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GPB and BAC: two novel models towards building an intelligent motor fault maintenance question answering system

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ABSTRACT

Generally, the existing methods for constructing a knowledge graph used in a question answering system adopted two different models respectively, one is for identifying entities, and the other is for extracting relationships between entities. However, this method may reduce the quality of knowledge because it is very difficult to keep contextual information consistent with the same entities in the two different models. To address this issue, this paper proposes a model called GPB (GlobalPointer + BiLSTM) which integrates the BiLSTM into GlobalPointer through concatenation operations to simultaneously guarantee the rationality of identified entities and relationships between entities. In addition, to enhance the user experience using an intelligent motor fault maintenance question answering system, a model called BAC (BiLSTM + Attention + CRF) is proposed to identify named entities in user questions, and the BERT-wwm model is used to classify user intentions to improve the quality of answers. Finally, to verify the advantages of the proposed model GPB and BAC, comparative experiments and real application effects of the developed question answering system are demonstrated on our built motor fault maintenance dataset. The experimental results indicate that the constructed knowledge graph and developed question answering system provide engineers with high-quality motor maintenance knowledge services.

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KEYWORDS
Knowledge graph; question answering system; motor fault maintenance; GlobalPointer; BiLSTM

1. Introduction

The exponential growth of manufacturing industry data and the rapid development of big data technology have not only transformed the manufacturing process but also brought forth new opportunities, challenges, and advancements in equipment maintenance (Xia et al. 2022). As a pivotal component extensively employed to drive various industrial machinery, motors play a central role (Lyu et al. 2022). The motor predictive maintenance not only efficiently reduces production downtime resulting from accidents, but also

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prevents wastage of machine operational time due to premature component switching. Moreover, motor predictive maintenance offers interpretability for causal analysis of motor faults and correlated assessment of critical component damage. It provides recommendations for pertinent maintenance strategies, thereby furnishing comprehensive repair guidance for engineering personnel and elevating the intelligent maintenance proficiency of motors (Xia et al. 2022). However, currently, the implementation of intelligent motor maintenance faces some challenges, that is, the maintenance data lacks of unified description standards and unclear sharing mechanisms, and has obvious semantic heterogeneity. These issues impede data acquisition, exploration, sharing, reuse, and semantic inferential analysis within the motor fault maintenance sector, severely hindering the extensive integration and intelligent application of motor fault maintenance big data.

To address the above-mentioned issues, a graph modelling method is widely used in real-world engineering applications (Dengqiang et al. 2021). By explicitly modelling domain knowledge, this method can support and improve the accuracy of downstream tasks including intelligent maintenance question answering (Q&A) system (Zhou et al. 2022b), condition-based maintenance expert system (Yang et al. 2023), intelligent search of maintenance strategies (Cardoso, Da Silveira, and Pruski 2020), accelerated maintenance process (Hossayni et al. 2020), assembly process for complex components(Zhou et al. 2022a), human-machine collaborative assembly-commissioning for complex products (Xuemin et al. 2022), integration of heterogeneous assembly information (Chen et al. 2020), fault location (Lv et al. 2020) and fault tracking (Qiu et al. 2020) and so on. Knowledge Graph (KG) which combines information extraction and fusion, knowledge representation and reasoning, machine learning and neural networks and other artificial intelligence methods is a technical method of graph modelling to represent the relationship between entities. KG can not only perform human-level perception, but also simulate the reasoning process of the human brain (Zhou et al. 2021), and is gradually enriching existing manufacturing systems with more cognitive intelligence. Its goal is to mine the knowledge hidden in different multisources, such as sensory data and internet open data (Zheng et al. 2021) in the industrial field. Therefore, building a motor maintenance KG to realise motor predictive maintenance has great potential. However, the existing methods of constructing knowledge graphs usually adopt two different models, one is used to identify entities, and the other is utilised to extract relationships between entities. this implementation pattern may reduce the quality of knowledge, that is, relationships of identified entities are inaccurate. Therefore, how to simultaneously extract entities and relationships between entities to construct a motor fault maintenance KG (MFMKG) is still in its infancy.

In the context, this paper first proposes a model called GPB which performs jointly entities and its relationships and establishes a knowledge graph from motor fault maintenance text, and then develops an intelligent motor maintenance Q&A and proposes another model called BAC which can identify named entities from questions raised by users and uses pre-trained BERT-wwm to classify users' intents. Aiming to help engineers improve the efficiency of motor maintenance services, the goal of this work is to develop an intelligent Q&A based on MFMKG by extracting value information from large-scale and multisource motor maintenance textual data.

To achieve this objective, the rest of the paper is organised as follows. Section 2 reviews the state-of-the-art research on knowledge graph and its applications, and identifies the research gaps. Section 3 introduces the proposed method. The performance analysis of the

BAC model and the application effects of the GPB model are validated in Section 4. Finally, Section 5 concludes the paper and discusses future works.

2. Relate work

2.1. Fault diagnosis KG

A knowledge graph is a structured semantic network in which nodes represent entities or concepts, and edges represent interactions between entities (Ji et al. 2021). This graphical representation of knowledge intuitively reveals the connections between entities in a domain, providing strong support for knowledge sharing, querying, and derivation, which is beneficial for users to manage, utilise, and develop knowledge. In recent years, knowledge graphs have shown great application value in various fields, especially in the industrial field (Shi et al. 2022; Zhou et al. 2023). The existing methods for constructing knowledge graphs can be roughly divided into two categories: semantic analysis-based methods (Liu, Zhou, et al. 2023) and deep learning-based methods (Chen et al. 2020). The semantic analysis-based needs to a perform mapping and construct a syntax tree when constructing a knowledge graph, in order to convert natural language into machine-understandable semantics. The disadvantage is that it requires researchers to be familiar with the knowledge related to natural language processing. On the contrary, when using deep learning-based methods to construct knowledge graphs, there is no need to explicitly construct syntax trees and a large amount of labelled data (Gu et al. 2021), only the entities and relationships of the studied problem need to be considered. Therefore, deep learning-based methods are more suitable to construct large-scale knowledge graphs (Liu et al. 2021).

Currently, deep learning-based methods have become the mainstream method for constructing knowledge graphs. For example, to address the lack of a unified and standardised representation of assembly data sources for wind turbines and the low reusability of historical assembly data, Liu et al. (2023b) used deep learning models such as BERT-BiLSTM-CRF and Encoder + Decoder, to construct a multimodal knowledge graph to recommend the assembly sequence of wind turbines. Lv et al. (2023) proposed a digital twin architecture based on biomimetic LIDA cognition to implement unmanned maintenance of machine tools. To achieve self-awareness of physical devices, deep learning models such as LSTM and VGG were used to extract knowledge from multisource heterogeneous maintenance data and construct a knowledge graph. Generally speaking, in complex fault diagnosis scenarios, ordinary knowledge graphs cannot fully and correctly represent the indivisible multivariate relationships that connect two or more entities. In the end, Li et al. (2023) proposed the concept of a knowledge hypergraph, which utilises deep learning models such as Mask R-CNN, ResNet50, and ALBERT-BiLSTM-CRF for multivariate knowledge extraction and constructs a knowledge hypergraph, providing a new solution for achieving cognitive intelligence for fault diagnosis. Although these deep learning-based methods have been widely applied to construct domain-specific knowledge graphs, entities and relationships between entities are extracted separately using different models in most cases, which may lead to reduce the quality of knowledge in knowledge graphs since it is very difficult to keep contextual information consistent of the same entities in the two different models.

