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Research on Precipitation Prediction Model Based on Extreme Learning Machine Ensemble

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ABSTRACT

Precipitation is a significant index to measure the degree of drought and flood in a region, which directly reflects the local natural changes and ecological environment. It is very important to grasp the change characteristics and law of precipitation accurately for effectively reducing disaster loss and maintaining the stable development of a social economy. In order to accurately predict precipitation, a new precipitation prediction model based on extreme learning machine ensemble (ELME) is proposed. The integrated model is based on the extreme learning machine (ELM) with different kernel functions and supporting parameters, and the submodel with the minimum root mean square error (RMSE) is found to fit the test data. Due to the complex mechanism and factors affecting precipitation change, the data have strong uncertainty and significant nonlinear variation characteristics. The mean generating function (MGF) is used to generate the continuation factor matrix, and the principal component analysis technique is employed to reduce the dimension of the continuation matrix, and the effective data features are extracted. Finally, the ELME prediction model is established by using the precipitation data of Liuzhou city from 1951 to 2021 in June, July and August, and a comparative experiment is carried out by using ELM, long-term and short-term memory neural network (LSTM) and back propagation neural network based on genetic algorithm (GA-BP). The experimental results show that the prediction accuracy of the proposed method is significantly higher than that of other models, and it has high stability and reliability, which provides a reliable method for precipitation prediction.

Keywords: Mean generating function; Principal component analysis; Extreme learning machine ensemble; Precipitation prediction

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1. Introduction

In recent years, due to the intensification of some natural factors and human activities, the global climate has changed severely, resulting in the frequent occurrence of various extreme natural disasters. For example, the rainstorm in Henan on July 20, 2021 affected 13.3198 million people in 1573 townships and towns in 150 counties of Henan Province, and the death toll reached 71 [1]. Precipitation data usually implicate rich information. Through the analysis of precipitation data, we can get the development law of data, and then predict the future precipitation in the precipitation area, so as to enormously reduce the critical harm of precipitation anomaly to society and people [2].

The traditional statistical methods have their own limitations, need to collect a large number of precipitation data and have high requirements for the quality of data, what is more, the complexity of precipitation causes makes its data nonlinear, which makes it difficult to predict [3,4]. However, the mathematical and statistical models used in traditional methods require complex computing power [5], and may be time-consuming and have little impact. With the development of science and technology, data acquisition methods are gradually diversified. The traditional precipitation prediction model can not meet the development needs of current precipitation prediction.

With the rapid progress of computer technology, machine learning technology is favored by many scholars. The application of artificial intelligence to the field of meteorology is also rising after more than 10 years of silence [6]. A neural network is widely used in various fields because of its fairly good adaptive learning ability and nonlinear mapping ability. Yu Xiang et al. applied ensemble empirical mode decomposition to decompose the original rainfall time series into a batch, and then used Support Vector Regression (SVR) to predict the short-term component intrinsic model function [7]. Yuanhao Xu et al. proposed particle swarm optimization (PSO) to optimize the super parameters of extended short-term memory (LSTM) neural network [8]. The real-time target detection method based on the convolutional neural network (CNN) classifier proposed by V.R.S. Mani et al. has achieved ideal results [9]. Zihao Zhang et al. proposed a variable weight neural network to solve a multivariable, strongly nonlinear, dynamic and time-varying problem [10].

Thanks to it being based on a least square algorithm, an extreme learning machine (ELM) has strong computing power and good generalization performance. Yong Ping Zhao et al. set up one-stage transfer learning ELM (OSTL-ELM) and two-stage transfer learning ELM (TSTL-ELM). OSTL-ELM makes use of one stage to extract information from two domains, while TSTL-ELM uses two stages to realize the separate adaptation of the target domain. The network weights of these two methods are generated by calculation rather than iteration. Only a small amount of target domain data is needed to acquire high diagnosis accuracy [11], CNN is combined with ELM, and the network is optimized based on the developed metaheuristic algorithm [12]. By transforming the structure of the ELM hidden layer, the threshold network can pass through adaptive stochastic resonance, and find the appropriate generalization performance of the threshold network by using the fast learning algorithm of ELM [13]. Xiao et al. employed regularized extreme learning machine (RELM) to distinguish fault types and identify faulty components. At the same time, LU decomposition was used to solve the output matrix of rELM, so as to shorten the training time of RELM [14]. Yang Ju generates an extreme learning machine classifier with large differences by randomly assigning hidden layer input weights and biases [15]. Chen Yang changed the distribution of hidden layer node parameters and randomly selected input weights for each ELM. Meanwhile, he searched for the optimal number of hidden nodes for each base learner and averaged the output consequences of all base learners [16].

