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Study on Combustible Classification Method Based on Optimized BP Neural Network

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Abstract

In this paper, combustible classification method based on optimized BP neural network is applied by referring to existing combustible classification method and aiming at the vegetation in the region of Hannuo River in Greater Higgnan Mountains. Combustible classification method based on ground type and stand factor is used according to features of BP neural network model. The results indicate that the classification method proposed in this paper owns high precision and good robustness.

Keywords*: BP neural network; combustible classification; stand factor*

1. Introduction

The forest as a valuable natural resource not only offers large quantities of timbers and forest by-products for people in production and life, but also plays a great role in preserving soil and water, beautifying the environment, preventing and treating pollution as well as maintaining ecological equilibrium [1-3].

Forest fire is one of the severest disasters which destroy the forest. It not merely can burn a large area of woods, animals and resources in the woods in a moment, but can exert a far-reaching influence on balance of natural ecology. Forest destruction will result in long-term climate imbalance, water and soil loss, river blockage, flash flood and farmland destruction. It even directly threatens agricultural production and residents' personal and property security. However, manpower, forest fire fighting and rescue require huge material resources and financial resources. It is often too late to fight against forest fires due to insufficient resources [4-7].

Nevertheless, forest fire combustion is a very complicated process, and many natural factors influence forest fire behaviors, such as terrain, vegetation and meteorological factor. In order to describe forest combustion process, people initially applied mathematical model to simulate forest fire spreading process. Forest fire spreading model exports quantitative relation expressions between forest fire behavior and various natural factors through mathematical treatment under simplified conditions [8-9]. When a forest fire happens, forest fire behaviors which are about to happen can be predicted according to these relation expressions so as to put out the fire and carry out routine forest fire management. But, forest fire spreading model is static and non-visual, and it cannot reflect dynamic changes and spatial features of forest fire spreading. As computer graphic processing capacity improves, spatial information technology cored by remote sensing and geographical information system develops, and cellular automaton and rough set theory which can simulate complex system theory are proposed, implementation of real-time and dynamic spreading model of forest fire via the computer becomes an inexorable

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trend by choosing appropriate forest fire spreading model and combining current technical means and research methods. Based on experimental study, this paper puts forward a combustible classification method based on optimized BP neural network. The experiment shows such method has good classification effect.

2. BP Neural Network

2.1. BP Neural Network Mode

BP neural network usually consists of input layer, hidden layer and output layer. All layers are interlinked, and nodes of each layer are not connected. The number of nodes at the input layer is usually the dimensionality of input vector. The number of nodes at the output layer is usually the dimensionality of output vector. Nowadays, no standard can be used to confirm the number of nodes at the hidden layer. Three-layer BP neural network with one hidden layer (sufficient nodes at the hidden layer) is able to approach any nonlinear continuous function with any precision in a closed set [10]. The network topology is shown in Figure1.

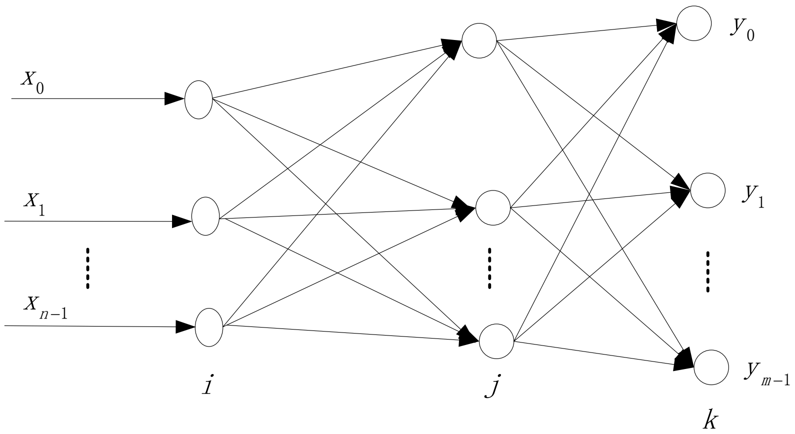

Figure 1. Network Topology of Neural Network

Input vector of BP neural network is assumed to be $x \in R^n$, where $x = (x_0, x_1, ..., x_{n-1})^T$. There are n_1 neurons at the hidden layer, and their input is $x' \in R^{n_1}, x' = (x'_0, x'_1, ..., x'_{n-1})^T$. There are m neurons at the output layer, and their output is $y \in R^m$, $y = (y_0, y_1, ..., y_{m-1})^T$. The weight from the input layer to the hidden layer is w_{ij}, and the threshold value is θ_i. The weight from the hidden layer to the output layer is w'_{jk}, and the threshold value is θ'_k. The output of neural network at each layer is

