Journal of Computing and Electronic Information Management
ISSN: 2413-1660 | Vol. 21, No. 1, 2026

Research on Weak Formation Interval Identification in Oil Drilling Based on CNN-BiLSTM-MHA Model

Yuchi Hu

School of Computer Science, Xi`an Shiyou University, Xi`an, 710065, China

Abstract: Weak formation intervals in oil drilling are critical sections that may induce complex downhole problems, such as wellbore instability and borehole enlargement. Their accurate identification is of great significance for improving drilling safety and operational efficiency. To address the limitations of traditional weak formation identification methods, including strong dependence on expert experience, high subjectivity, and insufficient utilization of local logging responses and depth-wise sequential dependencies, this paper proposes a weak formation identification method based on a CNN-BiLSTM-MHA model. First, weak formation identification samples are constructed using logging curves and well trajectory parameters, and data preprocessing is performed through missing value handling, outlier correction, standardization, and sliding-window sampling. Then, a convolutional neural network is used to extract local response features, a bidirectional long short-term memory network is employed to model forward and backward dependencies along the depth direction, and a multi-head attention mechanism is introduced to enhance the representation of key intervals and critical features. Finally, comparative experiments and ablation experiments are conducted to verify the effectiveness of the proposed model. Experimental results show that the proposed model achieves an Accuracy, Precision, Recall, and F1-score of 91.52%, 90.28%, 90.15%, and 90.21%, respectively, outperforming comparative models such as SVM, XGBoost, TCN, and Informer. The proposed method can provide methodological support for intelligent identification of weak formation intervals in oil drilling.

Keywords: Weak formation intervals in oil drilling; Convolutional Neural Network; Bi-directional Long Short-Term Memory l; Attention Mechanism.

1. Introduction

1.1. Research Background and Significance

Weak formation intervals are typical complex and sensitive sections encountered during oil drilling. Their development often weakens wellbore stability and may induce engineering problems such as borehole enlargement and wellbore instability[1]. Under geological conditions involving complex structural settings and multiple pressure systems, the identification of weak formation intervals becomes more difficult, which may delay the adjustment of drilling parameters and amplify engineering risks[2]. Therefore, refined identification of weak formation intervals is not only related to downhole safety control, but also directly affects drilling efficiency and engineering economy.

For a long time, the identification of weak formation intervals has mainly relied on offset well comparison, manual interpretation of logging curves, and field experience. Although these methods have certain engineering applicability, they commonly suffer from strong subjectivity, low identification efficiency, and insufficient consistency in complex well sections[3]. With the continuous improvement of logging data acquisition and data processing techniques, automatic layering and intelligent interval interpretation based on logging curves have gradually become important approaches for improving identification efficiency[4]. Compared with traditional experience-based judgment, data-driven methods can more effectively mine the coupling relationships among multiple logging parameters and their continuous variation patterns along the depth direction, showing better application potential in weak formation interval identification.

1.2. Current Research Status at Home and Abroad

In the field of intelligent logging identification, machine learning methods have been applied to stratum identification and lithology classification, demonstrating that data-driven models can effectively improve the automation level and classification accuracy of logging interpretation[5]. In studies related to abnormal interval identification, which is closely associated with weak formation intervals, ensemble learning methods have been used for vulnerable formation discrimination, indicating the feasibility of intelligent algorithms in identifying complex and sensitive intervals[6]. These studies provide a methodological basis for weak formation interval identification. However, most existing methods still rely on manually constructed features, and their ability to jointly represent local abnormal responses and vertically continuous features remains limited.

With the development of deep learning, convolutional neural networks, recurrent neural networks, and their improved structures have been gradually applied to logging interpretation tasks. Among them, deep models show stronger advantages than traditional machine learning methods in extracting complex features[7]. Meanwhile, studies on time-series representation learning indicate that fully exploiting contextual dependencies along the depth direction can further improve the accuracy and generalization ability of logging identification tasks[8]. Overall, existing studies provide useful methodological support for logging sequence modeling and intelligent identification. However, for the specific task of weak formation interval identification in oil drilling, there is still a lack of a targeted model that can simultaneously consider local feature extraction, bidirectional sequence modeling, and key feature enhancement. Therefore, this paper constructs a CNN-BiLSTM-MHA model to improve the accuracy and stability of weak formation interval identification in oil drilling.