2.2. KG Q&A

In recent years, the rapid development of big data technology and knowledge graph technology has led to an increasing amount of data being collected and stored (Jiang et al. 2023b). Knowledge graph Q&A can provide background knowledge and experiences for machines, thereby achieving traceability of Q&A (Bi et al. 2023; Hu et al. 2023), which is of great significance for some proprietary fields that require high quality of answers. At present, there are four main methods for constructing knowledge graph Q&A: rule-based methods, information retrieval-based methods, semantic analysis-based methods, and large language model-based methods. The rule-based approach is the earliest one whose main idea is to classify problems and then match answers with rules (Mahmud et al. 2015). For example, Riloff and Thelen (2000) designed seven rules using natural language processing techniques such as morphological analysis, part of speech tagging, semantic class tagging and entity recognition, and developed a reading comprehension Q&A. The rule-based method is easy to implement and does not require background knowledge. However, the limitation is that it can only establish good rules for limited vertical fields and require a lot of manpower to develop rule templates.

The information retrieval-based method applies traditional information extraction technologies to solve problems in Q&A. Its basic idea is to search for all entities related to the subject entity of the problem from the knowledge graph as candidate answers, and then select the best answer from the sorted candidate answers (Jiang et al. 2023a). For example, to answer natural language questions over a KG, Yan et al. (2021) used a personalised PageRank algorithm to retrieve candidate answers from a subgraph of the KG. The subgraphs are constructed based on heuristic rules, which makes many irrelevant entities and relations included in the KG. To address the problem, some pruning strategies were employed to delete incorrect answer paths to reduce the size of the subgraphs (Lu et al. 2021). In addition, Zhang et al. (2022) presented a trainable subgraph retriever to search for answers. However, it is a kind of black-box analysis method which reduces the interpretability of the entire process.

Semantic analysis-based methods typically use traditional machine learning or deep learning models (Li et al. 2022; Peng et al. 2022; Siddharth, Li, and Luo 2022) to perform semantic analysis on problem statements and generate query statements for the knowledge base. For example, Liu, Zhou, et al. (2023) proposed to use a multi-network collaboration model BERT-BiLSTM-CRF-BERT and background knowledge to construct a Q&A. Liu, Ji, et al. (2023) employed a deep learning model based on BERT to extract mineral entities and relationships, and constructed an efficient Chinese mineral Q&A. In addition, they also developed a BERT-based model for parsing the intent and related entities of the question to generate query statements based on predefined problem templates, which are then processed by mineral knowledge graphs and returned with answers. To achieve intelligent Q&A for bridge defect maintenance, Yang et al. (2023) developed a bridge detection knowledge graph Q&A that integrates BERT and hierarchical cross-attention mechanism. Zhu et al. (2023) proposed an ocean engineering knowledge graph framework to achieve intelligent Q&A. The proposed framework defined an ocean engineering ontology and constructed an ocean engineering-oriented knowledge graph using a top-down approach. They used the T5-Pegasus model to generate natural answers by retrieving answer entities from the knowledge graph, with an accuracy rate of up to 89.6%. Although we can see that the semantic analysis-based method can parse natural language into the logic of knowledge base queries, making the inference process more interpretable, few works investigate to improve the quality of answers by means of an attention mechanism.

Large language model-based methods, such as ChatGPT (Antaki et al. 2023), are the most mainstream now. Since the end of 2022, ChatGPT's powerful language comprehension and generative abilities have driven intelligent Q&A into people's daily lives (Liu et al. 2023c), and have also attracted the strong attention of scholars in the field of intelligent manufacturing (Xia et al. 2024). However, large language models parameterise knowledge, resulting in a poor interpretability of answers and reasoning ability in proprietary domains (Chang et al. 2023). If the answer is not accurate, technical backtracking cannot be performed. Based on the above analysis, this paper mainly adopts semantic analysis-based methods to implement an intelligent motor fault maintenance Q&A. We use the proposed GPB model to construct a MFMKG, the proposed BAC model to extract the subject entity of the question and search for the final answer based on the MFMKG.

2.3. Research gaps

The literature review reveals two important research gaps. Firstly, there is a lack of a collaborative method of multiple neural networks to transform text into machine-understandable semantics. Few studies investigate how triplets are effectively extracted to optimise the construction of knowledge graphs. Second, there is a lack of methods that can improve the quality of answers by accurately identifying user intentions. Few works study the problem of how multivariate relationships are used to represent user queries to enhance the reasoning ability of Q&A.

This paper attempts to bridge these research gaps by proposing two novel models called GPB and BAC. GPB combines global pointers and BiLSTM to extract rich relationships of triples from motor fault texts, which directly obtains relationships between entities and avoids the cumbersome process of extracting entities first and then extracting relationships between entities in traditional methods, optimising the construction process of knowledge graphs. BAC aims to improve the accuracy of user intent recognition and enhance the interpretability and traceability of Q&A by accurately identifying entities of questions through the combination of BiLSTM, attention mechanisms, CRF, and BERT-wwm.

3. Proposed method

3.1. General idea

The general idea of this work consists of three stages. In the first stage, a model called GPB is proposed to build an MFMKG. In the second stage, another model BAC is proposed to perform named entity recognition for the questions raised by users in order that the developed Q&A can better understand the intents of users. Since the accuracy of name entity recognition directly affects the performance of the Q&A, a pre-trained BERT-wwm is further used to analyse users' intentions. Finally, an intelligent Q&A based on MFMKG is developed in the third stage. In the following subsections, we focus on the presentation of two proposed models and the development of the intelligent Q&A.

3.2. GPB model for constructing MFMKG

GlobalPointer is a transformer-based model specially designed to solve alignment problems in sequence generation tasks. However, traditional transformers perform poorly on long-distance dependencies. To obtain richer context information and better alignment effects, this work integrates bidirectional long short-term memory (BiLSTM) into GlobalPointer to enhance the long-distance dependence modelling ability of GlobalPointer since BiLSTM can better capture long-distance dependencies and semantic information in sequences. By integrating the BiLSTM into the GlobalPointer, the proposed model GPB (GlobalPointer + BiLSTM) can simultaneously fuse BERT pre-trained representation and BiLSTM context information to further improve the performance of the alignment task.

The structure of the proposed model GPB is shown in Figure 1, which aims to extract the triples (*Entity_output*, *Head_output*, *Tail_output*) from motor fault maintenance text. The input of the model is sentences from motor fault maintenance text. The execution process of the model is as follows. First, each sentence is converted into a pair of *token_id* and *segment_id* which is fed into the BERT pre-trained model, then the BERT pre-trained model encodes each sentence using the transformer structure and outputs the context information of each sequence. Next, BiLSTM is applied to the obtained context information to learn a richer semantic representation. After, the output of the BERT pre-trained model and the output of the BiLSTM layer are concatenated to obtain a new sequence. Finally, the new sequence is fed into the GlobalPointer which maps the input into three probabilities. *Entity_output* denotes the probability of the starting position of an entity. *Head_output* indicates the probability of a head entity relationship. *Tail_output* denotes the probability of a tail entity relationship. Therefore, the proposed model GPB can simultaneously predict the entity position and the relationship between the head and tail entities.

