Application research on BP-ANN models of lightning prediction with spatio-temporal characteristics

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ABSTRACT

To improve the accuracy and learning performance of lightning prediction models, a BP-ANN binomial classifier for lightning prediction based on incremental learning and spatiotemporal characteristics is proposed. By using incremental methods and learning historical data based on the spatiotemporal characteristics of the data, various BP-ANN models are established to predict and classify new data, and then the category of the new data is determined by majority voting. Three lightning prediction models were constructed: incremental learning-based BP-ANN model, spatiotemporal characteristic based BP-ANN model, and BP-ANN model combining incremental learning and spatiotemporal characteristic. The prediction accuracy and learning performance were tested on a real lightning dataset, and the results show the advantages and disadvantages of incremental learning, spatiotemporal characteristic, and their combination.

Keywords: Lightning prediction, incremental learning, spatio-temporal characteristics, BP-ANN, binomial classifier

1. INTRODUCTION

Lightning disasters[1-4], as one of the most serious natural disasters, have a significant impact on the electronic age. Therefore, predicting lightning has become a hot topic of concern for meteorological departments in recent years. In recent years, many researchers have conducted research on lightning prediction and proposed many prediction models. In addition to using traditional methods such as linear regression, point clustering, and multiple linear regression equations to design prediction models, many researchers currently use advanced intelligent computing, machine learning, and data mining technologies to study lightning prediction models. Liu et al.[2] studied the thunderstorm release prediction technology using T511 numerical prediction product sites based on a binary particle swarm naive Bayesian classifier. Zhou et al.[3] used support vector machine (SVM) classification method to establish a thunderstorm potential prediction model in the region, and tested the predictive ability of the model with test samples. At the same time, they compared the predictive performance with logistic regression model and Bayes discriminant method. Ni et al.[4] proposed a CNN LSTM deep neural network for meteorological data and established a thunderstorm prediction model for the next 6 hours in Beijing. Zhang et al.[5] conducted research on thunderstorm prediction methods based on improved genetic wavelet neural networks, Hu et al.[6] conducted thunderstorm prediction research based on Bayesian classification methods, Wang et al.[7] conducted thunderstorm prediction research based on least squares support vector machines, Tian[8] constructed a model based on convective parameters for thunderstorm potential prediction, Jin[9] used ARIMA-NN integrated models for thunderstorm prediction research, and Zhang[10] analyzed thunderstorm monitoring and warning data using meteorological satellites and radar observations. Although the above models have achieved good results, there are two shortcomings in summary: (1) they have not achieved spatiotemporal feature classification, resulting in an inability to improve accuracy; (2) Without implementing incremental learning, meteorological lightning data will continue to be generated over time, so the absence of an incremental learning mode will undoubtedly result in a lot of redundancy and waste. Therefore, this article intends to use BP (Back Propagation), BP Artificial Neural Networks, ANN (Artificial Neural Network)[11-19], spatiotemporal characteristics, and incremental learning[20-23] techniques were applied to the binary classification of meteorological lightning.

ANN provides a new classification method for pattern recognition, which has some characteristics that traditional pattern recognition methods do not have: strong discrimination performance, fast classification speed, and easy training. Among various models, BP-ANN is the most mature and widely used. According to Kolmogorov's theorem, a three-layer

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BP-ANN can complete any n-dimensional to m-dimensional mapping, that is, having one hidden layer is sufficient. At the same time, considering simplicity and practicality, a hidden layer is also more superior.

In response to the two problems described above in lightning prediction research, this article explores them from two aspects: (1) Considering the spatiotemporal characteristics of sample data and establishing different models based on the differences in spatiotemporal characteristics, learning and constructing corresponding prediction models for data with different spatiotemporal characteristics; (2) Considering that actual data increases over time and historical data gradually increases, this article adopts an incremental method to establish an incremental learning mode, which uses the learning sample data generated in the later stage to adjust existing models and achieve the goal of incremental learning. Based on this, this article studies and designs a binomial classifier for lightning prediction with spatiotemporal characteristics that can be incrementally learned.

2. OVERVIEW OF THE 1BP-ANN MODEL

2.1 Neural network learning algorithms

Let $X_i=\{x_1,x_2,...,x_n\}$ represents the input of attributes for a piece of data, $W[][]$, For the connection strength, which is the weight, $b[]$ is set as the threshold. The activation function and the output O_{num} of the num th neuron are described as follows:

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

$$O_{num} = \begin{cases} 1, & f(\sum_{j=1}^{n} x_i W[j][num] - b[num]) > 0.5 \\ 0, & f(\sum_{j=1}^{n} x_i W[j][num] - b[num]) \le 0.5 \end{cases} \tag{2}$$

where $\sum X_i W_i$ is the activation value.