At present, ensemble learning technology has received great attention from scholars. Ensemble learning is a technology to create and combines multiple machine learning models to produce an optimal prediction model. The most common is an ensemble classifier based on neural network technology and using bagging, boosting and random subspace combination technology [17]. The algorithm proposed by Luká š Klein is based on a new combination of stack integration and basic learners. Wide and deep neural networks are used as meta-learners. The research results show that the algorithm achieves satisfactory results [18]. Madhurima Panja proposes an integrated wavelet neural network (XEWNet) model with exogenous factors. Compared with statistical, machine learning and deep learning methods, XEWNet performs better in 75% of the short-term and long-term predicted cases of dengue fever incidence rate [19]. A neural network ensemble method considering parameter sensitivity is proposed to solve the problem of convergence and relatively low accuracy of training [20].

Huang proposed that ELM has significant characteristics such as fast learning speed and excellent generalization performance in both regression and classification tasks [21]. However, due to the weights and deviations between the input layer and the hidden layer is randomly generated, the generated model is different each time. Ensemble learning can combine the advantages of ELM and make up for its disadvantages. In order to improve the accuracy and stability of ELM training and retain the advantages of ELM learning, a new ensemble model based on an extreme learning machine is proposed in this paper. The ensemble model is based on the extreme learning machine with different kernel functions and supporting parameters, and the submodel with the minimum root mean square error is found to fit the test data.

Owing to the complex mechanism and factors affecting precipitation change, the data have strong uncertainty and significant nonlinear variation characteristics. Therefore, in this paper, firstly, the mean-generating function method is used to extend the precipitation sequence, and the principal component analysis is used to reduce the dimension of the extension matrix. The processed data are used as the independent variable and the original precipitation sequence is used as the dependent variable to establish the extreme learning machine ensemble precipitation prediction model. The research structure of this paper is shown in **Figure 1**.

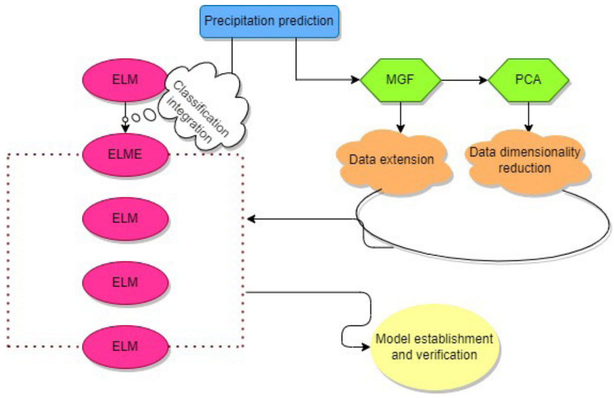

Figure 1. The structure of this study.

2. The proposed methodology

2.1 Mean generating function

For the sake of solving the problem the predicted value tends to be close to the average value of the series when multi-step prediction is carried out on time series data [22].

Wei Fengying and other scholars enriched the concept of arithmetic mean in mathematical statistics, and proposed the algorithm of mean generation function (MGF) [23].

Assuming the precipitation data series as $\{y_t, t=1,2,\cdots,N\}$. The mean value of $\bar{y}=\frac{1}{N}\sum_{j=1}^{N}y(i)$ is $y(t)$. The MGF is calculated as follows:

$$y_l(i)=\frac{1}{n_l}\sum_{j=0}^{N_l-1}y(i+jl), i=1,2,\cdots,l, 1\le l\le Q \tag{1}$$

where $N_l=INT\left(\frac{N}{l}\right), Q=INT\left(\frac{N}{2}\right), l$ is the period of the mean generating function, Q is the maximum length of the cycle, INT is rounded.

The periodic extension sequence is obtained by periodic extension calculation.

$$Y_l(t)=y_l\left[t-l\cdot INT\left(\frac{t-1}{l}\right)\right], \qquad t=1,2,\cdots,N+p \tag{2}$$

where p is the number of steps to forecast the future, thus the extended mean generating function sequence matrix can be obtained.

$$Y^* = \begin{bmatrix} Y_1(1) & Y_1(2) & \cdots & Y_1(N+P) \\ Y_2(1) & Y_2(2) & \cdots & Y_2(N+P) \\ \vdots & \vdots & & \vdots \\ Y_Q(1) & Y_Q(2) & \cdots & Y_Q(N+P) \end{bmatrix}_{Q\times(N+P)} \quad (3)$$

Then the first column in the extensive matrix of the MGF is marked as y_1, the second column is recorded as y_2,..., the Q column is recorded as y_Q.

2.2 Principal component analysis

PCA is a dimensionality reduction algorithm favored by various scholars. That is, high-dimensional data are mapped to low-dimensional space through some linear projection, so as to maximize the amount of data information in the projection dimension and to achieve the purpose of using fewer data and retaining more source data [24]. The main flow of principal component analysis is shown in **Figure 2**.

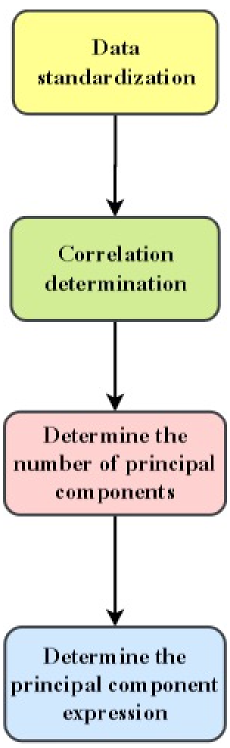

Figure 2. The flow of principal component analysis.

