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The Prediction Research of Population Density Based on Deep Learning in Grain Stored Insects

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Abstract

Precision of pests, in stored grain insect population density, has been a hot and difficult research in pest detection and control system. The accuracy of prediction of pest density will directly affect to warehouse grain temperature and the food quality etc. In order to improve the accuracy, the paper which using the depth study method, established an insects density prediction mode with the depth of the belief network as the core. The model is applied to the algorithm of deep learning predictive control. According to the temperature and humidity of the grain obtained from the actual measurement and the initial density of the pest, we predicted the pest density. Simulation results show that the root mean square error is small between the predictive value and actual value, high prediction accuracy. The deep learning algorithm is applied to the population density of pests is effective.

Keywords*: deep learning, population density, deep confidence network, predictive and control Introduction*

1. Introduction

The harm of the pest in grain storage is a major technical problem that have an influence on the quality and safety of grain storage at present. The bottleneck problem is pest population density detection and prediction. And the population density of grain stored insects is a crucial measure to simulate and verify pest occurrence and growth trend. Grain reserves cycle in the United States and Japan generally maintained at 1-2 years, so it should take measures when per ton of food exists five head of pests. However, due to different national conditions, China's grain reserves cycle is in 3-5 years, in addition to the number of pests in a certain period increase with a doubling of power series, so the decision standard of dealing with insect pest is basically per ton of exits 2 head pests.

Traditional prediction of pest population density basically is to rely on statistics, but its large workload and the high labor intensity seriously affect the efficiency and accuracy of forecast. The article take the Deep Learning (Deep Learning, DL) modeling method can make up for the inadequacy. Deep Learning is a branch of the machine learning. It also is an extension of neural network, and its main character is to obtain the expression of different abstract layer for original data by multi-level learning, and then improve the accuracy of classification and prediction. The layered idea of Deep Learning model

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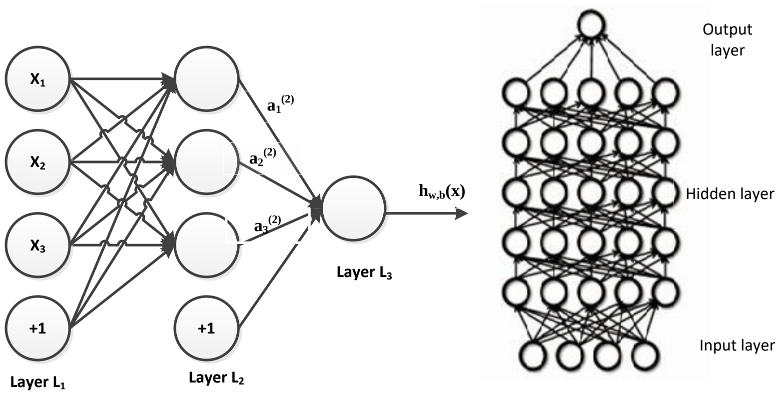
achieve hierarchical expressed for input information, which greatly improve the timeliness and accuracy to the whole operation.

2. The Basic Theory of Deep Learning Algorithm

Deep Learning is a new field of machine Learning. It is a mathematical model to simulate human brain's analysis and study that based on neural network, which imitate the brain mechanisms to identify the target and sense information [1]. The traditional neural network algorithm have two main ways to select features, one is manual and it is very arduous, anther is heuristic and it mainly depends on professional knowledge. The superior level of selection mainly is association with experience and luck, and it also needs a lot of time to algorithm adjust. But Deep Learning algorithm involved in the study of feature selection in the absence of people. The representative results are Auto Encoder that was lunched by Hinton in 2006[2], which made amazing progress on the handwritten digit recognition.

Deep Learning mainly have three characteristics: 1) the hierarchical structure. It emphasized the depth of model structure;2) Deep Learning clearly highlight the characteristics of the importance of self-learning, its cognitive process is step by step and abstracted gradually;3) its train mechanism is different from the training of the neural network. Deep Learning hierarchical model (Figure 1) is similar with neural network and the system mainly includes input layer, hidden layer (many layers) and output layer. Compared with neural network, the number of hidden layer is more, which show the strong ability of learning essential characteristics of data concentrations from a few samples, and greatly improve the generalization ability and computing speed of complex classification problems.



