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Abstract. The grape is one of the four fruits in the world and its cultivation area and production has been ranked first in the world. The area is growing in our country after the reform and opening up which is significant for the rural economic development and farmers' income. However, the growing of grape diseases and insect pests has become one of the important problems in the development of grape planting industry. In the paper, intensive and overall surveys and studies of the research progress of the early warning model of the disease and insect are made firstly and then the comparison and analysis of rough set and artificial neural network are presented. Finally, we collected a large amount of data from grape planting base of the grape and wine engineering technology research and development center in Beijing. Based on the real-time sensing data technologies of Internet of things and the intelligent grape early warning model based on rough neural network established in the paper, we did a number of experiments and its validity was verified. The model can provide beneficial references for the research of other crops diseases and insect pests.

Keywords: rough set; artificial neural network; grape disease and insect; early warning model

0 Introduction

The farming population is numerous and agriculture holds dominant position in the national economy. However, the level of agricultural science and technology information is relative backwardness in agriculture[1]. How to increase the technological content and ensure the ability to resist the disaster in the course of agricultural production have become a development trend and research focus. The greenhouse fruit and vegetable disease and especially the explosive diseases must be conducted before the disease symptom displays. Therefore, the research pays attention to emphasize on giving out the alarm before the disease symptom is shown, such as we can send out alarm through collecting and analyzing information as well as the weather forecast before the symptom is shown[2-5].

At present, several countries such as Israel, America, Japan, and Spain put more research on greenhouse crop disease early warning system. In China, the introduction of agricultural early warning has elaborated the basic theoretical knowledge, as well as the natural disaster warning[6]. In recent years, the early-warning analysis theory of the macroeconomic and regional forest resource field has been applied to agriculture field[7]. For example, LiXin Bai[8] has built bollworm disaster early warning index system based on the evaluation method. According to the local climatic environment and the actual situation of crop planting in Beijing, Lili[9] set up pear plant diseases early warning system. Ming Li and ChunJiang Zhao[10] studied cucumber downy mildew early warning system in the sunlight greenhouse environment. Shuwen Liu and Qingwei Wang[11] studied the grapes diagnosis based on neural network and Yingfeng Cui and Shiping Wang[12] constructed grape intelligent diagnosis network model. However, taking into account the application cost and other factors, there is less intelligent and practical early warning system in agriculture and still less for large area promotion. In recent years, with the rapid development of networking and cloud computing technology and combined with network real time sensing data, there is a huge advantage for us to do facility agriculture disease early warning based on agricultural cloud services platform. It is still in the primary stage of the research for early warning analysis and decision based on a large number of real-time sensing data in agriculture. So it is necessary to further improve the algorithm model of early warning analysis and the precision.

The grape downy mildew is one of the most serious diseases for the grape[13]. Its incidence is closely related to the light, temperature, humidity in the micro-environment. So we took the grape in the area of yanqing country in Beijing as an example and collected real-time sensing data in grape micro environment through various sensing nodes and wireless communication network and then researched and constructed the grape diseases and insect pest warning model based on rough neural network which provides service for the intelligent analysis of grape diseases and insect pests, the agricultural precision production such as prediction and warning decision, the visual management and Intelligent decision analysis[14].

1 the Construction of Rough Neural Network-based Early Warning Model

1.1 Comparison of Rough Set and BP Artificial Neural Network

BP neural network has strong anti-interference ability and processes large amounts of information in parallel and arbitrarily approximates non-linear function. But it can't simplify information and reduce input data. In addition, the built network is more complicated if there is large amounts of input data. Rough set theory doesn’t need prior knowledge to remove redundant information without additional data in the process of data analysis and processing, but also execute algorithm in parallel. However, its anti-interference ability is insufficient[15-18].

