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1229: MULTIMEDIA DATA ANALYSIS FOR SMART CITY ENVIRONMENT SAFETY

Fire danger forecasting using machine learning-based models and meteorological observation: a case study in Northeastern China

Zhenyu Chen[1] · Chen Zhang[1] · Wendi Li[1] · Lanyu Gao[1] · Liming Liu[1] · Lei Fang[2,3,4] · Changsheng Zhang[1]

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Abstract
Wildfire is one of the primary natural disturbance agents in the forests of China. The forecast of fire danger is critically important to assist stakeholders to avoid and mitigate wildfire-induced hazards and losses to both human society and natural ecosystems. Currently, fire danger rating methods often focus on fire weather classification based on fixed thresholds, which has shortcomings in generalizability and robustness. Based on historical fire occurrence data and meteorological data of Northeastern China from 2004 to 2015, we proposed a forest fire danger rating classification and forecasting model by combining the advantages of the Canadian Fire Weather Index (FWI) system and two machine learning models such as the Long Short-Term Memory (LSTM) network and Random Forest (RF) model. The method is divided into two stages. The first stage is the LSTM-based FWI system indexes prediction. In the first stage, the future FWI system indexes are obtained through the LSTM-based prediction model, and the RMSE and MAE of the prediction results are calculated to verify the prediction performance of the model. The second stage is random forest-based fire danger rating prediction method. In the second stage, we use the random forest method to get the fire danger occurrence probability and present the fire danger rating classification scheme. Then we verify the reliability of the fire danger rating classification scheme by using the forest fire danger data in Qipan Mountain. Our method predicts two randomly selected future intervals, and the prediction accuracy is 87.5%. The experimental results show that our machine learning-based forest fire danger rating classification method can provide a new idea for forest fire danger warnings.

Keywords Fire danger forecasting · Machine learning · Canadian fire weather index · LSTM · Random forest

Extended author information available on the last page of the article

1 Introduction

All over the world, forest fires occur frequently every year. Take the U.S. for an example, since 1983, the National Interagency Fire Center has documented an average of approximately 70,000 wildfires per year [10]. These fires generate large amounts of smoke pollution, release greenhouse gases, and unintentionally degrade ecosystems, causing losses to natural ecology and human life [12]. In order to effectively reduce the destructive impact of forest fires, timely prediction of forest fires has become increasingly important and urgent, which has attracted extensive attention all over the world.

Forest fire danger prediction is so important for sustainable and forward-looking forest fire management [33], as it provides buffers of preventive preparation for a period of time, helping relevant departments to design effective preventive measures and facilitate response plans to potential fire danger. However, forest fire danger prediction is still a very difficult problem. Since the 1920s, fire danger forecasting works have attracted the attention of a large number of researchers. Many countries and organizations in the world have deeply studied the prediction of forest fire danger [3, 7, 11, 14, 16, 23, 25, 36] and are committed to developing a fire danger early warning system [4, 5, 24, 26, 30]. At present, the fire danger prediction methods studied in China mostly use the relationship between fire danger and meteorological factors and the early climate characteristics, and can only predict the fire danger in the short term. The National Fire Danger Rating System (NFDRS) of the USA and the Canadian Forest Fire Danger Rating System (CFFDRS) are the most advanced and widely used fire danger early warning systems in the world. Considering a variety of indexes, they can predict medium and long-term fire danger.

Although great progress has been made in forest fire danger early warning, there are still some problems. First, the accuracy of fire danger prediction needs to be improved. Second, the universality of fire danger prediction method is not high. In view of the above problems, we need a more general fire danger early warning method, which has high prediction accuracy and can use the future fire danger index data. To overcome the above problems, some researchers have introduced machine learning methods [1, 19, 31, 32]. Machine learning methods can deal with prediction and classification problems well, so it helps to improve the accuracy of fire danger prediction.

In recent years, most machine learning-based fire danger prediction models have been optimized from both the model and data perspectives. Optimization from a model perspective mainly focuses on model selection and improvement. Many researchers have used artificial intelligence algorithms to solve the problem of forest fire danger prediction. Abid et al. [1] introduced a genetic algorithm based machine learning algorithm to predict fire. Zhang et al. [41] used the CNN network in deep learning to predict fire danger. Kalantar et al. [18] studied the application of a variety of machine learning algorithms in fire danger prediction. Janiec et al. [17] compared the effects of two artificial intelligence algorithms on fire danger prediction. Optimization from a data perspective mainly focuses on the complexity and representativeness of the data type. Related researchers have recently been using different types of data that affect fire danger to make predictions. Alonso-Betanzos et al. [2], predict fire danger based on data such as temperature, precipitation, humidity, historical fire, etc. Li et al. [21] combined meteorological, terrain, vegetation, infrastructure, and socio-economic data to predict fire danger. Sayad et al. [29], based on remote sensing data, extracted three indexes of NDVI, LST, and TA from the remote sensing data to predict fire danger. Sakr et al. [28] combined simplified weather indexes (precipitation and relative humidity) to predict the occurrence of fire danger.

Unfortunately, the accuracy of forest fire danger predictions is still hampered by many factors. Among these factors, the forest fire danger dataset is a major factor limiting the predictive performance of current machine learning-based fire danger prediction models. Currently, the collection of fire danger data is seriously hindered by two difficulties. One is the regional and low frequency of fire occurrences since it is difficult for researchers to collect forest fire danger data for specific study areas. The other is that collecting fire danger data on-site will consume a lot of human and financial resources. So far, most forest fire danger prediction methods have employed only a small dataset, which will not only seriously affect the prediction effect of the model but may also lead to serious model overfitting, seriously hindering the application of the model in practice.