$$\begin{cases} x'_j = f\left(\sum_{i=0}^{n-1} w_{ij} x_i - \theta_j\right), j = 0, 1, ..., n_1 - 1 \\ y_k = f\left(\sum_{j=0}^{n_1-1} w'_{jk} x'_j - \theta'_k\right), k = 0, 1, ..., m - 1 \end{cases} \quad (1)$$

Obviously, it will complete the mapping from n-dimensional space vector to m-dimension space vector. Activation function f (x) is unipolar Sigmoid function:

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$$f(x) = \frac{1}{1+e^{-x}} \tag{2}$$

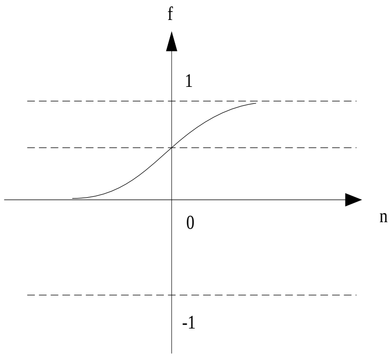
f (x) is characterized by continuous derivability, and

$$f^{'}(x) = f(x)(1 - f(x)) \tag{3}$$

Based on the need of application, bipolar Sigmoid function may be adopted.

$$f(x) = \frac{1-e^{-x}}{1+e^{-x}} \tag{4}$$

Unipolar Sigmoid function and bipolar Sigmoid function are shown in Figure2 and Figure3, respectively.



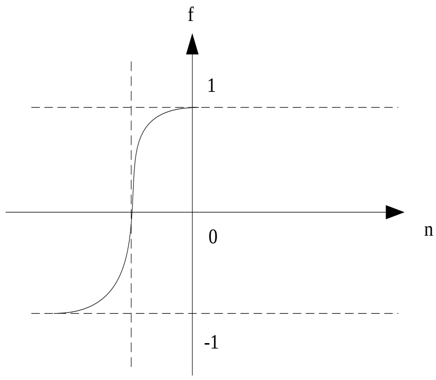


Figure 2. Unipolar Sigmoid Function **Figure 3. Bipolar Sigmoid Function**

Assuming there are P learning sample vectors, corresponding expected output is $d^{(1)}, d^{(2)}, ..., d^{(p)}$. Learning corrects the weight through the error and makes $y^{(p)}$ approach $d^{(p)}$. To simplify derivation, the threshold values of all computational node are incorporated into weight vector. In other words, assuming $\theta_1^{'} = w_{nl}^{'}$, $\theta_k^{'} = w_{nk}^{'}$, $\theta_j^{'} = w_{nj}^{'}$, $x_{n_1}^{'} = x_n = -1$, the dimensionality of corresponding vectors $w, w^{'}, x, x^{'}$ in Formula (1) increases by 1.

When a sample (assuming the Pth sample) is inputted into the network and generates output, mean square error is the sum of square error of each output unit, *i.e*.

$$E^{(p)} = \frac{1}{2}\sum_{k=0}^{m-1}(d_k^{(p)} - y_k^{(p)})^2 \tag{5}$$

When all samples are inputted once, the overall error is

$$E_A = \sum_{p=1}^{P} E^{(p)} = \frac{1}{2}\sum_{k=0}^{m-1}(d_k^{(p)} - y_k^{(p)})^2 \tag{6}$$

Assuming w_{sp} is a connection weight in network, according to gradient descent method, weight correction amount under batch processing is

$$\Delta w_{sp} = -\eta \frac{\partial E_A}{\partial w_{sq}} \tag{7}$$

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2.2. BP Neural Network Training

Nodes at each layer are set. Assuming there are 11 input neuron nodes $x_1, x_2, \cdots, x_{11}$, 5 output neuron nodes $y_1, y_2, \cdots y_5$ and 100 hidden-layer neuron nodes $z_1, z_2, \cdots, z_{100}$, and expected output T is $t_1, t_2, \cdots, t_5$, the output z_j of hidden-layer nodes, actual output y_l of output nodes and the error ε of output nodes can be calculated according to the following formulas:

$$z_j = f\left(\sum w_{ij} x_i - \theta_j\right) \tag{8}$$

$$y_l = f\left(\sum w_{jl} z_i - \theta_l\right) \tag{9}$$

$$\varepsilon = 0.5 \sum_{l=1}^{m} \left(t_l - y_l\right)^2 \tag{10}$$

Where, w_{ij} is the weight between input layer and hidden layer, and θ_j is the threshold value; w_{jl} is the weight between hidden layer and output layer, and θ_l is the threshold value.