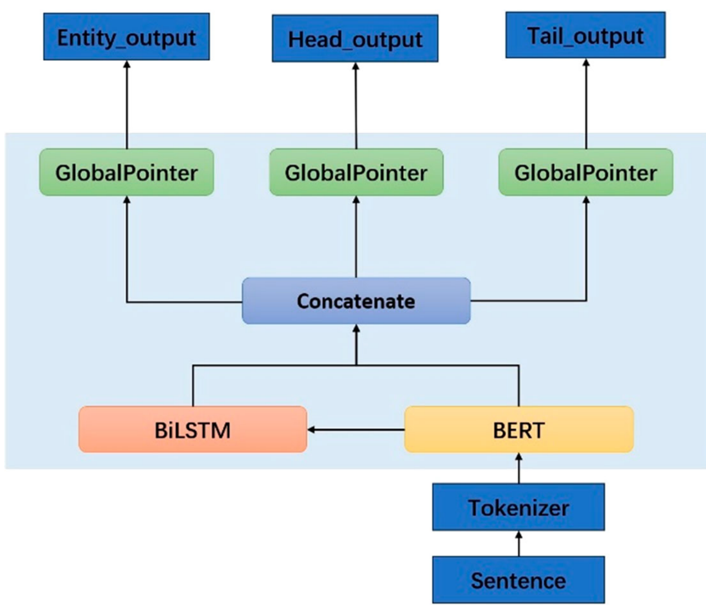


Figure 1. The structure of the proposed model GPB.

3.3. BAC model for identifying name entities

To understand users' questions, BAC model is proposed to extract the named entity in the question fed into the motor fault maintenance intelligent Q&A. Figure 2 depicts the structure of BAC model which consists of four layers. The first layer is an embedding layer which converts the input question into a word vector. BiLSTM layer is the second layer. It takes a word vector as an input and captures the contextual information in the input question associated with the word vector. Since it can obtain the forward hidden state and backward hidden state of each position, the semantic and grammatical relationship of each word in the context of the sentence can be better understood. In addition, to enhance the model's ability to perceive the key information of the input sequence, the attention mechanism is introduced in the third layer. A learnable attention weight vector is used to adaptively weigh and average the hidden state of each position to obtain the feature representation after attention weighting. This enables the BAC model to focus more intensively on information relevant to the named entity so as to improve identified accuracy. In the last layer, a CRF model is used to jointly model the labels of the entire sequence by defining a label transition matrix where each item is a transition probability between labels. The Viterbi algorithm is applied to find the label sequence with the highest probability.

To reduce the computation cost in this work, the padding length of each batch of BAC model is dynamically calculated according to the longest text length in the batch. For example, assuming that there are L words in a input sequence $X = [x_1, x_2, \ldots, x_L]$, where x_i is a 300-dimensional word vector representing the word embedding of the ith position. The output of the model is the predicted labels of X. Each output corresponds to a tagging of

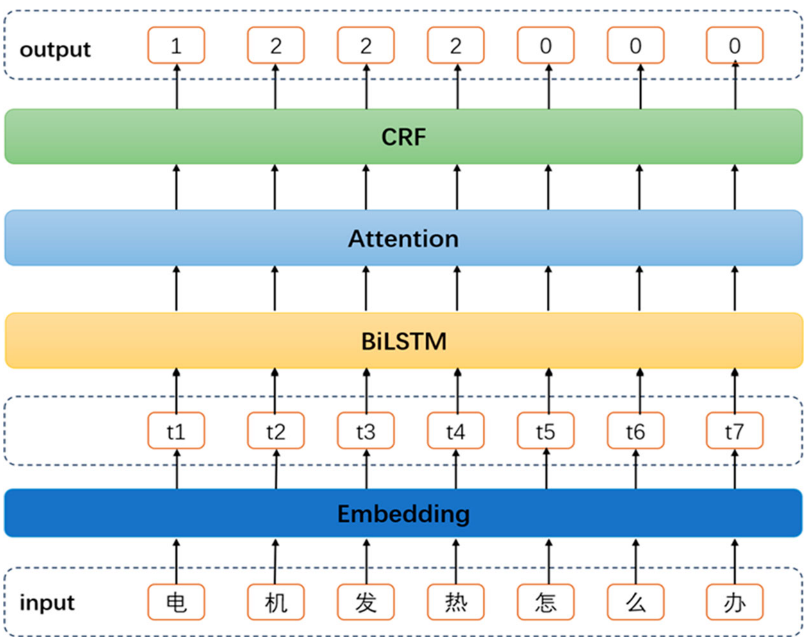


Figure 2. The structure of the proposed model BAC.

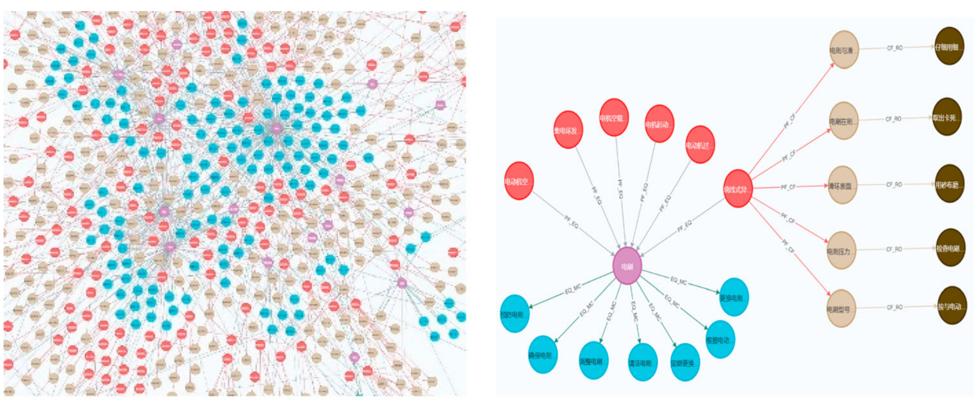
each word in X. We take five different labels as an example to illustrate the sequence tagging tasks. For the output label sequence $Y = [y_1, y_2, \ldots, y_L]$, where $y_i \epsilon \{0, 1, 2, 3, 4, 5\}$ represents the predicted result for the ith word in the input sequence X.

3.4. Development of the intelligent Q&A

This motor fault maintenance intelligent Q&A consists of four modules including motor fault maintenance KG module, question analysis module, question classification module, and query processing module.

