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RESEARCH ARTICLE

Study on Chinese Semantic Entity Recognition Method for Cabin Utilizing BERT-BiGRU Model

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ABSTRACT Name Entity Recognition (NER) aims to recognize entities in the engine room domain from unstructured engine room domain text. But in the engine room domain, the entities are diverse and complex, and there is a nesting phenomenon, resulting in a low entity recognition rate. In this paper, a deep learning method incorporating language models is proposed to enhance the entity recognition performance within the engine room. domain. Firstly, the Bidirectional Encoder Representation from Transformers (BERT) language model is employed to train text feature extraction, acquiring a matrix of vector representations at the word level. Secondly, the trained word vectors are fed into the Bidirectional Gated Recurrent Unit (BiGRU) for contextual semantic entity feature extraction. Finally, the global optimal sequence is extracted by combining with the Conditional Random Field (CRF) model to obtain the named entities in the ship cabin semantics. The experimental results show that the proposed algorithm can obtain better F1 values for all three types of entity recognition. Compared with BERT-BiGRU, the overall accuracy of entity identification, recall rate and F1 value are improved by 1.35%, 1.45% and 1.40%, respectively.

INDEX TERMS Entity recognition, BERT-BiGRU, CRF, deep learning, turbine engineering.

I. INTRODUCTION

As artificial intelligence algorithms continue to evolve and data analytics technology progresses, it is widely acknowledged that the future of ship development will inevitably be driven towards intelligence, with intelligent cabins playing a pivotal role in shaping intelligent ships [1]. In the development of intelligent ships, the collection, aggregation, processing, visualization of data, as well as the identification and extraction of data through machine learning are conducive to both the effective operation of the engine room system and the reliable management of the ship. Therefore, it is crucial to explore adaptable and expandable approaches for accumulating ship cabin knowledge.

The explosive growth of big data and artificial intelligence requires proper representation and organization of massive amounts of knowledge [2]. A knowledge graph can be described as a semantic network that unveils the connections among entities. It serves as a significant form of knowledge representation in the era of big data and acts as a fundamental resource for AI applications [3]. As the core power source of the ship, the engine room of the ship undertakes the function of placing and managing the main mechanical equipment of the ship. Equipment in the engine room includes engines, generators, propulsion systems and other important components, which ensure the normal operation of the ship. The cabin usually takes into account ventilation systems to ensure air circulation, safety equipment such as fire alarm systems and fire suppression equipment to respond to emergencies, and good maneuverability for crew maintenance and operation. Therefore, in the face of the massive information in the Marine engine room, it has become increasingly important to study how to quickly select the data valuable for fault cause location from the massive text data, and build a complete knowledge system for the field of Marine engine room fault diagnosis, and the knowledge graph can meet this demand.

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After the construction of the knowledge graph in the field of Marine engine room fault diagnosis, The location and cause of the fault can be retrieved according to the known fault phenomenon, thus reducing the number of downtime maintenance, reducing operating costs, improving production efficiency, and reducing the negative impact of the fault.

The task of NER is a critical step in the process of creating a knowledge graph. The precision of NER directly impacts the extraction of relationships and the accuracy of the knowledge graph, subsequently influencing the effectiveness of downstream tasks [4]. Therefore, this research article presents NER in the domain of ship cabins, which serves as a cornerstone for the development of subsequent knowledge graphs, offering enhanced data support for fault diagnosis and prediction, energy-saving and optimization, operation monitoring and safety management, and data-driven decision-making support in ship cabins.

