Research on Realization of Coal Mine Impact Ground Pressure Signal Early Warning Based on BP Neural Network and LSTM

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Abstract. With the reduction of coal resources makes deep coal seam mining important, but also increases the ground stress and geological complexity, especially impact ground pressure.AE signal monitoring technology plays an important role in preventing impact ground pressure by real-time monitoring of cracks and stress changes in coal rock. In this paper, wavelet analysis and RFE techniques are used to extract key features from signals, and BP neural network is chosen as the classification model after comparing multiple machine learning models. Random Forest is accurate but has low recall, and LSTM suffers from slow classification and poor generalization, neither of which is applicable. Compared with prophet and ARIMA models, LSTM performs better in high-frequency data prediction and dealing with fluctuating data, so it constructs a coal mine impact ground pressure signal early warning system based on BP neural network and LSTM to improve the accuracy of coal mine safety monitoring. The innovation of this paper is to use different network frameworks for classifiers and predictors, and by using feature extraction techniques, data transformation is performed to maintain the accuracy of the results while reducing the model complexity, improving the response speed, and enhancing the model generalization ability.

Keywords: AE Signal, BP Neural Network, LSTM, Feature Extraction, Prophet Model.

1. Introduction

AE signal detection technology is of great significance to the coal industry, because with the decrease of coal resources and the increase of deep coal seam mining, impact ground pressure accidents occur frequently, and AE signal monitoring technology can effectively prevent and reduce these accidents [1]. A study by China University of Mining and Technology showed that the rate of impact ground pressure accidents was reduced by about 40% within two years in coal mines that used AE signal monitoring technology. In addition, at the international level, China's AE signal monitoring technology has attracted attention and technical exchanges and cooperation with international research organizations [2]. Accurate mathematical models, such as BP neural network, LSTM and ARIMA models, are essential to improve the accuracy of AE signal monitoring [3]. Studies in the journal Mining Science have shown that the application of accurate mathematical models can increase the monitoring accuracy to more than 85% [4]. In this paper, through wavelet analysis, RFE and other feature extraction techniques, key features of time series signal data are extracted, and BP neural network is used as a classified as well as LSTM as a predictor to realize the early warning work of coal mine impact ground pressure signals. Compared with previous studies, the warning model in this paper realizes the conversion of time series data through feature extraction techniques, so that the data can be better adapted to the BP neural network when classifying, and improves the accuracy and response rate of the model. The early warning model achieves a faster classification speed compared to the LSTM model that directly uses time series data, while maintaining a similar accuracy rate, so that it can achieve the dual purpose of signal prediction and classification, thus realizing the early warning, and improving the model's generalization ability and response rate by reducing the model's complexity. The data in this paper comes from the May 1, 2024 Mathematical Modeling Competition (cumt.edu.cn) attachment, which contains acoustic emission data collected from January 9, 2019 - January 7, 2020, and is divided into five signal types: normal operation data, precursor feature data, disturbance signal data, sensor break data, and work surface rest data.

2. Research on signal early warning model

2.1. Ideas for the construction of the early warning model

This paper mainly focuses on the use of acoustic emission (AE) signal acoustic intensity, time and category information to provide early warning of the danger of impact ground pressure in the deep mining process of coal mines [5]. The core of the study is to construct a comprehensive model that can accurately capture the characteristics of AE signals and predict the occurrence of impact ground pressure accordingly. The process of model construction includes three main steps: extraction of acoustic features, classification of signals, and hazard prediction based on this information.

2.2. Innovation of Early Warning Model

LSTM (Long Short-Term Memory Network) and BP neural network are two important models used for processing time series data in deep learning [6].LSTM is able to effectively capture long-term dependencies through its gating mechanism, which is very suitable for processing AE (acoustic emission) signals with temporal dynamic characteristics. Using LSTM to learn the temporal characteristics of AE signals, normal and abnormal patterns can be recognized so that early warning can be issued. Wavelet analysis, as a time-frequency domain analysis tool, can provide time-frequency characteristics of signals, which helps to identify mutations and abnormalities in AE signals and enhance the recognition capability of the warning system. The sliding window technique, on the other hand, can be used to process non-smooth signals and extract features at different time scales to provide richer input data for the early warning model.

