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Intelligent question answering method for construction safety hazard knowledge based on deep semantic mining

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ABSTRACT

Timely safety hazard management can reduce the probability of safety accidents at construction sites. However, the formulation of safety hazard management measures is a time-consuming and labor-intensive process. This paper describes a safety hazard knowledge question answering method to automatically generate safety hazard management measures. The method builds a deep learning network fusing Bidirectional Encoder Representation from Transformer (BERT), Bidirectional Gated Recurrent Unit (BiGRU), and Self-attention mechanism to extract text semantic features. Taking the text semantic feature extraction mechanism as a subnet, an answer selection model based on a Siamese neural network is built to implement the deep matching of safety hazard questions and management measures. Experimental results from hydraulic engineering construction demonstrate that the proposed model outperforms the existing answer selection model. Meanwhile, a question answering system based on the proposed model is developed to address safety hazard management problems, which verifies the reliability and applicability of the model.

1. Introduction

Safety hazard control is a key step in construction site safety management, playing an important role in ensuring the life and health of workers and improving construction efficiency [1,2]. Managers need to analyze the content of safety hazards in a timely manner and formulate hazard management measures to reduce the probability of site accidents [3,4]. Safety hazard management measures are the most direct way to solve construction site safety hazard problems [6,7]. However, most existing safety hazard management measures are obtained using manual methods. Managers formulate safety hazard management measures by combining experience knowledge and safety hazard management standards [5]. Construction site safety hazards are recorded and stored in the form of text. Managers need to analyze the text content, obtain key information, and then formulate safety hazard management measures. Thus, each safety hazard management measure requires a lot of time [8]. When the number of hidden safety hazards is large, the efficiency of safety hazard controls cannot meet the requirement of safety management at a construction site, which increases the risk of disasters caused by safety hazards. Furthermore, the formulation of safety hazard management measures mainly relies on experience knowledge and standards, and the richness of experience knowledge will directly affect the formulation effect of management measures. Construction site safety hazards are characterized by a large volume, various types, and complex information, which increases the difficulty of safety hazard management. It is necessary for managers to be able to formulate accurate safety hazard management measures in a short time. Managers cannot quickly and accurately apply experience knowledge and standards to address very large safety hazard management, which can easily lead to errors in the formulation of safety hazard management measures. Meanwhile, the experience knowledge of safety hazard management is stored in the form of text, which is difficult to directly convert into usable information. Managers must extract key knowledge from large amounts of text to manage construction site safety hazards. The process of knowledge extraction is lengthy, and the accuracy of knowledge extraction is unstable. Therefore, it is necessary to establish intelligent construction site safety hazard management methods based on text knowledge in order to realize the automatic generation of safety hazard management measures and reduce the management burden on managers.

Safety hazard problems and management measures are mostly presented in un/semistructured text form. Thus, it is essential to extract and analyze key information and knowledge from text data [9]. Currently,

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natural language processing (NLP) has been widely used in text processing, which can transform text data into usable knowledge [10,11]. Initially, NLP technology mainly used rules to analyze text data, such as vocabulary statistics, syntactic analysis, and semantics. It can convert text knowledge into a form that can be directly used by computers without considering the richness of text data [12,13]. Rule-based text data processing relies heavily on a rule database, and the richness of the rule database directly affects the effect of knowledge extraction. A machine learning method overcomes the dependence on the rule database, which can intelligently extract the knowledge and features from text data. Machine learning can automatically mine text knowledge by exploring the semantic relationships among texts. To address text processing problems, many machine learning methods, such as a Support Vector Machine (SVM), Naive Bayes (NB), and K-Nearest Neighbor (KNN), have excellent performance in text classification and machine translation [14,15]. Although machine learning methods can extract text semantic features, it is difficult to realize deep analysis of text content. Deep learning can deeply mine the semantic relationships and obtain potential key features in text. A large number of deep learning models have been developed, such as a Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), and Bidirectional Encoder Representation from Transformer (BERT), which can be directly applied to text processing tasks such as text classification, intelligent question answering, and machine translation [16–20]. The above methods can realize end-to-end text information extraction and meet the requirements of multiple text processing tasks, providing technical support for safety hazard text knowledge mining.

Safety hazard text is mainly presented in the form of question-answer pairs in the process of safety hazard management. The question text refers to the content of safety hazards on a construction site; the answer text is the management measures corresponding to a safety hazard problem. Because management measures are formulated according to the content of the safety hazard problem, there is a strong correlation between the question text and the answer text. The safety hazard text contains large amounts of management knowledge, which provides an effective approach for the intelligent generation of safety hazard management measures. However, the safety hazard text contains a large number of technical terms and vague expressions, which can easily lead to text analysis errors and affect the accuracy of answer text extraction. Technical terms can transmit a lot of text knowledge, but it is easy to ignore the role of technical terms in text analysis, which may cause the absence the important features; vague expressions refer to the presentation of technical terms in the form of fuzzification and colloquialism, which affects the accuracy and reliability of text information expression and easily lead to feature extraction errors. To avoid the impact of technical terms and vague expressions on text analysis, it is essential to deeply analyze the context semantics, strengthen the local features of the text, obtain the characteristic of the technical term, and define the information in the vague expression. Therefore, this study proposes an intelligent question answering method combining a Siamese neural network and deep learning to address the construction site safety hazard question. The BERT model is used to quantify the safety hazard text and obtain the text word vector; a Bidirectional Gated Recurrent Unit (BiGRU) and Self-attention mechanism are used to build a subnet of the Siamese neural network. This method can extract the semantic features of problem and answer text from the global and local perspectives, and then the semantic features are used to measure the correlation between texts and realize the intelligent generation of safety hazard management measures.

The innovations and contributions of this study are summarized as follows: 1) a text feature extraction method integrating BERT, a BiGRU, and Self-attention mechanisms is proposed, which strengthens the safety hazard text features and improves the accuracy of text analysis; 2) an answer selection model that takes a Siamese neural network as the framework and a text feature extraction method as a subnet is built to realize the deep match between safety hazard question and the answer; 3) to improve the efficiency of safety hazard management, a question answering system is developed, which can extract experience knowledge from safety hazard text data and realize intelligent generation of safety hazard management measures.

2. Literature review

2.1. Safety hazard text analysis methods

Safety hazard texts contain considerable experience knowledge. It is significant for improving the safety management efficiency to accurately extract text knowledge [21]. To accurately obtain safety hazard text knowledge, scholars have proposed a large number of text analysis methods, which are divided into two types: generative and discriminative methods [22]. A generative method adopts a generative model to automatically generate text knowledge under unsupervised conditions, which can improve the efficiency of text analysis. Xu et al. [23] proposed an improved approach to automatically identify safety risk factors from a large number of accident reports. The method quantifies the importance of risk factors and provides support for safety management decisions. Zhong et al. [24] proposed an intelligent text mining method combining deep learning and an LDA model to extract text knowledge and visualize accident narratives. The proposed model can automatically extract accident information and improve the efficiency of text analysis. Wang et al. [25] integrated text mining technology and complex network methods to extract key knowledge from safety hazard text and form a risk network. It is emphasized that the proposed model can quickly capture text information and provide a reference for the formulation of management measures. Unlike generative methods, discriminative methods are adopted to analyze the difference in text features and evaluate the text category. Zhang et al. [26] defined 11 construction site safety accident categories and proposed an accident classification method fusing five baseline models to realize intelligent classification of safety accidents. The accuracy and reliability of the proposed model have been verified by comparison with other accident classification models. Fang et al. [16] developed a BERT-based deep learning approach to automatically classify safety hazard information. The BERT in the model can accurately analyze the context relationship and improve the accuracy of safety hazard recognition. Chen et al. [27] proposed a CNN-based text intelligent classification model, which can quickly identify the location and category of safety hazards. The model can provide key information for safety hazard analysis and is significant for reducing the probability of safety accidents.

