Automatic Severity Classification of Coronary Artery Disease via Recurrent Capsule Network

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Abstract—Coronary artery disease (CAD) is one of the leading causes of cardiovascular disease deaths. CAD condition progresses rapidly, if not diagnosed and treated at an early stage may eventually lead to an irreversible state of the heart muscle death. Invasive coronary arteriography is the gold standard technique for CAD diagnosis. Coronary arteriography texts describe which part has stenosis and how much stenosis is in details. It is crucial to conduct the severity classification of CAD. In this paper, we employ a recurrent capsule network (RCN) to extract semantic relations between clinical named entities in Chinese coronary arteriography texts, through which we can automatically find out the maximal stenosis for each lumen to inference how severe CAD is according to the improved method of Gensini. Experimental results on the corpus collected from Shanghai Shuguang Hospital show that our proposed method achieves an accuracy of 97.0\% in the severity classification of CAD.

Index Terms—Electronic health records, coronary artery disease, severity classification; recurrent capsule network; relation extraction

I. INTRODUCTION

A large amount of electronic health records (EHRs) data has been accumulated since the wide use of medical information systems in China. However, most of these records are written in natural language, which cannot be processed by computers directly. For example, coronary arteriography is the gold standard technique for the diagnosis of coronary artery disease (CAD). However, after writing the results of coronary angiography on EHRs, doctors have to classify the severity of CAD manually based on the coronary angiography results, according to the method of Gensini [1]. Since coronary arteriography texts describes which part has stenosis and how much stenosis is in details, if we can extract the relations between clinical named entities in coronary arteriography texts, we can automatically find out the maximal stenosis for each lumen, and inference how severe CAD is under the guide of the method of Gensini. Thus, one of the key issues to conduct the severity classification of CAD is relation extraction, i.e., extract the relations between clinical named entities in coronary arteriography texts.

Fig. 1 shows an illustrative example of relation extraction in the sentence “左前降支中段40%狭窄，右前降支，右回旋支未见明显狭窄。” (40\% of the middle of left anterior descending branch has stenosis and no obvious stenosis has been seen in the right anterior descending branch and the right circumflex coronary artery), in which the relations <left anterior descending branch, r:modifier(e1,e2), stenosis> , <left anterior descending branch, r:percentage(e2,e1), stenosis> should be extracted.

The relation extraction task is full of challenges due to the following reasons: (1) Different modifiers may share the same lumen, and different lumina may share the same modifiers. It denotes long-term dependency in a coronary arteriography sentence. (2) The same sentence can be expressed in different ways, such that “40\%狭窄” and “狭窄40\%” express the same meaning (i.e. 40\% of sth. has stenosis).

A number of methods have been proposed for the relation extraction task. These methods are usually based on supervised methods or semi-supervised methods via deep neural networks, such as convolutional neural networks (CNNs) [2]–[4] and recurrent neural networks (RNNs) [5]–[7]. However, these existing methods all use only a neuron (i.e. scalar) to represent the classification probability via a sigmoid function or a softmax function, which limit the expressive ability of neural networks.

In this paper, we employ a recurrent capsule network (RCN) model to extract entity relations. Specifically, after clinical named entity recognition (CNER), words and their corresponding entity type features are first transferred into
embedding vectors, then fed into a recurrent layer to capture high-level features. Finally, a capsule layer is used for relation classification, where the length of the capsules (i.e., vectors) is used to represent the probability that the corresponding relation exists, and different orientation of a capsule can represent different cases under the relation, so the model can achieve a stronger expressive ability. Extensive experimental results on the coronary arteriography texts collected from Shanghai Shuguang Hospital show that our RCN model obtains the best performance compared with baseline methods.

The contributions of this paper can be summarized as follows.

- We present an effective method for the automatic severity classification of CAD from EHRs. A recurrent capsule network model is employed to extract semantic relations between clinical named entities in Chinese texts.
- We conduct extensive experiments on the coronary arteriography texts collected from Shanghai Shuguang Hospital. Experimental results demonstrate that our proposed method outperforms the baseline methods.