There exist complementary relationships between rough set theory and BP neural network in many aspects. For instances, we combine them and obtain a process that concentrates the knowledge reduction and no prior knowledge and strong anti-interference performance which can improve accuracy and noise resistance of the system. The result of the comparing analysis is as shown in table 1-1:

Table 1-1. the comparison of the rough set and BP neural network

	Rough set theory	BP neural network
self-learning ability	weaker	stronger, with increasing learning network
the reasoning method	serial reasoning way	implement parallel computing
data processing	qualitative and quantitatively	quantitatively
prior knowledge	without prior knowledge	need experience and multiple trial before the network structure designed
knowledge representation	by neatly	connotative, through parameters
noise proof	affected by noise	good ability of resisting noise
redundant data processing	determine the attribute and value of the decision table	almost cannot be handled
rule discovery method	determine the relationships between data in the reduction process	through a nonlinear mapping
interpretability	easier	the transparency is poor in knowledge acquisition and knowledge reasoning process
knowledge maintenance	maintenance is difficult when data size is large	the learning time is long and it is easy to be trapped in local minimum when data size is large
integration capability	the integration with various software calculation methods is easily and closely	the integration with the fuzzy set, the rough set and genetic algorithm is easily and closely
generalization ability	weaker	strong generalization ability

1.2 the Constructing Idea of RS-BPANNs Model

According to their features we build the early warning model based on rough set and BP artificial neural network (hereinafter referred to as RS-BPANNs). We collect the grape diseases information case, experimental data and expert experience over the years to build an attribute decision-based matrix which is used to reduce the attribute and then design suitable BP Neural Network to train the model. The model will become knowledge rules to judge the crop disease when it achieves certain accuracy. The knowledge model library is perfected through feedback information of diagnosis results and finally the accuracy of the early warning is improved. The decision knowledge acquisition model based on RS-BPANNs is shown in figure 1-1:

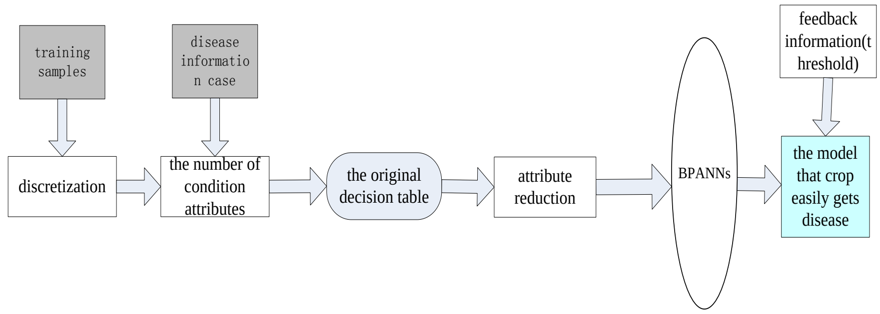

Fig 1-1. Decision knowledge acquisition model based on RS-BPANNs

1.3 the Constructing Steps of RS-BPANNs Model

The paper takes grape downy mildew as an example to build RS–BPANNs-based early warning model. The rough set theory is used to reduce the attributes of the training sample data and then determine the relationship among attributes. The module is divided into two parts: the preprocessing of the rough set and the artificial neural network learning. The whole process includes the following four steps:

1) Build the grape downy mildew case database: the way to obtain comprehensive grape downy mildew cases is various and the cases in the paper are mostly from document literature, expert discussion and experimental data at the grape planting base of the grape and wine engineering technology research and development center in Beijing that are saved in the form of vector. The data which is described using natural language can be converted into the corresponding data and is saved into the database in the form of matrix.

2) Express the case data through the decision table. A lot of original judgment information is represented by the decision table. Among them, C represents condition attribute value. D represents the decision attribute value. all grape downy mildew cases are represented as U. V is the range of attribute values. The representation of the original case decision table is T=(U，C，D，V). The value is equal to 0 or 1.

3) Reduce the decision table: take out the redundant attributes without changing the classification of the decision table. The reduction is realized through calculating the positive region of the decision attribute of the condition attributes in the paper. The input condition attribute set is represented as C={C1，C2，...，Cn} and the decision attribute set is D={D1，D2，...，Dn}.The steps of reduction algorithm are as follows:

1. Calculate the positive region of D, $pos_c(D)$
2. Remove attributes C_j from C, $C_w=C-\{C_j\}$
3. Calculate the positive region of C_w, $pos_{c_w}(D)$

4. If $pos_c(D)= pos_{c_w}$（D）

Remove C_j. Otherwise, reserved

5. Ergodic all attributes

6. Output a reduction that C is relative to D

The main idea of the reduction algorithm is that the condition can be removed if a condition in the set C is removed and it will not affect the decision result. Otherwise, the condition is reserved. The operation is complete until generating a reduction about C.

