Alleviating Medical Load: Automated Medical Triage System Utilizing Text Classification BERT with Transformer Architecture

A PROJECT REPORT

Submitted by

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in partial fulfillment for the award of

the degree of

BACHELOR OF ENGINEERING

in

COMPUTER SCIENCE AND ENGINEERING

RAJALAKSHMI ENGINEERING

COLLEGE ANNA UNIVERSITY,

CHENNAI

MAY 2024

RAJALAKSHMI ENGINEERING COLLEGE, CHENNAI

BONAFIDE CERTIFICATE

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Abstract:

This study presents a medical triage system designed to alleviate the strain on hospital triage systems by categorizing patients' inquiries or descriptions of symptoms and recommending suitable consulting rooms. Initial investigation into healthcare challenges in China emphasized the critical need to ease triage pressures in hospitals. We gathered Medical Question and Answer datasets, comprising queries and responses annotated with the symptoms labels. Utilizing this structure of the given data, we have employed the we employed model called “Bidirectional Encoder Representations from Transformers”, a prominent model in the field of NLP, as the cornerstone of our infrastructure, supplemented by task-specific improvements. We have developed two models using distinct data source. One of the model was trained on data associated with the five most prevalent symptom tags, while the other utilized the entire dataset. For the latter, we identified special terms, calculated tag overlaps, and grouped the tags into 20 categories. Both models underwent thorough training employing various strategies, resulting in promising accuracy rates: 85% and 96% for top1 and top2, respectively, on the smaller dataset, and 66.2% and 78.3% on the larger dataset. These findings were carefully analyzed and incorporated into the development of our online medical system. Given similar data distributions, our approach has the potential to assist patients in diagnosing ailments and mitigate some of the triage challenges encountered in medical treatment. Additionally, the methodology employed in our model shows promise for application in various domains, such as enhancing library book searches. Consequently, our system offers a wide range of potential applications.

Keywords: Healthcare Triage, Artificial intelligence, Transformer-based models, Natural Language Processing, and Document categorization

INTRODUCTION

Recently, the hospital has observed a rise in patient numbers. As per the Health Development Statistical Communique of the nation, there were a total of 8.72 billion visits to medical and healthcare facilities in China in 2019, reflecting a growth of 410 million or 4.9% compared to the preceding year [1]. Patients who lack familiarity with the symptoms and conditions may encounter the difficulty when attempting to register, placing strain on the hospital's triage system. This issue is prevalent in many Chinese hospitals. This issue is particularly important at the Associated People's Hospital at Yunyang Medical College: "We are a first-class tertiary hospital with around 200 outpatient intakes every day on average. Across multiple sites, the facility accommodates more than thirty different types of professional consulting rooms. The affected peoples who lack the familiarity with the outpatient environment often find themselves at the wrong door, leading to medical disorders. [2]. Although hospitals deploy multiple triage stations based on patient volume, a lack of skilled personnel at these stations results in increased pressure and decreased effectiveness in managing the workload, This situation culminates in substandard assistance and dissatisfaction among patients. Researchers have scrutinized the deficit in staffing, particularly within the pediatric department, in Shandong, China. "Between 2011 and 2015, the proportion of care for children in our province showed a yearly rise, although it consistently remained below the nationally suggested ratio of 1∶1.5 to 1∶2, which is notably lower than the WHO's guideline of 1∶4." Furthermore, some workers lack experience in handling various ailments, resulting in patients receiving incorrect advice. Several proposed solutions address this issue. For example, in order to make appointment scheduling easier, researchers at Nanjing University of Science and Technology [4] created the Hospital Registration app on mobile phone. Additionally, specific scholars have created frameworks for medical conversational bots, such as the Effective application of Intelligent [5, 6], even though Triage applications are not their main area of interest. Based on these results, we claim that creating a new triage system for medical is vital to relieve the burden on hospital triage centers and improve the effectiveness of medical resource distribution. Based on the aforementioned findings, our plan involves developing a fresh medical triage system that requires a NLP model to adept at processing extensive texts for our text categorization objective. Based on the self-attention process, the transformer structure[7] greatly improves performance on lengthy text jobs. Bidirectional Encoder Representations from

Transformers [8] is a later proposal that aims to achieve good performance on a variety of applications by fully utilizing word context. We add more classification components to the pre-trained Bidirectional Encoder Representations from Transformers in order to make it more in line with our goals. Since our dataset contains more than 4,000 distinct tags, we begin by constructing a model named triageberts, which is initially trained on the five most common tags, to assess its viability.