In addition, there are still many problems with existing machine learning-based forest fire danger prediction models. Most of these methods often have a very short prediction time period, and generally can only predict the fire danger of the next day, and cannot provide effective guidance for fire danger prevention and control in advance. In order to improve the prediction time, it may be a good idea to use a time series prediction method suitable for medium to long-term prediction of forest fire danger. At present, the commonly used medium and long-term time series prediction methods mainly include LSTM models and machine learning methods (such as ARIMA), which are mostly applied to predict economic data indexes, traffic data, ecological data (e.g., water quality and pm2.5), medical and health data, etc. [20, 27, 35, 37, 39]. There is little research on fire danger index data prediction using time series prediction model. Wu et al. [38] used the LSTM model to detect tunnel fire sources, which did not involve the prediction of forest fire danger. Li et al. [22] used the LSTM model of attention mechanism to predict the burning area of wildfire. Different from these papers, we focus more on the prediction of future fire danger ratings. Besides, most of these researches only focus on the binary classification of fire danger, using simple machine methods [2, 21, 28, 29], to get the result of whether fire danger occurs or not. Thus, the prediction results often have large deviations and cannot be well applied to actual forest fire danger prevention. Unlike these researches, our research focuses on multi-classification and leverages fire danger ratings to provide a more accurate fire danger assessment.

Although most existing studies [17, 21, 29] have made some contributions to the prediction or forest fire danger classification, they have not analyzed the internal relationship between prediction and classification and organically combined them. Different from them, our machine learning-based forest fire danger rating classification method combines prediction and classification. We propose a more general fire danger early warning method with two stages, which has high prediction accuracy and can use the future fire danger index data. The first stage is the LSTM-based FWI system indexes prediction method. The second stage is the random forest-based fire danger rating prediction method. To implement our approach, we need to overcome several challenges. First, future FWI system indexes need to be predicted with high accuracy. Second, the fire danger rating needs to be divided reasonably. To tackle the first challenge, we compare the prediction accuracy of several prediction models. Finally, we choose the LSTM-based model to predict the future FWI system indexes. To deal with the second challenge, we compare the classification performance of three machine learning methods and select random forest as our final classification model. Then we use the random forest to get a fire danger rating classification scheme to divide the fire danger rating reasonably.

The main contributions of this paper are as follows: we propose a more general forest fire danger prediction method with high prediction accuracy, which can help build a forest fire danger early warning system. Our method takes the FWI system indexes data as the basis for fire danger classification to ensure the authority. We collected 11,322 historical FWI system indexes data in the Qipan Mountain area and 3963 fire danger data in Northeastern China. We propose the LSTM-based prediction model, which is better than ANN, ARIMA, GDBT, and SVR. In addition, we study the prediction effect of different time lengths by considering the influence of Time lag based on the model. We select random forest as the final classification method by comparing the classification performance of the three machine learning methods for fire danger data, and then we propose a more accurate and objective forest fire danger rating classification scheme, which can divide forest fire danger into different ratings. The effectiveness of our classification method is verified by the real fire danger data in the Qipan Mountain area.

The rest of this paper is as follows: the second part introduces the main research methods, the third part evaluates our machine learning-based forest fire danger rating classification methods, and the fourth part summarizes and discusses future research work.

2 Materials and methods

2.1 The overall working flow

We propose a machine learning-based forest fire danger rating classification method, and the method overview is shown in Fig. 1. First, we preprocess the collected data. Preprocessing consists of data preparation and data analysis. Second, the preprocessed data of the Fire Weather Index (FWI) system are used as the input data of LSTM based prediction model in the first stage. The model inputs the predicted six index data into the random forest model in the second stage. Then, the fire danger occurrence probability data obtained from the random forest model is input into the fire danger classification scheme to obtain the final fire danger rating.

2.2 Datasets

2.2.1 Fire occurrence record of northeastern China

We collected 3963 fire occurrence data from 2004 to 2015 of the Northeastern China, which was consisting of 1088 wildfires and 2875 prescribed burnings. The wildfires [6, 8] here included forest fires, grassland fires, and shrubland fires that occurred accidently, while the prescribed burnings were ignited and manipulated by humans in low fire weather conditions that normally none natural fire can occur. Thus we considered the wildfires as the validated fire occurrence, and labeled the prescribed burnings as non-fire in the following modeling works. Figure 2a shows the annual number of fire occurrence in Northeastern China between 2004 and 2015. It shows that the number of fires that occurred in 2007

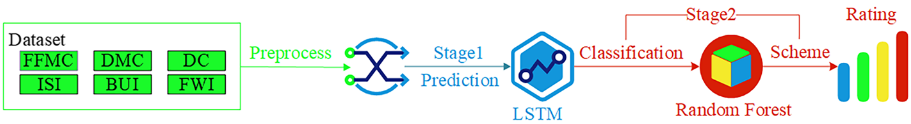

Fig. 1 Overview of our forest fire danger rating classification method

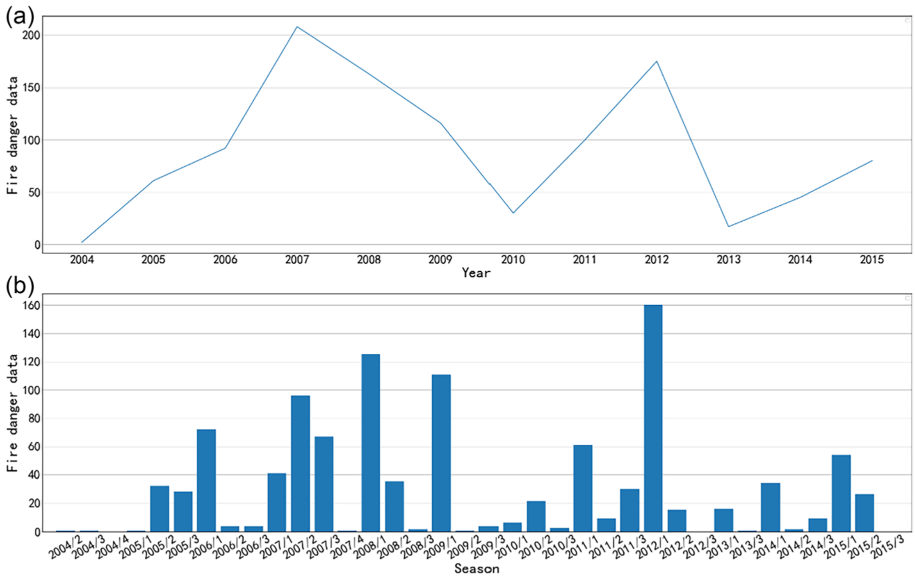

Fig. 2 The number of fires from 2004 to 2015

is the highest. Figure 2b shows the number of fires in each season from 2004 to 2015. It shows that fire danger occurred the most frequently in spring and summer, so we need to strengthen fire prevention in spring and summer. For the convenience of drawing, the number 1 in Fig. 2b represents spring (March to May), the number 2 in Fig. 2b represents summer (June to August), the number 3 in Fig. 2b represents autumn (September to November), and the number 4 in Fig. 2b represents winter (December to February).

