as the test set, and the number of sample labels is shown in Table 1.

The sample library is divided into three categories: training set, validation set, and test set. The reason is that in the process of training the model because the model training to extract depth features is carried out on the training set, so through continuous iteration, its accuracy on the training set is generally high, but perhaps to ensure that its accuracy using the validation set for training is also relatively high. The test set is used to test the accuracy of the model training after the model training is completed and is used to test the generalization ability of the model.

$$\max_{w,b,\xi}\left(\frac{1}{3}\|W\|^2 - C\sum_{i=1}^{N}\xi_1\right), \quad C \geq 0. \tag{2}$$

To solve the problem, this study uses arbitrary horizontal and vertical flip, distortion, cropping, or brightness adjustment of the image enhancement to reduce the gap between the number of samples of different kinds of crops, to solve the problem of uneven distribution of the number of features. This method is simple and effective, and most importantly, the method can provide effective broadening of training, while also helping the network to train more generalized capabilities and enhancing the network's ability to tolerate input sample distortion during feature extraction.

$$K(x_i, x_j) = \varphi(x_i^2)^T \varphi(x_j). \tag{3}$$

The quality of the input samples largely affects the accuracy of the model because the structural or quantitative differences that can exist between the original data not only generate many complex operations but also impose limitations on the generalization ability of the model [19]. The essence of the neural network learning process is the distribution of the learning data, and without centralization as well as normalization, the distribution of the training data will be different for each batch. In the large direction, the neural network needs to find a balance among these multiple distributions, and in the small direction, as the distribution of input data is constantly changing in each layer of the network, this will also lead to each layer of the network in finding a balance. It becomes difficult for the neural network to converge.

Table 1: Number of sample labels.

Category	Training samples (pieces)	Sample area (square kilometers)
Rice	1357	0.41
Corn	278	0.54
Momordica aurantia	478	0.42
Safflower	247	0.58

$$\text{RRMSE} = \frac{\text{RMSE}}{y_j}. \tag{4}$$

As can be seen from Figure 3, the original data is moved to the vicinity of the origin after the centralization process, and the features of the original data in different dimensions have the same scale through the normalization process, so that when using the gradient descent method to optimize the parameters, the impact of different features is the same, and the weight parameter values can converge more quickly. Therefore, the gradient is not too large when training the network, and the optimal solution search process tends to be smooth and accelerates the convergence of the weight parameters, thus making it easier to converge to the optimal solution correctly.

By preprocessing the sample images, we obtained a crop disease dataset with higher image quality. The crop disease areas are more obvious, and the disease features are clearer, and the influence of some additional image interference information is removed. The characteristics of the crops in the original farmland and their growing environment are quite different and difficult to control, and they are constantly changing. In the process of subsequent experiments, the regular image size provides great convenience for the calculation of various image features, and the clear image texture also enhances the accuracy of the calculation of detailed features of the sample images [20]. In our experiments, we found that in the task of actual crop disease image detection, the preprocessing of image samples has a significant impact on the later experiments. The method of extracting feature information of diseased crop images using manually designed feature detection operators and then

