Intelligent Evaluation Method of Cement Bond Quality Based on Convolutional Neural Network

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Abstract. The quality of cement bond is related to the safety of oil and gas well production and the service life of casing. At present, acoustic variable density logging (VDL) is the most widely used method for evaluating cementing quality in oil fields. The data interpretation of VDL still needs to rely on manpower, and the accuracy of interpretation results is restricted by human factors, and the workload is heavy. Oilfields have accumulated a large number of practically verified VDL interpretation results. It is of great research value and application potential to sort out these historical data and mine them with the help of deep learning technology, and establish an intelligent analysis method instead of humans to explain the cementing quality. In this study, the VDL cementing quality evaluation reports of several oil wells were collected. Through data preprocessing, the acoustic variable density images were standardized and segmented along the borehole direction. The cementation conditions of the first interface and the second interface corresponding to each segment of the acoustic variable density image were marked, and a sample set for cement bond quality evaluation was established. The cementing quality evaluation problem is transformed into an image classification problem, and the convolutional neural network method is introduced. On the basis of LeNet5, AlexNet and other classic image recognition architectures, considering the characteristics of acoustic variable density images, a personalized convolutional neural network (CBQNet) for cementing quality evaluation is designed, including 28 layers and more than 32 million learnable parameters.

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Using historical cementing quality evaluation samples to train and analyze the performance of convolutional neural network, the results show that: CBQNet has a training accuracy rate of 95.9% and a verification accuracy rate of 95.4% in the first interface cementing quality evaluation. In the cementing quality evaluation of the second interface, the training accuracy rate reached 90.8%, and the verification accuracy rate reached 88.1%. It shows that the convolutional neural network realizes efficient and accurate interpretation of cementing quality by mining and learning the interpretation results of historical VDL data, and provides a new method for cementing quality evaluation.

Keywords: Cement Bond Quality Evaluation · Convolutional Neural Network · VDL Logging · Pattern Recognition

Nomenclature

a_k	Output of the kth sample;
C	Cross-entropy loss function;
i, j	Number of neurons;
j	Total number of neurons of layer;
k	Number of sample;
n	Total number of samples;
$relu_i(\boldsymbol{x})$	ReLU function;
$softmax_i(\boldsymbol{x})$	Softmax function;
$\boldsymbol{x}$	Vector of parameters for each neuron in a neural network layer;
x_i, x_j	Parameter for the ith and jth neurons;
y	Label value;
y_k	Label value of the kth sample

1 Introduction

Cementing is a key technology in the process of oil and gas field development, and the quality of cement bond has a direct impact on the life and productivity of the well. During the cementing process, it is difficult to ensure good cementing quality in the entire well section due to the properties of the medium in the well, the cementing operation environment and various factors during the construction process [1–3]. Unqualified cementing quality may lead to reduced well life and oil layer pollution. How to evaluate the cementing quality reasonably, locate unqualified well sections in time, and give reasonable remedial measures has become an important task of cementing.

Cementing quality evaluation is mainly based on the analysis of the cementation of the two interfaces. Interface I is the cemented interface between the casing and the cement sheath, and interface II is the cemented interface between the cement sheath and the formation. No matter whether the cementation quality of the interface I or the interface II does not meet the standard, it is easy to cause downhole oil-water channeling, and even destroy the regional geostress balance, resulting in casing damage [4–6].

In the 1970s, acoustic variable density logging (VDL) technology was developed for cement bond evaluation. The VDL logging tool adopts the single-send and double-receive mode. The sound wave is emitted from the transmitter, and the sound wave passes through various interfaces in the well and is finally received by the receiver. There are two source distances for receivers. The 3ft source distance receiver is used to measure the casing wave sound amplitude, which is used for the evaluation of the interface I. The 5ft source distance receiver is used to measure the full wave of the sound wave, and the acoustic variable density image is obtained after processing, which can reflect the cement bonding of the interface I and interface II. VDL logging technology has become more and more mature and has become the most widely used cementing quality evaluation technology. However, at present, the data interpretation of VDL still needs to rely on manpower, and the accuracy of interpretation results is restricted by human factors, and the workload is heavy [7–9].