More accurate and robust warning models can be constructed by combining the advantages of LSTM and BP neural networks. LSTM is responsible for capturing long-term dependencies, while BP networks perform fast weight adjustment and mapping. In addition, the time-frequency feature extraction of wavelet analysis and the localization property of wavelet transform can identify the anomalous features in AE signals more accurately. This kind of early warning system, which integrally applies multiple technologies, can improve the monitoring and analyzing ability of AE signals and provide scientific basis for early warning of coal mine impact ground pressure risk.

3. Early warning model construction and empirical analysis

3.1. Data visualization and analysis

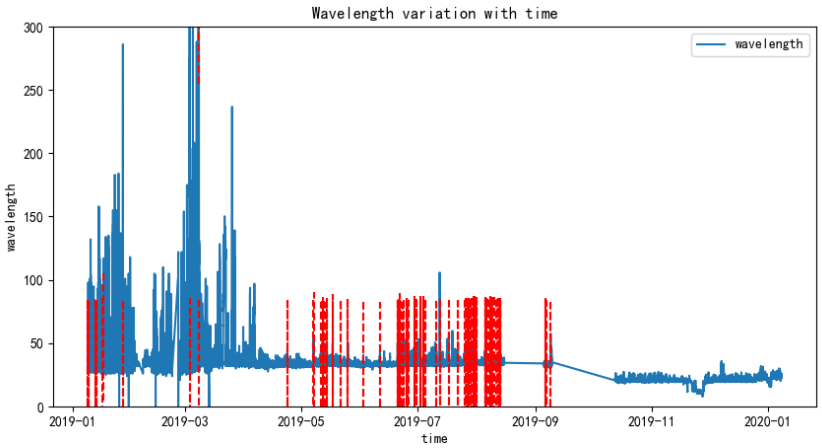


Figure 1. Time series acoustic intensity and classification line graphs.

As shown in Figure 1, the data are more fluctuating in the early stage and flatter in the middle and late stage. The signal category changes drastically in the middle period, and should focus on extracting features and learning; the acoustic wave intensity as a whole shows a gradual flattening trend, so when making predictions, focus on the fluctuation of the data in the middle and late period, but also learn and analyze the fluctuation data to improve the generalization ability of the model [7].

3.2. Feature extraction of time series data

In this paper, the construction includes four kinds of time series data feature extraction methods, including sliding window technique, trend analysis, frequency domain analysis and wavelet analysis, to convert the continuous data features on the time series into the feature set of each data point, which in turn provides the data basis for the classification of the subsequent BP neural network. The four feature extraction methods provide a total of 19 data features for each data point, and in order to improve the data feature learning rate and quality, the data feature set is subjected to customized recursive feature elimination (RFE), which reduces its features from 19 to 8. The reduction in the number of features is achieved while guaranteeing the quality of the data features, which reduces the subsequent feature learning time and improves the classification results.

Table 1. Feature selection after recursive feature elimination.

Number	Feature Name	Selected	Ranking
0	Sound wave intensity (AE)	True	1
15	rolling_min	True	1
14	rolling_max	True	1
13	rolling_mean	True	1
12	day_of_week	True	1
11	hour	True	1
18	nonlinear_trend	True	1
4	max	True	1
16	fft_amplitude	False	2
2	mean	False	3
3	std	False	4
1	energy	False	5
6	median	False	6
9	energy_ratio_scale_2	False	7

As can be seen from Table 1, the 0th, 15th, 14th, 13th, 12th, 11th, 18th, and 4th features are considered to be the main features, which contain most of the classified information of the AE signal data, and the selected features belong to the four parts respectively, which indicates a reasonable choice of the classified feature extraction method for the AE signal data, and therefore we believe that the composite index obtained from the recursive feature elimination can be used as the AE signal data to some extent. Observation index.

