Research on Record Named Entity Recognition of Chinese Electronic Medical based on LSTM-CRF

Gang Ding

Abstract—**In the Chinese electronic medical record named entity recognition task, in order to avoid the disadvantage of manually extracting features and consuming a lot of time and energy, the long and short time memory network model (LSTM) is combined with the conditional random field model (CRF) to extract the electronic medical record text sequence, including symptoms and signs, body parts, examination and check, treatment, and disease and diagnosis of five types of entities, through the LSTM-CRF model for named entity recognition. Firstly, the electronic medical record dataset is subjected to desensitization processing and manual sequence labelling, etc. Secondly, the electronic medical record text sequence is vectorized and represented by the combined word embedding technique, and then use the LSTM model to encode the semantics of the entity and extract the feature of the word vector containing the above information, so as to dig out the potential semantic relationship between the texts; Then the word vector feature sequence is input into the CRF model, and the corresponding entity is extracted. Finally, three evaluation indexes of accuracy, recall and F1 score are identified from the entity, and the LSTM-CRF model is used to identify the performance of the electronic medical record named entity. The experimental results show that the LSTM-CRF model can effectively mine the body parts and treatment entity information in the electronic medical record, and it is a good entity recognition model.**

Index Terms—**Chinese text, long and short time memory network, conditions random filed, entity recognition**

I. Introduction

IN the field of named entity recognition, there are three kinds of methods: rule matching method, statistical machine learning method and deep learning method. (1) Rule matching method [1]: the recognition effect of this method is highly dependent on prior knowledge, weak generalization ability, poor portability, and it needs to update the rule template at any time; (2) Methods based on statistical machine learning include support vector machine (SVM) [2], hidden Markov model (HMM) [3], maximum entropy model (ME) [4] and conditional random field (CRF) [5], The structure of conditional random field model is simple, and it can be used alone or combined with other complex networks. These machine learning methods need to extract features manually, which consumes a lot of manpower and time efficiency is low. (3) Deep learning based approach: in natural language processing (NLP), the context of text data is dependent and relevant. Recurrent neural network (RNN) has memory function, which can save the information of current input and historical input. In theory, it can deal with any length of text sequence, but in practice, the gradient will disappear or explode, and it is difficult to learn long-time dependent features. Therefore, graves et al. [6] improved RNN, proposed long short term memory network (LSTM) model, added control gate mechanism, and reached a climax in the application of LSTM network model.

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EMR information extraction includes named entity recognition (NER) and relation extraction. The main task of NER is to identify clinical entities from a given EMR document, They are classified into five pre-defined categories, including symptoms and signs, body parts, examination and check, treatment and disease and diagnosis; The main task of relationship extraction is to discover and establish the relationship between two entities, including the relationship between symptoms and signs and examination and the relationship between disease and diagnosis and treatment.

In recent years, the research on named entity recognition of Chinese EMR has made great progress in China. Yu Nan et al. [7] combined with many basic features and advanced features, such as language symbol features, word boundary features and context window features, combined with conditional random field, can achieve Chinese EMR entity recognition well. Li Wei et al. [8] proposed a Chinese EMR entity recognition algorithm based on the combination of conditional random appearance and rules, which meets the clinical needs of EMR information extraction. Yang Hongmei et al. [9] collected 240 cases of EHR data sets with hepato-cellular carcinoma, and used the model of bidirectional long-term and short-term memory network combined with conditional random field to realize the automatic named entity recognition of EHR text.

Because the unstructured EMR contains a large number of medical terms and proper noun abbreviations, the recognition model is required to have the ability to explain the interdependence between the input sequence and the above information. Therefore, the combination of LSTM model and CRF model is applied to Chinese EMR named entity recognition, which is based on the electronic medical record corpus, the pre-processed corpus is combined with word embedding, and the word vector sequence is represented by word2vec. Then the word vector sequence is input into LSTM-CRF model to realize EMR entity recognition, and the entity recognition performance of the model is verified by test

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set. Finally, the experimental results are analyzed and the recognition performance of the model is evaluated. Compared with the traditional EMR entity recognition research, LSTM-CRF model can not only automatically construct text features containing the above information, but also greatly reduce manual intervention. Moreover, it further strengthens the potential semantic relevance between the current information and the above information. The results show that LSTM-CRF model can achieve good recognition effect in unstructured text processing.

