APPLICATION OF SURVEYING AND MAPPING TECHNOLOGY BASED ON DEEP LEARNING MODEL IN PETROLEUM GEOLOGICAL EXPLORATION

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ABSTRACT

Surveying and mapping technology is one of the key technologies used in petroleum geological exploration and has made significant contributions to geological exploration. However, with the development of science and technology, traditional surveying and mapping technology has low work efficiency and poor information accuracy, which limits its application. This study proposes a surveying and mapping technology based on the 1DCNN-LSTM deep learning model. Through feature selection and feature optimization, the important features extracted by 1DCNN are predicted through LSTM, and the development direction of surveying and mapping technology is optimized and predicted to promote the development of new surveying and mapping technologies. application. By using the orthogonal test to optimize the input factors, determine the relative order of the influence of the factors, and use the 1DCNN-LSTM and BP neural network to train and verify the input factors respectively. The research results show that 1DCNN-LSTM has higher prediction accuracy, and the prediction accuracy is The results show that the 1DCNN-LSTM deep learning model used in the optimization of petroleum geological exploration and mapping technology in this study has strong practical significance.

KEYWORDS

1DCNN-LSTM; Mapping technology; Deep learning model; Neural network; Optimization.

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1. INTRODUCTION

The traditional surveying and mapping technology has low work efficiency and requires a lot of human resources to complete the survey work, but the final information accuracy is poor [1]. Under the rapid development of modern social science and technology, new surveying and mapping technologies with better performance have been developed. Digital surveying and mapping are the main forms, and they have been applied to the fields of hydrogeology, petroleum engineering, and other fields, and played their due role in the field of geological exploration. It greatly promotes the development of the exploration field, especially the geological exploration, and the accuracy requirements of the surveying and mapping technology are increasing day by day [2-3]. Therefore, it is extremely necessary to optimize the surveying and mapping technology.

At present, there is little research on the optimization of surveying and mapping technology, and it is of great significance to use deep learning models to optimize surveying and mapping technology. In recent years, some scholars have done a lot of work. Lu X H [4] established a prediction model of surveying and mapping technology through regression analysis using cutting parameters as independent variables. Beruvides [5] used the vibration signal sent out during the training process to establish the prediction model of surveying and mapping technology by using the adaptive neuro-fuzzy inference system and obtained a higher fitting index and better generalization ability. Some researchers [6] used the improved particle swarm algorithm to optimize the node selection of the hidden layer of the BP network and established the prediction model of the surveying and mapping technology. In addition, some researchers [7] proposed a parameter synchronization optimization algorithm for GA signal feature recognition and mapping prediction, established a GA-WPT-ELM prediction model, and obtained high prediction accuracy. With the development of artificial intelligence, deep learning makes data processing and results in prediction more efficient and accurate [8]. Its long short-term memory (LSTM) neural network algorithm improves the gradient disappearance problem of traditional recurrent neural networks (RNN) and provides a new method for the prediction of sequence data. Prediction problems are applied in the field of new technologies [9]. Wang M W et al. [10] established a long short-term memory model and realized the prediction of the wear of surveying and mapping tools by taking advantage of its advantages of solving the accumulation effect. Some researchers [11] proposed a traditional surveying and mapping stage identification model based on a deep LSTM neural network, which can more accurately reflect the wear state of surveying and mapping compared with traditional machine learning methods. Yu [12] proposed a state recognition method based on LSTM, which has higher recognition accuracy than BP neural network algorithm and SVM algorithm..

Although the LSTM network solves the problem of vanishing gradients, it has poor performance for batch sequence data processing, resulting in lower accuracy of the model in result prediction [13-14]. In this paper, taking petroleum surveying and mapping technology as the research object, a prediction model based on the combination of one-dimensional convolution and long short-term memory (1DCNN-

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LSTM) neural network is established to solve the problem of batch sequence data processing, sample key feature learning, and small sample data processing. Mapping technology optimizes precision problems. Through examples and experiments, the effectiveness of the 1DCNN-LSTM prediction model for the prediction of the development of mapping technology is verified.

2. CORRELATION MODEL THEORY

2.1. LONG SHORT TERM MEMORY (LSTM)

Compared with the traditional RNN, the core idea of the LSTM neural network is to introduce "three gates" in each memory unit, use the three gates to interact with the unit state, and change the information borne by the united state. The retention of information is selectively determined within neurons. The most widely used LSTM network structure is shown in Fig.1.