Based on the findings, our plan is to develop a novel medical triage-system that necessitates the use of a NLP model proficient in processing extensive texts for our text categorization objective. The transformer architecture [7], leveraging the self-attention mechanism, notably enhances performance in tasks involving long texts. Subsequently, BERT model are introduced to maximize the contextual understanding of words resulting in outstanding performance across a multitude of tasks. We adapt the pre-trained BERT model to suit our objective by integrating supplementary categorization elements. Considering our dataset includes more than 4,000 unique tags, our initial step involves developing a model named TriageBertS, which is trained on the five most prevalent tags, to assess feasibility. Utilizing the promising outcomes from the initial model, we detect the presence of commonly recurring terms within the tags and consolidate data by evaluating overlaps between tags and keywords. Following, we proceed to train our second model, using a dataset comprising 20 classes. This dataset incorporates a category encompassing all tags that remain unmerged due to their low occurrence frequency. We then assess the performance of TriageBertL using diverse evaluation techniques. Ultimately, we have developed a web-app to deploy our model, enabling its practical use in real-world scenarios.

APPROACH

A. Data cleaning and preprocessing

1) ***Concerning TriageBertS*** :

We gather data from four medical question-answering datasets

(Ehealthforumqas, Icliniqqas, Questiondoctorqas, and Webmdqas), comprising 29,752 question-answer pairs and 4,008 unique tags, all presented in JSON format. We conduct a frequency analysis for each tag, aiming to refine the research focus and enhance the precision of our model. Initially, we narrow down the dataset by selecting data points associated with tags ranked among the top five most commonly utilized. These tags consist of exercise, sexual intercourse, pregnancy, menstruation, and influenza. In Table 1, the distribution of QA data for each label, along with the total quantity, is presented. After the selection process, we merge each question and response into a unified string, utilizing [SEP] as a separator, and assigning [0,1,2,3,4] to represent the five labels sequentially.

2) ***Concerning TriageBertL*** :

For optimizing the utilization of the data sources, we implement a thorough data cleaning procedure. Following the removal of invalid or empty tags, 26,417 elements remain in the dataset.
We prioritize tags based on their frequency and integrate the most common ones with our existing data to establish categories such as respiratory, gastrointestinal, and others. Next, we identify and tally the words associated with their respective categories, storing them in a dictionary table. This enables the remaining tags to contribute their votes and be assigned to the appropriate categories based on their shared words. In total, there are 20 categories, including a separate category for leftover data that doesn't align with any other category. The distribution of data numbers for each category is presented in Table 2.

TABLE I: NUMBER OF QA DATA IN ACCORDANCE WITH LABELS

Class	tag	No
Leftover Data	20	5333
OB/GYN	5	2222
GI	7	2044
Substance Abuse and Addict	20	403
Cerebrum	12	177
Renal	19	23

TABLE II. THE DATA NUMBERS OF EACH CATEGORY

Class	**tag**	**No**
Workout	5	331
Intimacy	3	705
Gestation	6	2341
Monthly Cycle	1	807
Influenza	8	300
Overall	-	4,487

B. Architecture of Model:

Typically, we utilize Google's publicly available pre-trained BERT model as the core of our framework. Subsequently, we augment it with additional input and classification layers tailored to suit the input structure and output categories specific to our project. Figure 1 illustrates the general steps of our investigation.

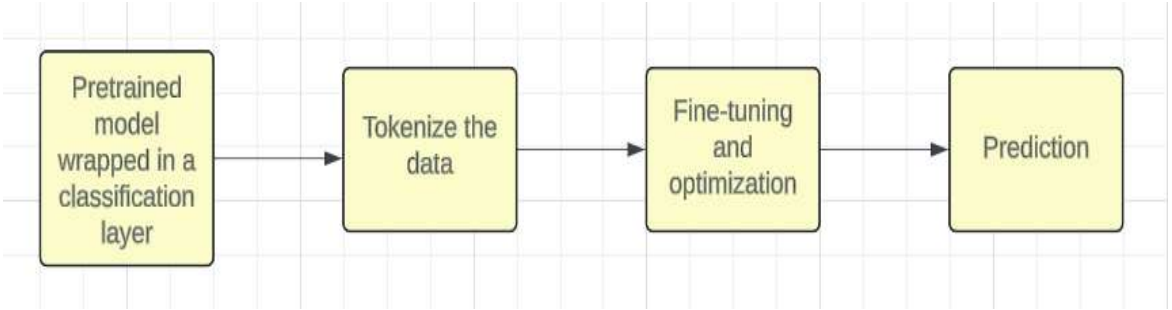


Fig 1. Depicts overview working of the model.