II. Processing Model

A. LSTM

Recurrent neural network (RNN) has the property of weight sharing [10], which can predict the following information by using the above information. The structure pattern of the recurrent neural network is shown in Figure 1[11]. At time t, the input of the hidden layer includes the output of the previous hidden layer and the input of the current input layer. It can be seen that RNN has the function of storing historical information.

Long short time memory network (LSTM) is a kind of time cycle neural network improved from RNN. Compared with RNN, LSTM introduces memory unit [12] and three control gate structures composed of input gate, forget gate and output gate [13]. It makes the network have the ability to selectively retain and discard state values, and can capture long distance information better and overcome the problem of gradient disappearance or gradient explosion [14]. LSTM is composed of input layer, hidden layer and output layer, and there are connections between the hidden layers. The network structure pattern of LSTM is shown in Figure 2. When processing sequential text, the output of LSTM at the last time will be used as the input of t time, so the above information can be well preserved. At time t, the input of the memory unit includes the output $h_{t\text{-}1}$ of the hidden layer at the previous time, the state variable $c_{t\text{-}1}$ of the memory unit and the input information x_t of the input layer at the current time. The output of the memory unit includes the state variable c_t of the memory unit and the output h_t of the hidden layer at the current time.

In a memory unit at time t, the forgetting gate f_t passes first. The role of forgetting gate is to decide what information to discard from the current cell state. The input of the forgetting gate is the hidden layer state variable $h_{t\text{-}1}$ of the previous time and the input information x_t of the input layer of the current time, and its output is f_t. f_t is then dot multiplied by the state variable $c_{t\text{-}1}$ of the memory unit at the previous moment to assign the value to the state variable of the current memory unit. The specific calculation formula is formula (1):

$$f_t = \sigma(U_f x_t + W_f h_{t-1} + b_f) \qquad (1)$$

Where U_f, W_f and b_f are the parameters of forgetting gate.

Then through the input gate i_t. The role of the input gate is to determine how much to choose from the newly acquired information to update the status. The input gate structure consists of sigmoid layer and tanh layer. The calculation formula is shown in formula (2) (3):

$$i_t = \sigma(U_i x_t + W_i h_{t-1} + b_i) \qquad (2)$$

$$g_t = \tanh(U_g x_t + W_g h_{t-1} + b_g) \quad (3)$$

Where, U_i, W_i, b_i, U_g, W_g and b_g is an adjustable parameter.

Then, according to the above formula (3), the memory unit state $c_{t\text{-}1}$ is updated to memory unit state c_t. The calculation formula is as follows:

$$c_t = f_t \odot c_{t-1} + i_t \odot g_t \qquad (4)$$

Where: $\odot$ denotes the product of matrix elements.

The last one is the output gate o_t. The output gate determines how much information there is to generate the hidden layer state variable h_t. The calculation formula is shown in formula (5) (6):

$$o_t = \sigma(U_o x_t + W_o h_{t-1} + b_o) \qquad (5)$$

$$h_t = o_t \odot \tanh(c_t) \qquad (6)$$

Where, U_o, W_o and b_o is the parameter of the output gate.

B. Conditional Random Field

Conditional random field is based on probabilistic undirected graph model. Let G=(V,E) be an undirected graph, where V is the node of the undirected graph and E is the edge of the undirected graph. Let X be the random variable of the observation sequence of the input model, and Y be the random variable of the corresponding state sequence, that is, X and Y are jointly distributed, expressed by P=(X,Y). Then, in an undirected graph, the node V represents the variable Y, and the edge e represents the dependency between the variable X and the variable Y.

