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Fault diagnosis for on-board equipment of train control system based on BERT+CNN_BiLSTM

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Abstract: The on-board equipment as core equipment of train control system plays an important role in the process of high-speed train operation. At present, its fault diagnosis only depends on the experience of on-site operators and diagnosis efficiency is relatively low. To realize automatic fault diagnosis and improve diagnosis efficiency of the on-board equipment of train control system, a fault diagnosis model called BERT+CNN_BiLSTM was proposed, which combined bidirectional encoder representations from transformers (BERT) model, convolutional neural network (CNN) and bidirectional long short-term memory (BiLSTM). Firstly, the BERT model was used to transform the application event log (AElog) into a text vector representation that can mine semantic information recognized by computer. Secondly, CNN and BiLSTM were used to extract fault features and combine them to enhance spatial and temporal capability of the model. Finally, fault classification and diagnosis of on-board equipment of train control system was realized by using Softmax. In the experiment, taking an actual on-board equipment as the research object, the AElog generated during the train operation was selected as texperimental data to verify the performance of BERT+CNN_BiLSTM model. The results showed that compared with traditional machine learning algorithm, BERT+BiLSTM model and BERT+CNN model, the pecision, recall and $F1$ of BERT+CNN_BiLSTM model were 92.27%, 91.03% and 91.64%, respectively, which indicates that the proposed BERT+CNN_BiLSTM model has a better overall performance in the fault diagnosis of on-board equipment of high-speed train control system.

Key words: on-board equipment; fault diagnosis; bidirectional encoder representations from transformers (BERT); application event log (AElog); bidirectional long short-term memory (BiLSTM); convolutional neural network (CNN)

0 Introduction

The train control system is the core of high-speed trains and the on-board equipment is the key equipment of the train control system, which is responsible for monitoring the safe state of trains. If a fault occurs, a safety accident may take place.

At present, fault diagnosis for on-board equipment of train control systems mainly depends on the work experience of in-situ engineers, which is uncertain and low efficient. With the development of related field technologies, train control systems have become more complex, networked and intelligent, which enables intelligent automatic diagnosis of on-board equipment by providing assistant decision-making for signal analysis and maintenance personnel, so that the safe operation and transport efficiency of trains can be improved.

Fault diagnosis for on-board equipment of train control system consists of text vectorization, feature extraction and classification. Liang et al.used term frequency-inverse document frequency (TF-IDF) to vectorize fault text of vehicle-mounted devices. This model does not take into account the relationship between words, and the generated vector latitude is very large. Yang et al.[3-5] proposed a word embedding model for fault data vectorization, which integrates the context features into word vector and has lower vector dimension. Traditional machine learning algorithms, such as Bayesian network (BN), support vector machine (SVM) and k-nearest neighbor (KNN), have achieved good results in fault diagnosis. However, they belongs to shallow learning and the semantic information mining of vector is not enough, so classification performance is limited.

In 2006, Hinton et al. proposed deep learning theory[6] and now it has been developed and applied in many research fields[7-9]. For example, Google proposed a pre-training bidirectional encoder representations from transformers (BERT) model based on deep learning theory[10], which shows excellent performance in natural language processing.

In our work, to achieve intelligent automatic diagnosis of on-board equipment, we selected fault data source from AElog and transformed them into text vector by BERT model. Considering convolutional neural network (CNN) has a great advantage in extracting spatial features from word vectors whereas it is not sensitive to temporal feature processing of word vectors, we proposed a fault diagnosis model based on BERT+CNN_BiLSTM (Bidirectional long short-term memory) for feature extraction and classification of faults. Firstly, CNN and BiLSTM were used to extract the spatial and temporal features of fault text data, then the fault features were combined, and finally the combined feature vectors was classified in the Softmax layer. To verify the validity and accuracy of the proposed model, the AElog of in-situ fault data were downloaded for comparison and the results show that the BERT+CNN_BiLSTM model is superior to other models in such precision, recall and $F1$. Therefore, it has higher practicability and guidance value in fault diagnosis for on-board equipment of train control system.

1 On-board equipment of train control system

1.1 Composition of on-board equipment

At present, there are many kinds of on-board equipment in train control system. In this study, a certain type of on-board equipment was selected as the research object, and its structure is shown in Fig.1[11].