1) ***Model Building*** *:*

Initially, we acquire the pre-trained model of Bidirectional Encoders Representation from Transformer. Bidirectional Encoders Representation from Transformer receives a class label, input1, seperator, and input2 as the format of input. We omit the first integer in each output unit, which serves as the classification label, to integrate with our Classification component.

Fig 2 Demonstrates the detailed framework of the BERT System.

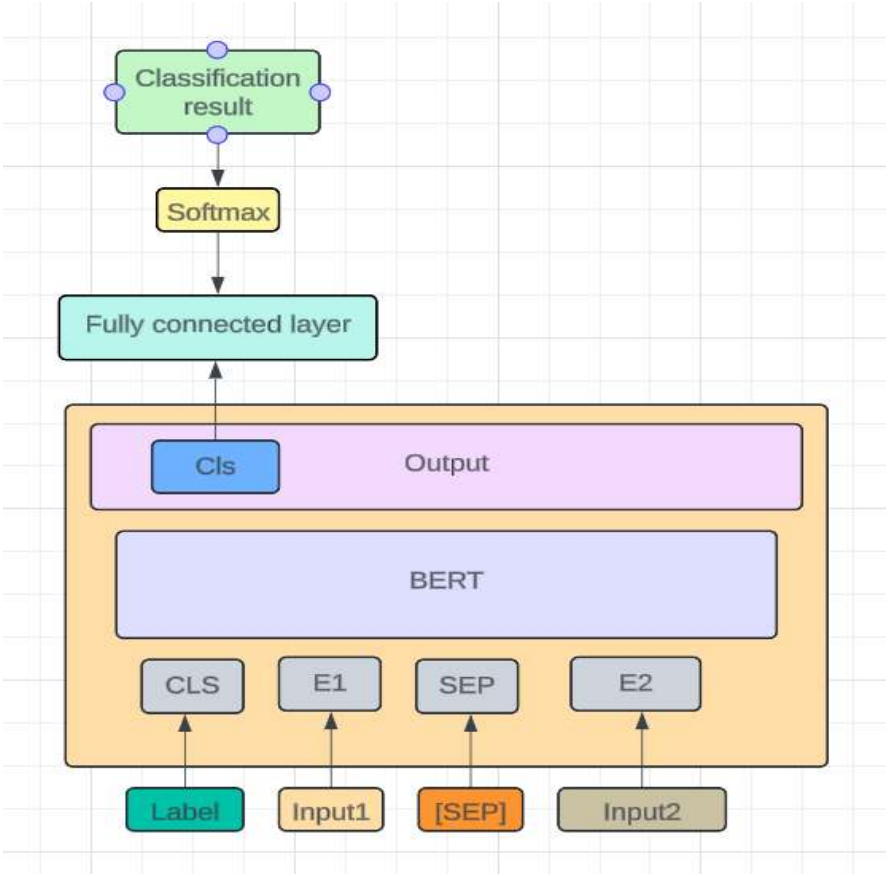


Fig 2: Framework of Model

2) ***Data tokenization*** *:*

By eliminate the stop words, and apply them to the root form of our data source, and then convert the terms into representations of numbers using a predefined tokenizer. Subsequently, we trim any excess data of tokenization that exceeds the maximum length of 400 and padding with zeros those sequences shorter than this threshold to ensure consistent input length. Additionally, we then encode the labels into one-hot vectors to align

with the output layer of our model, which utilizes softmax activation.

3) ***Optimization and Fine-tuning of the data*** *:*

In order to maximize data efficiency, we implement a 10-fold cross-validation strategy with our training dataset. We utilize categorical cross-entropy as our loss function and optimization of Adam, configuring the learning rate to 0.00001. Furthermore, we incorporate Keras' early stopping mechanism and apply the learning rate reduction strategy based on plateau detection to mitigate overfitting risks and improve the model's performance on the set of validation. TriageBertS undergoes 5 training epochs, while TriageBertL undergoes 10 epochs of training. Throughout the training phase, TriageBertS achieves a 85% of top-1 accuracy rate and a 96% of top-2 accuracy rate. Conversely, It attains a comparatively lower 65% of top-1 accuracy rate and a 78% of top-2 accuracy rate. This outcome is understandable considering the larger dataset size and increased diversity in labels. We meticulously document the training progression of Model, illustrating batch loss, top-1 accuracy, and top-2 accuracy in Fig 3, while presenting epoch loss, top-1 accuracy, and top-2 accuracy in Fig 4.

