An Adaptive Multi-Neural Network Model for Named Entity Recognition of Chinese Mechanical Equipment Corpus

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Mining entities from open Chinese mechanical equipment texts has become prevailing in the intelligent manufacturing field. However, compared to named entities in other domains, it is very hard to determine entity boundaries in mining Chinese mechanical equipment texts because there is not a unified standard for entity simplification, and digits and units are mixed in the text. To address the issue, this paper presents an entity boundary-define strategy and constructs a mechanical equipment-oriented corpus called MECorpus using open Chinese mechanical equipment texts by combining domain knowledge. A multi-neural network collaboration model Adaptive-BERT-BiLSTM-CRF-Rating (ABBCR) is then proposed for mechanical equipment named entity recognition. The novelty of ABBCR is characterized with its adaptive input mechanism and rating score ability for identified entities. Various experiments about ABBCR model selection, evaluation and application are conducted on MECorpus. Experimental results show that ABBCR model provides high quality mechanical equipment entities for constructing the mechanical equipment knowledge graph. ABBCR combining with large language model is proved to be a promising method to manage the complex mechanical equipment expertise.

named entity recognition; multi-neural network collaboration; fuzzy boundary; adaptive mechanism; bidirectional encoder representations from transformers

1. Introduction

Named entity recognition (NER) is the core step of building a knowledge graph. It aims to extract specific types of entities from complex structured, unstructured, semi-structured data, such as person names, place names, organization names, etc., and classify these entities with specific meanings. Generally, there are four kinds of methods in NER researches including rule-based methods (Jiang, Mark and Salvatore 2023; Yan 2011), unsupervised learning methods (Nadeau and Sekine 2007), feature-based supervised learning methods (Liu et al. 2007) and deep-learning based methods (Rosa et al. 2019;

Zhang et al. 2022). Although the rule-based method has high accuracy in specific domains, it depends on expertise. So it is not scalable. For unsupervised learning method, although it does not need training examples manually labelled, it requires a careful selection of unsupervised algorithms to obtain high accuracy. Similarly, feature-based supervised learning methods not only need a huge manual annotation corpus, but also careful feature engineering to obtain better accuracy. By contrast, since deep learning (DL)-based methods automatically extract features needed for the NER from raw input in an end-to-end manner, it has become a mainstream method (LeCun, Bengio and Hinton 2015) in industrial sectors such as design innovation (Jiang and Luo,2022), design creation (Jiang, Atherton and Sorce 2023) and generalizing design requirements in complex design (Chen and Morkos 2023) and so on.

Compared with NER researches in other domains, mechanical equipment NER faces a challenge that the entity boundary is fuzzy because there is not a unified standard for the entity simplification, and digits and units are mixed in the text, which leads to entities obtained by dividing with different boundaries having different meanings. For example, for the description of "Low temperature alarm function", it can be considered that "Low temperature" and "Alarm" are equipment performance entities of a certain mechanical equipment type respectively, and "Function" is a meaningless entity. Obviously, for a certain mechanical equipment type, "Low temperature alarm function" is an entity with completely independent meaning. In addition, various abbreviations and parameters of mechanical equipment are mixed with text, which also make it difficult to determine an entity boundary. Taking the abbreviation " FCU" as an example, its meaning is obscure since there are no regularities on the simplification of a named entity expression because of the uniqueness and professionalism of the industrial domain. Additionally, the parameter expression of "No load maximum driving speed km/h28213030" containing letters and digitals make mechanical equipment NER more difficult.

To solve the above challenge, we present an entity boundary-define strategy and construct a mechanical equipment-oriented corpus called MECorpus using open Chinese mechanical equipment texts by combining domain knowledge. An adaptive multi-neural network model ABBCR is then proposed for mechanical equipment NER. The main contributions of this research can be highlighted as follows:

(1) A mechanical equipment-oriented corpus called MECorpus is constructed. To the best of our knowledge, it is the first attempt to establish a public Chinese corpus in mechanical equipment domain.

(2) A multi-neural network collaboration model ABBCR is proposed for mechanical equipment named entity recognition. The novelty of ABBCR is characterized with its adaptive input mechanism and rating score ability for identified entities.

(3) A mechanical equipment intelligent Q&A application is developed based on the knowledge graph using the proposed ABBCR to build under the framework of the large language model. This application is proved to be a promising method to manage the complex mechanical equipment expertise.

The rest of the paper is organized as follows. Section 2 reviews the related work. The study roadmap of this work is presented in Section 3. The construction process of the Chinese mechanical equipment corpus is described in detail in Section 4. Section 5 illustrates the proposed ABBCR model. The performance analysis of the proposed model and its application are presented in Section 6. Finally, summaries and future works are discussed in Section 7.

2. Related work

This work builds on existing studies of NER for various domains. Relevant literature on these topics such as NER dataset, DL-based NER model and DL-based NER for industry domains is presented in this section.

2.1. NER Datasets

A NER dataset is a collection of one or more annotated entities. Early NER datasets had few entity types and were only suitable for coarse-grained NER tasks. With the increasing of various kinds of text sources, more and more NER datasets have been developed, and entity types in the datasets has also increased significantly (Li et al. 2022). In recent years, the rapid development of the digital economy has given rise to an upsurge in the application of knowledge graphs. More and more industries, such as production design (Bhattacharya and Chakrabarti 2023), engineering design (Zuo et al. 2022b) and design creativity (Zuo et al. 2022a), have begun to build domain knowledge graphs and use them as technical support for scenario-oriented application services. However, the NER datasets used in these domain-specific knowledge graphs are constructed by enterprises themselves according to their application requirements, and are important private resources of enterprises. Therefore, some new NER methods developed in academia cannot be tested on real NER datasets because they cannot be shared publicly. To solve this problem, before studying how to extract entities from mechanical equipment Chinese texts, this paper first uses open mechanical equipment Chinese text data to build a mechanical equipment NER dataset named MECorpus.

2.2. DL-based NER model

In recent years, DL-based NER models have become a research focus since it can be trained in an end-to-end paradigm (Li et al. 2022). It consists of three layers including the distributed representation for input, context encoder and tag decoder from input to output. The distributed representation for input means that the DL-based NER model can automatically learn the semantic and syntactic properties of word from the text. In the existing NER models, there are three types of distributed representations such as word-level representation, character-level representation and hybrid representation. Word-level representation is essentially pre-trained word embedding. Studies utilize word embeddings for NER. For example, Habibi et al. (2017) applied deep learning and word embeddings in biomedical NER. Thorne and Akhondi (2020) investigated the qualities of different word embeddings for NER on patents from different domains. Besides the word-level representation, researchers also considered how to learn the character-level representation from an end-to-end neural network (Kuru et al. 2016; Tran et al. 2017). Character-level representation has two advantages. One is that it can naturally handle out-of-vocabulary. The other is that it can infer representations for unseen words. To improve the performance of NER model, some studies combined word-level representation and character-level representation in different ways as the input of context encoder (Li et al. 2017; Ma et al. 2016). There are two commonly used methods of combining word-level and character-level representations. One is concatenation, for example, Ma et al. (2016) used convolutional neural network (CNN) to extract the representations of character-level of words. Then, the character representation vector is concatenated with word embeddings before feeding into a RNN context encoder. Lamp et al. (2016) applied bidirectional long short term memory (LSTM) to extract character-level representations and concatenated them with pre-trained word embeddings from a word lookup table. Gridach (2017) used character-level representations and word embeddings concatenation methods to recognize biomedical named entities. Another approach is to use gate mechanisms. For example, Rei et al. (2016) combined word embedding and character-level representation using gate mechanisms. In addition to word-level and character-level representations, some studies have also integrated additional information into the final representation of words, such as lexical similarity (Ghaddar and Langlais 2018) and language dependency (Jie and Lu 2018). This type of distributed representation that adds additional information is called hybrid representations. Its advantage is that it can improve the performance of NER, but the limitation is that it damages the generality of NER systems.