In this experiment, linear chain conditional random field is used, let $X=(X_1,X_2,\cdots,X_n)$, $Y=(Y_1,Y_2,\cdots,Y_n)$ be sequences of linear random variables. Given the input variable X, the conditional probability distribution P=(X,Y) of the output variable Y with respect to X constitutes a conditional random field.

During model learning, the conditional probability model $P(Y \mid X)$ is obtained by using training corpus and maximum likelihood estimation [15]. Where, λ and θ Represents the estimated parameter.

For a given input sequence X, the output sequence Y with the maximum conditional probability $P(Y \mid X)$ is obtained.

III. The Method of this Paper

In the research of Chinese EMR named entity recognition, the experiment is divided into three steps, and the flow chart is shown in Figure 3. Firstly, pre-processing the self-built EMR corpus includes data desensitization, manual sequence annotation and entity segmentation with stuttering segmentation tool. Secondly, each entity in the dataset is expressed by word embedding technique and used as the input of LSTM-CRF model to train the model. Finally, each entity in the test set is extracted by the model and classified into a predefined label, and the entity recognition performance of LSTM-CRF model is evaluated and analyzed.

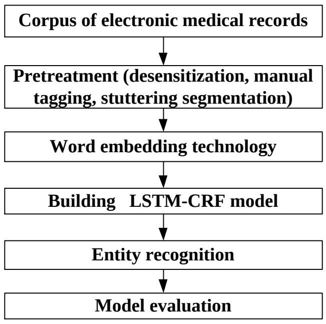


Fig. 3. Entity recognition experiment flow chart of electronic medical records

A. LSTM-CRF Model

LSTM-CRF model combines LSTM network model with CRF model to build a joint neural network model. The overall structure of LSTM-CRF model is shown in Figure 4. The model structure mainly includes word vector layer, LSTM network layer and CRF layer. The first layer is the word vector layer, which is used to represent the word vector distribution of the input text sequence. The second layer is LSTM network layer, which uses word vector as input to further construct the feature expression of text sequence. LSTM recurrent neural network model can learn a large range of text sequence information, so it has certain advantages in solving the problem of entity recognition. The third layer is CRF layer, which classifies the text features extracted from LSTM network layer to achieve the purpose of entity recognition.

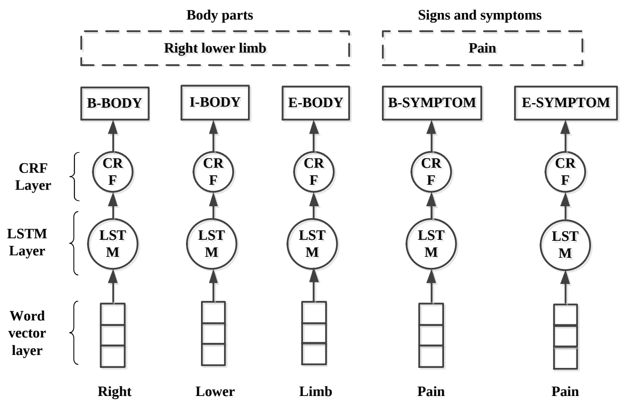


Fig. 4. Entity recognition model structure diagram of electronic medical records based on LSTM-CRF model

In this paper, we build a long-term and short-term memory network to learn the sequence information of EMR text, and extract the text features of the above information automatically, and use CRF model to calculate the tags corresponding to the sequence entities. Considering the complexity of the recurrent neural network and the efficiency of entity recognition, a three-layer model structure is adopted when building the LSTM-CRF joint network model. In the experiment, the number of nodes in the LSTM memory cell is set to 512, the loss function of the network is set to cross entropy loss function, and the Adam optimization method is used to continuously update the parameters and minimize the loss. In order to prevent over fitting and improve the generalization ability of the model, dropout is added to the network model, and the value is set to 0.1.