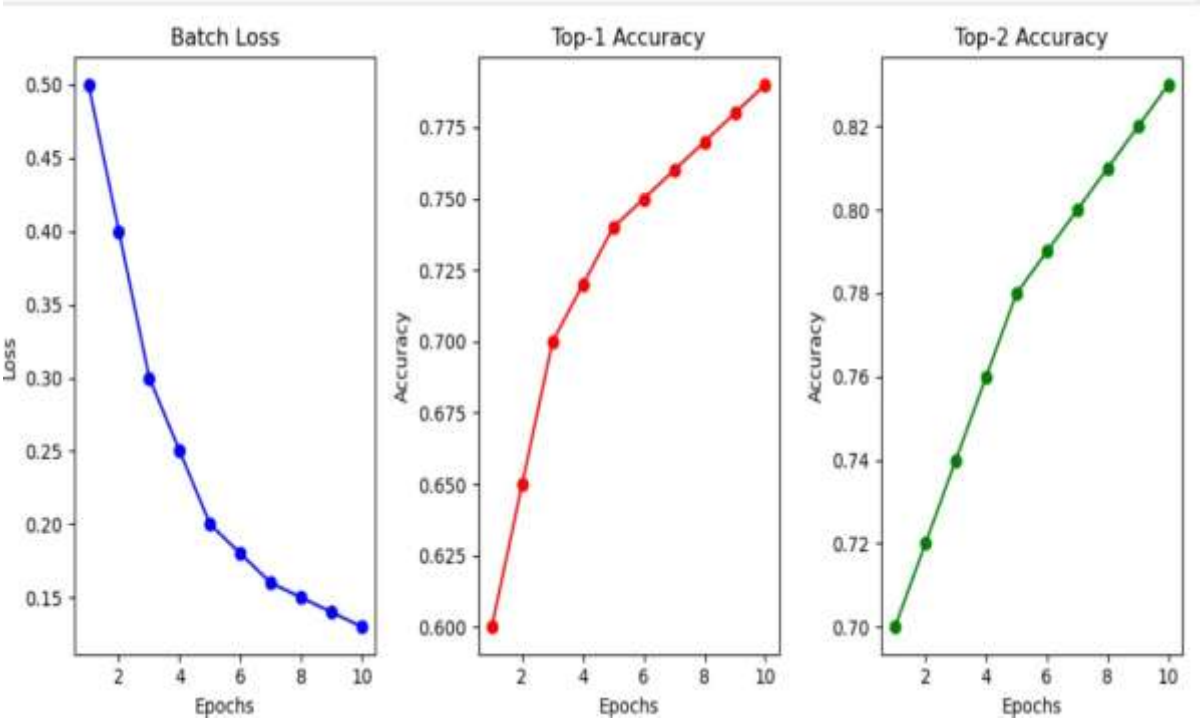


Fig 3: The above image illustrates the Batch loss, top1 accuracy rate, and top2 accuracy rate chart.