The context encoder is the intermediate layer of the NER model, whose main function is to generate local and global features around each word. The widely-used context encoder structures in NER models include CNN, recurrent neural networks (RNN), recursive neural networks and Transformers. Among them, LSTM and its variants have achieved significant results in sequence data modelling. For example, BiLSTM-CRF (conditional random field) is the first and most commonly used context encoder structure for NER (Huang et al. 2015). Based on the works of (Huang et al. 2015), a body of studies have applied BiLSTM as the basic structure to encode context information. For example, Ju et al. (2018) handled nested NER by improving the standard LSTM model. Katiyar et al.(2018) proposed a neural network model for identifying nested entities by dynamically stacking flat NER layers. Each flat NER layer employs BiLSTM to capture sequential context. The proposed model integrates the output of the LSTM layer in the current flat NER layer to construct new representations for the identified entities and then inputs them into the next flat NER layer. Currently, with the popularity of bidirectional encoder representations from transformers (BERT) (Devlin et al. 2019) and generative pretrained transformer (GPT) (Radford et al. 2018), embedding language models pre-trained with Transformer is becoming a new paradigm for NER. On the one hand, this is because these language model embeddings are contextualized and can be used to replace traditional embeddings; On the other hand, embedding these language models can be further fine-tuned through an additional output layer, which not only improves performance of NER models but also reduces significantly training time for NER tasks.

The tag decoder is the output layer of NER models, which takes context dependent representations as input and generates tags corresponding to the input sequence. There are four commonly-used architectures of tag decoders including multilayer perceptron+softmax (MLP+ softmax) layer, CRF, RNN, and pointer networks. A large number of early NER models used MLP+softmax layer as tag decoder in specific-domain NER tasks (Tomori, Ninomiya and Mori 2016). By contrast, CRF is the most common choice for tag decoders. Many DL-based NER models use CRF as the tag decoder on top of an BiLSTM layer (Huang et al. 2015; Lin et al. 2019). Currently, although CRF is widely used, there are still some studies exploring the use of RNN and pointer networks as tag decoders. For example, Shen et al. (2017) found that RNN label decoders outperform CRF and train faster when the number of entity types is large. Zhao et al. (2017) first applied pointer networks to generate sequence tags. However, a major drawback of RNN and pointer network decoders lie in greedily decoding, which indicates that the input of the current step requires the output of the previous step. This mechanism may have a powerful impact on speed and hinder parallelization.

2.3. DL-based NER for industrial domains

With the rapid development of advanced manufacturing (Lyu et al. 2022a; Lyu et al. 2022b), more and more textual data has emerged in the industrial field. Industrial text classification based on manufacturing discipline, construction of fault text corpus to assist fault analysis, and building of fault knowledge graph play an important role in industrial digital transformation. Aman and Binil (2021) classified entities related to manufacturing science into 12 categories and trained a character-level BiLSTM-CRF entity recognition model using over 500000 scientific abstracts related to manufacturing science. The trained model is used for automatic classification of industrial texts. A communication equipment fault corpus is built by analysing the fault text characteristics of communication equipment of the industrial internet of things (IIT) and designing entity classification principles (Liang et al. 2022). A character-level ALBERT-BiLSTM-CRF model are then employed to identify fault entities for real-time fault analysis and efficient troubleshooting of communication equipment of the IIT. He et al. (2022）analyzed the features of the critical power equipment maintenance record texts, divided entities in the power field into seven categories, and extracted the text features using the progressive multi-level root feature extraction method based on characters. A BiLSTM-CRF model was utilized to identify the entities for building a knowledge graph of power equipment maintenances. Although these NER models have been successfully applied in the industrial field, the corpus for these applications mainly comes from abstracts of manufacturing related journals and maintenance records of specific equipment. It can be seen that, currently, there is a lack of NER research related to mechanical equipment texts.

3. Study roadmap of this work

Figure 1 depicts the study roadmap of this work, which contains three main modules. The first module is constituted of three data processing steps of obtaining MECorpus dataset. As we all known, DL-based NER models require a big and annotated corpus. However, data annotation is time-consuming and expensive. For many specific domains, this is a big challenge. Since there is no publicly available mechanical equipment dataset for NER researches, Chinese mechanical equipment texts related to road machinery from industrial open data are firstly collected. After comparing the text characteristics of NER in general domain and mechanical equipment domain, a mechanical equipment corpus called MECorpus is built with the help of the domain experts, which lays a foundation for mechanical equipment-oriented NER researches.

Aiming to identify the mechanical equipment entities for MECorpus, a mechanical equipment NER model ABBCR with scoring function is proposed in the second module, combining the requirements of NER application in the mechanical equipment domain and the most popular NER structure based on deep learning. The proposed ABBCR model is an adaptive multi-neural network model which can efficiently and accurately recognizes entities in MECorpus dataset. The last module is about the application of ABBCR model. A mechanical equipment knowledge graph is first built using ABBCR model. Subsequently, the constructed mechanical equipment knowledge graph is used to develop an intelligent Q&A which provides potential users with a fast way to obtain information on mechanical equipment of interest.

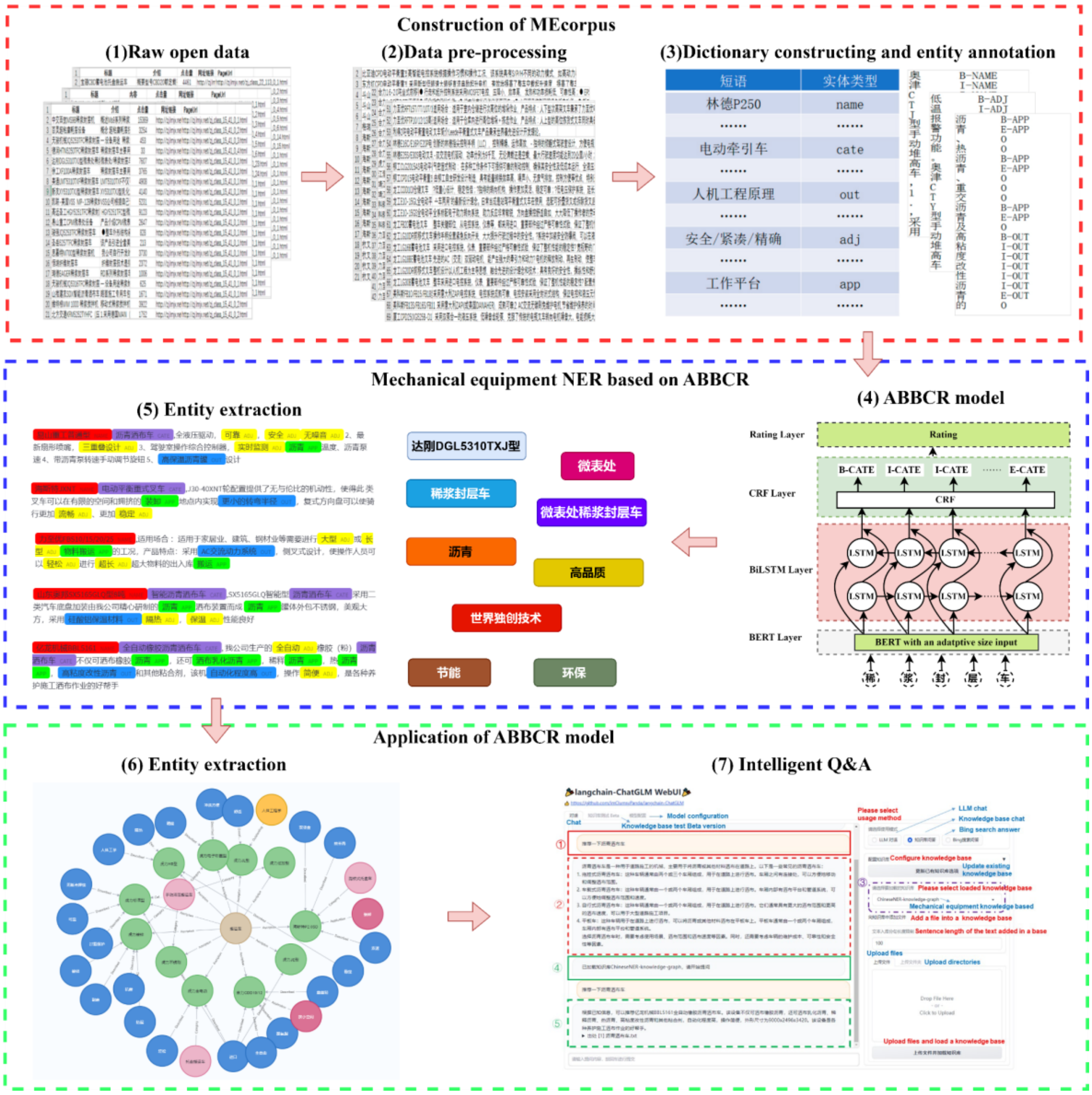


Figure 1. Study roadmap of this work.