2.2.2 Fire weather index

We adopt the more authoritative FWI system index. Forest Fire Weather Index (FWI) system is an important part of the Canadian Forest Fire Danger Rating System (CFFDRS). CFFDRS is one of the most widely used systems with mature technology in the world. After modification and improvement, the system can be applied to any region and country in the world. The FWI system consists of six parts and requires four types of data: temperature, relative humidity, wind speed, and precipitation within 24 h. FWI system is widely used not only to predict the occurrence of fires, but also to predict the probability of lightning strikes, the height of canopy scorch, the consumption model of forest ground during fires, and to evaluate the characteristics of fires (e.g., area of fires and number of fires). The FWI system structure diagram is shown in Fig. 3.

The daily weather observation datasets from 1989 to 2019 of the Northeastern China were obtained from the China Meteorological Data Service Centre (http://data.cma.cn/). The datasets are collected from approximately 133 meteorological stations distributed in study area. Fire occurrence data were counted from 2004 to 2015. According to the date of each wildfire and prescribed burning, we obtained the daily meteorological factors which consist of the maximum air temperature, relative humidity, 10-m open wind, speed, and 24-hr accumulated precipitation as the inputs to calculate the Canadian fire weather index. For each fire event, we obtained the FWIs values according to their occurrence date and the

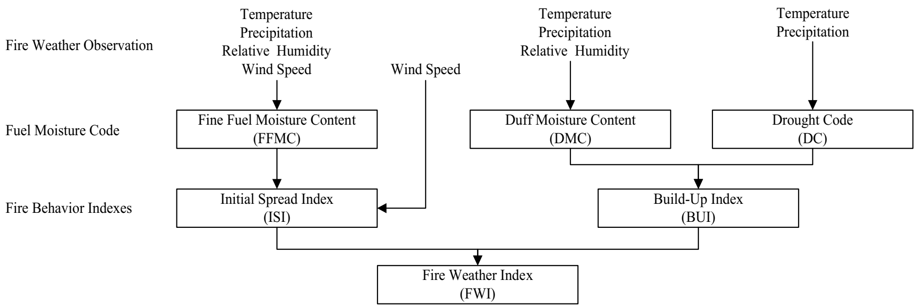

Fig. 3 FWI system structure diagram

nearest meteorological station. Taking the meteorological station near Qipan Mountain as an example, the statistical information of this meteorological station is shown in Table 1.

2.3 Data analysis

Temporal correlations [20, 34, 42, 44] are often used for correlation analysis of time series data. We take the meteorological station near the Qipan Mountain as an example to conduct time correlation analysis on FWI system indexes. We measure the temporal correlations by using an autocorrelation function. For the time lag k, the autocorrelation coefficients can be calculated as follows:

$$\rho_k = \frac{\mathrm{cov}(\varphi(t), \varphi(t+k))}{\sigma_{\varphi(t)} \cdot \sigma_{\varphi(t+k)}} \tag{1}$$

Where $Cov(\bullet)$ and $\sigma(\bullet)$ denote the covariance and the standard deviation, respectively, $\varphi(t)$ denotes the FWI system index value at time t and $\varphi(t+k)$ denotes the FWI system index value at time $(t+k)$.

The time correlation of 6 indexes of the FWI system at station A is shown in Fig. 4.

It can be seen from Fig. 4 that the autocorrelation function values of the six indicators of the FWI system have an obvious downward trend with the increase of time lags, which indicates that the earlier the index data has less influence on the original index data. Therefore, the time lag length will affect the prediction effect. From Fig. 4, considering the autocorrelation coefficients of the six indexes, the time lag length should be no more than 6. When we use LSTM based prediction model to predict fire danger indexes in the future,

Table 1 Statistical information of meteorological station near Qipan Mountain

	FFMC	DMC	DC	ISI	BUI
number	11,322.000	11,322.000	11,322.000	11,322.000	11,322.000
mean	72.848	14.261	215.559	1.697	22.440
std	18.414	14.814	130.610	1.379	20.950
25%	66.651	4.101	118.618	0.643	6.882
50%	81.266	10.400	202.478	1.505	17.763
75%	84.964	18.847	306.393	2.444	30.530

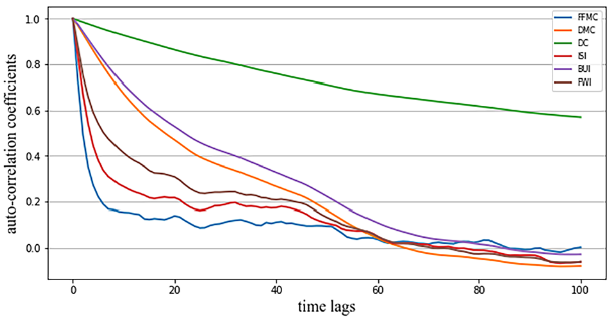

Fig. 4 The changes of autocorrelation coefficient of each indicator with increasing of time lags

it is necessary to conduct experiments with different time lag lengths, so as to improve the accuracy of prediction.