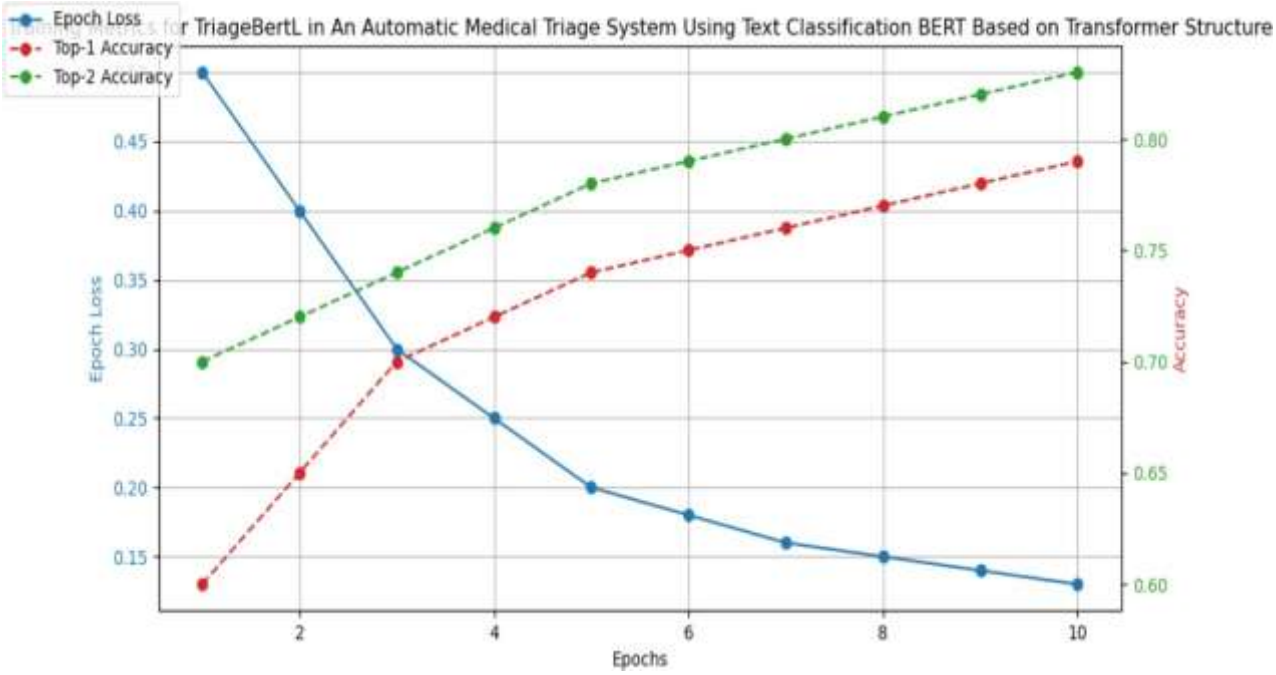


Fig 4: The above image displays Epoch loss, accuracy rates of top1 and top2 charts.

4) ***Model Prediction****:*

We conduct label predictions for specific unlabeled sentences and store them in a separate CSV file. The unlabeled medical test outcomes sourced from Google Search [9] are organized in a CSV file alongside corresponding IDs. These texts exhibit variations compared to our original dataset. Within the resulting CSV file, we pair these IDs with the predicted labels. As detailed in Table 1, the label 'exercise' corresponds to code 4, while 'sexual contact' is represented by code 2. Texts 1 and 2 pertain to exercise, accurately predicted by our algorithm, while Texts 3 and 4 discuss sexual activity, with our model correctly identifying their labels. Figure 5 provides insight into the section of the unlabeled data awaiting prediction, while Figure 6 displays a segment of the anticipated labels.

data_predict

id	contents
1	despite regular cardio exercise and eating healthy i can't seem to lose weight? . okay maybe i can't lose weight is misleading but i am losi
2	how to raise hdl. my hdl level is low (20). i do not smoke never have and exercise on a regular basis. what can i do to raise my hdl levels? .
3	i am having some minor urinary incontinence after having prostate sugery. how do i handle sex in this situation? many men face some drib
4	what can you use to protect yourself from infection during oral sex? 1. condoms - don't forget they can come in flavors 2. you can cut a cc

Figure 5 shows a portion of the unlabeled data

Results

Test_id	Predicted_type
1	4
2	4
3	2
4	2

Figure 6.The above figure represents the predicted results

C. Analyzing and Modifying the Model :

*1) **Analysing the accuracy :***

We have evaluated the performance of our model on testing set and construct a confusion matrix visualising the alignment between the actual labels and the predicted outcomes, illustrates in fig 7. Upon analysis, we observe that class 3 demonstrates the highest accuracy, while classes 14, 15, and 19 exhibit relatively lower accuracy rates. We attribute this variability in performance to the imbalanced distribution of our dataset. As displayed in the Table 2, class 3 contains highest amount of data points (5,475) among other classifications, except for class 19. However, classes 14 and 15 each contain fewer than 200 data points. Notably, despite class 19 having more data than class 3, it results from the merging of all remaining data points. This indicates that numerous misclassified data points should have been combined into other classes during pre-processing. Hence, by refining our combining technique, we anticipate potential improvements in the overall performance of our model.

Fig 7. Presenting the confusion matrix featuring actual labels juxtaposed with predicted labels.