3.4.1. MFMKG module

The MFMKG module refers to our developed motor fault maintenance KG, as shown in Figure 3, which is built using the GPB model. It contains more than 3600 knowledge nodes and more than 4600 relationships. Figure 3(a) is a global MFMKG that displays all motor fault knowledge mined from the dataset we collected. Figure 3(b) shows a local MFMKG. Taking the fault phenomenon node *PF* in Figure 3(b) as an example, PF means 'The brush of a wound asynchronous motor catches fire, and the slip ring overheats or burns out', it can be seen that PF is connected to five fault cause nodes *CF* through the fault cause relationship *PF_CF*. *PF* is connected to one fault equipment node *EQ* through the fault occurrence location relationship *PF_EQ*. Each fault cause node *CF* is again connected to the corresponding repair suggestion node *RO* through the repair suggestion relationship *CF_RO*, while the faulty equipment node *EQ* is connected to seven maintenance suggestion nodes *MC* through the equipment maintenance relationship *EQ-MC*. In addition, the faulty equipment node *EQ* also intersects with the other five faulty phenomenon nodes *PF* through the fault occurrence location relationship *PF_EQ*. So various different fault phenomena, fault causes, fault equipment, fault maintenance and maintenance recommendations form an MFMKG by various semantic links, which provides engineers with a detailed analysis of motor faults and practical maintenance suggestions.



(a) A global MFMKG (b) A local MFMKG

Figure 3. The constructed MFMKG. (a) A global MFMKG; (b) a local MFMKG.

Table 1. Five Q&A template.

Question type	Explanation of fault type
PF_CF	Find out the cause of the known fault
EQ_PF	Query possible fault phenomenon of known equipment
CF_RO	Query maintenance opinions of known cause
PF_EQ	Locate specific equipment of known fault phenomenon
has_Part	Query component composition

3.4.2. Question analysis module

The question analysis module adopts the proposed BAC model to extract key entities in user questions to guarantee the answers given by the system are as consistent as possible with what users want. If the identified entity exists in the MFMKG, the system will use the entity directly. However, if the entity in the users' question does not exist in the knowledge graph, the system will use a method of similar word search to match the entity in the knowledge graph.

3.4.3. Question classification module

In the question classification module, aiming to limit the user's questions to a certain range, a pre-trained BERT-wwm model is used to classify questions. To achieve the objective, five motor fault maintenance Q&A templates in Table 1 are designed in this work. It indicates there are five kinds of users' intentions in the motor fault maintenance Q&A. For example, when the user asks a question of 'what fault will happen to the rotor' to the Q&A, the BERT-wwm model judge the user's intention as question type *EQ_PF*.

3.4.4. Query processing module

The query processing module includes a question answer retrieval sub-module and a knowledge retrieval sub-module. The task of the question answer retrieval sub-module is to identify and judge the entities and intentions output by the question analysis module. If the information from the problem analysis module contains the user's intention, the intelligent Q&A generates and retrieves query statements in the knowledge retrieval sub-module. Otherwise, the intelligent Q&A performs a simple question answer match to further narrow the search. After, the results returned by the question classification module are converted into Neo4j's Cypher language, and the Q&A template is called according to the corresponding question type. Finally, the query result is combined with the Q&A and transmitted to the user's interactive interface. The process of question answer is displayed in Figure 4.

4. Case study

4.1. Dataset

Aiming to develop a practical motor fault maintenance Q&A, this paper collected a large amount of motor fault maintenance text from three different sources. The first source is to search for literature and research reports related to motor fault maintenance on China national knowledge infrastructure (CNKI). As we all know, CNKI is one of the most famous platforms in China for disseminating the latest academic research findings and collecting a large number of papers related to motor fault maintenance. The research findings of all papers come from the practical engineering applications of motor fault maintenance.

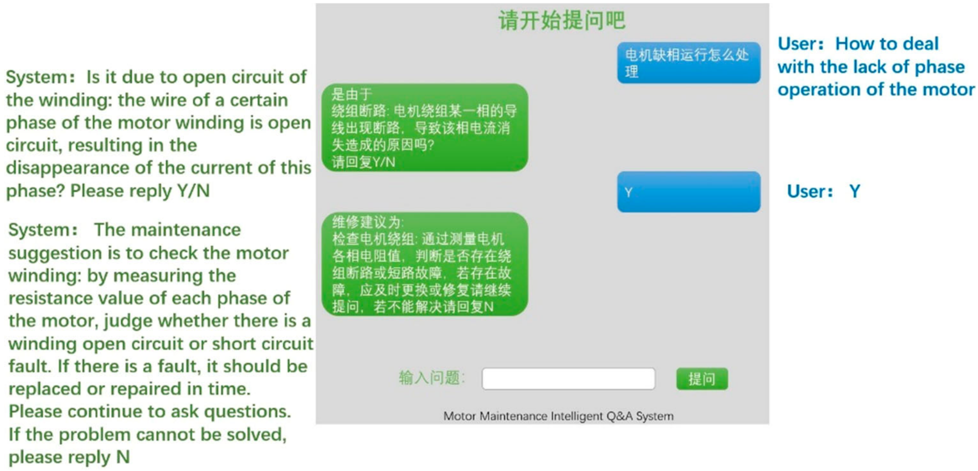


Figure 4. The user interface of the developed intelligent Q&A.

Therefore, collecting motor fault maintenance data from CNKI can ensure the rationality and preemption of the dataset constructed in this paper. Figure 5 shows a fragment of the paper 'Fault diagnosis and maintenance of electric motors'. From Figure 5, it can be seen that this segment describes common faults and maintenance measures of asynchronous motors. The different colour rectangular boxes display different entities that this segment described including seven faulty devices, two fault phenomena, one fault cause, and one maintenance suggestion.

The second approach is to consult with motor maintenance personnel. We select the technical manual 'Practical Technical Manual for Motor Maintenance (Second Edition)' recommended by maintenance personnel from motor maintenance companies as one of the data sources for this study. This manual provides a detailed introduction to the installation, operation points, daily maintenance, troubleshooting, and various maintenance techniques of small and medium-sized motors. Due to the extensive maintenance experiences of motor maintenance personnel, the technical manual they recommend can ensure the rationality of the dataset constructed in this paper. Figure 6 shows a table example in the technical manual, which is about common faults and their solutions for three-phase asynchronous motors. The first row of the table shows that the fault phenomenon of 'the motor cannot start after the power is turned on' may be caused by four fault reasons, and four maintenance suggestions are provided.

The third way is to crawl open data on the Internet. We select the three websites that motor maintenance personnel most frequently visit when encountering maintenance problems (such as '与非网' https://www.eefocus.com, '中芯巨能网' https://www.icanic.cn/ and '知乎' https://www.zhihu.com/) and a technical forum. These public online communities connect motor manufacturers, motor users, and motor maintenance personnel. The generative contents of these two communities essentially are motor fault maintenance text. Therefore, the third source can also ensure the rationality of the dataset constructed in this paper. Figure 7 shows four possible causes and corresponding maintenance suggestions for a motor with an unbalanced no-load current and large three-phase difference from the website zhihu (https://www.zhihu.com/).