Then, network training is constructed. BP neural network applies counter-propagation learning algorithm to adjust the weight, and utilizes mean square error and gradient descent to correct network connection weight. Training error of output layer and training error of hidden layer can be calculated by the following formulas:

$$\delta_{jl} = y_l\left(1 - y_l\right)\left(t_l - y_l\right) \tag{11}$$

$$\delta_{ij} = \sum_{l=1}^{m} \delta_{jl} \times w_{jl}\left[1 - \left(x_j\right)^2\right] \tag{12}$$

Where, δ_{jl} is training error of output layer; δ_{ij} is training error of hidden layer. Under the function of training error, the weight of the $n0$th iteration can be adjusted to:

$$w_{jl}\left(n_0 + 1\right) = w_{jl}\left(n_0\right) + x_j \eta \delta_{jl} + \alpha\left[w_{jl}\left(n_0\right) - w_{jl}\left(n_0 - 1\right)\right] \tag{13}$$

$$w_{ij}\left(n_0 + 1\right) = w_{ij}\left(n_0\right) + x_i \eta \delta_{ij} + \alpha\left[w_{ij}\left(n_0\right) - w_{ij}\left(n_0 - 1\right)\right] \tag{14}$$

Corresponding threshold value can be adjusted to:

$$\theta_j\left(n_0 + 1\right) = \theta_j\left(n_0\right) + \eta\delta_j + \alpha[\theta_j\left(n_0\right) - \theta_j\left(n_0 - 1\right)] \tag{15}$$

$$\theta_l\left(n_0 + 1\right) = \theta_l\left(n_0\right) + \eta\delta_l + \alpha[\theta_l\left(n_0\right) - \theta_l\left(n_0 - 1\right)] \tag{16}$$

Where, η is learning rate; α is factor of momentum. η searches step size according to the gradient, so as long as network does not vibrate, a larger value can be taken for η. α. Aims to accelerate convergence and prevents vibration.

According to the above network triaging process, error calculation, weight and value adjustment are conducted continuously for each training sample until all samples are trained, and the error meets precision requirement. Figure 4 shows network training chart. After training, neural network can classify the data.

2.3. Input and Output Node Setting

(1) Based on ground type

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Since geomorphic features of a forest, coverage degree, aboveground vegetation and site conditions are diverse in different geographic positions, complicated forest must be divided into the minimum forest territory unit with the same internal features and obvious differences in the adjacent part, *i.e*. extensive area of forest is divided into different group types for rational management.

Usually, group types involve many factors. In accordance with classification requirements, the following group classification factors serve as the classification conditions: dominant tree species, site type, canopy density, soil texture, soil sub-type, soil thickness, vegetation type, vegetation height, vegetation coverage, vegetation distribution and slope position *etc*. Thus, the 11 factors may serve as the input nodes of neural network.

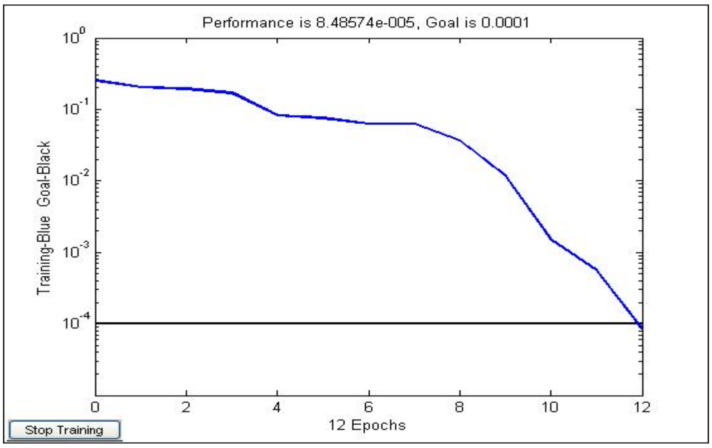

Figure 4. Neural Network Training Chart

Existing stand data are classified according to 11 stand factors. 1000 data are selected for each factor, and 11000 known compartment data serve as the input data. Table 1 shows some stand factor data.