2.4 Fire danger index prediction model based on LSTM

FWI system indexes data we collected are time series data. The common methods [9, 35, 39, 43] used for time series data prediction are ARIMA, SVR, GDBT, ANN, and LSTM. The Autoregressive moving average model (ARIMA) is a commonly used time series prediction method. It is a combination of the autoregressive process (AR) and the moving average process (MA). ARIMA can approximately describe the time series by establishing a model, so as to predict the future data. ARIMA model is relatively simple and can well predict time series data, but it also has some limitations. ARIMA requires time series data to be stable or stable after differential differentiation. Although ARIMA has a good prediction effect on stable time series data, it often has a poor effect if the prediction time is long. SVR is to find a regression plane so that all data in a set are closest to the plane. GDBT is based on the CART tree. The prediction value is the weighted sum of the prediction results on all weak classifiers, and the prediction result on each sample is the mean value of the leaf node where the sample is located. Because of its powerful data analysis and processing ability, neural network can well predict time series data. As a simple neural network model, ANN is composed of input layer, hidden layer, and output layer, which is the comparison object of LSTM based prediction model in this paper. Compared with general neural network, the recurrent neural network (RNN) can deal with the changes in series data better. LSTM is a special RNN [13, 15, 40], which can avoid the gradient appearance and keep the dependency information of the time series. It is suitable for the prediction of long-time series. When the amount of data is large, LSTM can better learn the characteristics of the data. So it is more suitable for the prediction of our fire danger data indexes than SVR and GDBT. In Section 3.2, we compare the LSTM-based prediction model with ARIMA, SVR, GDBT, and ANN, and finally select the LSTM model for fire danger index prediction. The specific structure of the LSTM-based prediction model adopted in this paper is shown in LSTM based model in Fig. 5.

In order to better evaluate the prediction accuracy of the model, we need to evaluate the difference between the predicted value and the real value, and use the reverse normalization operation to restore the data to the original range for comparison with the real data. RMSE and MAE are used to evaluate the accuracy of prediction. These indicators can be formulated as follows:

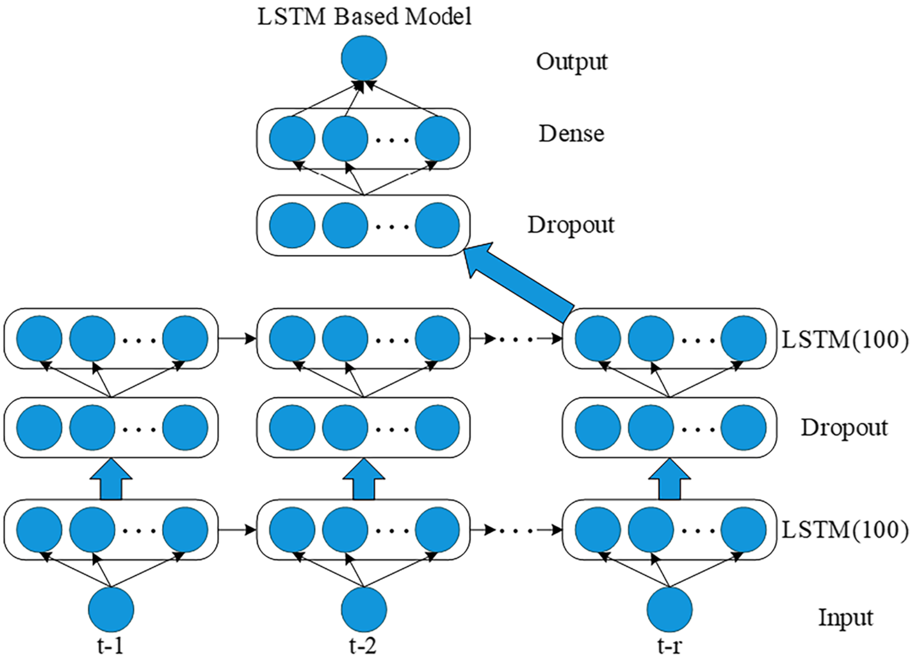

Fig. 5 LSTM based prediction model

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_i - y_i^*\right)^2} \tag{2}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - y_i^*\right| \tag{3}$$

Where y_i^* and y_i denote the observed FWI system index value and the predicted FWI system index value, respectively, n is the number of test samples.

In the first stage, the non-normalization of data will affect the prediction accuracy of the model. When the subsequent LSTM model predicts the future FWI fire danger index data, in order to eliminate the influence of singular sample data points and improve the accuracy of the model, it is necessary to normalize the FWI system index. We use Eq. 2 for normalization.

$$\tilde{x}_i = \frac{x_i - \min(x)}{\max(x) - \min(x)} \tag{4}$$

Where $max(x)$ and $min(x)$ denote the maximum value and the minimum value of the original data set, respectively, $\tilde{x}_i$ denotes the normalized data and x_i denotes the original data.

In order to verify the prediction performance of LSTM based prediction model, first, we determine the parameters of the model through experiments and set the optimal number of neurons and time lag. Then, using the real fire danger data of stations near Qipan Mountain, we calculate the RMSE and MAE of the prediction results and compare the prediction effects of LSTM based prediction model with ARIMA, SVR, GDBT, and ANN. After that, we select the fire danger data of two adjacent stations to further verify the prediction performance of LSTM based prediction model. Finally, we test the influence of prediction time length and time lags on prediction effect.

2.5 Fire danger rating prediction method based on random forest

Most of the existing forest fire danger prediction methods [2, 17, 21, 28, 29] use machine learning methods to predict forest fire danger, such as neural network, support vector machine, decision tree, random forest, and so on. In related studies, the prediction effect of neural network is better than that of support vector machine. Therefore, we compare the fire danger prediction effects of decision tree, random forest, and neural network, and finally selects random forest as our experimental model.

In the process of predicting the fire danger rating, we use 3963 fire point data collected in Northeastern China as experimental data set to train three machine learning method models. The decision tree is generated by the CART algorithm, which is simple to calculate and has strong interpretability. It can analyze large data sources in a relatively short time, which is suitable for the characteristics of large amounts of data in this paper. At the same time, we set the maximum depth of the tree to 15, and prune the decision tree accordingly. As an integrated learning method, the random forest is composed of multiple decision trees. When classifying, each decision tree will vote for the category of input data. Finally, the category with the largest number of votes in the decision tree is the final classification category, and the probability of classification is the largest. The random forest model in this paper is composed of 30 decision trees. The random forest algorithm designed above can reduce the occurrence of overfitting to a certain extent. The random forest we used is shown in Fig. 6. The neural network algorithm adopts artificial neural network (ANN), which is composed of input layer, hidden layer, and output layer. It uses ReLU as the activation function.