4) The obtaining rules of neural network: take the condition attributes and decision attributes gotten after attribute reduction as the input variables and output variables of the neural network. We use the neural network to train the sample and to learn and finally get a decision information model.

On the basis of the decision information model, feedback information is added when the plant diseases and insect pests of early warning system is realized in order to record the validity of the decision information and count the accuracy of the trained decision information model, which make the decision information easy managed and optimized. The whole process of the system is shown as the figure 1-2.

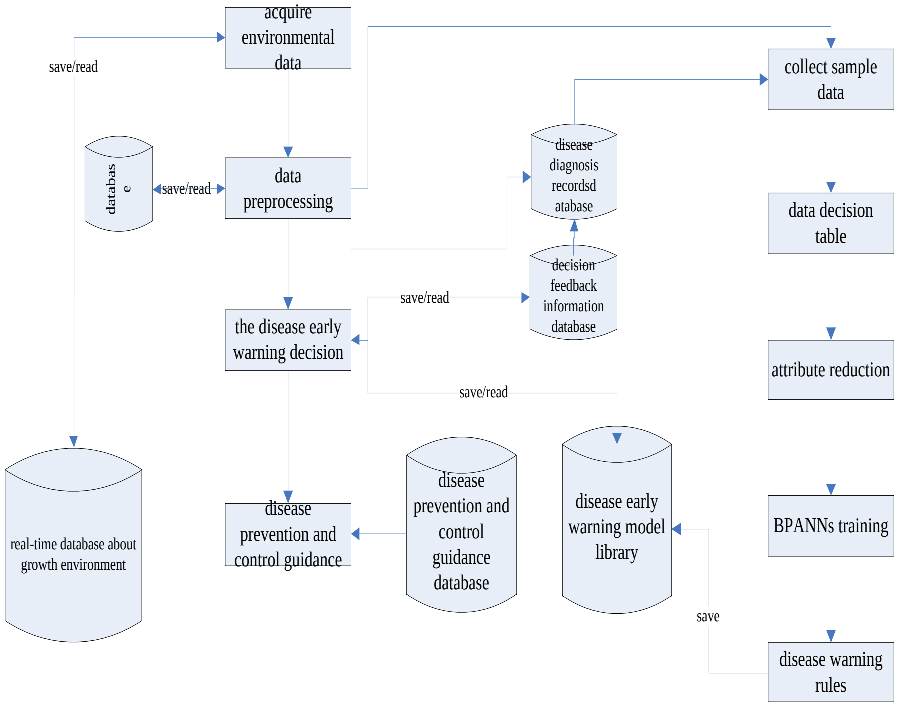

Figure 1-2. the flow of the plant diseases early warning system

2. Experimental Analysis

2.1 Data Acquisition

The paper takes grape downy mildew as example to analyze rough neural network-based early warning model. The original data is gathered from air temperature and humidity, soil temperature and moisture(the depth of 20cm), light intensity and CO_2 concentration collected every 15 minutes time. The following data shown in table 2-1 is acquired from grape berries period in greenhouse and the acquisition time is from 7 am to 5 pm and the data collected every time is done average processing.

Table 2-1. The data gotten in grape berries period

time	air temperature /^{o}C	air humidity /%	soil temperature /^{o}C	air moisture /%	light intensity /lx	CO_2 /μL/L
7	15.9	92.1	10.2	35.8	0	445
8	17.3	91.6	12.5	36.4	24625	379
9	21.8	68.7	15.6	36.4	38652	324
10	26.5	51.7	21.7	36.9	45689	254
11	29.5	45.2	25.5	35.7	47895	278
12	32.8	48.9	28.8	35.7	50127	201
13	28.3	57.4	23.7	35.9	51257	156
14	28.2	55.8	23.8	35.7	38784	158
15	27.6	64.9	22.1	35.7	21784	121
16	24.3	67.5	19.0	35.7	7523	122
17	20.3	83.7	16.4	35.7	0	154

It shows that the change process of various greenhouse environmental factors in grape berries period during one day. Organizing the sensors' data and feedback information from sensor, we obtain the original decision table shown in table 2-2.