Table 1. Some Stand Factor Data

Compart-ment No.	Dominant tree species	Site type	Canopy density	Soil texture	Soil sub-type	Soil thickness	Vegetation type	Vegeta-tion height	Vegeta-tion coverage	Vegetation distribution	Slope position
1	Coniferous forest	Face the sun, gentle slope	0.500	Loam	Typical dark brown soil	Medium	Brachybotrys paridiformis	0.4	80	Even	The whole slope
2	Coniferous forest	Face the sun, gentle slope	0.500	Loam	Typical dark brown soil	Medium	Brachybotrys paridiformis	0.4	80	Even	The whole slope
3	Coniferous forest	Face the sun, gentl	0.500	Loam	Typical dark brown soil	Medium	Brachybotrys paridiformis	0.4	80	Even	The whole slope

		e slope									
4	Mingled forest	Shade the sun, gentle slope	0.700	Loam	Typical dark brown soil	Thick	Horsetail	0.4	60	Even	The whole slope
5	Mingled forest	Shade the sun, gentle slope	0.500	Loam	Dark color dark brown soil	Medium	Horsetail	0.4	70	Even	Upper part
6	Mingled forest	Face the sun, gentle slope	0.500	Loam	Dark color dark brown soil	Medium	Horsetail	0.4	70	Even	Upper part
7	Coniferous forest	Face the sun, gentle slope	0.500	Loam	Typical dark brown soil	Medium	Brachybotrys paridiformis	0.4	80	Even	The whole slope
8	Coniferous forest	Face the sun, gentle slope	0.500	Loam	Typical dark brown soil	Medium	Brachybotrys paridiformis	0.4	80	Even	The whole slope
9	Mingled forest	Face the sun, slope	0.700	Loam	Typical dark brown soil	Medium	Cyperus rotundus L.	0.4	70	Even	The whole slope
10	Broad-leaf forest	Face the sun, gentle slope	0.700	Loam	Typical dark brown soil	Thick	Horsetail	0.4	80	Even	Middle part
11	Mingled forest	Shade the sun, gentle slope	0.700	Loam	Typical dark brown soil	Thick	Horsetail	0.4	60	Even	The whole slope
12	Broad-leaf forest	Face the	0.700	Loam	Dark color	Medium	Pteridophyte	0.4	70	Even	The whole

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		sun, gentle slope			dark brown soil						slope
13	Mingled forest	Shade the sun, gentle slope	0.700	Loam	Typical dark brown soil	Thick	Horsetail	0.4	60	Even	The whole slope
14	Mingled forest	Shade the sun, gentle slope	0.500	Loam	Dark color dark brown soil	Medium	Pteridophyte	0.4	60	Even	Upper part
15	Poplar woods	Face the sun, gentle slope	0.500	Loam	Typical dark brown soil	Medium	Brachybotrys paridiformis	0.4	80	Even	Middle part
16	Coniferous forest	Shade the sun, gentle slope	0.500	Loam	Typical dark brown soil	Medium	Brachybotrys paridiformis	0.4	80	Even	The whole slope
17	Broad-leaf forest	Shade the sun, gentle slope	0.000	Loam	Dark color dark brown soil	Medium	Horsetail	0.4	60	Even	Upper part
18	Mingled forest	In the shade, slope	0.500	Loam	Typical dark brown soil	Medium	Pteridophyte	0.4	60	Even	The whole slope
19	Mingled forest	In the shade, slope	0.700	Loam	Typical dark brown soil	Medium	Cyperus rotundus L.	0.4	70	Even	The whole slope
20	Coniferous forest	Face the sun, gentle slope	0.700	Loam	Typical dark brown soil	Medium	Cyperus rotundus L.	0.4	80	Even	The whole slope

In combustible type division of Canadian forest fire spreading model, forests are classified into 5 categories: coniferous forest, broad-leaf forest, mingled forest, cutover land and open ground. Since the research on forest fire spreading in the region of Hannuo River in Greater Higgnan Mountains is based on this model, output nodes can be set according to the 5 categories, where water area is set as incombustible.