Assuming that there are m samples $\{X^1, X^2, \cdots, X^M\}$, each sample has n-dimensional features $X_i = (x_1^i, x_2^i, \cdots, x_N^i)^T$. Every feature x_j has its own eigenvalue. Centralize all features.

$$\overline{x_n} = \frac{1}{M}\sum_{i=1}^{M} x_n^i \quad (4)$$

Using matrix science, the relationship between eigenvalues λ of the covariance matrix C and its corresponding eigenvectors u is gained.

$$Cu = \lambda u \quad (5)$$

The primitive feature is projected onto the selected characteristic vector. For each sample X^i, the original feature is $(x_1^i, x_2^i, \cdots, x_N^i)^T$, and the new aspect obtained after projection is $(y_1^i, y_2^i, \cdots, y_k^i)^T$. The computing formula of the new feature is:

$$\begin{bmatrix} y_1^i \\ y_2^i \\ \vdots \\ y_k^i \end{bmatrix} = \begin{bmatrix} u_1^T * (x_1^i, x_2^i, \cdots, x_n^i)^T \\ u_2^T * (x_1^i, x_2^i, \cdots, x_n^i)^T \\ \vdots \\ u_k^T * (x_1^i, x_2^i, \cdots, x_n^i)^T \end{bmatrix} \quad (6)$$

For each and every specimen X^i, the dimension is reduced from the original N features of $Xi = (x_1^i, x_2^i, \cdots, x_N^i)^T$ to the new K properties, and the purpose of dimension reduction is achieved.

2.3 Extreme learning machine

The learning process of the ELM algorithm can be summarized as given a regression objective function or classification objective function, as long as the size of hidden nodes in a feedforward neural network is nonlinear and continuous, it can randomly generate the connection weight and threshold between the input layer and phase hidden layer without adjusting the size of hidden nodes, It can approach the target continuous function randomly or classify the classified targets, which improve the counting rate and model prediction accuracy. The structure of ELM is shown in **Figure 3**.

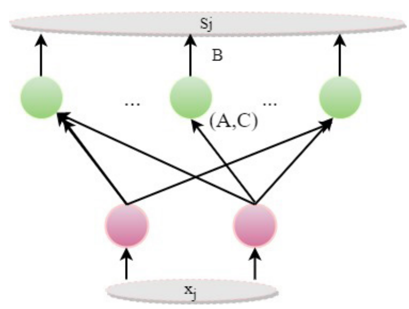

Figure 3. The structure of ELM.

ELM consists of an input layer, a hidden layer and an output layer. Assuming that the neurons in the input layer be n, the neurons in the hidden layer be r, the neurons in the output layer be m, and the training set be $\{x_j, s_j \mid x_j \in R, s_j \in R, j=1,2,\cdots,Q\}$.

In the ELM model, the connection weight between the input layer and the hidden layer and the threshold of the hidden layer neuron is emerged randomly [25], and the connection weight A is set as:

$$A=\begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & & \vdots \\ a_{r1} & a_{r2} & \cdots & a_{rn} \end{bmatrix}_{r\times n} \tag{7}$$

where a_{ij} represents the connection weight of the i th neuron in the hidden layer and the j th neuron in the input layer. Set the connection weight B between the hidden layer and the output layer as:

$$B=\begin{bmatrix} b_{11} & b_{12} & \cdots & b_{1m} \\ b_{21} & b_{22} & \cdots & b_{2m} \\ \vdots & \vdots & & \vdots \\ b_{r1} & b_{r2} & \cdots & b_{rm} \end{bmatrix}_{r\times m} \tag{8}$$

where b_{jk} represents the connection weight of the j th neuron in the hidden layer and the k th neuron in the input layer. If the deviation of hidden nodes is C, that is, the threshold of hidden layer neurons, there is

$$\mathrm{C}=[c_1,c_2,\cdots,c_r]'_{1\times r} \tag{9}$$

In general, the first step of ELM training is to use a stochastic-created fastened quantity of neuron nodes to construct the hidden layer. The activation function may be whatever nonlinear function. The commonly used activation functions include the sigmoid function, tanh function, relu function, etc. Let the activation function of hidden layer neurons be $g(X)$. Then from the figure, the output S of the network can be expressed as:

$$S_j=\begin{bmatrix} s_{1j} \\ s_{2j} \\ \vdots \\ s_{mj} \end{bmatrix}_{m\times Q}=\begin{bmatrix} \sum_{i=1}^{r} b_{i1} g\left(a_i x_j+c_i\right) \\ \sum_{i=1}^{r} b_{i2} g\left(a_i x_j+c_i\right) \\ \vdots \\ \sum_{i=1}^{r} b_{im} g\left(a_i x_j+c_i\right) \end{bmatrix}_{m\times 1}, \quad j=1,2,\cdots,Q \tag{10}$$

where $a_i=[a_{i1},a_{i2},\cdots,a_{in}]$; $x_j=\left[x_{1j},x_{2j},\cdots,x_{nj}\right]^T$.