The above text analysis methods realize intelligent safety hazard knowledge mining and verify the applicability and reliability of text mining technology and deep learning methods in safety hazard text analysis. However, existing methods focus on risk factor identification, knowledge network establishment, safety hazard classification, etc. There is less research on intelligent safety hazard management measure generation, and the relationship between safety hazard questions and management measures is ignored, which reduces the application efficiency of text knowledge. Therefore, it is necessary to establish an intelligent generation mechanism for safety hazard management measures, which can reduce the task burden of managers and improve the efficiency of safety hazard management.

2.2. Intelligent question answering system

An intelligent question answering system is an information retrieval tool that allows users to ask questions with natural language, and the system searches or filters the answers from candidate documents [28]. Unlike traditional information retrieval methods, an intelligent question answering system has stronger pertinence and needs to obtain an accurate answer. Originally, the concept of a question answering system was a database query, the user's question was converted into a query statement, and the answer corresponding to the question was found in the database [29]. With the development of natural language processing technology, large-scale document sets have played an important role in question answering systems. Many practical question answering systems have been developed, such as Watson and Cortana [30–33].

Furthermore, deep learning methods were introduced into question answering systems to deeply analyze the relationship between the question text and answer text, which achieved a good application effect [34,35]. Compared with traditional question answering methods, deep learning can realize deep semantics analysis and obtain comprehensive text features [36,37]. Furthermore, deep learning models are end-to-end, and users can directly obtain an answer by inputting question text. Lowe et al. [38] used a Long Short-Term Memory (LSTM) model to analyze text semantics and achieve intelligent matching between questions and answers. The proposed model provides an effective method for the application of deep learning in question answering systems. Wu et al. [39] proposed a Sequential Matching Network (SMN), which uses a CNN and RNN to deeply analyze the question text and answer text. It has been experimentally shown that an SMN performs better than state-of-the-art methods in answer selection. Shao et al. [40] designed an answer selection network structure fusing a Transformer and Bidirectional Long Short-Term Memory (BiLSTM) to obtain global information and sequence features in question or answer sentences. The proposed model can produce a better performance compared with several competitive baselines. Zhong et al. [41] integrated NLP technology and deep learning to develop a robust end-to-end methodology and address questions raised about building regulations. The proposed model provides precise and rapid answers to user questions from a collection of building regulations, which improves the efficiency of retrieving queries. Ma et al. [42] proposed a Hierarchical Matching Network (HMN) fusing RE2 and a GRU model to capture important matching information from the word level and utterance level. The proposed model significantly outperformed existing baseline models.

The above studies indicate that a deep learning method can improve the performance of question answering systems, which provides a reference for the application of question answering systems in safety hazard management. However, there are many technical terms in safety hazard text, so existing question answering systems cannot be directly utilized. Moreover, the expression of safety hazard text varies, and there are some colloquial and vague expressions, which increases the difficulty of text analysis and easily leads to answer selection error. Therefore, it is necessary to establish an intelligent question answering system suitable for construction safety hazards to realize the automatic generation of safety hazard management measures.

3. Answer selection model

Answer selection is the key step of knowledge intelligent question answering, and can improve the efficiency of safety hazard management. The answer selection depends on the semantic correlation between texts in intelligent safety hazard question answering. Thus, a Siamese neural network and deep learning method are used to deeply analyze the safety hazard problem and management measure from the perspective of global and local features and then realize an intelligent match between the question text and answer text.

3.1. BERT-based text quantification

Construction site safety hazard management texts are highly discrete and fragmented, which increases the difficulty of text feature extraction. Therefore, it is necessary to establish a safety hazard text quantification mechanism to convert complex and fragmented text into a form that algorithms can process and understand. There are many text data quantification methods, such as one-hot, word2vec, and doc2vec. These methods provide an effective approach for text quantification, which can express text information in the form of word vectors. However, word vectors calculated using these methods ignore the context semantic relationship. A BERT model overcomes the shortcomings of existing methods in text quantification. It is built using unsupervised training on a large amount of unlabeled corpus data. Furthermore, BERT can learn the general representation of words and obtain context information, which can process the colloquial and vague expressions in the safety hazard text [43]. BERT adopts a bidirectional Transformer structure to analyze the text content and obtain word embedding results by a pre-training model and fine-tuning [44]. Furthermore, a BERT model uses the technology of masking characters to strengthen the memory of context information and obtain more text features (see Fig. 1).

To ensure the accuracy of safety hazard text quantification and improve the computational efficiency of the model, this study uses safety hazard dataset to fine-tune the BERT model. The input of the BERT model is based on the character level, and each character contains three parts: word feature information, paragraph feature information and location feature information. The word feature information is used to convert each character in the input text into a fixed-dimensional vector; the paragraph feature information is used to distinguish text paragraphs where characters are located; and the location feature information is used to describe the text location where the characters are located, which can distinguish the role of the same character in different contexts. The BERT input layer is built by fusing the word, paragraph and location feature information (see Fig. 1). A transformer mechanism is used to extract the text features from the inputted text information and obtain a safety hazard text vector, which is described as:

$$\begin{cases} V_i^Q = \left(v_{i1}^Q, v_{i2}^Q, \ldots, v_{in}^Q\right) \\ V_i^A = \left(v_{i1}^A, v_{i2}^A, \ldots, v_{im}^A\right) \end{cases} \tag{1}$$

where V_i^Q is the vector of the i-th safety hazard question text; V_i^A is the vector of the i-th safety hazard answer text; v_{i1}^Q is the vector of the first character in the i-th safety hazard question text; and n and m are the lengths of the characters in the safety hazard question text and answer text, respectively.

3.2. Global feature extraction

It is necessary to extract text features and obtain valuable information from quantified safety hazard text. Generally, features extracted from text are global features, which can be obtained by analyzing the semantic relationships. In text feature extraction, popular methods include an RNN, LSTM, and GRU [21,45,46]. However, safety hazard texts are presented in the form of sequences, which may lead to the problem of gradient explosion and disappearance and affect the convergence of the model. LSTM and a GRU can solve the gradient problem and obtain long-distance dependency relationships. A GRU is a variant of LSTM. Compared with an LSTM model, a GRU has the characteristics of a simple structure, fewer parameters, and high training efficiency. A GRU model has a fast convergence speed and low overfitting risk, so this study adopts a GRU model to extract the global features.

The hidden state is used to transmit information in the GRU model, which is divided into two parts: the update gate and the reset gate (Fig. 2). The update gate z_t determines the information that the GRU unit needs to retain and add; the reset gate r_t determines the discarded information. A GRU model is formed by multiple GRU units, and the input to the GRU unit is the text quantized result V_t and hidden state h_{t-1}. Combined with the input data, the update gate and reset gate are calculated, which is defined as follows:

$$\begin{cases} r_t = \sigma(W_{xr} V_t + W_{hr} h_{t-1}) \\ z_t = \sigma(W_{xz} V_t + W_{hz} h_{t-1}) \end{cases} \tag{2}$$

where W_{xr}, W_{hr}, W_{xz}, and W_{hz} are weight matrixes; $\sigma(\cdot)$ is the sigmoid function; and the calculation result r_t from the reset gate and hidden state h_{t-1} are used to obtain candidate hidden state $\widetilde{h}_t$, which can be

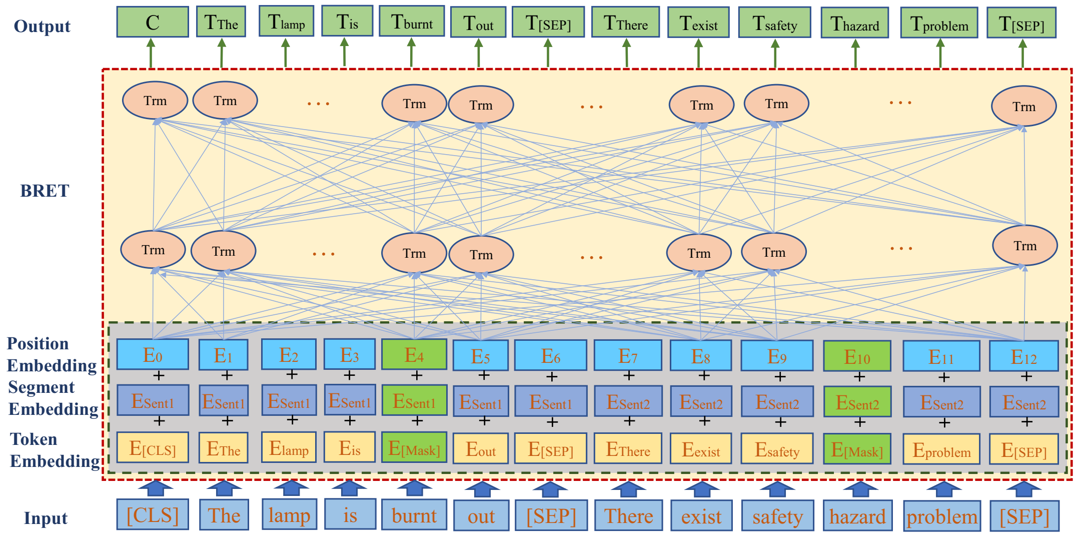

Fig. 1. BERT model.