In order to verify the superior classification performance of random forest, the experimental data sets are classified by decision tree, random forest, and neural network respectively. The performance of three machine learning methods is verified by classification metrics and cross-validation.

The classification metric is calculated based on the confusion matrix. The confusion matrix can show the classification results of three machine learning methods, and show the number of correct and wrong predictions of each fire danger rating. The performance of the three machine learning methods can be evaluated by accuracy, recall, F1-score, and AUC, which can be obtained by using confusion matrix. These indicators can be formulated as follows:

$$accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{5}$$

$$precision = \frac{TP}{TP + FP} \tag{6}$$

$$recall = \frac{TP}{TP + FN} \tag{7}$$

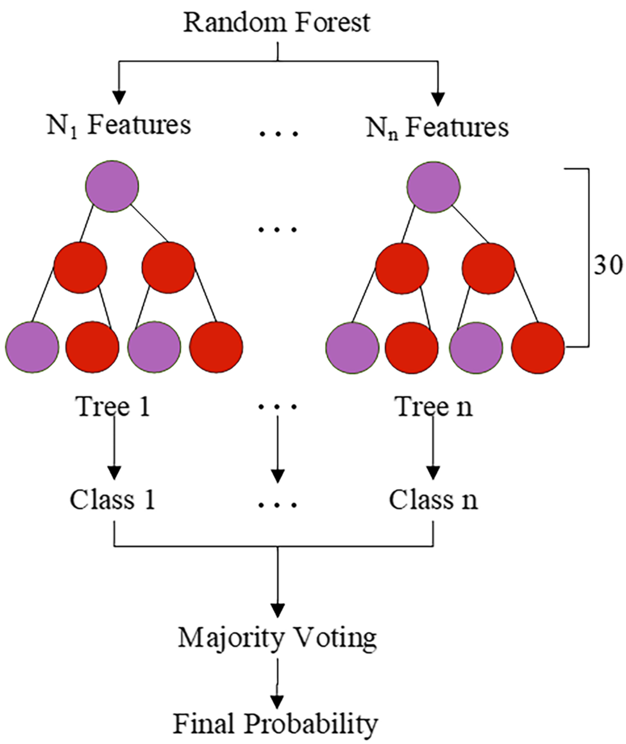

Fig. 6 Random forest model

$$F1 - score = \frac{2 * precision * recall}{precision + recall} \tag{8}$$

Where TP denotes the sample data that is actually positive and predicted to be positive, FP denotes the sample data that is actually negative and predicted to be positive, FN denotes sample data that is actually positive and predicted to be negative, TN denotes sample data that is actually negative and predicted to be negative. The AUC index is defined as the area under the ROC curve. The larger the AUC index is, the better the classification effect is.

This paper also uses random split cross validation, which divides the sample data and combines them into different training sets and test sets. Training set is used to train the model and test set is used to evaluate the quality of the model. On this basis, multiple groups of different training sets and test sets can be obtained, which can effectively evaluate the performance of three machine learning methods. In the random split cross validation, the whole experimental data set is randomly sampled to generate a training set and a test set. The test set accounts for 20% of the data, and then three machine learning methods are used for prediction experiments.

In the actual fire danger prediction, if we directly predict that the fire danger occurs or does not occur, there is a certain contingency. In order to better warn the fire danger, this paper proposes a fire danger classification scheme, which is realized through the following steps:

(1). During fire danger classification, the fire danger data are marked as occurrence (1) and non-occurrence (0), and the probability that each fire danger data is divided into 0 and 1 is obtained by random forest method.
(2). Then we analyze the probability data that all fire danger data are divided into 1, and obtain the mean and standard deviation of probability data to determine the approximate range of fire danger classification.
(3). By adding and subtracting the mean (recorded as μ) and standard deviation, we calculate their sum and difference respectively, and record them as β and α, use the value of μ, β, α to divide the fire danger occurrence probability into four intervals. The end points of the interval are 0, α, μ, β, 1. We mark the four intervals as four ratings from low to high, which are recorded as rating 1, 2, 3, and 4, so as to establish the relationship between fire danger occurrence probability and fire danger rating.

In order to verify the practicability of this classification scheme, we use the real data of Qipan Mountain to verify the classification scheme, and the experimental results confirm the reliability of the classification scheme. Finally, we input the future data of time series prediction into the random forest model, and use our classification scheme to classify the fire danger rating of the future data, which further verifies the practicability and reliability of our forest fire danger classification method.

3 Results

The research area takes Qipan Mountain of Northeastern China as the core, including some forest areas in nearby Fushun City. The reason is that this area contains many forest areas and has just had a fire recently. Therefore, the research on this area will help to prevent forest fire danger in time.

3.1 Selection of prediction model parameters

Before establishing the structure of our LSTM model, we need to determine several super parameters in the model, including the number of neurons in each layer and the time lag. In the experiment of selecting these super parameters, we train our model with the data of 30 years from 1989 to 2018 and predict the data in the next day.

First, we evaluate the impact of the number of neurons on the model and select the number of neurons from the candidate set {50, 100, 150}. We randomly combined the above three cases and compared the experimental results of each combination. The prediction performance was shown in Table 2. According to the results, we selected the group (100, 100) of neurons as the parameters of our model since it has the lowest RMSE and Mae, indicating that it has the best prediction performance.

Next, we tested the impact of different time lags on the prediction performance. The neuron parameters are (100, 100), which is the best. The time lag parameters are selected from the candidate set {3, 6, 9, 15, 21, 24}. The prediction performance of each time lag is shown in Table 3. The longer the time lag is, the more complex the model training is. Based on the above experimental results, when the prediction length is 1 day, the time lag is set to 6, which is most suitable for our model.

Table 2 Prediction performance of different neuron number combinations

Layer1 No.Nodes	Layer2 No.Nodes	RMSE	MAE
50	50	0.3423	0.2642
50	100	0.3642	0.2680
50	150	0.3323	0.2525
100	50	0.3596	0.3001
100	100	0.3253	0.2441
100	150	0.3314	0.2408
150	50	0.3351	0.2653
150	100	0.3350	0.2466
150	150	0.3426	0.2434

In real life, we may need to predict a longer time length. The optimal time lag of different prediction time lengths is different. In subsequent experiments (see Section 3.3), we obtained the optimal time lag of different prediction time lengths.