It also can be expressed by the following formula:

$$HB=S' \tag{11}$$

where H is the hidden layer output matrix of ELM. Because the connection between weight A and the threshold C of the hidden layer is generated randomly and preserves constant during the training process. Therefore, the connection weight between the hidden layer and the output layer B can be obtained by solving the least square solution of the following equations:

$$\min\left\|HB-S^T\right\| \tag{12}$$

The solution to Formula (12) is:

$$\hat{B}=H^+S^T \tag{13}$$

where, H^+ is the Moore Penrose generalized inverse matrix of the matrix H [26].

2.4 Extreme learning machine ensemble

As weights and offsets between the ELM input layer and hidden layer are generated randomly, the models created are diverse at every turn, and their performance is also extremely discrepant. In order to surmount the problem of low precision of a single ELM model and instability results caused by randomly setting input weights, an extreme learning machine ensemble method is proposed in this paper to enhance the degree of accuracy and stability of precipitation prediction. Its structure is shown in **Figure 4**.

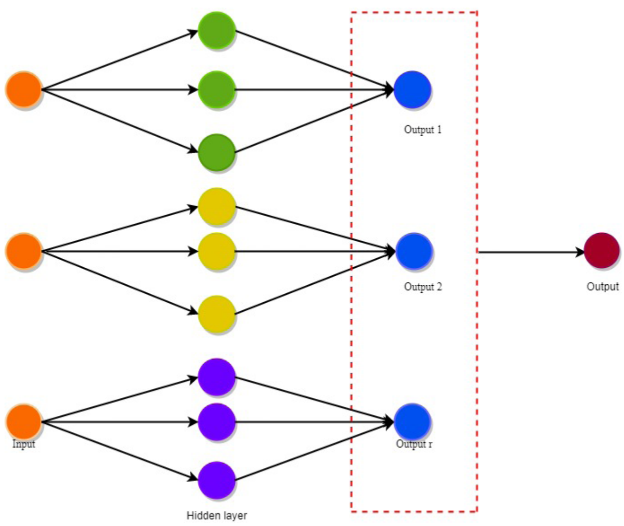

Figure 4. Network structure of ELME.

In order to ensure high accuracy and good stability of the results obtained by the ensemble model, this paper will select the model with the minimum average absolute percentage error among the ELM model trained by different kernel functions,

$$\min M\hat{E}(\hat{s}_j) = \frac{100}{\mathrm{n}}\sum_{i=1}^{j}\frac{|s_j - \hat{s}_j|}{|s_j|}$$
$$\text{Let} \min M\hat{E}(\hat{s}_j) = \frac{100}{\mathrm{n}}\sum_{i=1}^{j}\frac{|s_j - \hat{s}_j|}{|s_j|} = w \tag{14}$$

At this point, the optimization problem is:

$$\begin{cases}\min \frac{1}{2}\|w^2\| \\ s.t. y_j\left(w\hat{s}_j + c\right) \geq 1\end{cases} \tag{15}$$

For solving the constrained optimization problem, the solution of the initial problem and the optimal problem can be gained by solving the dual problem.

The Lagrange multiplier $\alpha_j \geq 0$ is introduced into inequality (15), and the Lagrange multiplier method takes advantage of solving the above quadratic programming problem, then the above posture can be written as:

$$L(w,c,\alpha) = \frac{1}{2}\|w^2\| - \sum_{j=1}^{n}\alpha_j\left(y_j\left(w\hat{s}_j + c\right) - 1\right) \tag{16}$$

Let $\theta(w) = \max_{\alpha_j \geq 0} L(w,c,\alpha)$

On the basis of the duality of Lagrange, the dual problem of the original optimization problem can be transformed by the minimax problem:

$$\begin{aligned}\min_{w,c}\theta(w) &= \min_{w,c}\max_{\alpha_j \geq 0} L(w,c,\alpha) \\ &= \max_{\alpha_j \geq 0}\min_{w,c} L(w,c,\alpha)\end{aligned} \tag{17}$$

Find the partial derivatives of B and C respectively.

$$\begin{aligned}&\frac{\partial L}{\partial w} = 0 \Rightarrow w = \sum_{j=1}^{n}\alpha_j y_j \hat{s}_j \\ &\frac{\partial L}{\partial c} = 0 \Rightarrow \sum_{j=1}^{n}\alpha_j y_j = 0\end{aligned} \tag{18}$$

Bring the outcome into Equation (16) to obtain:

$$\begin{aligned}L(w,c,\alpha) &= \frac{1}{2}\sum_{i,j=1}^{n}\alpha_i\alpha_j y_i y_j \hat{s}_j^T\hat{s}_i - \sum_{i,j=1}^{n}\alpha_i\alpha_j y_i y_j \hat{s}_j^T\hat{s}_i - b\sum_{j=1}^{n}\alpha_j y_j + \sum_{j=1}^{\mathrm{n}}\alpha_{\mathrm{i}} \\ &= \sum_{j=1}^{n}\alpha_j - \frac{1}{2}\sum_{i,j=1}^{n}\alpha_i\alpha_j y_i y_j \hat{s}_j^T\hat{s}_i\end{aligned} \tag{19}$$