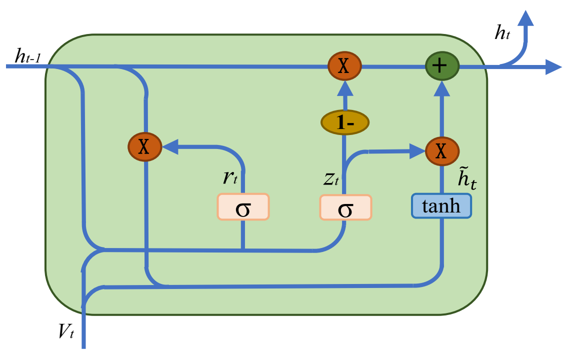

Fig. 2. GRU unit.

denoted as:

$$\widetilde{h}_t = tanh\left(\widetilde{W}_x V_t + \widetilde{W}_r (r_t \otimes h_{t-1})\right) \quad (3)$$

where $\widetilde{W}_x$ and $\widetilde{W}_r$ are weight matrixes and $\otimes$ is the multiplication operation. The update gate information and candidate hidden state are used to update the content of the GRU unit and obtain the final hidden state h_t, which is defined as:

$$h_t = (1 - z_t) \otimes h_{t-1} + z_t \otimes \widetilde{h}_t \quad (4)$$

where $(1 - z_t) \otimes h_{t-1}$ is the valuable information retained by the GRU unit; $z_t \otimes \widetilde{h}_t$ is the selective memory for the candidate hidden state; and h_t is the final hidden state, which indicates how much existing information is input to the next GRU unit.

The transfer text information is unidirectional in a GRU model, ignoring the influence of the context and ambiguous words. Therefore, based on the GRU structure, a Bidirectional GRU model (BiGRU) is built to analyze text content from forward and backward sequences and capture text semantic features. It can be described as follows:

$$\begin{cases} \overrightarrow{H} = \left\{ \overrightarrow{h}_1, \overrightarrow{h}_2, \cdots, \overrightarrow{h}_i, \overrightarrow{h}_{i+1}, \cdots, \overrightarrow{h}_L \right\} \\ \overleftarrow{H} = \left\{ \overleftarrow{h}_1, \overleftarrow{h}_2, \cdots, \overleftarrow{h}_i, \overleftarrow{h}_{i+1}, \cdots, \overleftarrow{h}_L \right\} \end{cases} \quad (5)$$

where $\overrightarrow{H}$ is the forward hidden state sequence; $\overleftarrow{H}$ is the backward hidden state sequence; $\overrightarrow{h}_i$ and $\overleftarrow{h}_i$ are the hidden state output by the i-th forward and backward GRUs, respectively; and L is the total number of GRUs contained in the BiGRU model. The output result is $H_j = \left[\overrightarrow{H}_j, \overleftarrow{H}_j\right]$ in the BiGRU model, where H_j is the j-th semantic feature matrix, and the dimension is $1 \times 2L$.

3.3. Local feature enhancement

The BiGRU model can comprehensively analyze the context information and obtain the global features. However, the BiGRU model cannot express the role of key information in the context. Furthermore, there are many technical terms and key words in construction safety hazard text, which contain much text information, especially in the knowledge question answering, and the technical terms and key words can comprehensively summarize the text content. To capture the local feature information of safety hazard text, a Self-attention mechanism is introduced to strengthen the text features and emphasize the role of technical terms and key words [47,48]. A Self-attention mechanism adopts a decoder-encoder framework, which can filter useful information and distinguish the importance of words. A Self-attention mechanism can strengthen the text features by analyzing the semantic effect of different words in the sentence, which is defined as:

$$C = [c_1, c_2, \ldots, c_i, c_{i+1}, \ldots, c_d] \quad (6)$$

where C is the feature vector calculated by the Self-attention mechanism; d is the length of the sentence; and c_i is the feature vector corresponding to the i-th word in the text.

$$c_i = \sum_{j=1}^{n} \mathrm{softmax}\left(s\left(e_i, k_j\right)\right) \cdot u_j \quad (7)$$

where $s(e_i, k_j)$ is the attention value calculated by the scaled dot product model; e_i, k_j, and u_j are the elements in the query space E, the key space K, and the value space U, respectively, which are denoted as:

$$\begin{cases} E = H \times W_E' \\ K = H \times W_K' \\ U = H \times W_U' \end{cases} \quad (8)$$

where W_E', W_K', and W_U' are the model parameters; H is the semantic feature matrix calculated by the BiGRU, and $H = [H_1, H_2, \ldots, H_d]$. According to the semantic feature matrix, the values of E, K, and U are calculated as $[e_1, e_2, \ldots, e_d]$, $[k_1, k_2, \ldots, k_d]$, and $[u_1, u_2, \ldots, u_d]$.

3.4. Siamese network-based deep semantic matching

The matching of the question text and answer text is a key step in safety hazard knowledge question answering. The question text records the safety hazard problems, and the answer text provides corresponding management measures for the questions. The core of safety hazard knowledge question answering is extracting text features from the question text and answer text and realize the matching of safety hazard texts. Obviously, safety hazard knowledge question answering is a text classification problem. Each safety hazard question corresponds to a targeted answer. However, there is no significant correlation between the answers, so it is difficult to determine the number of text categories. Moreover, there are differences in sentence structure and expression in question text and answer text, which increases the difficulty of text semantic matching. It is difficult for a single network structure to analyze the question text and answer text at the same time and address the problem caused by the diverse forms of question-answer pairs. A Siamese neural network provides an intelligent matching structure between question text and answer text, and can process the problems of uncertain text category, unfixed text expression, and inefficient text semantic analysis [49]. The core of a Siamese neural network analyzes the question text and answer text using two deep learning methods that can share weight [50,51]. Therefore, we propose an answer selection model (BGSA) fusing BERT, BiGRU, and Self-attention mechanism in Siamese neural network structure (see Fig. 3). The model uses BERT, BiGRU model and Self-attention mechanism as a subnet to deeply extract text features and realize deep matching between the question text and answer text. The model is defined as follows:

3.4.1. Input layer

The input layer is used to import the safety hazard text and establish a text data transmission channel, converting the semi/unstructured text into a vector that the model can understand. It provides data support for the construction safety hazard text feature extraction. The text quantification method in Section 3.1 is used to analyze the question text and answer text, and V^Q and V^A are obtained as the text quantification result.

3.4.2. Subnet A

The Siamese neural network includes two subnets: subnet A and subnet B. The Siamese neural network subnets are used to analyze the question text and answer text. Subnet A is used to extract the question text features, including two parts: global feature extraction and local feature enhancement. Subnet A of the Siamese neural network combining the BiGRU model in Section 3.2, the Self-attention mechanism in Section 3.3, and the word vector V^Q is built to extract the question text features C^Q. It can provide data support for text feature matching.