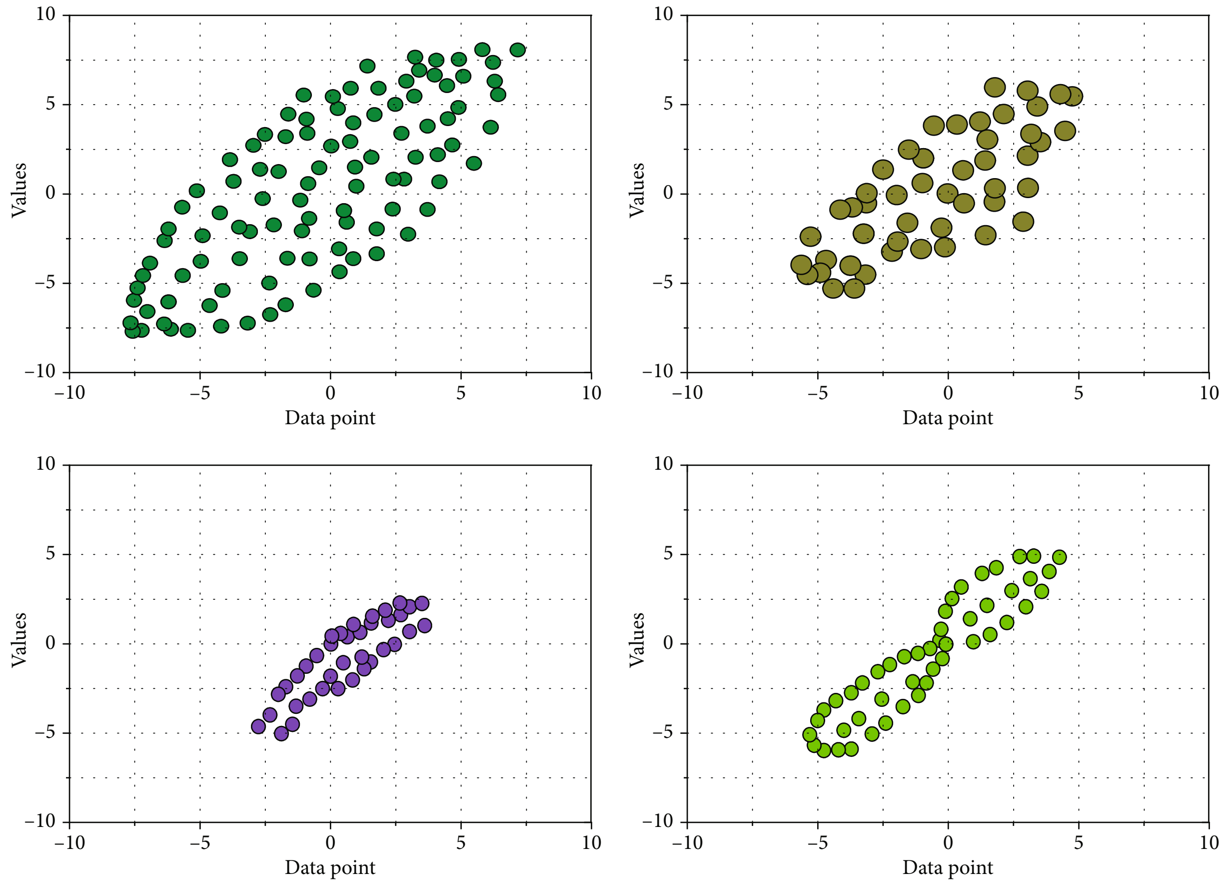

Figure 3: Data distribution under different processing methods.

classifying them by classifiers is a common means of disease detection under traditional methods. This type of traditional method classifies the extracted features by support vector machines to obtain the final disease identification results.

4. Analysis of Results

4.1. Intelligent Sensor Network Performance Result Analysis. Under the implementation of an intelligent sensing module, intelligent IoT devices such as collectors, sensors, and cameras can be deployed in agricultural production sites, which realize automatic real-time collection and monitoring of production site soil and air temperature and humidity, moisture, light, and other related environmental data. And with the realization of panoramic technology, users can view the park weather data, soil data, equipment status, etc. by logging into this system through cell phones or computers. In case of abnormalities such as high temperature and high humidity, the system will automatically issue an alarm to remind the base manager to deal with the abnormality in time.

The simulation results of the amount of data received by the coordinator nodes are shown in Figure 4. Over time, the LEACH-based routing algorithm suffers from data redundancy, and too many packets from cluster head nodes cause network transmission blockage and serious packet loss. The ACO-BP algorithm optimizes the network performance to a certain extent, but the solution time is long, the search capability is limited, and the data fusion effect is not ideal; the GA-ACO-BP algorithm is different from the ACO-BP algorithm and LEACH algorithm. The GA-ACO-BP algorithm receives the most data at the coordinator node compared to the ACO-BP algorithm and LEACH algorithm, which is due to the GA-ACO-BP algorithm optimizes the network performance, finds the global optimal solution quickly, improves the BP neural network data fusion effect, reduces data redundancy, reduces data transmission delay, and improves the wireless channel utilization.