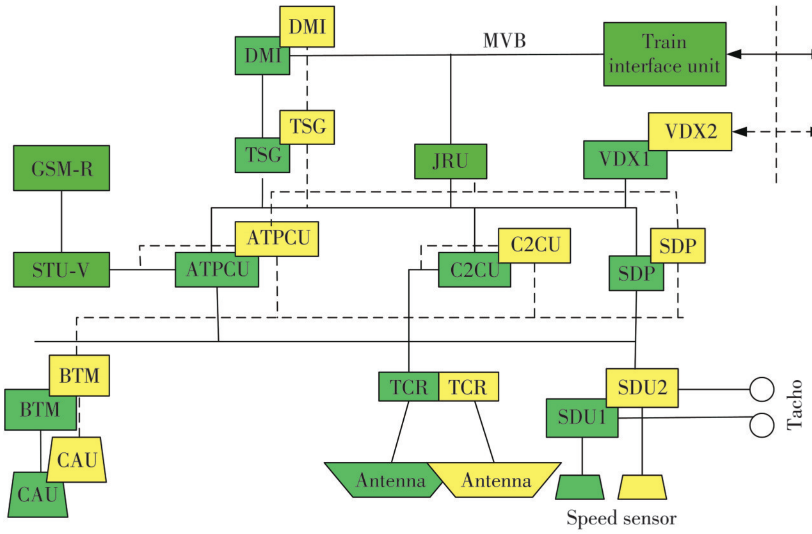

Fig. 1 Composition of on-board equipment

In Fig. 1, automatic train protection control unit (ATPCU) is the core computing control unit of train control system, which receives railway block center's (RBC) route descriptions and traffic permission and then calculates static curve and dynamic curve with ground responder to determine train position. Thus, the actual speed and position of the train can be monitored according to the mode curve, and relevant intervention can be carried out when the train overspeeds. When train control system is in operation, it is responsible for providing access to train interfaces, braking interfaces, ranging units and resource channels to C2CU and monitoring the working state of C2CU.

Train control computer unit-2 (C2CU) is the central control unit of train control system, which receives the data from balise transmission module (BTM) and monitors the train operation by combining the data from track circuit information receiving unit (TCR) and the current train calculation speed curve. In addition, it is responsible for sending km and track circuit information to driver-machine interface unit (DMI).

BTM receives the 1 023-bit transponder information through control antenna unit (CAU) and transmission cable, then checks and decodes the message into 830-bit valid information, and finally sends them to ATPCU and C2CU.

Speed and distance unit (SDU) is the input unit for speed and range, and provids the power for the speed sensor and the velocity radar signal module. When the train is running, SDU receives the pulse signal and converts it into digital signal, which is sent to speed distance processing unit (SDP) via multifunction vehicle bus (MVB).

SDP receives the raw pulse count from SDU, then the train direction, speed and distance data are obtained by smoothing and filtering, and finally the data are sent to ATPCU and C2CU.

Secure radio transmission unit (STU-V) consists of a communication message control unit (COMC) and a global confidential date (GCD), where COMC is responsible for the secure transmission of data and GCD is responsible for the encryption and decryption of data.

DMI displays the current speed, maximum speed limit, target speed, target distance, braking status and driver input and operation.

TCR adopts the working mode of 2×2 to 2, and two communication boards receive information from two sets of TCR mainframe, and communicates with automatic train protection (ATP) mainframe.

Global system for mobile-railway (GSM-R) includes a GSM-R wireless communication unit and two GSM-R radio antennae. The main function of vehicle radio is to register GSM-R network, and communicate between on-board equipment and RBC on the ground through network, so as to realize data interaction.

Vital digital input/output (VDX) is the interface unit between the train control equipment and the train. It inputs and outputs safety-related signals, such as emergency brake, when the train overruns.

Juridical recorder unit (JRU) receives the operation information of train control equipment through MVB and ProfiBus and records it in order to carry on the breakdown analysis and accident responsibility determination.

In addition, there are compact antenna unit (CAU), Doppler radar, speed sensor, train signaling gateway (TSG) and train interface unit, etc.

1.2 Data analysis of on-board equipment

ATPCU, C2CU, SDP and TSG are four modules of on-board equipment, among which ATPCU is the most important one. The scene uses DcuTerm tool, and the corresponding module downloads AElog file, which can real-time record the normal or abnormal operation of the modules of on-board equipment.

