Journal of Agricultural Sciences (Tarim Bilimleri Dergisi) 2024, 30 (2) : 216 – 228 DOI: 10.15832/ankutbd.1339516

Journal of Agricultural Sciences
(Tarim Bilimleri Dergisi)

J Agr Sci-Tarim Bili
e-ISSN: 2148-9297
jas.ankara.edu.tr

JAS

Few-shot Learning in Intelligent Agriculture: A Review of Methods and Applications

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ARTICLE INFO
Review Article
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Received: 08 August 2023 / Revised: 14 November 2023 / Accepted: 07 December 2023 / Online: 26 March 2024

Cite this article
Nie J, Yuan Y, Li Y, Wang H, Li J, Wang Y, Song K, Ercisli S (2024). Few-shot Learning in Intelligent Agriculture: A Review of Methods and Applications. *Journal of Agricultural Sciences (Tarim Bilimleri Dergisi),* 30(2):216-228. DOI: 10.15832/ankutbd.1339516

ABSTRACT
Due to the high cost of data acquisition in many specific fields, such as intelligent agriculture, the available data is insufficient for the typical deep learning paradigm to show its superior performance. As an important complement to deep learning, few-shot learning focuses on pattern recognition tasks under the constraint of limited data, which can be used to solve practical problems in many application fields with data scarcity. This survey summarizes the research status, main models and representative achievements of few-shot learning from four aspects: model fine-tuning, meta-learning, metric learning and data enhancement, and especially introduces the few-shot learning-driven typical applications in intelligent agriculture. Finally, the current challenges of few-shot learning and its development trends in intelligent agriculture are prospected.

Keywords: Few-shot learning; Intelligent agriculture; Meta-learning; Metric learning; Fine-tune; Data augmentation

1. Introduction

With the advancement and evolution of technologies, the development and application of machine learning have become more and more sophisticated (Yang et al. 2022). Represented by convolutional neural networks, machine learning has achieved results comparable to or surpassing humans in many tasks (Nie et al. 2023). Machine learning can achieve such proud results due to the massive data sets and prior knowledge behind it. Unlike humans, which can draw a tiger with a cat as a model, machine learning requires many datasets to train to ensure the accuracy of the results (Li et al. 2021; Li & Ercisli 2023). Currently, machine learning models usually rely on large datasets to ensure the accuracy of training results, which is difficult to achieve in some industries (Volkan et al. 2023). In particular, as represented by the agricultural field, the cost and difficulty of dataset collection and annotation are relatively high, and the construction of large datasets is expensive. In the traditional development of intelligent agriculture, a large amount of data is often required to support the control of the cultivation process of crops. By utilizing few-shot learning, the amount of data required can be significantly reduced, and the implementation cost is much cheaper. Therefore, in order to reduce the dependence on large datasets, the research on few-shot learning has begun to go into depth gradually, and how to reduce the massive demand of data for machine learning models through scientific methods has become a hot issue in current research (Parnami & Lee 2022; Yang et al. 2022).

Few-shot learning can be defined as machine learning with limited data supervision. A machine learning model learns feature information of relevant classes with only a few data samples (Wang et al. 2020). Inspired by the fact that human children can recognize an animal species through a few pictures in an encyclopedia, researchers want machine learning models to have such capabilities. Research on few-shot learning is gradually emerging. Especially in the field of intelligent agriculture, research on few-shot learning has been very popular, and many excellent modeling algorithms based on few-shot learning have been applied in the fields of crop image recognition and classification (Yang et al. 2022).

In the case of few-shot learning, researchers mostly conduct research from two perspectives. One is to start from the data, expand and supplement the data, and strengthen the diversity of data features. And the other is from the perspective of the network model. The network model plays a vital role in machine learning performance. A good network model framework structure and reasonable network model parameters can significantly improve the network model's accuracy, generalization ability, fast convergence ability, and other performance. Using different machine learning frameworks, researchers optimize and adjust the network model's parameters and structure to make it perform well in the case of few-shot data. Therefore, in the development of few-shot learning, it is possible to broadly classify few-shot learning into the following categories according to the specific methods used: few-shot learning based on model fine-tuning, few-shot learning based on meta-learning, few-shot learning based on metric learning, and few-shot learning based on data augmentation. The Basic ideas of each few-shot learning are shown in Table 1. At present, with the continuous development and optimization in few-shot learning, a large quantity of application cases of few-shot learning have emerged in many industries, such as remote sensing computer vision (Sun et al. 2021; Guo, Wang et al. 2022), intelligent agriculture (Li & Yang 2021; Nie, Wang et al. 2022a;), biomedicine (Yin et al. 2020), plant protection (Li et al. 2020; Li & Chao, 2021b), magnetic field physical and chemical parameter prediction (Nie et al. 2021; Nie et al. 2022), geological exploration (Liu et al. 2022), radar ranging (Yue Yang et al. 2021), point cloud segmentation (Guo et al. 2020), etc.

Table 1- The basic ideas and representative works of few-shot learning

Few-shot learning	*Basic ideas*	*Representative works*
Few-shot learning based on model fine-tuning	Fine-tuning the network model parameters to make the common network model still performs well with few-shot data	ULMFit (Howard & Ruder 2018) co-FCN (Rakelly et al. 2018) LM-BFF (Gao et al. 2020)
Few-shot learning based on meta-learning	Using the meta-knowledge learned by the model in various tasks to adjust the parameters of the model and improve the model’s fast convergence in few-shot tasks	MAML (Finn et al. 2017) ANIL (Raghu et al. 2019) MTL (Sun et al. 2019) MnnFAST (Jang et al. 2019)
Few-shot learning based on metric learning	Using embedding space, determining similarity among samples to reduce the overfitting problem of the model with few-shot data.	FSLM (L. Yang et al. 2020) AMN (Mai et al. 2019) IPN (Zhong Ji et al. 2020) SARN (Hui et al. 2019)
Few-shot learning based on data augmentation	Improve few-shot learning by increasing the diversity of the data and enhancing the original characteristics of the data to make it easier to be classified	TPN (Y. Liu et al. 2018) DAGAN (Antoniou et al. 2017) FATTEN (B. Liu et al. 2018)

This article will outline and respond to the research questions below:
1) How is the present state of studies about few-shot learning?
2) What is the practical application of few-shot learning in intelligent agriculture?
3) What are the challenges that few-shot learning will face in the future?
4) What are the prospects of few-shot learning in intelligent agriculture?