Traditional NER methods commonly involve the use of dictionary and rule-based approaches. These methods heavily rely on domain-specific dictionaries and the expertise of domain experts. Feature selection is often carried out through manual methods, resulting in a considerable level of subjectivity and labor-intensive procedures [5]. With the advent of machine learning, NER techniques have progressively relied on various statistical models. These models typically involve manually labeling a limited number of samples. by defining specific features, followed by training the model. This approach offers excellent portability and adaptability [6]. This mainly includes Hidden Markov Models (HMM) [7], CRF [8], Support Vector Machine Models (SVM) [9]. HMM enables the inference of hidden states in a Markov chain through a sequence of observed vectors. The HMM is based on two fundamental assumptions: The generation of observation vectors involves sampling from each probability density distribution corresponding to the state sequence, and its relatively fast training process facilitated by the Viterbi algorithm. However, HMM is limited in its ability to consider remote dependence and based on the assumption of independence. This constraint restricts the feature selection capabilities of the model, leading to local optimality. As a result, HMM is more appropriate for tasks such as short text entity recognition. The CRF model obtains the loss function values and updated transmission matrix of the network by jointly training the attention vectors and label vectors using the transmission matrix. This model has the capability to incorporate diverse contextual information and features a flexible functional design. SVM, which is a class of generalized linear classifiers used for binary classification of data through supervised learning, which is bounded by the separating hyperplane with maximum margin for the trained samples [10], [11]. Although this model can handle high-dimensional features, it suffers from the disadvantage of long training time [12].

With the advancement of deep learning technology, comparing with the traditional CRF model [13], [14], [15], [16], It has been established that deep neural network techniques require less manual intervention compared to traditional methods. They have the capability to achieve higher accuracy and recall by automatically extracting features from words, thereby reducing the subjectivity involved in feature selection and enhancing the accuracy of recognition results. However, commonly used single-entity recognition neural networks often focus solely on sample inputs and lack comprehensive consideration of output relationships. Therefore, many researchers address this limitation by proposing model fusion approaches to augment network models. In the literatures [17], [18], [19], [20], and [21], the traditional word vector approach is used, with Bidirectional Long Short-Term Memory (LSTM)-CRF as the core, and Convolutional Neural Network CNN model, attention mechanism, Recurrent Neural Network (RNN) model and so on are added to the core framework. Literature [22] proposes joint segmentation and CNN-BiLSTM-CRF model co-training to enhance the ability of Chinese named entity recognition model to recognise boundaries, and also introduces a method to generate pseudo-tagged samples from existing tagged data, which further improves the performance of NER. Literature [23] integrated manually crafted spelling features into the BiLSTM-CRF model tested on the CoNLL2003 dataset with a final F1 value result of 88.83%.

From the perspective of pre-training model, the preprocessing model uses word2vec, Glovede traditional word vector method. However, the word vectors generated by these methods are static and cannot solve the polysemy problem. In order to improve this problem, BERT [24] is widely used in NER tasks, which is a model based on transformers for bidirectional encoding, and has relatively good performance results in NER tasks [25]. Literature [26] builds a BERT-based optimisation model for external vocabulary feature extraction to tackle the issue of insufficient identification of rare entities during the NER process, a BERT-based optimization model is constructed. The evaluation results indicate that the model exhibits commendable performance in the NER task, effectively mitigating the low recognition rate problem for rare entities.

At present, research on the construction of fault knowledge graphs has been carried out in many fields at home and abroad. Reference [27] reveals the latent rules of faults by constructing a causal knowledge graph of railway operation faults, and proposes preventive measures accordingly; [28] constructs a multi-source heterogeneous power equipment knowledge graph to improve the management efficiency of power equipment and lay a knowledge foundation for fault diagnosis applications; [29] constructs a knowledge graph of fault information for power wireless private network terminals to achieve fault diagnosis and decision-making. These studies use knowledge graph technology to solve the problem of information isolation between data, and use graph databases to standardize the storage of unstructured data, thereby improving the utilization rate of fault knowledge in the field. But, there are fewer NER studies oriented to the field of engine room due to the following reasons:

(1) Engine room data has serious fragmentation, loose organization and limited normalization;

(2) When facing the huge amount of engine room domain knowledge, it is time-consuming and laborious to manually extract the key information and construct the dataset;

(3) The complexity and variety of entities in the engine room domain and the nesting phenomenon lead to a low recognition rate of entities.

Targeting the aforementioned issues, to solve the above problems, this paper studies the NER method for the field of Marine engine room, and builds an improved model combining BERT with bidirectional gated circulation unit and conditional random field, namely BERT-BIGRU-CRF model. By leveraging the capabilities of the model in context-based semantic extraction and feature prediction, two prominent challenges in NER, namely incomplete acquisition of semantic information and generation of unrealistic output sequences, are effectively addressed. This approach guarantees a more thorough comprehension of the text context and generates more accurate predictions, resulting in improved NER performance. Finally, experiments are conducted based on the ship cabin domain dataset, which achieves good recognition results and lays the foundation for realizing the knowledge graph of ship cabin domain.