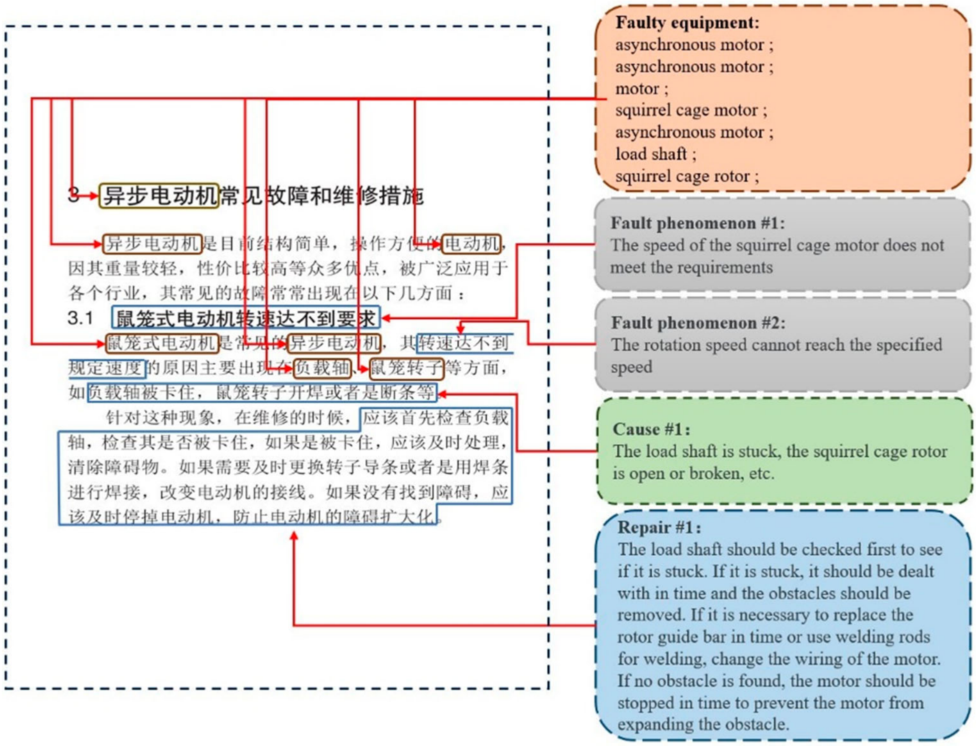


Figure 5. An example paper collected from CNKI.

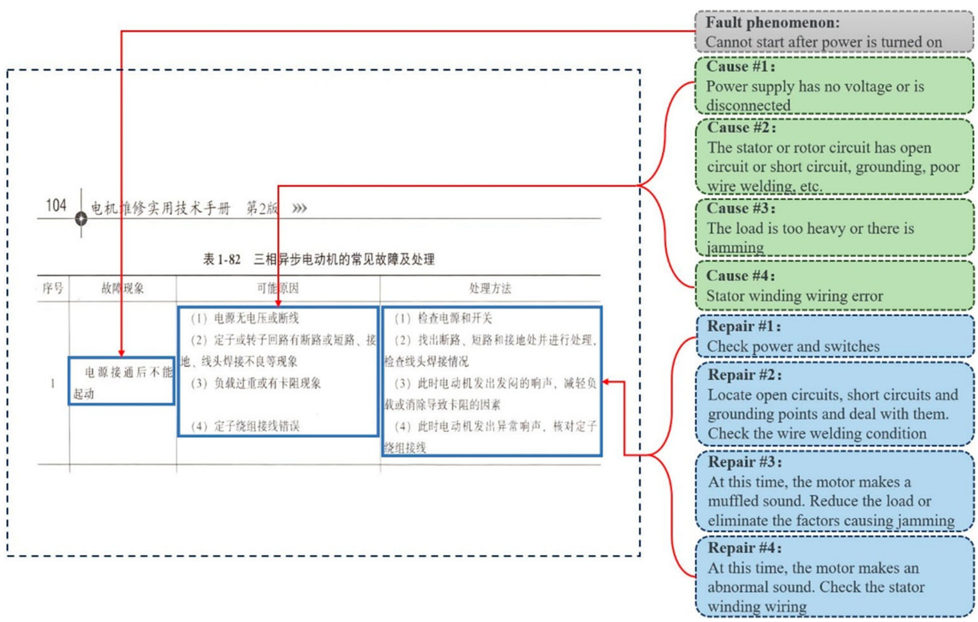


Figure 6. A table example in the technical manual.

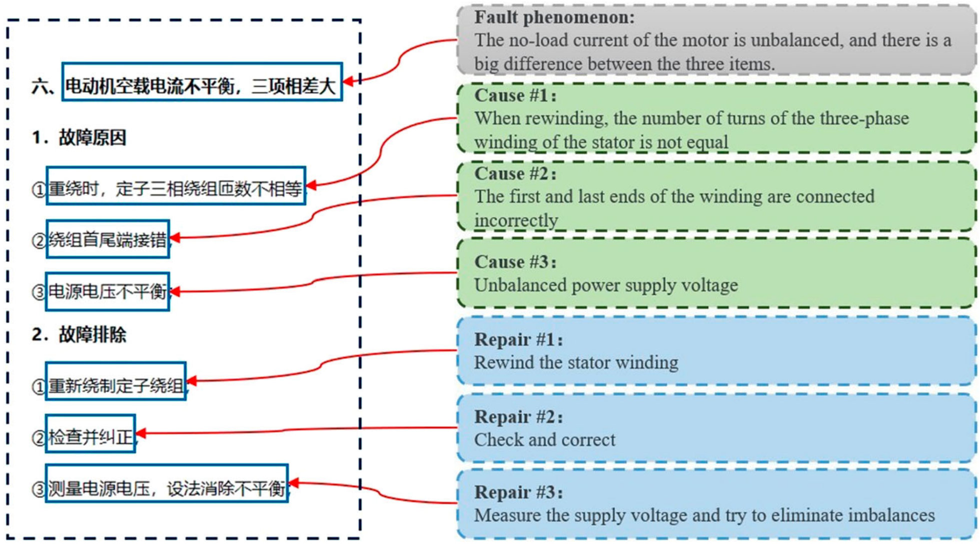


Figure 7. An example of fault diagnosis and repair from a website zhihu.

Table 2. The dataset statistical information.

Data source	Number of sentences		Size	
	Before cleaning	After cleaning	Before cleaning	After cleaning
Literatures and research reports	19,182	2987	68.4M	2.5M
technical manuals	9622	1931	22.4M	1.2M
Motor maintenance website	4304	1758	2.0M	0.5M
Total	33,108	6676	92.8M	4.2M

The text from the above three sources is summarised to form a raw dataset that covers motor fault descriptions, fault causes, repair suggestions, faulty equipment, daily maintenance records and so on. To ensure that high-quality knowledge can be extracted from the original dataset, we removed HTML tags and various special characters from the original dataset. The detailed statistical information of the original dataset and the dataset used for experiments after cleaning is shown in Table 2.