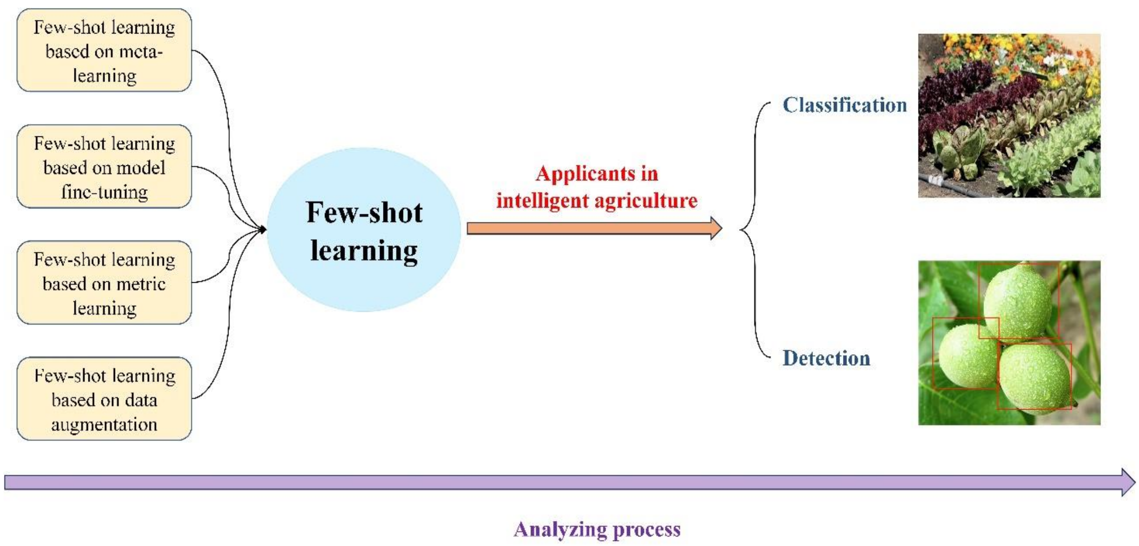

Figure 1- Narrative structure of article

The analyzing process of this paper is shown in Figure 1. We will first summarize the research status of few-shot learning based on model fine-tuning, few-shot learning based on meta-learning, few-shot learning based on metric learning, and few-shot learning based on data augmentation, then summarize the typical applications of few-shot learning in intelligent agriculture, and finally discuss and outlook the future challenges of few-shot learning and the prospect of its development in intelligent agriculture.

2. Few-shot learning based on model fine-tuning

The network model performance depends in part on the initialization parameters of the network model. Due to the small amount of data for few-shot learning, it is hard to train deep models. Many general models have poor convergence in few-shot learning, so since the advent of few-shot learning, the parameter optimization of network models has never stopped. Compared with the research of a new network model, it is easier to upgrade and optimize the key parameters of the old network model. Few-shot learning based on model fine-tuning will firstly train the network model on a dataset with a huge number of samples to generate a pre-trained model, and subsequently adjust the parameters of the top layer of the pre-trained model on the few-shot dataset so that the performance results of the parameter-adjusted network model on the few-shot dataset and the source dataset are similar to achieve the desired results. By fine-tuning the network model with parameters, the network's rapid convergence ability and the network generalization ability are improved. Few-shot learning based on model fine-tuning is shown in Figure 2.