The remaining sections of the paper are structured as follows: Section II presents the modeling framework of BERT-BiGRU-CRF for named entity recognition. In Section III, the design process and experimental results of the text annotation method for ship cabin semantic entity recognition are discussed. Section IV provides a summary and outlines future work plans for ship cabin NER.

II. SEMANTIC ENTITY RECOGNITION METHOD FOR ENGINE ROOM

The neural network model can be trained and learned on the dataset obtained from sequence annotation, and then the desired entities are recognized from the new text.The BERT-BiGRU-CRF model is made up of three components. Firstly, the input undergoes semantic representation through a pre-trained language model in the BERT layer, which generates word vectors containing contextual information. Then, these word vectors are used to create a word matrix that serves as the input for the BiGRU layer, where semantic encoding and feature extraction are performed. Finally, the CRF layer determines the tag sequence with the highest probability for ship cabin information, resulting in named entity recognition. Figure 1 illustrates the ship cabin semantic NER model based on the improved algorithm of BERT-BiGRU-CRF.

A. BERT PRE-TRAINING LANGUAGE MODEL

Relative to the traditional pre-training model, the BERT model is rooted in the structure of the self-attention mechanism to complete the pre-training task, which can learn the relationship between consecutive text segments and obtain contextualized contextual information.

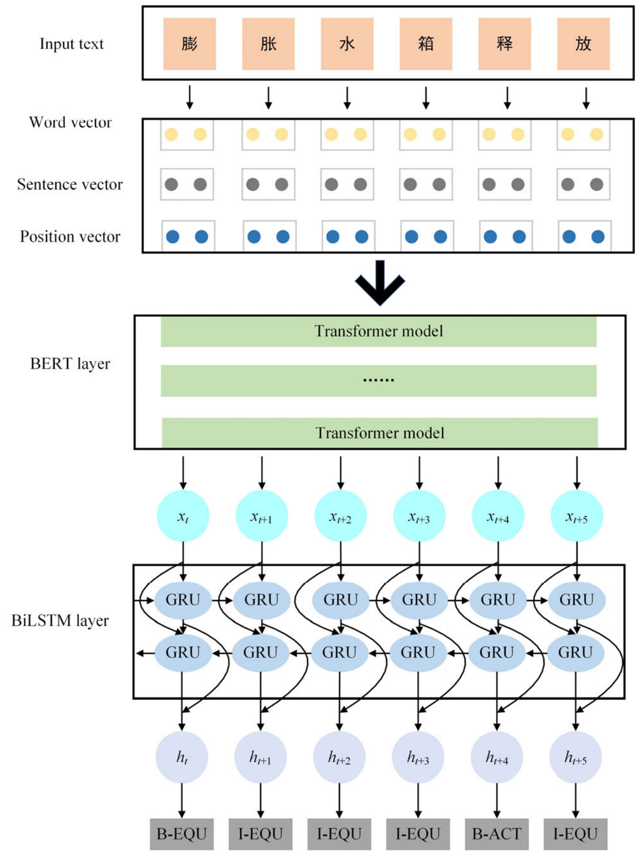

FIGURE 1. Structure of NER model for ship cabin domain based on BERT-BiGRU-CRF.

As shown in Figure 2, Input the text "通过膨胀水箱释放" into BERT layer at the input layer. First, the input text will be cut into a single Chinese character, and then the character vector of the word, sentence and position can be obtained by using multi-layer Transformer. The character vector is shown in formula (1), where e_c is the character word vector, e_s is the character sentence vector and e_p is a character position vector. Finally, they are combined as input vectors for BiGRU.

$$\mathrm{e} = e_c + e_s + e_p \tag{1}$$

B. BiGRU LAYER

The GRU is a type of RNN that was designed as a more streamlined alternative to the LSTM architecture. It addresses the issues of gradient vanishing and exploding that can occur in LSTM, while still being able to capture semantic dependencies and maintain long-term memory. In a BiGRU layer, the input consists of pre-trained word vectors obtained from the BERT layer. The output of the BiGRU layer predicts the labels for each word based on their corresponding scores. This can be visualized in Figure 3.