4. MEcorpus construction

4.1. Data preparation

The mechanical equipment corpus named MEcorpus is constructed based on the pavement mechanical equipment texts from the China Pavement Machinery Website(https://www.lmjx.net). The website owner of China Pavement Machinery Website is China Construction Machinery Association Road Machinery Chapter, which is one of the most authoritative and influential portal websites for pavement machinery in China. China Pavement Machinery Website has become the first e-commerce platform for construction machinery in China. It covers a variety of engineering machinery products, including road machinery, earthwork machinery, lifting machinery, concrete machinery, and piling machinery. The users who log in to the website have covered 35 provinces and regions in China and more than 150 countries worldwide. It is not only the preferred website for many construction units, lessees, and end users both domestically and internationally to obtain and compare product information, but also the most convenient channel for decision-makers, managers, and engineering technicians in Chinese construction machinery production and sales units to quickly understand industry trends, obtain business opportunities, and publish product procurement and sales information. According to monitoring data from non-profit web pages, as of December 17, 2023, China Pavement Machinery Website ranked 1080 in total in China, ranking third in the classification of mechanical industries in the Chinese region with a Page Rank value of 5. It covers over 10000 products in 18 categories of construction machinery which are visited by over 2.86 million end users and over 200 industry enterprises. Therefore, the data in China Pavement Machinery Website is reliable and validity, and collecting data from this website can ensure the high-quality and high availability of the dataset MECorpus (https://github.com/yyyiron/MECorpus).

We take 13 kinds of mechanical equipment such as transporters, electric forklifts, tractors, slurry seal trucks, asphalt distributors, crawler cranes, internal combustion forklifts, other kinds of forklifts, stone chip spreaders, horizontal directional drills, tower cranes, synchronous seal trucks and milling machines as examples, and crawl the original data of these mechanical equipment texts from the China Pavement Machinery Website. The original data is first pre-processed, and then divided the pre-processed data into sentences using full stop.

The size of dataset before and after data pre-processing is shown in Table 1. Each row in Table 1 represents a piece of text description of a mechanical equipment. The text description of each mechanical equipment consists of two parts including the title and the equipment introduction. The content of the title includes the mechanical equipment name and type. For example, "詹阳动力 JYL020H (Zhanyang power jyl020-h)" belongs to mechanical equipment name and "混合拖拉机(hybrid tractor)" represents a subcategory of a tractor. The equipment introduction mainly describes the outstanding characteristics and applicable scenarios of mechanical equipment. For example, the "驾乘舒适，适用于长途装载运输和中短途运输，尤其适用于集装箱运输(comfortable driving and riding, suitable for long-distance standard load transportation and medium and short distance transportation, especially suitable for container transportation)" in the equipment introduction describes the outstanding characteristics and applicable of the tractor.

Table 1. The statistical information of MEcorpus.

Category of mechanical equipment	Chinese name of mechanical equipment	Size of original dataset (Lines of texts)	Size of dataset after preprocessing (Lines of texts)

Transporters	运输车	217	97
Electric forklifts	电动叉车	356	118
Tractors	拖拉机	170	66
Slurry seal trucks	稀浆封层车	54	43
Asphalt distributors	沥青洒布车	169	102
Crawler cranes	履带吊	943	267
Internal combustion forklifts	内燃叉车	433	169
Other kinds of forklifts	其他种类叉车	130	31
Stone chip spreaders	石屑撒布机	17	16
Horizontal directional drills	水平定向钻	631	117
Tower cranes	塔吊	1730	137
Synchronous seal trucks	同步封层车	80	6
Milling machines	铣刨机	135	108
Total		5065	1277

4.2. Entities definition

Different from general NER based on standardized text, mechanical equipment NER faces a challenge of entity definition since the boundary of entities is ambiguous in mechanical equipment corpus. For example, the description "全自动沥青洒布车(fully automatic asphalt distributor)" can not only be regarded as an entity, but also be understood as two different types of entities. One is the entity of equipment performances "全自动(fully automatic)", the other is the entity of equipment types " 沥青洒布车(asphalt distributor) ". It can be seen that the different boundaries produce the different entities. However, there is only one true equipment entity "沥青洒布车(asphalt distributor) " that conforms to industrial mechanisms. To solve the problem, after referring to the English Chinese and Chinese English Dictionary of construction machinery and the suggestions of domain experts, the following six strategies for deciding entity boundaries are proposed in this work.

(1) ***Strategy 1*: **The brand name of mechanical equipment should be marked as an entity. If the brand name is highly similar, it should be simplified as an entity. For

example, "*BYD cpd15*" and "*BYD cpd20*" are similar brands and should be simplified as an entity "*BYD cpd* ".

(2) ***Strategy 2*****:** When the brand name of a mechanical equipment is connected with the name of an equipment type, it shall be annotated separately. For example, "海斯特 AXL 电动平衡重式叉车(*Hester Axl electric counterweight forklift)* " should be marked as "海斯特 AXL(*Hester axl*) " and "电动平衡重式叉车(*electric counterweight forklift*) " respectively. The former is the equipment name, and the latter is the equipment type.

(3) ***Strategy 3*****:** When marking the performance and application of an mechanical equipment, three cases need to be considered: 1) the description of an equipment appearance and its use experience, such as "平整光滑(*flat and smooth*) ", "视野开阔(*wide field of vision*) ", should be marked as an equipment performance; 2) the description of an equipment application, for example, "公路养护(*highway maintenanc*e)", "中短途运输(*medium and short distance transportation*)", should be tagged as an equipment application; 3) the description of the outstanding characteristic of an equipment, such as "AC 交流动力系统(*the latest AC traction control technology*) " and "自主知识产权(*independent intellectual property rights*) ", should be marked as an outstanding characteristics of an equipment.

(4) ***Strategy 4*****:** When marking the Chinese and English abbreviations of a mechanical equipment, two rules need to be followed: 1) the Chinese and English abbreviations of a mechanical equipment must be marked as an entity, for example, "*fcu*" is an entity; 2) it is necessary to understand the meaning of Chinese and English abbreviations of a mechanical equipment before assigning it an entity

type. For example, "*fcu*" represent an equipment performance entity since it denotes a fan coil unit in an equipment.

(5) ***Strategy 5*: **When an equipment application and its type occur adjacently front and back, it should be tagged as a whole and regarded as an equipment type. For example, when the description "乳化沥青(*emulsified asphalt*) " occurs before the description "稀浆封层车 (*slurry seal truck*) ", it should be marked as an entity " 乳化沥青稀浆封层车(emulsified asphalt slurry seal truck) ".

(6) ***Strategy 6*: **When extracting the specific equipment parameters, the entity in front of the number should be recognized as equipment parameters. For example, for the pair "铣宽(*milling width mm10002*), 铣深(*milling depth mm0-1803*) ", the pair "(铣宽,铣深)(*milling width, milling depth*) " is regarded as an equipment parameter.

Based on the above-mentioned six strategies, this paper gives six annotation rules of mechanical equipment entities. The descriptions before numbers or English letters in the title are defined as the equipment name. The descriptions after the number or English letter in the title are marked as the equipment type. The adjectives and adverbs in the equipment introduction are defined as equipment performance. Comparing all equipment of the same kind, the performance descriptions that an equipment has but other equipment does not have are tagged as the outstanding characteristics of the equipment. The descriptions of the equipment application in the equipment introduction are marked as the equipment application. The descriptions in front of the number with unit in the introduction are tagged as the equipment parameter.