The rest of the paper is organized as follows. In Section II, we briefly review the related work on relation extraction. In Section III, we present an effective method for the automatic severity classification of CAD. We report the computational results in Section IV. Section V is devoted to experimental analysis and some discussions. Finally, conclusions and possible research directions are given in Section VI.

II. RELATED WORKS

Due to its practical significance, relation extraction has attracted considerable research effort in the last decades and a lot of methods have been proposed in the literature. The existing methods can be roughly classified into three categories, namely supervised methods, semi-supervised methods and joint extraction methods.

Traditionally, supervised methods consider the relation extraction task as a relation classification problem, and utilize statistical machine learning methods to address it [8], [9]. Typical methods are support vector machines (SVMs) [10]. However, these statistical methods rely on pre-defined features, which makes their development costly. What’s more, feature engineering, i.e., finding the best set of features for classification, is more of an art than a science, incurring extensive trial-and-error experiments. Lately, with the popularity of deep learning, most focus has shifted towards deep neural networks.

A framework and joint extraction methods.

A. Framework

Given a coronary arteriography text, the whole diagram of the severity classification of CAD is shown in Fig. 2. Clinical named entities are first recognized and then relation extraction is made between the recognized entities. Finally, a severity score of CAD is determined for each patient based on the extracted relations according to the improved method of Gensini [1]. Note that due to the great challenges of extracting relations between clinical named entities, in this paper we focus on the relation extraction and employ a recurrent capsule network (RCN) model to solve it (see Section IV for details).
B. Clinical named entity recognition

Given a coronary arteriography text, we need to recognize some clinical named entities. These entities can be classified into following five categories.

- **Lumen**: An entity that represents a body part of coronary arteries, such as “左主干” (left main coronary artery), “左前降支” (left anterior descending branch) and “左回旋支” (left circumflex coronary artery).
- **Modifier**: An entity which modifies a lumen, such as “正常” (normal), “狭窄” (stenosis), and “闭塞” (occlusion).
- **Negative**: An entity that indicates something does not exist, such as “无” (no), “未” (not), and “未见” (unseen).
- **Position**: An entity that indicates the place where stenosis is located, such as “近段” (proximal segment), “中段” (middle segment), and “远段” (distal segment).
- **Percentage**: An entity that indicates the severity of stenosis, such as “60%”, “70%”, and “90%”.

Many studies have focused on the clinical named entity recognition (CNER) tasks and most of them formulate the task as a sequence labeling problem, employing various machine learning algorithms to address it [32], [33]. In our previous work [34], we also proposed a CNER model which combines data-driven deep learning approaches and knowledge-driven dictionary approaches. As to this task, due to the limited entities, here we simply utilize string matching and regular matching methods for entity recognition.

C. Relation extraction

Relation extraction is the task of finding semantic relations between pairs of entities, including modified relations, negative relations, percentage relations and position relations. It can be regarded as a multi-classification problem with two directions and an undirected no-relation class. In this paper, we employ a recurrent capsule network (RCN) model for relation extraction. We present the RCN model in Section IV

D. Severity classification

Once relation extraction is finished, for each patient, a severity score of CAD is determined based on the extracted relations by using the improved method of Gensini [1]. The scores of the right and left coronary arteries are required to obtained respectively. In all cases the angiography texts showing the most severe stenosis of each lumen is selected for grading:

\[
\text{score}_i = \begin{cases} 
1 & 1\% \leq \text{diameter}_i \leq 49\% \\
2 & 50\% \leq \text{diameter}_i \leq 74\% \\
3 & 75\% \leq \text{diameter}_i \leq 99\% \\
4 & \text{diameter}_i = 100\% 
\end{cases}
\]  

(1)

where \(\text{score}_i\) is the score of the \(i\)-th lumen and \(\text{diameter}_i\) is the maximum lesions of the \(i\)-th lumen’s diameter. That is, lesions of 1% to 49% of luminal diameter are given a score of 1, those of 50% to 74% a score of 2, those of 75% to 99% a score of 3, those of 100% (i.e. occlusion) a score of 4. Finally, for each patient, a total coronary score to reflect the extent of CAD is determined by calculating the sum of the scores for each lesion:

\[
\text{score} = \sum_i \text{score}_i 
\]  

(2)

We further classify the severity of CAD into three levels via the total coronary score, namely mild stenosis (between 0 and 7), moderate stenosis (between 8 and 14) and severe stenosis (over 14).