The GRU simplifies the LSTM by merging the input and forget gates into a single gate called the update gate z_t and the

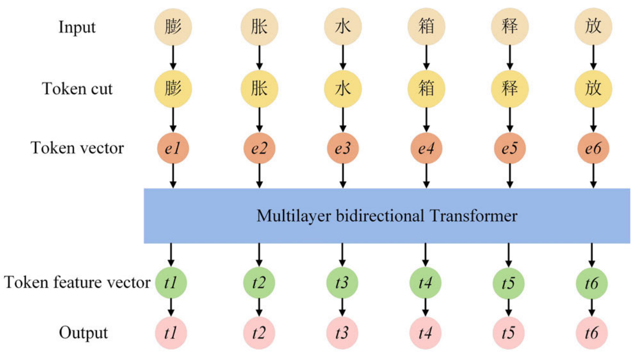

FIGURE 2. BERT structure diagram.

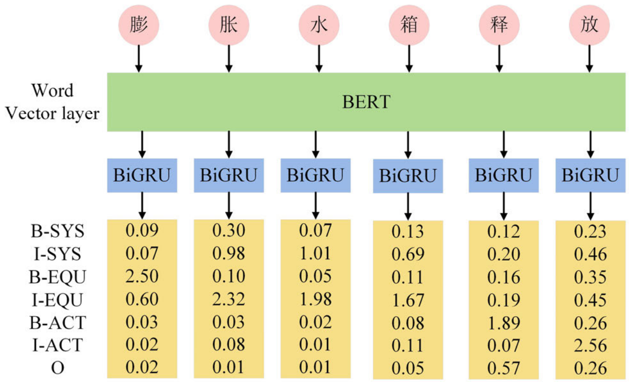

FIGURE 3. Structure of the GRU network model.

reset gate r_t, as shown in equation (2,3).

$$r_t = \sigma \left(W_r \left[h_{t-1}, x_t \right] \right) \tag{2}$$

$$z_t = \sigma \left(W_z \left[h_{t-1}, x_t \right] \right) \tag{3}$$

where σ represents the Sigmod activation function, x_t represents the current input, h_{t-1} represents the output at the moment before the hidden layer, $\boldsymbol{W_r}$, $\boldsymbol{W_z}$ are the weight matrix.

The one-way GRU state is output from front to back, and the context information cannot be fully considered. Therefore, this paper adopts BiGRU network, uses forward and reverse GRUs to extract the context information features, and adds the output weights. For example, the output of the BiGRU layer is 0.09 (B-SYS), 0.07 (I-SYS), 2.50 (B-EQU), 0.60 (I-EQU), 0.03 (B-ACT), 0.02 (I-ACT), and 0.02 (O). These numbers are the scores given to the ''膨'' word according to each label. For the word ''bulge'', its ''B-EQU'' label has the highest score, representing the greater the possibility of this category, so the word is temporarily labeled ''B-EQU''. The matrix that combines the output scores for each word is called the output matrix and will serve as the input to the CRF layer.

C. CRF LAYER

CRF is a type of Markov Random Field that models the conditional probability $P(Y|X)$, where Y represents the output

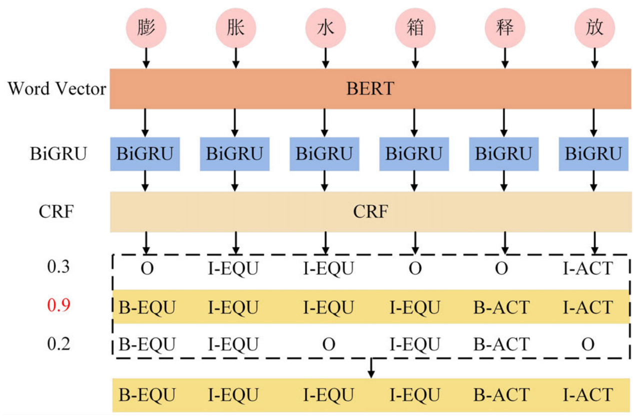

FIGURE 4. Plot of final output of BERT-BiGRU-CRF model.

variable, which is a sequence of labels, and X represents the input variable, which is an observed sequence requiring labeling. During the learning phase, the conditional probability model $P'(Y|X)$ is estimated using maximum likelihood estimation or regularized maximum likelihood estimation based on the training dataset. During prediction, given an input sequence x, we find the output probability y' that maximizes the conditional probability $P'(y|x)$.