Big data and deep learning technology are causing a new round of technological revolution. Breakthroughs have been made in many fields such as image recognition, voice processing, and unmanned driving [10]. Petroleum companies are also actively introducing artificial intelligence technology to promote intelligent transformation and upgrading [11, 12]. At present, the oil field has accumulated a large number of practically verified VDL interpretation results. It is of great research to sort out these historical data and mine them with the help of deep learning technology, so that it can replace humans in cementing quality interpretation. This has great research value and application potential.

In this study, we propose to apply convolutional neural network to the problem of cementing quality evaluation. Firstly, a sample set of cementing quality evaluation will be prepared based on the historical VDL data and the corresponding cementing quality interpretation results. After that, a cement bond quality evaluation model will be established based on convolutional neural network. The sample set will be mined and learned, and the performance of the model will be analyzed.

The paper is structured as follows: Sect. 2 provides an description of the preparation process for the cementing quality evaluation sample set. Section 3 discusses the design concept and outcomes of the convolutional neural network architecture for cementing quality evaluation. Section 4 presents the training process and performance analysis results of the neural network for cementing quality evaluation. Finally, Sect. 5 concludes the paper.

2 Preparation of Cement Bond Quality Evaluation Sample Set

2.1 VDL Logging Interpretation Image

VDL is a commonly used cementing quality detection method in the field. The principle is to reflect the bonding quality between cement and casing, and between casing and formation by using the large difference in acoustic impedance between cement and mud (or water) on the attenuation of sound waves propagating along the axial direction of the casing [2].

The VDL tool adopts the single-send and double-receive mode. The sound wave is emitted from the transmitter, and the sound wave passes through various interfaces in the well and is finally received by the receiver. There are two source distances for receivers. The 3ft source-distance receiver measures the sound amplitude of the casing wave, which is used for the evaluation of the first interface of cementing. The receiver with a source distance of 5ft is used to measure the full wave train of the sound wave, and then the components and amplitude of the first arrival wave are extracted through data processing, and the sound wave variable density map is obtained, which can reflect the cement cementation of the interface I and interface II. There are black and white strips on the acoustic variable density image, and the intensity of the signal is represented by the color of the strips. In the acoustic variable density image, combined with geological information and cementing slurry information, the cementing quality analysis can be carried out according to the clarity of the full wave train strips [13].

Figure 1 illustrates a typical image of cementing quality interpretation results. The figure presents six types of logging information, namely natural gamma ray logging (GR), caliper logging (CAL), acoustic amplitude logging (AC), acoustic time difference logging (CBL), magnetic positioning logging (CCL), and acoustic variable density logging (VDL). Additionally, the image displays the cementing quality analysis results of two interfaces, namely interface I and interface II, on the left side. The different tiles in the image correspond to different cementing qualities, including five distinct interpretation results, namely good cementation, moderate cementation, poor cementation, mixed mud zone, and mud zone.

