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Research on Text Generation of Medical Intelligent Question and Answer Based on Bi-LSTM and Neural Network Technology

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Abstract*—Text generation is a popular research direction in the field of natural language processing as well as artificial intelligence, especially in the medical field. Text generation technology plays an extremely important role in medical intelligent question and answer systems. In previous Q&A systems, the display of generated dialogues is usually limited to Q&A and is difficult to adapt to vertical domains with strong characteristics. In this paper, to solve the task of specialized Q&A in medical field and provide users with comprehensive answers. We propose a TensorFlow architecture-based approach to medical text generation that uses sequential models in Keras to transform the task into a classification problem by treating the text generation problem as a prediction problem. By training and experimenting with the model on a large-scale Chinese medical question-and-answer dataset, the results show that our model has a good fit with applications in this specific domain. The model can aggregate medical domain knowledge, extract useful treatment information and generate medical knowledge text. At the same time, through research, it is found that splitting questions into phrases and then inputting them into the model can effectively solve the problem of repeated sentences in the generated answers. Since the model we proposed can answer patients' questions well and accurately in most cases, this research provides an improvement direction for exploring medical intelligent question answering and text generation.

***Keywords*—text generation, smart question and answer, medical, TensorFlow, sequential model**

I. Introduction

In recent years, natural language processing (NLP) technology has achieved remarkable results in the medical field. Using natural language processing features, such as Tripathi P , Deshmukh M designed and implemented a fully functional system, a reverse medical dictionary, where users can search for their diseases and get instant diagnosis from the system at any time by sharing their symptoms [1]; Gundlapalli A V , South B R , Chapman W W et al. used natural language processing (NLP) methods to identify epidemiologically important factors such as infectious disease exposure history, travel or specific variables from unstructured data [2]. These studies demonstrate the great promise of natural language processing techniques in healthcare and look forward to further exploration and discovery.

As for the field of natural language processing, text generation and intelligent question and answer is an important and challenging task in the field of natural language processing. The purpose of text generation task is to generate text sequences that approximate natural language; the purpose of intelligent question and answer is to allow users to ask questions in natural language form and perform in-depth semantic analysis to better understand user intent and quickly and accurately access information in the knowledge base. T Liu et al. proposed Structure-aware Seq2seq Learning applied to Table-to-text Generation and their model was able to generate coherent and information-rich descriptions based on a comprehensive understanding of the content and structure of tables. [3]. In the existing research, there are still few attempts to use sequential linear model architecture for text generation and intelligent Q&A in the medical field. Therefore, we will adopt the sequential model provided by classical Keras. Our model generates complex natural language text by defining the divided word as X and the next word as Y. The neural network is trained on the statements and predicts the corresponding next word. Our model will use the medical text of double eyelids in medical aesthetics to build a neural network and perform deep learning as a way to predict the answer based on the input question to give the corresponding medical text.

In this study, we used the dataset about double eyelid medical aesthetics as training data, and after training the model, we found that the model can provide useful answers to the user based on the questions entered by the user.

II. Related Work

In the existing research on intelligent question and answer systems, the research work is generally carried out in three directions: project-related fields, model and method of building the systems, and optimizations of the question and answer systems.

In order to ensure that the designed QA system can cover the professionalism and particularity of the medical field. abacha, A Ben , and P. Zweigenbaum [4] proposed the medical QA system MEANS based on medical data context, combining NLP techniques and Semantic Web technologies to propose the medical question and answer system MEANS. athenikos, S. J. , and H. Han [5] categorized current QA methods where subcategories are based on semantics, inference and logic. They proposed that domain-specific typologies and question

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classifications need to be constructed, methods for generating answers from potentially conflicting evidence, and that semantic knowledge combined with logical and inferential mechanisms should be used more integrally, providing new ideas for investigating ways to improve the processing of nlp texts. Medical QA systems require continuous fine-grained algorithmic optimization because of the high accuracy of answers required by the application scenario. Chen, J. et al [6] used Kam method to generate more quality answers for medical QA.