As the transceiver distance d increases, reliable communication can be achieved when the strength of the received signal is higher than the sensitivity of the receiver, at which time the packet loss rate is 0; as the distance increases, the strength of the received signal is initially equal to the received sensitivity, and reliable communication can still be achieved near the shorter distance of the critical point; when the distance continues to increase, signal loss occurs, and the sudden change of the packet loss rate from 0 to 1 is completed in a shorter distance. Planting things can be fully tracked throughout the whole process, responsibilities can be subdivided, and natural disasters, pests, and diseases can be effectively prevented, and economic losses can be reduced. In this study, considering the measurement interval of 10 m in the transceiver distance measurement, the distance d where the packet loss rate of 1% is measured for

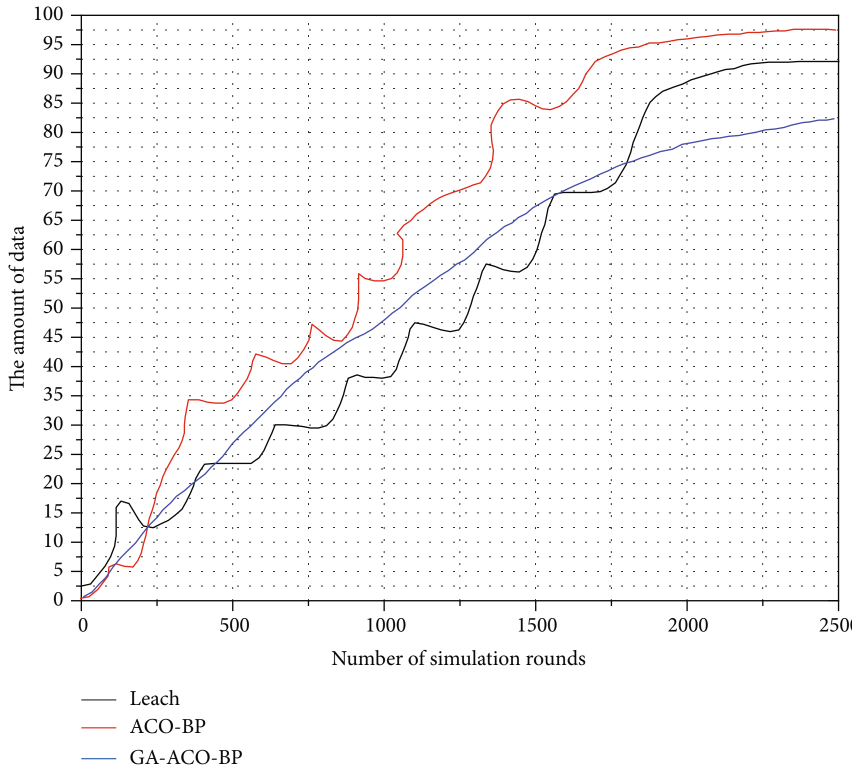

Figure 4: Amount of data received by coordinator nodes.

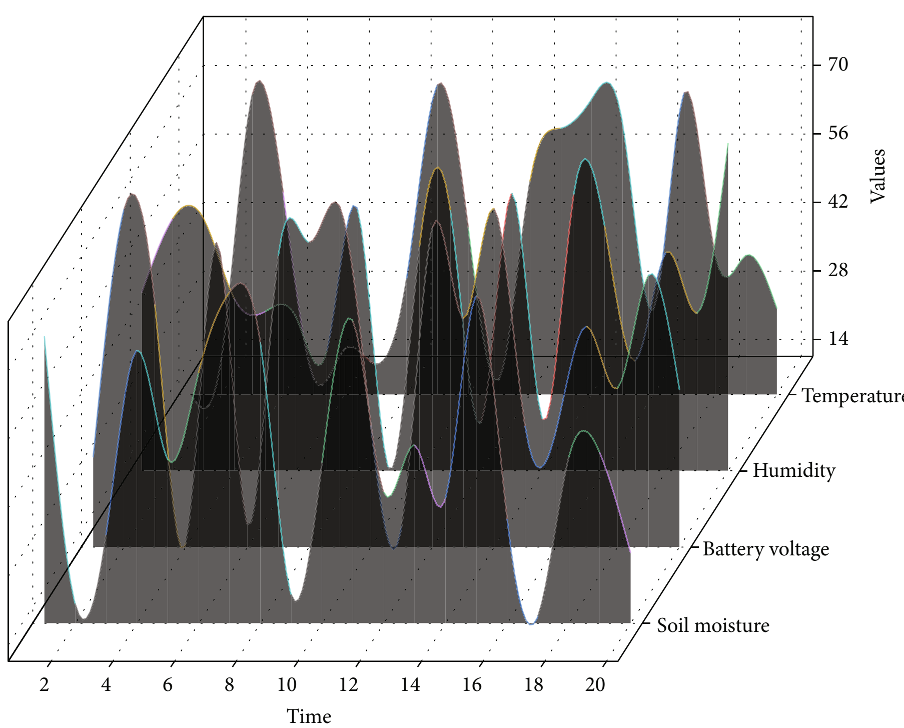

Figure 5: Data query results at a certain moment.