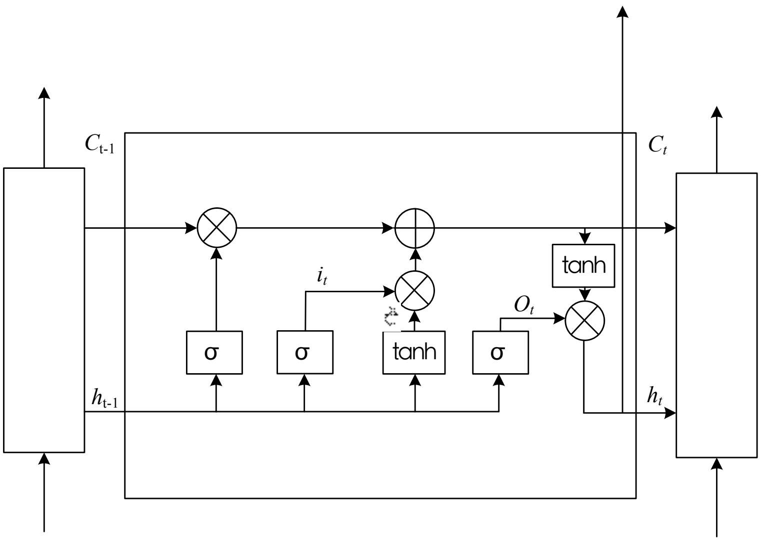

Figure 1. LSTM network structure.

As shown in Figure 1, the "three gates" of the LSTM network are the input gate which determines the retention of new information; the output gate Ot determines the output degree of information; the forgetting gate ft determines the retention of the original information state [15]. Its mathematical expression is as follows:

$$o_t = \sigma\left(w^o \cdot \left[h_{t-1}, x_t\right] + b^o\right) \tag{1}$$

$$h_t = o_t * \tanh\left(C_t\right) \tag{2}$$

In the formula: σ is the sigmoid activation function, the output range is 0~1; h_{t-1} is the input at the previous moment; x_t is the input at the current moment; W and b are the weight coefficients and bias terms corresponding to the three gates, respectively [16].

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The LSTM network reduces the number of network layers and the sequence length through three gated structures effectively solves the problem of gradient disappearance and realizes the prediction of sequence data [17]. However, due to the poor processing of batch sequence data in the LSTM network itself, this paper introduces a 1DCNN network structure to make up for this deficiency.

2.2. ONE-DIMENSIONAL CONVOLUTIONAL NEURAL NETWORK (1DCNN)

Convolutional neural network (CNN) is one of the most perfect algorithms in the field of deep learning [18], which is divided into one-dimensional, two-dimensional, and three-dimensional. Among them, 1DCNN is good at processing sequence data, so this paper selects the 1DCNN network for data processing, the structure is shown in Figure 2. As shown in Figure 2, the sequence data is input into 1DCNN for preliminary feature extraction [19], and the sub-sequences composed of high-level features are effectively extracted, and the interference information is removed as the input node of the LSTM layer. At the same time, the network can directly identify local simple patterns in the data and apply them to higher-level networks to form more complex network patterns [20].

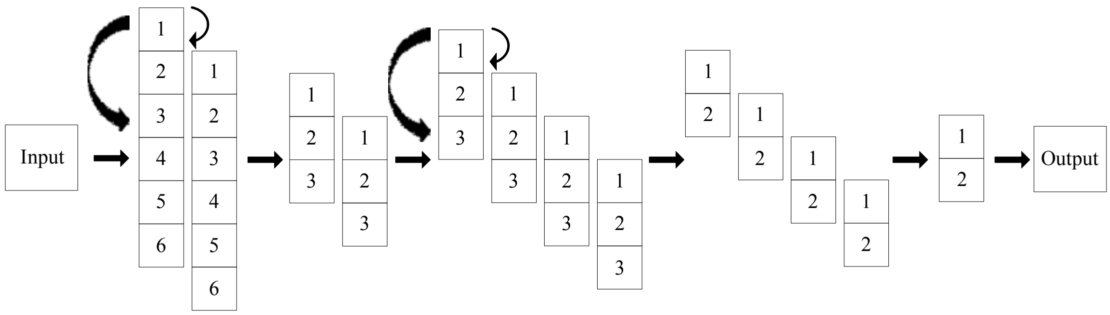

Figure 2. The structure of the 1DCNN convolutional layer.