The sequential model is stacked in multiple layers to build complex deep neural networks, including fully connected neural networks, convolutional neural networks, recurrent neural networks, and so on. The model is mainly used in the medical field for disease detection that cannot be accurately identified by the human eye [7], and has rarely been applied in research in the field of medical question and answe. Sequential model have achieved great performance in other domains, for example, Hassan, M.Y., and H. Arman[8] found in the research on the tensile strength of rock that the Keras sequence model is better than the competitive models such as Ridge regression, Lasso regression, MLR, etc. It can improve the model performance while preventing over-fitting, which inspired our research.

Neural networks are becoming increasingly popular for language modeling tasks. However, earlier neural networks used only fixed context length to predict the next word generated by the text and recurrent networks could not demonstrate the full advantages of recurrent models when trained on long text corpus. sundermeyer, M et al [9] addressed these problems using long short-term memory neural network architecture and made considerable improvements in WER. In recent years, LSTM has been widely used in question and answer systems with different requirements, for example, MinakshiTomer, and ManojKumar [10] used LSTM in a keyword-generated question and answer system in order to encode question sequences to a fixed length, which has a certain storage capacity and is better at handling vanishing gradients to make the generated output more user-friendly, and Chowdhury, I. et al [11] proposed a cascaded long short-term memory (LSTM) architecture with discriminant feature learning, which enables the model to correlate visual feature sequences and common lexical property (POS) tags with actual words, an approach that significantly improves the accuracy of visual question answering systems. one-hot [12] and TF-IDF [13] are the most common methods used to extract text features, and in this paper, one-hot coding is used, but it is known that when the number of categories is quite large, its feature space becomes large. Okada, S et al [14] proposed two methods of dividing the extracted subproblems in order to efficiently use one-hot coding to solve large optimization problems.

Overall, these studies emphasize the need for accuracy and humanization of generated answers for question and answer systems in the medical field. However, the model and algorithm optimization can be explored more deeply. So how to better combine and innovate natural language processing with neural network technology is also a challenge for the current research.

III. MODEL

In this paper, we use the sequential model provided by Keras, which is a linear structure with no redundant branches, and is a stack of multiple network layers. The model is constructed by passing a list of layers to the sequential model. Our model architecture is shown in Fig. 1.

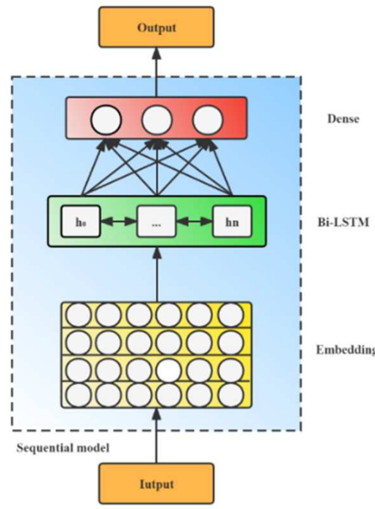

Fig. 1. Modeling the Q&A Task with Sequential Model

A. Embedded layer

Keras provides an embedding layer for neural networks with textual data. The above-mentioned Tokenizer API for Keras has been implemented so that each word is represented by a unique integer. It processes all words and gives them meaning in the neural network. The number of words needed for the embedding layer is set to all words in the corpus, and the vector space size of the embedded words is specified, which is based on experimental data and considered as a hyperparameter for the specific problem. The final input sequence length is the maximum sequence length minus one.

B. LSTM layer

Simple neural networks are often unable to cope with inputs of excessively long sentences, and it is unable to preserve the information memory of words that have been processed very earlier to the current word input moment, which is often referred to as the problem of gradient disappearance. Therefore, we added the LSTM layer with a control unit of memorized information that can help the generated utterances maintain a consistent contextual context, and the bidirectional LSTM layer [15] is able to go backwards or forwards in both directions for a specified length, so that the effect on the generated words, not only limited to adjacent words, can help the neural network converge more quickly.

