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Review Article

The Current Application Status and Expectation of Machine Learning in Unmanned Farm

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ABSTRACT

With the successful application of machine learning in biological information, face recognition and other fields, it also provides power for the development of unmanned farms. Firstly, this paper expounds the basic concepts of unmanned farm and machine learning. At the same time, it analyzes the application of machine learning in planting and animal husbandry. This paper expounds its application in field weed identification, crop pest detection and crop yield prediction in planting. In animal husbandry, this paper analyzes the application status of machine learning in accurate identification and classification of fish, pigs and other livestock, fish feeding decision-making system and production line prediction of chickens and cattle. It is pointed out that machine learning has some disadvantages, such as difficulties in obtaining and marking training samples, performance defects of embedded chips, and lack of professionals. A general unmanned farm database should be established to study the expert system that can predict the health status of animals and monitor the growth environment of animals in real time. The embedded research of machine learning should be strengthened, and machine learning combined with 5G, big data, sensors and other technologies will become the research direction of unmanned farm in the future. This paper summarizes the application status, problems and prospects of machine learning in unmanned farm, hoping to provide references for further research in the future.

Keywords: *Machine Learning; Unmanned Farm; Crop Management; Animal Husbandry; Accurate Identification; Production Forecast*

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1. Introduction

Agriculture is one of the most important industries in the world[1], because food is necessary for everyone. It ensures the survival of the global population. The rapid development of agriculture makes the hunger crisis no longer appear[2]. With the trend of growing global population, more agricultural labor force is needed to support agricultural production[3]. However, in the previous decades, the average age of farmers engaged in agricultural work is increasing rapidly. The proportion of people aged 45–64 engaged in agricultural work has increased from 33.48% in 2006 to 43.48% in 2016[4]. Therefore, the current agricultural research mainly focuses on improving higher quality agricultural production with less labor[1].

With the rapid development of information technology, the world's most cutting-edge technologies such as Internet of things (IoT)[5-6], robotics[7-8], big data[9] and artificial intelligence (AI)[10-11] are more and more widely applicated and mature in agriculture, making the conception of the operation mode of unmanned farm become reality, greatly liberating productivity and improving resource utilization. In the operation mode of unmanned farm, artificial intelligence technology plays the role of thinking and decision-making, and machine learning is one of the most important technologies of artificial intelligence[12].

With the gradual and successful application of machine learning technology in other scientific fields, such as bioinformatics[13], medicine[14], visual tracking[15], robotics[7], climatology[16], remote sensing image processing[17-18], agricultural scientists and scholars pay more and more attention to the application of machine learning in agriculture, which is also the most cutting-edge, modern and promising technology in agriculture[19]. Based on the introduction of the concepts of unmanned farm and machine learning, combined with the practical experience of machine learning technology in the ecological unmanned farm of Shandong University of Technology, this paper summarizes its application status and future development direction in the ecological unmanned farm, so as to provide reference for the better application of machine learning in the unmanned farm in the future.

2. Concepts of Unmanned Farm and Machine Learning Concepts

2.1 Concept of unmanned farm

With the over exploitation of China's agricultural resources, the available cultivated land is decreasing year by year. At the same time, the waste and development without cause or reason of agricultural resources have led to the deterioration of China's agricultural labor environment. Now, China's aging population is becoming more and more serious, there are fewer and fewer labor forces engaged in agricultural labor, and the predicament of no farming is becoming more and more obvious. The in-depth application of information technologies such as Internet of things, cloud computing, big data and artificial intelligence in the agricultural field[20] equipped the unmanned farm with the economic, social and technical conditions.

Unmanned farm is a new agricultural production mode, which does not require too much participation of labor force. Through the joint use of Internet of things, big data, artificial intelligence, the fifth generation (5G) technology and robots and other cutting-edge technologies, all production activities of unmanned farm are carried out with remote control in the whole process, so as to realize the independent operation of equipment, machinery and robots[1].

Unmanned farms use sensor technology to monitor the growth of animals and plants and the working conditions of various production equipment, and use reliable and efficient communication technology to transmit data to the cloud, such as LoRA wireless transmission communication technology[21]. The cloud platform analyzes and processes data through big data technology[22], generates production and operation decisions, then transmits the decision information to the robot, and finally the robot performs specific production activities.