2) *Combination of the input text of questions and answers:*

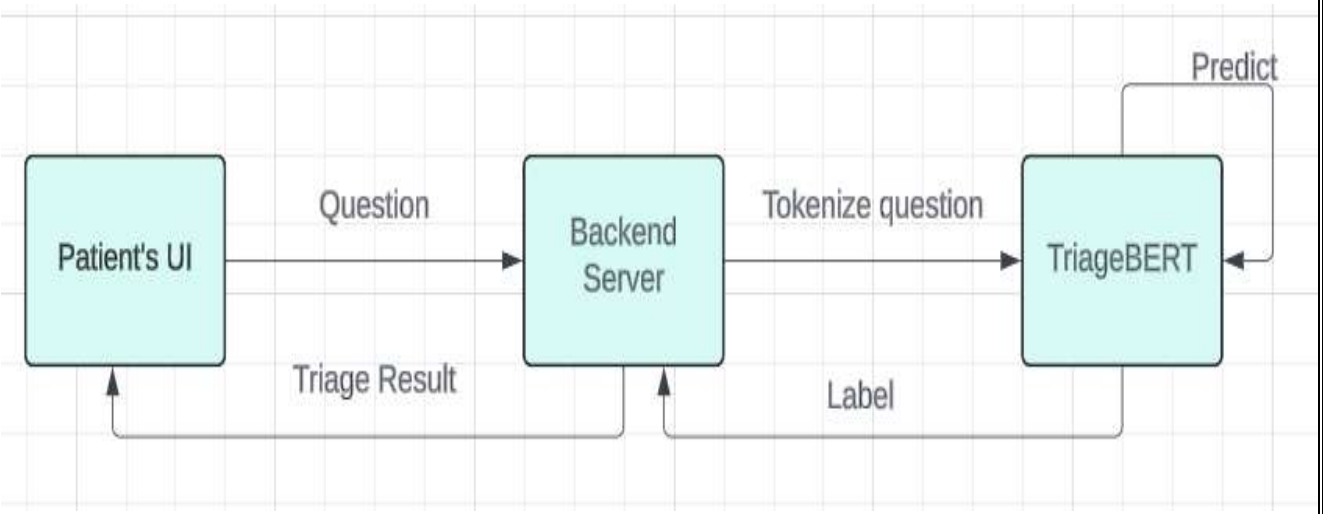
By assessing two approaches to text organization: utilizing solely questions and a combination of questions and responses. We opt for the combined format as it encompasses more information, particularly considering that questions tend to be much shorter than doctors' responses. By incorporating additional comprehensive data, we anticipate potential enhancements in our model's representation capabilities and accuracy. Initially, we envision practical scenarios where our model responds to patient inquiries with labels. Since patients typically seek answers to their questions, we exclude the responses from our analysis. Consequently, we utilize only the question section as text, leaving the response part empty.

Subsequently, we proceed to train our model using these texts. Interestingly, we observe an improvement in accuracy when questions and answers are amalgamated into a single text. This enhancement could be attributed to the answers provided by doctors, who possess greater expertise compared to patients. These responses likely contain valuable insights that influence the model's predictions positively. Having established the effectiveness of the combined approach, the next step is to explore practical applications. How can our model effectively provide solutions to patients' inquiries? We propose integrating diverse training models for bot of chat application through APIs into our upcoming projects. To respond to a patient's query, we might first employ the model to predicts the suitable answer. Next, we merge this predicted response with the patient's question to form a unified text. Our model then evaluates this combined text and generates expected tag.

D. *Creating the WebApplication* ***:***

We've developed a website application, to deploy and utilize our model online. The front end of our system is crafted using frontend frameworks, while the server is constructed using Tornado. Patients can interact via the Patient UI to ask questions or describe their symptoms, with the server receiving and processing their messages. Subsequently, our server leverages the application

programming interface of our model to generate predictions before providing the outcomes to the patients. The organizational structure of our system is illustrated in Fig 9.



Interaction

A. Interaction on accuracy of top2:

Upon generating the model produces forecasts for the testing set of data, it usually furnishes a set of probabilities corresponding to each label. If we opt for label with the probability of high rate and it precisely aligns with the true label, the prediction is deemed accurate; otherwise, it's considered incorrect. This method is frequently denoted as accuracy rate of top-1. Conversely, accuracy rate of top-2 involves selecting the two labels that has succeeding rate of probabilities. And then we consider our prediction is correct if the true label is among these top two labels. In this scenario, top-2 accuracy tends to be significantly greatest than accuracy rate of top-1.The practical complexity is given, a single medical text may be associated with two or more labels. As a result, there are occasions when the given model inaccurately forecasts the label with the greatest probability for a text, yet accurately recognizes the true label as the second most probability.