The hierarchical model of neural network

The hierarchical model of deep learning

Figure 1. The Hierarchical Model of Neural Network (left) and the Hierarchical Model of Deep Learning (right)

Characteristics of self-learning is a chief breakthrough of Deep Learning, through Learning a Deep nonlinear network structure to realize the complex function approximation, which can use less parameters present complex function (Figure 2). Formed by combining low-level features more abstract high-level layers to express category or features, and transform the feature expression of the sample in the original space into a new feature space by feature conversion, so that the classification or prediction is more easily.

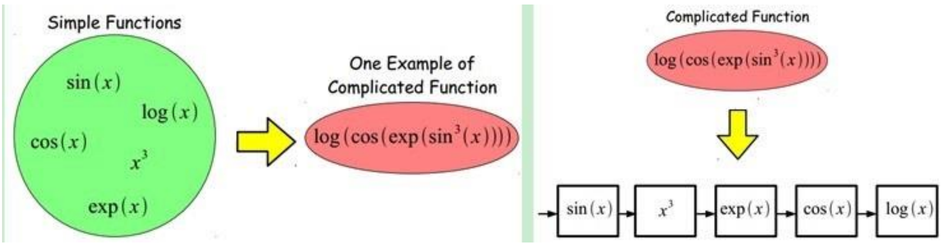


Figure 2. Complex Function Model

Deep Learning and neural network is adopted very different training mechanism. Back propagation is used in traditional neural network. Simply, using iterative algorithm to train the network with random initialization and calculate the output of the current network, then according to the difference between the current outputs and label to change the parameters of each layer until convergence. .However, deep learning is a layer-wise training mechanism entirely. The reason is that if the mechanism of back propagation is adopted, for a deep network (layer 7 above), the residual has become too small when spread to the layer so that so-called gradient diffusion is presented.

3. The Research Insect Population Density Prediction Model

3.1. The Prediction Identification Model Design of Insect Population Density

Deep Belief Network (DBN) within deep learning is introduced to establish the prediction identification model of pest population density based on DBN algorithm. Pest densities basic recognition model structure diagram is shown in Figure 3. In Figure 3, x (t) is four dimensional input vector of the benchmark system for the pest population density, *i.e.* temperature, humidity, moisture and pest initial density; y (t) is the system output, the output is population density (head/t);y * (t) is identification output of the forecast of population density by the encoding algorithm model; Otherwise, it obtains error coefficient by subtracting between y* (t) and y (t), if error exceed the scope of regulation, the training begin until within the prescribed scope, by contrary, the DBN algorithm is applied to the pest population density basic recognition model, according to the different input parameters to predict the population density corresponding to the output.