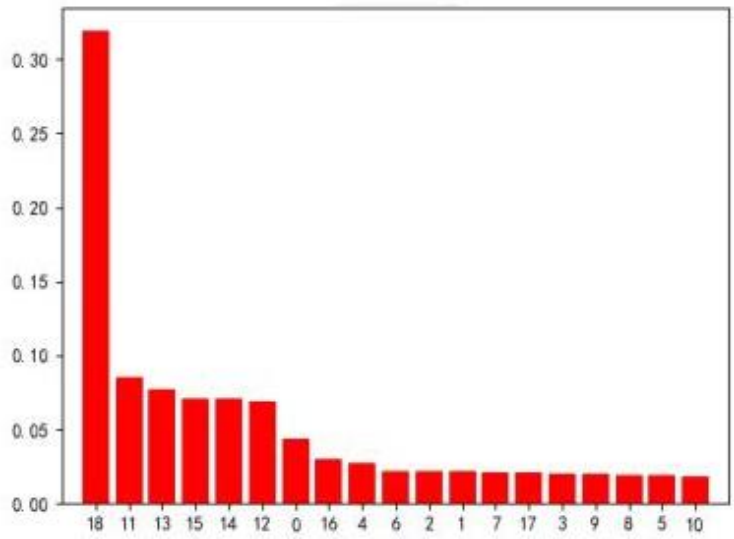


Figure 2. Importance of features.

As can be seen from Figure 2, 8 features in the top nine of feature importance are retained in recursive feature elimination, indicating that the algorithm is effective on feature screening of AE signal data. The trend feature of nonlinear trend accounts for more than 0.3, the features obtained through the sliding window technique and the time features occupy positions 2 to 7, and the frequency domain features are located in the 8th, indicating that the classification features are affected by multiple factors, and the top 9 data features account for more than 75%.

3.3. Classification network model construction and evaluation

3.3.1. Analysis of signal classification results using the random forest model

Table 2. Random forest classification effects.

	Precision	Recall	f1-score	Support
0	0.98	0.73	0.84	3167
1	1.00	0.86	0.92	447
2	1.00	0.73	0.85	295
3	0.99	1.00	1.00	118472
Accuracy			0.99	122381
Macro avg			0.90	122381
Weighted avg			0.99	122381

As can be seen from Table 2, for category 3, the model is almost perfect, with very high precision and recall, and an F1 score of 1.00. This indicates that the model is very effective in dealing with data from the main categories. Overall, the accuracy of the model is 0.99, indicating excellent overall performance. The macro-mean and weighted mean were 0.90 and 0.99, respectively, reflecting the model's equilibrium performance on all categories and its overall performance considering the sample size. Overall, this model performs well when dealing with large amounts of data.