4.3. Entities tagging

The annotation of mechanical equipment named entities in the MECorpus dataset consists of three steps: 1) defining entity categories, 2) annotating entities, and 3) format conversion. The domain experts involved in entity annotation are all workers from the production workshops of two large construction machinery companies. In the first step, the role of domain experts is to determine the information that users are most concerned about when purchasing and using mechanical equipment based on their own work experiences. According to the feedback of domain experts and six entity annotation rules described in Section 4.2, this paper ultimately defines six types of mechanical equipment named entities including equipment name, equipment type, equipment performance, equipment application, outstanding characteristics of equipment and equipment parameters, as shown in the first column of Table 2. In the second step, experts manually annotate each paragraph of text in the dataset MECorpus based on defined entity categories.

In the third step, first, the experimenters in this work convert each entity to the BIEO annotation mode, as shown in columns 3 to 5 of Table 2. Although BIO and IOB are also annotation mechanisms used for NER. However, BIO cannot clearly indicate the end position of an entity, which may lead to errors when identifying nested mechanical equipment entities or mechanical equipment entities composed of multiple words. Similarly, the label B in IOB is only used to distinguish the boundaries of two consecutive named entities of the same type, and cannot be used for the starting position of the named entity, which may result in incorrect recognition of two adjacent named entities of different types of mechanical equipment. On the contrary, the BIOE annotation mechanism can provide clear boundary indications for entities, which is more conducive to improving the accuracy of entity recognition. Therefore, this paper adopts the BIEO annotation mode. Then, experts check whether the BIEO annotation mode for each entity is correct.

Table 2. Mechanical equipment named entity category.

Entity categories	Chinese name of entity categories	Beginning of an entity	Inner of an entity	End of an entity
Equipment name	设备名	B-NAME	I-NAME	E-NAME
Equipment type	设备种类	B-CATE	I-CATE	E-CATE
Equipment performance	设备性能	B-ADJ	I-ADJ	E-ADJ
Equipment application	设备应用	B-APP	I-APP	E-APP
Outstanding characteristics of equipment	设备突出特征	B-OUT	I-OUT	E-OUT
Equipment parameters	设备参数	B-PAR	I-PAR	E-PAR

4.4. Statistics of entities in MEcorpus

A mechanical equipment named entity corpus MEcorpus based on tag-level named entity annotation is constructed using the named entity tagging mechanism in Section 4.2 and the named entity categories mechanism in Section 4.3. The statistics of mechanical equipment entities in MEcorpus is shown in Table 3. MEcorpus has a relatively large number of entities in each category, which can be used as a corpus for NER in the domain of mechanical equipment.

Table 3. The statistics of entities in MEcorpus.

Entity categories	Chinese name of entity categories	Number of entities
NAME	设备名称	1289
CATE	设备种类	401
ADJ	设备性能	344
APP	设备应用	117
OUT	设备突出特征	122
PAR	设备参数	225

5. Proposed model

5.1. Pipeline of ABBCR

The overall bottom-to-top pipeline of the proposed model ABBCR is shown as Figure 2. Specifically, the pipeline consists of four parts including BERT layer, BiLSTM layer, CRF layer and Rating layer. Let denote the set D as MEcorpus, $D = \{d_1, d_2, \cdots, d_n\}$, where d_i is a piece of text of the ith equipment introduction. Assuming there are m sentences in the text of the ith equipment introduction after dividing the text into sentences, that is $d_i = \{s_{i1}, s_{i2}, \cdots, s_{im}\}$, where s_{ij} refers to the jth sentence in the ith equipment. Assuming that w_{ijk} is the kth character of s_{ij}, then $s_{ij} = \{x_{ij1}, x_{ij2}, \cdots, x_{ijn}\}$. The proposed model generates the feature vector $\boldsymbol{E}_k$ according to each character w_{ijk} in the text sequence, changes $\boldsymbol{E}_k$ into the character vector $\boldsymbol{T}_k$ with character and position features based on the character vector in Transformer (Trm) of BERT layer. The generative character vectors are fed into the forward LSTM $\boldsymbol{F} = \{\boldsymbol{F_1}, \boldsymbol{F_2}, \cdots, \boldsymbol{F_n}\}$ and backward LSTM $\boldsymbol{B} = \{\boldsymbol{B_1}, \boldsymbol{B_2}, \cdots, \boldsymbol{B_n}\}$. The BiLSTM layer extracts the context features to form features matrix P_k. The CRF layer captures the dependency between adjacent tags according to the feature vector of P_k and outputs the corresponding tags. Finally, the rating scores of extracted entities are computed by the score function in Rating layer.

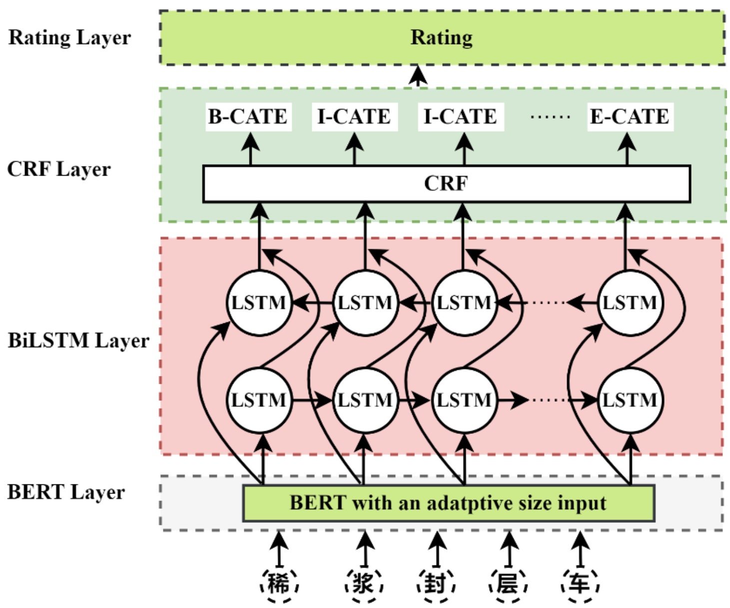


Figure 2. The bottom-to-top pipeline of the proposed model ABBCR.

5.2. Architecture of ABBCR

The network structure of ABBCR model are shown in Table 4. The first column in Table 4 represents the four different layers of the ABBCR model. The second column lists the main functions of each layer from the perspective of program implementation. The third and fourth column respectively represent the input and output when each function is realized. The fifth column indicates the number of layers of the network when realizing the main functions of each layer. The input of ABBCR model is a tensor ([1,80], [1,80], [1,80]), which indicates that each sentence has 80 characters. Each character has an entity category. When the value of the character vector is greater than 0, the third dimension of the tensor is 1, otherwise 0. Among them, the value of 80 is the interception length adaptively generated by the ABBCR model according to the number of full stops in MECorpus. The detailed explanation of ABBCR model structure is as follows:

Table 4. The network architecture of the ABBCR model.

Layer name	Main function of each layer	Input size	Output size	Number of layers

BERT layer	BertEmbeddings	[21128,768]	[1,768]	5
	BertEncoder	[1,80,768]	[1,80,768]	(4,12)
	BertPooler	[1,80,768]	[1,80,768]	2
BiLSTM layer	LSTM	[1,80,768]	[1,80,12]	1
	Dropout	[1,80,12]	[1,80,12]	1
	linear	[1,80,12]	[1,80,22]	1
CRF layer	Crf.loss	([1,80,22],[1,80],[1,80])	[1,1]	1
	Crf.decode	([1,80,22],[1,80])	[1,80]	1
Rating layer	Rating	{([1,80,19],[1,22]),[1,80]}	[1,1]	1

- *BertEmbedding*: convert the text into a corresponding character vector matrix. Each line in the matrix represents a character vector. The one-hot code of each character corresponds to its line number in the character vector matrix. The MECorpus contains 21128 characters.
- BertEncoder: take the output of the BertEmbedding layer as the input, and add a special symbol [cls] to represent a complete sentence for classification. After 12 levels of encoding, the character vector of each character is finally output. Each character in this experiment is a 768 dimensional vector.
- *BertPooler*: *BertPooler* module is used to solve sequence tasks. The sequence tasks only need the output corresponding to the [cls] position. Therefore, the full connection layer using the *BertPooler* module only receives the output corresponding to the first character ([cls]) in the *BertPooler* module.
- *LSTM*: the multilayer long short term memory network is used to deal with the output of *BertPooler* module.
- *Dropout*: during ABBCR model training, some elements of the input tensor are randomly set to zero with the Bernoulli distribution with probability p=0.05. Each channel will be independently zeroed at each operation.
- *Linear*: perform linear transformation on the data from LSTM layer.