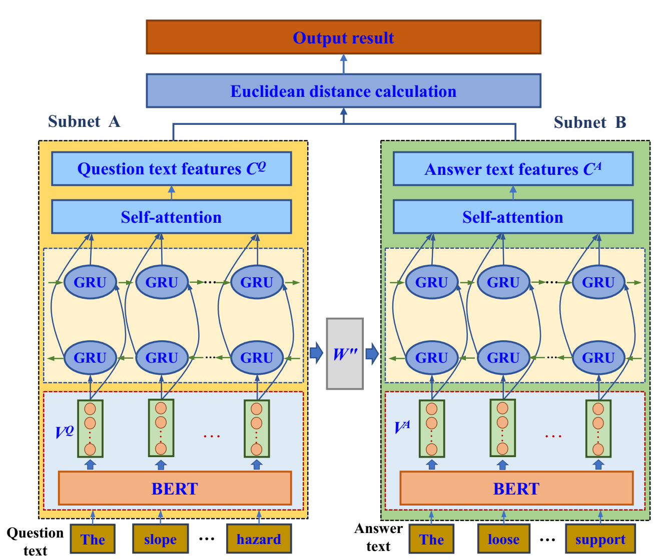

Fig. 3. Model framework of answer selection.

3.4.3. Subnet B

Subnet B is used to extract the answer text features. Similar to subnet A, subnet B adopts the BERT, BiGRU model and attention mechanism to analyze text features and obtain the feature quantization result C^A. Moreover, a weight sharing mechanism is established between subnet B and subnet A to improve the generalization ability of the network and improve the accuracy of text feature matching, which W'' is the shared weight of subnet A and subnet B.

3.4.4. Feature matching layer

The feature matching layer is used to calculate the similarity between features and realizes the intelligent selection of safety hazard answers. The Euclidean distance is used to measure the similarity between text features calculated by subnet A and subnet B. The matching degree between the question text and answer text is obtained by the similarity, which is defined as:

$$S(Q, A) = \left\| C^Q - C^A \right\|_2 \tag{9}$$

where $S(Q,A)$ is the matching degree between the question text and answer text and Q and A are the question text and answer text, respectively. $\|\cdot\|_2$ is the two-norm, which is used to calculate the Euclidean distance between text features. To measure the accuracy of the Siamese neural network, the contrastive loss function is adopted to calculate the loss value, which is defined as:

$$loss = \frac{1}{2G}\sum_{g=1}^{G}\left[Y \times S(Q,A)^2 + (1-Y) \times max(m - S(Q,A)\,,0)^2\right] \tag{10}$$

where G is the sample size; Y is the sample label, which is equal to 1 if the question text is related to the answer text; and m is the maximum Euclidean distance. A loss function is used to adjust the model parameters and obtain a stable network structure. The corresponding answers can be intelligently selected according to the input safety hazard questions, realizing the automatic question and answer of safety hazard knowledge.

4. Model analysis and application

4.1. Data collection and preprocessing

A total of 6325 safety hazard texts were collected from the construction site of a hydropower project. These texts describe the location, content, and management measure of safety hazards. Safety hazard problems are discovered and solved by the hydropower project site managers, and the safety hazard management processes are recorded in the form of texts. The safety hazard content is defined as the question text; the management measure is defined as the answer text, forming the safety hazard question-answer pair (see Table 1). Each safety hazard question corresponds to an answer. The answer selection model matches the question text and answer text to realize the intelligent generation of safety hazard management measures. The answer selection model needs to use positive and negative samples to train and obtain the relationships between the question text and the answer text. However, existing question-answer pairs of safety hazard belong to positive samples, so it is necessary to construct negative samples to strengthen the relationship between the question text and answer text. Negative samples are obtained by matching question text with other answer texts. Considering the balance of the samples, this study uses 6325 negative samples. The 1 and 0 are used to mark the positive and negative samples. If the question-answer pair is a positive sample, the sample is marked as 1;

Table 1
Text information samples and labels.

Sample	No.	Safety hazard question	Safety hazard management measure	Label
Positive example	1	The setup of lighting lamp does not meet the requirements (the height is less than 1 m).	It is required to set the height of the lighting lamp to be more than 2.5 m.	1
	2	3# tailrace linking pipe downstream has cracks and exist block falling.	Cleaning and repairing the position of cracks and block falling.	1
	…	…	…	…
	6325	The cliff rock mass is cracked, which may fall at any time.	The warning signs should be set up in the operation area below; the workers do not enter the area in rainy days; the worker should be arranged to strengthen supervision.	1
Negative example	1	The setup of lighting lamp does not meet the requirements (the height is less than 1 m).	The worker should coordinate the electrician to restore the illumination immediately.	0
	2	3# tailrace linking pipe downstream has cracks and exist block falling.	Clearing the loose parts and support them in time	0
	…	…	…	…
	6325	The cliff rock mass is cracked, which may fall at any time.	Waterproof fabric is used to provisionally close crack.	0

otherwise, it is marked as 0 (see Table 1).

The stopwords in the labeled question-answer pair are deleted, and the text content is retained to avoid the loss of text information. The labeled text is divided into three parts: 1) training data, which are used to extract text features and train the answer selection model (7590 data points); 2) validation data, which are applied to adjust the model's parameters (2530 data points); and 3) testing data, which are used to evaluate the performance of the model (2530 data points).

The calculation environment is Python 3.6, and the Siamese network structure is implemented via TensorFlow. The hyperparameters of the BGSA model are set as follows: number of GRU units is 256; number of epochs is 30; attention size is 100; learning rate is 0.03; dropout probability is 0.5; and word embedding dimension is 768.

4.2. Model performance analysis

The preprocessed question text and answer text are used to train the answer selection model. The accuracy and receiver operating characteristic (ROC) curve are adopted as evaluation indicators to verify the training effect and evaluate the model (see Fig. 4). ROC curve includes two parameters: true positive rate (TPR) and false positive rate (FPR), which can be calculated as:

$$\begin{cases} TPR = \dfrac{TP}{TP + FN} \\ FPR = \dfrac{FP}{FP + TN} \end{cases} \tag{11}$$

Which TP represents the number of true positives; FP represents the number of false positives; FN represents the number of false negatives; TN represents the number of true negatives.

In Fig. 4 (a), with the increase in the number of iterations, the accuracy of the model on the training and validation data tends to increase; when the number of epochs is equal to 20, the accuracy of the model is stable. Finally, the accuracy of the training data and the validation data are 89.78% and 88.67%, respectively, which proves the adequacy of model training and the accuracy of calculation. The area

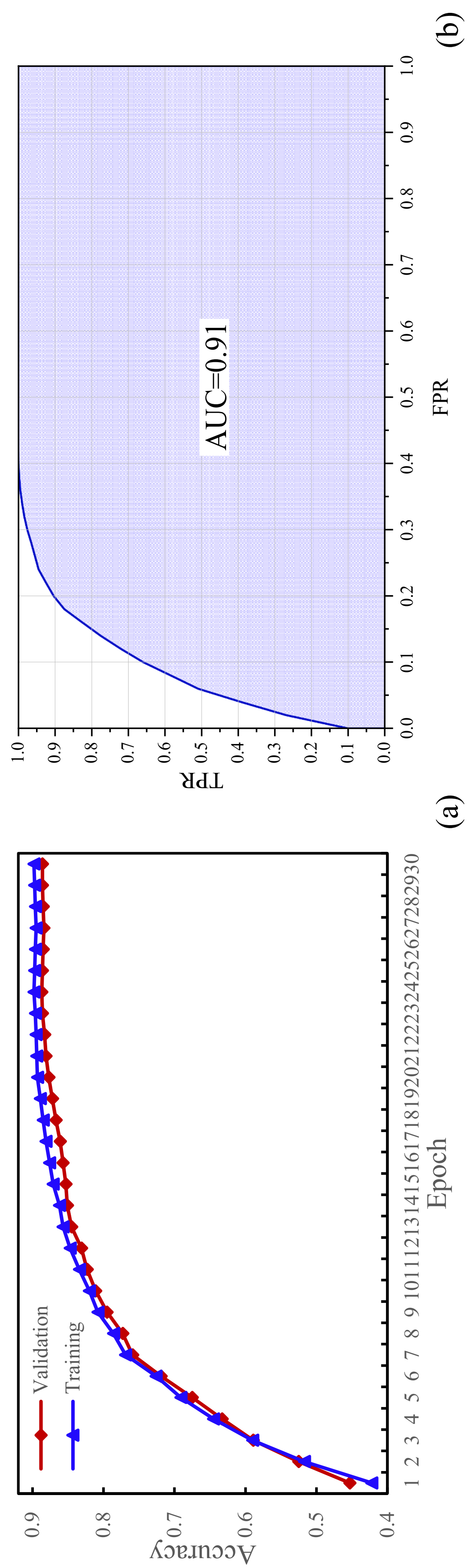

Fig. 4. Answer selection model evaluation results: (a) accuracy; (b) ROC curve.

under curve (AUC) is the area between ROC curve and X axial, which can quantify the effect of ROC curve. The larger the AUC value, the better the performance of model. Fig. 4 (b) shows the ROC curve of the model. We can obtain that the AUC value of the ROC curve is 0.91, which verifies the reliability and accuracy of model structure.