In the unmanned farm, the whole process of agricultural production and operation should achieve accurate management, self decision-making, unmanned operation and personalized service, so as to achieve the sustainable development goal of agricultural production. The architecture of unmanned farm is composed of foundation layer, decision-making layer and application service layer. Its roles and components are described as follows. (1). The foundation layer includes communication system and infrastructure system. (2). The decision-making layer is an intelligent decision-making cloud platform for unmanned farms, which analyzes, processes and stores a large number of data resources and generates decisions. (3). The application layer is the automatic operation equipment system, which uses intelligent agricultural equipment and Internet of things technology. It is the core component of unmanned farm.

The three-tier structure of unmanned farm plays different roles. The basic layer is essential to support the operation of other systems, and the infrastructure system and communication system of the basic layer are responsible for data collection and transmission. The decision-making level implements data management and makes decisions related to production and operation. The application layer uses machines instead of personnel for production operations. The three-layer structure cooperates with each other to realize the safe and reliable intelligent operation of the unmanned farm[1].

2.2 Machine learning

Machine learning is an important branch of artificial intelligence in the field of computer science. The name of ML was proposed by Samuel[23]. Machine learning is an intelligent method that enables computers to simulate human learning activities, acquire new knowledge, continuously improve performance and realize self-perfection. The basic principle of ML is to construct an algorithm, which can receive data and use statistical technology to predict the output, and update the output when new data is available[24].

Machine learning methods are divided into supervised learning, unsupervised learning and semi-supervised learning. Commonly used algorithms include artificial neural network and deep learning.

2.2.1 Supervised learning

Supervised learning is to obtain an optimal learning model through the training of existing training samples, and then use this learning model to map all inputs into corresponding outputs and make simple judgment on the outputs, so as to achieve the purpose of prediction and classification.

2.2.2 Unsupervised learning

The training samples of unsupervised learning do not have any labeled information. It is to discover the internal relationship of data by learning the training samples without labeled information, so as to provide a basis for further data analysis. It is applicable to scenes that do not have enough previous experience and are not suitable for manual labeling.

2.2.3 Semi-supervised learning

Semi-supervised learning is a collection of supervised learning and unsupervised learning. Part of the data in the training data set is labeled and the other part is unlabeled. A small amount of labeled data and a large amount of unlabeled data are used for learning, so as to obtain the corresponding output. In agriculture, there are usually a large number of unlabeled data due to the limitation of the scene, so the research of semi-supervised learning is very helpful for agriculture.

2.2.4 Artificial neural network

Artificial neural network, abbreviated as neural network (NN), is a mathematical model that simulates the neural system of human brain to process complex information. In fact, it is a complex network composed of a large number of simple components connected with each other. It is a system that can carry out complex logical operation and nonlinear relationship. It is one of the examples of supervised learning[25]. Artificial neuron is the basic information processing unit of artificial neural network operation. The structure of artificial neuron is shown in **Figure 1**.

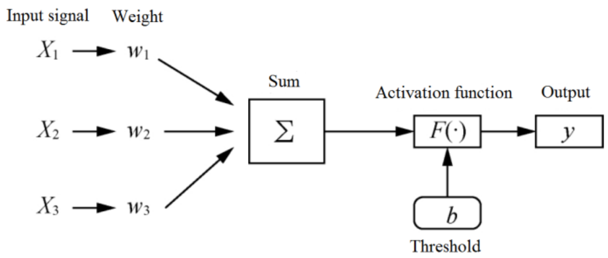

Figure 1. Structure diagram of artificial neural network.

The output of an artificial neuron to an input signal $X = [X_1, X_2 X_3 \dots X_m]^T$

$$y = f(u+b) \tag{1}$$

$$u = \sum_{i=1}^{m} w_i X_i \tag{2}$$

At present, artificial neural network has been more frequently used in information processing, prediction analysis and other fields[26].

2.2.5 Deep learning

Deep learning is a sub field of machine learning, which is developed on artificial neural network. Its core idea is to automatically extract multi-layer features in the data center through data driven[27] and nonlinear transformation[28]. In essence, it achieves the purpose of feature extraction and transformation by using nonlinear information processing mechanism and the combination of supervised and unsupervised training, so that the data relationship between samples can be successfully fitted[29]. Deep learning is a deep machine learning model. "Deep" is mainly reflected in the multiple transformation of features[30]. The deep network structure weakens the error features extracted by the previous layer of network to a certain extent, and represents the complex function with fewer parameters, making the network calculation more compact, so as to improve the efficiency and effect[28]. The powerful advantage of deep learning is feature learning, that is, automatically extracting features from the original data and combining lower-level features to form higher-level features[31]. There are many different types of networks for deep learning. The basic networks include deep confidence network, convolutional neural network, recursive neural network, etc.[32], and convolutional neural network is the most widely used in agriculture. The network model leNet-5 is a classical convolutional neural network, and its network structure is shown in **Figure 2**.