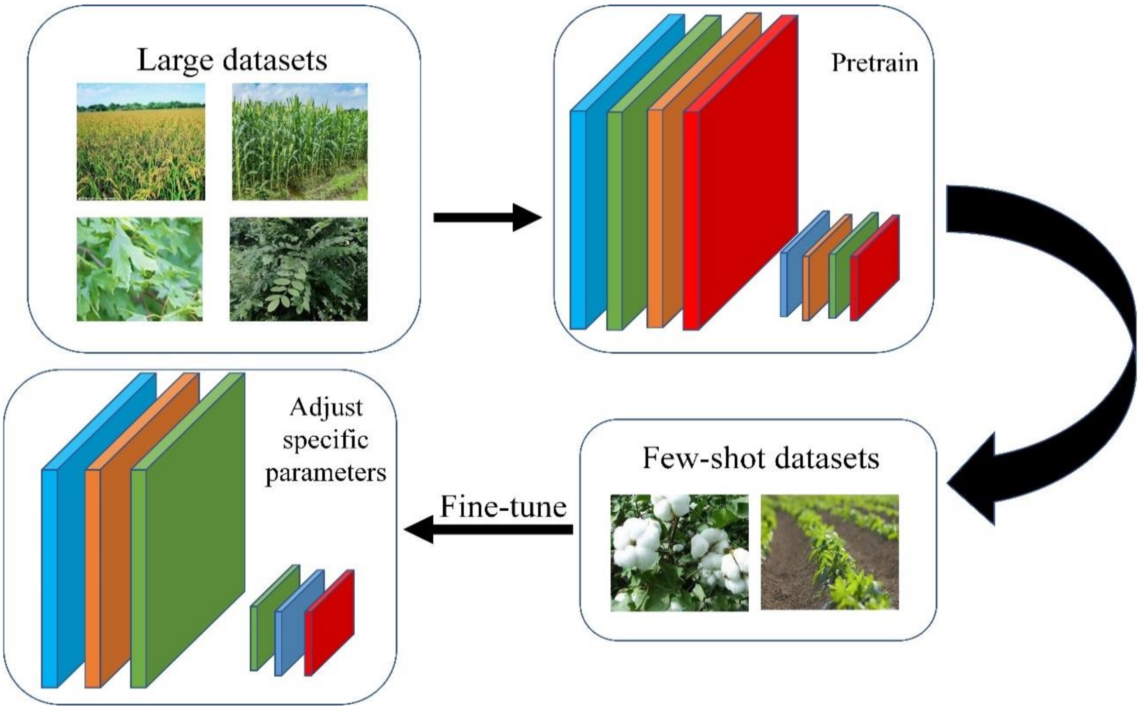

Figure 2- Few-shot learning based on model fine-tuning

Howard et al. (2018) proposed the Universal language model fine-tuning (ULMFit), a method mainly applied to text classification tasks, and obtained favorable results in multiple text classification missions. This method first pre-trains the language model, then fine-tunes the language model to achieve the expected effect by setting the learning rate and slanted triangular learning rates, and finally fine-tunes the classifier to further improve the text classification effect by adding a linear layer to the language model. ULMFit improves the convergence of the model on few-shot datasets and enhances the target classification effect by setting various learning rates for various layers of the language model and proposing slanted triangular learning rates. Rakelly et al. (2018) proposed co-FCN, by introducing conditional information, the network is able to perform semantic segmentation task with only a small amount of labeled data. The model fine-tuning method proposed by Nakamura & Harada (2019) improves the recognition accuracy and reduces the degree of model overfitting by reducing the learning rate when training on few-shot datasets, using an adaptive gradient optimizer, and adjusting the entire network. Chen et al. (2019) summarize and compare the existing methods. The authors study the influence of data, network structure and other factors on different methods, which provide directions and guidelines for subsequent research. Dhillon et al. (2019) verified the good effect of transductive fine-tuning for improving the performance of few-shot learning, analyzed the limitations of the current benchmarks, and proposed a new index to measure the performance of few-shot learning. Inspired by the GPT-3 model, Gao et al. (2020) proposed a model fine-tuning method LM-BFF based on a language model, which can fine-tune language models with few-shot samples. This method mainly includes automatically constructing templates and tag word maps, automatically combining templates and tag word maps into prompts, fine-tuning templates according to prompts, and dynamically selecting sample instances as input contexts. The authors' team conducted experiments on multiple few-shot datasets, and the results showed that LM-BFF method significantly outperformed other standard fine-tuning methods, and its average performance improvement could reach about 11%. Tian et al. (2020) concluded that the performance of embedding model plays an important role in few-shot classification. The authors used self-distillation to further enhance the feature extraction effect and realize the performance improvement. Boudiaf et al. (2021) found that the way in which inference is performed has a large impact on the performance of few-shot learning, which has often been overlooked by previous studies. The authors utilized a new loss containing complementary phases to improve the original performance. In order to solve the forgetting problem in few-shot learning, (Fan et al. 2021) designed Retentive R-CNN and tested its good performance through experiments. Kaul et al. (2022) presented a pseudo-labeling method for the target detection task. The method can generate high-precision pseudo-labels, eliminate the class imbalance problem, and improve the accuracy and effect of detection.

As a relatively simple and general method, few-shot learning based on model fine-tuning can significantly improve the problems of poor convergence, poor generalization ability, and poor recognition accuracy of ordinary networks in the face of few-shot datasets. Researchers have achieved fine-tuning of the network model by improving the pre-trained model or changing the learning rate of the network. However, it is notable that few-shot learning based on model fine-tuning is prone to overfitting problems, which will also become the focus of researchers' future research. For the intelligent agricultural field, using few-shot learning based on model fine-tuning to reduce the cost of data collection is a relatively easy way to realize. By changing the parameters and structure of traditional models, accurate analysis of agricultural data can be realized.

3. Few-shot learning based on meta-learning

Meta-learning focuses on allowing machine learning to acquire the ability to learn, allowing machine learning to learn, and its purpose is to make machine learning have the ability to carry out analogical associations like people (Wang et al.2022). Through this learning ability, machine learning can learn meta-knowledge in different tasks and apply this meta-knowledge to future tasks. Meta-knowledge includes loss, noise, optimizer, and so on. Few-shot learning based on meta-learning improves the effectiveness of few-shot learning by using meta-knowledge learned from other tasks to parameterize the target task model based on the target task training. At present, few-shot learning based on meta-learning includes model-agnostic meta-learning methods, meta-transfer learning methods, and memory-augmented neural network meta-learning methods.

3.1. Model- agnostic meta-learning method

The applicability of the model-agnostic meta-learning method is very broad, and most models can be used with this method. The model-agnostic meta-learning (MAML) framework proposed by Finn et al. (2017) is a typical representative, which optimizes the model by using gradient descent methods. The focus of MAML is to find a weight for the model with strong generality and universality, which enables the model to be well applied to the new task after several gradient descents and improves the model's fast convergence in the face of few-shot data tasks. But at the same time, MAML also has certain shortcomings. It is more sensitive to the network structure and its stability is not high during training. The model is also computationally intensive and takes a long time to train. In order to solve these problems, Antoniou et al. (2018) proposed various modifications to MAML by using Multi-Step Loss Optimization (MSL), Derivative-Order Annealing (DA), Learning Per-Layer Per-Step Learning Rates and Gradient Directions (LSLR), Cosine Annealing of Meta-Optimizer Learning Rate (CA) and other methods. Greatly improved its stability, generalization performance, convergence speed, and reduced its training time. Among them, MSL can mainly enhance the generalization performance and stability of MAML. DA can solve the gradient explosion problem in the training process. LSLR can reduce the computing memory and help alleviate the problems of overfitting. CA can adjust the meta-optimizer to improve the fitting effect and generalization performance of the model. Raghu et al. (2019) also optimized MAML, simplified and improved the MAML framework by removing the inner loop updates of all neural networks except the head, and proposed the Almost No Inner Loop (ANIL) algorithm.