The number of GRU units, the learning rate, and the dropout probability are selected to explore the reliability and robustness of the hyperparameters in the model. It is necessary to define the initial hyperparameters and change the value of each hyperparameters in the model parameter evaluation [21,52]. Moreover, the precision rate, recall rate, and F1 value are selected as evaluation indicators to determine the optimal hyperparameter value. Fig. 4 indicates that the optimal number of epochs is 20, so the initial hyperparameters are set as: number of epochs is 20, number of GRU units is 256, learning rate is 0.03, and dropout probability is 0.5. We adopt the control variable method to realize parameter evaluation. For example, when the number of GRU units is evaluated, it is only necessary to change the number of GRU units in the initial hyperparameters. The performance of the model is calculated with different hyperparameter values (Table 2).

Table 2 shows the calculation effect of the model for different hyperparameter values. Firstly, the number of GRU units is evaluated, and the other hyperparameters are set as: number of epochs is 20, learning rate is 0.03, and dropout probability is 0.5. It can be seen that with the gradual increase in the number of GRU units, the accuracy of the model tends to increase; when the number of GRU units reaches 256, the precision, recall, and F1 value of the model reach the maximum, which are 83.81%, 90.34%, and 86.95%, respectively. When the number of GRU units is small, the performance of the model on text semantics analysis is poor, and it is difficult to deeply extract text features, so the F1 value calculated by the model is low; when the number of GRU units increases, the model training appears to be overfitting, which leads to a decrease in the F1 value. Secondly, the learning rate is evaluated, and the determined optimal number of GRU units is substituted into the initial hyperparameters, so hyperparameters are set as: number of epochs is 20, number of GRU units is 256, and dropout probability is 0.5. The accuracy of the model tends to increase when the learning rate is less than 0.03; when the learning rate is 0.03, the precision, recall, and F1 value of the model reach the maximum; when the rate is less than 0.03, the accuracy of the model tends to decrease. Thus, the change in the learning rate will affect the optimization and adjustment of the hyperparameters in the model. Finally, the dropout probability is evaluated, the determined optimal number of GRU units and the optimal learning rate are substituted into the initial hyperparameters, so hyperparameters are set as: number of epochs is 20, number of GRU units is 256, and learning rate is 0.03. When the dropout probability is 0.5, the precision, recall, and F1 value of the model reach the maximum. When the dropout probability is less than 0.5, the number of discarded hidden units is excessive, which decreases the accuracy of the model. When the dropout probability is greater than 0.5, the model exhibits overfitting, the accuracy of the model decreases, and the F1 value drops to 81.66%. By comparing the calculation effect of different hyperparameters, the reliability of the hyperparameters is verified.

To verify the superiority of the BERT+BiGRU+Self-Attention in text feature extraction, the different Siamese neural network subnets are set to calculate the accuracy of answer selection, and the results are shown in Fig. 5.

Fig. 5 shows the accuracy of different Siamese neural network subnets. When the subnet of the Siamese neural network is BERT+BiGRU+Self-attention, the accuracy of the model is 86.07%. Compared with the model that the subnet is CNN, LSTM, or BERT, the accuracy of the model fusing BERT, BiGRU, and Self-attention mechanism is increased by 10.90%, 9.68%, 6.82%, respectively, which illustrates the superiority of the model fusing BERT, BiGRU, Self-attention mechanism in text feature extraction. When the subnet of the Siamese neural network is BiGRU+Self-attention, the accuracy of the model is reduced by 4.76%, which proves the importance of the BERT model in feature extraction; when the subnet of the Siamese neural network is BERT+BiGRU, the accuracy of the model is reduced by 2.71%, which emphasizes the importance of feature enhancement and further verifies the performance of the BERT+BiGRU+Self-attention.

To further validate the BGSA model, its performance was compared to that of other models (e.g., an HMN, BERT, SMN, GRU, LSTM, and CNN) [37,39,41,42,53], and the results are shown in Fig. 6.

In Fig. 6, the accuracy of the BGSA model is 86.07% in the answer selection; the accuracy of the HMN and SMN models are 79.65% and 76.81%, respectively, which shows the superiority of the hybrid model in safety hazard knowledge question answering. The accuracy of the BERT model is 77.12%, which indicates that the BERT model can accurately extract contextual information. This shows that the BERT can effectively improve the effect of answer selection. The accuracy of the GRU model is higher than LSTM and CNN models, which further illustrates the applicability of the GRU in safety hazard text processing. Compared with the HMN, BERT, SMN, GRU, LSTM, and CNN models, the accuracy of the BGSA model is increased by 6.34%, 8.95%, 9.26%, 14.04%, 14.38%, and 15.75%, respectively, which further demonstrates the validity and applicability of the proposed model.

4.3. Safety hazard knowledge intelligent question answering

A simple and convenient operating system can avoid complicated data processing procedures, which can promote the promotion and application of a model and enable the model to better serve the management of construction site safety hazards. Therefore, the answer selection model is used to develop a safety hazard knowledge question answering system. This system can automatically generate safety hazard management measures using dialog and form an end-to-end problem-solving mechanism. To meet construction site safety hazard management requirements, the intelligent knowledge question answering system is divided into three parts: 1) Safety hazard knowledge question answering. Users can intelligently obtain answers according to the input safety hazard problems, and the questions and answers are displayed in the interface in the form of a chat (Fig. 7). Meanwhile, the system can

Table 2
Model parameter evaluation.

Hyperparameters value		4	8	16	32	64	128	256	512	1024
	Precision	0.6517	0.6745	0.6801	0.7195	0.7648	0.8068	**0.8381**	0.8146	0.8012
GRU	Recall	0.7243	0.7518	0.7732	0.7915	0.8236	0.8843	**0.9034**	0.8976	0.8735
	F1	0.6861	0.7111	0.7237	0.7538	0.7931	0.8438	**0.8695**	0.8541	0.8358
Hyperparameters value		**0.01**	**0.02**	**0.03**	**0.04**	**0.05**	**0.06**	**0.07**	**0.08**	**0.09**
	Precision	0.8137	0.8264	**0.8381**	0.8319	0.8213	0.8107	0.8076	0.8034	0.8013
Learning rate	Recall	0.8872	0.8969	**0.9034**	0.8992	0.8891	0.8797	0.8703	0.8675	0.8619
	F1	0.8489	0.8602	**0.8695**	0.8642	0.8539	0.8438	0.8378	0.8342	0.8305
Hyperparameters value		**0.1**	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**
	Precision	0.7758	0.7863	0.8092	0.8134	**0.8381**	0.8213	0.8106	0.8065	0.7916
Dropout	Recall	0.8113	0.8319	0.8803	0.8963	**0.9034**	0.8851	0.8637	0.8593	0.8433
	F1	0.7932	0.8085	0.8433	0.8528	**0.8695**	0.8520	0.8363	0.8321	0.8166

