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Research on Constructing a Departmental Guidance Model Using TextCNN, BiLSTM, and BERT

Jieqi Li*

Communication University of China, Beijing, China

*Corresponding author: 202229013077n@cuc.edu.cn

Abstract. Current departmental guidance platforms in intelligent systems predominantly rely on selective options, necessitating patients to select pertinent medical information before scheduling an appointment. However, most patients' lack of specialized medical knowledge frequently results in misregistration incidents. Moreover, the focus of existing research on medical guidance systems does not emphasize or distinguish among specialized departments, leading to reduced consultation efficiency, overstretched resources in specific departments, and potential delays in patient treatment. This study aims to develop a departmental guidance model utilizing TextCNN, BiLSTM, and BERT. Initially, it involves training the base models of TextCNN, BiLSTM, and BERT on departmental guidance under uniform hyperparameters and environmental settings, comparing the outcomes to ascertain each model's strengths and weaknesses. Subsequently, an innovative hybrid model is proposed incorporating an attention mechanism, capitalizing on their synergistic features to address the challenge of low accuracy in guiding specialized departments. This hybrid model achieved an accuracy rate of 96.0%, precision of 95.7%, recall of 95.5%, and an F1 score of 95.6%, all demonstrating superior performance and significantly surpassing the experimental results of the standalone foundational models. Therefore, this study concludes that the innovative model can accurately direct patients to the appropriate specialized department based on their symptom descriptions.

Keywords: intelligent system, TextCNN, BiLSTM, Hybrid Vehicle.

1. Introduction

As artificial intelligence technology advances, intelligent hospitals have become feasible, leveraging big data and deep learning to match patients with the appropriate departments and doctors[1]. However, current intelligent guidance platforms are primarily choice-based, necessitating that patients manually select relevant medical information for registration and appointment scheduling. This method presents several shortcomings: most patients lack the required professional medical knowledge, leading to misregistrations due to the difficulty in choosing specialized departments. While broad categories like gynecology, pediatrics, internal medicine, and surgery are easily distinguishable, differentiating among sub-specialties within these categories—such as endocrinology, cardiology, neurology, and gastroenterology in internal medicine—proves challenging. Consequently, this can result in registration errors, decreased consultation efficiency, overburdened resources in certain departments, and potentially delayed treatment opportunities for both the individual and other patients. The challenge of accurately classifying sub-specialties exists in patients' subjective assessments and within the medical guidance systems themselves. Previous studies in the field have not focused sufficiently on distinguishing between sub-specialties. Given the critical nature of medical resources, this paper proposes an innovative model that emphasizes and differentiates among sub-specialties.

In recent years, various advanced technologies have been proposed to optimize the guidance process. For instance, a doctor recommendation guidance system that utilizes ATERDE and the AHP data gravity classification algorithm combines time series data and the Analytic Hierarchy Process to recommend doctors based on patient symptoms and doctors' specialties, thus improving patient consultation efficiency[2]. Another study leveraging TextRNN uses a pre-trained model to convert patient conditions into word vectors. It employs a bidirectional long short-term memory network to extract features and predict the department necessary for the patient's consultation, thereby facilitating intelligent guidance[3]. Additionally, a department recommendation classification model that integrates the CTRM model with a classification voting algorithm has shown strong generalization capabilities, significantly improving accuracy and F1 scores[4].

This research is aimed at developing a departmental guidance model utilizing TextCNN, BiLSTM, and BERT. It seeks to solve the problem of low accuracy in guiding to specialized sub-departments by taking advantage of these models' unique strengths and complementary characteristics. For instance, TextCNN's computational efficiency and sensitivity to local features can mitigate BERT's high computational demands when processing lengthy texts and the relative deficiency of BiLSTM in local information extraction. BiLSTM addresses TextCNN's limitations in handling time series[5], especially about the sensitivity needed for sequencing symptom development. BERT's capability for global comprehension addresses the high-level feature abstraction of TextCNN and the shortcomings of BiLSTM in understanding lengthy texts and the overall context, though at a lower computational efficiency. Such integrative utilization renders the guidance model more comprehensive and adaptable to different scenarios. Through model integration and the introduction of an attention mechanism, this study aims to improve the precision of the guidance system, enabling patients to more accurately select the appropriate specialized sub-departments, thus enhancing medical efficiency and addressing the shortage of medical resources.