Let the ith input data of the convolution layer be I_i, the convolution kernels are W_i, each with n pieces, the bias is B_i, the activation function is f, and the downsampling operation is to further reduce the dimension of the features of the convolution output., and input the corresponding output to the fully connected layer, the fully connected layer obtains the classification result of this round after weight transformation and activation, and the corresponding classification error is obtained by comparing with the true value of the classification [21]. Let the input feature of the fully connected layer be T, the corresponding weight is W, the bias is B, and the activation function is f, the output of the convolutional layer and the pooling method formula is as follows [22]:

$$O_t = f(WX + b) \tag{3}$$

$$O_t = ReLU\left[\left(\sum_{i=0}^{\lambda-1} W_i x_{t+i}\right) + b\right] \tag{4}$$

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$$P\left(y^{i}=j \middle| x^{i};\theta\right)=\frac{e^{\theta_{j}T_{x}i}}{\sum_{K=1}^{K} e^{\theta_{j}T_{x}i}} \tag{5}$$

Among them, W is the convolution kernel, $X \in RT \times n$ is the input word vector matrix, and parameter b is the bias term. Commonly used nonlinear activation functions are Sigmoid or ReLU. x is the output vector of the previous neural network [23].

2.3. DCNN-LSTM NETWORK MODEL CONSTRUCTION

2.3.1. MODEL BUILDING

Based on the ability of 1DCNN layer data processing and LSTM layer data prediction, a 1DCNN-LSTM surface roughness prediction model was established [24]. Its structure is shown in Fig.3, including a one-dimensional convolutional layer, a Batch-Normalize layer, an LSTM layer, and a fully connected layer [25]. After the data is input, through the Conv algorithm, the features are identified and then entered into the LSTM layer and the fully connected layer.

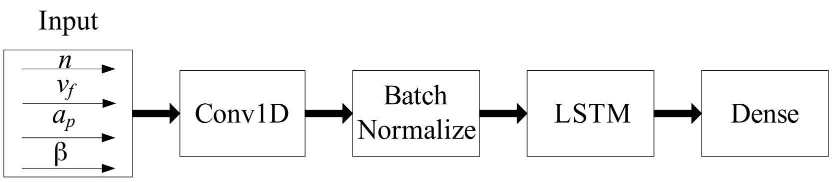

Figure 3. 1DCNN-LSTM prediction model structure.

2.3.2. MODEL PARAMETER DETERMINATION AND DATA PREPROCESSING

There are many influencing factors of surveying and mapping technology, mainly including field surveying and mapping n, network layout vf, dynamic real-time surveying and mapping ap, and geodetic surveying control network point β. There is a complex nonlinear relationship between these four parameters and new surveying and mapping technology. Therefore, based on the establishment of the prediction model framework, the prediction model is optimized through parameter selection [26], and the specific steps are as follows:

(1) Input layer and output layer. The four milling parameters n, vf, ap and β are used as the input node of the prediction model, and the surface roughness Ra is used as the output node of the prediction model.

(2) Hidden layer. The hidden layer plays a key role in the network architecture. The number of filters (filters) of the one-dimensional convolutional layer of the model is 1, the size of the convolution kernel (kernel_size) is 3, and the stride (stride) is 1, and the padding (padding) is 1. The LSTM layer node is 2, and the fully connected layer node is 2.

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(3) Learning rate. To adjust the appropriate learning rate parameters and avoid going over the optimal solution or the model falling into the local optimal solution, through continuous testing and adjustment, the Adam algorithm model is used, and the learning rate parameter is finally selected as 0.001.

(4) Data preprocessing. In this dataset, n, vf, ap and β of each group of experiments constitute a set of input parameters, the output parameters are the micro-milling surface roughness of each group, and the input parameters and output parameters constitute a set of sample data.

The purpose of preprocessing the sample data is to normalize the data features of each dimension to the same value range so that the model training effect is better and the generalization ability is stronger. For this purpose, all input data are normalized to [0, 1] in this paper, and the normalization formula is:

$$y_i = \frac{x_i - x_{i\min}}{x_{i\max} - x_{i\min}} \tag{15}$$

In the formula: x_i is the original data; x_{min} is the minimum value in the original data; x_{imax} is the maximum value in the original data; y_i is the normalized value, and yi∈[0,1].

After data preprocessing, the data can be used as an input layer node for Ra prediction.

3. TEST AND RESULT ANALYSIS

3.1. ORTHOGONAL TEST TO OPTIMIZE INPUT FACTORS

In the micro-slot milling experiment, this paper mainly considers the influence of spindle speed n, feed rate vf, milling depth ap, and micro-milling cutter helix angle β on the surface roughness. To fully consider the influence of the above four factors on the surface roughness in a small number of experiments, a four-factor and five-level orthogonal experiment were carried out, and the parameters are shown in Table 1.