Thus, in light of the restraint condition, it is transformed into a convex quadratic programming problem:

$$\begin{aligned}&\max \sum_{j=1}^{n}\alpha_j - \frac{1}{2}\sum_{i,j=1}^{n}\alpha_i\alpha_j y_i y_j \hat{s}_j^T\hat{s}_i \\ &s.t. \alpha_j \geq 0 \\ &\sum_{j=1}^{n}\alpha_j y_j = 0\end{aligned} \tag{20}$$

According to the above conditions, the unique solution α_j^* of quadratic programming can be acquired, and the optimal decision function form can be obtained after sorting:

$$f(s) = sign\left(\sum_{j=1}^{n}\alpha_j y_j\left(\hat{s}_j, \hat{s}_i\right) + c\right) \tag{21}$$

The pseudo of ELME is shown in Algorithm 1.

Algorithm 1

Begin

Input $x_i = [x_1, x_2, \cdots, x_k, x_{k+1}, \cdots, x_j]^T$

Output: $f(s)$

Generate randomly: a and c;

for i=1 **to** j.

Set activation function：sine、sigmoid、hardlim;

Calculate S and B;

end for

for i=1 to k

Sort min $\mathrm{M\hat{E}}(s)$;

Set $y_j\left(w\hat{s}_j + c\right) \geq 1$;

Introducing Lagrange multiplier;

Calculate α_j;

End

3. Empirical research

3.1 Modeling data

Liuzhou is the largest industrial base in Guangxi. The sustained and stable economic development of Liuzhou is of great importance to the development of Guangxi. Therefore, the real data on precipitation in Liuzhou from Guangxi Meteorological Bureau are selected in this paper. The aggregate data are 213 data from 1951 to June, July and August 2021. A total of 180 data from 1951 to June, July and August 2010 are used as the training data set to establish the precipitation fitting model, and the data from June, July and August 2011 to 2021 are used as the test data set to optimize the verification model.

The precipitation data used in this paper first employs MGF method to extend the monthly precipitation series of Liuzhou from 1951 to 2021 in June, July and August, and takes the value that the cumulative contribution rate of principal component variance reaches 90%, so as to further reconstruct the original data. Then, take 10 steps of extension, establish the mean generating function extension matrix for the reconstructed succession data, and receive the mean generating function extension matrix, and then employ PCA to reduce the dimension of the data obtained by MGF and extract effective data properties.

3.2 Model performance evaluation

In order to directly perceived through the senses observe the effect of model fitting, training data and test data are made use of in this paper to drill and test the model, and the indicators in **Table 1** are used to measure the quality of the model.

Table 1. Performance evaluation metrics.

Number	Metric	Value
1	Root Mean Square Error (RMSE)	$RMSE=\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(x_i-\hat{x}_i\right)^2}$
2	Symmetric Mean Absolute Percentage Error (MAPE)	$sMAPE=\frac{100\%}{\mathrm{n}}\sum_{i=1}^{n}\frac{\lvert\hat{y}_i-y_i\rvert}{\left(\lvert\hat{y}_i\rvert+\lvert y_i\rvert\right)/2}$
3	Pearson correlation coefficient (PCC)	$PCC=\frac{\sum_{i=1}^{n}(x_i-\bar{x}_i)\sum_{i=1}^{n}\left(\hat{x}_i-\bar{\hat{x}}_i\right)}{\sqrt{\sum_{i=1}^{n}\left(x_i-\bar{x}_i\right)^2\sum_{i=1}^{n}\left(\hat{x}_i-\bar{\hat{x}}_i\right)^2}}$

where x_i indicates the observed value, and $\hat{x}_i$ represents the fitting value. $\bar{x}_i$ represents the mean of monthly precipitation observation value, and $\hat{x}_i$ represents the equal value of model output value.

Evaluation indexes 1 and 2 can be used to measure the deviation between the actual observation value and the fitting value of precipitation. The smaller the value, the smaller the deviation between them. Evaluation index 3 can perceive whether the model can correctly predict the precipitation trend. The greater its value, the more accurate the model can predict the future precipitation trend.

3.3 Result analysis

In order to verify the quality of ELME model. In this paper, the proposed ELME model is compared with representative machine learning methods such as ELM, GA-BP and LSTM. For the ELM model, this paper trained a total of 15 cases in which five activation functions of "Sigmoid", "Sine", "Hardlim", "Radbas" and "Tribas" were combined with three hidden neurons of 10, 20 and 30. The parameter combination with the best training effect was selected, which was the activation function "sine" with hidden neuron 30. The parameters were employed in the training of ELM. For GA-BP model, the parameters of the genetic algorithm are set as follows: crossover probability is 0.3, mutation probability is 0.1. For the LSTM model, the parameters are set as follows: Solver is "Adam", gradient threshold is 1, and the initial learning rate is 0.01. After 125 rounds of training, the learning rate is reduced by multiplying factor 0.2. The fitting results of the four models for 60 training data of precipitation in June, July and August in Liuzhou are presented in **Figure 5**, **Figure 6** and **Figure 7**. The data in **Table 2** specifically illustrate the fitting precision and fitting effect of the four models on the training data.