AElog files was stored in txt documents on the stack, and each document can record a maximum of 250 records. When the records reach 250, a new record will cover the original record, that is, the last event is recorded at the beginning of the file, thus the file was read from the bottom to the top of the records one by one. The AElog contains system time, time stamp, file name, line and task number of output exception as well as severity level of the exception[12]. It also gives a brief description of abnormal causes, abnormal types, and so on, which contains very important fault information and is the main basis for judging the fault types of on-board equipment.

1.3 Fault types of on-board equipment

According to typical fault cases and field experiences of on-board equipment, the faults of on-board equipment are mainly concentrated in BTM, ATPCU, TIU, SDU, GSM-R and DMI [13]. The common fault types of a Railways Bureau from January 2020 to January 2022 were statistically analyzed. The fault types and operating states description are listed in Table 1.

Table 1 Failure types and operating states description of on-board equipment

Correlation module	Encoding	Fault type	Operating states description
BTM	T1	BTM port invalid	[BTMS] BTM1 Status Telegram invalid Status port invalid in BTM1
	T2	All-zero transponder	[BGH] Expected balise not foundIL A Detect balise reported
	T3	BTM test timeout	BTM Transmission Test failed after 168 hours
	T4	Permanent BSA error	[BTMS] BSA permanent errorBSA Permanent Error, active BTM1
	T5	Run BSA error	[BTMS] BSA temporary errorBSA temporary Error, active BTM1
Train interface	T6	VDX message invalid	BI-H A Telegram from VDX1 is not valid
	T7	VDX port invalid	VDX out port failed(invalid too long): VDX2_FS
	T8	Emergency brake relay(EBR *) failure	BI-H EBR* state wrongBI－H EBR* feedback timeout
	T9	Bypass relay(BP) fault	VDX bypass port switched to invalid
	T10	Redundant Brake Relay(RB) fault	BI-H RBR feedback timeoutVDX RBR port switched to invalid
	T11	Brake feedback relay(BFB) fault	Wrong feedback Timeout expires 137 114 Time 135 214 BI-H EBFR state wrong
ATPCU related failure	T12	A core code mode conversion is invalid	(MS)A－kernel mode transition invalid
	T13	MA A/B code is inconsistent	VC:end of MA!a=1035916270 b=1035733370
	T14	ATPCU Hardware failure	A LOG MSG SPL－Initialise－104
SDU related failure	T15	SDU failure	SDU Error *
	T16	Tacho failure	Tacho Error *
	T17	Speed sensor failure	Speed sensor failure *
GSM-R related failure	T18	MT failure	Remove error : Fewer modems registered than installed
	T19	GSM-R network anomaly	RD R: 1-2 Network resource not available
DMI related failure	T20	DMI failure	MMI dead in active cabin, MMI down in active_cabin

2 Fault diagnosis model based on BERT+CNN_BiLSTM

The fault diagnosis model of on-board equipment based on BERT+CNN_BiLSTM is shown in Fig. 2, which is composed of data processing, feature extraction and fault diagnosis classification. Data processing part, cleaning the AElog file to get the short English text which contains only the running status statement, and generating the text vector form by BERT model. in order to reduce the imbalance of data samples, a few classes of samples are synthesized automatically using the synthetic minority oversampling technique (SMOTE). Feature extraction layer inputs the word vector after data processing into CNN and BiLSTM respectively to realize automatic extraction of text space and time series features, then the features are fused and spliced by the full connection layer, and finally the classification diagnosis is realized by Softmax.