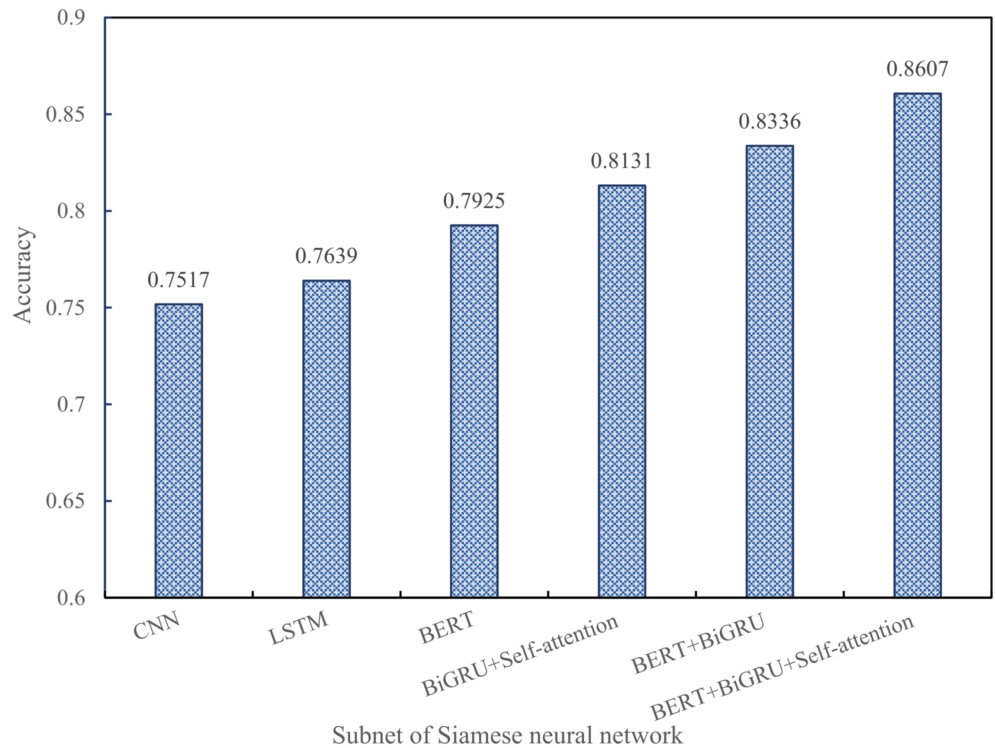

Fig. 5. Subnet of Siamese neural network subnets.

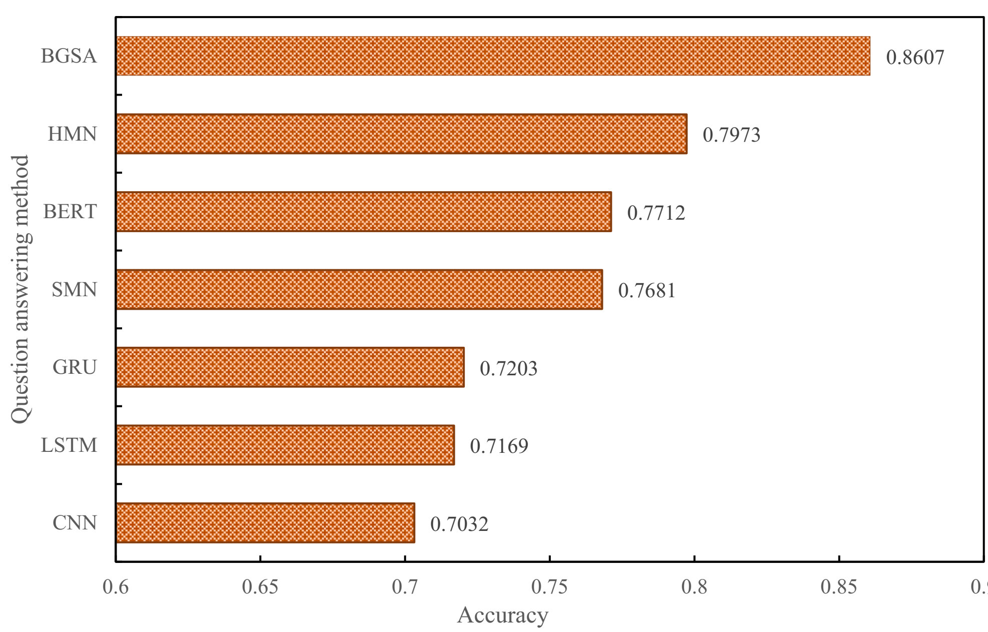

Fig. 6. Accuracy of various question answering methods.

show common problems, and users can quickly understand the occurrence of safety hazards on the construction site. 2) Historical record exhibition. The system can display the knowledge question answering records that users have searched. We can understand the safety hazards that have occurred in the recent period. Meanwhile, to facilitate the management of construction safety hazards, this part provides a question answering record export function, which can select the safety hazards knowledge question answering records that need to be exported. The records are saved in Excel format, which can provide data support for the compilation of the safety hazard list (Fig. 8). 3) Batch processing of safety hazards. If there are a large number of safety hazard problems on a construction site, an approach obtaining answers one-by-one has difficulty meeting the requirements of safety management. Batch processing provides a simple processing method for massive safety hazard problems. Users only need to import text documenting a safety hazard question, and the system can quickly export the corresponding answer to the question (Fig. 9). Moreover, users can select the questions and answers that need to be exported according to the management requirements.

The safety hazards on hydraulic engineering construction sites have

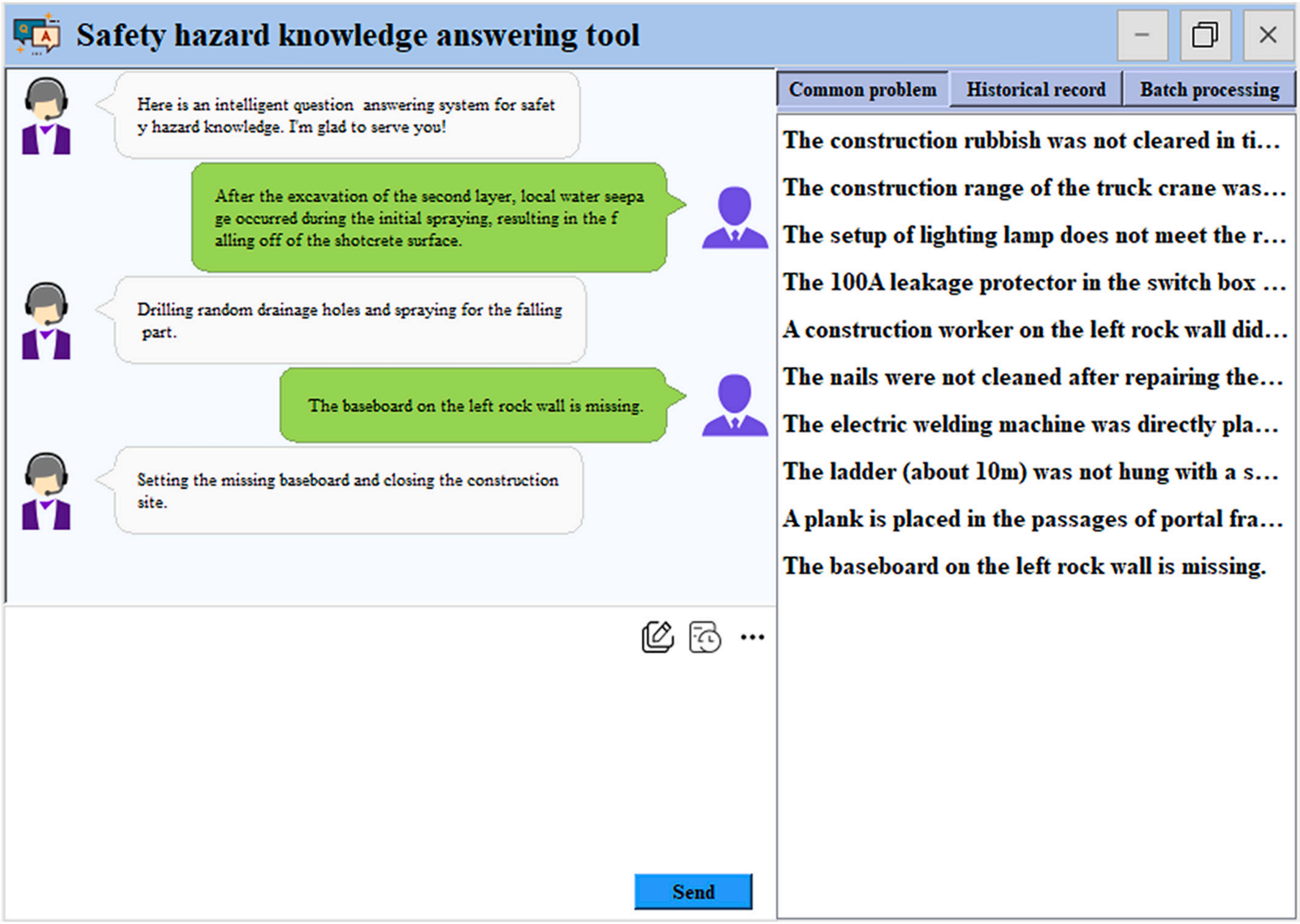

Fig. 7. Safety hazard knowledge question answering interface.