Table 1. Orthogonal parameter factor level table.

Level	Field surveying and mapping coefficient	Network speed	Dynamic real-time mapping depth	Geodetic Control Dot Spiral Angle
1	5	1.5	10	25
2	15	3.0	15	30
3	25	4.5	20	35
4	35	6.0	25	40
	45	7.5	30	45

The range analysis method was used to process the experimental results to obtain the relationship between each factor and the surface roughness Ra, as shown in Figure 4.

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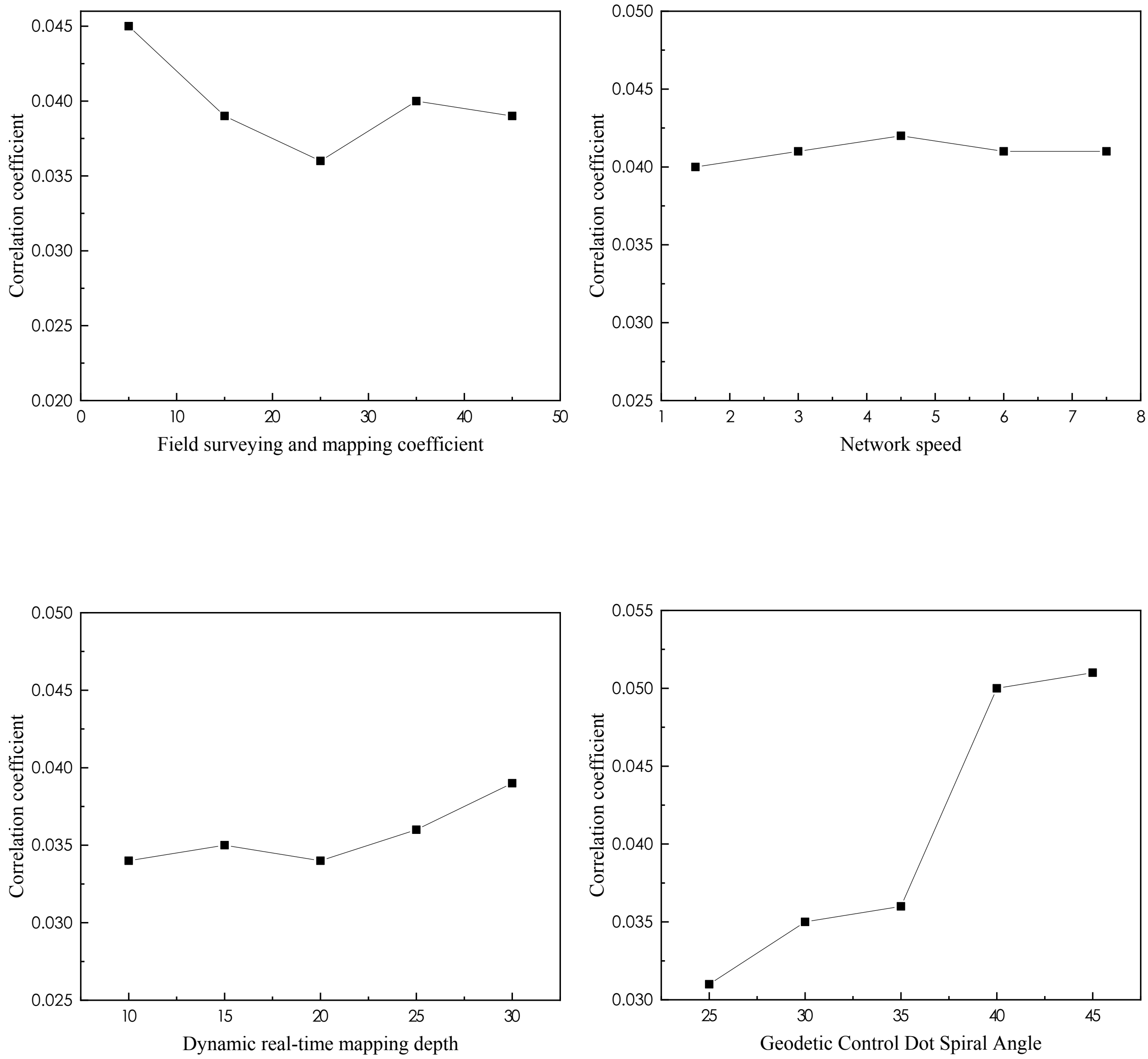

Figure 4. The relationship between the experimental factors and the Ra value of the surveying and mapping technology, a) field surveying and mapping coefficient; b) network speed; c) Dynamic real-time mapping depth d) Geodetic control network point helix angle.

