Survey on Application of Intelligent Agriculture Based on Deep Belief Network

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Abstract: With the improvement of modern technology, agricultural development continues to be precise, refined and intelligent. The traditional model has low recognition accuracy. Deep belief network (DBN) has strong feature extraction and learning ability. Based on the principle of transmission DBN network, this paper gives the application research progress of the model in intelligent agriculture from the perspective of DBN improvement direction, and finally discusses the challenges and new directions of DBN in the application field of intelligent agriculture.

1 INTRODUCTION

With the rapid development of Internet of things, big data, artificial intelligence and other technologies, agricultural development is moving towards precision, refinement and intelligence (Guo 2019). These agriculture data have the characteristics of large volume, high authenticity, fast generation speed and many data types (Guo et al. 2019). The traditional methods include linear polarization, wavelet filtering and machine learning models have poor generalization ability, low recognition accuracy and instability (LV, Li, et al. 2019).

In order to analyze the growth status of various crops and animals and monitor the agricultural growth environment, deep learning theory is widely used. Deep belief network (DBN) is a typical deep learning model, which constructs a nonlinear deep-seated network structure through self-learning, so as to extract the high-level features of data and accurately fit complex functions (Li et al. 2020). It has been widely used in intelligent agriculture fields such as crop classification, pest prediction, weed identification, breeding monitoring and crop yield prediction.

2 DBN THEORY

DBN is formed by superposition of multiple neurons, and its constituent element is restricted Boltzmann machines (RBMs), which belongs to a probability generation model (Liu, Wang, et al. 2018). By training the weights between its neurons, the whole neural network generates training data according to the maximum probability. As shown in Figure 1, it is a three-tier DBN model.

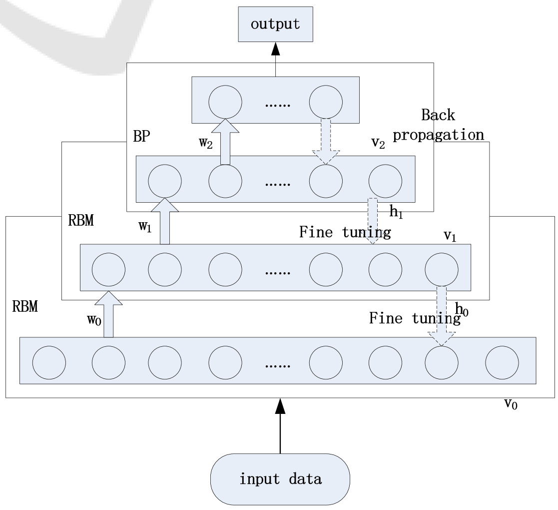

Figure 1: The structure of DBN.

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2.1 RBM Structure and Working Principle

RBM is composed of one layer of dominant neurons and one layer of recessive neurons, and the two layers of neurons are fully connected in two directions, so it is also called neural perceptron. The structure is shown in Figure 2.

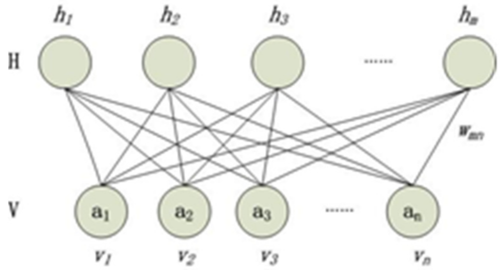

Figure 2: The structure of RBM.

An RBM contains m visual units and n hidden units. For a given set of states (v, h), the energy possessed by RBM as a system is defined as (HAN etc. 2017):

$$E(v,h|\theta) = -\sum_{i=1}^{n} a_i v_i - \sum_{j=1}^{n} b_i h - \sum_{i=1}^{n}\sum_{j=1}^{m} v_i W_{ij} h_j \quad (1)$$

Where $\theta = \{W_{ij}, a_i, b_j\}$is the parameter of RBM, W_{ij} is the connection weight between the visible unit i and the hidden unit j, $a_i$represents the paranoia of the visible unit i, and j represents the bias of the hidden unit. When the parameters θ are determined, the joint probability distribution of (v, h) can be obtained based on formula:

$$\mathrm{P}(\mathrm{v},\mathrm{h}|\theta) = \frac{e^{-E(v,h|\theta)}}{Z(\theta)} \quad (2)$$

$$\mathrm{Z}(\theta) = \sum_{v,h} e^{-E(v,h|\theta)} \quad (3)$$

Z(θ) is the normalization factor.