3.2 Performance evaluation of prediction model

The commonly used time series prediction methods introduced in Section 2.4 include ANN, ARIMA, GDBT, and SVR. In order to select the prediction method suitable for the fire danger index dataset of Qipan Mountain, we compared these four prediction methods with our LSTM-based prediction model. We took the station A as the comparison object, trained the model by using the FWI data of the Qipan Mountain from 1989 to 2018, and predicted the FWI data of the first day of 2019. RMSE and MAE were selected as the evaluation metrics of prediction performance. The RMSE and MAE of each prediction method are shown in Table 4.

From Table 4, we can see that the prediction effect of LSTM based prediction model is better than ANN, ARIMA, GDBT, and SVR. Therefore, we select LSTM based prediction model to predict the future fire danger index data of the Qipan Mountain. However, ARIMA has the worst prediction performance. This is mainly because ARIMA is applicable to the data with obvious periodicity, but the FWI data used in this paper measures the occurrence index of fire danger, which has no obvious periodicity, so ARIMA is not applicable to the FWI data used in this paper. The experimental results also show that the MAE value and RMSE value of ARIMA are significantly different from other methods.

In order to further verify the prediction performance of the LSTM-based prediction model, we took the station B and station C around station A to test the prediction effect of

Table 3 Prediction performance of different time lags

Time lag	RMSE	MAE
3	0.3397	0.2599
6	0.3253	0.2441
9	0.3301	0.2560
15	0.3397	0.2432
21	0.3591	0.2645
24	0.3343	0.2661

Table 4 RMSE and MAE of prediction results of five prediction methods

Method	RMSE	MAE
LSTM	0.3253	0.2441
ANN	0.3505	0.2957
ARIMA	9.1125	10.2313
GDBT	0.3643	0.2998
SVR	0.3622	0.2633

the model. For station B, the RMSE and MAE of the prediction results are 0.064 and 0.054 respectively. For station C, the RMSE and MAE of the prediction results are 0.056 and 0.041 respectively. We can see that the RMSE and MAE of station B and station C are low, which verifies that our model has good prediction performance. However, the RMSE and Mae of the prediction results of station B and station C are different from that of station a, indicating that the data characteristics of different stations are quite different.

3.3 Selection and comparison of prediction time length

Because the prediction effect of different time lengths is different, we often want to predict a longer time in real-life applications. Therefore, we compared the prediction effect of different prediction time lengths, so we can choose the best prediction length in practical applications. The prediction time length we tested includes 2, 4, 6, 8, 10, 12, and 14. For the interest of space, we choose the optimal neuron parameter with the prediction time length of 1 day. In addition, from Section 3.1, time lag has an impact on the prediction effect. We use the grid search method to obtain the optimal time lag with different time lengths. The results are shown in Table 5.

From Table 5, we can find that when the prediction length is greater than 4, the longer the prediction time, the worse the prediction effect. In addition, the prediction effect is greatly affected by the length of time lag. In real-life applications, we need to balance the relationship between prediction effect and prediction time length to ensure high prediction effect under the prediction length, and then we can get a more accurate fire danger rating. Combining the prediction length and prediction effect, we choose the prediction length of 4 days and the time lag of 27 days.

Table 5 Influence of prediction time length and time lag on prediction effect

Length	Time lag	RMSE	MAE
2-day	27	0.0508	0.0502
4-day	27	0.0423	0.0325
6-day	24	0.1050	0.0916
8-day	18	0.2158	0.1733
10-day	21	0.2527	0.2151
12-day	6	0.3604	0.2327
14-day	27	0.3912	0.3142

3.4 Comparison of fire danger classification models

First, we used the 3963 fire danger data collected to compare the classification performance of three machine learning methods: decision tree, random forest, and neural network, and got the fire classification scheme. Fire danger data includes FFMC, DC, DMC, ISI, BUI, and FWI of the FWI system and fire occurrence status (with fire recorded as 1 and without fire recorded as 0). Taking FFMC, DC, DMC, ISI, BUI, and FWI as the input features and fire occurrence status as the label, three machine methods are used to classify fire danger data respectively. The data set is divided into two parts, 80% of which are used for training and 20% for testing. The classification accuracy of the three machine learning methods in the test set is 82.47%, 85.50% and 88.02% respectively. We can see that the classification performance of random forest is better and significantly better than the other two methods. In order to enhance the accuracy and reliability of the experimental results, we added recall, F1-score, and AUC to compare the classification performance of the three methods, and adopted the cross-validation method.

Based on the confusion matrix, precision, recall, and F1-score are calculated respectively. In the test set, the precision, recall, and F1-score of neural network are 0.6848, 0.7842, and 0.7311 respectively, the precision, recall, and F1-score of decision tree are 0.7917, 0.7095, and 0.7484 respectively, and the precision, recall, and F1-score of random forest are 0.8802, 0.7012, and 0.7806 respectively.

The cross-validation of this paper adopts random split cross-validation. The random split cross-validation randomly divides the samples according to the specified proportion. In order to be consistent with the above experiment, 80% of the data is used for training and 20% of the data is used for testing. The accuracy of random split cross-validation experiment is shown in Fig. 7.