It can be seen from the figure that the dynamic real-time surveying and mapping depth and the geodetic control network point helix angle have similar effects on the surveying and mapping technology, the correlation coefficient increases with the increase of its value, and the geodetic control network point helix angle has the most significant impact on the surveying and mapping technology; surveying and mapping The technical correlation coefficient decreases with the increase of the field surveying and mapping coefficient; however, the influence of the network deployment speed is not significant, so a slightly larger network deployment speed can be adopted to improve the correlation coefficient of the surveying and mapping technology. In addition, for the field surveying and mapping coefficient, with the increase of the abscissa, the correlation coefficient shows a downward trend, while the distribution speed has almost no change. However, for the dynamic real-time mapping depth and the geodetic control mesh point helix angle, both show an upward trend with increasing depth and angle.

3.2. DCNN-LSTM MODEL PREDICTION AND RESULT ANALYSIS

To obtain accurate and credible batch training data sets, 139 groups of random experiments were performed, and 164 groups of training data sets were obtained. Combined with various influencing factors, the main parameters of the random experiment are shown in Table 2. To make the model training more balanced, the dataset is randomly distributed before training, and then the normalized dataset is input into the model to start training [27]. The epochs are chosen to be 5000 times, during the training process of each epoch, all training datasets will be trained once, and the network automatically calculates the gradient of the batch loss concerning the weights and updates the weights accordingly.

Table 2. Parameter range

Field surveying and mapping coefficient	Network speed	Dynamic real-time mapping depth	Geodetic Control Dot Spiral Angle
5000-75000	1.5-100	6-100	25,30,35,40,45

The 164 datasets are divided into two groups, of which 150 are training sets and the remaining 14 are validation sets. The training process of the 1DCNN-LSTM model is shown in Figure 5. It can be seen from the figure that when the training round reaches 3000 times, the training accuracy has reached about 95%, and the verification accuracy has reached about 91%, indicating that the accuracy is high. Very stable and meets forecast requirements. To verify the accuracy of the 1DCNN-LSTM prediction model, 15 sets of experimental parameters were designed for testing, and the experimental data were normalized and input into the two prediction models of the 1DCNN-LSTM neural network and BP neural network, respectively. prediction results.

Table 3. Prediction results

Number	1DCNN-LSTM Neural Network		BP neural network	
	Ra predicted value	Error percentage	Ra predicted value	Error percentage
1	0.1681	4.2	0.2181	11.09
2	0.0861	3.1	0.2132	12.15
3	0.0192	5.1	0.1055	16.33
4	0.0523	6.4	0.0755	21.36
5	0.0490	0.8	0.0489	18.55
6	0.0207	5.1	0.0230	20.91
7	0.0568	3.2	0.0110	4.64
8	0.0772	2.1	0.0225	9.24

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9	0.1191	9.1	0.0762	6.22
10	0.0875	7.8	0.0868	3.81
11	0.0542	6.1	0.0871	25.1
12	0.1121	5.3	0.0940	13.84
13	0.0258	2.2	0.0123	11.2
14	0.1391	10.1	0.1012	13.6
15	0.0913	7.1	0.0847	22.2

As shown in Table 3, to compare the prediction accuracy of the two models, the average relative prediction error is used as the evaluation index, and the formula is as follows:

$$\delta = \frac{\sum_{i=1}^{n} \left| R_{ai} \right| - \overline{R_{ai}}}{\sum_{i=1}^{n} \overline{R_{ai}}} \tag{16}$$

In the formula: δ is the average relative prediction error; Ra_i is the predicted value of each model; Ra_i^- is the measured value of the milling test.