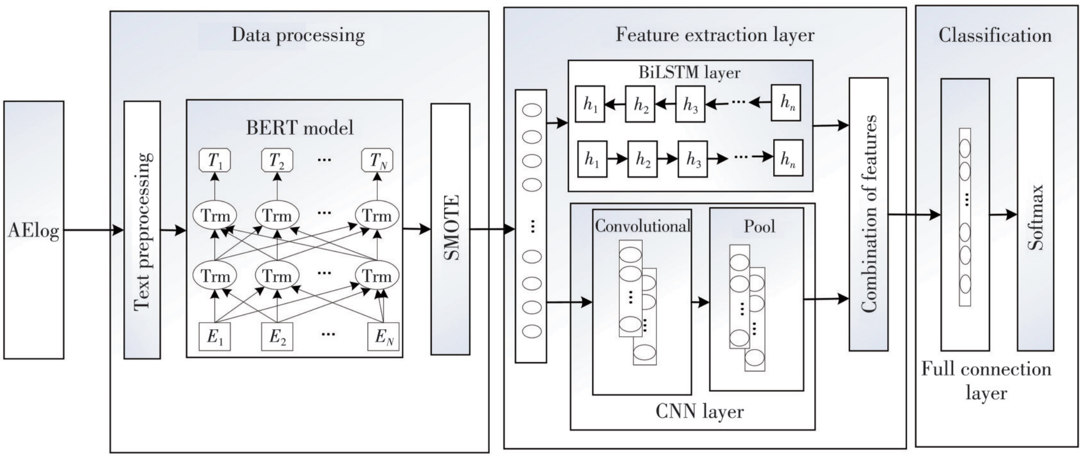

Fig. 2 Fault diagnosis model of on-board equipment

2.1 Word vector based on BERT

2.1.1 Data pre-processing

The information recorded in AElog file is unstructured text information, which cannot be recognized by computer directly, so text processing method is used firstly to transform AElog file into recognized numerical character to describe text, including software version, system time, time stamp, file name, task number, and so on. When the on-board equipment is normal or out of order, key information can be expressed and a corpus containing only the operating states description can be formed.

2.1.2 BERT model

As shown in Fig. 3, the embedding section of BERT model is composed of word vectors, sentence vectors and position vectors. According to the operating states described in Table 1, the input section of the model is shown in Fig. 4. The encoding layer is formed by a stack of 12 or 24 transformer encoder modules (Trm) [14].

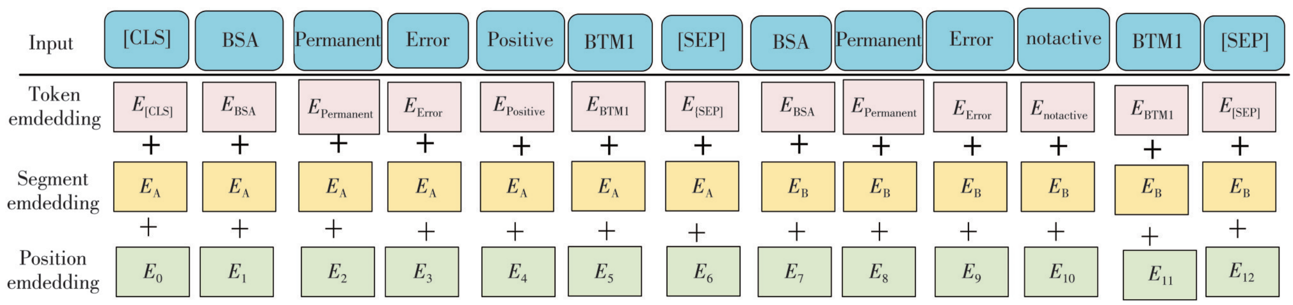

Fig. 3 Input embedded in BERT model

The BERT-Base model was used in this study. The parameters settings were as follows: hidden and attention, 12; Input hidden word vector dimension, 768; and the maximum position vector dimension, 512. Furthermore, Gelu was adopted as the nonlinear activation function of the encoder. The parameter settings were finely adjusted as follows: class, 21; max_seq_length, 512; batch_size, 16; learning, 2e-5; checkpoint step frequency, 300, with GPU for acceleration. The BERT model is responsible for transforming the experimental data into high-quality text representation of sentences' semantics.

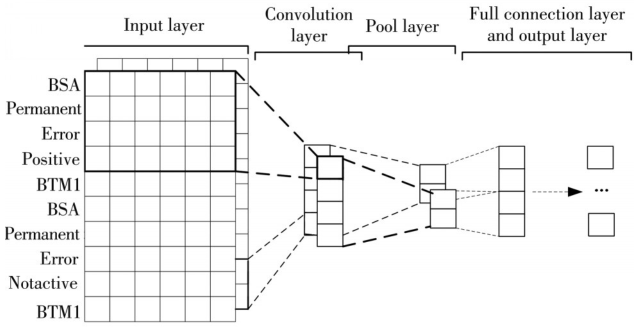

Fig. 4 CNN model

2.2 Feature extraction and classification

As shown in Fig. 5, input layer is the word vector generated by BERT model, the dimension of the sentence is (10, n). The concatenation of input layer and convolution layer is chosen as $4\times n$. Since the weight is shared, the feature of the input layer can be extracted and the model complexity can be reduced. There are two kinds of pool layers: average pool and maximum pool. In this study, the maximum pool method was used to aggregate the information and reduce the dimension. The whole connection layer and output layer integrate local features and use Softmax function to output the probability distribution of all kinds of faults.

