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Application of deep learning in smart agriculture research

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Abstract. With the breakthrough of deep neural network research, deep learning technology has developed rapidly and has been widely used in the area of smart agriculture and has achieved great accomplishment in target detection and recognition, numerical weather forecasting and data analysis. This paper summarizes the application of deep learning technology in three aspects: detection and identification of pests and diseases, weather forecast and breeding. At the same time, this paper further discusses the major challenges and future development directions of the application of deep learning technology in the area of smart agriculture, and provides a reference for further research into deep learning in the area of smart agriculture. Accurate identification of crop pests is an important prerequisite for pest prediction and control. Image recognition has recently emerged as the primary technological tool for pest management due to its benefits of high efficiency, cheap cost, and simple operation. Future trends in the realm of pest identification and detection include the fusion of transfer learning and deep learning. Deep learning has great advantages in computing efficiency, accuracy, portability, synergy, flexibility, and ease of use. It will be possible to change the traditional meteorological observation mode, accelerate and improve the processing of meteorological observation data. Future development trends include combining the benefits of deep learning and numerical forecasting. Deep learning has made many advances in the fields of genomics, transcriptomics, proteomics and synthetic biology, and can provide a powerful driving force for the fields of crop breeding and plant genomics. Standardized collection, processing, storage and management of data, and the establishment of an open and shared database are some of the future research directions.

Keywords: Deep Learning, Smart Agriculture, Detection and Identification of Pests and Diseases, Weather Forecast, Breeding.

1. Introduction

The accuracy of target identification and recognition has improved thanks to deep learning, which also significantly cuts the time required for manual feature extraction thanks to significant advances in deep learning neural network training and increased processing power. This also enables deep learning to achieve many results in numerical weather forecasting and data analysis.

At present, most of the applications of deep learning in the area of smart agriculture have begun to be implemented, but related applications still need further optimization and improvement. The application of deep learning in the area of smart agriculture has been summed up by certain academics. Zhang Meng et al. described the application of deep learning in image recognition of crop pests and diseases[1]. Du Zhitao et al. introduced the application status of machine learning in the area of meteorology[2]. In addition to introducing the use of deep learning in plant genomics, Hou Xiangying also examined the future potential of deep learning in crop genetic advancement [3]. The above work is an introduction to the application of deep learning technology in a specific aspect of smart agriculture, and lacks an overview of the overall situation in recent years.

This essay divides the application of deep learning in the area of smart agriculture into three main aspects: detection and identification of pests and diseases, weather forecast, and breeding, and analyzes the research background, main achievements, research progress, challenges, and corresponding solutions for each aspect. This paper provides a reference for further research on deep learning in the area of smart agriculture.

2. Pest detection and identification

Recent advances in deep learning have been made in a number of artificial intelligence domains. Its unique feature description method can learn features autonomously driven by training data and has good universality and adaptability. Convolutional neural networks (CNN), a well-known example of deep learning, excel at image identification, classification, and recognition. Compared with traditional algorithms for extracting features manually or relying on prior knowledge, CNN can directly generate local perceptual regions on the image, and obtain key features in the image autonomously through multi-layered filter training,which greatly reduces the training error due to human misjudgment. Cheng Xi et al. used GoogLeNet and AlexNet models to identify stored grain pest images, and the accuracy rates were both above 95% [4]. Liu et al. designed an agricultural pest classifier using local feature learning through a deep convolutional neural network, and the average accuracy on the test dataset was 95.1%[5]. With a recognition accuracy rate of 91.5%, Yang Guoguo et al. suggested a deep learning model based on a convolutional neural network that can swiftly and precisely find and identify 23 different pests from the tea garden environment [6]. In view of the characteristics of pest images with high interspecific similarity, large intraspecific variability, rich posture changes, and easy occultation by crops, CNN has better adaptation than traditional methods and can achieve higher performance in multi-type pest image recognition.