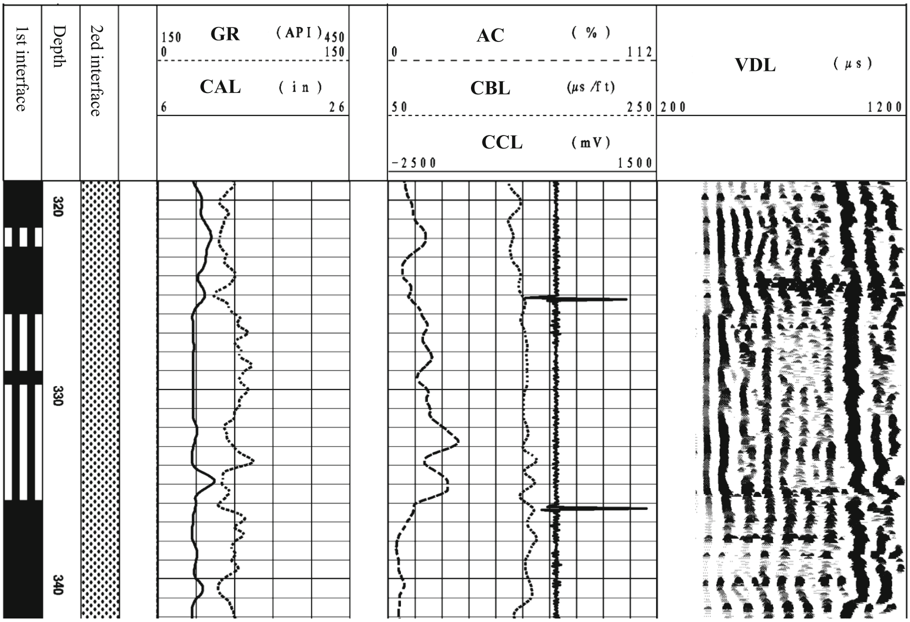


Fig. 1. A typical image of cementing quality interpretation results.

2.2 Sample Set Preparation

Cementing quality interpretation result images from oil fields were collected. The entire interpretation result image was segmented along the borehole direction with a width of 1m, results many independent images for each meter, each with a size of 1886 × 41 pixels.

Each meter of the interpretation result image was further cropped to intercept the VDL image part, the interpretation result part of the interface I, and the interpretation result part of the interface II. Specifically, the VDL image part was cropped to a size of 511 × 41 pixels, while the interpretation result parts of the first and second interface sections were cropped to sizes of 73 × 41 pixels each. An example of resulting images is presented in Fig. 2.

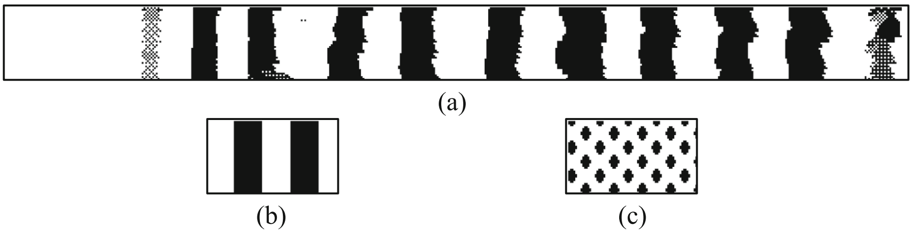
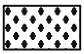
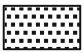
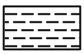


Fig. 2. An example of resulting images cropped from an interpretation result image. (a) VDL image part. (b) interface I interpretation result part. (c) interface II interpretation result part.

The VDL image in Fig. 2(a) is a black and white image that can be transformed into a matrix of size 511 × 41, where each element in the matrix takes a value of either 0 or 1. In this matrix, 0 represents a white pixel and 1 represents a black pixel. Similarly, the images in Fig. 2(b) and Fig. 2(c) are black and white and represent the interpretation results of the first and second interfaces. During the preparation of the sample set, the interpretation results of the wellbore interfaces were transformed into vectors using the one-hot encoding method, as shown in Table 1.

Table 1. Interpretation results and corresponding one-hot code.

Image of interpretation results	Description of interpretation results	One-hot code
	good cementation	[1 0 0 0 0]
	moderate cementation	[0 1 0 0 0]
	poor cementation	[0 0 1 0 0]
	mixed mud zone	[0 0 0 1 0]
	mud zone	[0 0 0 0 1]

The cement bond quality evaluation sample set was obtained by processing the interpreted image for each meter of each well. A total of 3351 samples were prepared in this study. Each sample contains an input image, and two labels representing the cementing quality of the first interface and the second interface, respectively.

3 Architecture Design of Convolutional Neural Network for Cementing Quality Evaluation

Given that the input for evaluating cement bond quality is the VDL image, a convolutional neural network (CNN) with robust image feature learning and classification abilities was chosen. CNN is the leading algorithm in computer vision research, especially in image recognition, and has demonstrated a range of successful applications [14]. As a deep learning algorithm, CNN is inspired by the visual cortex structure in animals that adaptively extracts spatial hierarchical information from images through layers of various visual neurons. CNN typically includes three kinds of layers, namely, convolutional layers, pooling layers, and fully connected layers. The convolutional and pooling layers are utilized for image feature extraction, where the former leverages different convolutional kernels to scan the feature maps for extracting features from diverse perspectives, and the latter reduces the dimensionality of the features. The fully connected layer maps the extracted features to the final output.