BiGRU+Attention solves the problem of long-distance dependence in text information processing, and obtains the specific score of each label by calculating the optimal output label, but it cannot solve the dependency relationship between labels, such as ''I-EQU'' label cannot be immediately connected to ''B-ACT''. Therefore, the output label cannot be used as a reasonable prediction of the model. Here, the core function of adding CRF model is to transfer the dependency between the modeling labels of the fractional matrix, add useful constraints, such as adding constraints such as ''B-SYS is incorrect, NER should start with 'I-''', ensure the validity of the final prediction results, and greatly reduce the wrong prediction sequence. Thus output a globally optimal reasonable tag sequence.

The CRF layer ensures the validity of the final prediction by adding useful constraints, such as ''B-SYS is incorrect, named entity identification should start with 'I-'', and the incorrect prediction sequence is greatly reduced.

By combining the output matrix P of BiGRU layer and the conversion matrix A of CRF layer, the label path with the highest score can be calculated, as shown in Figure 6. The predicted score for calculating the input sequence X is shown in equation (4).

$$\text{score}\,(\mathrm{X},\mathrm{y}) = \sum\nolimits_{i=0}^{n} A_{y_i, y_{i+1}} + \sum\nolimits_{i=1}^{n} P_{i, y_i} \tag{4}$$

The transformation matrix $A_{i,j}$ represents the transition probabilities from the ith label to the jth label.

The Viterbi algorithm is employed to compute the globally optimal collection of label sequences, as depicted in equation (5).

$$y^* = \arg\max score(X, y') \tag{5}$$

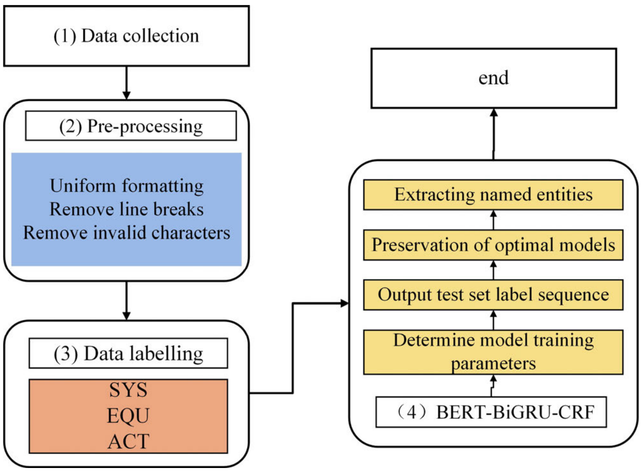

FIGURE 5. Flowchart of semantic entity recognition for engine room.

After the "膨胀水箱释放" passes through the BERT layer, BiGRU layer, and CRF layer, the final output is (B-EQU), (I-EQU), (I-EQU), (I-EQU), (I-EQU), (I-EQU), (B-ACT), and (I-ACT).

III. CASE STUDY OF SEMANTIC ENTITY RECGNITION IN ENGINE ROOM

An overview of the engine room NER is shown below.

The NER task process consists of data collection, data preprocessing, data labeling and model training. The dataset uses the guidance manual of the turbine simulator, which is more specialized and targeted in the field of ship cabin than other public datasets, so it is a good reference value to choose this dataset for the study of ship cabin NER. Data preprocessing starts with normalization of the text format, followed by text data enhancement and deletion of meaningless line breaks and characters, and finally slicing the text, merging adjacent phrases, and splicing long and short texts. The entity annotation selects three entities in the dataset, namely "系统" (system, SYS), "设备" (equipment, EQU) and "动作" (action, ACT), as data types. The semantic dataset is annotated according to the BIO labelling system using suitable text annotation software, and the text dataset is partitioned into three categories, namely the training set, validation set, and test set, based on a suitable ratio. The model training uses the BERT-BiGRU-CRF model to determine the different hyperparameter values for entity recognition and conducts multiple rounds of training until the training requirements are met, and completes the NER task for the text in the test set.