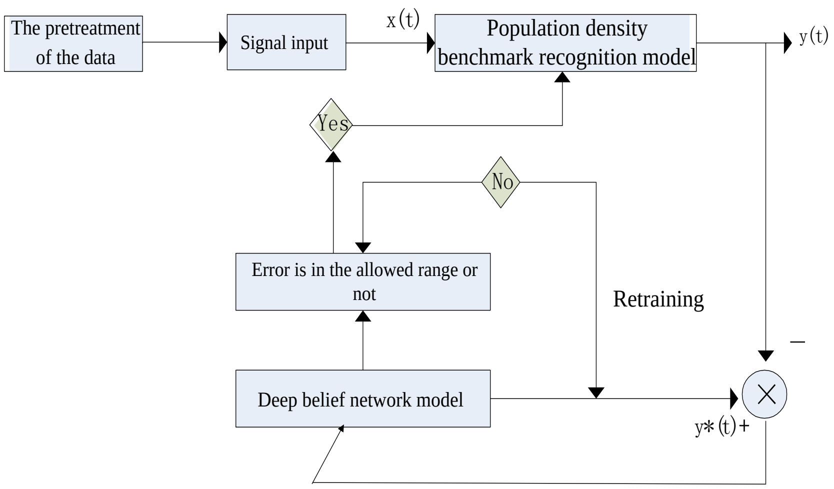


Figure 3. Insect Population Density Benchmark Recognition Model Structure

3.2. The Prediction Identification Model Training Algorithm Based on the Pest Population Density

DBN is the Bayesian Probability Generation Model, which is consisted of multiple Restricted Boltzmann Machines layer[3]. The two layers on above is the non-directional symmetric connections, the layer on below obtain directional connection from a layer of top, the status of bottom unit is visible input data vector .DBN is composed of several structural unit stack, as shown in Figure 4, the structural unit network is limited as a visual layer and a hidden layer, the hidden layer units are trained to catch higher order data correlation that expressed in the visual layer. In stack, the number of visual layer neuron in RBM unit is equal to the number of previous hidden layer neuron in RBM. According to deep learning mechanism, inputting the first layer sample training units, and training the second layer in the second RBM model make use of its output, then stack RBM model make use of increase layers to improve the model efficiency. In the process of unsupervised beforehand training, the reconstruction of input is realized from the top layer decode state to the layer units below when DBN coding is inputted to the top layer RBM [4].

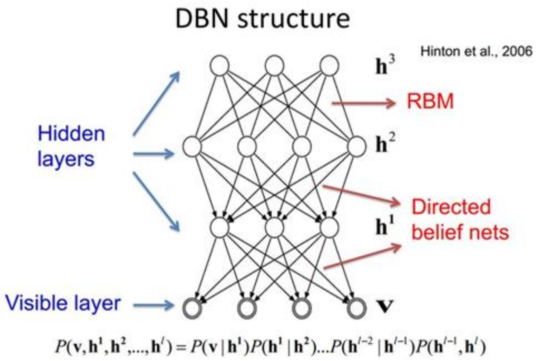


Figure 4. The Structure of DBN

RBM is undirected graph probability model based on energy[5], the joint probability distribution that defined by the energy function of input x and hidden variable h is

$$\mathrm{p(x,h)} = \frac{e^{-energy(x,h)}}{Z} \tag{1}$$

The normalization constant Z in (1) is called as partition function[6]. Observed marginal probability distribution of the input x is

$$\mathrm{p(x)} = \sum_{\mathrm{h}} \mathrm{p(x,h)} = \sum_{\mathrm{h}} \frac{\mathrm{e^{-energy(x,h)}}}{\mathrm{z}} \tag{2}$$

The introduction of free variables can change the (2) into

$$\mathrm{p(x)} = \frac{\mathrm{e^{-freeEnergy(x)}}}{\mathrm{z}} \tag{3}$$

The $\mathrm{z} = \sum_{\mathrm{x}} \mathrm{e^{-freeEnergy(x)}}$ in (3) is $\mathrm{freeEnergy(x)} = -\log\sum_{\mathrm{h}} \mathrm{e^{energy(x,h)}}$ (4)

Introducing θ expresses the parameter of model, the (3) is figured out logarithm and derivative into[7]

$$\frac{\varphi\mathrm{logp(x)}}{\varphi\theta} = -\frac{\varphi\mathrm{freeEnergy(x)}}{\varphi\theta} + \frac{1}{\mathrm{Z}}\sum_{\mathrm{x}} -\mathrm{e^{-freeEnergy(x)}}\frac{\varphi\mathrm{freeEnergy}(\tilde{\mathrm{x}})}{\varphi\theta} \tag{5}$$