- *Crf.loss*: the log likelihood of the text is calculated according to the relevant linear data, the input tag sequence and the emission fractional tensor.
- *Crf.decoder*: Viterbi algorithm is used to find the best decoding of tag sequence under the condition of given emission fractional tensor, so as to convert text coding into Chinese fonts with the help of 22 methods including [cls].
- *Rating:* according to the conversion results of the function *Crf.decoder*, the predicted rating score of this sentence is obtained, and the error between the predicted and actual rating score is calculated.

5.3. Role of rating layer

Rating layer of ABBCR play two roles in this study. First, from the perspective of model learning, it is regarded as a tunable parameter for improving the performance of ABBCR model. During of the training of ABBCR model, the error between the sum of the rating scores of the entities identified by the ABBCR model and the sum of the ratings scores of the actual entities in the training dataset is used to determine whether the ABBCR model needs to be further trained, whether overfitting occurs, whether model parameters need to be adjusted, and whether the optimization algorithm needs to be optimized. In this work, we set the error interval to be [0.02,0.05]. This is because we observe that the ABBCR model converges within this interval during at least one hundred training evaluations.

Second, from the perspective of application of model, by analysing the original mechanical equipment dataset with domain experts, it is found that the number of equipment performance entities and outstanding characteristics of equipment entities corresponding to the same type but different brands are different. This means that numbers of identified entities can reflect progressiveness or good usability of the equipment. Consequently, for the same type of equipment, the higher the score of the entity identified by the ABBCR model, the better the progressiveness or availability of the equipment. So, the role of Rating layer is used to distinguish different equipment.

6. Experiments

6.1. Model selection

6.1.1. Experimental setup

This work selected the most commonly used 10-fold cross validation to establish the ABBCR model and selected the optimal parameters for the ABBCR. There are three main reasons for choosing 10-fold cross validation: 1) fully utilized the dataset MECorpus to let more data in MECorpus can be trained; 2) improve the accuracy and stability of model evaluation to reduce ABBCR performance errors caused by random data partitioning; 3) select the optimal hyperparameter combination and improve the performance of the model to reduce the risk of overfitting of ABBCR.

The specific process of 10-fold cross-validation consists of two steps in this work. First, MEcorpus is divided into 10 subsets of equal size. Each subset is obtained by stratified sampling. The union of 9 subsets is used as the training data, and the remaining one is used as the test data. A total of 10 groups of training data and test data are obtained. Second, Precision, Recall, and F1-score values are applied to the model evaluation. There are a total 10 tries for each training and testing, respectively.

All experiments are run on a single NVIDIA Geforce GTX1080 Ti GPU, and the experimental environment is Python 3.7.0, Pytorch and machine learning toolkits scikit-learn. Each experiment in this work used 10-fold cross validation ten times. Based on the mean value of 10 trials, the optimal hyperparameters used in the ABBCR model are selected and shown in Table 5.

Table 5. Hyperparameters used in ABBCR.

Hyperparameter	value
Batch_size	64
Dropout	0.05
Epochs	100
Hidden_dim	256
Learning rate	0.001
Weight_decay	0
Eps	1e-10
Embedding_dim	768

6.1.2. Rating determination of entity categories

The of rating score for different type of entities is determined by qualitative and quantitative analysis. Qualitative analysis adopts a manual approach, in which the experimenter of this work and domain experts jointly determine the ground truth for setting rating scores in the quantitative analysis process. The ground truth contains three cases: 1) after analysing the dataset MEcorpus, it is found that the number of equipment performance entities and outstanding characteristics of equipment corresponding to different mechanical equipment are different; 2) according to feedback from domain experts, the outstanding characteristics of equipment is more attractive to consumers than general features; 3) referring to the star rating mechanism in the e-commerce field, the rating score in the Rating layer of ABBCR is taken as a positive integer with an interval of [1,5]. Moreover, according to case 2, we divide the six types of entities into two classes, denoted as A and B. Class A only includes an entity category of the outstanding characteristics of equipment. The remaining five classes belong to Class B. The rating score of entities belonging to the same class are the same.

Based on the above-mentioned qualitative analysis, in the quantitative analysis stage, we conducted the experiments under 10 different combinations, as shown in Table 6, in the terms of two evaluation metric such as F1-score and convergence time of training ABBCR model. From Table 6, it can be seen that: 1) the performance of ABBCR model achieves 0.8 at least. The performance of combination (4, 2) is the lowest, at 0.827, and combination (3, 1) is the highest, at 0.8933, with a difference of 6.6%. This indicates that the different rating combination used in this work does not have a significant impact on the performance of ABBCR model; 2) when the difference in rating score between Class A and Class B is the same, the convergence time of the model training for different combinations varies little. But the larger the difference, the higher the overall performance of the model (except for combinations (4, 2)). This shows the outstanding characteristics of equipment and other general features need to be clearly distinguished; 3) as the difference between the rating score of Class A and Class B increases, the convergence time of the model training under different combinations shows an increasing trend. Among them, combination (5,1) took the longest time of 143.5 seconds. This means that the more obvious of the distinction between entities A and B, the greater the error between the predicted rating scores and the actual rating scores, leading to an increase in model training time. Based on these analyses, we select the combination (3,1).It corresponds to the highest model performance and an appropriate convergence time. Thus, the rating score for the entity type "outstanding characteristics of equipment" is set to 3, while the rating score for all other entity types is set to 1 in the experiments of this paper.

Table 6. Quantitative analysis of ten combinations of rating scores.

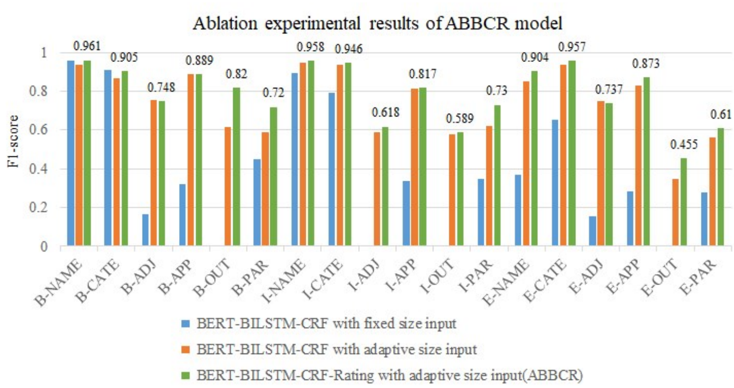
Combination（A,B）	F1-score	Convergence time of training ABBCR（s）
（2，1）	0.840	111.2
（3，1）	0.893	120.4
（4，1）	0.889	127.2
（5，1）	0.857	143.5
（3，2）	0.843	115.8
（4，2）	0.827	125.5
（5，2）	0.840	130.5
（4，3）	0.838	110.5

（5，3）	0.851	124.6
（5，4）	0.841	110.7

6.2. Model evaluation

6.2.1. Ablation experiments

To verify the impact of the two improved points "the adaptive input mechanism and rating score ability" on the overall performance of ABBCR, ablation experiments were conducted. Since the ABBCR model is mainly composed of BERT, BiLSTM, CRF and Rating layer, three models were selected in the experiments, namely BERT-BiLSTM-CRF with fixed size input, BERT-BiLSTM-CRF with adaptive size input, and BERT-BiLSTM-CRF with adaptive size input+Rating layer as three baseline model to compare with ABBCR. The entity-level performance of three different models were observed in the experiments. The experimental results are shown in Figure 3. It can be seen that 1) the performance of BERT-BiLSTM-CRF with adaptive length input is better than that of BERT-BiLSTM-CRF with fixed length. This indicates that determining input size into the model based on the position of the full stop in the input text can improve the performance of NER compared to the existing fixed size input; 2) The performance of the ABBCR model constructed by adding a Rating layer to BERT-BiLSTM-CRF with adaptive size input is also better than that of BERT-BiLSTM-CRF with adaptive length. Similarly, this means that design a rating function in the Rating layer can also improve



the performance of NER.