A. TRAINING TEXT ANNOTATION METHODS

Before the annotation, we consulted 5 chief engineers who have been working in the field of Marine engine room for many years and 10 professors in the field of Marine engine room. After many discussions and analyses, we confirmed the entity type of the data set in the field of Marine engine room required in the research process of this paper. During the annotation process, we first conducted training for 10 doctoral and postgraduate students majoring in Marine engineering. The annotation work was carried out according to the confirmed entity type. After the annotation was completed, we sent the annotation file to 15 chief engineers and professors for annotation verification, and determined the final annotation version.

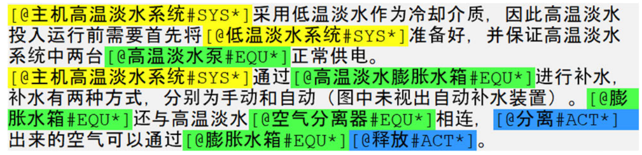

FIGURE 6. YEDDA entity labelling diagram.

TABLE 1. Example of BIO labelling.

symbol	Entity Label	symbol	Entity Label
主	B-SYS	高	E-EQU
机	I-SYS	温	I-EQU
高	I-SYS	淡	I-EQU
温	I-SYS	水	I-EQU
淡	I-SYS	膨	I-EQU
水	I-SYS	膨	I-EQU
系	I-SYS	水	I-EQU
统	I-SYS	箱	I-EQU
通	O	补	O
过	O	水	O

In this paper, YEDDA [30] annotation software is used, which will provide the annotators with existing recommendations based on historical annotations, and the recommendation system will keep updated online during the entire annotation process to provide the annotators with real-time systematic recommendations to avoid repeated annotation. Moreover, in order to evaluate and monitor the annotation quality of different annotators, the software will import all annotation files into the multi-annotator analysis toolkit, and in the annotation process, the accuracy of annotation files can be evaluated and the differences between different annotators can be analyzed.

So in this paper, the engine room training text is annotated using the BIO format with the assistance of the YEDDA tool. The entities of the seawater system, main seawater pump, and starting are annotated by using "B-SYS" to denote the beginning of an entity word, "I-SYS" to denote the middle or the end of an entity word, and "O" to denote a non-entity word. The annotated text information is then exported to a ".anns" file format for storage, and the results of annotation are presented in Table 1.

The types of entities annotated in the engine room text corpus consists of three distinct categories: system (SYS), equipment (EQU), and action (ACT). The data is partitioned into training set, validation set, and test set using an 8:1:1 [31] ratio. Table 2 presents the distribution of the three entity types in both the training and test sets.

TABLE 2. Distribution of data sets.

	Training set	Validation set	Test set	Total quantity
SYS	1185	150	150	1485
EQU	1264	158	158	1580
ACT	1362	171	171	1704
Total quantity	3811	479	479	4769

TABLE 3. Model parameter settings.

Parametric	Value	Parametric	Value
Word vector dimension	100	GRU layers	2
Sentence length	30	GRU hidden layers	128
Batch size	30	Optimiser	Adam
Epochs size	50	Learning rate	0.001

B. ASSESSMENT INDICATORS AND PARAMETERIZATION

1) PARAMETER SETTINGS

Although the BERT-BiGRU-CRF model has been extensively studied for NER tasks, there is still a lack of research in the domain of engine room analysis. Therefore, in this study, we conducted experiments on a Windows platform, employing Python 3.7.15 as the runtime environment and Python 1.6.0 as the deep learning framework. The optimal model parameters were obtained through parameter training on the training data, and the specific parameter settings are detailed in Table 3. Assessment of indicators

2) ASSESSMENT OF INDICATORS

In this paper, we utilize the commonly employed evaluation metrics in the domain of named entity recognition, namely precision (P), recall (R), and F1-score (F1) [32], which are calculated as:

$$\mathrm{P} = \frac{Num_T}{Num_P} \times 100\% \tag{6}$$

$$\mathrm{R} = \frac{Num_T}{Num_R} \times 100\% \tag{7}$$

$$\mathrm{F1} = \frac{2 \times P \times R}{P + R} \tag{8}$$

where N_{umT} represents the count of correctly predicted entities, N_{umP} the number of entities in the predicted results, and N_{umR} the number of entities in the original dataset annotations.