It is difficult that figured out partition function[8], therefore to training it with the approximation of logarithmic likelihood gradient $\frac{\varphi\mathrm{logP(x)}}{\varphi\theta}$, using obey the free energy gradient of the data distribution sample $\mathrm{x}\sim\mathrm{p(x)}$ and the model distribution sample $\tilde{\mathrm{x}}\sim\mathrm{p}(\tilde{\mathrm{x}})$to define the rules of the model parameters update

$$\mathrm{E}_{\hat{\mathrm{p}}}\left[\frac{\varphi\mathrm{logP(x)}}{\varphi\theta}\right] = -\mathrm{E}_{\hat{\mathrm{p}}}\left[\frac{\varphi\mathrm{freeEnergy(x)}}{\varphi\theta}\right] + \mathrm{E}_{\mathrm{p}}\left[\frac{\varphi\mathrm{freeEnergy}(\tilde{\mathrm{x}})}{\varphi\theta}\right] \tag{6}$$

Among them: $\hat{p}$ is the empirical probability distribution of training data set, and p is a model probability distribution, E_p and $E_{\hat{p}}$ is the expectations under the corresponding

probability distributions. the first part is easy to calculate in (6) [9], usually replaced with the average approximation of training sample; The second part contains samples collected

from the model p sampling, which usually use some approximate sample to replaced algorithm[10].

It can use the approximate maximum likelihood stochastic gradient descent to train BRM algorithm, which usually adopt the Monte Carlo Markov chain (Monte - Carlo Markov chain, MCMC) method to get the sample models [11].

The training process of DBN is as follows:

a) The first layer be regarded as an initial input model, using unsupervised training method, made the original input reconstruction error diminish;

b) The output of hidden unit of DBN model be convinced that the input of another

layer [11];

c) Iterated initialization parameters of each layer according to b);

d) Using the output of the last hidden layer as input, and inflict a supervised layer (usually the output layer), and initialize the layer parameters [12];

e) Adjust the all parameters of DBN according to the supervision criterion, which compose DBN.

4. The Prediction and Result of Population Density for Grain Stored Insects

4.1. The Collection of Training Samples

All training datas are from Qingyuan state grain reserve in the Baoding of Hebei province. The grain and population of insect is regard as research object and benchmark within experiment. A total of 30 groups of data are collected by stick insect acquisition methods in three mouths of July, August and September in 2014. The storage of grain house is 5700 tons and insect of grain is Liposcelis entomophily and granary ventilate by negative pressure and spraying 50 kg of inert powder. All collected datas is training data of deep belief network. Otherwise, select 15 sets as the validation data, and finally use the rest of the 15 sets of datas to test the prediction performance of the network. Part of the experiment data are shown in Table 1.

Table 1. All the Experiment Data

Time	Lo cal	Quantity/H ead	Temperature/ ℃	Humidity/ %	Initial density/Head/ton
April	1	380	31.5	62.5	0.23
	2	420	32.0	67.4	
	3	440	32.6	68.0	
	4	520	34.2	63.2	
	5	490	33.7	67.3	
May	1	430	33.4	71.2	0.34
	2	510	35.6	73.7	
	3	470	32.9	68.3	
	4	420	33.3	69.5	
	5	440	31.9	59.7	
June	1	510	34.3	66.4	0.21

	2	530	33.3	68.7	
	3	620	35.6	74.3	
	4	640	35.9	72.8	
	5	700	36.2	75.4	
July	1	400	31.4	63.7	0.38
	2	450	32.9	73.0	
	3	500	35.1	58.6	
	4	420	32.2	68.4	
	5	400	31.7	67.7	
August	1	400	31.4	63.7	0.20
	2	450	32.9	73.0	
	3	500	35.1	58.6	
	4	420	32.2	68.4	
	5	400	31.7	67.7	
September	1	210	22.5	62.7	0.22
	2	250	23.4	61	
	3	280	23.7	50.5	
	4	190	25.7	59.7	
	5	330	28.3	63.7	

4.2. The Pretreatment of the Data

The prediction parameters of pest population density include the initial density of the pest, grain temperature and humidity [14], as a result of these predictors are different data types and order of magnitude, therefore, the original data need to be normalization processing .This article uses the method of maximum minimum to normalized processing of original data, the data after processing is in between 0 and 1, it is conducive to training algorithm. Computational expressions are as follows [15]:

$$\overline{\mathrm{X}} = \frac{(\mathrm{X}-\mathrm{X}_{min})}{\left(\mathrm{X}_{\max}-\mathrm{X}_{\min}\right)} \tag{7}$$

In the type, $\overline{\mathrm{X}}$ is the processing of data, X is as the original data, $\mathrm{X}_{\max}$and X_{min} are the maximum and the minimum of the original data respectively [16].