Consider the intricate text: 'During my pregnancy, I always fell ill. It feels like I catch every bug in the air, and I can't seem to shake off a cold. I'm puzzled.' From this passage, it's clear that the patient's primary concern is their health rather than their pregnancy, which aligns with our categorization. However, the model might easily prioritize pregnancy as the most likely label due to its explicit mention in the text. While the flu isn't explicitly stated, there are implicit references to it. As a result, the model identifies the flu as the second most probable label. This prediction is classified as accurate under a top-2 accuracy metric but considered incorrect under a top-1 accuracy metric. Despite the model's inability to interpret context as humans do, even when it correctly identifies the true label as the second most likely in this scenario, we still regard the prediction as accurate.

Therefore, the top-2 accuracy metric encompasses a broader spectrum of potential labels, including genuine ones. It accommodates more complex and less precise scenarios. In our evaluation of healthcare text categorization, accuracy rate of top-2 demonstrates notably superior performance compared to accuracy rate of top-1.

We address more scenarios in our top-2 accuracy optimization where the top-k accuracy's K value rises. Increasing the K value will result in an increase in the matching label range. The probability of incorporating the accurate label will rise. Higher K values possess the capability to assess a wider label of array that could encompass the authentic label. This adaptation accommodates less precise and more intricate circumstances. The lower K value, on the other hand, indicates a narrower range of labels with a lesser likelihood of including the true symbol. It adjusts to more specific, less complex situations. Weighing the K value in the real world of medical texts is necessary to achieve high accuracy while taking the circumstances into account.

B. *Modifying the methodology of data processing and include additional practical data:*

By looking at how better data merging or processing techniques could improve model performance by accurately classifying data. Additionally, using real-world data could enhance the model's fit for real-world triage settings, since the datasets we are using are question-answering datasets rather than medical triage-specific.

C. Other Applications:

There are additional applications for this concept beyond providing answers to medical queries. For instance, it is utilized in the AI robot that the library uses to classify books. Book-related inquiries and corresponding answers are compiled in a question and answer structure, with book genres acting as classification tags. The model is subsequently trained to the point where AI can proficiently classify unfamiliar books.

D. Contrast with the seq2seq architecture:

By employing the seq2seq framework, we can contrast our model with an alternative architecture [10]. The accuracy outcomes of the seq2seq model are directly showcased, followed by the availability of data for download. Subsequently, we convert the data into the CSV format compatible with our model's requirements, retrain it, and evaluate the model's performance. Table 3 juxtaposes the accuracies of the two models trained on the same dataset.

Epoch	**The accuracy of Seq2Seq Model**	**The Bert Model's Accuracy**
1/5	0.2683	0.4274
2/5	0.2879	0.4314
3/5	0.3677	0.6445
4/5	0.5134	0.8198
5/5	0.5890	0.8515

We find that the Bert model outperforms the seq2seq model notably when subjected to identical data conditions. This superiority is largely attributed to the Bidirectional Encoders Representation from Transformer model's sophisticated NN and the immense efficacy of its self-attention mechanism, alongside its distinctive data segmentation technique and cross-training strategy. These combined advantages contribute to Bert's heightened accuracy. While Bert training consumes more time compared to seq2seq, this discrepancy in time is deemed acceptable in exchange for the superior accuracy it provides.

Outcome

Within this manuscript, we introduce TriageBert, a text classification framework, accompanied by a web-centric platform designed to alleviate overall workload on hospitals. Our duo of models, TriageBertS and TriageBertL, is crafted employing disparate data pre-processing methodologies, thereby yielding datasets of varying magnitudes. Next, we examine our discoveries and suggest possible improvements to our model. Subsequently, we develop a web triage system utilizing our model. Lastly, we investigate different model tweaks, carry out model comparisons, and delve into broader applications of our methodology.

We observe a significant improvement in combined text accuracy compared to plain text performance. Similar techniques could be applied to classify books in libraries, and the technology holds promise for assisting with hospital. To bolster the accuracy of our AI system and adequately cater to patients' queries, our objective is to broaden the training dataset, integrate more intricate tags, and refine the algorithm through further investigation. Our ultimate vision entails transitioning manual triage processes into a comprehensive automated inquiry system.

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