4.2. Evaluation metric

In this section, we select *Precision*, *Recall*, $F1$ and *Accuracy* as the performance metrics to evaluate the performance of the proposed models GPB and BAC. *Precision* denotes the fraction of true samples in the samples predicted to be positive. *Recall* means the proportion of samples that are predicted to be positive in true samples. $F1$ is the harmonic average of *Precision* and *Recall*. They are computed as shown in Equations (1)–(5), respectively. Among them, TP, TN, FP and FN, respectively, refer to the number of true positive samples, positive negative samples, false positive samples, and false negative samples under a category.

$$Precision = \frac{TP}{TP + FP} \tag{1}$$

$$Recall = \frac{TP}{TP + FN} \tag{2}$$

$$F1 = \frac{2 * Precision * Recall}{Precision + Recall} \tag{3}$$

$$\text{Accuracy} = \frac{TP + TN}{TP + FN + TN + FP} \tag{4}$$

4.3. Performance analysis of BAC model

In this section, we select two baselines BiLSTM + CRF and BiLSTM to compare with BAC. The experimental results are shown in Figures 8–11. Figure 8 shows the accuracy changes of three models. It can be seen that (1) the accuracy of BAC experienced a decrease in the early stages of training, which may reflect an optimisation procedure of parameters of BAC. However, as the training progresses, the accuracy of BAC gradually reaches a peak of 0.932 and ultimately maintains stable fluctuations around 0.928; (2) the accuracy of BiLSTM + CRF is lower during 0–350 epochs, but finally achieves 0.926; (3) the performance of BiLSTM is worst. The curve fluctuates severely during 0–600 epochs, especially in the later stages where it decreases and only rises in very few epochs. Based on the above observations, for tagging tasks containing complex features, we conclude that (1) BiLSTM + CRF is suitable

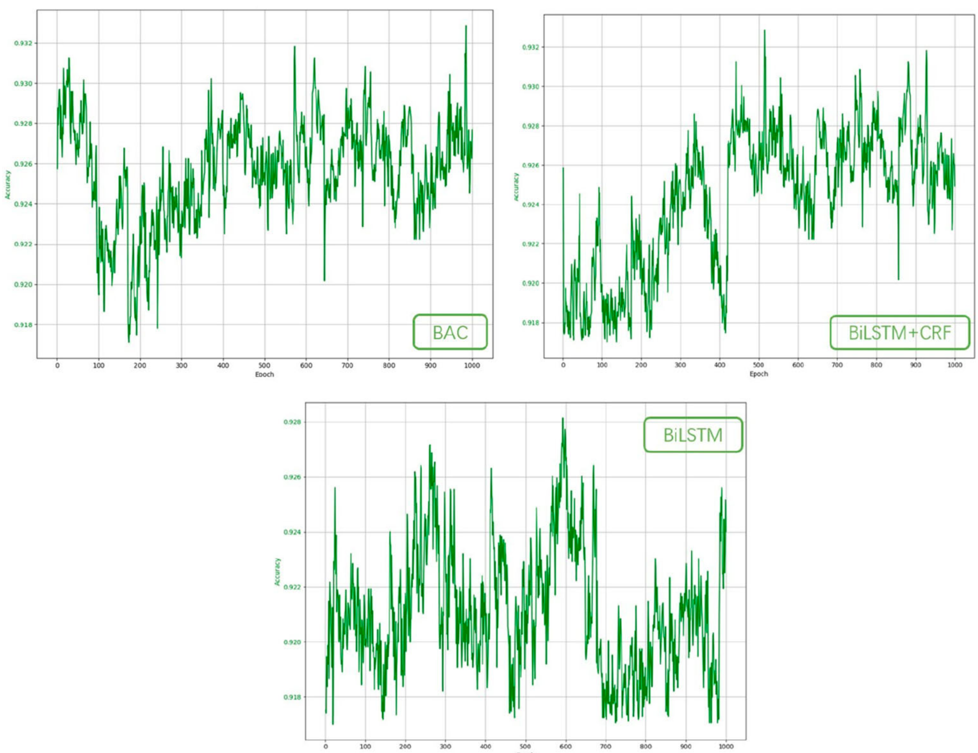


Figure 8. The accuracy curve of three models.

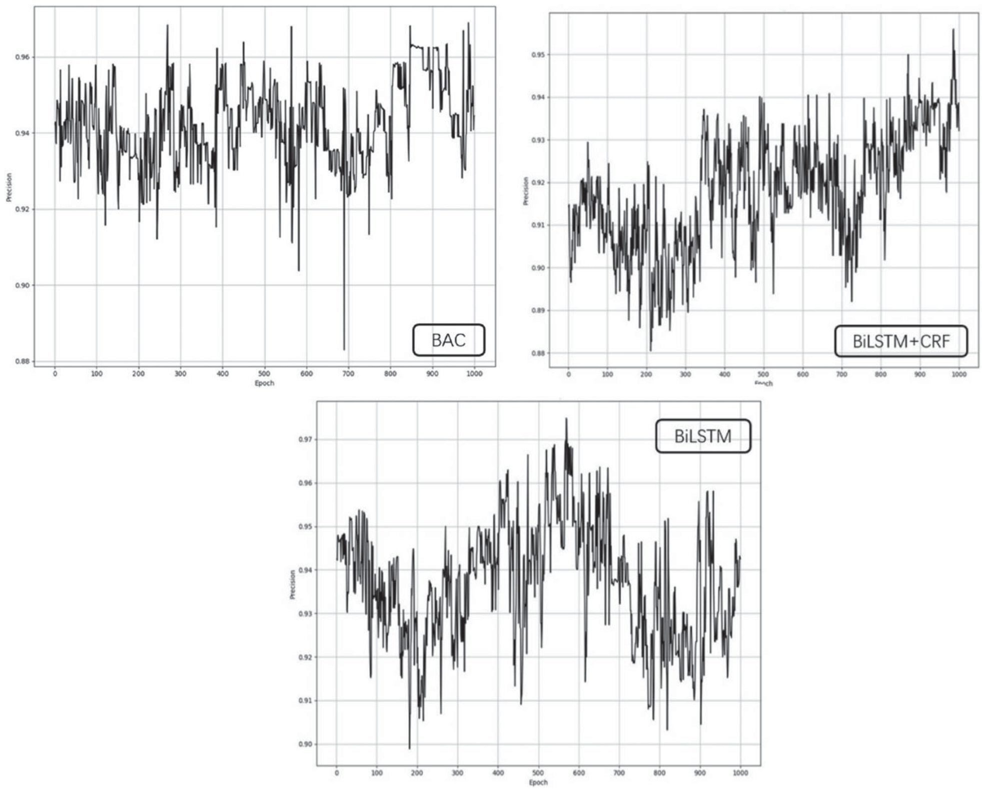


Figure 9. The precision curve of three models.

to a certain degree, whereas BiLSTM is not; (2) BAC performs excellently and characterises with stability and is a reliable choice.

Figure 9 shows the precision changes of three models. It can be observed that (1) BAC keeps a high precision throughout the entire training, with only a few epochs dropping below 0.92. It indicates that BAC can effectively identify entities. (2) The precision of BiLSTM + CRF is slightly lower, fluctuating mostly between 0.90 and 0.94. Combining the first observation, we can conclude that adding an attention layer into BiLSTM + CRF benefits from extracting the key information of entities. (3) The precision of BiLSTM has a decent trend in the early stages of training. As the training continues, the value gradually becomes large. However, the fluctuation is very large. This shows that BiLSTM faces challenges when dealing with complex entities.