For different problems, the number and logical relationship of convolutional layer, pooling layer and fully connected layer are different, that is, the design of convolutional neural network architecture is different. Due to the inexplicability of neural network algorithms, the current neural network architecture design still lacks general standards and specifications, and relies more on experience and trial and error. According to the characteristics of the cementing quality evaluation problem, combined with the classic network architectures such as LeNet-5, AlexNet, VGGNet, GoogleNet and ResNet in the image recognition field [15], the architecture of the convolutional neural network for cementing quality evaluation is designed and named as CBQNet. Its architecture parameters are shown in Table 2.

The designed convolutional neural network, CBQNet, for evaluating the quality of cementing contains a total of 28 layers, including 6 convolutional layers that all utilize 3×3 small convolutional kernels and 3 pooling layers that all use 2×2 maximum pooling method. With the exception of the Softmax activation function used before the classification output, all intermediate layers use the ReLU activation function. The formulas of Softmax and ReLU activation functions are:

$$softmax_i(x) = \frac{\mathrm{e}^{x_i}}{\sum_{j=1}^{J} \mathrm{e}^{x_j}} \; (i = 1, 2, 3, \cdots, J) \tag{1}$$

$$relu_i(x) = \max(0, \mathrm{e}^{x_i}) \; (i = 1, 2, 3, \cdots, J) \tag{2}$$

The CBQNet has a total of over 32 million learnable parameters. To avoid issues related to overfitting and lengthy training times, five dropout layers were added. During training, the dropout layers randomly select a certain proportion of neurons to stop

Table 2. Architecture parameters of CBQNet.

Layer No.	Layer Type	Settings	Dimensions	Learnable Parameters
1	Image Input		511 × 41 × 1	
2	Conv2D	Size: 3 × 3 No.: 32 Stride: 1 × 1	509 × 39 × 32	Weights: 3 × 3 × 1 × 32 Bias: 1 × 1 × 32
3	Activation	Function: ReLU	509 × 39 × 32	
4	Conv2D	Size: 3 × 3 No.: 32 Stride: 1 × 1	507 × 37 × 32	Weights: 3 × 3 × 1 × 32 Bias: 1 × 1 × 32
5	Activation	Function: ReLU	507 × 37 × 32	
6	Pooling	Type: Max Pooling Size: 2 × 2 Stride: 2 × 2	254 × 19 × 32	
7	Dropout	Ratio: 5%	254 × 19 × 32	
8	Conv2D	Size: 3 × 3 No.: 64 Stride: 1 × 1	252 × 17 × 64	Weights: 3 × 3 × 32 × 64 Bias: 1 × 1 × 64
9	Activation	Function: ReLU	252 × 17 × 64	
10	Conv2D	Size: 3 × 3 No.: 64 Stride: 1 × 1	250 × 15 × 64	Weights: 3 × 3 × 64 × 64 Bias: 1 × 1 × 64
11	Activation	Function: ReLU	250 × 15 × 64	
12	Pooling	Type: Max Pooling Size: 2 × 2 Stride: 2 × 2	125 × 8 × 64	
13	Dropout	Ratio: 5%	125 × 8 × 64	
14	Conv2D	Size: 3 × 3 No.: 128 Stride: 1 × 1	123 × 6 × 128	Weights: 3 × 3 × 64 × 128 Bias: 1 × 1 × 128
15	Activation	Function: ReLU	123 × 6 × 128	
16	Conv2D	Size: 3 × 3 No.: 128 Stride: 1 × 1	121 × 4 × 128	Weights: 3 × 3 × 128 × 128 Bias: 1 × 1 × 128
17	Activation	Function: ReLU	121 × 4 × 128	
18	Pooling	Type: Max Pooling Size: 2 × 2 Stride: 2 × 2	61 × 2 × 128	
19	Dropout	Ratio: 5%	61 × 2 × 128	

(*continued*)

Table 2. (*continued*)