2. Model Design

2.1. Convolutional Neural Network

Convolutional Neural Networks (CNN) are typical deep learning models mainly used to extract local features from data. In the weak formation interval identification task, logging curves usually exhibit obvious local response characteristics, such as borehole enlargement, increased acoustic travel time, resistivity variation, and combined anomalies in density and neutron curves. By sliding convolution kernels over the input logging sequence, CNN can automatically extract the combined variation features among multiple logging parameters within local depth intervals, thereby reducing the dependence on manually designed features. Meanwhile, the parameter-sharing mechanism of convolutional layers can reduce model complexity and improve the ability to capture local abnormal responses of weak formation intervals.

2.2. Bidirectional Long Short-Term Memory Network

Bidirectional Long Short-Term Memory (BiLSTM) is an improved structure of LSTM and is suitable for processing sequential data with continuous variation characteristics. Weak formation intervals generally do not appear as isolated single-depth anomalies, but rather as continuous abnormal intervals within a certain thickness range. BiLSTM learns logging sequence information from both forward and backward directions, enabling the model to integrate contextual features from the intervals before and after the current depth point. In this way, it can more completely characterize the variation patterns of weak formation intervals along the depth direction. Compared with unidirectional LSTM, BiLSTM can make fuller use of bidirectional dependencies in logging sequences and improve the identification ability for weak formation boundaries and continuous intervals.

2.3. Multi-Head Attention Mechanism

The core idea of the Multi-Head Attention (MHA) mechanism is to perform parallel modeling of the input sequence from multiple feature subspaces and assign different weights to different depth positions and feature information. In weak formation interval identification, the contributions of different logging parameters to the identification result are not the same, and the importance of different depth positions also varies. MHA can learn the internal correlations of logging sequences from different perspectives through multiple attention heads, highlighting key intervals and critical features closely related to weak formation identification, thereby enhancing the model’s representation capability for complex logging response patterns.

2.4. Overall Model Framework

This paper proposes a weak formation interval identification model that integrates Convolutional Neural Network, Bidirectional Long Short-Term Memory, and Multi-Head Attention. The overall framework of the model consists of six layers, namely the input layer, CNN layer, BiLSTM layer, MHA layer, fully connected layer, and output layer. The input layer receives logging sequence samples constructed by preprocessing and sliding-window sampling. The CNN layer is composed of convolutional layers, batch normalization layers, and multi-scale pooling layers, where the convolutional layers are used to extract local response features from logging sequences, the batch normalization layers are used to accelerate model training and stabilize the training process, and the multi-scale pooling layers are used to reduce feature dimensions and capture response patterns at different scales.