In terms of recall, it can be seen from Figure 10 that: (1) the recall curve of BAC steadily increases from 0.70 to 0.76 in the early stages of training. After a brief performance decline, it gradually recovers and reaches a peak of 0.78 during 600–700 epochs. In the later stage of training, after a slight fluctuation, it returns to its optimal performance level again. This demonstrates BAC has an excellent good learning ability; (2) the recall value of BiLSTM + CRF shows significant fluctuations during training, decreasing from 0.77 to around 0.70, then gradually recovering to around 0.75, and finally slowly decreasing to around 0.71. This indicates that although the BiLSTM + CRF model has some learning abilities, it

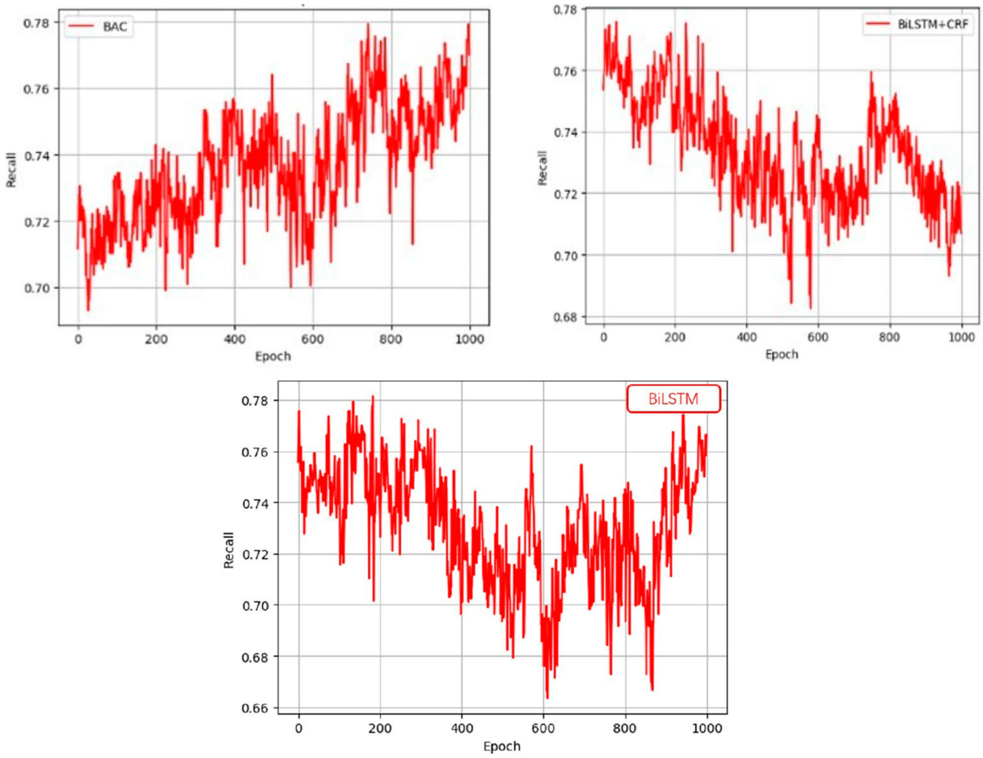


Figure 10. The recall curve of three models.

is slightly inferior to the BAC model in terms of data adaptability and stability; (3) the recall curve of BiLSTM fluctuates more significantly, decreasing from 0.76 to 0.68, and then slowly rebounding to around 0.76. This volatility indicates that BiLSTM lacks robustness when dealing with complex sequential tasks.

Figure 11 shows the F1 of three models. It can be seen from Figure 11 that: (1) BAC has a significant fluctuation in the early stages of training from 0 to 500 epochs, which may be attributed to the instability of the model in learning and adapting to data features in the initial stage. However, as the training time increases, its F1 gradually stabilises and shows a trend of approaching 1. This indicates that BAC can successfully capture key features of the data and has strong generalisation ability; (2) compared to the two baseline models, the F1 of BiLSTM + CRF fluctuates continuously throughout the entire training with a large amplitude. Although F1 approaches 1 at some epochs, this means that enhancing the feature learning ability of BiLSTM + CRF requires a longer time; (3) although the F1 of the BiLSTM fluctuates less than that of the BiLSTM + CRF model, its optimal F1 is only about 0.86, far from the F1 of the BAC model. Based on the above analysis, it can be concluded that compared to BiLSTM and BiLSTM + CRF models, the BAC model exhibits superior performance in NER tasks on any of four indicators such as accuracy, precision, recall and F1. Therefore, the BAC model is a powerful and stable named entity recognition framework suitable for handling complex sequence annotation tasks.

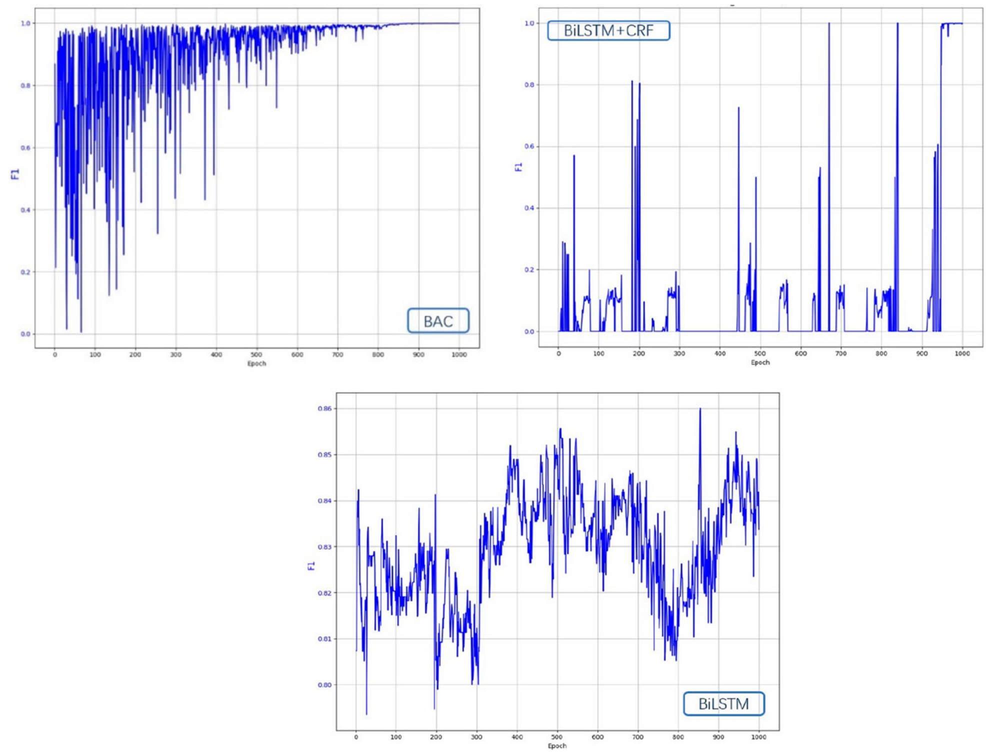


Figure 11. The F1 curve of three models.