The LSTM is calculated as follows:

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

$$f_t = \sigma\left(W_f x_t + U_f h_{t-1} + b_f\right) \tag{2}$$

https://towardsdatascience.com/intuitive-explanation-of-exponential-moving-average-2eb9693ea4dc
https://towardsdatascience.com/understanding-deep-learning-optimizers-momentum-adagrad-rmsprop-adam-e311e377e9c2

$$o_t = \sigma\left(W_o x_t + U_o h_{t-1} + b_o\right) \quad (3)$$

$$\tilde{c}_t = tanh\left(W_c x_t + U_c h_{t-1} + b_c\right) \quad (4)$$

$$c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t \quad (5)$$

$$h_t = o_t \odot \tanh\left(c_t\right) \quad (6)$$

The input gate, oblivion gate and output gate are respectively represented by i_t ,f_t , and o_t are denoted. $\tilde{c}_t$ is the candidate state obtained by a nonlinear function; at each moment t, the internal state of the LSTM network c_t records the history information up to the current moment. h_t is the hidden state at moment t. σ is the logical sigmoid function.

The Bi-LSTM structure consists of two LSTM stacked above and below, which can effectively utilize past features and future features, as shown in the following Fig.2.

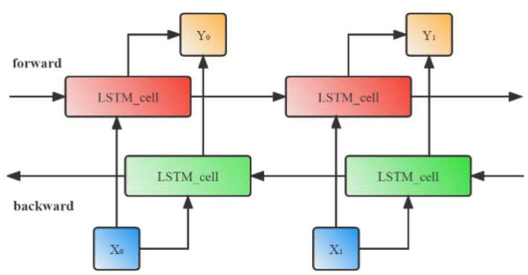

Fig. 2. Schematic diagram of bidirectional LSTM structure

C. Fully connected layer

A Softmax nonlinear activation function is used in the fully connected layer, which is achieved by passing the activation when building the layer. This activation function transforms the output of the neural network into multiple categories. Additionally, we use a unique one-hot encoding technique to map each word in the corpus to a neuron node, activating unit neurons when a word is predicted.

Finally, we use adam as the model optimizer, and cross-entropy as the loss function, since classification is done here.

The Adam optimizer dynamically adjusts the learning rate of each parameter. The formula is given by

$$m_t = \mu m_{t-1} + \left(1 - \mu\right) g_t \quad (7)$$

$$n_t = \upsilon n_{t-1} + \left(1 - \upsilon\right) g_t^2 \quad (8)$$

$$\hat{m}_t = \frac{m_t}{1 - \mu^t} \quad (9)$$

$$\hat{n}_t = \frac{n_t}{1 - \upsilon^t} \quad (10)$$

$$\Delta\theta_t = -\frac{\hat{m}_t}{\sqrt{\hat{n}_t} + \epsilon}\eta \quad (11)$$

where m_t, n_t are first-order moment estimates and second-order moment estimates of the gradient, respectively, which can be viewed as estimates of the expectation $E\left|g_t\right|$, $E\left|g_t^2\right|$; $\hat{m}_t$, $\hat{n}_t$ are corrections to m_t, n_t so that they can be approximated as unbiased estimates of the expectation. $\Delta\theta_t$ forms a dynamic bound on the learning rate Sand has a well-defined range.

From Fig.3, comparing the four common optimizers, the performance can be seen as follows:

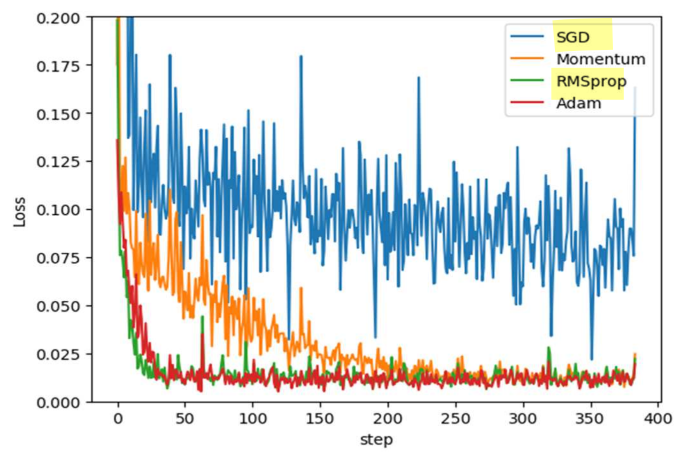

Fig. 3. Performance comparison of common optimizers

It can be seen that choosing adam as the optimizer for this project model gives better results.