As can be observed in **Figure 5**, **Figure 6** and **Figure 7**, the fitted values and real values of ELM, LSTM, GA-BP and ELME on Precipitation in Liuzhou in June, July and August have roughly the same trend. Among them, there is a section with a good fitting effect and a section with relatively considerable fitting error, and the fitting effect is consistent with the general experimental data fitting situation. Obviously, the fitting effect of LSTM, GA-BP and ELME model is closer to the real value in June and July. In August, it can be seen that the ELME model still has the same trend with the real value and the difference between each real value and the fitted value is not gigantic.

As can be seen from **Table 2**, the correlations of

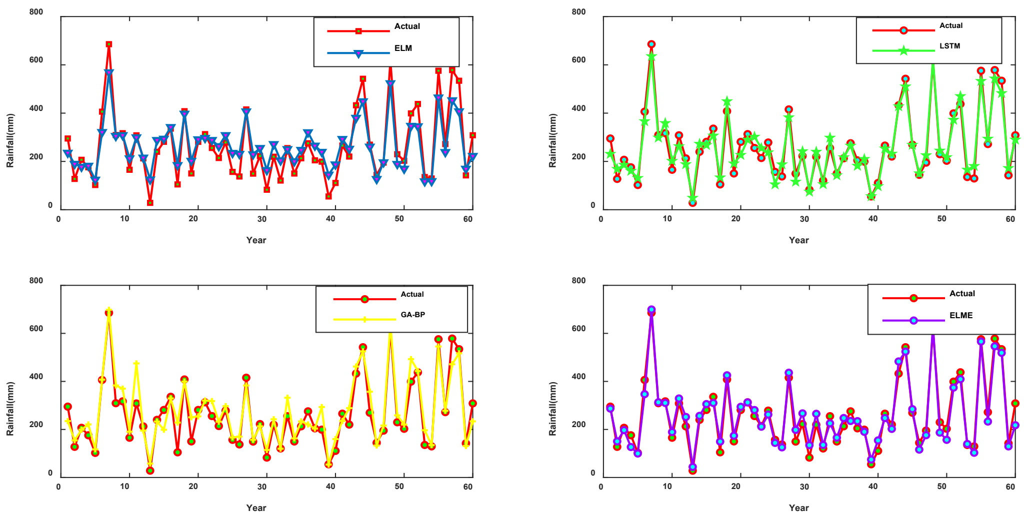

Figure 5. Fitting effect of training data of four models in June.

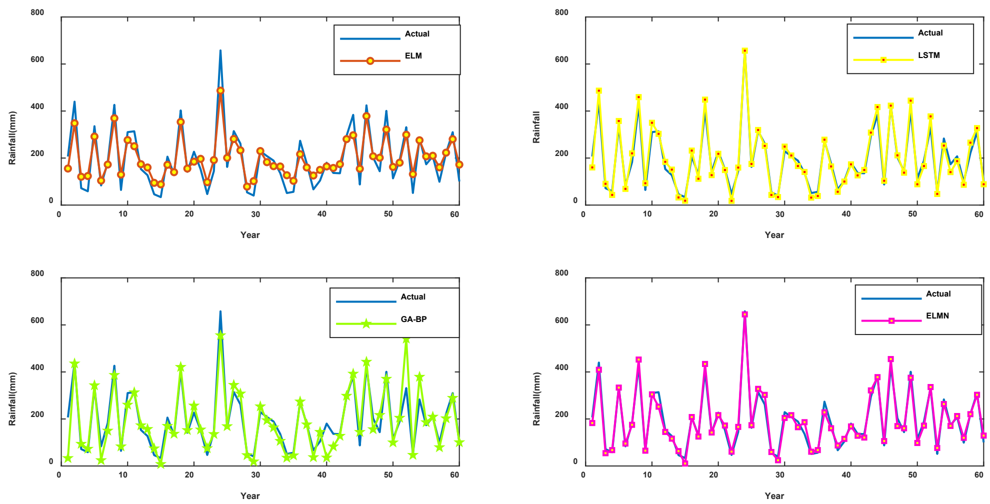

Figure 6. Fitting effect of training data of four models in July.