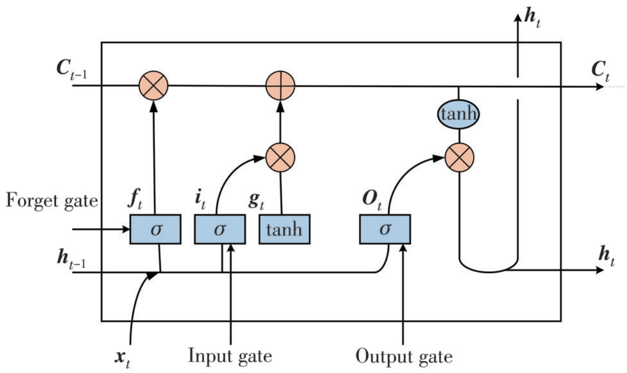

Fig. 5 Neuron's structure of LSTM model

To solve the problem of gradient dispersion or disappearance of recurrent neural network, long short-term memory model (LSTM) was applied[15]. As shown in Fig. 6, the LSTM uses neuron's forget gate, input gate, and output gate memory sequence history information to get the whole semantic text sequence information.

The formulae to update an LSTM unit at time t are shown as follows.

Forget gate controls how much information is forgotten and the output at time t is expressed as

$$f_t=\sigma\left(W_{\mathrm{f}}[\boldsymbol{h}_{t-1},\boldsymbol{x}_t]+\boldsymbol{b}_{\mathrm{f}}\right). \tag{1}$$

Input gate controls the amount of information in the input memory unit and the output at time t is expressed as

$$\boldsymbol{i}_t=\sigma\left(\boldsymbol{W}_{\mathrm{i}}[\boldsymbol{h}_{t-1},\boldsymbol{x}_t]+\boldsymbol{b}_{\mathrm{i}}\right). \tag{2}$$

Output gate controls the weight of the output unit and the output at time t is expressed as

$$\boldsymbol{O}_t=\sigma\left(\boldsymbol{W}_{\mathrm{o}}[\boldsymbol{h}_{t-1},\boldsymbol{x}_t]+\boldsymbol{b}_{\mathrm{o}}\right). \tag{3}$$

The output of the LSTM unit is the memory cell and hidden state at time t, which is expressed as

$$\boldsymbol{g}_t=\tanh\left(W_{\mathrm{c}}[\boldsymbol{h}_{t-1},\boldsymbol{x}_t]+\boldsymbol{b}_{\mathrm{c}}\right), \tag{4}$$

$$\boldsymbol{C}_t=\boldsymbol{f}_t\boldsymbol{C}_{t-1}+\boldsymbol{i}_t\boldsymbol{g}_t, \tag{5}$$

$$\boldsymbol{h}_t=\boldsymbol{O}_t\tanh(\boldsymbol{C}_t). \tag{6}$$

where $\boldsymbol{\sigma}$ is the element-wise sigmoid function; $\boldsymbol{W}_{\mathrm{f}}$, $\boldsymbol{W}_{\mathrm{i}}$, $\boldsymbol{W}_{\mathrm{c}}$ and $\boldsymbol{W}_{\mathrm{o}}$ are the weight matrices for the hidden state $\boldsymbol{h}_t$; $\boldsymbol{x}_t$ is the input vector at time t; $\boldsymbol{b}_{\mathrm{f}}$, $\boldsymbol{b}_{\mathrm{i}}$, $\boldsymbol{b}_{\mathrm{c}}$ and $\boldsymbol{b}_{\mathrm{o}}$ represent the bias vectors; $\boldsymbol{g}_t$ is the standby unit vector at time t; $\boldsymbol{C}_t$ is the state vector at time t; and $\boldsymbol{h}_t$ is the hidden state vector at time t, which stores all the useful information.

To get enough information in the future, BiLSTM was proposed as shown in Fig. 6, which can fully excavate the deep semantic information[16].