The categorical_cross entropy loss function focuses on only one outcome, so it is generally used with the softmax activation function for single-label classification, which is formulated as follows:

$$Loos = -\sum_{i=1}^{n} y_i \log \hat{y}_i \quad (12)$$

Finally, the user can enter a question, and the length of the expected response generation. After converting the sentence into a sequence through a for loop and filling it, it is passed to the trained neural network model to predict the most likely index of the next word in the current sentence. A reverse query of the index will find the corresponding word sorting output.

D. Strengths and limitations

The advantage of the sequential model used in this thesis is its plasticity and simplicity, which is applicable to the fields related to feature extraction and migration learning. When it is used in a text generation project, there is no need to significantly modify the basic architecture, and the number of layers and related configurations can be flexibly customized according to the project requirements, so that the layers can be stacked and related to each other to obtain better results. At the same time, this model has only adjacency between layers, so the compilation is fast, the operation is simple, and the code is readable.

However, the model also has some limitations. The simple linear structure makes it impossible to connect layers arbitrarily, and it can only have single input and single output, which lacks richness of results. The inability to implement neural networks with complex topological models is also an obvious limitation of the model.

IV. DATASET

This experiment uses a medical text dataset about double eyelids in the medical aesthetic field. This experiment uses the medical text dataset of double eyelid in the field of medical aesthetics which contains 5000 samples. The dataset consists of queries and answers, i.e., the questions asked by the customers related to double eyelid surgery and the answers formed in response to the questions asked by the users. Sample data are as follows in TABLE I.

TABLE I. SCHEMATIC TABLE OF TRAINING DATA

Question	Answer
割完双眼皮可以吃螃蟹吗?	可以吃，不会有太大的影响。手术后，要注意伤口的保护，不要感染，定期复查可以做，双眼皮手术通常需要三个月才能恢复，毕竟手术，为了防止感染，最好不要吃，为了防止眼睛发炎和螃蟹是一种寒冷的食物，吃它会给伤口增加负担。不要吃辛辣的食物，多吃含有胶原蛋白的食物。
全切双眼皮包括去皮去脂吗	目前常规手术里全切双眼皮的优势包括去皮去脂，也就是相对于埋线双眼皮或者微创三点小切口双眼皮来说，其是可以去皮去脂的。此外，绝大多数患者都存在皮肤松弛和脂肪臃肿的问题，并且全切双眼皮包含去皮去脂的项目，因此可以使患者过于臃肿和皮肤松垂的现象得到进一步的改善。
埋线双眼皮是永久性的吗	埋线双眼皮手术并非永久性，大部分患者维持时间较长，但部分患者维持时间较短，若患者眼轮匝肌较丰厚，不适合进行埋线双眼皮手术，双眼皮可能在术后短时期内便消失；若进行埋线双眼皮手术的医生操作技巧不纯熟或缝合时层次不确切，双眼皮可能在短期内消失；若线材质量较差，可致使其脱落或断裂，双眼皮在短时间内即会消失。

V. MEDICAL TEXT GENRATION EXPERIMENT

A. Data pre-processing

First, we convert the original dataset csv format to txt file format for better use of NLP technology.

Second, the architecture uses the precise mode of the Jieba tool to subdivide the Chinese text data, and saves the subdivided text as txt in the form of a suffix, which is convenient for directly inputting the model for training later, which can reduce the coupling between corpora. The vocabulary is reorganized according to the basic Chinese grammar. Taking the first sentence of the schematic table of training data, the word separation is performed as an example in TABLE II.