B. Data set pre-processing

For the recognition of Chinese EMR entities, it is necessary not only to understand the regularity of the formation of text sequence itself, but also to consider the particularity and complexity of named entities. So it is difficult to identify named entities accurately. The Chinese EMR data set used in this study comes from paid data. The single visit record of a single patient is an EMR in .txt format. The named entities of EMR mainly include five categories: symptoms and signs, body parts, examination and test, treatment, disease and diagnosis. The data set pre-processing process includes:

(1) Desensitization of EMR: On the premise of not changing the semantic expression of EMR and protecting the authenticity of EMR, in order to reduce the interference of entities unrelated to medical clinical information, the content of EMR is reduced. Because the patient's name, age, address and other privacy information are recorded in the electronic medical record, in order to protect the patient's privacy, it is necessary to desensitize the patient's information, so as to obtain the real clinical medical record corpus without privacy.

(2) Manual sequence annotation: In the preparation of the data in the early stage, the unstructured electronic medical record data needs to be labelled manually. In the labelling process, the entities related to clinical medicine are taken as the objects, and the entities are classified into their categories according to the format of <label>entity</label>. Table I introduces the relevant information of entity categories. In the expression of EMR sentences, it is easy to see that a sentence contains many kinds of entities. For example, the sentence "pain in the left lower limb" contains both the entity category of "left lower limb", that is, body part, and the category of "pain", that is, symptoms and signs. So there is a nested relationship between entities. The annotation example of EMR is shown in Figure 5.

TABLE I
NAMED ENTITY CLASSIFICATION

Entity category	Category definition	Sequence labelling
Symptoms and Signs	Symptoms are subjective feelings described by patients; Physical signs are objective facts observed externally	<Symptoms and signs> Abdominal distension, vomiting </Symptoms and signs>
Body Parts	It refers to the anatomical part of human body where diseases, symptoms and signs occur	<Body parts> Lower limbs </Body parts>
Examination and Check	It refers to the basis provided for clinical diagnosis and treatment through laboratory technology and medical equipment	<Inspection and inspection> Chest X-ray, abdominal X-ray </Inspection and inspection>
Treatment	It usually refers to the process of intervening or changing a specific state of health	<Treatment> Surgical treatment in hospital </Treatment>
Disease and Diagnosis	Disease is the cause of patients in unhealthy state; Diagnosis is to identify the	<Disease and diagnosis> gastrointestinal perforation </Disease and

	disease according to the symptoms	diagnosis>
Entity category	Category definition	Sequence labelling

<symptoms and signs> metastatic right lower abdominal pain for 2 days </symptoms and signs> before admission <symptoms and signs> there was no obvious cause of abdominal pain in 2 days </symptoms and signs>, <symptoms and signs> persistent pain around umbilicus </symptoms and signs> , <symptoms and signs> less severe </symptoms and signs> , <symptoms and signs> no shoulder back, perineal radiation pain </symptoms and signs> , <symptoms and signs> no nausea </symptoms and signs> , <symptoms and signs> no vomiting </symptoms and signs> , <symptoms and signs> no shivering </symptoms and signs> , <symptoms and signs> with fever </symptoms and signs> , <symptoms and signs> temperature 41.0℃ </symptoms and signs> , <symptoms and signs> occasionally sour, belching </symptoms and signs> , <symptoms and signs> no diarrhea </symptoms and signs> , <symptoms and signs> there's no need to worry </symptoms and signs> , <symptoms and signs> no pain or hematuria </symptoms and signs> , <symptoms and signs> no chest tightness, chest pain, dyspnea </symptoms and signs> , <symptoms and signs> no cough, expectoration and hemoptysis </symptoms and signs>. not paying attention to abdominal pain, <symptoms and signs> the pain was gradually transferred and fixed in the right lower abdomen </symptoms and signs> . they were examined by B-ultrasound in our hospital, <disease and diagnosis> the diagnosis was acute appendicitis </disease and diagnosis> <treatment> give anti infection, rehydration and other treatment </treatment> For the sake of surgical treatment, acute appendicitis was admitted to our department. Since the onset of the disease, <symptoms and signs> the general condition is good </symptoms and signs> , <symptoms and signs> reduced diet </symptoms and signs> .