Figure 3. The effective analysis of the ABBCR model.

6.2.2. Performance comparison

In this section, we selected six baseline models, and divided it two categories from the perspective of model boundary sensitivity, as shown in Table 7. The goal of dividing baseline models into two categories is to observe whether boundary-sensitive models, such as CRF, HMM, and GlobalPointer, are better than the ABBCR model which is a multi-network collaborative model. The entity-level experimental results are shown in Table 7. The experimental results show that the proposed ABBCR model is better than the other baseline models for NER in the mechanical equipment domain.

Table 7. Comparison of entity recognition model effects.

Comparative models	Model name	Precision	Recall	F1-score
Proposed model	ABBCR	**0.850**	**0.775**	**0.806**
The first type baseline models	LSTM-CRF	0.513	0.531	0.554
	BiLSTM-CRF	0.576	0.445	0.486
	BERT-BiLSTM-CRF	0.832	0.757	0.788
The second type baseline models	CRF	0.232	0.247	0.174
	HMM	0.179	0.056	0.062
	GlobalPointer	0.257	0.242	0.277

By observing the experimental results of the first class of baseline model in Table 7, it is found that compared with BiLSTM-CRF, the BERT pretraining can learn more text features. Compared with LSTM-CRF, the proposed model improves the *Precision* by 33.7%, the *Recall* by 24.4%, and the *F1-score* 25.2%. Compared with BiLSTM-CRF, the proposed model improves the *Precision* by 27.4%, the *Recall* by 33%, and the *F1-score* 32%. Compared with BERT-BiLSTM-CRF, proposed model improves the *Precision* by 1.8%, the *Recall* by 1.8%, and the *F1-score* 1.8%. This is because the character level feature vectors in the first type baseline models only considers the characteristics of characters and ignores the contexts of the character. The proposed ABBCR model combines character features, sentence features, and position features to generate character vectors, and uses Transformer to train character vectors, which fully considers the impact of contextual information on entities identification.

Meanwhile, for the second types of baseline models, it is found that compared with CRF, the proposed model improves the *Precision* by 61.8%, the *Recall* by 52.8.1%, and the *F1-score* 63.2%. Compared with HMM, the proposed model improves the *Precision* by 67.1%, the *Recall* by 71.9%, and the *F1-score* 79.8%. Compared with GlobalPointer, the proposed model improves the *Precision* by 59.3%, the *Recall* by 53.3%, and the *F1-score* 52.9%. This is because the baseline models such as CRF and HMM do not consider sentence features and character position features, resulting in a significant gap in *Recall* and *Precision* compared to the proposed ABBCR model in this paper. In addition, GlobalPointer model has strict requirements for the boundary of entities, but boundaries of entities of mechanical equipment corpus are fuzzy, resulting in lower accuracy. This indicates that the GlobalPointer model is not suitable for NER in the field of mechanical equipment. In addition, Tables 8 and Table 9 illustrate the performances of different models in identifying tag-level entities of different categories in detail. From Table 9, it is found that boundary-sensitive models performed very poorly on dataset MECorpus. This means that the second type of baseline models is not comparable. Hence, in subsequent experiments, we only focus on the first type of baseline models.

Table 8. Experimental effects of the first type baseline models and ABBCR on identifying various of tag-level entities.

Entity category	ABBCR			LSTM-CRF			BiLSTM-CRF			Bert-BiLSTM-CRF		
	Precision	Recall	F1-score	Precision	Recall	F1-score	Precision	Recall	F1-score	Precision	Recall	F1-score
NAME	**0.9157**	**0.886**	**0.9407**	0.6707	0.516	0.5613	0.5257	0.484	0.5023	0.864	0.871	0.884
CATE	**0.941**	**0.9533**	**0.9473**	0.856	0.798	0.8247	0.862	0.805	0.8327	0.9293	0.9497	0.9397

ADJ	**0.8853**	0.761	**0.847**	0.5717	0.255	0.3497	0.5327	0.276	0.332	0.859	**0.7707**	0.809
APP	0.8207	0.6023	0.6957	0.316	0.1923	0.255	0.5517	0.3173	0.4247	**0.85**	**0.7133**	**0.7733**
OUT	**0.6433**	**0.6683**	**0.655**	0	0	0	0	0	0	0.5993	0.3867	0.4653
PAR	**0.863**	0.8443	0.8573	0.672	0.4173	0.515	0.77	0.6173	0.6767	0.8603	**0.8533**	**0.8577**

Table 9. Experimental effects of the second type baseline models and ABBCR on identifying various of tag-level entities.

Entity category	ABBCR			CRF			HMM			GlobalPointer		
	Precision	Recall	F1-score	Precision	Recall	F1-score	Precision	Recall	F1-score	Precision	Recall	F1-score
NAME	0.9157	0.886	**0.9407**	0.0647	0.1118	0.082	0.3817	0.2827	0.1797	0.14	0.22	0.17
CATE	0.941	**0.9533**	0.9473	0.3628	0.3696	0.2707	0.0833	0.0202	0.0325	0.33	0.19	0.16
ADJ	**0.8853**	0.761	0.847	0.4095	0.0797	0.1308	0.4408	0.025	0.0284	0.45	0.33	0.57
APP	**0.8207**	0.6023	0.6957	0.2353	0.2906	0.251	0	0	0.0317	0.22	0.39	0.19
OUT	0.6433	**0.6683**	0.655	0.004	0.2222	0.0079	0.1667	0.0032	0.0284	0.09	0.04	0.13
PAR	**0.863**	0.8443	0.8573	0.3145	0.407	0.3039	0.0037	0.0037	0.0733	0.31	0.28	0.44

6.2.3. Context sensitivity of ABBCR

In addition, this paper also uses context sensitivity as an indicator to study the degree of dependence of the ABBCR model on contextual information. A good NER model can correctly understand the meaning of entities based on contextual information. Context sensitivity of a NER model refers to the proportion of correctly recognized entities to the number of real entities. The better the context sensitivity of the model, the more entities can be correctly recognized. Therefore, we randomly selected 100 texts from the MECorpus dataset. These 100 texts cover the introduction of four types of mechanical equipment including electric forklifts, transporters, asphalt distributors, and slurry seal trucks. Since each text corresponds to an introduction of different mechanical equipment, these 100 texts essentially express that the entities that the model needs to recognize are located in different contexts. Then, ABBCR, LSTM-CRF, BiLSTM-CRF, BERT BiLSTM-CRF are used to extract entities from these 100 texts. To ensure the fairness of the comparison results, the recognition results of each model were manually checked and entities that did not match semantics were removed. Table 10 lists the number of entities recognized by ABBCR and three baseline models, and Table 11 shows the context sensitivity of different models. From Table 11, it can be observed that 1) compared to BERT-BiLSTM-CRF, BiLSTM-CRF has a 0.32 decrease in context sensitivity, which indicates that adding BERT pretraining to a NER model can better represent the contextual information of tokens; 2) The ABBCR model has the highest context sensitivity with 0.65, followed by the BERT-BiLSTM-CRF model with 0.56. This means that improving the input and adding rating scores for entities for BERT-BiLSTM-CRF model can further enhance the correct understanding of entity context information in a NER model.

Table 10. The number of entities identified by different models from 100 texts.