To achieve these goals, the paper first evaluates the performance of TextCNN, BiLSTM, and BERT in intelligent departmental guidance, subsequently combining them with an attention mechanism to construct a new integrated model. Through comprehensive steps, including data collection, text preprocessing, base model selection, performance evaluation, and model integration, the research unfolds to contribute to the development and practical application in the medical guidance field.

2. Data and Methods

2.1. Data Source

This study employs a dataset comprising 500 textual entries derived from patient descriptions and inquiries regarding their symptoms across five sub-specialties within internal medicine, sourced from https://ask.39.net/. The dataset is segmented into two portions: the initial 400 entries designated for training purposes and the subsequent 100 for testing. Advanced tokenization methods are utilized for cleansing the text, segmenting words, and vectorizing patient descriptions.

2.2. Methods

The methodology of this study is structured in two phases. The first phase entails training three models—TextCNN, BiLSTM, and BERT—on the task of departmental guidance. This phase involves observing the statistical metrics produced and visualizing the training process to ascertain each model's relative strengths and weaknesses when processing the custom dataset.

The second phase involves the innovative integration of the TextCNN, BiLSTM, and BERT models, achieved by incorporating an attention mechanism to bolster the contextual linkage of data.

TextCNN Model: Introduced by Yoon Kim in 2014, the TextCNN model adapts the CNN's input layer for text classification purposes. Despite its structural similarity to traditional CNN networks used for image processing, TextCNN is simplified yet yields higher accuracy[6]. Comprising just a single convolutional layer, one max-pooling layer, and a concluding softmax layer for n-class classification, TextCNN's primary advantage lies in its straightforward architecture. Even when leveraging pre-trained word vectors, this simplicity delivers commendable results, outperforming benchmarks across multiple datasets[7]. The model's streamlined structure results in minimal parameters, reduced computational demands, and accelerated training times. A single V100 machine can converge within roughly half an hour after training on 1.65 million data points over 260,000 iterations.

BiLSTM Model: The Bi-directional Long Short-Term Memory (BiLSTM) model integrates two LSTMs: one processes the input sequence forwards, and the other in reverse. The outputs from both LSTMs are merged only after the computation of all time steps. The forward LSTM generates a result vector after six-time steps; similarly, the backward LSTM produces another vector after six steps. These vectors are concatenated to furnish the final BiLSTM output[8].

BERT Model: The BERT model features a structure of multiple bidirectional transformer encoders. Fundamentally, BERT learns the feature representation of the input sequence, subsequently applying this learned representation to various downstream tasks. The bidirectional architecture addresses the limitations imposed by unidirectional structures on pre-trained representations. Neither solely left-to-right nor right-to-left configurations, nor even the simplistic concatenation of left-to-right features, as seen in ELMo, suffice. This inadequacy arises because the pre-trained BERT model, destined for diverse tasks, necessitates knowledge of both the preceding and succeeding context for each word within the sequence, integrating information from both directions[9].

As depicted in the innovative model's flowchart, this research processes textual data utilizing each of the three models to extract information, which is then refined via an attention mechanism before reaching the final label output through a fully connected layer (Figure 1).

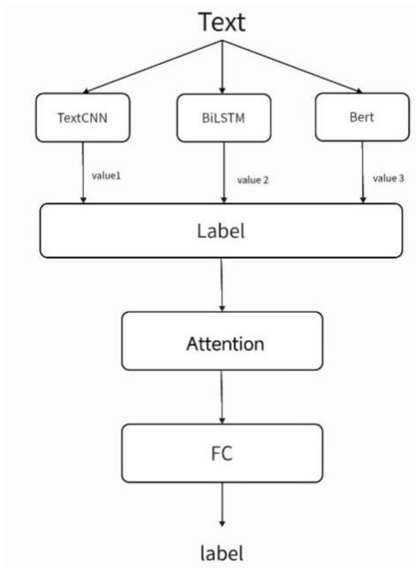

Fig.1 The innovative model's flowchart

2.3. Evaluation Metrics

This study employs four evaluation metrics: accuracy, precision, recall, and the F1 score.