3.3.2. Analysis of signal classification results using BP neural network

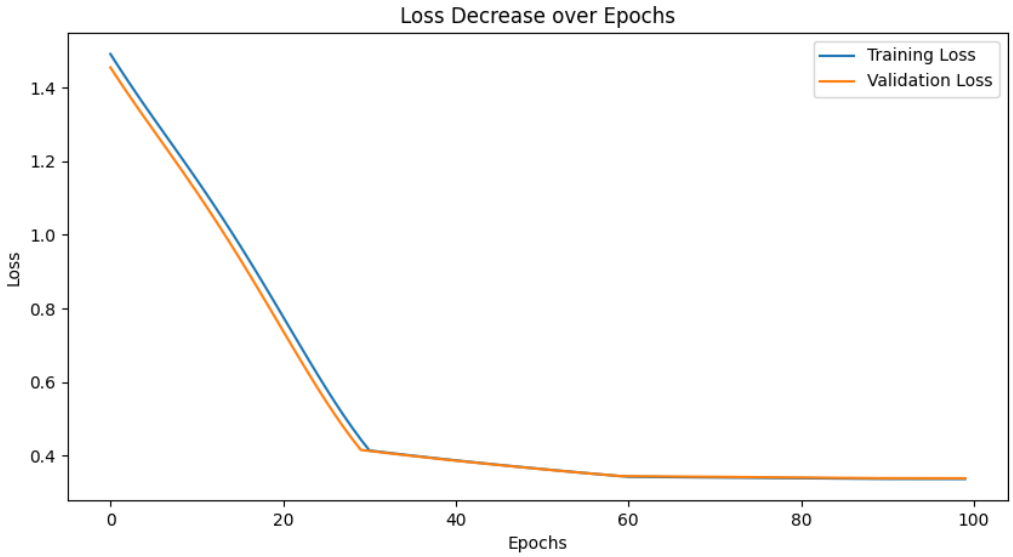


Figure 3. Line graph of loss function.

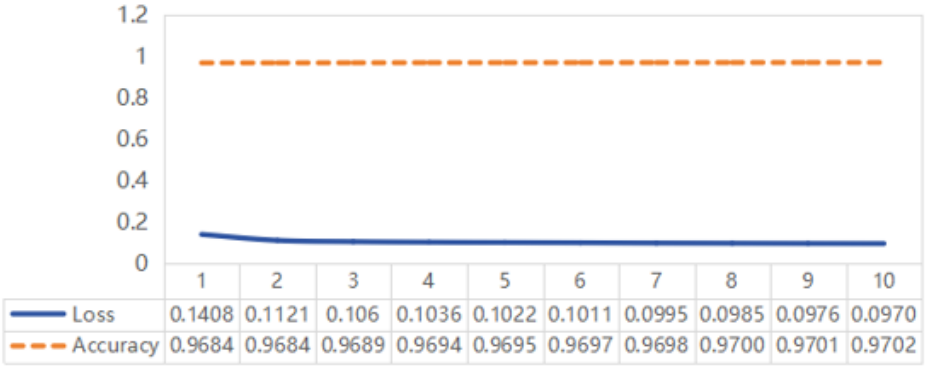
As shown in Figure 3, the loss function values of the BP neural network for the training and validation sets are about 0.35 after 100 rounds of learning. The loss function values for both categories decrease throughout the training process and stabilize after the 60th round.

Table 3. BP neural network classification effect

Test Accuracy	Precision	Recall	F1 Score
0.9681	0.9371	0.9681	0.9523

As shown in Table 3, this BP neural network model demonstrates excellent performance on the test set. The accuracy of the model is 96.81%, indicating that it is able to correctly classify the input samples with high probability. In addition, the model has a precision rate of 93.71%, which means that when the model predicts that a sample belongs to a positive class, the prediction has a high level of confidence. The recall is 96.81%, which is consistent with the precision rate, showing the model's efficiency in identifying all positive class samples with a very low risk of underreporting. The F1 score is 95.23%, which is close to the ideal value of 1, further confirming that the model strikes an excellent balance between precision rate and recall rate. Together, these metrics indicate that this BP neural network has a high degree of classification accuracy and reliability on the test data [8].

3.3.3. Analysis of signal classification results using LSTM neural network



	1	2	3	4	5	6	7	8	9	10
Loss	0.1408	0.1121	0.106	0.1036	0.1022	0.1011	0.0995	0.0985	0.0976	0.0970
Accuracy	0.9684	0.9684	0.9689	0.9694	0.9695	0.9697	0.9698	0.9700	0.9701	0.9702

Figure 4. Loss function and accuracy line graphs.

As shown in Figure 4, the loss function of the LSTM neural network is about 0.097 for the training set after 10 rounds of learning. Throughout the training process, the value of the loss function of the training set decreases and gradually stabilizes.