The description of the backpropagation process is as follows:

By giving input $X_i=\{x_1, x_2, ..., x_n\}$ and expected output $Y_i=\{y_1, y_2, ..., y_n\}$, we calculate the actual output value and start the threshold correction process from back to front.

Formula for modifying the weights from the output layer to the hidden layer and the output neuron threshold:

$$E_{[k]} = (out[k] - O_k) \cdot O_k \cdot (1 - O_k) \tag{3}$$

$$E'[t] = \sum_{k=1} (W[t][k] \cdot E[k]) \cdot O'_t \cdot (1 - O'_t) \tag{4}$$

$$W[i][j] = W[i][j] + r \cdot e[j] \cdot X[i] \tag{5}$$

$$b[j] = b[j] + r \cdot e[j] \tag{6}$$

Due to differences in the calculation of node error formulas between the hidden layer and the output layer, they are written separately here, $E[k]$ is the error of the k-th node in the output layer, and similarly, $E'[t]$ is the error of the t-th hidden layer node, $out[k]$ is the ideal output of the k-th node in the output layer, O_k represents the actual output of the k-th node in the output layer, O'_t represents the output value of the t-th node in the hidden layer. $W[i][j]$ represents the weight value from the i-th node in the previous layer to the j-th node in the next layer, which is the learning rate, $B[j]$ represents the threshold of the j-th node in the current layer, $E[j]$ represents the error of the j-th node in the current layer, which is $E[j]$ for the output layer and $E'[t]$ for the hidden layer, $X[i]$ is the output of the i-th node in the previous layer.

2.2 Strategies for determining learning outcomes

The output result of the neural network classifier studied in this article is binary data, that is, for the output layer, this article sets the size to 2. There are two strategies for determining learning outcomes in classifiers:

Strategy 1 is based on limiting the error range (i.e., the accuracy standard) to determine whether to terminate learning and obtain learning results. When the learning error exceeds the specified range, continue to loop learning and change its weight until the error is within a certain range.

Strategy 2 determines whether to terminate learning and obtain learning results based on the number of learning attempts. To learn certain predetermined data content a certain number of times, it is necessary to analyze a large amount of sample data in order to establish a reasonable threshold for the number of times.

For the judgment of the learning results of the classifier designed in this article, a combination of learning times and errors is used. In order to prevent the problem of neural network convergence, when the learning frequency reaches a certain number but the accuracy is too low, restart learning. Table 1 shows the confusion matrix on how to calculate the accuracy of learning results.

Table 1. Confusion matrix of learning results.

	Predicted to be true	**Predicted as false**
Actual is true	A	C
Actual is false	B	D

$$correct = \frac{A+D}{A+B+C+D} \tag{7}$$

The algorithm description for whether to continue learning is as follows:

Algorithm for whether to continue learning

If   *correct>Correct_Thre1&&num>Num_Thre*1   then
         Execute model storage program
Else   if *num>Num_Thre*2 then
         Execute model storage program
Else   if *num>Num_Thre*3*&&correct<Correct_Thre2*   then
         num=0，Start learning again
Else   *num*++;

Among them, *num* is the number of learning times counted, *correct* is the accuracy rate, Correct-Thre1 and Correct-Thre2 are accuracy thresholds, *Num_Thre*1, *Num_Thre*2, and *Num_Thre*3 are thresholds for the number of learning iterations.

3. A BP-ANN MODEL FOR LIGHTNING PREDICTION BASED ON INCREMENTAL LEARNING AND SPATIOTEMPORAL CHARACTERISTICS

3.1 Construction of incremental learning models with spatiotemporal characteristics

Considering the strong spatiotemporal characteristics of lightning occurrence and the fact that lightning data belongs to temporal data, this paper constructs seasonal and regional BP-ANN models based on the existing BP-ANN model and learns from seasonal and regional data, respectively. In addition, in order to enhance the prediction accuracy of the model and improve the time performance of model learning and prediction, this paper adopts an incremental approach for learning, that is, by correcting the original model parameters on the incremental data. This section will provide descriptions of the BP-ANN model for lightning data based on incremental learning, the BP-ANN model for lightning data based on spatiotemporal characteristics, and the BP-ANN model for lightning data based on incremental learning and spatiotemporal characteristics.