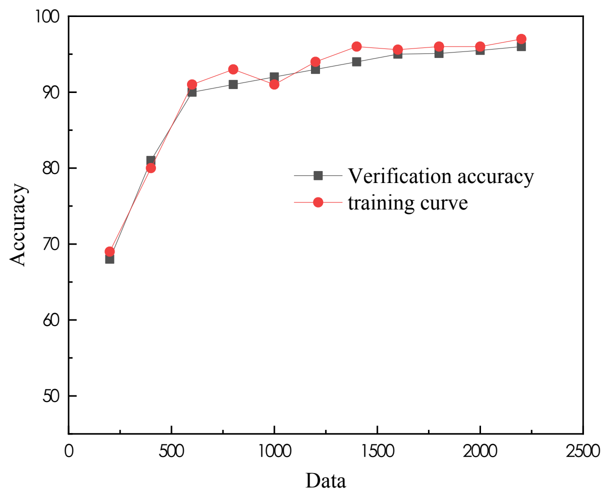

Figure 5. 1DCNN-LSTM prediction model training process

According to the evaluation indicators, the 1DCNN-LSTM model is 5.90%, while the BP model is 14.92%, and the evaluation effect of the 1DCNN-LSTM model is much higher than that of the BP model. It shows that the sample features adaptively extracted by the 1DCNN layer can better reflect the efficient data processing capability of the network layer than the artificial extraction features, and the short sequence samples composed of high-level features can effectively improve the prediction accuracy for the data extraction and analysis of the LSTM layer. Based on this, the prediction model established by the 1DCNN-LSTM network can accurately predict the improvement direction of the mapping technology under different parameters, which fully proves that the prediction model has strong applicability and

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high prediction accuracy. According to the above results, it can be concluded that the model meets the requirements of accurate prediction [28].

3.3. APPLICATION OF NEW TECHNOLOGY OF SURVEYING AND MAPPING IN PETROLEUM GEOLOGICAL EXPLORATION

3.3.1. FIELD SURVEYING AND MAPPING

When using new surveying and mapping technology for field surveying and mapping work, it is necessary to select an accurate measurement point to ensure the accuracy of the measurement results[29-30]. Since this measurement point has a decisive impact on the accuracy of the entire measurement Make preparations such as the frame to ensure that the technology can be effectively used.

3.3.2. CLOTH NET

In the work of network layout, it is necessary to use connection points or line connections to achieve it. When performing network layout work for different measurement areas, it is necessary to do a good job of understanding the local terrain and formulate a reasonable network layout strategy according to the situation of the measurement area. For example, in the process of work, two different ways of construction network and information network are formulated according to the needs. At the same time, reasonable network distribution can also ensure the network strength during work, to ensure that the system can make full use of the network for efficient data measurement and storage, and at the same time make the measurement results more accurate.

3.3.3. DYNAMIC REAL-TIME MAPPING

The dynamic real-time surveying and mapping work requires a base station, and at the same time surveying and mapping, it is ensured that each device is used reasonably to improve the accuracy of the surveying and mapping work. In the survey work, it is necessary to use a large number of wireless transmission technology, and the obtained surveying and mapping results are sent to the information receiving station. When observing whether the rover at the scene can receive the information sent from different sending stations, it can also rely on the data transmitted by the base station. to locate. The base station and the mobile station can use the data observed by themselves and the difference value transmitted by themselves to calculate to obtain the relative positions of different stations, to output and store the three-dimensional coordinates.

3.3.4. GEODETIC CONTROL NETWORK

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The new surveying and mapping technology in the geodetic control network is to use satellite positioning technology to complete the measurement of the basic control network. Since my country has a very large land area, the distance between each geodetic control network Measuring tool does not perform effective distance measurements. In the measurement of the urban control network, measurement tools need to be used frequently, and the measurement tools need to cover a larger area and have higher accuracy. The new technology of surveying and mapping has the above characteristics, can meet the requirements of related surveying work, and has the advantage of simple operation, which can solve the above surveying problems.

4. CONCLUSION

The traditional surveying and mapping technology has low work efficiency and requires a lot of human resources to complete the survey work, but the final information accuracy is poor. This study, this paper takes petroleum surveying and mapping technology as the research object, and establishes a prediction model based on the combination of one-dimensional convolution and long short-term memory (1DCNN-LSTM) neural network, using orthogonal optimization to optimize input parameters, increase prediction accuracy, and at the same time with BP The accuracy of the neural network is compared, and the following conclusions are obtained: (1) The input parameters of the 1DCNN-LSTM optimized by the orthogonal test optimization method, the results predicted by the model have high prediction accuracy, high prediction effectiveness, and correlation. The influencing factors are the dynamic real-time surveying and mapping depth and the geodetic control network point helix angle, field surveying, and network layout; (2) The prediction accuracy of 1DCNN-LSTM for oil exploration surveying and mapping technology is significantly higher than that of BP neural network, and the errors of the two are the highest, respectively. 10.1% and 25.1%; (3) The sample features adaptively extracted by the DCNN layer can better reflect the efficient data processing capability of the network layer than the artificially extracted features, and the short sequence samples composed of high-level features are for the data of the LSTM layer. Extraction analysis effectively improves prediction accuracy.