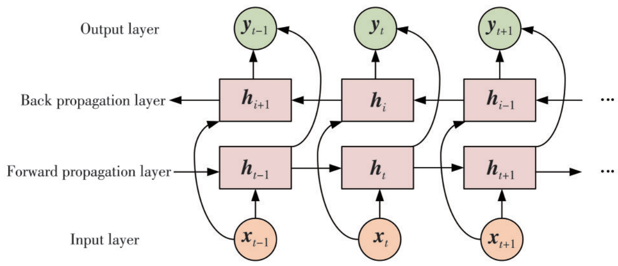

Fig. 6 Schematic diagram of BiLSTM model

The output layer of BiLSTM meodel at time t is expressed as

$$\boldsymbol{y}_t=\boldsymbol{W}\left[\vec{h};\overleftarrow{h}\right]+\boldsymbol{b}_y, \tag{7}$$

where $\boldsymbol{W}$ is the weight matrix for the hidden state; $\vec{h}$, $\overleftarrow{h}$ are forward hidden vector and back hidden vector at time t, respectively; and $\boldsymbol{b}_y$ is the bias vector of output layer at time t.

3 Experiment and analysis

3.1 Experimental data and evaluation index

To verify the proposed model, the fault state descriptions in each ATPCU document were divided into groups of 1—10 sentences based on the fault data provided by a railway bureau, and 659 sets of fault samples and 7 125 sets of normal data were available. As shown in Fig.8, 659 sets of fault samples were proportionally extracted. Since the numbers of different fault types were imbalanced, we used the SMOTE algorithm to automatically generate a few types of fault samples. The number of fault samples generated by the algorithm is 2 443 in total, and the the numbers of different types of generated fault samples tend to be balanced compared with that of raw fault samples, as shown in Fig.8.

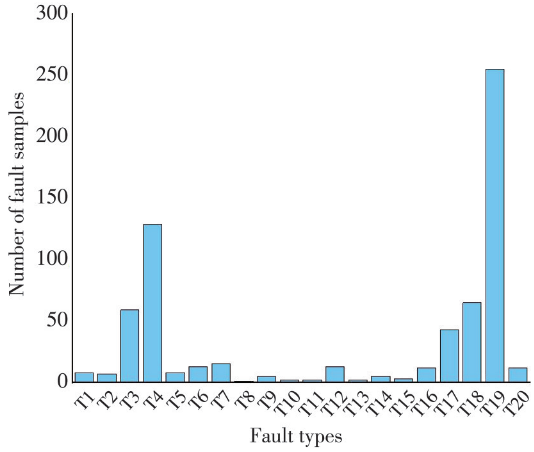

Fig. 7 Chart of fault samples

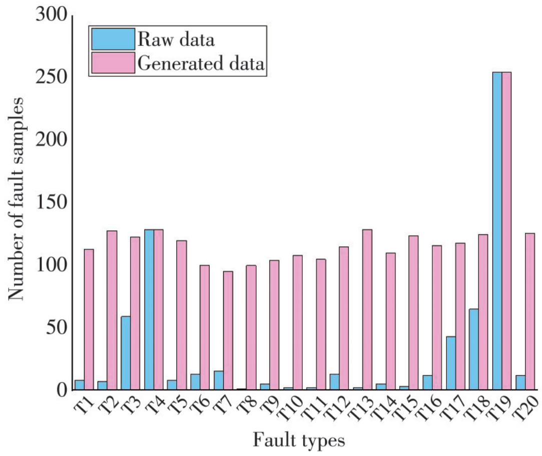

Fig. 8 Comparison of raw samples and generated samples

In this study, 2 443 sets of fault samples and 7 125 sets of normal operation samples were adopted. For the downstream task, 90% of the samples were randomly selected to form the training set, and 10% was used as the test set.

The samples were divided into 21 types, including 20 types of fault samples and one type of normal sample. The confusion matrix was used to present the diagnosis results, which was expressed as $N \times N$ (N is 21). The rows of the matrix represent the actual types, the columns represent the forecast types, and the diagonal values represent the correct predicted samples. The evaluation indexes precision (P), recall (R) and $F1$ based on the confusion matrix were selected as the evaluation indexes and expressed as

$$P = \frac{1}{N}\sum_{i=1}^{N} P_i, \quad P_i = \frac{n_{i,i}}{\sum_{j=1}^{N} n_{i,j}}, \tag{8}$$

$$R = \frac{1}{N}\sum_{j=1}^{N} R_j, \quad R_j = \frac{n_{j,j}}{\sum_{i=1}^{N} n_{i,j}}, \tag{9}$$

$$F1 = \frac{2PR}{P+R}, \tag{10}$$

where P_i represents the precision of fault type i; the element $n_{i,j}$ of the matrix represents the number of samples diagnosed as type j in type i; R_j represents the recall of type j; $n_{i,i}$ is the number of samples that type i is predicted to be type i, that is, the number of samples that are correctly predicted. The overall accuracy and recall of the model are calculated separately for each sample and then averaged.