Layer No.	Layer Type	Settings	Dimensions	Learnable Parameters
20	Fully Connected	No.: 2 048	1 × 1 × 2 048	Weights: 2048 × 15616 Bias: 2048 × 1
21	Activation	Function: ReLU	1 × 1 × 2 048	
22	Dropout	Ratio: 5%	1 × 1 × 2 048	
23	Fully Connected	No.: 512	1 × 1 × 512	Weights: 512 × 2048 Bias: 512 × 1
24	Activation	Function: ReLU	1 × 1 × 512	
25	Dropout	Ratio: 25%	1 × 1 × 512	
26	Fully Connected	No.: 5	1 × 1 × 5	Weights: 5 × 512 Bias: 5 × 1
27	Activation	Function: Softmax	1 × 1 × 5	
28	Output		1 × 1 × 5	28

participating in computations. This not only reduces computation time, but also transforms a single large-scale model into a collection of relatively smaller models, which effectively improves the model's ability to generalize.

4 Neural Network Training and Performance Analysis

4.1 Training Parameter Setting

Neural network training is the process of finding the weights between the convolutional kernels in the convolutional layers and the neurons in the fully connected layers, with the aim of minimizing the difference between the calculated output of the output layer and the true label given in the sample set. The selection and setting of the loss function and optimizer play a critical role in neural network training. First, the data samples are input into the neural network, then the current model performance is evaluated through the forward propagation process and the loss function. Next, the optimizer updates the weights of the learnable parameters in the neural network based on the size of the loss, using the backward propagation process.

The loss function used for training CBQNet is the cross-entropy loss function, which measures the distance between two probability distributions. Its expression is as follows:

$$C = -\frac{1}{n}\sum_{k=1}^{n}\left[y_k \ln a_k + (1 - y_k)\ln(1 - a_k)\right] \tag{3}$$

In this study, the optimizer used is Adadelta, an improved and extended version of the Adagrad algorithm. Compared with Adagrad, Adadelta no longer accumulates all past gradients, but adjusts the learning rate based on the moving window updated by the gradient, making it more robust. The main parameters for setting the Adadelta algorithm include a learning rate of 1.0, a decay rate of 0.95 for the moving average of gradient squares, a blur factor of 1×10^{-6}, and a learning rate decay value of 0 after each parameter update.

During the training process, 20% of the samples were randomly selected as the validation set, and the remaining 80% of the samples were used as training data. The total number of training epochs was set to 30, and 100 samples were fed into the neural network for each training iteration. The training environment was set up using Keras and TensorFlow. The workstation was equipped with an Intel Xeon E5-2673 v3 12C/24T 2.40 GHz processor and 64 G 2 400 MHz DDR4 ECC memory.

As each input image in the wellbore cementing quality evaluation sample set corresponds to two labels, representing the cementing quality of the first and second interfaces, respectively, two training processes are required during neural network training. The first training process uses the cementing quality of the first interface as the output, resulting in the CBQNet-1 neural network model for analyzing the quality of the first interface. The second training process uses the cementing quality of the second interface as the output, resulting in the CBQNet-2 neural network model for analyzing the quality of the second interface.

4.2 Performance Analysis

The accuracy and loss of CBQNet-1 during training are shown in Fig. 3 and Fig. 4. It can be seen from Fig. 3 that after the first training epoch, the model's training accuracy and validation accuracy were 78.5% and 84.2%, respectively, with a significant gap between them, indicating that the training was not sufficient. With the increase of training epochs, the training accuracy of the model showed a stable upward trend, with a fast-then-slow increase rate, and the training accuracy had exceeded 99% after 20 epochs. The upward trend of validation accuracy was consistent with that of training accuracy before the 12th epoch, and then validation accuracy showed some fluctuations without significant improvement. After 12 epochs of training, the training accuracy and validation accuracy of the model were 95.9% and 95.4%, respectively. Although further training could still improve the training accuracy, the validation accuracy no longer improved significantly, and the gap between the two began to increase, indicating that further training would lead the model to overfitting. From Fig. 4 we can see that the trend of the training loss and validation loss during training was basically the same as that of the accuracy, further indicating that the ideal effect could be achieved after 12 epochs of training.