3.2. Meta-transfer learning method

Meta-transfer learning method incorporates the advantages of meta-learning and transfer learning. A Meta-Transfer Learning (MTL) model was proposed by Sun et al. (2019). In general, deep neural networks are easy to overfit few-shot data, so meta-learning usually uses shallow neural networks, but shallow neural networks will harm the model's performance. MTL models can make good use of deep neural networks to improve model performance under the condition of normal fitfully. Since then, to continue to enhance the MTL model's performance, Sun et al. (2020) introduced the hard task (HT) meta-batch scheme after research, which improved the learning efficiency, fast convergence ability, and accuracy of MLT. Soh et al. (2020) extended meta-transfer learning to zero-sample learning, and found general initialization parameters suitable for internal learning by using the external and internal information of the image. The image recognition effect was good, and the recognition speed was fast.

3.3. Memory-augmented neural network meta-learning method

The memory-augmented neural network meta-learning method is an early proposed method for few-shot learning. Compared with traditional neural networks, memory-augmented neural networks add memory modules and reading and writing mechanisms, which can efficiently learn the display strategy of the corresponding task. Santoro et al. were inspired by the Neural Turing Machine (NTM) (Santoro et al. 2016) and used it to few-shot learning. The author uses an external memory module to store sample features and optimize the read and write mechanism using meta-learning to achieve effective few-shot classification and prediction. To further enhance memory-augmented neural networks performance, Jang et al. (2019) proposed the MnnFAST architecture, suitable for large-scale memory networks. MnnFAST can effectively reduce memory bandwidth consumption and eliminate cache contention. At present, the research on memory-augmented neural network meta-learning is mainly divided into two aspects: hardware (Rae et al. 2016) and network structure (Gulcehre et al. 2017). Relevant researchers hope to further improve memory-augmented neural network meta-learning by enhancing the capacity, speed, architecture or neural network structure of hardware memory modules.

As a popular few-shot learning method, the diversity of methods based on meta-learning is self-evident through the above combing. Allowing machine learning to gain the ability to learn has been a long-standing desire of relevant researchers and an important means of solving few-shot data tasks. Few-shot learning based on meta-learning has broad development prospects in the future. Relevant researchers will continue to optimize meta-learners, improve the interpretability of meta-learning theoretically, and enhance meta-learning performance when performing few-shot data tasks experimentally. In intelligent agriculture, there have been many cases and attempts to utilize few-shot learning based on meta-learning. By combining the features of meta-learning with other methods, related researchers have made good progress in crop detection, farmland segmentation, and so on.

4. Few-shot learning based on metric learning

Metric learning, also called similarity learning. It relies on a set distance function to measure the distance between different samples, and this distance represents the difference between two samples. A larger distance means that the features of the two samples are more different, and a smaller distance means that the features of the two samples are more similar. The distance function is a key part of metric learning as a standard for measuring the distance between samples and is often used as distance functions for deep learning, such as Mahalanobis distance, Euclidean distance, Manhattan distance, or cosine similarity. The metric learning framework generally includes an embedding module and a metric module. The embedding module is responsible for embedding samples into the vector space, and the metric module classifies samples by judging the similarity between samples according to the distance function. The few-shot learning methods based on metric learning mainly include the few-shot learning method based on Siamese neural network, the few-shot learning method based on Matching network, few-shot learning method based on Prototype network, and the few-shot learning method based on Relation network. A generic model for metric learning is shown in Figure 3.