the first time is identified as its transmission range or transmission distance, which is the coverage range of the node. From the packet loss rate data in Figure 5, it can be obtained that the packet loss rate grows faster when the sending and receiving distance d is less than 60 m, and the packet loss rate grows relatively flat with d when d is greater than 60 m.

In the control system, ensuring the accuracy and effectiveness of the control device is a prerequisite for control,

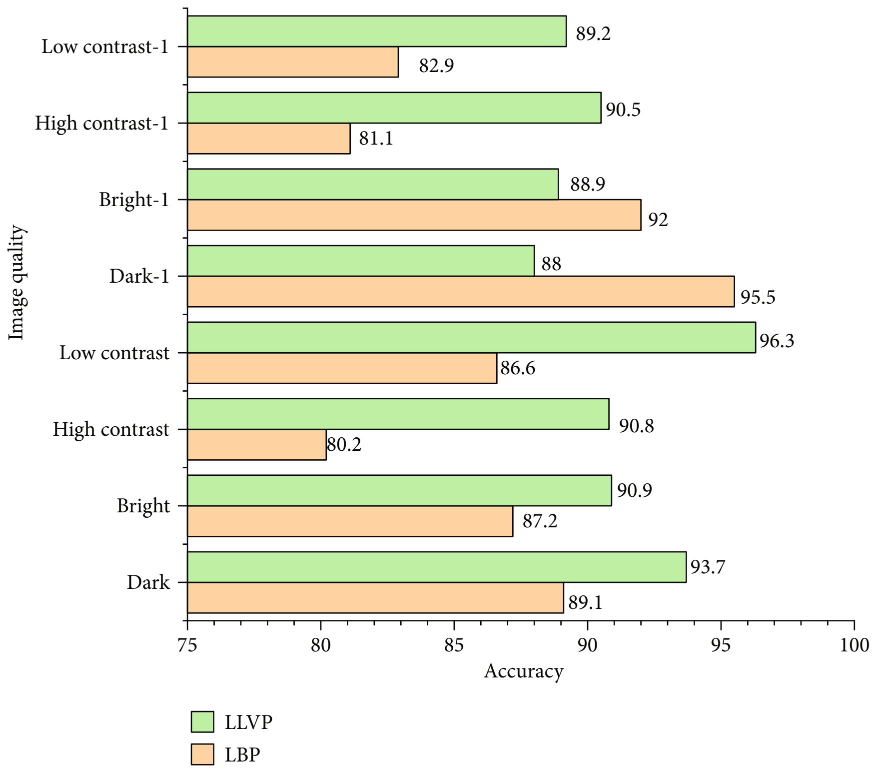

Figure 6: Comparison of experimental results of feature operators.

so the definition of controller status and device status is essential in the control protocol. The handling of the failure of devices or controllers and the relationship between various types of control devices are usually decided based on the specific system. Exploring a fast and accurate crop classification method for UAV remote sensing images is of great significance for the rapid acquisition of digital information of small- and medium-scale farmland and for precision agricultural management. In agricultural IoT, the data collected by sensor nodes are uploaded to the network layer through aggregation nodes. The uploaded information mainly includes the data of each relevant parameter collected by the sensor nodes, the status information of the control-related devices, the status information of the controller itself, etc. The agricultural IoT middleware is a database system, including the processing of real-time data and historical data. Real-time data is the most important part of the monitoring system, which provides the basis for the controller's action execution and is the focus of the user's attention to grasp the system. The middleware provides the data query function, and the GUI provides the historical data query function.

Parameter management can complete the filtering of specified data types in specified areas so that users can easily find the data they need; the system reserves sensor data types, so that data can be added according to the actual farming conditions, ensuring the scalability of the system; users can set the best-growing conditions through crop growth to improve agricultural production management.