Incremental learning[15,16] can solve the problems of large data volume and resource waste caused by repeated learning, thereby improving system performance. The differentiation of spatiotemporal characteristics can further improve system accuracy. Therefore, this article combines two methods to construct a BP-ANN model for lightning prediction based on incremental learning and spatiotemporal characteristics.

Definition 1 sample dataset.

The sample dataset for learning is defined as:

$$S = <U, A, D>$$

(8)

S is the dataset, $U=\{X_1, X_2, ..., X_m\}$ constitute a sample dataset with a finite number of sample data, $A=\{a_1, a_2, ..., a_k\}$ is a set of attributes composed of a finite number of attributes in the sample data, that is, each sample data X_i, $i=1, 2, ..., m$. A vector composed of k attribute values, denoted as $X_i=(x_{i,1}, x_{i,2}, ..., x_{j,k})$, $x_{j,k}$ represent the data values of sample X_i on the j-th attribute. $D=\{d_1, d_2, ..., d_t\}$ is a set of decision attributes composed of a finite number of decision attributes in the sample data.

Definition 2 classification model sets.

The classification model set is defined as a triplet:

$$Model(S) = (id, accuracy(S), TW(S))$$

(9)

Among them,

$$TW = (W[][], W_1[][], b[], rate)$$

(10)

In the above definition, S is the sample dataset, The id is the model number, *accuracy* is the learning accuracy of the corresponding model, while *accuracy(S)* records the information that the learning accuracy of this model changes with the sample dataset, TW is the weight information of the corresponding model, $W[][]$ is the weight value from the input layer to the hidden layer, $W_1[][]$ is the weight from the hidden layer to the output layer, $b[]$ is the threshold, and the initial value of the weight and threshold is a random number between [-1, 1], *rate* is the learning rate. The $TW(S)$ record represents the information that the weight information in the model changes with the sample dataset.

Definition 3 spatiotemporal characteristics.

The spatiotemporal characteristics are defined as the following binary:

$$R = (season, area)$$

(11)

Then, the classification model under the given spatiotemporal characteristic R is defined as the following triplet:

$$Model(S_R) = (id(R), accuracy(S_R), TW(S_R))$$

(12)

where $id(R)$ is the number under the spatiotemporal characteristics, $accuracy(R)$ is the learning accuracy of the corresponding model under this spatiotemporal characteristic, while $TW(S_R)$ is the weight information corresponding to the model under this spatiotemporal characteristic.

For a given dataset $S=\{S_1, S_2, ..., S_m\}$, we classify it according to its spatiotemporal characteristics, and assume that there exists Class $r=season \times area$ spatiotemporal characteristic data $TR=\{R_1, R_2, ..., R_r\}$, respectively $S_{R1} \cup S_{R2} \cup ... \cup S_{Rr}=S$, and for each given data, the spatiotemporal characteristics have uniqueness, so $S_{Rp} \cap S_{Rq}=\varphi$, $p \neq q$, $0<p \leq r$, $0<q \leq r$, The model can be established as: $Model(S_{R1})$, $Model(S_{R2})$, ..., $Model(S_{Rr})$, and $id(R_p) \neq id(R_p)$, $p \neq q$, $0<p \leq r$, $0<q \leq r$.

Definition 4 incremental learning models with spatiotemporal characteristics.

For a given dataset $S=\{S_1, S_2, ..., S_m\}$, The corresponding spatiotemporal characteristic classification model is: $Model(S_{R1})$, $Model(S_{R2})$, ..., $Model(S_{Rr})$, and $id(R_p) \neq id(R_p)$, $p \neq q$, $0<p \leq r$, $0<q \leq r$, For the newly added dataset $S_c=\{S_c, S_{c+1}, ..., S_{c+i}\}$, $i>0$, $c>0$;

We classify S_i according to its spatiotemporal characteristics, and assume that there are λ spatiotemporal characteristics $TR_1 = \{R_1^c, R_2^c, ..., R_\lambda^c\}$ in this new dataset. After classifying the spatiotemporal characteristics of the new dataset, it is: $S_{R_1}^c \cup S_{R_2}^c \cup ... \cup S_{R_\lambda}^c = S_c$, and $S_{R_p}^c \cap S_{R_q}^c = \varphi$, $p \neq q$, $0<p \leq r$, $0<q \leq r$.