3. Weather forecasting

Weather forecasts play an important role in agricultural production. By mastering the weather conditions, farmers can rationally arrange agricultural activities to minimize the damage to agricultural production caused by weather changes so as to ensure high agricultural yields. At present, meteorological forecasting methods are divided into numerical meteorological forecasting and numerical driving methods. The former uses statistical or machine learning techniques to estimate the future development of the atmosphere, while the latter relies on large-scale computers to solve atmospheric physical models and produce forecast results. Numerical forecasting methods have been developed for a long time, and their atmospheric physical models have been continuously improved, so they have become the mainstream meteorological forecasting methods. However, due to the coordination problem of the physical model, the forecast deviation occurs in some cases. In addition, due to the long time required for large-scale numerical calculation, it faces the disadvantages of high cost and slow response in the forecast of sudden weather and short-term weather. In contrast, the deep learning model has been trained and its prediction results are almost real-time.

It is more suited for short-term and abrupt weather forecast since it is cheaper and faster to respond than the numerical forecast method. However, due to the chaotic nature of meteorological models, the long-term forecast accuracy of deep learning networks is not as good as numerical calculations. Liu Xinda conducted a comparative analysis of shallow machine learning and deep learning methods, using the data of the NOAA (National Oceanic and Atmospheric Administration) Yinchuan weather station from 1956 to 2015[7]. Among the 24 items of original data, 12 items of experimental data, including time, wind direction, and wind speed, were determined. Matlab and LibSVM software were used to estimate the air temperature using shallow neural networks, SVM models, SAE models, and DBN models, respectively. The experiment discovered that the prediction result utilizing deep learning (65%) was not much different from SVM but significantly higher than that of a shallow neural network (59%). The reason is that the network model of deep learning has fewer layers due to the influence of the amount of data. For example, the DBN model only builds 3 layers, which does not

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actually give full play to the benefits of deep learning in solving large data volumes. Yang Han screened the meteorological data in Shenyang from 1980 to 2014, retained the nine-dimensional attributes of the data, and selected a more optimized ReLU as the activation function[8]. In order to improve the network's ability to express time series, the RNN-LSTM network with an LSTM unit is utilized, and the FNN network and the ARIMA model are compared. After computing experiments in the TensorFlow environment, it was found that compared with the other two, RNN-LSTM showed a more accurate prediction value in temperature prediction, and as the prediction time increased, the accuracy decreased less than the other two.

The deep learning model with a multi-layer structure is better appropriate for meteorological prediction than the typical BP neural network due to the clear high-dimensional properties of meteorological data. In addition, meteorological data has obvious temporal characteristics, so models in deep learning that reflect time series well, such as the RNN-LSTM model, have significantly better prediction effects than ordinary models.

4. Breeding

Because traditional machine learning methods based on linear models do not take into account the molecular mechanism underlying the biological process, features learned on a gene cannot be applied to genes with similar molecular mechanisms and cannot predict the phenotypic effects of low-frequency and rare variants. This results in low model universality and adaptability. Deep learning models with genome sequences as predictors can overcome this difficulty. For the purpose of addressing the issue of model "overfitting" brought on by "evolutionary dependencies," the training set and test set data are not randomly distributed in units of single genes but rather in units of gene families. Then, the model was further analyzed by a variety of algorithms, and the key DNA motifs that regulate gene expression were obtained.

On the basis of this model, the relative expression levels of homologous genes were successfully predicted by using two species that were evolutionarily closely related, and the key DNA motifs that regulate the relative expression levels of homologous genes were further obtained. By simulating molecular biological processes, deep learning models can predict causal variants that directly cause phenotypes in natural populations, rather than variants that are closely linked to causal variants.

In several areas of genomics research, deep learning has outperformed conventional approaches, and its use in genomics has already led to important early applications in science and business. Deep learning has expanded a new research perspective for the research of genomics and crop breeding.The continuous improvement of algorithm accuracy has brought new opportunities to promote the research on the correlation between phenotype and genotype at different scales.

5. Challenges and future development

5.1. Pest detection and identification

The following obstacles must be overcome for deep learning to be used in pest detection and identification:

(1) Hardware conditions

Deep learning has high hardware requirements and requires a lot of computing power to process massive amounts of labeled data. Deep learning demands can no longer be met by standard CPUs. Hardware expenses are high because pricey GPUs and TPUs are used in mainstream computing. Numerous programs are still incompatible with use on mobile devices, and the corresponding gadgets are not very portable. Therefore, in terms of pest detection and identification, insufficient hardware facilities have affected the application of deep learning in this area.