The dynamic web design improves user interaction with the system and enhances the flexibility of the system. This data is collected into the farm data storage and management center and then processed and displayed on mobile devices such as mobile phones and tablets in the form of charts. The data of coordinator nodes are uploaded to the monitoring center through the RS232 interface, and the design of Java serial communication is completed. MySQL database is used to store the environmental information of farmland, and SQL language is executed to complete the operations of adding, deleting, modifying, and querying data. The software design of the monitoring center platform was completed, including the process design of the recording system, data display, parameter setting, and system report. A functional description of the system operation was made, and the system can meet the actual demand.

4.2. Experimental Results of the Image Detection System. For better comparative analysis, since the traditional method based on feature operator detection is often used for image classification and detection tasks with fewer categories, the experiments were divided into 5 groups and 10 groups for disease samples. Doing so is on the one hand kinder to the traditional method and at the same time avoids the problem that the small number of some image samples leads to an unbalanced database, which affects the determination of the experimental results. Therefore, effectively obtaining high-quality samples has become the primary key issue in model training. This is because we can artificially ensure that the number of images chosen for the 5 and 10 crop disease datasets is the same, with a balanced database of 400 samples. Finally, this method was also applied to the crop image database of all 20 disease categories. During the training

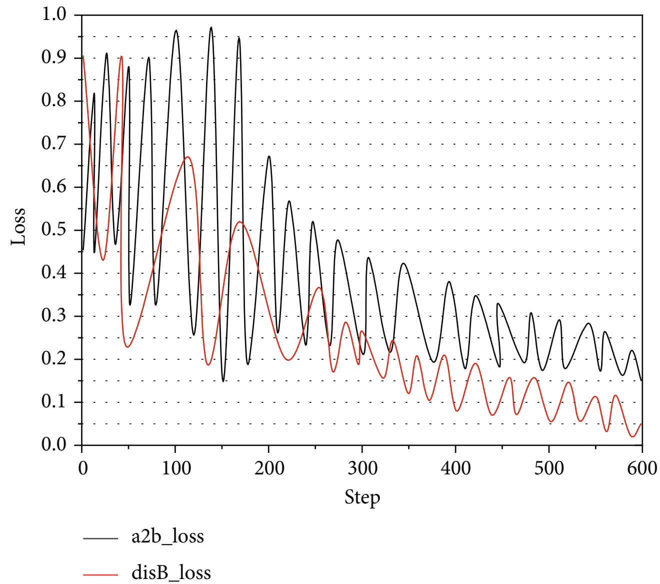

Figure 7: Loss curve of generator and discriminator.

process, the ratio of training samples to test samples is also an important factor affecting the final classification accuracy. Here, for each class of disease dataset images, the proportion of training samples to the total samples of that class of disease images is set to 0.8, and the specific experimental results are shown in Figure 6.

Through the experimental results of the traditional method and the improved method on the self-built crop disease image database, we can see that the proposed method of fusing the improved feature operator with SVM for crop disease detection is better than the traditional single LBP feature operator, with the highest accuracy of 89.75%. In particular, the proposed method has good results for both the disease images with blurred texture under low contrast in dark light and clearer images under high contrast in bright light.

For the detection of crop disease images with clearer image quality in a good acquisition environment, we found that the difference between the traditional method and the fusion improvement method proposed in this paper is not significant. However, for the task of detecting low-contrast images with dark light acquired under poor environmental conditions, the proposed fusion-improved feature operator makes up for the problem that the original features are easily affected by environmental factors and lead to feature loss. Not to mention a lot of workforce to lay cables, and wireless communication technology is not limited by the industrial environment, it has strong ability to resist environmental changes, and fault diagnosis is easier. It improves the detection performance of traditional manual feature-based operators in complex environments.

On the other hand, when data acquisition is performed for multiple types of crop disease images, there are many categories of disease images that are difficult to acquire, and the quantity and quality of the sample database in the preexperimental stage also directly affect the final experimental accuracy. Given the above experimental results, it is easy to find that the traditional method based on feature extraction combined with support vector machine classification detection has much room for improvement for crop disease image detection, especially for many different types of disease crop images. Wireless communication technologies mainly include long-distance communication technology and short-distance wireless communication technology. Therefore, to address the problem that the classification accuracy of the traditional method is not high and does not adapt to the detection of multiple types of crop diseases, a deep learning method based on an artificial neural network is introduced in the next section, and the detection experiments are conducted on a database containing 7342 images of different disease samples in 20 categories.