5. CONFLICT OF INTEREST

The authors declared that there is no conflict of interest.

REFERENCES

(1) Lu, W., Zhao, L. J., & Xu, R. (2021). **Remote sensing image processing technology based on mobile augmented reality technology in surveying and mapping engineering**. *Soft Computing,* (4). https://doi.org/10.1007/s00500-021-05650-3

(2) Shan, X., Wang, Y., Dong, M., & Xia, J. (2021). **Application Research and Analysis of Geographic Information System in Intelligent City Surveying**

and Mappinge. *Journal of Physics: Conference Series*, 1881(4), 042071. https://doi.org/10.1088/1742-6596/1881/4/042071

(3) Xc, A., Bta, B., Yan, L. A., Xx, A., Lei, L. C., Hk, A., & Jl, A. (2019). **Dynamic recrystallization behavior of the Ti–48Al–2Cr–2Nb alloy during isothermal hot deformation**. *Progress in Natural Science: Materials International*, 29(5), 587-594. https://doi.org/10.1016/j.pnsc.2019.08.004

(4) Lu, X., Wang, F. R., Xue, L., Feng, Y., & Liang, S. Y. (2019). **Investigation of material removal rate and surface roughness using multi-objective optimization for micro-milling of inconel 718**. *Industrial Lubrication and Tribology*, 71(6). https://doi.org/10.1108/ILT-07-2018-0259

(5) Beruvides, G., Casta?O, F., Quiza, R., & Haber, R. E. (2016). **Surface roughness modeling and optimization of tungsten–copper alloys in micro-milling processes**. *Measurement*, 246-252. https://doi.org/10.1016/j.measurement.2016.03.002

(6) Shi, Z. L., Gong, Y., Cao, M., & Xiao, S. (2010). **Discussion on the Application of Surveying and Mapping Technology in the Internet of Things Times**. *Modern Surveying and Mapping*, 65(4), 503-515. https://doi.org/10.1016/j.neuron.2010.01.035

(7) Shi, X., & Wang, B. (2021). **Application of New Surveying and Mapping Technology in the Construction of Smart City**. *E3S Web of Conferences*, 236, 04031. https://doi.org/10.1051/e3sconf/202123604031

(8) Wang, J., Ran, R., Song, Z., & Sun, J. (2017). **Short-Term Photovoltaic Power Generation Forecasting Based on Environmental Factors and GA-SVM**. *Journal of Electrical Engineering & Technology*, 12(1), 64-71. https://doi.org/10.5370/JEET.2017.12.1.064

(9) Zhang, X. Y., Deng, C. H., & Chen, T. T. (2011). **Ultra-Short-Term Ahead Generating Power Forecasting for PV System Based on Markov Chain for Error Series**. *Advanced Materials Research*, 347-353, 1498-1505. https://doi.org/10.4028/www.scientific.net/AMR.347-353.1498

(10) Wang, M., Zhou, J., Gao, J., Li, Z., & Li, E. (2020). **Milling Tool Wear Prediction Method Based on Deep Learning under Variable Working Conditions**. *IEEE Access*, 8, 140726-140735. https://doi.org/10.1109/ACCESS.2020.3010378

(11) Yi, S., Wang, X., & Tang, X. (2014). **Deep Learning Face Representation by Joint Identification-Verification**. *Advances in neural information processing systems*, 27. https://doi.org/10.48550/arXiv.1406.4773

(12) Yu, S., Zeng, W., Zhao, Y., Shao, Y., & Zhou, Y. (2012). **Modeling the Correlation of Composition-Processing-Property for TC11 Titanium Alloy Based on Principal Component Analysis and Artificial Neural Network**. *Journal of Materials Engineering & Performance*, 21(11), 2231-2237. https://doi.org/10.1007/s11665-012-0162-y

(13) Huang, Z., Wei, X., & Kai, Y. (2015). **Bidirectional LSTM-CRF Models for Sequence Tagging**. *Computer Science*. https://doi.org/10.48550/arXiv.1508.01991

(14) Li, M., Liu, X., & Xiong, A. (2002). **Prediction of the mechanical properties of forged TC11 titanium alloy by ANN**. *Journal of Materials Processing Technology*, 121(1), 1-4. https://doi.org/10.1016/S0924-0136(01)01006-8