(2) Scarcity of high-value samples in recognition model training

Most pests are highly stressed and concealed, and the field environment is complex and there are many unpredictable factors. The collection of pest images is much more difficult than other images, and the amount of data is far from the standard of deep learning. In addition, due to the high similarity between species of pests, some pests need to collect enough high-resolution sample images to build a usable identification model, which makes data accumulation difficult.

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In the future development of deep learning, the focus of investigation may be on how to reduce the need for deep learning on the sample size, and how to reduce the impact of the complex field environment on the recognition accuracy is an urgent task to be completed. The emergence of transfer learning in recent years has made this field have a good development prospect.At the same time, make relevant applications popular on mobile devices as soon as possible.

5.2. Weather forecasting

The following obstacles must be overcome for deep learning to be used in weather forecasting:

（1）The instability of meteorological data

Deep learning's image analysis and recognition technology is extensively employed in post-inversion forecasting, cloud image recognition on satellites, and meteorological radar. Based on a large amount of historical meteorological data, the forecasting effect of meteorological element data is better than that of numerical forecasting, but it is only suitable for stable climate conditions. Deep learning cannot be accurate in advance for extreme, abnormal, and abrupt catastrophic weather processes.

（2）The unpredictability of weather and climate systems

The climate system is a multi-instability source, dissipative, high-order nonlinear system. Deep learning forecasts are wrong because of the intricate internal relationships and arbitrary changes that cause the fluctuation and complexity of weather and climate.

Deep learning, image recognition, and other technologies will be used to play to their benefits in short-term and long-term forecasting, becoming a formidable complement to numerical forecasting. This is the future development trend. In addition, in the era of big data, massive multimedia data is constantly being recorded. How to utilize this data and convert it into the required information is an urgent problem that we need to solve. Building more effective deep models and larger and more accurate datasets is also the direction of development and progress in this field.

5.3. Breeding

The following obstacles must be overcome for deep learning to be used in breeding:

（1）Lack of cross-disciplinary talents

The dearth of cross-disciplinary talent is one of the barriers preventing deep learning techniques from being widely used in genomics. It is essential for those working in the field of genomics to become proficient in artificial intelligence technology methods and adapt it to the unique nature of the difficulties they face. The current talent pool cannot fully meet the requirements of this field, which also affects the application of deep learning in this field.

（2）Small amount of data for training, low reliability and low accuracy

The premise of intelligent breeding is to standardize the big data system, while agricultural data collection is difficult and inconsistent. Training deep learning models requires a lot of data. However, in the agricultural field, the accumulation of crop genotype and phenotype data is insufficient. Crop phenotypic data differ greatly, and it is difficult to control the reliability and accuracy of data collected by different people.

Future development trends may focus on recording high-quality breed data and preserving the full set of genomic and phenotypic data for non-ideal breeds so that data modeling can compare pros and cons and identify genes that regulate superior phenotypic traits. Standardize data collection, processing, storage and management, and establish an open and shared database.

6. Conclusion

This essay summarizes the application of deep learning technology in the detection and identification of pests and diseases, weather forecasting, and breeding, and further discusses the major challenges and future development directions of the application of deep learning technology in the area of smart agriculture. It can be concluded that compared with classical methods of machine learning techniques, deep learning CNN has better adaptation and can achieve higher accuracy in multi-type pest image recognition. However, deep learning has a large demand for samples, and the complex field environment has a great impact on recognition accuracy. The future research directions are how to reduce the need for deep learning on the sample size, and how to reduce the impact of the complex field environment on the recognition accuracy. Meteorological data has obvious high-dimensional and temporal features, so deep learning models are more suitable for meteorological forecasting. Nevertheless, due to the instability of meteorological data and the randomness of the climate system, deep learning cannot accurately predict extreme, abnormal, and sudden severe weather in advance. The goal of future research is to enhance the benefits of both deep learning and numerical forecasting. Deep learning, image recognition, and other technologies will be used to their full potential in short- and long-term forecasting, serving as a potent complement to numerical forecasting. Deep learning has opened a new research perspective for the research of genomics and crop breeding. With the continuous improvement of algorithm accuracy, it has brought new opportunities to promote research on the correlation between phenotype and genotype at different scales. On the contrary, the lack of cross-disciplinary talents and the lack of valuable data have become obstacles to the development of deep learning technology in the area of breeding. The future development trend lies in cultivating cross-field talents, standardizing the collection, processing, storage and management of data, and establishing an open and shared database.

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