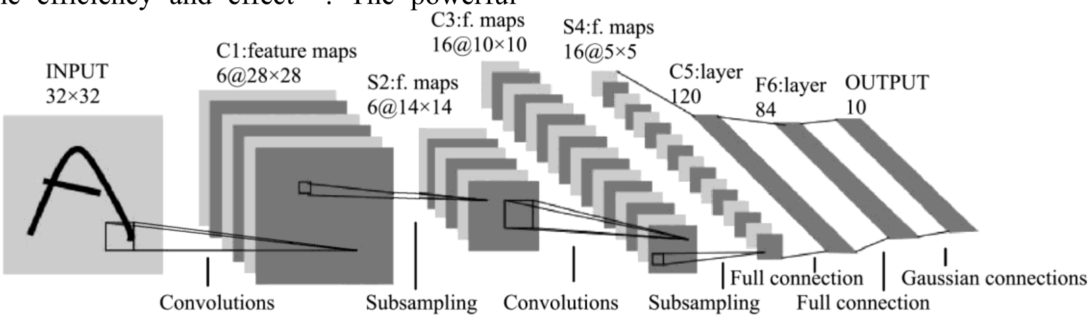

Figure 2. Structure diagram of leNet-5 network.

3. Application of unmanned machine learning on farm

As the key part of unmanned farm is artificial intelligence, and machine learning is one of the key technologies of artificial intelligence, machine learning technology is playing a more and more important role in unmanned farm. This section will discuss the application of machine learning in planting and animal husbandry.

3.1 Application of machine learning in planting industry

3.1.1 Application of machine learning in field weed identification

In agricultural production activities, weeds are inevitable accompanying plants in the field. At present, the main weeding methods used in China are chemical weeding, manual weeding, mechanical weeding, biological weeding, etc. The traditional weeding work is time-consuming and laborious. In today's situation of "no man farming", it is impossible to rely on the traditional weeding technology, so the weeding technology based on machine learning has become more and more important.

Using convolution neural network and deep learning to identify and detect weeds is the most widely used method at present. Andrea *et al.*[33] of Bonn University used convolutional neural network to distinguish corn plants and weeds in the early growth stage of crops, and trained the convolutional neural network with the data set generated in the segmentation stage, and the recognition accuracy reached 97.23%. Jiang Honghua *et al.*[34] improved the convolutional neural network when identifying weeds in the field, adding a binary hash layer behind the full connection layer. By comparing the full connection layer feature code and hash code, they found the labels of K images closest to them and classified them into the category with the highest frequency. This algorithm uses 5000 images for training and 1000 data sets for testing (the proportion of the training set to the test set is 5:1), and the field recognition accuracy is as high as 98.6% and the detection accuracy on other weed data sets was 95.8%. Flores *et al.*[35] from the Department of agriculture and bioengineering of North Dakota State University simulated the field conditions in the greenhouse environment, collected the image shape, color and texture feature values, and used support vector machine model (SVM), neural network (NN), random forest (RF), GoogLeNet and VGG-16 model for recognition and detection respectively. Finally, the recognition accuracy of VGG-16 model in distinguishing soybean seedlings and corn miscellaneous seedlings reached 96.2%, of which the accuracy is the highest among the above five model methods. Meng Qingkuan *et al.*[36] used deep separable convolution combined with compression and excitation network module to build a lightweight feature extraction unit to replace the VGG-16 network in the standard SSD model and improved the speed of feature extraction. The deep semantic information in the extended network was fused with the shallow detail information. The average detection accuracy of the improved deep learning detection model for corn and weeds is 88.27%. Liu Huili *et al.*[37] built a convolution neural network model with multi-scale hierarchical features based on the deep learning framework tensorflow, and applied the 4 times expanded unit convolution kernel to obtain the recognition model of corn seedling image. Its recognition accuracy reached 99.65%.