4.4. Application effects of GPB model

To verify the application effectiveness of the GPB model, a quantitative analysis was conducted in this paper. Since the GPB model is a collaborative network model composed of GlobalPointer and BiLSTM, this paper selects the GlobalPointer model as the baseline model and uses precision, recall, and F1 as performance evaluation indicators to verify the effectiveness of GPB. The experimental results are shown in Figures 12–14, respectively. Figure 12 shows the precision of the two models. It can be seen that the accuracy of GPB is higher than that of GlobalPointer and has a continuous and stable increasing trend, while GlobalPointer grows slowly in an oscillatory manner. This indicates that the BiLSTM layer in the GPB model can handle complex entity relationships and nested entities well. Figure 13 presents the recall of two models. It can be observed that GPB increases rapidly within 100 epochs, further grows after 550 epochs and reaches around 0.83 at 1000 epochs. Although GlobalPointer keeps an upward trend, the overall growth trend was not as good as that of the GPB model and ultimately reached about 0.7 at 1000 epochs. This shows that the BiLSTM of GPB model can more accurately capture long-range dependencies and complex contextual information in sequences. Figure 14 shows the F1 of two models. It can be seen that GPB model shows continuous improvement and has a small fluctuation, finally achieving around 0.84 at 1000 epochs. Compared to GPB model, GlobalPointer fluctuates more obviously than the GPB at each stage, ultimately reaching around 0.78 at 1000 epochs. This means that the GPB model can improve F1 by balancing precision and recall. From the

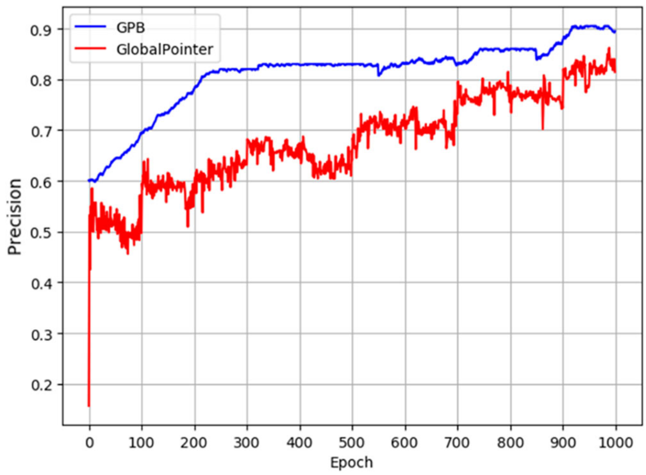


Figure 12. Precision of two models.

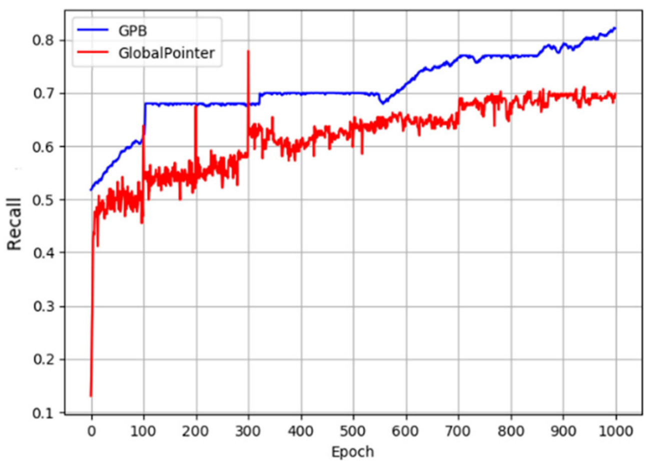


Figure 13. Recall of two models.

above quantitative analysis, it can be seen that the excellent performance of the GPB model in entity recognition is attributed to the introduction of BiLSTM.

In terms of qualitative analysis, we investigated the practical application effect of the developed intelligent Q&A in a motor fault maintenance company. Based on practical application feedback, maintenance engineers confirmed that compared to traditional manual retrieval and expert consultation methods, this Q&A exhibits significant advantages in terms of efficiency and accuracy and can significantly accelerate maintenance progress. For example, if there is an abnormal noise problem with the motor in a real-world industrial production scenario, manually identifying the cause requires professional maintenance personnel to accumulate a lot of experience, as there are many reasons that can cause this type of malfunction. If the repairman is a beginner, he will spend a lot of time repairing the problem. However, by using an intelligent Q&A, maintenance personnel only need to input relevant fault phenomena into the system, and the system can quickly provide possible

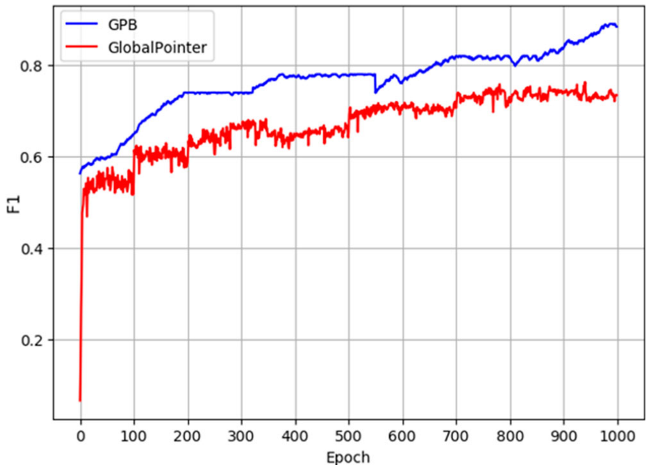


Figure 14. F1 of two models.

fault causes and solutions, greatly reducing downtime and production cost losses. In addition, in terms of accuracy, the actual application statistics within two months have proven that the accuracy of the system in various motor fault problems is as high as 85%. This high accuracy enables maintenance personnel to quickly identify the true source of the fault and avoid additional losses caused by incorrect diagnosis. This means that the proposed GPB model is a promising method for constructing an MFMKG.

5. Discussion

This paper develops an intelligent motor fault maintenance Q&A using the proposed GPB model and BAC model. The GPB model is a collaborative network model composed of GlobalPointer and BiLSTM, which has the ability to model long-distance contexts, ensuring the quality of knowledge in the constructed MFMKG. The BAC model is used to analyse user's questions and accurately identify user intents. Meanwhile, in terms of the performance evaluation indicators such as accuracy, precision, recall and F1, we compare and analyse the performance of the BAC model with two baseline models such as BiLSTM and BiLSTM + CRF on the constructed motor fault maintenance text dataset. The experimental results show that the BAC model is superior to the two baseline models. In addition, the efficiency and accuracy of constructing a knowledge graph using the GPB model have also been verified from the perspective of qualitative and quantitative analysis. After two months of actual operation, the accuracy of the system's answers reached 85%, indicating that the knowledge graph constructed by the GPB model is of high quality and practical.

There are certain restrictions on this study, though. For instance, (1) knowledge graph update: the MFMKG is constructed on the collected dataset using GPB, where new fault maintenance knowledge is not considered how to add to MFMKG, and (2) entity disambiguation: a similarity calculation is used to solve entity ambiguity, whereas the context of questions can be integrated into question analysis module in the Q&A. Therefore, the development of an intelligent motor fault maintenance question answering system can be further improved: (1) plan to introduce graph convolutional network and CRF to achieve a dynamic update of the knowledge graph, and (2) adopt entity linking technology based on knowledge graphs to further improve the accuracy of entity disambiguation.

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CRediT authorship contribution statement: Pin Lyu: writing – original draft, methodology, funding acquisition. Jingqi Fu: experiments, validation, system development. Chao Liu: conceptualisation, methodology, supervision. Wengbing Yu: data curation. Liqiao Xia: writing – review and editing.

Disclosure statement

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