The model selection and update strategy is: (1) If $\exists R_j^c = R_l, R_j^c \in TR_1 \& R_l \in TR$, that is, a model with model number $id(R_j^c)$ already exists in the model library, then we take out model $Model(S_{R_l}), id = id(R_j^c)$, learn data $S_{R_j}^c$, and generate a new

model $Model(S_{R_j}^c)$. Due to the same spatiotemporal characteristics, the *id* remains unchanged; (2) If $\forall R_j^c \notin TR \& R_j^c \in TR_1$, we establish a new model $Model(S_{R_j}^c)$.

The construction of the incremental learning BP-ANN model with spatiotemporal characteristics is shown in Table 2.

Table 2. Incremental learning BP-ANN model with spatiotemporal characteristics.

BP model	Number	Size	Explain
Input layer		k	$X_i=<x_{i,1}, x_{i,2}, \ldots x_{i,k}>$
Hidden layer		y	There are y hidden nodes in the middle layer
Output layer	Number of spatiotemporal characteristics	$d=2$	"0" "1"
			"1" "0"
Weight		$k×y+y×d$	Augmented assignment
Threshold		$y+d$	Augmented assignment
Learning rate		1	Augmented assignment

3.2 Incremental learning process and implementation algorithm with spatiotemporal characteristics

The structure of the incremental learning model with spatiotemporal characteristics is shown in Figure 1.
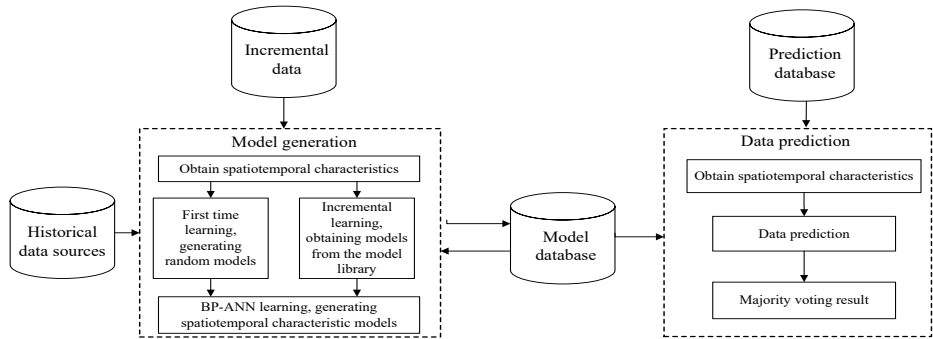

Figure 1. Structure diagram of incremental learning model with spatiotemporal characteristics.

The model generation algorithm and prediction result algorithm are described as follows:

Algorithm 1 Model Generation Algorithm

Step 1 Obtain the spatiotemporal characteristic *R*

 (1.1) Obtain the provided dataset *S*;

 (2.2) Obtain region codes through mapping relationships;

 (2.3) Obtain the spatiotemporal characteristic *R*, and the initial model number *num*=0;

 (1.4) Generate spatiotemporal characteristic number: *id*, check if there is a model with model number *id* in the model library. If it exists, proceed to Step 2; otherwise, proceed to Step 3.1.

Step 2 Generate Random Model

 (2.1) Generate random weights and thresholds, and proceed to Step 4.1.

Step 3 Incremental processing

 (3.1) Search for the spatiotemporal characteristic model with the corresponding model number id in the database;

(3.2) Retrieve the corresponding weight and other information from the database and proceed to Step 4.1.

Step 4 Generate Model

(4.1) Open the data file;

(4.2) Read the next data entry;

(4.3) Input weights and calculate the output of the intermediate hidden layer using Equations (1) and (2) respectively;

(4.4) Take the result obtained from the previous step as input, and then input it into Equations (1) and (2) to calculate the actual output;

(4.5) Obtain the output and calculate the error between the actual output and the ideal output using Formula (3);

(4.6) Input the results generated by 4.5 into Equation (5), and adjust the weights and thresholds from the hidden layer to the output layer in Equation (6);

(4.7) Enter the error result generated by 4.5 into Equation (4) and calculate the error of the hidden layer;

(4.8) Enter the result generated by 4.7 into Equation (5), and Equation (6) adjusts the weight and threshold of the input layer to the hidden layer;

(4.9) Is data read to the end? If so, NO=NO+1, proceed to the next step; Otherwise, proceed to Step 4.2;

(4.10) Determine whether relearning is necessary (NO>learning reset threshold&&accuracy<reset accuracy threshold). If yes, proceed to Step 1.1; otherwise, continue to the next step;

(4.11) Determine whether the end condition is met (NO>threshold for learning end times || accuracy>threshold for end accuracy). If it is met, proceed to the next step; otherwise, proceed to Step 2;

(4.12) Store the model information in the database;

(4.13) Determine whether num<H? If yes, num=num+1, then proceed to Step 2's 1, otherwise proceed to the next step;

(4.14) Algorithm ends.