From Fig. 7, we can see that the classification effect of random forest is significantly better than another two machine learning methods. At the same time, in the process of experiment, we obtained the AUC of three models. The average values of AUC of random forest, decision tree, and neural network are 0.9455, 0.8278, and 0.9169 respectively. The AUC of random forest are better than the other two models. In addition, the precision,

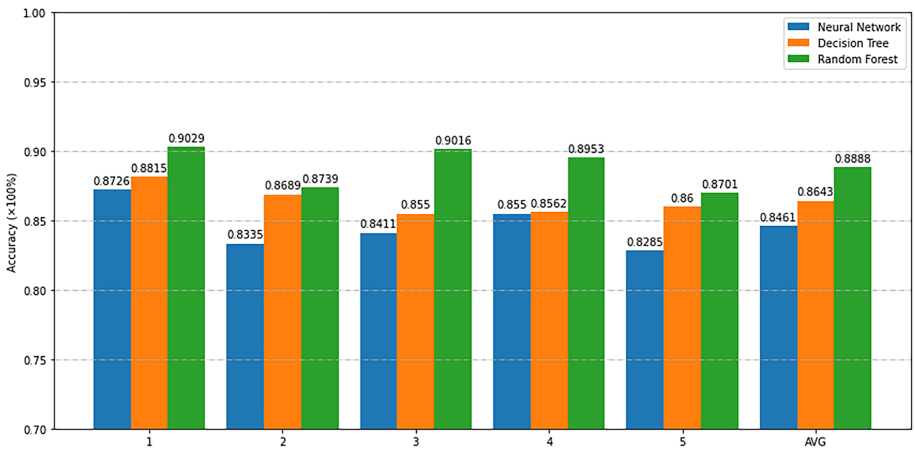

Fig. 7 Accuracy of random split cross-validation experiments with Neural Network, Decision Tree, and Random Forest

recall, and F1-score of the results of random forest classification have little difference, and precision and F1-score are greater than the other two methods, indicating that the stability of the random forest classification method is better and can better learn the characteristics of data.

From the above comparative experiments, we finally choose random forest as our classification model. In order to analyze the relationship between the six indexes of the FWI system and fire danger probability, we drew the partial dependence plots of the six indexes of the FWI system and the fire danger occurrence probability in random forest, as shown in Fig. 8.

From Fig. 8, we can get the relationship between the six indexes of the FWI system and the fire danger occurrence probability. The larger the ordinate value, the greater the fire danger occurrence probability. When the BUI is less than 10, the fire danger occurrence probability decreases with the increase of the BUI. When the BUI is greater than 10, the fire danger occurrence probability increases with the increase of the BUI. The fire danger occurrence probability in DC interval first decreases and then increases, reaching the maximum value near 450, and then decreases after 450. On the whole, the fire danger occurrence probability in DMC interval, FFMC interval, and ISI interval decreases first and then increases. The fire danger occurrence probability in FFMC interval and FWI interval first decreases and then increases. The fire danger occurrence probability in FWI interval first increases with the increase of FWI. When the FWI value is greater than 7.5, it gradually decreases and tends to be stable.

3.5 Fire danger classification scheme

Considering the limitations of simply using two categories to evaluate fire danger in real-life applications, some fire points judged as 1 may not have a fire, so we need to find more objective standards to warn the fire.

In real life, there are few high fire danger ratings, which are mostly concentrated in the high incidence period of fire danger. Because the mean can reflect the concentration trend of data, and the standard deviation can reflect the fluctuation degree of data, the combination of the two can well stratify the data. In order to evaluate the fire danger more objectively, we adopt the fire danger classification scheme in Section 2.5, and use the mean and standard deviation to divide the fire danger rating into four categories. The mean value of

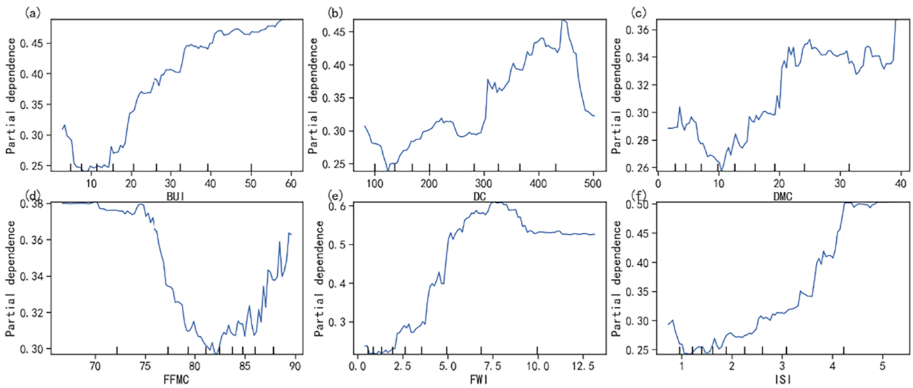

Fig. 8 Partial dependence plots of 6 FWI system indexes and fire danger occurrence probability

Table 6 The fire danger classification scheme

Fire Danger Rating	p
1	$p \leq 0.0511$
2	$0.0511 < p \leq 0.5$
3	$0.5 < p \leq 0.9489$
4	$p > 0.9489$

the probability of fire point data divided into 1 is 0.5000, the sum of the mean value and standard deviation is 0.9489, and the difference is 0.0511.

According to the fire danger classification scheme in Section 2.5, we finally divide the fire danger data into four ratings. For the probability p of a fire danger data, the fire danger classification scheme is shown in Table 6.

The period from March to May is the high incidence period of forest fire danger. If the forest fire danger status can be predicted in advance, it can be well used for early warning and prevention of forest fire danger. In order to verify the reliability of the above fire danger classification scheme in practical application, we took the data from March to May 2019 in Qipan Mountain of Northeastern China to test the fire danger classification scheme.

The random forest method was used to obtain the probability distribution of fire danger data in Qipan Mountain from March to May 2019. Using our fire danger classification scheme, it was obtained that the fire danger rating in Qipan Mountain is 4 for 25 days and 3 for 44 days from March to May, indicating that the forest fire danger in Qipan Mountain is prone to occur from March to May. On April 17, 2019, a forest fire occurred in Qipan Mountain. In order to further verify the applicability of our forest fire danger classification scheme, we separately took out the fire danger rating data of Qipan Mountain in April. The distribution of fire danger rating data is shown in Fig. 9.

From Fig. 9, we can see that the number of days with high fire danger rating in April 2019 in Qipan Mountain is relatively large and concentrated. In addition, as the inflection point, the fire danger occurrence probability increases significantly after the 9th, and the forest fire danger occurrence probability on the 17th is calculated as 1. Furthermore, the probability of fire insurance in the first seven days of the 17th is equal to or close to 1. It shows that the forest fire is very easy to occur between the 9th and 17th, which needs emergency prevention. The actual situation is that the forest fire occurred in Qipan Mountain on April 17, 2019, which proves the reliability and accuracy of our fire danger classification scheme.