IV. Recurrent Capsule Network

As mentioned above, our proposed method for the severity classification of CAD is composed of three components: clinical named entity recognition, relation extraction and severity classification. Since the clinical named entity recognition and the severity classification can be simply conducted by some pre-defined rules. Here we focus on the relation extraction, and employ a recurrent capsule network (RCN) to extract semantic relations between clinical named entities.

A. Main architecture of RCN

As shown in Fig. 3 the network integrates three key components, namely embedding layer, recurrent layer and capsule layer. The Chinese words in a coronary arteriography sentence are firstly represented as distributed embedding vectors through embedding layers, and then fed into the recurrent layers. For the recurrent layer, we employ long short-term memory (LSTM) [35] as the basic recurrent units to capture high-level features. Specifically, since the two entities in the sentence can divide the sentence into five segments (i.e. \(E_1\), \(E_2\), \(E_3\), \(E_4\) and \(E_5\)), we employ five LSTMs to handle the five segments, and output five feature vectors, respectively. Finally, an capsule layer is utilized to classify relations, where the lengths of capsules (i.e. vectors) are used to represent the
probabilities whether the corresponding relation exists or not, and the orientation of a capsule can represent different cases.

B. Embedding layer

Given a coronary arteriography sentence \( X = [x_1^T] \), which is a sequence of \( T \) words, the first step is to map discrete language symbols, including the words and their corresponding entity types, to distributed embedding vectors. Formally, we first lookup word embedding \( x_i' \in \mathbb{R}^{d_x} \) from word embedding matrix \( W_x \) for each word \( x_i \), where \( i \in \{1, 2, ..., T\} \) indicates \( x_i \) is the \( i \)-th word in \( X \), and \( d_x \) is a hyper-parameter indicating the size of word embedding. We also look up entity type embedding \( d_i' \in \mathbb{R}^{d_d} \) from entity type embedding matrix \( W_d \) for each type of the entity which \( x_i \) belongs to, where \( d_d \) is a hyper-parameter indicating the size of entity type embedding. The final embedding vector is created by concatenating \( x_i' \) and \( d_i' \) as \( e_i = x_i' \oplus d_i' \), where \( \oplus \) is the concatenation operator.

C. Recurrent layer

The long short-term memory network (LSTM) \(^{[35]} \) is a variant of the recurrent neural network (RNN), which incorporates a gated memory-cell to capture long-range dependencies within the data and is able to avoid gradient vanishing/exploding problems caused by standard RNNs.

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{lstm_cell.png}
\caption{Illustration of an LSTM cell.}
\end{figure}

The LSTM cell is illustrated in Fig. 4. For each position \( t \), LSTM computes \( h_t \) with input \( e_t \) and previous state \( h_{t-1} \), as:

\begin{align}
\hat{i}_t &= \sigma(W_i e_t + U_i h_{t-1} + b_i) \\
\hat{f}_t &= \sigma(W_f e_t + U_f h_{t-1} + b_f) \\
\hat{c}_t &= \tanh(W_c e_t + U_c h_{t-1} + b_c) \\
\hat{c}_t &= \hat{c}_t \circ \hat{i}_t + c_{t-1} \circ \hat{c}_t \\
o_t &= \sigma(W_o e_t + U_o h_{t-1} + b_o) \\
h_t &= o_t \circ \tanh(c_t)
\end{align}

where \( h, i, f, o \in \mathbb{R}^{d_h} \) are \( d_h \)-dimensional hidden state (also called output vector), input gate, forget gate and output gate, respectively; \( W_i, W_f, W_o \in \mathbb{R}^{d_h \times d_e}, U_i, U_f, U_o \in \mathbb{R}^{d_h \times d_h} \) and \( b_i, b_f, b_o \in \mathbb{R}^{d_h} \) are the parameters of the LSTM; \( \sigma \) is the sigmoid function, and \( \circ \) denotes element-wise production.