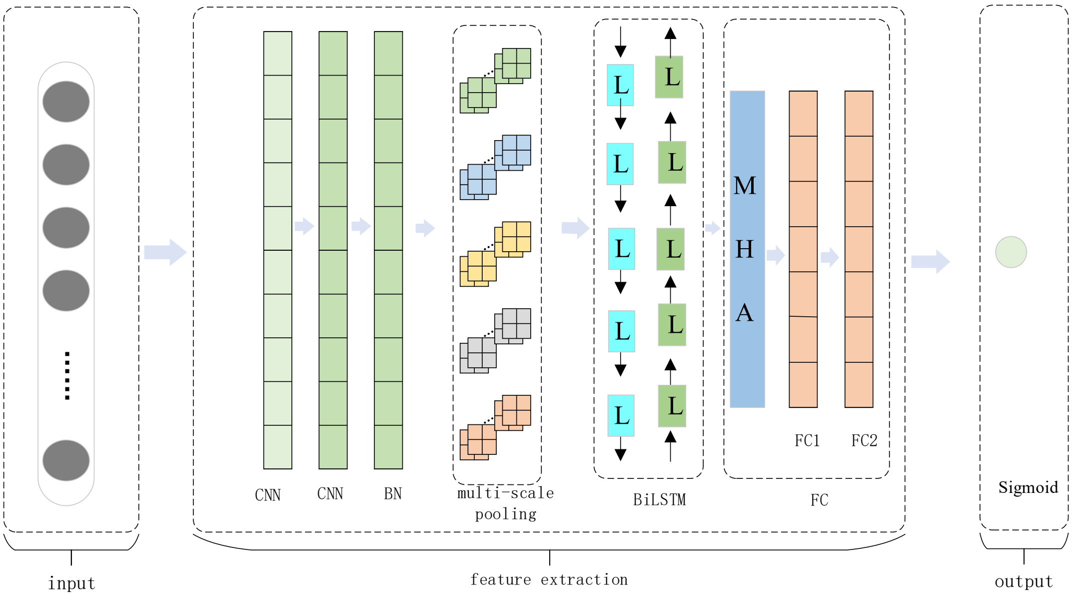

Figure 1. Overall framework of the CNN-BiLSTM-MHA model

The BiLSTM layer contains a bidirectional LSTM structure, which is used to capture forward and backward dependencies along the depth direction. By learning contextual information before and after the target depth point, the BiLSTM layer can better describe the continuous variation characteristics of weak formation intervals. The MHA layer performs feature weighting on the output of the BiLSTM layer. Through multi-head parallel attention calculation, it strengthens the model’s focus on key depth intervals and important logging parameters, thereby further optimizing feature representation.

The fully connected layer is composed of fully connected units and a Dropout operation. The fully connected units are used to further integrate the extracted features, while Dropout randomly discards part of the neurons during training to enhance model generalization and reduce the risk of overfitting. The output layer uses the Sigmoid activation function to predict whether the input sample belongs to a weak formation interval. The overall framework of the model is shown in Figure 1.

3. Experimental Design and Result Analysis

3.1. Experimental Environment and Dataset

The experiments were conducted on a Windows platform. Python was used as the programming language, and PyTorch was adopted as the deep learning framework. GPU acceleration was used during training to improve model training efficiency. The main model parameters were set as follows: batch size of 32, training epochs of 100, AdamW optimizer, initial learning rate of 0.0005, Dropout rate of 0.2, 128 hidden units in BiLSTM, and 4 attention heads in the multi-head attention module.

The experimental data were obtained from real logging data of an oilfield in the Shunbei area. According to the characteristics of the weak formation interval identification task, caliper, acoustic travel time, natural gamma ray, resistivity, density, neutron, well deviation, and azimuth were selected as input features to reflect differences in formation properties, borehole geometry changes, and well trajectory characteristics. Before being fed into the model, the raw data were processed through missing value handling, outlier correction, and standardization to reduce noise interference and the influence of different feature scales on model training.

Considering that weak formation intervals generally exhibit continuous development along the depth direction, a sliding-window strategy was adopted to construct samples. Multi-dimensional logging features of consecutive depth points were extracted within each window and used as a single input sample, while the interval label corresponding to the target depth point was taken as the output category. To ensure the reliability of the training results, the samples were divided into a training set and a test set. The training set was used for model parameter learning, and the test set was used to evaluate identification performance.

3.2. Evaluation Metrics

In this experiment, Accuracy, Precision, Recall, and F1-score were selected as evaluation metrics to comprehensively assess the performance of the proposed model in weak formation interval identification. Accuracy reflects the overall proportion of correctly classified samples. Precision indicates the proportion of samples predicted as weak formation intervals that are actually weak formation intervals. Recall represents the proportion of actual weak formation interval samples that are correctly identified. F1-score is the harmonic mean of Precision and Recall, which provides a balanced evaluation of the model performance. The calculation formulas are as follows:

$$Acc = \frac{TP+TN}{TP+TN+FP+FN} \tag{1}$$

$$P = \frac{TP}{TP+FP} \tag{2}$$

$$R = \frac{TP}{TP+FN} \tag{3}$$

$$F_1 = \frac{2\times P\times R}{P+R} \tag{4}$$

where TP denotes the number of weak formation samples correctly identified as weak formations, TN denotes the number of non-weak formation samples correctly identified as non-weak formations, FP denotes the number of non-weak formation samples incorrectly identified as weak formations, and FN denotes the number of weak formation samples incorrectly identified as non-weak formations.