Figure 7 shows the corresponding images produced by the network after the generative network when the number of iterations in the training process is 1, 50, 100, and 500, and the corresponding shape texture and light mask are input. From Epoch 10 in Figure 7, after 10 iterations of the whole training set, the leaf outline is not completely displayed; from Epoch 50, after 50 iterations of the whole training set, the leaf image generated by the model is clear, but the black rot disease area and the corresponding texture details are still not well displayed; from Epoch 100, after 100 iterations of the whole training set, the leaf outline is not completely displayed. Finally, Epoch 500 shows that after 500 iterations, the model is stable, and the images of grape leaves with black rot are visible.

The human eye can intuitively make a general judgment on the quality of an image, but it is necessary to refer to some indicators that are difficult to be detected by the human eye to evaluate an image. Therefore, in this paper, PSNR and MSE are also used to quantitatively evaluate the generated images. The first metric is the peak signal-to-noise ratio (PSNR), which judges the difference between different images by directly measuring the difference between pixel values, with larger values indicating less distortion. To interconnect the

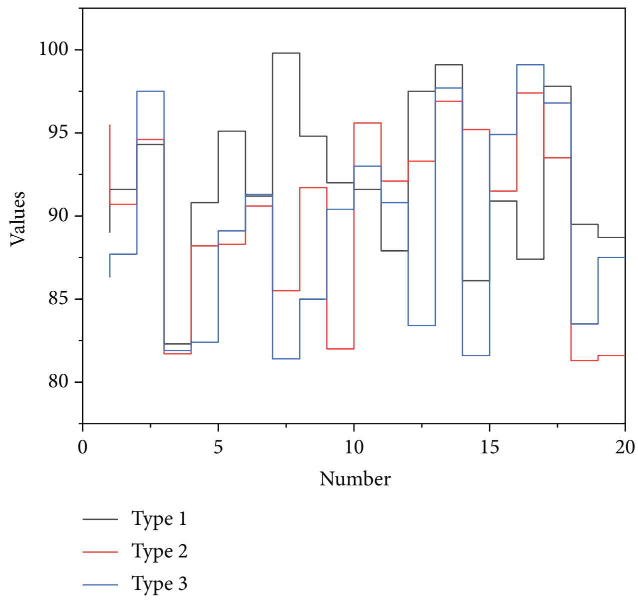

Figure 8: Experimental results.

wireless sensor devices and improve the matching degree with the system, it is required to work according to the wireless sensor network standard and work together to achieve the goal. Using the PSNR method, the difference in grayscale values of pixels between the generated image and the real sample image is calculated to judge the goodness of the generated image, as shown in Figure 8.

We can see that the detection accuracy of the convolutional network classification method is significantly improved compared with the traditional method regardless of the state of the data set, and the average classification accuracy can be significantly increased. After a large amount of accumulation and analysis of planting data, a digital map file of crop growth can be established to provide an objective basis for future inquiries and traceability. This also shows that the classification ability of the convolutional neural network is more advantageous for more target types than the traditional detection method based on artificial features combined with the SVM classification idea.

5. Conclusion

In this paper, we have established an agricultural WSN architecture and proposed a WSN system evaluation strategy for fine agricultural applications to provide a reference for the establishment of agricultural wireless sensor network industry standards, considering the demand for fine agricultural applications and network quality of service as the goal. First, the establishment of a crop disease database is crucial for the image detection task. Poor sample sets may fail to converge during model training, resulting in a low-precision model, which is meaningless for solving the classification problem. A perfect and high-quality sample image database is important for both feature extraction methods under traditional methods and deep learning methods based on big data, so this paper firstly establishes its experimental database. Secondly, for crop disease image detection, the experiments compare the advantages and disadvantages of traditional methods as well as deep learning methods and try to improve the traditional human feature-based detection methods. A personalized and customized strategy of own production experience is realized, which can control, optimize, and adjust the cultivation scheme of crops such as planting method and planting forecast in time. In this paper, we analyze the watermelon planting method of a base in Hunan Province, develop planting process specifications based on weather and other natural factors, carry out standardized planting, realize large-scale and efficient production, and generate growth digital files through farm manager and technician inspection records to build a traceable basis. The experiment proves that the improvement of traditional features can play a certain effect, but the detection accuracy has much room for improvement compared with deep learning methods.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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