Due to the current state \( h_t \), also take the previous state \( c_{t-1} \) and \( h_{t-1} \) into account, the final state \( h_T \), can be thought as the representation of the whole segment \( E_i \). However, the hidden state \( h_t \) of LSTM only takes information from past, not considering future information. One solution is to utilize bidirectional LSTM (Bi-LSTM) \(^{[36]} \), which incorporate information from both past and future. Formally, for any given sequence, the network computes both a left, \( \tilde{h}_T \), and a right, \( \check{h}_0 \), representations of the sequence context at the final timestep. The representation of the whole segment \( E_i \) is created by concatenating them as \( h = \tilde{h}_T \oplus \check{h}_0 \).

Since the two entities in the sentence can divide the sentence into five segments, we employ five LSTMs to handle the five segments, respectively. Specifically, considering the sentences in coronary arteriography texts may vary long, and the farther the distance between the context and an entity is, the less influence the context will have on relation classification, except that Bi-LSTMs are employed for the three middle segments (i.e. \( E_2, E_3 \) and \( E_4 \)), the left-to-right LSTM is employed for the left-most segment (i.e. \( E_1 \)), and the right-to-left LSTM is employed for the right-most segment (i.e. \( E_5 \)). Thus, the closer the context is to an entity, the more likely the context is remembered by the LSTM.

D. Capsule layer

The capsule layer is first proposed in \(^{[37]} \) for digit recognition. Different from traditional practice which use only a neuron to represent the classification probability via a sigmoid function or a softmax function, in this paper, a capsule is a group of neurons whose activity vector represents the instantiation parameters of a specific type of relation: The length of the activity vector is used to represent the probability that the corresponding relation exists, and different orientation of the vector can represent different cases under the relation, so the capsule can achieve a stronger expressive ability.

Considering that the length of a capsule is used as the probability of a relation, a non-linear squashing function is used to ensure that short vectors get shrunk to almost zero length and long vectors get shrunk to a length slightly below 1:

\begin{equation}
\nu_j = \frac{\|s_j\|^2 s_j}{1 + \|s_j\|^2 \|s_j\|}
\end{equation}

where \( \nu_j \) is the vector output of input capsule \( s_j \).

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{capsule_layer.png}
\caption{The capsule layer where the double-line arrows indicate squashing functions (take four classification as an example).}
\end{figure}
As illustrated in Fig. 5, the total input to a capsule $s_j$ is a weighted sum over all “prediction vectors” $\hat{u}_{ji}$ from the capsules in the layer below and is produced by multiplying the output $u_i$ of a capsule in the layer below by a weight matrix $W_{ij}$:

$$s_j = \sum_i c_{ij} \hat{u}_{ji} \quad (10)$$

$$\hat{u}_{ji} = W_{ij} u_i \quad (11)$$

where $c_{ij}$ are coupling coefficients that are determined by an iterative dynamic routing algorithm with a given number of iterations $r$ (see [37] for more details).

In training, a separate margin loss, $L_j$, for each classification capsule, $v_j$, is minimized:

$$L_j = R_j \max(0, m^+ - \|v_j\|^2) + \lambda (1 - R_j) \max(0, \|v_j\| - m^-)^2 \quad (12)$$

where $R_j = 1$ iff the relation $j$ exists and $m^+ = 0.9$, $m^- = 0.1$ and $\lambda = 0.5$. The total loss is simply the sum of the losses of all classification capsules.

V. EXPERIMENTAL STUDIES

As to relation extraction, we perform experiments to first evaluate our recurrent capsule network, than evaluate the final severity classification of CAD.

A. Dataset and evaluation metrics

The dataset consists of coronary arteriography texts collected from Shanghai Shuguang Hospital. Shanghai Shuguang Hospital is located in Shanghai, which is one of the highest ranked hospitals in China. After CNER, we asked two students as a group under a doctor’s guidance to manually annotate relations in these sentences and the final severity classification of CAD. Disagreements between the two annotators were resolved by the doctor. After the annotation, to make the dataset more suitable for our relation extraction task, we made several refinements as follows.

1) We add direction to the relation names, such that “r:percentage” is splitted into two relations “r:percentage(e1,e2)” and “r:percentage(e2,e1)” except for “no relation”. This leads to six relations in the dataset.