Model	Number of different type of entities						
	Equipment name	Equipment type	Equipment performance	Equipment application	Outstanding characteristics of equipment	Equipment parameters	Total
ABBCR	90	100	260	120	90	85	745
BERT-BiLSTM-CRF	90	92	200	114	81	80	657
BiLSTM-CRF	88	84	188	100	30	87	577
LSTM-CRF	80	70	150	79	20	56	455

Table 11. Experimental results of context sensitivity of different models.

Model	Number of entities correctly identified(A)	Number of entities incorrectly identified (B)	the number of real entities (C)	Context sensitivity [(A-B)/C]
ABBCR	1292	245	1603	0.65
BERT-BiLSTM-CRF	1263	366	1603	0.56
BiLSTM-CRF	800	416	1603	0.24
LSTM-CRF	888	399	1603	0.31

6.2.4. Computational costs of ABBCR

ABBCR is an improved version of the BERT-BiLSTM-CRF model. The first improvement is to segment the input before BERT layer. So the input size of ABBCR changes with the different positions of full stops in the text. The second improvement is that it adds a rating score calculation for the recognized entities after the CRF layer. Therefore, the time complexity of the ABBCR model mainly consists of four parts: 1)

BERT obtains the context representation of the input text; 2) BiLSTM models the context representation; 3) CRF models and optimizes the tags, and 4) calculate the rating scores of identified entities. Hence, its time complexity is $\mathrm{O}(N^2 \times L) + \mathrm{O}(N \times M \times K) + \mathrm{O}(N^2 \times C) + \mathrm{O}(\mathrm{C})$, where N represents the length of the input sentence, L represents the number of attention heads, M is the number of hidden units in BiLSTM, K represents the number of directions, and C is the number of tags. In the experiment, "bert-base-chinese" with 12 attention heads is used as BERT. The number of hidden units and directions of BiLSTM is 128 and 2, respectively. The number of tags is 6 in CRF. We still take BERT-BiLSTM-CRF, BiLSTM-CRF, and LSTM-CRF as the baseline models to compare with ABBCR.

Two experiments are conducted during analysing the computational cost of ABBCR. We first train the four models on MECorpus to observe the converge time of each model, and then take the specific text "筑马 ZQZ5168GLQ 沥青洒布车使用国家最新国四标准的东风 DFL1160BX4 天锦底盘作为承载平台，整车表现环保，节油，安全，舒适，可靠，动力强劲；同时具有良好的操纵稳定性，承载能力强，节能噪声小的特点" as a test data to observe the prediction speed of four trained models. Table 12 reports the experimental results. From Table 12, it can be seen that LSTM-CRF has a minimum calculation time and BERT-BiLSTM-CRF has the longest time. According to the above-mentioned time complexity analysis, the reason is obvious because the BERT pretraining is not used in LSTM-CRF. Interestingly, compared to BERT-BiLSTM-CRF, the computational cost of ABBCR is less. We think that the most direct reason is that the adaptive size input and the error between the predicted and actual rating score. The adaptive size input enables BERT-based word vector representation to better fit BERT pretraining since it essentially simulates the true distribution of entities. Meanwhile, the error between the predicted and actual rating score is beneficial for speedinpg up the gradient update.

Table 12. Training and prediction time of four models.

Model	Training time(s)	Prediction time(s)
ABBCR	120.4	10
BERT-BiLSTM-CRF	134.6	13.5
BiLSTM-CRF	130.1	12.3
LSTM-CRF	118.9	8.2

6.4 Model application

6.4.1. Mechanical equipment NER

To further verify the superiority of ABBCR in mechanical equipment NER task, we take any mechanical equipment text as an example in our experiment to call different trained models and observe their identified named entities. The experimental results are shown in Figure 4. We distinguish the recognized entities with different colours. In the experiment, the equipment name, type, performance, application, outstanding characteristics and parameters are highlighted in red, purple, yellow, green, blue and pink, respectively. Then, the rating score of different entities is calculated according to the score function in Rating layer in section 5.2 to get the rating score sum of the entities identified by different models. Table 13 shows the statistical information of Figure 4. It can be seen from Table 13 that, in terms of the number and rating scores of the identified entities, ABBCR model is the best and LSTM-CRF is the worst. This is because ABBCR correctly identified all types of entities, however, LSTM-CRF is unable to identify the entities of outstanding characteristics of equipment, and equipment performance entities. In addition, it can be also observed that the BERT-BiLSTM-CRF and BiLSTM-CRF cannot also identify all types of entities. For example, BERT-BiLSTM-CRF fails in identifying equipment performance entity. BiLSTM-CRF cannot identify the equipment performance entities and the entities of outstanding characteristics of equipment.

(a) ABBCR (b) BERT-BiLSTM-CRF

(c) BiLSTM-CRF (d) LSTM-CRF

However, an equipment performance is one of the indicators that users pay most attention when purchasing a mechanical equipment. Meanwhile, this further verifies the effectiveness of the adaptive size input and the rating function in ABBCR model.

Figure 4. Entity recognition of different models on the text of asphalt distributor truck.

Table 13. Effects of different models on a piece of mechanical equipment text.

Model	Number of different type of entities					
	Equipment name (red)	Equipment type (purple)	Equipment performance (yellow)	Equipment application (green)	Outstanding characteristics of equipment (blue)	Equipment parameters(pink)
ABBCR	1	2	2	4	1	1
BERT-BiLSTM-CRF	1	2	0	4	1	1
BiLSTM-CRF	1	2	0	4	0	1
LSTM-CRF	1	2	2	0	0	1

6.4.2. Mechanical equipment knowledge graph

The identified entities by the proposed ABBCR model can be used to construct a mechanical equipment knowledge graph with entity weights for industrial enterprises. Industrial knowledge graph is a graphical representation of industrial knowledge, which can be combined with various industrial applications (Xia et al. 2022; Xia et al. 2023; Zheng et al. 2021). In recent years, industrial knowledge graphs have been successfully applied in creative thinking in product design (Zuo et al. 2022a). For example, to facilitate product design experts to create a SAPPhIRE causal model based on the information extracted from technical documents, Bhattacharya and Chakrabarti (2023) proposed to build a knowledge graph of a sentence using the Parts-of-Speech tag of the words. First, four types of knowledge graphs such as Noun-Verb-Noun, Noun-Verb-Advance, Noun-Presentation-Noun, and Noun-verb-Objective, are constructed for each sentence. Second, these four types of knowledge graphs were connected with three different conditions to form a complete knowledge graph. Finally, experts used this complete knowledge graph to classify knowledge. To accelerate the generation of engineering design ideas (Zuo et al. 2022b) and support inference and recalling (Siddharth et al. 2022), engineering design patent technical documents are used to construct patent-based knowledge graphs. In addition, some researchers have utilized general semantic networks, knowledge graphs, and ontology database technologies to construct a large-scale comprehensive TechNet, to achieve the application of artificial intelligence in engineering design and innovation (Sarica, Luo, and Kristin 2020). Inspired by the above-mentioned studies, we use the mechanical equipment knowledge map constructed by ABBCR to achieve intelligent question answering of mechanical equipment in industrial manufacturing in this work.

To semantically associate the six types of entities identified by the ABBCR model, a piece of text corresponding to each kind of mechanical equipment is used as the main node in the process of construction. The semantic link " *mechanical equipment* ← *equipment name*" is defined using the main node and a sub-node which corresponds to an equipment name in each piece of text contained in raw dataset. By analogy, a total of eight semantic links are defined including "*equipment name* ← *equipment type*, *equipment name* ← *equipment performance, equipment name* ← *outstanding characteristics of equipment, equipment name* ← *equipment application, equipment name* ← *equipment parameters, equipment performance* ← *equipment parameters,* *Outstanding characteristics of equipment ← device performance, equipment application ← equipment type*". The constructed mechanical equipment knowledge graph is shown in Figure 5.