Table 4. Classification effect of LSTM network.

Loss	Accuracy
0.0980	0.9699

As shown in Table 4, the LSTM model performs very well on the validation set, with a loss value of only 0.0980, indicating that the discrepancy between the model's predictions and the actual values is very small, and an accuracy of 96.99%, meaning that the model is able to correctly classify nearly 97% of the validation set samples. These metrics show the strong generalization ability of the model, which can be well generalized to new data.

3.4. Predictive Network Model Construction and Evaluation

3.4.1. Analysis of signal prediction results using the ARIMA model

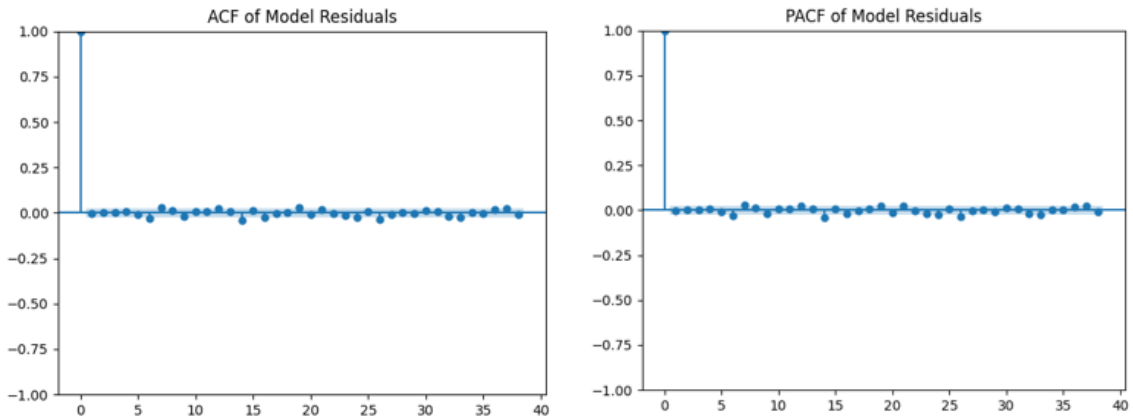


Figure 5. ACF and PACF of ARIMA model residuals.

As shown in Figure 5, after the first-order differencing, the ACF and PACF of the model residuals are reduced, indicating that after the first-order differencing, the time series is smooth and suitable for the model to make predictions.

Table 5. Predictive effect of ARIMA model.

AIC	BIC	HQIC
40980.07	41013.67	48991.73

As shown in Table 5, although the relatively low values of AIC and BIC indicate that the model is able to fit the data to some extent, the significantly higher values of HQIC may suggest that the model may have an overfitting problem in the face of larger sample sizes. The high values of HQIC in particular suggest that the penalizing effect of the model's complexity is more pronounced as the sample size increases. This could mean that the model, in its current form, may not be able to make accurate predictions for new, unseen data.

3.4.2. Analysis of signal prediction results using LSTM neural network

Table 6. Prediction results of LSTM network.

Train MSE	Train RMSE	Train MAE
1519.45	38.98	36.68
Test MSE	Test RMSE	Test MAE
467.77	21.63	21.47

As shown in Table 6, the performance of the LSTM network on the training set (MSE of 1519.45, RMSE of 38.98, and MAE of 36.68) shows that the model's predictions on the training data are somewhat biased, which may be due to the presence of noise in the training data, suggesting that the model does not suffer from an overfitting condition on the training set. There is a significant improvement in the performance of the model on the test set relative to the training set (MSE of 467.77, RMSE of 21.63, and MAE of 21.47), which suggests that the model is able to generalize better and provide more accurate predictions on unseen data.