2) We calculate the frequency of each relation with two directions separately. To better balance the relation dataset, 85% “no relation” sentences are discarded.

3) We performed standard random splitting on the relation dataset, with 70% training and 30% test sets.

The statistical characteristics of the relation dataset are shown in Table I and the dataset of the final severity classification are shown in Table II.

To evaluate the methods, we use the standard and widely-used performance metrics [38], [39], i.e., precision (P), recall (R) and $F_1$-score ($F_1$) for relation extraction and the final severity classification of CAD. We also report the accuracy of the final severity classification of CAD.

\begin{table}[h]
\centering
\caption{Statistical Characteristics of the Relation Dataset}
\begin{tabular}{|c|c|c|c|}
\hline
Relation Name & Training & Test & Total \\
\hline
r:modifir(e1,e2) & 754 & 314 & 1,068 \\
r:negative(e2,e1) & 296 & 110 & 406 \\
r:position(e1,e2) & 257 & 132 & 389 \\
r:percentage(e1,e2) & 70 & 30 & 100 \\
r:percentage(e2,e1) & 176 & 80 & 256 \\
no relation & 1,384 & 593 & 1,977 \\
\hline
Total & 2,937 & 1,259 & 4,196 \\
\hline
\end{tabular}
\end{table}

\begin{table}[h]
\centering
\caption{Statistical Characteristics of the Final Severity Classification}
\begin{tabular}{|c|c|c|}
\hline
Severity Level & Number & Percentage \\
\hline
Mild Stenosis & 145 & 72.5% \\
Moderate Stenosis & 45 & 22.5% \\
Severe Stenosis & 10 & 5.0% \\
\hline
Total & 200 & 100.0% \\
\hline
\end{tabular}
\end{table}

B. Implementation details

After CNER, Chinese words are first segmented via Jieba Chinese segmentation module [1] then pretrained 128-dimensional word vectors and entity type vectors in the embedding layer are obtained using the word2vec method [40] on both the training data and the test data, and they are updated during the training process. The size of each LSTM hidden states in bidirectional LSTMs (Bi-LSTMs) and unidirectional LSTMs (Uni-LSTMs) is set to 64 and 128, respectively. The dimension of the capsules is set to 64, and the iterative number $r$ of dynamic routing is set to 4. To minimize the margin loss, the whole network is trained by Adam optimization algorithm [41] with default parameter settings and the batch size is set to 128.

C. Comparisons with baseline methods of relation extraction

We compare RCN models with five state-of-the-art methods. These five reference algorithms have been widely used for relation classification.

- **CNN + MaxPooling [3]:** It took words and their positions as input, and utilized a CNN with max-pooling to extract lexical and sentence level features. Finally, a softmax function is used to classify relations.

- **BiLSTM + MaxPooling [5]:** It sent words to a Bi-LSTM network with max-pooling, and used a softmax function to classify relations.

- **BiLSTM + Attention [6]:** It exploited an attention-based Bi-LSTM network to receive input words, and used a softmax function for relation classification.

- **CRNN + MaxPooling** and **CRNN + Attention [13]:** They employed a CRNN architecture that combines RNNs and CNNs in sequence. **CRNN + MaxPooling** took words as input and utilized a max-pooling strategy along with a softmax function to classify relations.

https://github.com/fxsjy/jieba
**CRNN + Attention** is an attention-based pooling technique.

Note that our model utilize entity type features which is not exploited in the baselines, we also report the results of the baselines with entity type features.

Table **III** shows the comparative results of our model and the baselines. First of all, we can observe that our model with entity type features outperforms these reference algorithms, with 95.59% in Precision, 97.45% in Recall and 96.51% in F1-score. The improvements compared with the original baselines without entity type features are 1.5, 1.5, 1.05, 0.45 and 1.2 points in Recall, 0.54, 1.64, 2.53, 1.63 and 1.77 points in F1-score, respectively. Without entity type features, our model also outperforms the reference algorithms without entity type features. Both the Recall and F1-score of our model achieve the best ones, and the Precision of our model is just below the CNN + MaxPooling method, which use an extra position feature, while our model does not. Secondly, the entity type features proposed by us can help improve performance of the original baselines. The benefits in F1-score brought by the entity type features are 0.27, 0.87, 2.28, 0.69 and 1.22 points, respectively. However, the improved performance is still worse than our model. Thirdly, among the baselines, it is interesting to note that without entity type features, attention-based pooling technique performs worse than conventional max-pooling strategy, which has also been observed earlier by Sahu and Anand [42] and Raj et al. [13], while with entity type features, attention-based pooling technique performs better than conventional max-pooling strategy.