3.3. Comparative Experimental Results and Analysis

To verify the effectiveness of the proposed CNN-BiLSTM-MHA model, SVM, XGBoost, TCN, and Informer were selected as comparative models. All models were tested on the same dataset under the same experimental conditions. The experimental results are shown in Table 1.

Table 1. Performance Comparison of Different Models

Model	Accuracy(%)	Precision (%)	Recall (%)	F1 (%)
SVM	74.82	73.41	71.96	72.68
XGBoost	77.35	75.94	74.22	75.07
TCN	80.67	79.43	77.86	78.64
Informer	83.48	82.13	81.02	81.57
CNN-BiLSTM-MHA	91.52	90.28	90.15	90.21

As shown in Table 1, traditional machine learning models can perform classification to a certain extent in the weak formation interval identification task, but their overall performance is relatively limited. Among them, the Accuracy, Precision, Recall, and F1-score of the SVM model are 74.82%, 73.41%, 71.96%, and 72.68%, respectively, which are the lowest among all comparative models. This indicates that SVM has limited ability to represent the nonlinear relationships among complex logging features and the continuous variation patterns of formation intervals. The performance of XGBoost is improved compared with SVM, indicating that ensemble learning models have certain advantages in nonlinear fitting. However, their ability to characterize deep temporal features remains limited.

In contrast, temporal deep learning models show better identification performance. The Accuracy, Precision, Recall, and F1-score of the TCN model reach 80.67%, 79.43%, 77.86%, and 78.64%, respectively, indicating that the temporal convolutional network structure can more effectively extract local temporal features from logging sequences. The Informer model further improves the performance, with an Accuracy of 83.48% and an F1-score of 81.57%, suggesting that the attention mechanism has certain advantages in capturing dependency relationships in logging sequences.

The proposed CNN-BiLSTM-MHA model achieves the best results across all evaluation metrics. Specifically, its Accuracy, Precision, Recall, and F1-score reach 91.52%, 90.28%, 90.15%, and 90.21%, respectively. Compared with Informer, the best-performing comparative model, the proposed model improves Accuracy, Precision, Recall, and F1-score by 8.04, 8.15, 9.13, and 8.64 percentage points, respectively. The experimental results demonstrate that the proposed model can more effectively identify weak formation and non-weak formation samples, showing higher accuracy and stability.

The main reason for these performance differences is that the proposed model integrates three advantages: local feature extraction, bidirectional temporal modeling, and key feature enhancement. The CNN module can extract discriminative local abnormal response features from logging sequences. The BiLSTM module can characterize forward and backward dependencies along the depth direction. The MHA module further improves the model's attention to key depth intervals and critical feature channels.Therefore, he CNN-BiLSTM-MHA model exhibits superior comprehensive performance in the weak formation interval identification task.

3.4. Ablation Experiment Analysis

To further verify the contribution of the CNN, BiLSTM, and MHA modules to the performance of weak formation interval identification in oil drilling, ablation experiments were designed. Three model structures, namely CNN-MHA, BiLSTM-MHA, and CNN-BiLSTM, were constructed and compared under the same dataset and experimental conditions. The results are shown in Table 2.