high randomness and disorder, which causes a problem of low efficiency in safety management. Workers cannot timely and accurately obtain safety hazard management information for large numbers of safety hazard problems, which may delay the management of safety hazards and cause construction accidents. The safety hazard knowledge question answering system provides an intelligent dialog mechanism. Users can input construction site safety hazard questions. The system uses subnet A to analyze the inputted text and extract text features; then subnet B will analyze the answer texts that derive from safety management standards and professional data. The text feature extracted by subnet A and subnet B is adopted to achieve the semantic matching and obtain matching degree between question text and answer text. We select the answer text with the highest matching degree value as the management measure of safety hazard. Fig. 7 shows the operation process of the question answering system. If a manager inputs "The baseboard on the left rock wall is missing", The feature of the inputted question text is analyzed by the answer selection model, and the answer text with the largest matching degree is selected, so "Setting the missing baseboard and close the construction site" is regarded as the management measure of safety hazard problem. Finally, the management measure will be fed back to the manager in the form of dialog to guide safety hazard management. Furthermore, the system intuitively displays common safety hazard problems, which enables users to quickly discover key issues in safety hazard management and adjust safety hazard management plans in a timely manner.

To facilitate the management of safety hazards, managers need to summarize the safety hazard content and management measures to build a safety hazard list. However, the process of list compilation is time consuming and labor intensive. Therefore, the system provides a mechanism to convert historical records into a safety hazard list. The historical records are safety hazard problems that have been processed by the system. We can clearly understand the safety management situation at the construction site by the historical records. Furthermore, the system can aggregate the scattered safety hazard problems on the construction site, which is helpful for the unified management and analysis of safety hazards. The safety hazards question and management measure can be exported and saved as Excel documents, which realizes the intelligent generation of a safety hazard list. Fig. 8 shows the export function of historical records. The historical record demonstrates the safety hazard problems that managers have inquired in the recent period. The management measures are generated by semantic matching. Meanwhile, the system records the query time of safety hazard problems so as to obtain the occurrence time of the safety hazards, which contributes to the development of safety management plan. Users can select safety hazard knowledge question answering records to build safety hazard lists, which can reduce the pressure on managers and realize intelligent safety hazard management.

The system provides a batch processing function for a large number of safety hazards, importing collected safety hazards into the system and directly outputting the corresponding answers. Moreover, the system can intelligently form a safety hazard management list according to user requirements. Fig. 9 shows the batch processing function. When there are a large number of safety hazard problems at the construction site, managers only need to import all the problems into the system in the form of documents. The batch processing function can orderly analyze the safety hazard problems in the documents, which uses the answer

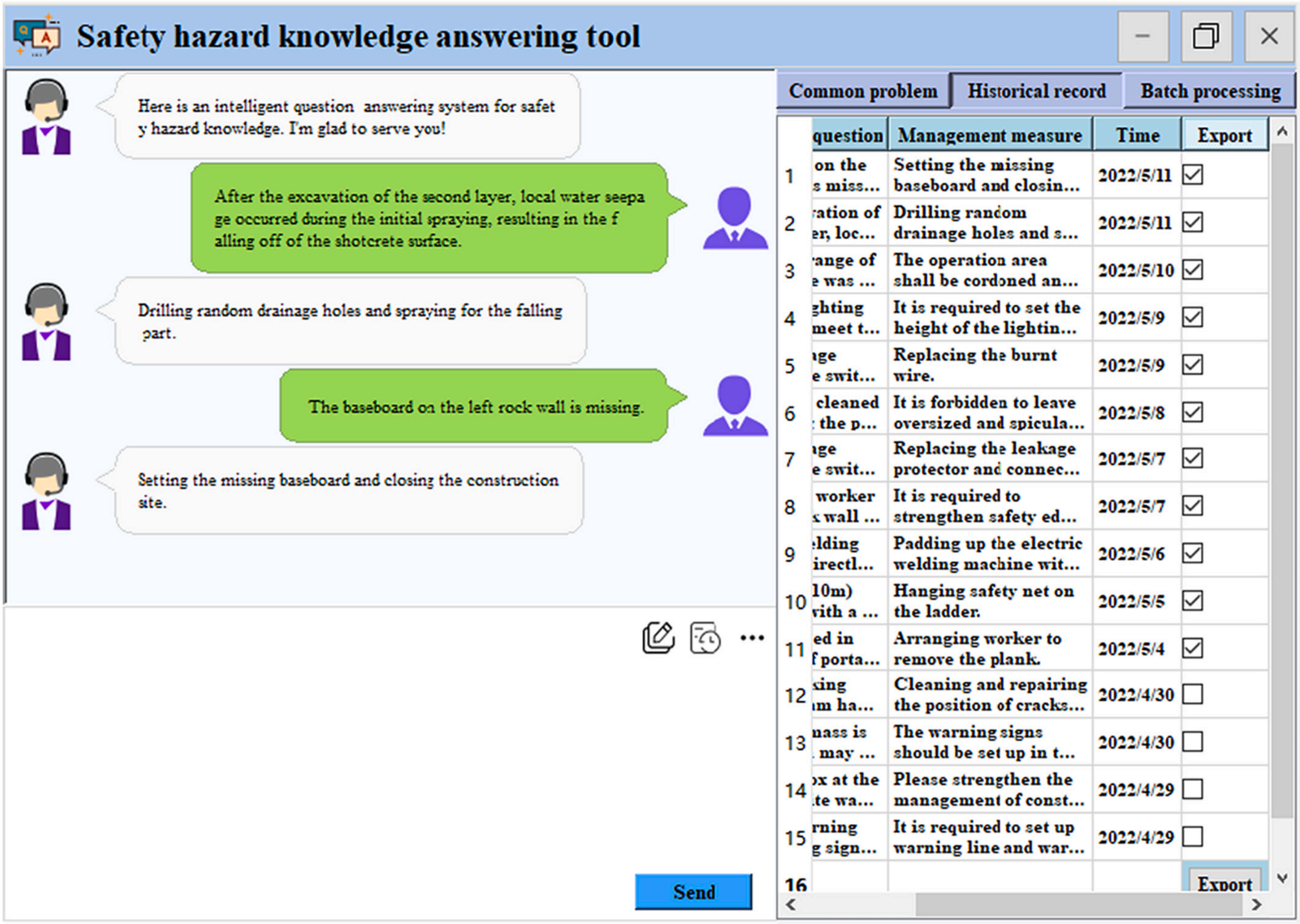

Fig. 8. Historical knowledge question answering record.

selection model to extract text feature, calculate the matching degree and obtain the management measures for each problem. The safety hazard problems in the document and management measures are listed on the system interface. Managers can selectively export the problems and management measures according to requirements. Meanwhile, the system exports the safety hazard problems and management measures in Excel format, which improves the management efficiency of construction site safety hazards.