Because RBM has a special structure of connection between layers and no connection within layers, when the visible cell state is given, the activation states of each hidden cell are conditionally independent. Therefore, the activation probability of the hidden unit is:

$$\mathrm{P}\left(h_j = 1\middle|\mathrm{v},\theta\right) = \sigma(b_j + \sum_i v_i W_{ij}) \quad (4)$$

$\sigma(\mathrm{x}) = \frac{1}{1+\exp(-x)}$Sigmoid activation function.

The maximum likelihood estimation method is used to maximize the above formula to obtain the RBM parameters θ, and then the contrast divergence algorithm is used to obtain the RBM parameters $\theta = \{W_{ij}, a_i, b_j\}$. The update rules are as follows:

$$\Delta w_{ij} = \varepsilon\left(\langle v_i h_j\rangle_{P(h|v)} - \langle v_i h_j\rangle_{recon}\right) \quad (5)$$

$$\Delta b_i = \varepsilon(\langle v_i\rangle_{P(h|v)} - \langle v_i\rangle_{recon}) \quad (6)$$

$$\Delta a_j = \varepsilon\left(\langle h_j\rangle_{P(h|v)} - \langle h_j\rangle_{recon}\right) \quad (7)$$

Where, ε is the learning rate, $\langle\cdot\rangle_{P(h|v)}$represents the limit of partial derivative function under P(h|v) distribution, $\langle\cdot\rangle_{recon}$ represents the limit of the partial derivative function under the distribution of the reconstructed model.

3 APPLICATION OF DBN IN INTELLIGENT AGRICULTURE

The application of DBN in intelligent agriculture generally includes three processes: application data acquisition, feature extraction, recognition and prediction. Data acquisition: collect influencing factors and other parameters according to the actual needs of agriculture; Feature extraction mainly completes the mapping from data space to feature space by DBN unsupervised learning; Recognition and prediction mainly realizes the transformation from feature space to decision space through DBN supervised learning. At present, the main research directions focus on the direct application of DBN and the improvement of network topology, learning process and network parameters.

3.1 Direct Application

In order to improve the efficiency of maize breeding, Article (Yu et al. 2019) is proposed a haploid identification method based on DBN multi variety mixed maize. Through the comparative analysis of SVM, BPR and DBN, the recognition rate of DBN method increased most significantly and the recognition accuracy improved fastest; Aiming at the problems of strong subjectivity and insufficient accuracy of the existing benchmark land price evaluation model, Article (Wang et al. 2018) is proposed an agricultural land benchmark land price evaluation method based on the idea of deep earning. Through repeated experiments, the number of visible and hidden layers and the number of neurons in each layer were determined, and compared with SVM and BP, The accuracy of the model is 6.76% higher than that of the other two models when the time consumption of the model is basically the same; Article (Li et al. 2018) is carried out disease early warning by monitoring pig cough sound, proposed a method to identify pig cough sound based on deep confidence network, and constructed a 5-layer pig cough sound recognition model, with a total recognition rate of 93.21%; Article (Wang et al. 2018) is proposed a depth belief network model with two hidden layers to improve the accuracy of wheat aphid prediction; Article (Guo et al. 2019) is used Gaussian filtering to preprocess the number of images, and designed a DBN containing three hidden layer restricted Boltzmann machines for rice sheath blight recognition, with an average recognition accuracy of 94.05%. The specific progress analysis is shown in Table 1.

3.2 Topology

The network structure of DBN determines the change of network performance, and there is no clear system for the construction of DBN model. On the one hand, the current research is mainly based n the standard structure optimization of DBN. Coefficient DBN has been designed in the field of intelligent agriculture, which is connected with other neural networks such as convolution and self-encoder; On the other hand, the combination with other methods is reflected in the combination of preprocessing method and feature extraction method to design a new optimization model (sohu 2017).
Article (Liu 2018) is proposed a forest land change detection method based on sparse DBN model, which is, adding regular items to RBM to complete the automatic classification of image spots, which

Table 1: Progress in direct application of DBN.