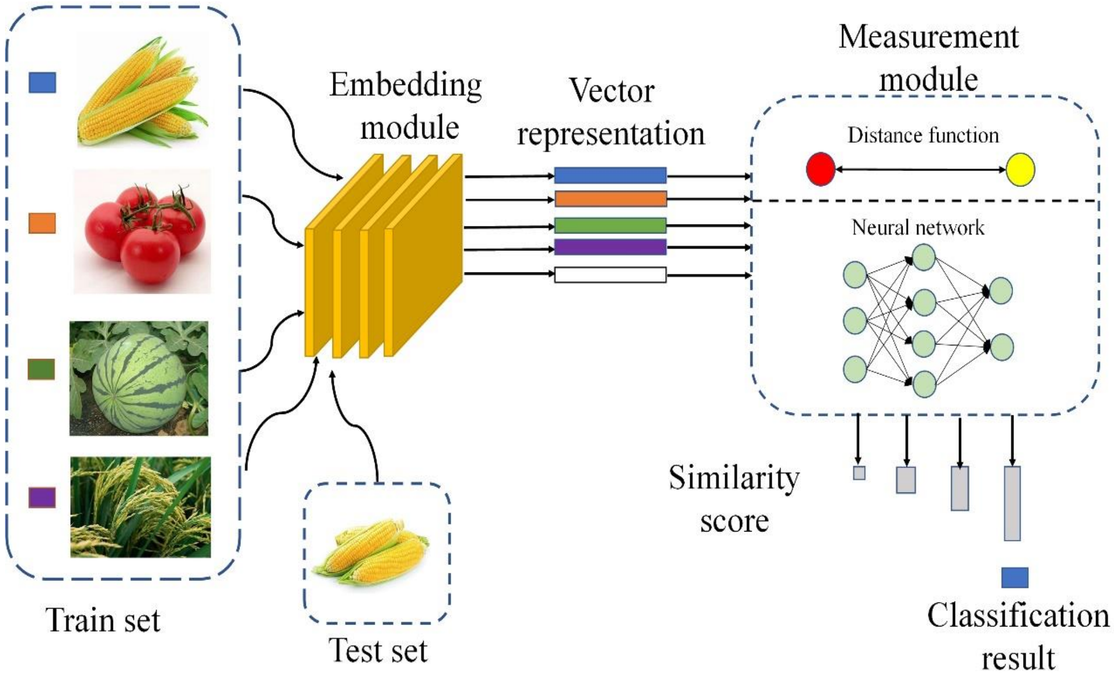

Figure 3- A generic model for metric learning

4.1. Few-shot learning based on Siamese neural network

A few-shot learning method based on Siamese neural network was first proposed by Koch et al. (2015) and the authors used Siamese neural networks to classify and identify single-sample data. The Siamese neural network can be viewed as two neural networks connected by the shared weight method. It contains two inputs, each of which maps one sample input to a highdimensional feature space and outputs a representation. Then the distance function calculates the distance between the two samples to judge the similarity between the two samples. Based on Siamese neural network, Zhou et al. (2020) proposed a few-shot learning model FSL-SCNN, which is used for intelligent anomaly detection in industrial cyber-physical systems. The authors constructed a CNN-based Siamese neural network, which uses optimized features to calculate the distance between samples, alleviates the overfitting problem and improves anomaly detection accuracy. Yang et al. (2020) propose another model FSLM, in which the two subnetworks of the model consist of a self-attention model with the equal parameters. Compared with other few-shot learning methods, the FSLM model has superior accuracy and high robustness in text sentiment analyzing tasks. At present, the few-shot learning method based on Siamese neural network has developed relatively maturely, but its future still has a large development space due to the limitation of hardware conditions.

4.2. Few-shot learning based on Matching network

The most prominent feature of the Matching network is the introduction of an attention mechanism based on cosine distance. The cosine distance calculates the similarity between the training sample and the test sample, and then the similarity is normalized to obtain the attention distribution of the test sample on the training sample. Vinyals et al. (2016) proposed Matching network and applied it to one-shot learning problems in 2016. By introducing attention and memory mechanisms into learning tasks, the authors improved task accuracy on the ImageNet dataset by about 5%. Inspired by Matching network, Bartunov et al. (2018) came up with a Generative Matching Network. The authors improved the model's dynamic prediction performance by adjusting additional input datasets so that the model could quickly learn new concepts that were not in the training data. Mai et al. (2019) proposed an Attentive Matching Network (AMN) to solve the few-shot problem, which uses a feature-level attention mechanism to make the embedding network have better feature extraction capabilities. The authors also introduce a new complementary cosine into the loss function to boost the fit of the network on few-shot tasks.

4.3. Few-shot learning based on Prototype network

To continue to enhance the metric learning performance when facing few-shot tasks, a Prototype network model was proposed by Snell et al. (2017). The basic concept of the Prototype network is first to project the sample into the metric space, then calculate the center of each sample class, and determine the category to an input sample is judged according to the distance from input samples to the centers of different categories. Fort et al. (2017) used the Prototype network extension to generate Gaussian prototypical networks. Unlike prototype networks, a portion of the encoder output in Gaussian prototypical networks is represented as a Gaussian covariance matrix. The authors conducted experiments and tests on the Omniglot dataset, and the results were significantly better than the Prototype network. Ji et al. (2020) improved the Prototype network and proposed Improved Prototypical Networks (IPN). The author's work mainly includes two aspects. The first is proposing an attention analogy strategy, assigning different weights to different representative samples to get more representational weighting prototypes. The second is proposing a distance scaling strategy, which decreases the intra-class differences and enlarges the inter-class differences. These two works enhance the Prototype network's capability to use intra-class distribution information and enhance network's classification performance. Pahde et al. (2021) proposed a multimodal prototype network. The authors designed a cross-modal feature generation framework that can enrich the low-fill embedding space for few-shot data and better use auxiliary information. When processing computer vision tasks, multimodal prototype networks can simultaneously use data from other modalities represented by text to improve classification effects.

4.4. Few-shot learning based on Relation network

Siamese neural networks, Matching networks, and Prototype networks all require distance functions to calculate similarity, but the commonly used distance functions are not applicable to special tasks. To address those special issues, the Relation network came into being. In 2018, Sung et al. (2018) proposed a Relation network model. It calculates the distance between samples and analyzes the similarity between samples by constructing a neural network. The relationship network generally includes two sections. One is the embedding module, which is for withdrawing feature information of the sample. The other is the relation module, which calculates and compares similarities and outputs the similarity scores among samples. Hui et al. (2019) proposed a self-attention relation network (SARN) based on the Relation network model. The authors add an attention module to the Relation network model and use it to enhance the learned features. Wu et al. (2019) proposed a Position-aware relation network (PARN). The traditional Relation network uses CNN for distance calculation. The authors improved by introducing a deformable feature extractor (DFE) and designing a dual-correlation attention mechanism (DCA) to improve the detection accuracy of the network while making the network more lightweight.

Few-shot learning based on metric learning is now relatively mature. The emergence and development of the Relation network have made few-shot learning based on metric learning get rid of the shortcomings of only relying on a distance function. Compared with the traditional relying on distance function for similarity measurement, relying on deep neural networks for similarity measurement method has a wider range of application and higher classification accuracy. Relation network will also become the main direction of the few-shot learning based on metric learning in the future. As a comparatively well-established method, few-shot learning based on metric learning is playing an increasingly important role in intelligent agriculture. Especially in crop species, pest and disease identification, metric learning provides ideas and guidelines for solving agricultural few-shot problems.

5. Few-shot learning based on data augmentation

Data has a very important impact on the results of machine learning, and high-quality datasets are indispensable for satisfactory learning results, especially for few-shot learning (Li et al. 2022). To make few-shot learning have a high accuracy rate, relevant researchers began to study few-shot learning methods based on data augmentation. The researchers mainly start from two perspectives, one is to expand the original data, and the other is to enhance the characteristics of the data. Data enrichment refers to adding new data to the original data, such as unlabeled or synthetic labeled data. Feature enhancement refers to adding new features that are more obvious and easier to distinguish from the original data. There are three main methods of few-shot learning based on data augmentation: methods based on unlabeled data, methods based on data synthesis, and methods based on feature enhancement.