Algorithm 2 Data Prediction Algorithm Description

Step 1 Obtain the spatiotemporal characteristics of the data

(1.1) Obtain the provided dataset S;

(1.2) Obtain the region code;

(1.3) Obtain the spatiotemporal characteristic R, and the initial model number num=0;

Step 2 Data prediction

(2.1) Search for the corresponding model number id in the database;

(2.2) Extract the model and calculate the actual output O_{num};

(2.3) Determine if num<H? If yes, num++, proceed to Step 2.1; otherwise, continue to the next step;

Step 3 Majority voting result

(3.1) Calculate $t = \sum_{num=0}^{9} O_{num}$. If $t<5$, proceed to Step 3.2; otherwise proceed to Step 3.3;

(3.2) Output "1" and proceed to Step 3.4;

(3.3) Output "2" and proceed to Step 3.4;

(3.4) Algorithm End.

4. MODEL TESTING AND RESULT ANALYSIS

4.1 Test environment and test datasets

The operating environment is shown in Table 3.

Table 3. Testing platform information of the system.

Development platform System	Windows XP, Win7
Development language	Java, Java Swing
IDE Tools	MyEclipse10.0
Database system	SQL Server 2008
Hardware devices	Computer
Data set	Meteorological lightning data
Other	Java runtime environment JRE, configuration of environment variables

The meteorological lightning data comes from the meteorological product data of the Laps system of the Jiangxi Provincial Meteorological Department and the lightning data monitored by the Jiangxi Provincial Lightning Monitoring and Positioning System. The Laps system provides a mesoscale meteorological data analysis field for a total of 8 hours (00, 03, 06, 09, 12, 15, 18, 21 hours) with 21 vertical layers (starting from 100 hpa and each layer spaced 50 hpa) spaced 3 hours apart. The selected area for this test is between longitude 113.5-118.54 and latitude 24.5-30.035, with a grid resolution of $0.045*0.045$. There is a total of $112*123=13776$ grids, which means there are 13776 meteorological samples at each time. This test was conducted at a certain time of the year in different seasons. The specific brief explanation is as follows: (1) 13776 non discretized data (denoted as dataset A) are selected from July to September, 182 data with lightning occurrence (denoted as "1" attribute), and 13594 data without lightning occurrence (denoted as "0" attribute); (2) 13776 non discretized data are selected from April to June (denoted as dataset B), including 150 data with the "1" attribute and 13626 data with the "0" attribute; (3) 13776 non discretized data (denoted as dataset C) are selected from January to March, including 139 data with the "1" attribute and 13537 data with the "0" attribute; (4) 13776 non discretized data (denoted as D dataset) are selected from November to December, including 70 data with the "1" attribute and 13706 data with the "0" attribute. The specific data used for training and testing can be found in the subsequent test results table.

We will sample and discretize the Laps data as a lightning decision table, with a total of 313 conditional attributes. The decision attribute refers to whether lightning has occurred, represented by 0 or 1. Based on this, this article sets the parameter k in Table 2 to 313, which means k=313, d=2. In addition, this article sets the middle-hidden layer to 10, so there is y=10. Before generating models and predicting data, it is necessary to preprocess the data source[16], which includes discretization, sampling, and normalization.

Training end condition: Learn from the original data, stop learning when the accuracy is above 99% or when the learning frequency reaches 15000 times, and the model is stored in the database.

4.2 Testing and result analysis of the BP-ANN model for incremental learning

For the actual data mentioned above, this article conducted tests on both non incremental learning models and incremental learning models, and the results are shown in Tables 4 and 5.

Table 4. Test results of non-incremental learning models.

Data	Training data (number of records)		Test data (number of records)		id	Time consumption T (s/Group)	Frequency/ group	Accuracy (average)/ %	Forecast accuracy/ %
	Positive example	Counter example	Positive example	Counter example					
A	172	172	10	100	x	180	5500	99.4	100

Data	Training data (number of records)		Test data (number of records)		id	Time consumption T (s/Group)	Frequency/group	Accuracy (average)/%	Forecast accuracy/%
	Positive example	Counter example	Positive example	Counter example					
A+B	312	312	20	200	x	420	6800	98.9	93
A+B+C	441	441	30	300	x	1440	15000	97.6	91
A+B+C+D	501	501	40	400	x	1740	15000	95.8	88

Table 5. Test results based on incremental learning model.