3.2 Model validation and analysis

Windows 1064 bit was used in the experiment environment, the processor is AMD RYZEN54500U with Radeon Graphics 2.38 GHz, GPU 7.7 GB and the memory is 16 GB. Python programming language was used, word vectors were obtained using Google's pre-training model bert-as-service, and the tensorflow framework based on Keras was adopted for deep learning.

Visual confusion matrix was used to verify the effectiveness of the proposed model in fault diagnosis of on-board equipment. The confusion matrices of BERT+BiLSTM model, BERT+CNN and BERT+CNN_BiLSTM model are shown in Fig.9, Fig.10 and Fig.11, respectively. The numbers 1—20 in the matrix correspond to the fault types T1—T20 in Table 1, and Nor represents the normal sample's number.

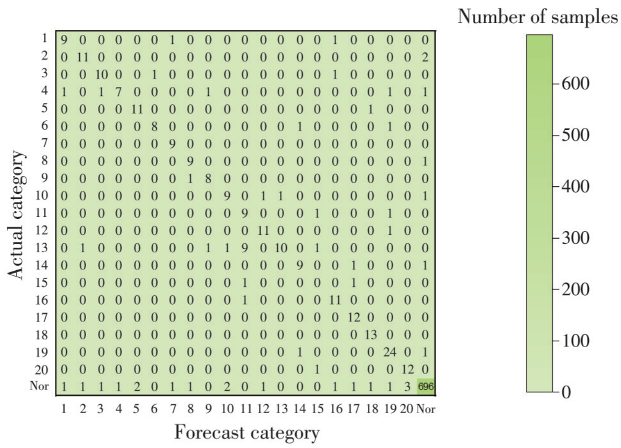

Fig. 9 Confusion matrix for BERT+BiLSTM model

It can be seen that the ratio of fault samples' number to normal samples' number can be as high as seventy times and it appears seriously imbalanced, which means that fault samples are easy to be predicted as normal ones. However, compared with BERT+BiLSTM model and BERT+CNN model, the recognition rate of BERT+CNN_ BiLSTM model is higher for both fault samples and normal samples.