Furthermore, we compare class-wise performance of our RCN model with baseline methods. The comparative results are summarized in Table **VI**. Firstly, we clearly observe that our model achieves No.1 in three relations (i.e. r:modifier[e1,e2], r:negative[e2,e1] and r:percentage[e2,e1]) and No.2 in one relation (i.e. r:percentage[e1,e2]) among all the five relations. The F1-scores are higher than 90.00 except for r:percentage[e1,e2] relation because of its low frequency (only 70 instances) in the training set. Secondly, we also obtain the same observation on the proposed entity type features as mentioned above that they can help improve performance of the original word embedding features.

**D. Evaluation of severity classification of CAD**

To evaluate the effectiveness of our proposed severity classification method, we randomly select 200 coronary arteriography texts for evaluation. The results are shown in Table **V**. First of all, our method obtains an overall Accuracy of 97.00%. Only six texts are classified into the wrong level. Secondly, most of the coronary arteriography texts (72.5%) belongs to mild stenosis in practice. Our method achieves an relative high performance in terms of Precision (100%), Recall (98.62%) and F1-score (99.31%). Thirdly, our method is a little confused with moderate stenosis and severe stenosis. The precision, recall and F1-score of moderate stenosis are all 93.33%. It is still acceptable. As to severe stenosis, which appears rarely (5%) in practice, though the precision is merely 75.00%, but the recall is 90%. That is to say, only one text of severe stenosis is not recognized by our method.

**VI. Analysis and Discussion**

In this section, we conduct two groups of experiments to respectively investigate the effect of the input features with different routing iterations, and the interest of the Uni/Bi-LSTMs and the capsule layer.

**A. Effect of the input features with different routing iterations**

To study the effect of the input features and the routing iterations in our model, we experimentally compare the performance between different input features with different routing iterations. As shown in Table **VI**, our model achieves the best performance when adopting words and their entity types as input with 4 routing iterations. The Precision, Recall and F1-score are 95.59%, 97.45% and 96.51%, respectively. Comparing the model inputs, we can observe that the performance of our model with entity type features is better than that without entity type features. The benefits are 0.66 in Precision, 0.63 in Recall and 0.65 in F1-score on average. Comparing the five lines in the table, we can observe that whatever inputs are used, the performance (in terms of F1-score) first grows then drops down with the increase of iterative number r. When words are only used, our model achieves its best performance with r = 2. And when words and entity types are both used, our model achieves its best performance with r = 4.

**B. Interest of Uni/Bi-LSTMs and capsules**

To analyze the interest of Uni/Bi-LSTMs and capsules, we compare our model with that all using Bi-LSTMs or replacing the capsule layer by a fully-connected layer with a softmax function. The results are illustrated in Table **VII**. From the table, we can observe that the F1-score of our model is higher than that all using Bi-LSTMs by 0.29%, and higher than that using a softmax layer by 0.35 point. It indicates the interest of the proposed Uni/Bi-LSTMs and capsules.

**VII. Conclusions and Future Works**

In this paper, we present an effective method for the severity classification of coronary artery disease in EHRs. In our method, a recurrent capsule network model is employed to extract semantic relations in coronary arteriography texts. Specifically, words and their corresponding entity type features are first transferred into embedding vectors, then fed into a recurrent layer to capture high-level features. Finally, a capsule layer is used for relation classification. Experimental results on the corpus collected from Shanghai Shuguang Hospital shows that our RCN model achieved an F1-score of 96.41% in relation extraction and an Accuracy of 97.0% in the final severity classification of CAD. In future, we plan to use our recurrent capsule network model to solve other NLP tasks.
TABLE III
COMPARATIVE RESULTS OF OUR RCN MODEL AND BASELINE METHODS