In weed management in the field, by improving various machine learning algorithms, the recognition accuracy of weeds has been very high, but most of them are planted and collected in the laboratory, and no field test is carried out in the field. Due to the more complex environment in the field, it will increase the recognition difficulty of machine learning algorithm. We should strengthen the landing experiment and improve the algorithm model through the real field scene, making the machine learning algorithm better applied to the field weed identification project.

3.1.2 Application of machine learning in pest detection

In agriculture, in addition to the great impact of weeds on crops, pest control is another important issue of crop planting. In terms of pest control, the current common practice is to spray chemical agents evenly in the planting area. Although this method is the most effective, the use of chemicals will also cause environmental pollution and threaten environmental safety[38]. Due to the application of in-depth learning in precision agriculture, precision spraying is realized in the process of pest control, and the use of pesticides is reduced.

Pantazi *et al.*[39] used the methods of artistic neural network (ANN) and XY-Fusion network to detect and identify healthy silymarin plants and plants infected by aspergillus niger. Using XY-Fusion method, the detection accuracy reached 95.16%. Ebrahimi *et al.*[40] used SVM classification method to detect thrips on crop canopy images, and used a new image processing technology to detect parasites that may appear on strawberry plants. Support vector machines with different kernel functions were used to classify parasites and detect thrips. The results show that the support vector machine model with regional index and brightness as color index had the best classification effect, and the average error was less than 2.25%. Chung *et al.*[41] proposed a nondestructive method to distinguish infected rice seedlings and healthy seedlings at the age of 3 weeks by using machine vision. They developed a support vector machine (SVM) classifier to distinguish infected and healthy seedlings, and used genetic algorithm to select the basic features and optimal model parameters of SVM classifier. The results show that the proposed method had the accuracy of 87.9%, realized automatic detection of infected plants, improved grain yield, and reduced the time consumption. Zhang Yinsong[42] carried out target detection and recognition of armyworm board pests. He adopted SSD target detection algorithm that can detect in real time, and reduced the problem of small size of pests on the basis of SSD algorithm. Deconvolution was used to realize the feature fusion of high-level and low-level, and then the fused features were used to establish the feature pyramid. Then he detected layer by layer to obtain the optimal recognition model. The results show that the accuracy of model recognition is 91.8%. In terms of the problems of low image recognition accuracy and low model training efficiency of the traditional leNet-5 model in the classification of complex texture images, Liu Zhiyong *et al.*[43] improved the traditional leNet-5. They used the PReLU function as the activation function, added the concept structure module group to the network, adopted the dropout strategy and added batchnormalization, etc., and proposed the improved leNet-5 model. In the experiment of identifying tomato diseases and pests, its improved model recognition accuracy is as high as 95.3%. Moshou *et al.*[44] identified and detected winter wheat infected with yellow rust, nitrogen stressed plants and healthy plants, and adopted the method based on SOM neural network and hyperspectral reflection imaging. The results show that the accuracy of identifying nitrogen stressed plants was 100%, that of plants infected with yellow rust was 99.92%, and healthy plants was 99.39%.

3.1.3 The role of machine learning in output prediction

Crop yield prediction plays a very important role in unmanned farm operation and is of great significance to improve the production and management level of the farm. You team[45] abandoned the traditional methods used in the field of remote sensing and adopted convolution neural network (CNN) and long-term and short-term memory network (LSTM, a time recursive neural network) to automatically extract relevant features from the original data, and used the deep Gauss process to integrate the spatio-temporal information of the data to evaluate their methods in the task of predicting soybean yield. The results show that their model has a prediction accuracy 15% higher than that of the U.S. Department of Agriculture averagely. Ali *et al.*[46] carried out the work of estimating grassland biomass in small-scale farms with intensive management in Ireland. They adopted the methods of multiple linear regression (MLR), artificial neural network (ANN) and adaptive neuro fuzzy inference system (ANFIS) model, in which the ANFIS model combines the advantages of artificial neural network and fuzzy logic and is evaluated in two intensively managed grassland farms in Ireland. The results show that ANFIS has better effect than the other two methods.

By summarizing the relevant literature of machine learning in the planting industry, it is found that the improved machine learning algorithm has great recognition accuracy and prediction effect, which shows that machine learning can be applied in unmanned farms, but the embedded research of the algorithm should also be strengthened and field tests should be carried out, so that machine learning can be better applied in unmanned farms and promote the intelligent development of unmanned farms faster.