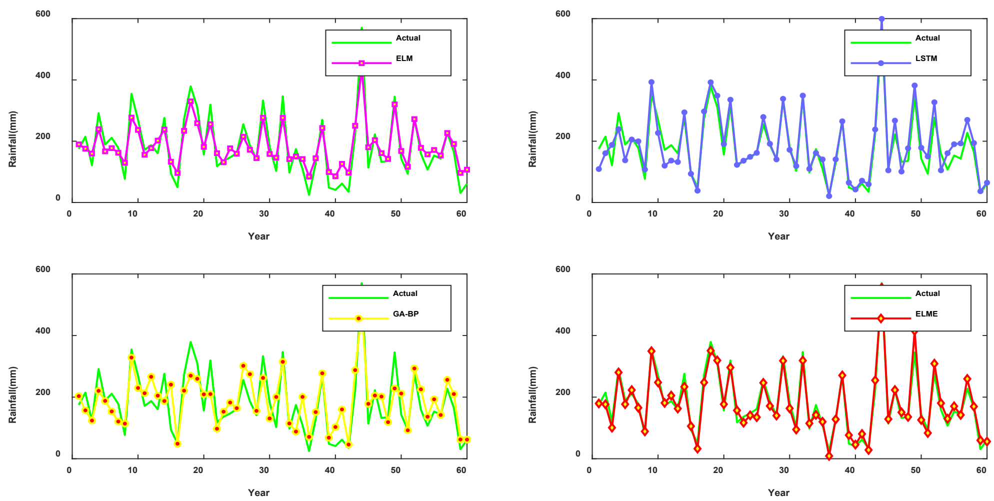

Figure 7. Fitting effect of training data of four models in August.

the four models in June, July and August are highly correlated, indicating that the four models can make correct predictions on the precipitation trend. In addition, the RMSE value of ELM model was 59.418 and sMAPE value was 0.220 in June, the RMSE value of LSTM model was 31.566 and sMAPE value was 0.129, and the RMSE value of GA-BP model was 50.811 and sMAPE value was 0.158, while RMSE value of ELME model is 30.253, sMAPE value is 0.127. In modeling the factor under the same conditions, ELME the precision of the model, relative to the ELM model LSTM model, GA-BP model increased by 42.272%, 1.550% and 19.620% respectively. Meanwhile, in the precipitation data in July ELME the precision of the model, relative to the ELM model LSTM model, GA - BP model increased by 53.169%, 10.135% and 46.800%, respectively. August precipitation data model of ELME the precision of the model, relative to the ELM model LSTM model, GA - BP model increased by 48.031%, 20.482% and 54.007% respectively. The above data show that the fitting accuracy of ELME model based on precipitation data in different months is significantly better than that of ELM model, LSTM model and GA-BP model in training data.

One aspect of evaluating a model is its fitting effect, but more vital is its prediction effect, that is, the generalization ability of the model. Based on the above training model, the test data of precipitation in Liuzhou city in June, July and August are fitted, and the fitting results are shown in **Figure 8**, **Figure 9** and **Figure 10**. The data in **Table 3** specifically illustrate the fitting precision and fitting effect of the four models on the test data.

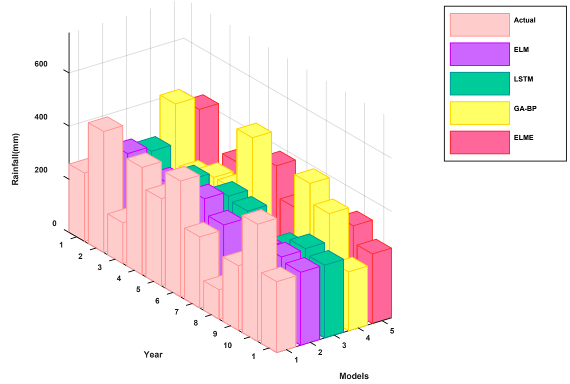

Figure 8. Four models were tested for data fitting in June.

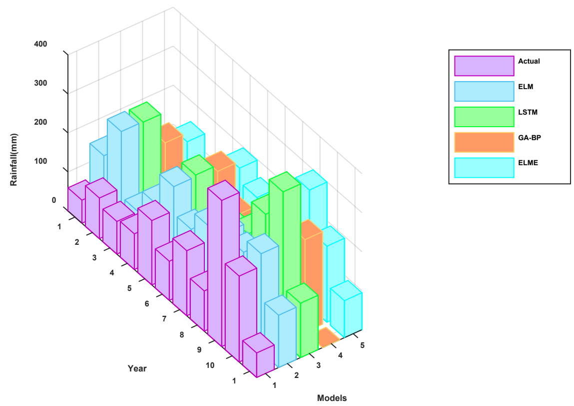

Figure 9. Four models were tested for data fitting in July.

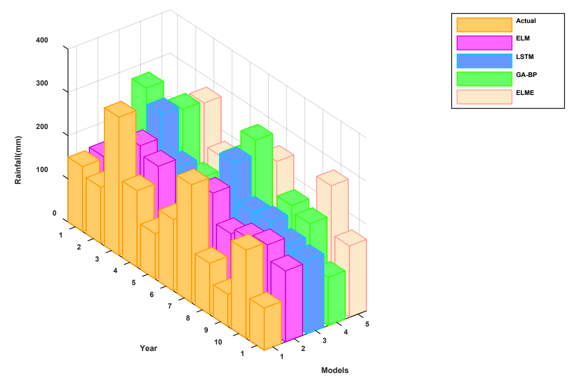

Figure 10. Four models were tested for data fitting in August.