(2) Based on stand factor

Due to diversified forest appearance, varieties of trees, age, growing speed, growing density and site conditions, complicated forest must be divided into the minimum forest territory unit with the same internal features and obvious differences in the adjacent part, *i.e.*, extensive area of forest is divided into different group types for rational management.

Usually, stand includes many factors. In accordance with classification requirement, the following stand factors are selected as classification conditions: tree species composition, average age of trees, age group, age class, management type, origin, average diameter and average height. Thus, these 8 factors are set as input nodes of neural network.

Existing stand data are classified on the basis of 8 stand factors. As well, 1000 data are chosen for each factor, and 8000 known forest data serve as the input data. Table 2 shows some stand factor data.

Table 2. Some Stand Factor Data

Compart ment No.	Tree species composition	Avera ge age of trees	Age group	Age class	Management type	Origin	Avera ge diamet er	Avera ge height
1	4 Abies nephrolepis 3 spruce 1 Tilia 1 birch 1 color-leaved tree	50	Mediu m	Ⅲ	Closing hill for afforestation	Seed propag ation	18	14
2	4 Abies nephrolepis 3 spruce 1 Tilia 1 birch 1 fraxinus mandshurica	50	Mediu m	Ⅲ	Closing hill for afforestation	Seed propag ation	18	14
3	4 Abies nephrolepis 3 spruce 1 Tilia 1 birch 1 color-leaved tree	50	Mediu m	Ⅲ	Closing hill for afforestation	Seed propag ation	18	15
4	2 spruce 2 Abies nephrolepis 2 birch 2 Tilia 1 color-leaved tree 1 populus	85	Mature	Ⅴ	Selective cutting	Seed propag ation	22	17
5	3 Abies nephrolepis 2 spruce 2 Tilia 1 color-leaved tree 1 birch 1 populus	55	Mediu m	Ⅲ	Closing hill for afforestation	Seed propag ation	14	15
6	2 spruce 2 Abies nephrolepis 2 birch 1 Tilia 1 color-leaved tree 1 elm 1 weed tree	55	Mediu m	Ⅲ	Closing hill for afforestation	Seed propag ation	14	15
7	4 Abies nephrolepis 3 spruce 1 birch 1 Tilia 1 color-leaved tree	50	Mediu m	Ⅲ	Closing hill for afforestation	Seed propag ation	18	14
8	4 Abies nephrolepis 3spruce1 birch 1 Tilia 1 fraxinus mandshurica	50	Mediu m	Ⅲ	Closing hill for afforestation	Seed propag ation	18	14
9	3 Abies nephrolepis 2 spruce 2 birch 1 Tilia 1 color-leaved tree 1 fraxinus mandshurica	75	Near-mature	Ⅳ	Intermediate cutting	Seed propag ation	22	17

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10	4 populus 3 weed tree 1 birch 1 fraxinus mandshurica 1 spruce	15	Young	Ⅱ	Closing hill for afforestation	Seed propag ation	10	9
11	2 spruce 2 Abies nephrolepis 2 birch 2 Tilia 1 color-leaved tree 1 fraxinus mandshurica	85	Mature	Ⅴ	Selective cutting	Seed propag ation	22	17
12	2 Abies nephrolepis 2 Tilia 2 populus 1 spruce 1 color-leaved tree 1 elm 1 weed tree	55	Mediu m	Ⅲ	Intermediate cutting	Seed propag ation	14	15
13	2 spruce 2 Abies nephrolepis 2 Tilia 2 birch 1 color-leaved tree 1 Pinus koraiensis	85	Mature	Ⅴ	Selective cutting	Seed propag ation	22	17
14	3 Abies nephrolepis 2 birch 2 Tilia 1 spruce 1 elm 1 weed tree	55	Mediu m	Ⅲ	Closing hill for afforestation	Seed propag ation	14	15
15	7 populus 2 weed tree 1 Abies nephrolepis	21	Mediu m	Ⅲ	Closing hill for afforestation	Seed propag ation	12	12
16	4 Abies nephrolepis 3 spruce 1 birch 1 Tilia 1 color-leaved tree	50	Mediu m	Ⅲ	Closing hill for afforestation	Seed propag ation	18	14
17	4 Abies nephrolepis 3 spruce 1 birch 1 Tilia 1 color-leaved tree	55	Mediu m	Ⅲ	Closing hill for afforestation	Seed propag ation	14	15
18	2 Abies nephrolepis 2 birch 2 Tilia 1 pruce 1 elm 1 color-leaved tree 1 weed tree	85	Mature	Ⅴ	Intermediate cutting	Seed propag ation	22	17
19	2 Abies nephrolepis 2 spruce 2 Tilia 2 birch 1 color-leaved tree 1 fraxinus mandshurica	75	Near-mature	Ⅳ	Intermediate cutting	Seed propag ation	22	17
20	3 spruce 2 Abies nephrolepis 2 Tilia 1 color-leaved tree 1 birch 1 fraxinus mandshurica	55	Mediu m	Ⅲ	Closing hill for afforestation	Seed propag ation	16	14