5.1. Methods based on unlabeled data

This method enriches few-shot dataset by adding unlabeled data to it. Common methods mainly include unsupervised learning, semi-supervised learning, and transductive learning. In this case, unsupervised learning refers to learning training samples without labels, which does not require the dataset author to label the dataset. The class of the training samples is unknown and needs to be classified according to the similarity between samples. Ji et al. (2019) studied a method for unsupervised few-shot learning by self-supervised training, which generates pseudo-labeled training examples by progressive clustering and optimizes data feature representation by episodic training to improve few-shot learning accuracy. Khodadadeh et al. (2019) investigated an UMTRA algorithm for few-shot data classification tasks. The algorithm combines the characteristics of meta-learning and unsupervised learning, and authors conducted experiments on Omniglot and Mini-Imagenet datasets with very good results. Lee & Chung (2021) proposed an Early-Stage Feature Reconstruction (ESFR) method for few-shot data classification. After a series of studies, the authors found that early generalization features during unsupervised training greatly help identify new few-shot sample classification.

Applying semi-supervised learning to few-shot learning is always a popular field for machine learning. Nassar et al. (2021) investigated SemCo, a semi-supervised learning approach combining label combination and joint training. It fully considers the visual similarity between categories and improves the accuracy of image classification by training two classifiers separately and training them jointly. Li et al. (2021a) came up with a semi-supervised learning approach using confidence interval adaptive selection of unlabeled samples for pseudo-labeling. The authors fully considered the problems of domain splitting and few-shot parameters and conducted experiments on the PlantVillage dataset. The average improvement rate obtained was satisfactory. Chao & Li (2022) put forward a semi-supervised few-shot classification approach on the basis of KNN distance entropy. It uses KNN distance entropy to automatically assign pseudo-labels and improve the data quality and the effect of few-shot learning.

Transductive learning is a sub-problem of semi-supervised learning, which will utilize unlabeled data as test data to enhance the generalization ability of the model. Through transductive learning, the model is exposed to not only training samples but also test samples while learning, fully utilizing various feature information from the data. Liu et al. (2018) presented the TPN that fully uses the idea of transductive learning. The network uses a graph construction module to learn how to pass labels to unlabeled samples. According to transductive learning, a cross-attention network was also proposed by Hou et al. (2019), which improved the recognition rate of features by introducing cross-attention modules to generate cross-attention maps for category features and query sample features. The authors also proposed a transformation reasoning algorithm to increase the representativeness of features through iterative methods. Ma et al. (2020) combined the idea of transductive learning with a graph neural network to propose a Transductive Relation-Propagation Network (TRPN). The authors modelled support-query pairs for the first time in the industry to consider support-query pairs relationships in few-shot learning problems.

5.2. Methods based on data synthesis

The method based on data synthesis mainly adds the synthesized new labeled data to the few-shot data to complete the expansion of the few-shot data. The common methods include Generative Adversarial Network (GAN), improving the optimization encoder, etc. The Generative Adversarial Network model is shown in Figure 4. Mehrotra & Dukkipati (2017) propose a generative adversarial residual pairwise network based on the GAN and uses the residual pair to measure the similarities among samples to solve single-sample problem. Antoniou et al. (2017) propose a data augmentation generative adversarial network (DAGAN) based on a Generative Adversarial Network, which can automatically learn augmented data and improve the performance of classifiers. In order to continue to enhance the generalization performance and feature interpretability of the generated data, (Xian et al. 2019) combined Variational autoEncoder (VAE) and GAN to develop a feature generation framework F-VAEGAN-D2. It generates features with good interpretability and can better complete the classification task of few-shot images. Zhou et al. (2021) put forward a data augmentation approach FlipDA that automatically performs label inversion. The authors found that label-flipping data had a greater impact on performance than other data, so using generative models and classifiers to generate label-flipping data greatly improved the effectiveness and robustness of data augmentation.

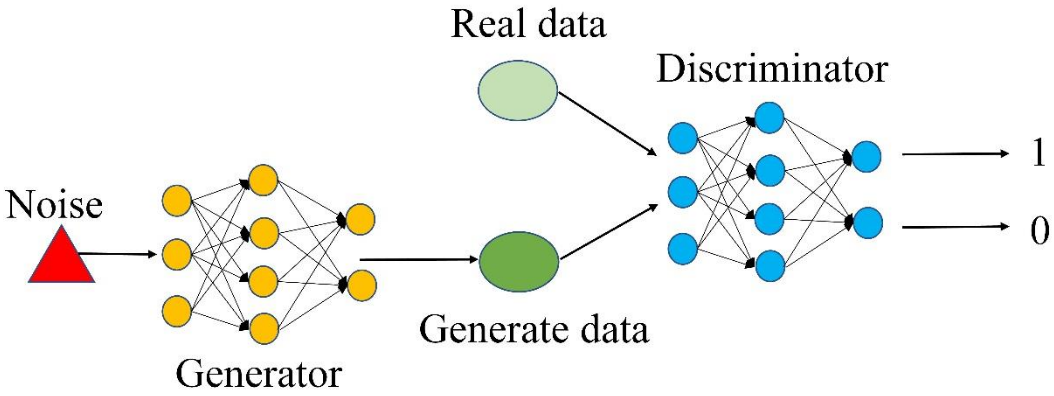

Figure 4- Generative Adversarial Network model

5.3. Methods based on feature enhancement

The main difficulties few-shot learning faces are the small amount of data and low sample diversity. As a common data augmentation method, the methods based on feature enhancement can make up for the lack of sample diversity. Its main principle is to improve the diversity of samples by enhancing the feature space of few-shot data.