3.4.3. Analysis of Signal Prediction Results Using Prophet's Model

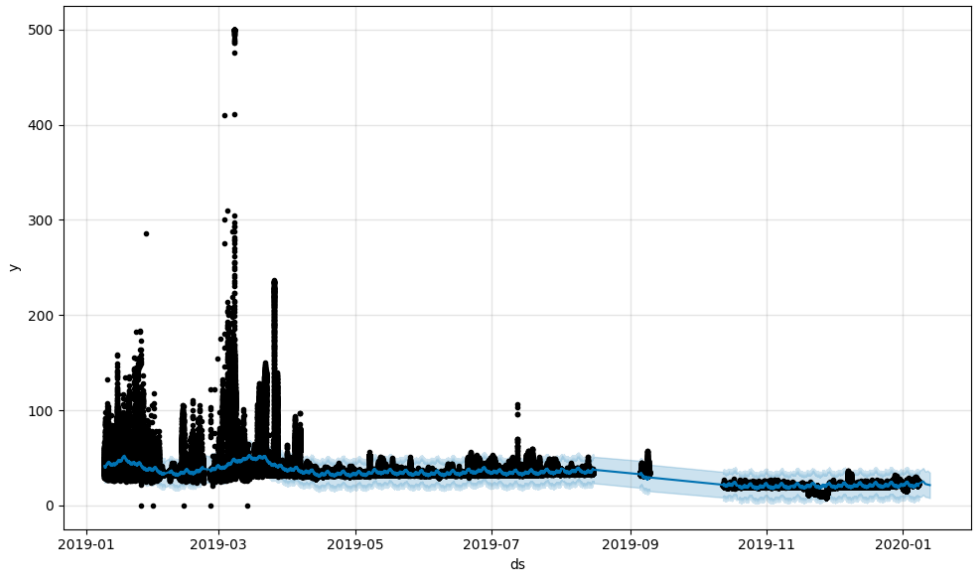


Figure 6. Sequence diagram of prophet model prediction.

As shown in Figure 6, the black dots in the figure represent data points over time. The blue line and the shaded area around it represent the model that predicts future values based on historical data, which demonstrates the predictive power of Prophet's model and its confidence interval for future

trends [9]. The overall fit of the model is relatively good after removing the highly fluctuating data points in the early period, and the almost complete fit is achieved for the middle and late data, which indicates that the model fits well for the smooth data, but it is difficult to achieve a complete fit for the fluctuating data, and it is difficult to achieve the fluctuating data when making predictions.

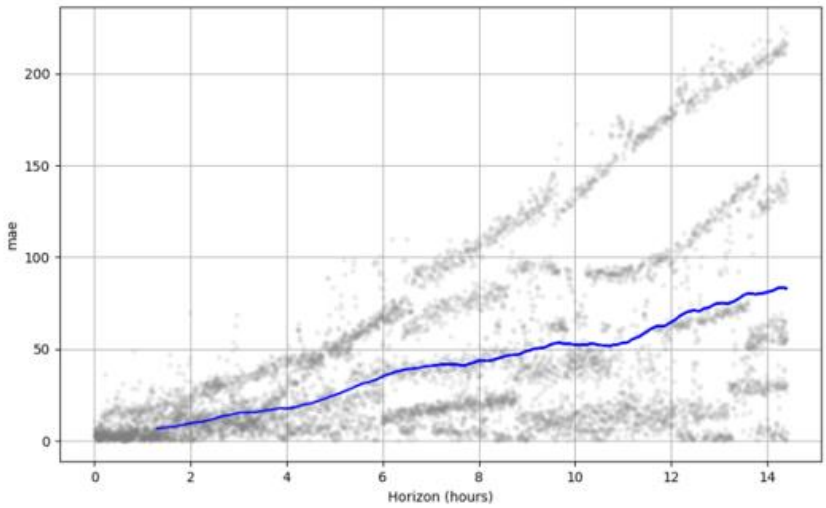


Figure 7. Distribution of the number of cross-validation MAE tests.