(15) Cai, W., Zhai, B., Liu, Y., Liu, R., & Ning, X. (2021). **Quadratic polynomial guided fuzzy C-means and dual attention mechanism for medical image segmentation**. *Displays*, 70, 102106. https://doi.org/10.1016/j.displa.2021.102106

(16) Miao, J., Wang, Z., Ning, X., Xiao, N., Cai, W., & Liu, R. (2022). **Practical and secure multifactor authentication protocol for autonomous vehicles in 5G**. *Software: Practice and Experience*. https://doi.org/10.1002/SPE.3087

(17) Liu, Z., Zhou, W., & Li, H. (2019). **AB-LSTM: Attention-based Bidirectional LSTM Model for Scene Text Detection**. *ACM Transactions on Multimedia Computing Communications and Applications*, 15(4), 1-23. https://doi.org/10.1145/3356728

(18) Ning, X., Duan, P., Li, W., & Zhang, S. (2020). **Real-time 3D face alignment using an encoder-decoder network with an efficient deconvolution layer**. *IEEE Signal Processing Letters*, 27, 1944-1948. https://doi.org/10.1109/LSP.2020.3032277

(19) Sagnika, S., Mishra, B., & Meher, S. K. **An attention-based CNN-LSTM model for subjectivity detection in opinion-mining**. *Neural Computing and Applications*, 1-14. https://doi.org/10.1007/s00521-021-06328-5

(20) Ning, X., Gong, K., Li, W., & Zhang, L. (2021). **JWSAA: joint weak saliency and attention aware for person re-identification**. *Neurocomputing*, 453, 801-811. https://doi.org/10.1016/j.neucom.2020.05.106

(21) Shan, W. (2022). **Digital streaming media distribution and transmission process optimisation based on adaptive recurrent neural network**. *Connection Science*, 34(1), 1169-1180. https://doi.org/10.1080/09540091.2022.2052264

(22) Chen, Y., Wang, L., Hu, J., & Ye, M. (2020). **Vision-Based Fall Event Detection in Complex Background Using Attention Guided Bi-directional LSTM**. https://doi.org/10.1109/ACCESS.2020.3021795

(23) Qi, F., Gao, C., Lan, W., Yue, Z., Song, T., & Li, Q. (2018). **Spatio-temporal fall event detection in complex scenes using attention guided LSTM**. *Pattern Recognition Letters*, S016786551830504X-. https://doi.org/10.1016/j.patrec.2018.08.031

(24) Yan, C., Pang, G., Bai, X., Liu, C., Xin, N., Gu, L., & Zhou, J. (2021). **Beyond triplet loss: person re-identification with fine-grained difference-aware pairwise loss**. *IEEE Transactions on Multimedia*. https://doi.org/10.1109/TMM.2021.3069562

(25) Nguyen, T. (2019). **Spatiotemporal Tile-based Attention-guided LSTMs for Traffic Video Prediction**. https://doi.org/10.48550/arXiv.1910.11030

(26) Ying, L., Nan, Z. Q., Ping, W. F., Kiang, C. T., Pang, L. K., Chang, Z. H., Nam, L. **Adaptive weights learning in CNN feature fusion for crime scene investigation image classification**. *Connection Science*. https://doi.org/10.1080/09540091.2021.1875987

(27) Li, D., & Lasenby, J. (2022). **Spatiotemporal Attention-Based Graph Convolution Network for Segment-Level Traffic Prediction**. *IEEE Transactions on Intelligent Transportation Systems*, 23(7), 8337-8345. https://doi.org/10.1109/TITS.2021.3078187

(28) Hu, X., Liu, T., Hao, X., & Lin, C. (2022). Attention-based Conv-LSTM and Bi-LSTM networks for large-scale traffic speed prediction. The Journal of Supercomputing, 1-24. https://doi.org/10.1007/s11227-022-04386-7

(29) Juárez, F. F., Esenarro, D., Díaz, M., y Frayssinet, M. (2021). **Model based on balanced scorecard applied to the strategic plan of a peruvian public entity**. *3C Empresa. Investigación y pensamiento crítico*, 10(4), 127-147. https://doi.org/10.17993/3cemp.2021.100448.127-147

(30) Xu Bo, Wang Ran, Peng Baoying, Alqurashi Fahad Abdullah & Salama Mohamad. (2021). **Automatic parameter selection ZVD shaping algorithm for crane vibration suppression based on particle swarm optimisation**. *Applied Mathematics and Nonlinear Sciences, 7*(1), 73-82. https://doi.org/10.2478/AMNS.2021.1.00075