In order to address the issue of data expansion in feature space, Liu et al. (2018) put forward a FeATure TransfEr Network (FATTEN). It is a feature transfer network that enables effective end-to-end training and can well record the feature trajectory of object attitude transformation. The authors conducted experiments on one-shot data and few-shot data to verify the good performance of FATTEN. Chen et al. (2018) achieved the enhancement of the feature space of few-shot data using semantic information. The authors propose a two-way network model TriNet. It first uses ResNet-18 network to withdraw the characteristics of input image, then maps the image characteristics to the semantic space for feature enhancement using TriNet's encoder, and finally maps the characteristics back to the image using the TriNet's decoder. Shen et al. (2019) used an uncertain attention mechanism on the model to improve model's generalization ability when facing few-shot data, and achieved optimization of network performance by using high-level features to guide the bottom-level features.

In summary, few-shot learning based on data augmentation has greatly progressed. Data is a crucial point in machine learning, and it is important to solve few-shot problems in terms of data viewpoint. Through data expansion and character enhancement, few-shot learning based on data augmentation can solve most few-shot issues with broad development prospects. From the perspective of data augmentation, further mining and expansion of agricultural data can reduce the cost of intelligent agriculture deployment and enhance the effectiveness and utilization of intelligent agriculture, leading to its wider application in some developing countries.

6. Applications of few-shot learning in intelligent agriculture

In the field of intelligent agriculture, researchers usually use devices represented by drones for data acquisition. The cost of data acquisition is high, the amount of data is few, and it is suitable to use few-shot learning for the research of related problems. Compared with traditional methods of intelligent agriculture, utilizing few-shot learning can reduce the difficulty and cost of data collection and further expand the scope of intelligent agriculture applications. At present, the application of few-shot learning in the field of intelligent agriculture mainly includes plant disease identification, pest identification, crop detection, and so on (Subburaj et al. 2023; Varol et al. 2022). We summarize few-shot learning’s common applications in intelligent agriculture and count the number of publications in the Web of Science (WOS) Core Collection database and Engineering Village (Ei Village) database over the last five years. The details are given in Figure 5 and Table 2. Also, the detailed specific applications of few-shot learning in intelligent agriculture over the past few years are further described.

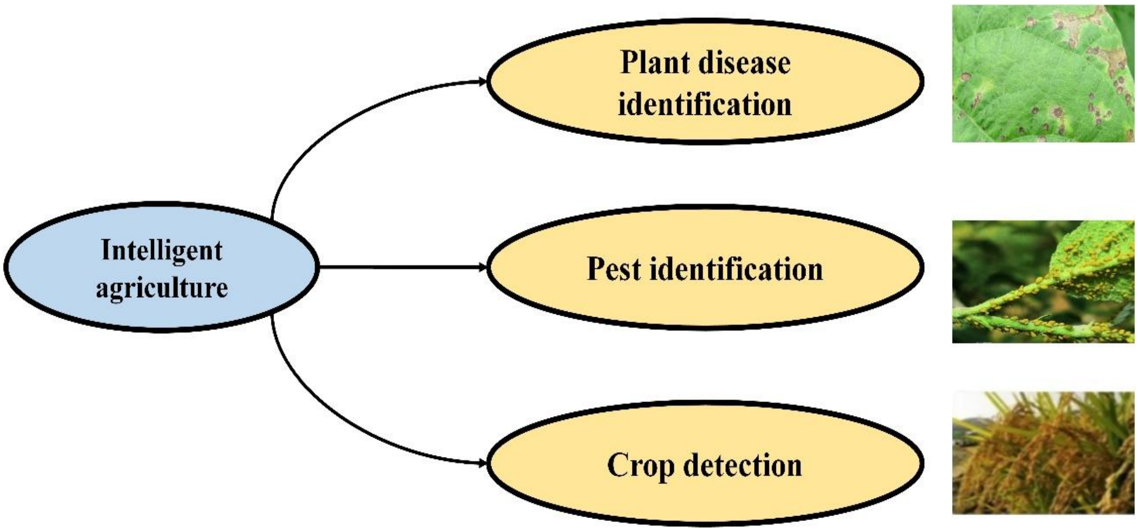

Figure 5- Common applications of few-shot learning in intelligent agriculture

Table 2- Literature publications on common applications of few-shot learning in intelligent agriculture

Common application	*Publish time*	*Search condition*	*Number of literatures*	
			WOS	*Ei Village*
Plant disease identification		Topic = few-shot learning And Topic = plant disease	37	31
Pest identification	2019-2023	Topic = few-shot learning And Topic = pest	18	14
Crop detection		Topic = few-shot learning And Topic = crop detection	25	25

6.1. Plant disease identification

Recognition and classification of plant diseases has always been an important problem facing intelligent agriculture, and how to extract disease features efficiently and realize high-precision classification is the direction of related researchers' continuous efforts. Argüeso et al. (2020) solved the problem of plant disease classification using few-shot learning. The authors used plant leaf images as the basis for the classification of different plant diseases and used a deep learning network model with triple loss, which greatly reduced the data sample requirements during training while improving the classification accuracy. Nuthalapati et al. (2021) realized the classification of plant diseases by using metric learning. The authors also produced a few-shot plant disease dataset, which provides some help for the subsequent related research. Chen et al. (2021) proposed an LFM-CNAPS model based on meta-learning. The model can predict unknown plant diseases with a small number of annotated samples, and at the same time, it can generate classification heatmaps for visualization. The authors produced a few-shot dataset of plant diseases and validated the LFM-CNAPS model on this dataset, obtaining good classification results. Wang et al. (2021) also improved meta-learning and proposed an IMAL model. The model has good fitting ability and generalization performance, and can achieve accurate classification of plant diseases. Aiming at the problem of limited feature extraction ability of few-shot learning, (Lin et al. 2022) enhanced the effect of plant disease feature extraction and improved the recognition of plant diseases by using the attention mechanism.