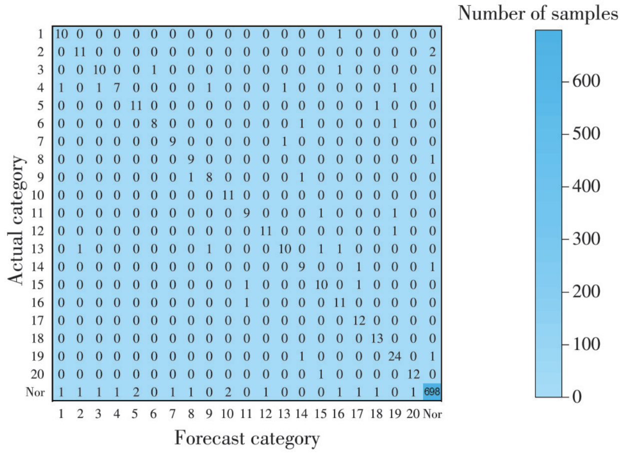

Fig. 10 Confusion matrix for BERT+CNN model

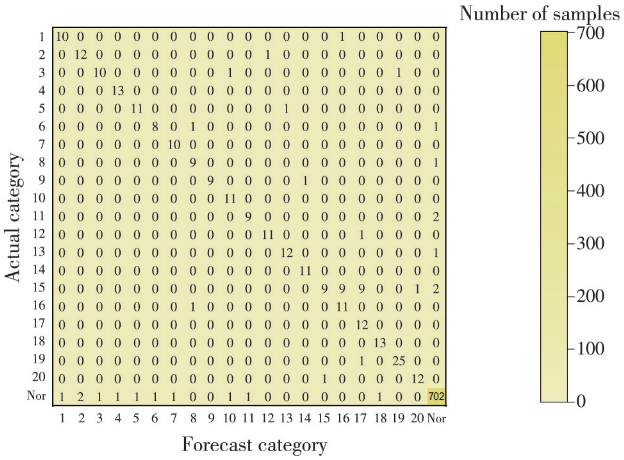

Fig. 11 Confusion matrix for BERT+CNN_BiLSTM model

To verify the whole effect of BERT+CNN_ BiLSTM model, we first compared it with the traditional machine learning algorithms NB, SVM and KNN on the test set using precision, recall and $F1$ value. The above models all use text vectors that are not balanced by SMOTE algorithm as input, and the performance comparison is shown in Table 2.

Table2 Performance comparison of different models

Model	Precision/%	Recall/%	$F1$/%
BN	83.61	67.92	74.95
SVM	86.35	69.42	76.94
KNN	68.23	57.82	62.60
SMOTE-SVM	85.64	75.32	81.01
BERT+BiLSTM	86.03	83.23	84.61
BERT+CNN	87.34	84.76	86.03
BERT+CNN_BiLSTM	92.27	91.03	91.64

It can be seen that the sensitivity of KNN to uneven sample distribution leads to poor classification results; SVM has good generalization ability and its classification performance is improved, whereas its precision, recall and $F1$ are still lower than that of BERT+CNN_ BiLSTM model. SMOTE-SVM combines SVM owing to its best overall performance and SMOTE algorithm for vector processing as the input, and thus the evaluation indexes are increased, especially the uneven data processed by SMOTE algorithm improves the classification effect of classifier. Compared with BERT+BiLSTM model and BERT+CNN model, BERT+CNN _BiLSTM model is superior in precision, recall and $F1$. The results show that the model not only can learn global and local effective features, but also can incorporate self-attention mechanism and bidirectional time series features. Therefore, it performs better in fault classification and recognition.

4 Conclusions

The experimental data used in this study were from the operating logs produced by the train, which recorded the operating states before and after the fault, and provided a strong support for the experimental demonstration.

In the process of AElog data processing, it was found that there exists a serious imbalance of fault types, which caused some errors in the classification accuracy of a few samples. Therefore, SMOTE algorithm was adopted to solve the problems in the data layer. As for the problems of the algorithm layer, random forest(RF) or cost sensitivity(CS), was considered. The features are extracted by CNN and BiLSTM, respectively and then fused. Finally, softmax classifier was used for classification diagnosis. The field data and comparative results show that the proposed model has a good performance in the fault diagnosis of on-board equipment of train control system, which is of great significance to ensure the safety of railway transportation and improve transport efficiency.

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Declaration of conflicting interests

The authors have no conflict of interests related to this publication.

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基于BERT+CNN_BiLSTM的列控车载设备故障诊断

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摘　要: 列控车载设备作为列车运行控制系统核心设备, 在高速列车运行过程中发挥着重要作用。目前, 其故障诊断仅依赖于现场作业人员经验, 诊断效率相对较低。为了实现列控车载设备故障自动诊断并提高诊断效率, 提出了BERT+CNN_BiLSTM故障诊断模型。首先, 使用来自变换器的双向编码器表征量(Bidirectional encoder representations from transformers, BERT)模型将应用事件日志(Application event log, AElog)转换为计算机能够识别的可以挖掘语义信息的文本向量表示。其次, 分别利用卷积神经网络(Convolutional neural network, CNN)和双向长短时记忆网络(Bidirectional long short-term memory, BiLSTM)提取故障特征并进行组合, 从而增强空间和时序能力。最后, 利用Softmax实现列控车载设备的故障分类与诊断。实验中, 选取一列实际运行的列车为研究对象, 以运行过程中产生的AElog日志作为实验数据来验证BERT+CNN_BiLSTM模型的性能。与传统机器学习算法、BERT+BiLSTM模型和BERT+CNN模型相比, BERT+CNN_BiLSTM模型的准确率、召回率和$F1$分别为92.27%、91.03%和91.64%, 表明该模型在高速列车控制系统故障诊断中性能优良。

关键词: 车载设备; 故障诊断; 来自变换器的双向编码器表征量; 应用事件日志; 双向长短时记忆网络; 卷积神经网络

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