4.3. The Experimental Results and Analysis

Based on DBN pests in population density prediction simulation results are shown in Figure 5 below. Through artificial screening of actual density value is shown in Figure 6. Can be seen from the diagram of the training sample after 7 that predicted and actual values is similar, the accuracy reached 75% to 80%, and the sample size within 7 predicted value and actual value is large, basic continued accuracy within 40%, part of the point even only about 20%. And the density of prediction accuracy is around 1.5 per ton. Because when the population density is lower than the identification model of the kernel function (1.5), the logarithmic of temperature $\log t$ and the logarithm of population density $\log d$ is a nonlinear relationship, the model identification error is large; And when the density is greater than 1.5 per ton, it is happened to be in line with the identification model of the kernel function, the logarithm of the temperature is a linear relationship with the logarithm of population density, relatively easy to measure precise values.

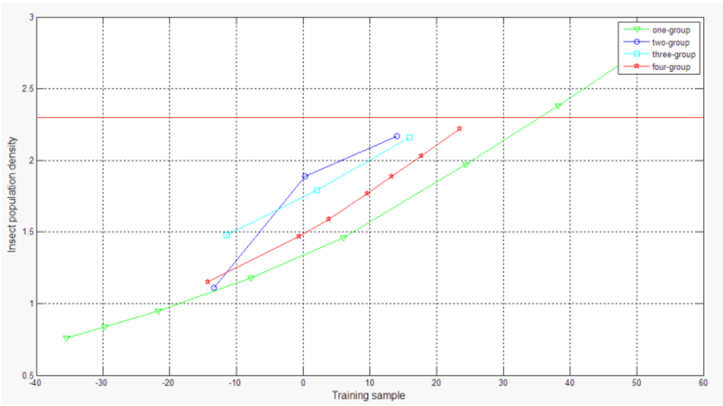


Figure 5. The Prediction Result of Insect Population Density

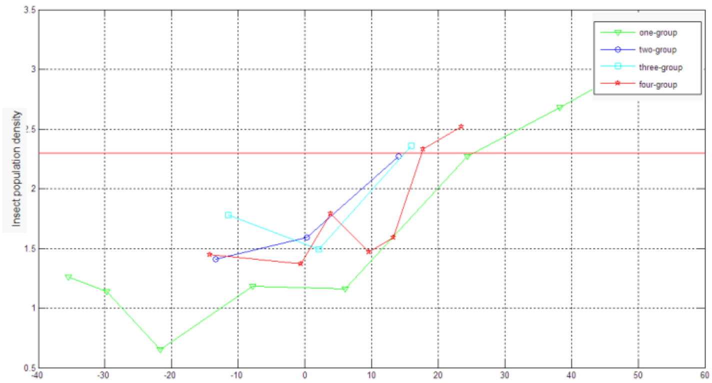


Figure 6. The Real Result of Insect Population Density

5. Conclusion

Liposcelis entomophila is regard as the research object in the article Based, using the deep learning algorithms to established pests population density prediction system identification model with DBN, and appliing the model to study in the depth of the pest in predictive control algorithm[9],. Through the advance gathering sample data to identify model of training, training after the model can identify the input data (temperature, humidity, and the initial density) of insect pests and non-linear relation between the output data (population density), according to the input data to predict the population density. The simulation results show that population density prediction model based on DBN algorithm has better prediction precision. Through the training data mining and analysis, the pests in population density has an important guiding significance to the development of prediction technology.

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