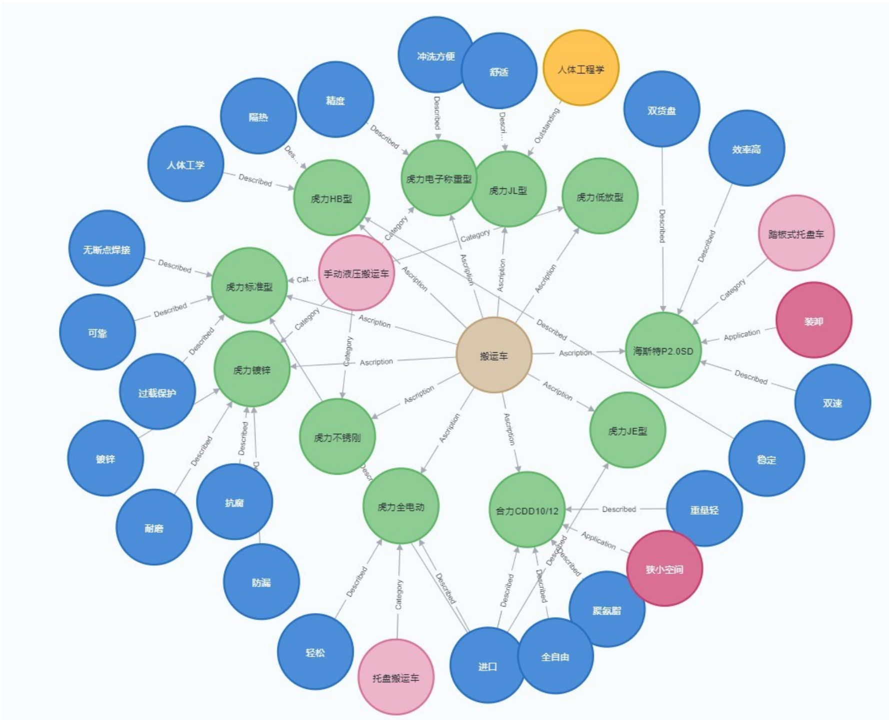


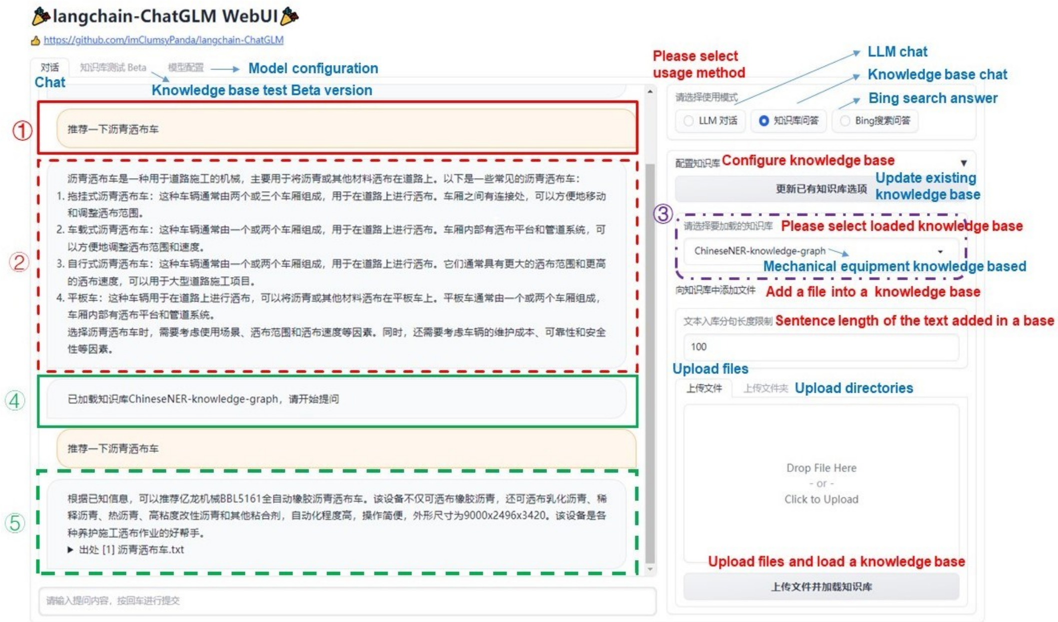
Figure 5. An example of a mechanical equipment knowledge graph.

6.4.3. Mechanical equipment intelligent question answering

In this section, we combined the knowledge graph constructed based on the ABBCR model with a big language model to construct an intelligent Q&A application of mechanical equipment. The goal is to further validate the efficacy of the ABBCR model by analysing the quality of answers which are only given by large language models (act as a robot) or our application. The construction of an intelligent Q&A application with a local knowledge base includes three steps: 1) select a large language model. In this experiment, the langchain-chatglm open-source framework was selected as the large language model; 2) using graph embedding to transform the structural information of the knowledge graph constructed in section 6.4.2 into a text vector library; 3) deploy the chatglm model. Figure 6 illustrates the intelligent Q&A application constructed in this paper and an example of answering a question.

From Figure 6, it can be seen that when a potential user who wants to purchase an asphalt distributor asks the robot the question "Please recommend an asphalt distributor"(rectangular box with number ①), the answer of the large language model is “4 different styles of asphalt distributors and their corresponding appearance descriptions” (rectangular box with number ②). Obviously, this is a very general answer which cannot provide potential users with valuable information such as the performance, outstanding features, and parameters of asphalt distributors. This indicates that the large language model has the ability to quickly understand user questions. However, since it is trained on a wide corpus rather than a specialized corpus of mechanical equipment, it lacks a deep understanding of professional terminologies and contexts in the field of mechanical equipment. Therefore, it can only find entities of the same type as the user's question from the corpus, and cannot mine other types of entities related to the entities in the question, resulting in low quality of answers.

However, after we loaded the knowledge base corresponding to the knowledge graph constructed based on ABBCR (rectangular boxes numbered ③ and ④), the big language model provided a very detailed and specific answer (rectangular boxes numbered ⑤), including some key information related to the question, such as " (亿龙机械 BBL5161) Yilong Machinery BBL5161(equipment name) " and " (全自动) fully automated" (equipment performance), " (外观尺寸) appearance and dimensions" (equipment parameters) and " (全自动橡胶沥青洒布车) fully automatic rubber asphalt distributor trucks" (outstanding characteristics of equipment). The answer contains multiple different types of entities. Obviously, these specific mechanical equipment information, especially the outstanding characteristics of equipment, play a crucial role in the user's purchase decision. This means that the robot has learned entity relationships related to the asphalt distributor (equipment name) in the user question from the local



knowledge base, and found other types of entities in the field of mechanical equipment from the wide corpus. This means our application can better understand the users' question, enrich entities related to the entity of the asphalt distributor (equipment name), and organize more coherent responses, thereby improving the quality of answers.

Figure 6. Application of ABBCR combined with large language model

7. Conclusion

The mechanical equipment NER has the challenges of difficult entity boundary definition and no specific rules. To address the issues, this paper proposes a kind of entity annotation rule which contains six strategies of dividing entity boundaries. Combined with the domain expertise, the corpus of mechanical equipment named entities MEcorpus is constructed and a mechanical equipment NER model ABBCR is proposed. Through the comparison of the experimental results of six baseline models from two different model architectures, the ABBCR model shows an absolute advantage on MEcorpus. The advantage of the proposed ABBCR model has twofold: 1) use an adaptive size input; 2) computing the rating score of identified entities.

However, there are two limitations in this work: 1) MEcorpus only contains the data from a single data source, which may cause that the analysis of the characteristics of entities in the mechanical equipment domain is not comprehensive, resulting in incomplete entity types in the corpus; 2) ABBCR model lacks of a good interpretability because it is an improved version of DL-based BERT-BiLSTM-CRF model. Therefore, future research should be carried out to: 1) enrich entity types to extend the size of MEcorpus by increasing the diversity of data sources of mechanical equipment; and 2) creating entity representations that are human readable to improve and achieve high performance on NER tasks out of the box.

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CRediT authorship contribution statement

Pin Lyu: Writing-original draft, Methodology, Funding acquisition. Yongyong Yue: Experiments, Validation. Pai Zheng: Conceptualization, Methodology, Supervision, Funding acquisition. Wengbing Yu: Data curation. Liqiao Xia: Writing-review & editing. Chao Liu: Formal analysis.

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.

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