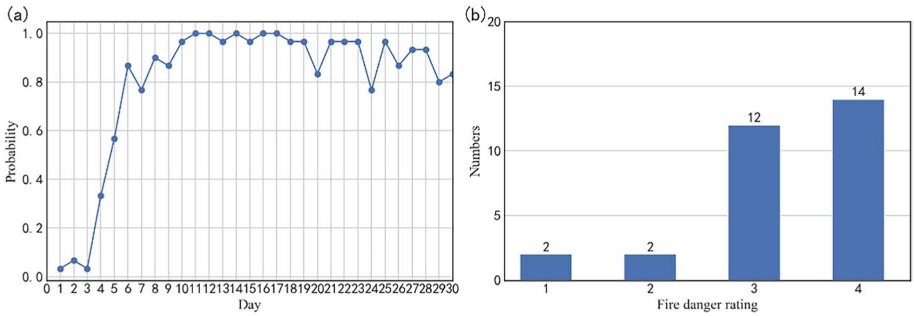

Fig. 9 The distribution of fire danger rating in April 2019 in Qipan Mountain

3.6 Application of forest fire danger rating classification method

In order to further verify the reliability of our forest fire danger rating classification scheme, we planned to use our forest fire danger rating classification method to predict the fire danger rating in 2019, and used the real FWI system data in 2019 for verification. Before the prediction experiment, we first confirmed the prediction time length. From Table 5, comprehensively considering prediction time length and prediction effect, we selected the time lag of 27 and the prediction length of 4. We selected the first four days of 2019 and randomly selected the interval with the time length of 4, from October 11 to October 14. We used our forest fire danger rating classification method to predict the fire danger rating of the above two intervals, as shown in Table 7.

From Table 7, we can see that the fire danger rating predicted by our method is correct in 7 of 8 days. The prediction accuracy is high, which further proves the reliability of our method.

4 Discussion

4.1 Overview

In this work, we propose a forest fire danger rating classification method based on machine learning. The classification method of forest fire danger rating established by us includes two stages. The results indicate that the fire danger prediction accuracy is closely related to the prediction time length, time lag, classification model, and prediction model. We finally selected the optimal classification model and prediction model, and selected the appropriate prediction length and time lag. In the test experiment, our method's prediction accuracy is 87.5%. Our study provides a more general fire danger early warning method, which can be used to build a fire danger early warning system.

4.2 Limitation

There are some limitations that we need to overcome in future work. First, the prediction time length needs to be longer. We only predict the fire danger rating in the next 4 days in the test experiment. The length of prediction time needs to be improved. Although we

Table 7 The prediction results of the forest fire danger rating classification method

Date	True Value	Predicted Value
2019-1-1	2	2
2019-1-2	2	2
2019-1-3	2	2
2019-1-4	2	2
2019–10-11	3	3
2019–10-12	4	3
2019–10-13	3	3
2019–10-14	3	3

predict the next four days to verify the accuracy of our method, our method can predict a longer time. Note that, at present, fire danger prediction is mostly short-term prediction, which only predicts 1–3 days. Our method is enough to be applied to short-term and medium-term fire danger prediction. However, it is still necessary to work on improving the medium and long-term prediction accuracy of the model, and we leave the improvement of the prediction model to future work.

Furthermore, due to the difficulty of data collection, we have only collected fire danger data from Qipan Mountain and fire data from Northeastern China, and have not verified the prediction and classification effect of our model across the China, but the experiments in this paper show that our model has a good prediction effect on the surrounding area of Qipan Mountain. It will have strong universality in northeast China and other areas with similar climate characteristics to Qipan Mountain. In the future, we will collect data from other regions to verify and improve our model.

4.3 Lessons learned

Since fire danger forecasting is extremely challenging work, it is non-trivial to build an early fire danger forecasting system. According to our findings, it is difficult to establish a relationship between weather data and fire danger ratings. We leverage the authoritative FWI system indexes which can be extracted from weather data to develop a reliable and convincing fire danger method, i.e., our two-stage fire danger prediction method. Another lesson is that the traditional danger classification method (i.e., binary classification) is not suitable for fine-grained fire danger prediction. We fit this gap by designing a fire danger classification scheme that can divide the fire danger into 4 categories.

5 Conclusions

Every year, forest fire will burn thousands of hectares of forest, destroy the ecological environment, threaten biodiversity, cause a large number of property losses, and even cause casualties. Therefore, it is necessary to do preventive work in advance and predict the occurrence of forest fires as accurately as possible. In this paper, we proposed a machine learning-based forest fire danger rating classification method, which can effectively solve the problem that forest fire danger is difficult to predict. The classification method of forest fire danger rating established by us includes two stages. The first stage is the prediction method of FWI system index based on LSTM, which can achieve short-term and medium-term fire danger prediction and has a high prediction accuracy. The second stage is the fire danger rating prediction based on random forest. In this stage, we proposed a fire danger rating classification scheme that can help evaluate the fire danger status more objectively and accurately. The experimental results show that our forest fire danger rating classification method has a high practical application value and can serve as a warning for future fire danger prevention. We believe that our method can help fire danger early warning and inspire further exploration of fire danger prediction.

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Data availability The datasets analysed during the current study are available from the corresponding author on reasonable request.

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Authors and Affiliations

Zhenyu Chen[1] · Chen Zhang[1] · Wendi Li[1] · Lanyu Gao[1] · Liming Liu[1] · Lei Fang[2,3,4] · Changsheng Zhang[1]

✉ Lei Fang
leifang@sdu.edu.cn

✉ Changsheng Zhang
zhangchangsheng@mail.neu.edu.cn

1 Northeastern University, Shenyang 110819, People's Republic of China

2 Environment Research Institute, Shandong University, Qingdao 266237, People's Republic of China

3 CAS Key Laboratory of Forest Ecology and Management, Institute of Applied Ecology, Chinese Academy of Sciences, Shenyang 110016, People's Republic of China

4 Big Data Research Center for Ecology and Environment, Shandong University, Qingdao 266237, People's Republic of China