| Method               | Input                                        | P   | R   | F1  |
|---------------------|----------------------------------------------|-----|-----|-----|
| CNN + MaxPooling [3]| Word + Position                              | 95.54 | 96.53 | 95.97 |
|                     | Word + Position + Entity Type*              |     |     |     |
| BiLSTM + MaxPooling [5]| Word Only                                   | 94.45 | 94.30 | 94.37 |
|                     | Word + Entity Type*                         |     |     |     |
| BiLSTM + Attention [6]| Word Only                                   | 95.52 | 95.95 | 95.74 |
|                     | Word + Entity Type*                         |     |     |     |
| CRNN + MaxPooling [13]| Word Only                                   | 96.51 | 96.40 | 96.26 |
|                     | Word + Entity Type*                         |     |     |     |
| CRNN + Attention [13]| Word Only                                   | 99.54 | 95.80 | 94.88 |
|                     | Word + Entity Type*                         |     |     |     |
| Our RCN model       | Word Only                                   | 99.54 | 96.85 | 95.99 |
|                     | Word + Entity Type*                         |     |     |     |

* The entity type features are proposed by us.

TABLE IV
CLASS-WISE PERFORMANCE (IN TERMS OF F1-SCORE) OF OUR RCN MODEL AND BASELINE METHODS

| Method               | Input                                        | r:modifier (e1,e2) | r:negative (e2,e1) | r:position (e1,e2) | r:percentage (e1,e2) | r:percentage (e2,e1) |
|---------------------|----------------------------------------------|-------------------|-------------------|-------------------|-------------------|-------------------|
| CNN + MaxPooling [3]| Word + Position                              | 96.33             | 99.54             | 96.21             | 80.00             | 97.53             |
|                     | Word + Position + Entity Type*              |                   |                   |                   |                   |                   |
| BiLSTM + MaxPooling [5]| Word Only                                   | 96.28             | 99.09             | 96.66             | 81.16             | 96.20             |
|                     | Word + Entity Type*                         |                   |                   |                   |                   |                   |
| BiLSTM + Attention [6]| Word Only                                   | 95.33             | 99.09             | 94.62             | 81.16             | 96.20             |
|                     | Word + Entity Type*                         |                   |                   |                   |                   |                   |
| CRNN + MaxPooling [13]| Word Only                                   | 94.87             | 99.09             | 93.44             | 73.85             | 95.65             |
|                     | Word + Entity Type*                         |                   |                   |                   |                   |                   |
| CRNN + Attention [13]| Word Only                                   | 97.15             | 99.09             | 93.85             | 83.87             | 98.14             |
|                     | Word + Entity Type*                         |                   |                   |                   |                   |                   |
| Our RCN model       | Word Only                                   | 96.77             | 99.54             | 93.08             | 76.47             | 98.14             |
|                     | Word + Entity Type*                         |                   |                   |                   |                   |                   |

* The entity type features are proposed by us.

TABLE V
PERFORMANCE OF OUR AUTOMATIC SEVERITY CLASSIFICATION METHOD

|               | P     | R     | F1    |
|---------------|-------|-------|-------|
| Mild Stenosis | 100.00| 98.62 | 99.31 |
| Moderate Stenosis | 93.33 | 93.33 | 93.33 |
| Severe Stenosis | 75.00 | 90.00 | 81.82 |
| Overall Accuracy |       |       | 97.00 |

TABLE VI
COMPARISONS BETWEEN DIFFERENT INPUT FEATURES WITH DIFFERENT ROUTING ITERATIONS

|         | Word Only | Word + Entity Type |
|---------|-----------|--------------------|
| P       | R         | P                 | R           | F1       | P     | R     | F1     |
| 1       | 94.53     | 93.80             | 94.97       | 96.23    | 95.61 |
| 2       | 95.14     | 96.85             | 94.74       | 97.30    | 96.01 |
| 3       | 94.69     | 96.25             | 95.15       | 97.15    | 96.14 |
| 4       | 94.95     | 95.80             | 95.59       | 97.45    | 96.51 |
| 5       | 93.25     | 97.30             | 95.43       | 97.00    | 96.21 |

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