C. ANALYSIS OF EXPERIMENTAL RESULTS

1) PERFORMANCE ANALYSIS OF THE BERT-BIGRU-CRF MODEL

In the process of engine room entity recognition training, for the BERT-BiGRU-CRF model the corresponding precision, recall, and F1-score are shown in Figure 7. From the figure, it is apparent that the model exhibits a higher growth rate of indicators during the initial 15 epochs of training. This paper presents a named entity recognition model that shows accelerated learning and improved training outcomes for engine room text data. After 35 epochs, the value of each indicator tends to be stable, and the F1-score reaches the maximum value of 93.01% for the first time in the 47th epoch. After 50 epochs of training, each parameter tends to be stable, and the change is smooth, demonstrating that the model exhibits strong robustness.

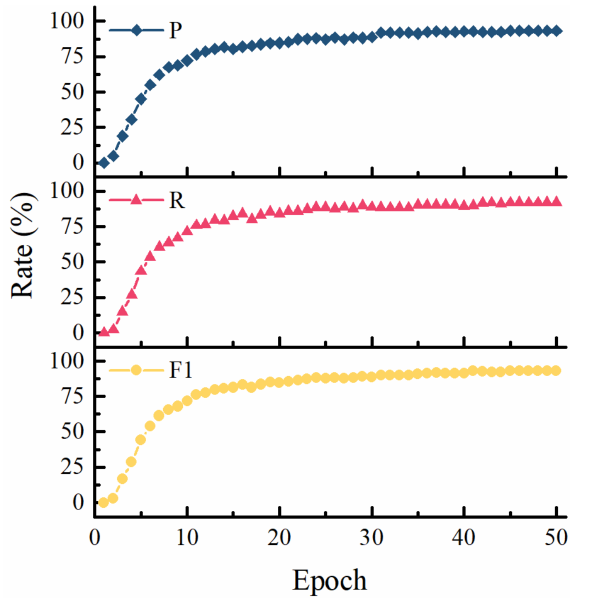

FIGURE 7. Graph of changes in evaluation indicators P, R and F1.

2) COMPARISON WITH OTHER MODELS

To confirm the efficacy of the BERT-BiGRU-CRF model on the engine room dataset, we conducted experiments on the validation and test sets using different models: BiGRU-CRF, BiLSTM-CRF, BERT-BiLSTM-CRF, and BERT-BiGRU-CRF. The trained parameters were utilized as the model parameters for each approach. All models were trained using the same framework and parameter settings. The Table 4 presents the named entity recognition NER experimental results for each model.

As can be seen from Table 4, in the data set of ship engine room, TextCNN model can extract local features according to different convolution kernel sizes, so that the extracted feature vectors are diverse and more representative. The accuracy P, recall rate R and F1 values of this model reach 81.79%, 81.46% and 81.62%. The Lattice-LSTM model incorporates lexical information to avoid the impact of entity segmentation errors, so the accuracy P, recall R and F1 values reach 82.90%, 82.82% and 82.86%. the BERT-BiLSTM model achieved an precision of 85.94%, recall of 85.67%, and F1-score of 85.80%. Compared to the BERT-BiLSTM model, the BiGRU-CRF model has a simpler structure and performs slightly better in ship's engine room domain recognition. The precision has improved by 3.95%. Although there has been

TABLE 4. Distribution of different model performance comparisons for engine room training text.