In the case of plant diseases, which are more diverse and have fewer samples, these problems can be adequately addressed using few-shot learning. Existing methods have demonstrated the bright future of few-shot learning in the field of plant disease identification.

6.2. Pest identification

Pests is a key factor affecting crop harvesting, using few-shot learning to accurately discover and identify pests is an important method to improve crop yield. Li et al. (2020) applied few-shot learning to identify cotton pests and diseases and greatly reduced the difficulty of collecting cotton pest and disease datasets by using few-shot learning. The authors extract the characteristics of disease and pest pictures and designed corresponding control programs and embedded terminals to realize the identification of pest species on cotton. Pandy et al. (2022) implemented rice pest recognition using meta-learning approach. The authors concluded that there are many species of rice pests and it is not realistic to collect a large amount of sample data for each pest, and this problem can be well solved by using few-shot learning based on meta-learning. Gomes et al. (2022) utilized a prototype network to achieve accurate recognition of pests. At present, the use of few-shot learning for pest identification and the construction of corresponding hardware terminals for control has become a popular direction for the development of few-shot learning in the field of intelligent agriculture.

Pests tend to be small in number and are often confused with the environmental context. Therefore, few-shot learning needs to further improve the ability to extract features in complex backgrounds to improve the recognition accuracy.

6.3. Crop detection

Crop detection first requires precise classification of the desired crop. Mixed planting is a popular way of planting nowadays. When working in large fields, farmers often mix several different crops to promote each other's growth and improve the yield and economic benefits. Thus, how to classify the crops in the field and how to accurately detect the desired crops have become a hot topic of concern. Bargiel et al. (2017) combined the climatic changes with remote sensing images, and proposed a high-precision crop classification method which is able to accurately classify crops such as maize and oilseed rape. Zhong et al. (2019) designed a one-dimensional convolutional layer deep learning model, which realizes an efficient classification. Once the crop has been classified, the location of the crop needs to be accurately located and the crop contours need to be precisely segmented. Hamuda et al. (2017) designed a crop detection network based on color features and morphological features with 99.04% detection accuracy. Zheng et al. (2019) constructed the CropDeep dataset, which contributes to few-shot crop classification and detection in intelligent agriculture. Zhao et al. (2020) designed a crop detection method based on transfer learning, which provides a reference for intelligent agriculture.

Few-shot learning has been relatively well developed for crop detection. In the future, researchers need to focus on data acquisition methods and conduct continuous research from the perspective of reducing data acquisition costs.

In summary, the application and development of few-shot learning in the field of intelligent agriculture has made great progress and has become an indispensable part of the development of intelligent agriculture. We have reason to believe that few-shot learning will make outstanding contributions to promoting the further development of intelligent agriculture.

7. Challenges and prospects

Based on the above summary of few-shot learning development and applications, we have the following views on the main challenges that few-shot learning will face going forward:

1) Smaller sample size means higher risk of overfitting. Further improving the over-fitting ability of few-shot learning is a major challenge for the future, and researchers need to continue to carry out in-depth research.

2) As technology continues to develop, data collection is becoming less difficult. At this time, the original few-shot data is likely to be expanded, just based on the amount of data defining few-shot may not be applicable. How to define few-shot and many-shot still need relevant scholars to study?

3) It is still worth exploring how to transfer few-shot learning methods from some specific fields to other emerging fields and increase their interpretability.

Based on the above summary of few-shot learning development and applications, we have the following views on the development prospects of few-shot learning in intelligent agriculture:

1) The overfitting problem is a severe test for few-shot learning based on model fine-tuning. The focus of future development will be to address the overfitting problem; researchers will continue to pay attention to the learning rate of different layers of the network to find ways to address the issue.

2) Concerning few-shot learning based on meta-learning, researchers will keep optimizing meta-learner, drive the continuous development of few-shot learning through meta-learning, apply few-shot learning based on meta-learning more diversified in intelligent agriculture.

3) For few-shot learning based on metric learning, the key research approach in the future will be the optimization and improvement of metric methods. Using neural networks for similarity calculation will be the mainstream trend of few-shot learning in intelligent agriculture.

4) For few-shot learning based on data augmentation, researchers need to make good use of unlabeled data further, make good use of a large amount of useful feature information hidden behind unlabeled data, and use various methods to enhance the ability to extract foreground objects in the complex background.

5) Overall, few-shot learning has a bright future in intelligent agriculture.

To summarize, the role of few-shot learning in intelligent agriculture will be more and more important. An essential feature of intelligent agriculture is to reduce the workload of related personnel and the cost of related work. By utilizing few-shot learning, the dependence of intelligent agriculture on a large amount of data will be reduced, and the degree of smartness will be further enhanced. For few-shot learning, the future focus is to further enhance the feature extraction ability and data augmentation ability, improve the accuracy of detection and segmentation, and increase the ability to accurately recognize the target in a complex background. Meanwhile, the existing literature mostly illustrates and improves the method of few-shot learning, and lacks research in hardware implementation. Therefore, it is necessary to further promote the hardware deployment effect of few-shot learning and reduce the cost of hardware deployment, so that it can be more widely used in intelligent agriculture.

8. Conclusions

In this paper, we summarize the main methods and development of few-shot learning from four aspects: few-shot learning based on model fine-tuning, few-shot learning based on meta-learning, few-shot learning based on metric learning, and few-shot learning based on data augmentation. In addition, we also describe and analyze the different applications of few-shot learning in intelligent agriculture, predict the future challenges and development prospects of few-shot learning. After exploring and summarizing, we can find that the development of few-shot learning is inseparable from people's desire to reduce the data collection workload and cost. Because some data are difficult to collect in large quantities, few-shot learning can achieve such rapid and high-quality development. As a typical representative of the high cost of data collection and the difficulty of data collection, the development of few-shot learning used in intelligent agriculture is even more diverse and novel. With the continuous advancement and development of machine learning technology, few-shot learning will eventually show its potentials in various fields represented by intelligent agriculture.

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