As shown in Figure 7, the MAE test numbers of the predicted data under each time period under six cross-validation rounds [10]. The blue line is the fitted curve of the six cross-validation data, and the average MAE of the data points is about 45, and the MAE test number of the predicted data points under some cross-validation rounds is higher than 200, which is less accurate. According to the distribution of the data points, it is found that the model will show a gradual increase in the trend of error increase in long time prediction, which indicates that it is difficult to carry out a long time and high frequency prediction task.

4. Conclusion

In this study, by comparing and analyzing different machine learning models, this paper decided to use BP neural network and LSTM network as classification and prediction models. Although the Random Forest model performed well in some aspects, its recall did not meet the expected criteria and therefore was not selected. On the other hand, the LSTM model, although it suffers from the risk of overfitting during training and has a relatively slow learning rate, it performs excellently on the prediction task and is able to adapt and fit a wide range of different data patterns. In particular, the ability of LSTM models to handle time series data makes them the predictive model of choice. In addition, compared to the inability of the prophet model to make predictions for long and high-frequency data, as well as the limitations of the ARIMA model in dealing with highly fluctuating data, the LSTM demonstrated greater adaptability and prediction accuracy.

These findings not only provide a clear technical route for the current study, but also provide valuable experience and guidance for future model selection and optimization under similar data patterns, especially when complex time series data and prediction tasks need to be handled. At the same time, our findings also exemplify the potential of applying machine learning techniques to interdisciplinary problems and encourage researchers in other fields to explore these advanced analytical tools, which provide guidance for data-driven machine learning-based model selection and optimization for early warning systems in real-world applications, and help to improve the effectiveness and reliability of the system.

References

[1] Zhao Hanjun, Zhang Xiaofeng, Zhao Ruidong, et al. Oil and gas field station pipeline safety early warning method based on BP neural network [J]. Oil and Gas Field Surface Engineering, 2024, 43(04):33-40.

[2] Liu Xinxiang, Gu Yujiong, Ma Jiwei, et al. Sliding bearing fault diagnosis based on acoustic emission signal feature extraction [J]. Turbine Technology, 2024, 66(01):1-6+28+52.

[3] Wang Pengfei, Shi Jian. AE eigen-signal analysis of Y/YY pipe node members under static load [J]. Journal of Plastic Engineering, 2022, 29(12):209-216.

[4] Hui Hongping, Zhong Bailiang, ZHOU Yongsong, et al. Ultrasonic power frequency tracking technique based on BP neural network algorithm[J]. Modern Electronic Technology, 2024, 47(10):159-163.

[5] Zhao Zhongchen, Liu Limin, Xie Hui, et al. A review of DRFM-based radar active jamming signal recognition algorithm [J]. Electro-Optics and Control, 2024, 31(04):65-74.

[6] Liu Wenke. A methodological model of debris flow infrasound monitoring and early warning based on HHT algorithm [J]. Science and Technology Innovation, 2021(13):11-12.

[7] Li Yuan, Wang Qian. Research on detection and identification of signal mutation points and application [J]. Journal of Beijing Union University, 2024, 38(02):51-58.

[8] Zou Hongmei, Zhu Chengtao. Comparative study of medium- and long-term prediction of reservoir inflow runoff based on LSTM and BP neural network [J/OL]. Hydrology: 1-8[2024-05-14]. https://doi.org/10.19797/j.cnki.1000-0852.20230413.

[9] Tan Zengsheng, Wang Zhibing. Regional electricity consumption prediction based on WPA-Prophet model [J]. Modern Information Technology, 2024, 8(06):132-135.

[10] Gao Jieru, Wei Linjing, Li Yue, et al. PM2.5 concentration prediction model based on Prophet-LightGBM [J/OL]. Software Guide: 1-9[2024-05-14]. http://kns.cnki.net/kcms/detail/42.1671.TP.20240425.1142.020.html.