3.2 Application of machine learning in animal husbandry

The main application scenarios of machine learning in animal husbandry are fishing grounds and farms. On the one hand, it is used to accurately identify animals, monitor animal behavior in real time, and provide growth information for producers. On the other hand, machine learning technology is mainly applied to the monitoring of production lines to provide producers with production information to create the greatest economic value.

3.2.1 Application of machine learning in accurate identification of livestock

The intelligent identification of fish by machine learning lays a foundation for further prediction of fishery situation. The accurate prediction data of fishery situation can solve the problem of the lack of fishery standard service based on the standard system in most fishery standard service systems. It can provide data decision-making basis for the revision guide of fishery standards[47], and offer real-time monitoring of fish growth and health data for fishery owners, providing data support for fish farming.

Using deep learning to identify and detect fish is the most common method. Wang Wencheng *et al.*[48] used ResNet50 network to identify and detect turbot, yellowfin snapper, goldfish and mullet, and the test accuracy was more than 96%. They also developed a GUI visual interface using PyQt5. Through the interface operation, the test results were consistent with the prediction category. At the same time, they used DSOD framework to do real-time tracking and detection of underwater targets, and greatly improved the detection accuracy of small targets without losing the detection speed. Yuan Hongchun *et al.*[49] adopted a multi-scale retinal enhancement algorithm (MSRCR) based on Faster R-CNN secondary migration learning and color restoration, which solves the problems of insufficient number of fish samples and rapid detection of blurred fish images. The test results show that the method useing the network trained by the fish data set with a small number of samples has a detection accuracy of 98.12%. Li Qingzhong *et al.*[50] used the improved YOLO detection algorithm and migration learning to solve the problem of rapid detection of underwater robot fish targets based on video images in a non restrictive environment. Compared with the traditional YOLO algorithm, the improved algorithm improves the detection performance of small targets and overlapping targets, and the detection accuracy reaches 89%. Wang Ye[51] proposed a fish recognition model base on residual network. They used the ResNet50 as basic network, built network by using transfer learning, and introduced attention mechanism, inserting the nonlocal operator of attention mechanism into the residual network in the form of module. The results show that the identification accuracy of the improved network model reaches 98.16%.

With the adoption of intensive management, accurate identification of livestock such as pigs and cattle has become an important issue in farms. Hansen team[52] proposed a non-invasive biometric method for animal face recognition. They tested the method with Fisherfaces, VGG-Face pre- trained face convolution neural network (CNN) model and their own CNN model, and they trained it with artificially expanded data sets. The results show that the recognition accuracy of their own CNN model reached 96.7%.

Accurate identification and classification of livestock plays an important role in animal husbandry. In the research of livestock identification in recent years, scholars have improved the machine learning algorithm, which has reached a very high recognition accuracy and laid a solid foundation for livestock behavior identification and health monitoring.

3.2.2 Application of machine learning in livestock production prediction

Machine learning has the ability to detect and warn problems early, which plays a very important role in animal husbandry. It can monitor poultry in real time, find problems in the production process in time, and take timely actions to avoid these problems and reduce economic losses. Real time production monitoring of animals in farms can timely adjust production strategies and maximize benefits. At present, machine learning is widely used in this field. Morales team[53] used the egg production data of 478,919 hens on the farm and the method of support vector machine to find the problems in the egg production curve. This technology can send an alarm one day in advance to warn that there are problems in the production curve, and the accuracy rate is 98.54%. Alonso *et al.*[54] used the support vector machine regression method to predict the weight of beef cattle a few days before slaughter, and measured 144 animals for 390 times. The average absolute error was 4.27% of the real value.

3.2.3 Application of machine learning in livestock feeding decision

In aquaculture, fish feeding is of great significance not only to reduce the cost, but also to improve the yield of fish. Zhou *et al.*[55] used the near infrared computer vision and neuro fuzzy feed control method to realize the purpose of automatic feeding according to the appetite of fish. The test results show that the accuracy of feeding decision of the model reaches 98%. Zhao Jian[56] monitored the local sudden behavior of fish herds that can characterize the hunger degree of fish herds in circulating water culture. They adopted recursive neural network, particle advection scheme and improved motion influence map. The experimental results show that the average detection accuracy reached 98.91% and the average recognition accuracy reached 89.89%.