Table 2-2. Grape downy mildew original decision table

air temperature /^{o}C	air humidity /%	soil temperature /^{o}C	air humidity /%	light intensity /lx	CO_2 concentration /μL/L	Downy mildew
19.2	94.7	10.7	66.5	0	388	Y
23.5	97.3	16.4	80.1	0	421	Y

15.7	80.5	16.4	34.9	0	433	N
24.8	95.7	19.8	58.8	7468	367	Y
28.4	86.2	23.5	38.7	34954	284	N
31.2	53.5	26.1	31.8	46541	158	N
12.8	86.5	7.5	29.3	0	309	N
18	93.7	10.2	71.3	0	516	Y
21.0	90.9	16.2	75.6	7962	251	Y
…	…	…	…	…	…	…
23.2	95.3	18.6	65.4	2762	241	Y

The above table shows that whether grape downy mildew appears or not in the various greenhouse environmental factors. There are 100 items data which constitute the case table. Among them, U is a finite case set. $A = C \cup D$, C is the condition attribute set. Through the study of grape downy mildew material, there is the stipulation that it is low when air temperature is below 18°C and high when it is above 25°C. It is low when the humidity is below 50% and high when it is above 90%. It is low when the soil temperature is below 10°C and high when it is above 20°C. (We concluded that the surface air temperature is generally 5°C higher than the soil temperature when air temperature is relatively stable from the data gathered by sensor without the case of air temperature shock.). It is low if soil humidity is below 50% and high for above 80%. It is low if light intensity is under 30000 lx and high for above 40000 lx. It is low if CO_2 the concentration is under $100\mu L \bullet L^{-1}$ but high for above $1000\mu L \bullet L^{-1}$.

The range of the condition attribute value is 0 represents that do not belong to the property and 1 is on behalf of belonging to the attribute. C_1 represents the berries period, C_2 represents that the air temperature is low, C_3 represents that air temperature is just right, C_4 represents the air temperature is high. C_5, C_6 and C_7 respectively represents air humidity is low, moderate and high. C_8, C_9 and C_{10} respectively represents soil temperature is low, moderate and high. C_{11}, C_{12} and C_{13} respectively represents soil moisture is low, moderate and high. C_{14}, C_{15} and C_{16} respectively C_{17}, C_{18} and C_{19} respectively represents the concentration of CO_2 is low, moderate and high. The case data table of the samples is shown in the table 2-3.

Table 2-3. Grape Downy mildew case data

U	C 1	C 2	C 3	C 4	C 5	C 6	C 7	C 8	C 9	C 10	C 11	C 12	C 13	C 14	C 15	C 16	C 17	C 18	C 19	D
x 1	1	0	1	0	0	0	1	0	1	0	0	0	1	1	0	0	0	1	0	1
x 2	1	0	1	0	0	0	1	0	0	1	0	0	1	0	1	0	0	0	1	1
x 3	1	0	1	0	0	0	1	0	1	0	0	0	1	1	0	0	1	0	0	1
x 4	1	1	0	0	0	1	0	1	0	0	0	1	0	0	1	0	0	1	0	0

x5	1	0	1	0	0	0	1	0	1	0	0	0	1	1	0	0	1	0	0	1
x6	1	0	1	0	0	0	1	0	1	0	0	0	1	1	0	0	1	0	0	1
x7	1	0	0	1	0	1	0	1	0	0	0	1	0	0	0	1	1	0	0	0
x8	1	1	0	0	0	0	1	1	0	0	0	0	1	1	0	0	0	1	0	1
x9	1	0	1	0	0	0	1	0	1	0	0	0	1	1	0	0	0	0	1	1
x10	1	0	1	0	0	0	1	0	1	0	0	0	1	1	0	0	1	0	0	1
x11	1	0	1	0	0	0	1	1	0	0	0	1	0	1	0	0	0	1	0	1
..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..
X100	1	1	0	0	0	1	0	1	0	0	1	0	0	0	1	0	0	1	0	0

It can be seen from the above table that the object *x3*、*x5*、*x10 are* the same instance because their attribute value domains are same. According to the attribute reduction method only one case is retained and the other needs removing. And classify each equivalence relation relative to the domain U after dealing with the duplicate lines.