Fig. 5. Examples of manually annotated electronic medical record

(3) Jieba word segmentation and part of speech tagging: Jieba word segmentation is a common Chinese word segmentation tool, which has many functions such as Chinese word segmentation and keyword extraction. In the process of entity extraction, not only the entity should be classified into the correct category, but also the entity boundary should be recognized correctly. The annotation strategies commonly used in named entity recognition are bio pattern, bio pattern and bio pattern, which is adopted in this paper. Where "B" refers to the beginning of the entity, "I" refers to the middle part of the entity, "O" refers to the unmarked entity, "e" refers to the end of the entity, "s" refers to the single word representation of the entity. Call the Jieba word segmentation tool in Python to automatically cut the whole EMR text into small entity blocks, and label and label each entity block. The example of EMR processed by Jieba segmentation is shown in Figure 6.

lower limbs	n	B-BODY
skin	n	E-BODY
pigment	n	B-CHECK
composure	v	I-CHECK
.	x	E-CHECK
bilateral	n	B-CHECK
knee tendon	n	I-CHECK
reflex	v	I-CHECK
existence	v	E-CHECK
,	x	O
double	m	B-CHECK
side	v	I-CHECK
babinski	eng	I-CHECK
sign	v	I-CHECK
negative	n	E-CHECK

Fig. 6. Example of electronic medical record processed by Jieba segmentation

In Figure 6, the first column represents the input entity sequence, the second column represents the part of speech of the entity, and the third column represents the label of the entity classification label.

(4) Word embedding: In this paper, after Jieba word segmentation, we use word embedding method to express entity with distributed vector, combining word feature and part of speech feature to reflect corpus information, which can optimize the effect of entity recognition.

C. Evaluation index

In this paper, precision, recall and F1 value are used as the indicators to evaluate the performance of model recognition. The formulas for calculating the accuracy rate, recall rate and F1 value are shown in formula (8), formula (9) and formula (10):

$$Precision = \frac{TP}{TP+FP} \times 100\% \qquad (8)$$

$$Recall = \frac{TP}{TP+FN} \times 100\% \qquad (9)$$

$$F1 = \frac{2 \times Precision \times Recall}{Precision + Recall} \times 100\% \qquad (10)$$

Where, TP (true positives) is the number of correctly recognized entities in the test set, FP (false positives) is the number of wrongly recognized entities in the test set, and FN (false negatives) is the number of unrecognized entities.

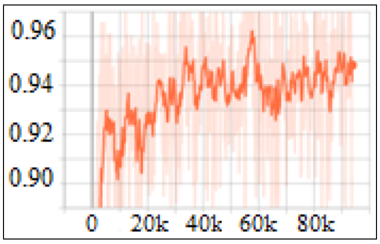
IV. Experimental Conditions and Results

A. Experimental Condition

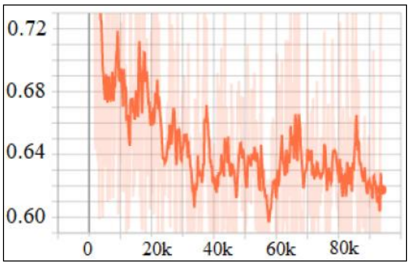
The experimental environment of this paper is Linux 64bit operating system, and the processor is Intel(R) Xeon(R) W-2012@2.9GHz, memory is 16G The experimental platform adopts Python 2.7 programming language, builds Tensor Flow environment, and uses Jieba word segmentation tool. High value medical clinical information is extracted from admission records and stored in plain text format. A total of 335 data were used in this study, 235 of which were used as training set and 100 as test set.