Table 2 Ablation Experiment Results

Model	Accuracy (%)	Precision(%)	Recall(%)	F1(%)
CNN-MHA	86.94	85.72	84.38	85.04
BiLSTM-MHA	85.87	84.61	83.24	83.92
CNN-BiLSTM	87.76	86.55	85.68	86.11
CNN-BiLSTM-MHA	91.52	90.28	90.15	90.21

As shown in Table 2, different module combinations have a clear impact on the performance of weak formation interval identification. The Accuracy, Precision, Recall, and F1-score of the CNN-MHA model are 86.94%, 85.72%, 84.38%, and 85.04%, respectively, indicating that the convolutional network can effectively extract local abnormal response features from logging sequences. With the introduction of the multi-head attention mechanism, the model's ability to focus on critical features is also enhanced to some extent. The BiLSTM-MHA model achieves an Accuracy of 85.87% and an F1-score of 83.92%, which are slightly lower than those of the CNN-MHA model. This suggests that relying only on bidirectional temporal modeling can capture contextual dependencies along the depth direction, but its ability to extract local abnormal patterns is relatively limited.

After combining CNN with BiLSTM, the Accuracy of the CNN-BiLSTM model increases to 87.76%, while its Precision, Recall, and F1-score reach 86.55%, 85.68%, and 86.11%, respectively. Its overall performance is better than that of CNN-MHA and BiLSTM-MHA. This indicates that the combination of convolutional feature extraction and bidirectional temporal modeling can more effectively represent the characteristics of weak formation intervals, where local abnormalities and vertical continuity coexist, thereby improving the identification capability of the model.

The complete CNN-BiLSTM-MHA model achieves the best results across all evaluation metrics, with an Accuracy of 91.52%, Precision of 90.28%, Recall of 90.15%, and F1-score of 90.21%. Compared with the CNN-BiLSTM model, the complete model improves Accuracy by 3.76 percentage points, Precision by 3.73 percentage points, Recall by 4.47 percentage points, and F1-score by 4.10 percentage points. These results indicate that, on the basis of convolutional feature extraction and bidirectional temporal modeling, the introduction of the multi-head attention mechanism enables the model to focus more accurately on key depth intervals and feature channels that play important roles in weak formation identification, further improving identification performance.

Overall, the CNN, BiLSTM, and MHA modules perform different but complementary functions in the weak formation interval identification task. CNN is mainly responsible for extracting local abnormal response features, BiLSTM models forward and backward dependencies along the depth direction, and MHA further enhances the representation of critical features. After integrating the three modules, the model achieves significant improvements in accuracy, recall, and overall discrimination capability, demonstrating that the proposed CNN-BiLSTM-MHA model has a reasonable structure and strong adaptability to the task.

4. Conclusion and Outlook

4.1. Conclusion

To address the problems in weak formation interval identification in oil drilling, such as the strong subjectivity of traditional methods, insufficient representation of complex logging features, and inadequate utilization of continuous variation patterns along the depth direction, this paper proposes a weak formation identification method based on the CNN-BiLSTM-MHA model. The proposed method uses a convolutional neural network to extract local abnormal response features from logging sequences, employs a bidirectional long short-term memory network to model forward and backward dependencies along the depth direction, and introduces a multi-head attention mechanism to enhance the representation of key intervals and critical features.

In this study, a weak formation identification dataset was constructed based on logging data, and the performance of the proposed model was verified through comparative experiments and ablation experiments. The experimental results show that the proposed model outperforms traditional machine learning models and general deep learning models in terms of Accuracy, Precision, Recall, and F1-score. This indicates that the integration of CNN, BiLSTM, and MHA can effectively improve the accuracy and stability of weak formation interval identification in oil drilling. Overall, the proposed method can well adapt to the characteristics of weak formation identification, where local abnormalities and vertical continuity coexist, and has certain engineering application value.

4.2. Outlook

Although the proposed method achieves good experimental performance in the weak formation interval identification task, there is still room for further improvement. Future research can be carried out from the following aspects:

(1) The data scale can be further expanded by incorporating logging samples from different well areas and geological conditions, so as to improve the generalization ability and applicability of the model.

(2) More geological and engineering parameters related to the development of weak formation intervals can be introduced to construct a richer input feature system, thereby enhancing the model's identification capability under complex formation conditions.

(3) The interpretability of the model can be further strengthened by analyzing the contributions of different

logging parameters and depth intervals to the identification results, providing a clearer basis for the engineering application of intelligent weak formation identification.

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