Count the dependence degree of D relative to C and get $pos_c(D)=\{x_1,x_2,x_3,x_4, x_6,x_7,x_8, x_9,x_{11},\ldots\}$

$$k = {|pos_c(D)|} / {|U|} = 81/81 = 1 \qquad (2\text{-}1)$$

So we get the conclusion that decision attribute depends entirely on condition attributes and then calculate the relationship between *$pos_c(D)$* and $pos_{c-c_j}(D)$ to get (2-2) .

$$pos_{c-c_1}(D) = \{x1, x2, x3, x4, x6, x7, x8, x9, x11, ...\} = pos_c(D) \qquad (2\text{-}2)$$

Finally, we get the final reduced table which includes the key factors that affect the grape downy mildew which is shown in table 2-4.

Table 2-4. The data gotten after the attributes reduction

U	C1	C2	C3	C4	C5	C6	C7	C11	C12	C13	C14	C15	C16	D
x1	1	0	1	0	0	0	1	0	0	1	1	0	0	1
x2	1	0	1	0	0	0	1	0	0	1	0	1	0	1
x3	1	0	1	0	0	0	1	0	0	1	1	0	0	1
x4	1	1	0	0	0	1	0	0	1	0	0	1	0	0
x6	1	0	1	0	0	0	1	0	0	1	1	0	0	1
x7	1	0	0	1	0	1	0	0	1	0	0	0	1	0
x8	1	1	0	0	0	0	1	0	0	1	1	0	0	1
x9	1	0	1	0	0	0	1	0	0	1	1	0	0	1
x11	1	0	1	0	0	0	1	0	1	0	1	0	0	1
…	…	…	…	…	…	…	…	…	..	…	..	..	…	…
X81	1	1	0	0	0	1	0	1	0	0	0	1	0	0

The design of BP neural network is mainly divided into the following steps:

1) The design of the input layer and output layer: It should be based on application need. The number of the output node is 1 in the experiment and there are 19 properties for the objects in input layer. But the number of the core attributes is taken as the number of input layer after attribute reduction. The number of the input node N is set as 12.

2) The design of the hidden layer: It includes the design of the layer number and the neuron number each layer which mainly relies on experience. It can increase the processing capacity of neurons if we add the amount of the hidden layer. The paper uses three layers BP neural network structure. The experimental results show that single layer can meet the demand in the determination of the boundary problem of the small network.

Through the above process we can extract the knowledge rules in grape berries period:

If C_3 is between 18°C and 25°C /1 and
C_7 > 90%/1 and
C_{13} > 80%/1 and
C_{14} < 30000lx
Then D(Downy mildew)

We can get the knowledge rules that grape downy mildew is easily appear in every period at grape growth stage which can guide the judgment of grape downy mildew. At the same time, according to the feedback information knowledge rules are optimized.

2.2 Comparison and Analysis

The paper makes comparison and analysis of BP artificial neural network model and rough BP artificial neural network model through training and testing the same sample and then analyzing of the test results of each model and the length of training time.

It is concluded that the combination of the rough set and BP neural network can decrease the redundancy attributes and optimize the structure of neural network and shorten the training time and also improve the effect of training. Therefore, the model based on the RS-BPANNs has certain advantage. The following table is the results of the two models in the aspect of the training time and accuracy.

Table 2-5. Result comparison of different methods

	the training time（s）	**accuracy %**
BP artificial neural network	0.7	90
rough BP artificial neural network	0.5	94

3. Conclusions

The facility agriculture is very important in the process of agricultural modernization in our country. Taking advantage of Internet of things, we can obtain real-time information of the infrastructure environment and build early warning model to make decision analysis of facility crop diseases whose purpose is to realize the timeliness, accuracy, convenience and practicality of the facility agriculture disease early warning.

The paper is mainly for facility agriculture and constructs a grape diseases early warning model based on rough neural network. The paper gets the effectiveness of the early warning model and provides a reference for the construction of plant diseases early warning model through analyzing the real-time sensor data from the grape downy mildew.

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