5. Discussion

The intelligent generation of management measures can improve safety hazard management efficiency. Currently, the investigation and resolution of safety hazards are completed by managers. Managers need to record safety hazard content and formulate safety hazard measures based on safety management experience. The safety hazard management measure generation process is lengthy and time-consuming. Generally, the experience knowledge is derived from historical safety hazards management data. Existing studies have verified the value of safety hazard data in actual applications, but there are few studies on safety hazard knowledge intelligent question answering. Therefore, this study proposes an answer selection model to solve safety hazard problems, promote the promotion and dissemination of safety hazard management knowledge, and realize the intelligent management of safety hazards. The answer selection model proposed in this study is applied in hydraulic engineering safety hazard management. The F1 value is 86.95%, and the performance of the model outperforms other answer selection models, which proves the applicability and accuracy of the model. Compared with other models, the superiority of the model is reflected in two aspects. First, this study adopts a BERT model to quantify safety hazard management text and analyze contextual semantic information. Moreover, a BiGRU model is used to extract the global features and analyze the syntactic and semantic relationships of text. Furthermore, a Self-attention mechanism is adopted to analyze the local features and strengthen the text features, which ensures the accuracy of text feature extraction. Second, this study adopts a Siamese neural network to analyze question text and answer text. The matching degree between the texts is measured by the Euclidean distance. Meanwhile, unlike existing methods for calculating the text matching degree, the Siamese neural network has a weight sharing mechanism, which ensures the consistency of text training and enhances the generalization ability of the model.

To promote the application of the answer selection model, a question answering system suitable for safety hazard management is built to quickly obtain safety hazard management measures. The system not only simplifies the operation process of the answer selection model but also improves the efficiency of solving safety hazard problems. Managers can obtain management measures according to safety hazard problems at construction sites in a timely manner. The answers fed back to the question answering system are based on experience data and knowledge, which have high reliability and applicability and can provide decision support for construction site safety hazard management. Meanwhile, safety hazard knowledge question answering has strong operability and comprehension. Users only need to input safety hazard questions, and the system can quickly output the corresponding answers, which is helpful for the promotion and application of the system.

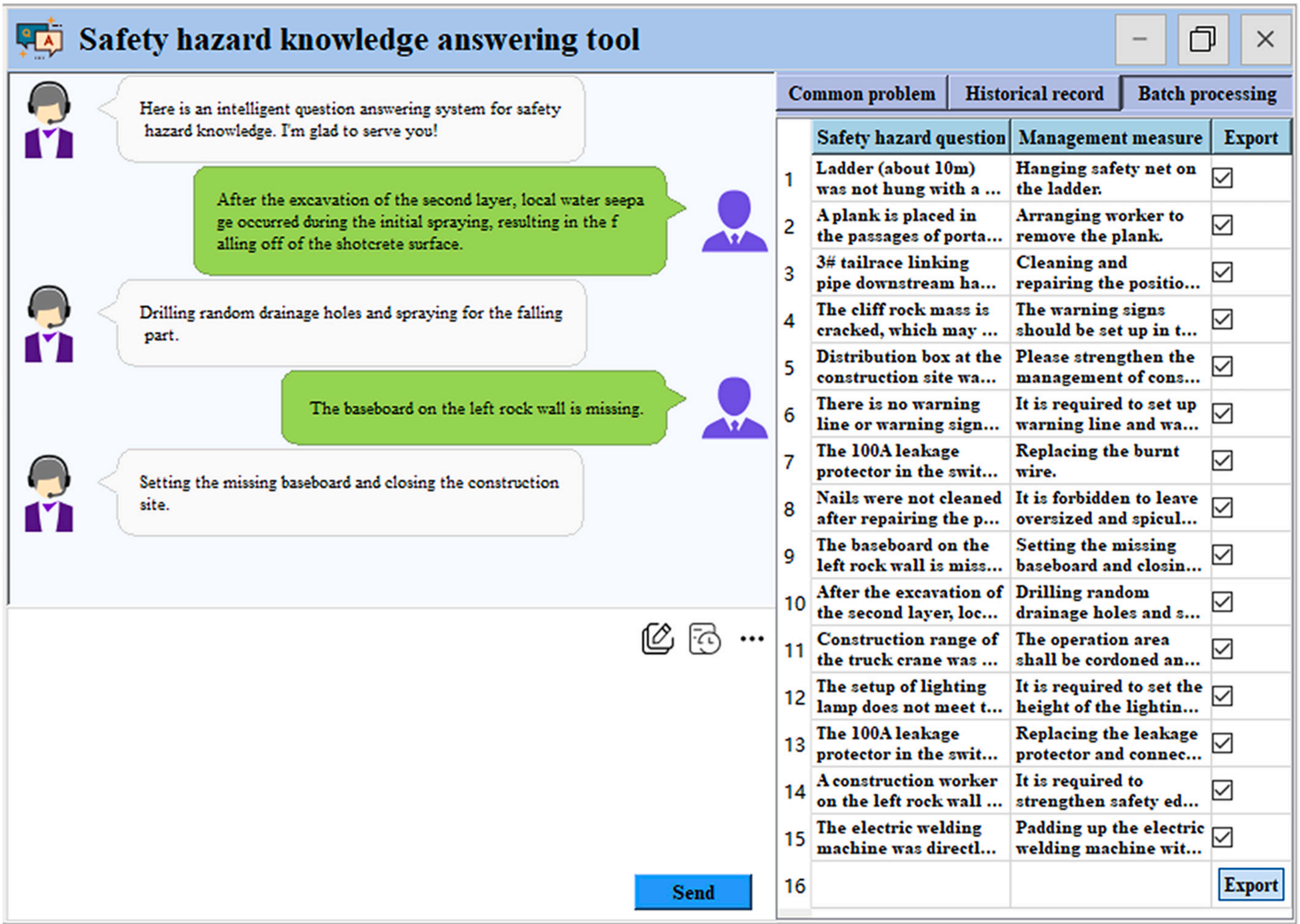

Fig. 9. Batch processing of safety hazards.

Unlike existing safety hazard management systems, the safety hazard question answering system not only provides a dialog function but can also display common safety hazards, output safety hazard historical records, and realize the batch processing of safety hazard problems. These functions can visually present the construction site safety hazard and automatically form a management list according to the requirements, which saves human and material resources in safety management.

6. Conclusions

An intelligent knowledge question answering system is helpful to improve the efficiency of safety hazard management, but the answer selection mainly depends on the experience knowledge in historical data. How to accurately extract experience knowledge from massive text is an urgent problem. Therefore, an answer selection model based on a Siamese neural network is built to achieve the intelligent generation of safety hazard management measures.

(1) BERT is used to analyze contextual semantic information and obtain text word vectors. The text data are converted into an intelligible vector. The BiGRU is adopted to analyze the semantic relationship of the text and extract the global features. The key information is considered to strengthen local features. A safety hazard text feature intelligent extraction model fusing global features and local features is built to deeply analyze safety hazard text, which provides approach support for safety hazard knowledge question answering.

(2) An answer selection model based on a Siamese neural network is built to intelligently match the question text and answer text. A text feature extraction model is used as a subnet of the Siamese neural network and the Euclidean distance is used to measure the matching degree between texts. Hydraulic engineering safety hazard text was used to train the answer selection model, and the F1 value of the model was 86.95%, which is superior to other answer selection classification models. Moreover, a knowledge question answering system based on an answer selection model was developed to automatically generate safety hazard management measures, which further verifies the reliability and applicability of the model proposed in this study.

(3) The model proposed in this study realizes the automatic processing of massive safety hazards within a short time, promotes the popularization and application of safety hazard management knowledge, and realizes and improves an intelligent level of safety management. The research effort enriches the theoretical system of safety hazard management, which can provide necessary key information for construction site decision making, and it is an important prerequisite to realize intelligent construction safety management.

(4) The answer selection model proposed in this study has high accuracy and reliability and can intelligently generate safety hazard management measures. However, there is room for further refinement. There are various safety hazards at construction sites, especially on large-scale projects. The model in this study is based on existing experience knowledge to determine the safety hazard management measures. It is difficult to directly obtain relevant

experience knowledge for new safety hazards, which may affect the accuracy of safety hazard answers. Therefore, future work should establish automatic safety hazard collection and training mechanisms that can ensure the real-time updating of information and improve the accuracy of answer selection. On the other hand, the system proposed in this study is mainly used for the formulation of management measures, which cannot show the closed-loop management information of safety hazards. Thus, it is essential to develop a safety hazard tracking management mechanism that can automatically obtain the safety management effect and form an intelligent management system fusing information collection, control, and feedback.

Data availability statement

Data generated and analyzed during this study are available from the corresponding author by request.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgments

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