author	Propose method	data sources	input	output	Accuracy	Insufficient
Yu Yunhua	DBN	Collection of data from a suburban experimental base in Beijing	Haploid and diploid grains of 10 varieties	Corn seed species	+6.92%	Strong dependence on sample quality
Wang Hua	DBN	Puning farmland benchmark land price evaluation standard system	19 index evaluation factors	Predicted land price	+6.76%	Subjective setting of hidden layers and neurons
Li Xuan	DBN	School owned boutique pig farm	The sound of 10 Landrace	Pigs Cough recognition	-	Lack of comparative analysis with other algorithms
Xiu Mei Wang	DBN	Yantai plant protection station and related data sets in Shandong Province	mpact data related to wheat aphid occurrence	Occurrence degree of wheat aphids	8.1%	Aphid data samples are few, and the hidden layer is 2
Guo Dan	DBN	Collect the images of Rice Sheath Blight in northern cold area	Preprocessed image data	Occurrence degree of rice sheath blight	3.65%	Manual experience value setting of model parameters

Table 2: Progress in topology structure of DBN.

author	Propose method	data sources	input	output	Accuracy	Insufficient
Liu Run dong	Sparse DBN	Correlation speckle image	Forest land cover index	Forest land and non forest land identification	-	practicability needs to be further verified
Du Jiaxin	DBN+CNN	Multi place video image data set	Forest smoke and smoke-free image	Smoke and smokeless identification	+10.03%	Convolution kernel is set manually
Zhu Zhihui	PCA+DBN	Jingzhou yukou poultry industry Co., Ltd	180 pieces of Jingfen No. 1	male and female classification	+20%	The training time of DBN model is long
Zhou Xiangyu	PCA＋wavelet+DBN	Pond 2-6 of balidian experimental base	16 pond environmental data	Ammonia nitrogen content	MAPE -0.013 9	High calculation time cost
Ying Yi Chen	EMD+GRU+DBN	Microclimate data of a greenhouse in Nanjing	3 kinds of temperature related monitoring information	Temperature in the next 1H	+11.1%	Less feature selection
Lu Wei	EEMD+PCA+DBN	Fluorescence spectra of rice seed soaking solution	Lianjing 7 and Wuyunjing	germination percentage	10%	optimization cannot be guaranteed

can effectively identify forest land and non-forest land information in high-resolution remote sensing; A deep confidence convolution network forest fire image recognition model is proposed in article (Du 2020), which makes feature learning, feature extraction and classifier reconstruction form a DBN_ CNN model improves the probability of forest fire smoke recognition; The machine vision acquisition system is constructed in (Zhu et al. 2018). For the full information features of chicken egg images, the principal component analysis and deep belief network model are used to realize the male and female recognition of three kinds of chicken embryos, and the accuracy is as high as 83.33%;There are many influencing factors of ammonia nitrogen content in pond culture environment and the correlation is complex, (Chen et al. 2019) through principal component analysis PCA, the main factors affecting the change of ammonia nitrogen content are selected as model input, the noise is eliminated by wavelet threshold method, and then the prediction is realized by DBN network. Compared with the traditional model, the average percentage error is significantly reduced; The greenhouse is complex and changeable, the representation ability of environmental factors is low, and the learning time is long, which brings inconvenience to the temperature prediction of agricultural greenhouse (Zhou et al. 2019) A greenhouse prediction method based on improved depth belief network combined with empirical mode decomposition and gated cycle unit is proposed; The spectral data are decomposed into EEMD by ensemble empirical mode in (Lu 2018), and the dimensionality is reduced by PCA through principal component analysis. The prediction model of germination rate based on DBN is established to predict the germination rate of rice seeds nondestructively, which has high accuracy. It's shown in table 2.

3.3 Learning Process

The learning process of DBN includes two stages: forward unsupervised training and reverse supervised fine tuning of RBM. Optimizing the number and structure of RBM stack or improving the reverse fine tuning algorithm are the two main research hotspots. Article (Zhou et al. 2019) introduces glia to improve the depth belief network. Each neuron in the hidden layer will be connected with a glia to predict the greenhouse temperature, and verified its effectiveness in the complex time series environment of the greenhouse; Article (Zhang et al. 2017) added a priori information of winter jujube diseases and pests into RBM based on the improved deep belief network, and the prediction accuracy was improved by more than 20 percentage points through experimental comparison (Xu et al. 2017) proposed a DBN-LSSVR model based on deep belief network fusion least squares support vector regression machine to predict the dissolved oxygen content, which has high prediction