B. Experimental Result

In order to further verify the overall effect of LSTM-CRF model on Chinese EMR named entity recognition, this paper analyses LSTM-CRF model with three evaluation indexes of five types of entity recognition accuracy, recall rate and F1 value. As shown in Fig. 7, Fig. 7(a) and Fig. 7(b) respectively show the relationship between the training times and the accuracy of the training set of LSTM-CRF model, and the relationship between the training times and the average loss. In Figure 7 (a), the abscissa represents the training times of the experiment, and the ordinate represents the recognition accuracy of the training set. It can be seen from the figure that with the increase of training times, the overall curve presents a trend of increasing accuracy, but there is a small range of fluctuation; In Figure 7(b), the abscissa represents the training times of the experiment, and the ordinate represents the average loss during the training process. It is obvious from the figure that with the increase of training times, the average loss value gradually decreases, which indicates that the network structure learning rate of the model is better.



(a) LSTM-CRF model accuracy curve



(b) LSTM-CRF model loss mean curve

Figure 7: Training process of LSTM-CRF model

Figure 8 shows the F1 value results of five entity recognition types in EMR: symptoms and signs, body parts, examination and test, treatment, disease and diagnosis. It can be seen from the figure that different types of entities also affect the recognition results. From the F1 value, we can know that body parts and symptoms and signs have the best recognition effect, and the F1 values are 89.8% and 80.0% respectively. The recognition effect of inspection entity is the second; the F1 value was 73.1%. The recognition effect of disease, diagnosis and treatment entities is not ideal.

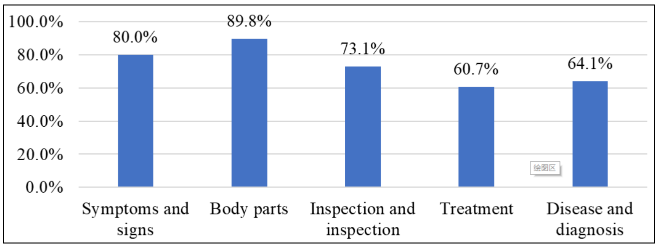


Fig. 8. Results of F1-score for different types of named entities recognition

Figure 9 shows the recognition accuracy and recall results of symptoms and signs, body parts, examination and inspection, treatment, disease and diagnosis in EMR. According to the analysis of the above five types of EMR entity recognition results, for the body part entity recognition, the accuracy rate is 91.0%, the recall rate is 88.7%, and the F1 value reaches 89.8%. There are many such entities in the training set, and the model fully learns the text features of such entities, so the recognition results are good.

For the treatment entity recognition, the accuracy and recall rate are more than 90%, and the F1 value is 90.7%. This is because the treatment entity expression in the electronic medical record text has a certain rule, and has a fixed expression format, for example, progesterone treatment after improvement, physical cooling, and surgery treatment after improvement and so on.

For the recognition of disease and diagnosis entities, the accuracy rate is 66.9%, and the recall rate is 61.7%. The accuracy rate and recall rate are low, mainly because the semantic expression of disease and diagnosis entities is very similar to symptom and sign entities, and there will be recognition errors between disease and diagnosis entities and symptom and sign entities.

For inspection and inspection entity recognition, the recognition accuracy rate is 75.6%, and the recall rate is 70.7%.

V. CONCLUSION

In this paper, LSTM-CRF model is applied to Chinese EMR entity recognition. LSTM model is used to automatically extract the text features containing the above information, which greatly alleviates the problem of traditional methods relying on manual feature extraction. CRF model is used as a classifier to output the maximum probability result sequence, so as to realize EMR entity recognition. Through the analysis of the accuracy, recall and F1 value, it is found that the accuracy, recall and F1 value of LSTM-CRF model in identifying the body part entities and treatment entities in EMR are more than 90%, which indicates that the recognition ability of LSTM can be obtained by representing the body part entities and treatment entities; However, the recognition of symptoms and signs, examination and examination, disease and diagnosis is poor.