Data	Training data (number of records)		Test data (number of records)		id	Time consumption T (s/group)	Frequency/group	Accuracy (average)/%	Forecast accuracy/%
	Positive example	Counter example	Positive example	Counter example					
A	172	172	10	100	x	180	5500	99	100
B	140	140	20	200	x	36	914	99	87
C	129	129	30	300	x	420	15000	98	78
D	60	60	40	400	x	220	15000	96	72

A, B, C and D are the data generated by increments. The learning method in Table 4 is to continuously repeat the learning process. First, learn A to generate the model, then generate B and relearn A and B together, and so on. Therefore, for the case where 4 sets of data are generated, the total learning time is T(A)+T(A+B)+T(A+B+C)+T(A+B+C+D)=3780 s/set. As shown in Table 5, under the incremental learning method, the total learning time is T(A)+T(B)+T(C)+T(D)=856 s/group.

But in the incremental learning mode, A. The accuracy of the data in groups B, C, and D has significantly decreased. Based on this, establishing a BP-ANN model with spatiotemporal characteristics can effectively improve the accuracy of prediction.

4.3 Testing and result analysis of BP-ANN model for lightning prediction with spatiotemporal characteristics

The test results of the proposed BP-ANN model with spatiotemporal characteristics are shown in Table 6.

Table 6. Test results of BP-ANN model based on spatiotemporal characteristics.

Data	Positive example		Counter example			Learning outcomes				Positive example	Counter example
	Training	Test	Training	Test	id	Accuracy /%	Frequency /group	Time consumption T (s/group)		Test	Test
A	172	10	172	100	x	99	5500	180		90	100
B	140	10	236	100	y	99	3400	120		100	99
C	129	10	129	100	z	99	13500	420		90	100
D	60	10	60	100	t	99	4500	60		80	91

Table 6 shows the information of the BP-ANN model under the spatiotemporal characteristics. It can be seen that when the models are established separately, the accuracy of Table 6 has improved significantly compared to Table 5, with a total time consumption of T=780 s/group. However, in practical applications, it is generally not possible to establish a

model for every set of data generated. Therefore, combining incremental learning with spatiotemporal characteristics to establish a model is undoubtedly more advantageous.

4.4 BP-ANN model testing and result analysis combining incremental learning and spatiotemporal characteristics

The test results of the BP-ANN model combining incremental learning and spatiotemporal characteristics are shown in Table 7.

Table 7. Test results of BP-ANN model combining incremental learning and spatiotemporal characteristics.

Data	Positive example		Counter example		Learning outcomes							
	Training	Test	Training	Test	id	Accuracy /%	Frequency /group	Time consumption T (s/group)	Positive example		Counter example	
									Same as R	Abnormal R	Same as R	Abnormal R
A	172	10	172	100	x	98	5500	180	98	30	93	49
B	140	10	236	100	y	98	914	36	97	77	99	59
C	129	10	129	100	z	99	13500	420	90	27	100	44
D	60	10	60	100	t	99	4500	60	80	48	91	69

Table 7 shows the testing and comparison of the BP-ANN model for lightning data by combining incremental learning with spatiotemporal characteristics. It can be seen that the incremental learning model can effectively solve the problem of decreased prediction accuracy and performance caused by the continuous increase of lightning data over time. And models based on spatiotemporal characteristics can improve the accuracy of model predictions by learning unique spatiotemporal feature data.

5. CONCLUSION

This article applies BP-ANN to the prediction of lightning data and constructs three different classifiers based on the spatiotemporal characteristics of lightning and incremental learning, namely the BP-ANN model for lightning data based on incremental learning, the BP-ANN model for lightning data based on spatiotemporal characteristics, and the BP-ANN model for lightning data based on incremental learning and spatiotemporal characteristics. We determine the final classification result by majority voting based on the classification accuracy of the test data on these three classifiers. Through actual data testing, it has been shown that the incremental learning model can effectively solve the problem of decreased prediction accuracy and performance caused by the continuous increase of lightning data over time. And models based on spatiotemporal characteristics can improve the accuracy of model predictions by learning unique spatiotemporal feature data.

The next step will continue to optimize the three models constructed, and conduct more in-depth and comprehensive comparative testing and result analysis on real datasets, as well as compare these three models with other advanced models that can be used for lightning prediction for comparative testing and result analysis.

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