Accuracy (A): The proportion of correctly classified samples out of the total samples, defined as A = (TP + TN) / N.

Precision (P): The ratio of correctly predicted positive observations to the total predicted positive observations, calculated as P = TP / (TP + FP).

Recall (R): The ratio of correctly predicted positive observations to all observations in the actual class, given as R = TP / (TP + FN).

F1 Score (F): The harmonic mean of precision and recall, expressed as F = 2 / (1/P + 1/R) = 2 * P * R / (P + R).

2.4. Comparison of TextCNN, BiLSTM, BERT, and the Innovative Model

Table 1: Comparison of evaluation metrics of each model

	TextCNN	BiLSTM	BERT	Innovation model
Accuracy	0.330	0.550	0.910	0.960
Precision	0.597	0.587	0.916	0.957
Recall	0.361	0.541	0.913	0.955
F1 score	0.290	0.548	0.914	0.956

Table 1 illustrates that TextCNN achieves an accuracy of only 33.0%, BiLSTM attains 55.0% accuracy, and BERT demonstrates a significantly higher accuracy rate of 91.0%. This comparison reveals the lower accuracy and recall rates of TextCNN and BiLSTM, whereas BERT exhibits higher performance metrics but has not yet reached optimal diagnostic effectiveness.

On this foundation, the innovative model, operating under identical hyperparameters and environmental settings, surpasses the three foundational models in all statistical metrics, achieving an impressive accuracy rate of 96%. This marks a significant enhancement in the accuracy of departmental guidance tasks.

However, the limited dataset size and potential undertraining raise concerns that models, especially TextCNN and BiLSTM, which exhibited poor performance, might not have had sufficient training data to capture the full spectrum of features and variations in the data, leading to their underwhelming experimental outcomes. Future studies could expand the dataset for a more comprehensive analysis.

3. Conclusion

This research aims to construct a departmental guidance model to resolve prevalent issues in existing intelligent guidance platforms, including misregistrations, consultation inefficiencies, and strains on medical resources. An innovative model is devised by comparing the performances of the TextCNN, BiLSTM, and BERT models in departmental guidance tasks and amalgamating these models with the integration of an attention mechanism. The foundational models present distinct pros and cons: TextCNN is adept at processing local features but overall shows lower accuracy; BiLSTM excels in handling sequential information but is limited in processing global context; BERT boasts superior global understanding capabilities albeit at a higher computational cost. The experimental outcomes of the innovative model demonstrate superiority over the single models in accuracy, recall, and F1 score metrics, achieving an impressive 96% accuracy rate, significantly elevating the precision of departmental guidance tasks.

This study addresses the gap in sub-specialty classification accuracy within existing departmental guidance systems, offering patients more precise and personalized guidance services. Introducing attention mechanisms and model integration techniques enhances the model's intelligence level, presenting new directions for exploiting medical health big data. Additionally, this research provides valuable insights for medical informatics and intelligence, optimizing medical resource distribution, enhancing service efficiency, and improving patient care experiences.

Future investigations could further refine the performance of departmental guidance models by enlarging the dataset, enhancing model structures, and incorporating additional natural language processing technologies. Considering more information sources, such as real-time data and medical knowledge graphs, could augment the accuracy and intelligence of guidance. These endeavors will solidify the foundation for developing and applying medical guidance systems, ensuring better healthcare experiences for patients and making a more substantial contribution to the efficient allocation of medical resources. As technological advancements continue and the accumulation of medical health big data grows, departmental guidance models are poised to play an increasingly pivotal role, contributing significantly to the advancement of healthcare services.

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