The accuracy and loss of CBQNet-2 during training are shown in Fig. 5 and Fig. 6. It can be observed from Fig. 5 that after the completion of the first epoch, the model's training accuracy and validation accuracy were 40.3% and 46.7%, respectively, which were relatively low, indicating that a single round of training was insufficient for the neural network to fully grasp the rules between sample inputs and outputs. Similar to CBQNet-1, the model's training accuracy increased rapidly at first and then slowed down as the number of training epochs increased. After 20 epochs, the training accuracy

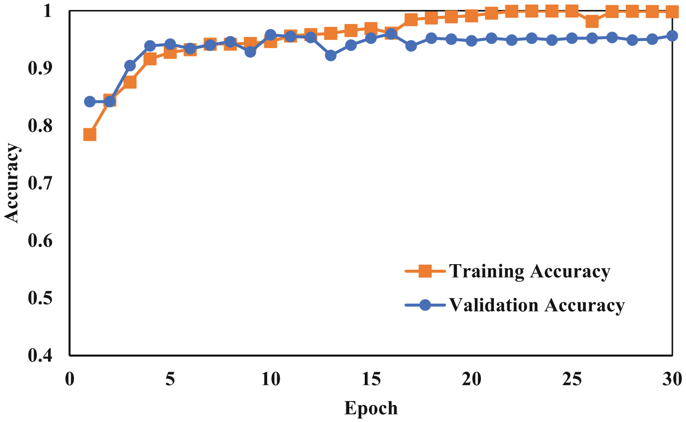


Fig. 3. The accuracy of CBQNet-1 during training.

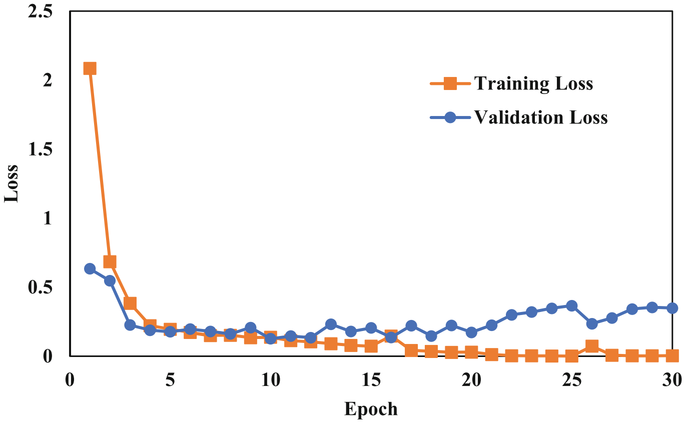


Fig. 4. The loss of CBQNet-1 during training.

exceeded 99%. The trend of the validation accuracy was consistent with that of the training accuracy before the 12th epoch. However, the validation accuracy showed a certain degree of fluctuation thereafter, with no significant improvement. After 12 epochs of training, the model's training accuracy and validation accuracy were 90.8% and 88.1%, respectively. From Fig. 6 we can see that the trend of the model's training loss and validation loss with respect to the number of training epochs was similar to the trend of the accuracy, which further indicates that the desired effect can be achieved after 12 epochs of training.

Overall, the accuracy of CBQNet-2 is lower than that of CBQNet-1, indicating that the analysis of the second interface bonding quality is more difficult than the analysis of the first interface bonding quality, which is consistent with the traditional understanding of manual analysis.

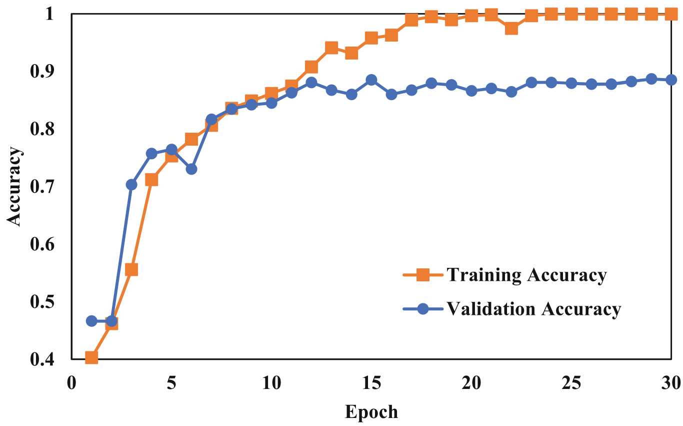


Fig. 5. The accuracy of CBQNet-2 during training.