The application of machine learning in animal husbandry has shown good results. It has a very good performance in accurate classification and identification, production prediction and feeding decision-making. Due to the need for more rigorous livestock breeding to ensure the accuracy of livestock information, the current machine learning can not completely solve the problems in artificial breeding, but the performance of machine learning can provide better information decision-making support for the breeding process. In the future technological development, machine learning will have a broader application field in the aquaculture industry.

4. Discussion and Prospect

After summarizing the above literature, machine learning technology mainly focuses on machine vision, using machine learning algorithm to detect target objects, but there are also some disadvantages in these applications.

1). The use of machine vision requires a large number of data sets for model training and verification. In the current environment of agricultural machine learning, there is no universal data set, and each experimental team collects the labeled data set by itself. Due to the influence of farmland environment, collecting the data set is time-consuming and labor-consuming, and the labeled data set needs manual labeling by professionals, so that there is no data set with a large amount of circulating data. This not only limits the detection accuracy of machine vision model, but also increases the application difficulty of machine learning in agriculture.

2). At present, machine learning needs high-quality hardware to meet its computing ability, but the current embedded chip has problems such as insufficient computing ability and slow computing speed. The performance breakthrough of embedded chip involves problems in other fields, and it is difficult to have greater research breakthrough in the short term.

3). The application of machine learning in agriculture requires both agricultural production experience and professional knowledge of machine learning. However, there is a serious shortage of professionals with both, which limits the development of machine learning technology in agriculture.

In the operation mode of unmanned farm, machine learning is essential. In view of the application status of machine learning in unmanned farm, we should also strengthen the research on the following aspects.

1). Nowadays, machine learning technology is mainly used in crop field weed management and pest detection. It has been widely used in crops, saving a lot of human, material and financial resources, but it is still less used in fisheries, cattle farms and pig farms. In the future, we should do more researches on animals. Using machine learning technology to dynamically monitor the growth status of animals, and using big data technology, combined with the production experience of experts, we can predict the health status of animals through their daily behavior, and establish a set of expert system, which can timely avoid the large-scale spread of animal diseases. At the same time, machine learning should also be used to monitor the growth environment of animals in real time, so as to provide decision support for improving the growth environment of animals.

2). At the same time, a set of high-quality database should be established in the unmanned farm. The database plays a very important role in machine learning. Therefore, a high-quality database will accelerate the application process of machine learning and greatly improve the management efficiency of the unmanned farm, which is of great positive significance to the construction of the unmanned farm.

3). With the rise of unmanned farm, it has produced a large amount of data in the field of production and intelligent equipment. Machine learning combined with 5G, sensors, big data and other technologies are used to transmit, integrate, process and apply these data, so as to build the farm management system into a real AI system.

4). In view of the problem that most of the current machine learning research are limited to the laboratory, we should strengthen the embedded research of machine learning technology and truly conduct the research in the laboratory in the field. We should strengthen the research on machine learning algorithm, reduce its dependence on the performance of embedded chip, and speed up the training speed and running speed of the algorithm, so as to speed up the application of machine learning in unmanned farms.

In short, the application of machine learning in unmanned farms will have a broader world.

5. Conclusion

This paper summarizes and introduces the relevant literature on the application of machine learning in agriculture in recent years. withdrawing on the practical experience of ecological unmanned farm in Shandong University of Technology, this paper expounds the application of machine learning in field weed identification, crop pest detection and crop yield prediction in planting industry, and its application in the accurate identification and classification of fish, pigs, sheep and other livestock in animal husbandry, fish feeding decision-making system and production line prediction of chickens and cattle. By summarizing the above literature and practical experience, it is concluded that machine learning has disadvantages in the application of unmanned farm, and there are considerable problems in data sets, professionals and embedded systems. Next by summarizing their own practical experience and current research level and problems in unmanned farms, this paper puts forward the development trend of machine learning in unmanned farms, mainly including the establishment of efficient databases, the establishment of "expert systems", and embedded research combined with multi-domain technologies and algorithms.

The application of machine learning in unmanned farms is developing rapidly, and it is also valued by more researchers. More machine learning technologies will be applied to unmanned farms to realize real unmanned operation and promote the rapid and sustainable development of agriculture.

Conflict of interest

The authors declare that they have no conflict of interest.

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