Table 2. Evaluation indexes of training data fitting effect of four models.

Models	**June**			**July**			**August**		
	RMSE	sMAPE	PCC	RMSE	sMAPE	PCC	RMSE	sMAPE	PCC
ELM	59.418	0.220	0.946	50.850	0.284	0.970	42.532	0.254	0.967
LSTM	31.566	0.129	0.977	22.940	0.148	0.989	32.072	0.166	0.958
GA-BP	50.811	0.158	0.942	51.071	0.250	0.925	58.558	0.287	0.826
ELME	30.253	0.127	0.978	21.061	0.133	0.986	21.133	0.132	0.979

4. Discussion

As can be seen from **Table 3**, the correlation of GA-BP model established by precipitation data in July is only 0.458 in test data, indicating that the correlation of GA-BP model in this month is not very content. Meanwhile, the correlation of GA-BP model established by precipitation data in June and August is 0.677 and 0.666 respectively. The correlation strength of the model is moderate. In addition, the correlation between ELM model and LSTM model based on precipitation data in July was 0.516 and 0.676 respectively, and the correlation between LSTM model based on precipitation data in August was 0.710, indicating that the correlation strength of models verified by this test data was relatively general. As for ELME model, the correlation coefficients in June, July and August are 0.896, 0.873 and 0.847 respectively, indicating that the model has a greater correlation with the precipitation data in any month.

For precipitation test data in different months, it can be seen from **Table 3** that the values of RMSE and sMAPE of ELME model are smaller than those of ELM, LSTM and GA-BP models. Among them, the sMAPE value of ELM, LSTM and GA-BP in June was 0.187, 0.251 and 0.352 respectively, while the sMAPE value of ELME model was 0.144, which compared with the other three models improved by 22.995%, 42.629% and 59.091% respectively. The accuracy of July model ELME was improved by 42.647%, 41.542% and 59.912% compared with model ELM, LSTM and GA-BP, respectively. The accuracy of the August model ELME was improved by 31.154%, 39.322% and 45.427% compared with model ELM, LSTM and GA-BP, respectively. The above data show that the fitting accuracy of ELME model based on precipitation data in different months is significantly better than that of ELM model, LSTM model and GA-BP model.

Based on **Table 2** and **Table 3**, it can be seen that under the same construction pattern, the ELME model has a significantly better fitting effect on precipitation data than LSTM model and ELM model, regardless of training data or test data. In addition, compared with ELME model, it can be found that ELME model has superior fitting stability in precipitation data.

5. Conclusions

In the modeling research of monthly precipitation forecast in atmospheric science, the one-dimensional time series observation data of various meteorological elements or climate elements can provide the most notable forecast information source. With the rapid development of machine learning technology, every machine learning prediction technology can provide crucial and useful forecast information. In this paper, MGF is used to extend the precipitation series, and PCA is used to reduce the dimension of the extended series, so as to establish the ensemble precipitation prediction model of an extreme learning machine.

A novel extreme learning machine ensemble is put forward in this paper. The ensemble model is based on the extreme learning machine with different kernel functions and supporting parameters, and the submodel with the minimum root mean square error is found to fit the test data. Consequently, the ELME model proposed in this paper reduces the complexity of the model and achieves better performance. In this paper, the precipitation data of Liuzhou from 1951 to 2021 in June, July and August were utilized to train the model, and the model was

Table 3. Evaluation indexes of fitting effect of test data of four models.

Models	June			July			August		
	RMSE	sMAPE	PCC	RMSE	sMAPE	PCC	RMSE	sMAPE	PCC
ELM	72.374	0.187	0.898	88.627	0.476	0.516	53.077	0.260	0.788
LSTM	84.686	0.251	0.822	88.671	0.467	0.676	55.663	0.295	0.710
GA-BP	109.454	0.352	0.677	88.910	0.681	0.458	69.072	0.328	0.666
ELME	57.049	0.144	0.896	45.685	0.273	0.873	40.119	0.179	0.847

compared with ELM, LSTM and GA-BP models. Experimental results show that the proposed ELME achieves accurate prediction in the field of precipitation, and the model has a simple structure, which can be used as an alternative to reduce the complexity of the model. This shows that ELME can be used in a variety of machine learning domains and has some general applicability, and the proposed algorithm can be verified on a variety of data sets in the future. However, the three activation functions in this paper are randomly set. At present, this structure cannot automatically select the three most appropriate activation functions. In the future, we can consider how to select the activation functions that are suitable for this structure at one time.

Author Contributions

All the authors have made significant contributions to the work of the report. Xing Zhang is mainly responsible for the construction of the idea of this article, the simulation experiment and the writing of the paper. Jiaquan Zhou is mainly responsible for controlling the full text; Jiansheng Wu is mainly responsible for providing ideas; Lingmei Wu is mainly responsible for simulation experiments, and Liqiang Zhang is mainly responsible for obtaining data.

Conflicts of Interest

The authors declare that they have no conflicts of interest to report regarding the present study.

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