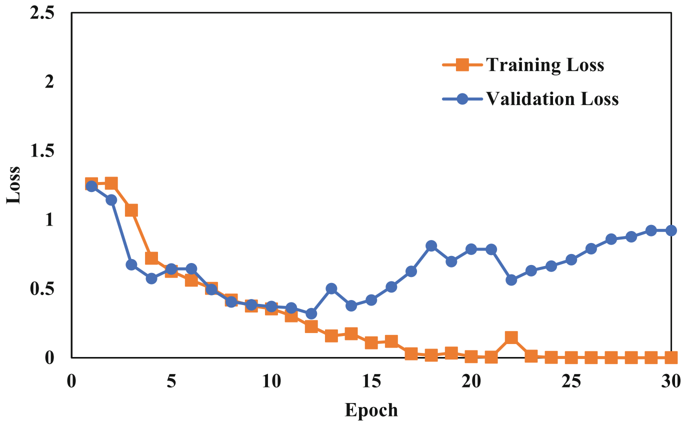


Fig. 6. The loss of CBQNet-2 during training.

The training time of CBQNet-1 and CBQNet-2 is shown in Fig. 7. From the figure, it can be observed that the training time of the two neural networks follows a similar trend. When the number of training epochs is small, the fluctuation in training time is stronger. However, with the increase in the number of training epochs, the training time of each epoch becomes more stable. The average training time per epoch is 188 s, indicating that the model's training efficiency is relatively high. If more samples are added in the future, it is possible to complete the training of a new model in a relatively short time.

Overall, the trained CBQNet-1 and CBQNet-2 can achieve high accuracy and automated analysis of the first and second interface cementing quality. They can save a lot of time spent on manual analysis, freeing petroleum engineers from simple and complicated work and allowing them to devote more energy to higher-level intelligent tasks such as operation management and anomaly handling.

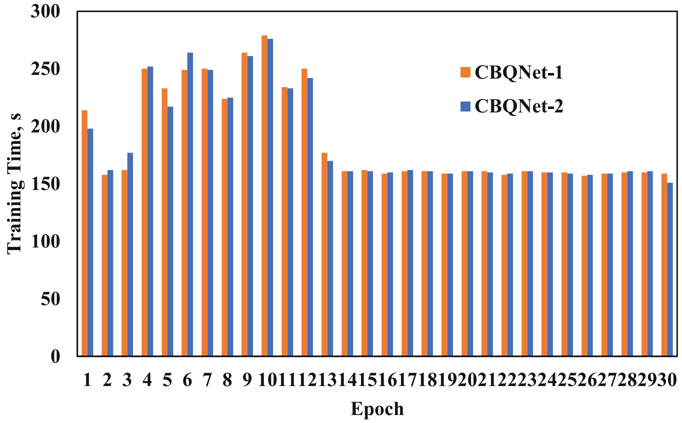


Fig. 7. The training time of CBQNet-1 and CBQNet-2.

5 Conclusion

A batch of historical cementing interpretation result images of oilfields were collected, and the images were standardized to establish a cement bond quality evaluation sample set. The sample set contains a total of 3351 samples, and each sample contains two labels of the cementing quality of the first interface and the second interface.

Combined with the characteristics of the cementing quality evaluation problem, the convolutional neural network was selected to carry out the personalized design of the network architecture, and a CBQNet with 28 layers and more than 32 million learnable parameters was constructed. After setting reasonable learning parameters, the CBQNet was trained with the ementing quality evaluation sample set, resulting in two models: CBQNet-1 for the cementing quality evaluation of the first interface and CBQNet-2 for the cementing quality evaluation of the second interface, with validation accuracy rates of 95.4% and 88.1%, respectively.

Future work will focus on expanding the cementing quality evaluation sample set, addressing the problem of uneven sample distribution, introducing more evaluation indicators, and further improving model accuracy.

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