For the long sequence EMR entity recognition task, EMR contains a lot of entity information, such as abbreviations of medical terms, ambiguous entities and special characters. It needs sufficient context information and dependency relationship to express its meaning more comprehensively. The unidirectional LSTM model can only capture the sequence information, but cannot learn the relevance and relevance between context information. In view of these shortcomings, we still need to find better models and training algorithms in the future, and then combine the word vector of text sequence with the word vector, to form the word vector to express the potential semantic information at a deeper level, so as to further optimize the entity recognition effect.

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Biographies

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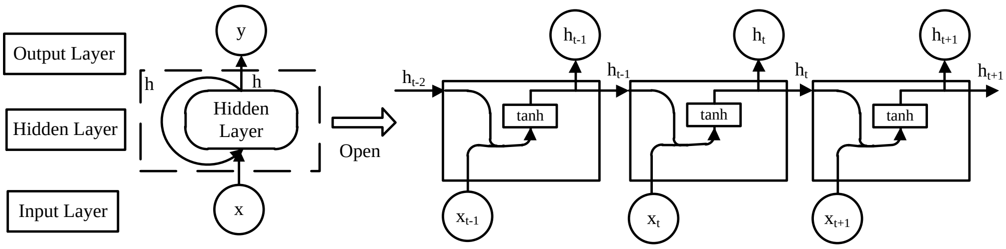

Fig. 1. Structure pattern of Recurrent Neural Network.

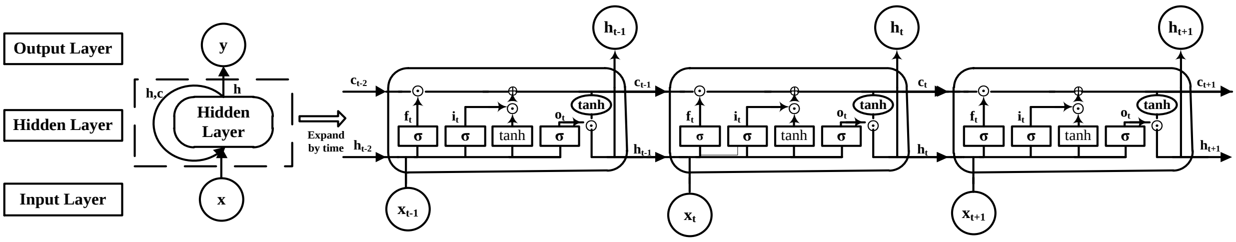

Fig. 2. Structure pattern of long and short time memory network.

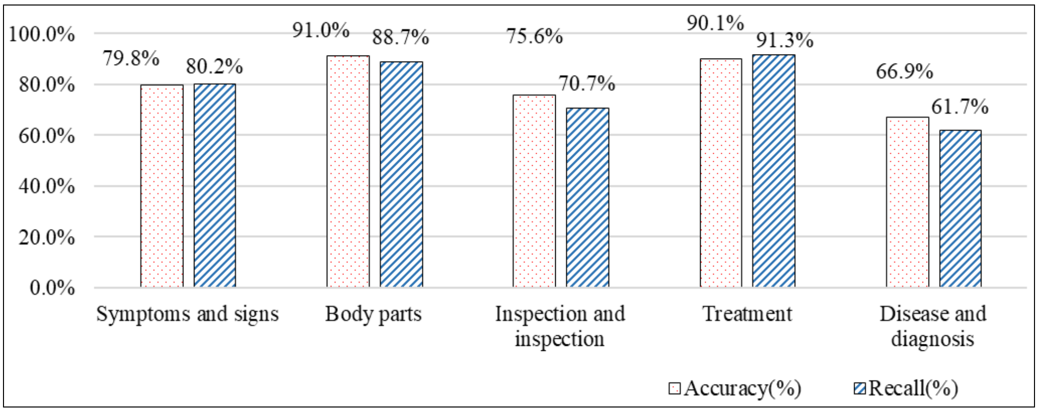

Fig. 9. Named entity recognition results of different types

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