Table 3: Progress in train learning of DBN.

author	Propose method	data sources	input	output	Accuracy	Insufficient
Zhou Xiang yu	Glial RBM	Pond 2-6 of balidian experimental base	16 pond environmental data	Ammonia nitrogen content	MAPE -0.013 9	High calculation time cost
Zhang Shan wen	Prior information RBM	Winter jujube planting base in Dali County	Soil, meteorological and pest information	Classification of 5 diseases and insect pests	+21%	Manual experience setting of model parameters
Xu Long Qin	DBN+LSSVR	A pond in Haiou Island shrimp culture base, Panyu District, Guangzhou	6 breeding environmental factors	Predicted value of dissolved oxygen	MAPE -8.84%	Parameter adaptive learning can be improved
Yuan Hong chun	ARIMA+DBN	Construction data of aquatic product traceability and safety early warning platform	Historical data of hydrolyzed oxygen	Future forecast	MAPE -7.2%	Time series data can be preprocessed
Li Jialang	Cross entropy + DBN	Yamanishi Proposed dataset	Drug protein	Protein sequence similarity	+5%	Practical application scenarios can be considered

Table 4: Progress in network parameter of DBN.

author	Propose method	data sources	input	output	Accuracy	Insufficient
Deng Xiang wu	DBN hidden layer node determination method	Paddy field of agricultural experimental base of Jiangmen Institute of Agricultural Sciences	Rice field weed image data	Weed category	-	Lack of comparative analysis with other algorithms
Xian Feng Wang	Adaptive learning rate DBN	Data of 10 cotton planting demonstration bases in Dali County, Weinan City	12 kinds of environmental information data	Classification of 5 diseases and insect pests	+2.8%	The calculation efficiency needs to be improved
Min Min Wu	PSW / GW optimize DBN initial weight	University experimental greenhouse	Lettuce sample image	Lead content	+11.1%	High computational complexity
Pang Qihua	Adaptive step size DBN	Breiman experiment case	Data of 12 environmental factors	Fruit category	+4.2%	Time series data can be preprocessed

accuracy and generalization ability. Article (yuan et al. 2017) the first mock exam and the deep belief network model are analyzed. An ARIMA-DBN model for predicting the water quality of aquaculture is established. The mean square error is significantly lower than that of the single model. Article (Li et al. 2018) is proposed a drug protein interaction prediction algorithm based on DBN, which outputs the interaction probability in the reverse fine-tuning stage, uses cross entropy as the loss function and soft-max as the output. It's shown in table 3.

3.4 Network Parameters

The network parameters of DBN mainly include the number of hidden layers, the number of neurons in each layer and the value of learning rate. At present, the determination of these parameters mainly depends on a priori knowledge or repeated experiments. Its disadvantages are large subjectivity and high time complexity. Therefore, it is also the research direction of DBN optimization. Article (Deng et al. 2018) in rice seedling stage as the research object, and optimized the number of DBN nodes in double hidden layer by selecting three node combination modes of constant value type, appreciation type and value reduction
type. Through comparative analysis, they have a higher recognition rate; (Wang et al. 2018) is proposed a DBN training model with adaptive learning rate in order to overcome the slow convergence speed of DBN in the prediction of cotton diseases and pests; Article (Wu et al. 2020) is proposed to build a lead content prediction model of lettuce leaves based on improved DBN algorithm. In order to avoid falling into local optimization in DBN training, PSO algorithm and GWO algorithm are used to optimize the initial weight and paranoia of DBN network, and the results have higher stability. Article (Pang et al. 2019) is analyzed the planting adaptability of tropical fruit trees and proposed an ALS-DBN recognition model. The adaptive step size algorithm and momentum term are introduced, and the recognition accuracy is as high as 97.72%. It's shown in table 4.

4 CONCLUSION

The application of DBN in intelligent agriculture is still in its infancy (Pang et al. 2020). This paper introduces the network structure and training process of DBN, and expounds its application in crop classification, pest prediction, weed identification, breeding monitoring and crop yield prediction from the perspective of DBN algorithm improvement and optimization. Future research can be improved from the following aspects: ①improve the topology of DBN and reduce the computational complexity; ②Feature extraction models suitable for different application scenarios; ③Expand the application of DBN in more fields of intelligent agriculture. DBN provides new ideas for the development of smart agriculture and ecological agriculture in the future.

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