Algorithmic Models	EVALUATION INDICATORS	SYS (%)	EQU (%)	ACT (%)	total
TextCNN	*P*	80.25	82.23	82.89	81.79
	R	80.28	81.35	82.75	81.46
	*F*1	80.26	81.79	82.82	81.62
Lattice-LSTM	*P*	81.30	83.12	84.28	82.90
	R	81.56	83.09	83.80	82.82
	F1	81.43	83.10	84.04	82.86
BERT-BiLSTM	*P*	83.79	87.01	87.01	85.94
	R	83.17	87.15	86.68	85.67
	*F*1	83.48	87.08	86.84	85.80
BiGRU-CRF	*P*	85.67	91.23	92.77	89.89
	R	85.78	90.11	91.63	89.17
	*F*1	85.72	90.67	92.20	89.53
BERT-BiGRU	*P*	90.12	93.61	94.35	92.70
	R	87.98	90.77	93.33	90.69
	*F*1	89.03	92.17	93.84	91.68
BERT-BiGRU-CRF	*P*	**92.24**	**94.51**	**95.37**	**94.04**
	R	**89.35**	**92.55**	**94.51**	**92.14**
	*F*1	**90.77**	**93.52**	**94.94**	**93.09**

an improvement in recognition performance, there is still significant room for improvement.

By incorporating the CRF model into the BERT-BiGRU model, the BERT-BiGRU-CRF model has shown significant improvements in precision, recall, and F1-score compared to both the BERT-BiGRU model and the BiGRU-CRF model. Specifically, the precision, recall, and F1 score have increased by 1.34% and 1.45%, 1.41% and 4.15%, and 2.97% and 3.56%, respectively. Experimental results indicate that introducing the CRF model during the recognition process of the ship's engine room dataset accounts for the dependencies between labels in the task, leading to improved recognition performance.

Overall, the proposed BERT-BiGRU-CRF model exhibits higher precision, recall, and F1-score compared to other models. This indicates that leveraging pre-trained models in the NER process allows for the utilization of contextual information within the text to obtain semantic features, effectively addressing the complex structure of engine room dataset entities and improving NER performance.

3) RESULTS OF IDENTIFICATION OF DIFFERENT TYPES OF ENTITIES

To enhance our understanding of the NER task in the engine room domain, we conducted an in-depth analysis of the BERT-BiGRU-CRF model's recognition performance across various entity types. After multiple rounds of training, we obtained the precision, recall, and F1-score for three entity types in the training text of the cabin when achieving the maximum F1-score. These values are presented in Table 5 as follows:

From Table 5, we observe that the BERT-BiGRU-CRF training model demonstrates a successful performance in accomplishing the NER task for engine room training text. The final overall F1-score is 91.67% and the overall classification performance is good. Among the three entity types,

TABLE 5. Recognition results of different types of named entities for engine room training text.

Named entity categories	*P*(%)	*R*(%)	*F*1(%)
SYS	89.78	88.62	89.20
EQU	93.56	91.25	92.39
ACT	93.58	93.26	93.41
Total	92.31	91.04	91.67

SYS is lower than the value of ACT and EQU, which indicates that the number of SYS-type entities in the dataset is relatively small, and the main body format is not uniform, and the composition is complex, such as "货油泵透平系统". In addition, during the training, the "货油泵" in the EQU entity may be interfered by the recognition of the entity as "货油泵 "and "透平系统 ", which makes it impossible to accurately identify the subject in most cases. The SYS results are slightly lower.

IV. CONCLUSION

Although there have been studies on NER tasks using the BERT-BiGRU-CRF model, there is a noticeable gap in NER research specifically focused on engine rooms. this paper is to tackle this gap by proposing a novel approach that leverages multi-feature fusion with the BERT-BiGRU-CRF model for engine room NER. The experimental results demonstrate that this approach outperforms some common typical NER algorithms in terms of precision, recall, and F1-values. Specifically, the recognition of three types of entities achieved precision of 93.24%, recall of 92.13%, and an F1-score of 92.68%. By successfully completing the NER task in the engine room domain, this method provides essential technical providing assistance for the development of engine room knowledge graphs. The accurate recognition of entity information by the model establishes the groundwork for subsequent relationship extraction and knowledge graph construction in the engine room domain. In future research, endeavors will be made to further expand the dataset size and explore the application of additional models in the engine room field. These endeavors aim to continually enhance the effectiveness of NER in the engine room domain and promote the overall progress of NER research in this specific domain.

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