In combustible type division process of Canadian forest fire spreading model, forests are classified into 16 categories. Since the research on forest fire spreading in the region of Hannuo River in Greater Higgnan Mountains is based on this model, output nodes can be set according to the 16 categories.

3. Experimental Results and Analysis

In this paper, data of 9702 compartments in the region of Hannuo River in Greater Higgnan Mountains serve as test samples and substitute them into well-trained network based on group type. Due to the features of neural network such as parallel running, self-learning and self-organization, fast calculation can be conducted and correct classification result can be given. Finally, group classification results in the region of Greater Higgnan Mountains by trained BP neural network are show in Table 3. Meanwhile, GIS is applied to visually reflect the group type classified by neural network according to different map layer.

Table 3. Group Classification in the Region of Hannuo River in Greater Higgnan Mountains

S/N	Name of groud	Compartment No.
1	Coniferous forest	1, 2, 3, 7, 8, 16, 23, 24, 27, 31, 33, 34, 35, ……
2	Broad-leaved forest	10, 12, 17, 18, 21, 22, 26, 30, 38, 39, 42, 43, ……
3	Mingled forest	4, 5, 6, 9, 11, 13, 14, 18, 19, 20, 25, 28, 29, ……
4	Cutover land	78, 80, 84, 87, 90, 91, 95, 99, 101, 104, 109, ……
5	Open ground	54, 63, 69, 77, 82, 96, 120, 124, 158, 162, 163……

In this experiment, 8000 groups of data are selected from compartment data in the region of Hannuo River in Greater Higgnan Mountains as test samples which are substituted into BP neural network based on stand factors for classification. Final classification results are shown in Table 4.

Table 4. Combustible Classification Based on Forest Fire Behavior in the Region of Hannuo River in Greater Higgnan Mountains

Classification code	Name of combustible type in Canadian model	Name of combustible type in the region of Hannuo River in Greater Higgnan Mountains
C-1	Spruce - lichen forest land	Spruce - lichen forest land
C-2	Northern spruce forest	Spruce forest
C-3	Mature short-leave pinewood or twisted-leave pinewood	Mature short-leave and twisted-leave coniferous forest (fallen leave – grass forest)
C-4	Immature short-leave pinewood or twisted-leave pinewood	Immature (fallen leave – grass forest), young, medium
C-5	Pinus koraiensis and white pine forest	Pinus koraiensis forest
C-6	Coniferous artificial forest	Coniferous artificial forest
C-7	Western yellow pine - Douglas fir - fir forest	Fir forest
D-1	Aspen forest, European polar forest	White birch - grass (pure forest)
M-1	Northern mixed deciduous forest	White birch – azalea - alder grove
M-2	Northern evergreen mixed forest	Dahurian larch – walnut – oak forest
M-3	Mixed deciduous forest containing withered balsam fir	
M-4	Evergreen mixed forest containing withered balsam fir	
S-1	Pinus banksiana or pinus contorta cutover land	Burned area
S-2	White spruce and balsam fir cutover land	
S-3	Coastal cedar, hemlock, Douglas fir and fir cutover land	
O-1	Grass land	Grass moo, water area

Through classifying combustible types in the area of Greater Khingan Mountains with trained BP neural network, it is found that the forest type in the area of Greater Khingan Mountains differs from that in Canada, i.e. 16 combustible type values correspond to 12 types.

4. Conclusion

In accordance with combustible classification in the region of Hannuo River in Greater Higgnan Mountains, original BP neural network model is optimized, and then combustible types are classified. Relative to Canadian model, other combustibles have good classification results, except mixed deciduous forest containing withered balsam fir,

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evergreen mixed forest containing withered balsam fir, white spruce and balsam fir cutover land, coastal cedar, hemlock, Douglas fir and fir cutover land. In follow-up research, the remaining 4 combustibles will be further studied.

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