TABLE II. SCHEMATIC TABLE OF SENTENCE PARTICIPLES

Original sentence	Sentence after the participle
割完双眼皮可以吃螃蟹吗？可以吃，不会有太大的影响。手术后，要注意伤口的保护，不要感染，定期复查可以做，双眼皮手术通常需要三个月才能恢复，毕竟手术，为了防止感染，最好不要吃，为了防止眼睛发炎和螃蟹是一种寒冷的食物，吃它会给伤口增加负担。不要吃辛辣的食物，多吃含有胶原蛋白的食物。	割完 双眼皮 可以吃 螃蟹吗 ？ 可以吃 ， 不会 有太大 的 影响 。 手术 后 ， 要 注意 伤口 的 保护 ， 不要 感染 ， 定期 复查 可以 做 ， 双眼皮 手术 通常 需要 三个 月 才能 恢复 ， 毕竟 手术 ， 为了 防止 感染 ,最好 不要 吃 ， 为了 防止 眼睛 发炎 和 螃蟹 是 一种 寒冷 的 食物 ， 吃 它 会 给 伤口 增加 负担 。 不要 吃 辛辣 的 食物 ， 多吃含 有 胶原 蛋白 的食物 。

B. Feature Engineering

Next, our model uses the text module and sequence module provided by the keras preprocessing package to process the text. A python list is created for the data, and fit_on_texts is used to create the dictionary, which consists of a set of key-value pairs containing the subdivided words and each word is assigned a unique integer value. tokenizer class obtains the length of the word index, which allows statistical counting of all words in the corpus to support vector representation of the text generated based on the dictionary bit sequence, and adds to the statistical dictionary system unrecorded words, the overall word count is added by one. The input data is defined as a list, and each line of the corpus is serialized using the texts_to_sequences method to transform the sentences into numeric codes. The list is iterated to produce sequences of different lengths for the sentences, followed by simply traversing the loop through all the sentences to find the length of the longest sentence in the corpus. Using the pad_sequences method, all sequences are populated according to the length of the longest sequence so that they are of the same length. And the sequences are pre-populated with zeros in front of the sentences to make it easier to extract the corresponding tag values of the sentences. To make the next text prediction generation smooth, we create prediction and tag values, and transform the sequences into input X and tag Y of the neural network, with tag Y being the last character.

TABLE III. DICTIONARY OF TRAINING DATA

Dictionary
{'，': 1, '的': 2, '双眼皮': 3, '。': 4, '手术': 5, '在': 6, '会': 7, '、': 8, '是': 9, '皮肤': 10, '要': 11, '可以': 12, '进行': 13, '伤口': 14, '有': 15, '埋线': 16, '也': 17, '术后': 18, '方式': 19, '和': 20, '做': 21, '恢复': 22, '形成': 23, '后': 24, '情况': 25, '可能': 26, '如果': 27, '不': 28, '使': 29, '一定': 30, '睑': 31, '我们': 32, '患者': 33, '；': 34, '医生': 35, '效果': 36, '吗': 37, '比较': 38, '自然': 39, '不同': 40, '时间': 41, '冰敷': 42, '能': 43, '或者': 44, '愈合': 45, '消肿': 46, '组织': 47, '求美者': 48, '切开': 49, '板': 50, '对': 51, '热敷': 52, '割': 53, '将': 54, '以及': 55, '瘢痕': 56, '好': 57, '祛除': 58, '一个': 59, '方法': 60, '建议': 61, '之后': 62, '双眼': 63, '皮肉': 64, '条': 65, '修复': 66, '眼轮': 67, '匝': 68, '或': 69, '而': 70, '这种': 71, '通过': 72, '内': 73, '怀孕': 74, '肿胀': 75, '原因': 76, '较': 77, '多': 78, '若': 79, '以': 80, …}

C. Model Settings

Finally, in this experiment, we use the sequence model to create a neural network for learning prediction, set the number of words required for the embedding layer to be all words in the corpus that dimension is 64, and the last word is the sequence as a label; then we add Bidirectional Long Short-Term Memory (Bi-LSTM) This not only uses past information, but also captures subsequent information. For example, in the vocabulary tagging problem, the lexicality of a word is determined by the context word, so the bidirectional LSTM can make good use of the context information. Here, the cell state is set to 50, that is the length of the processed context. The activation function used in the context is softmax; the loss function is categorical cross-entropy; the optimizer is adam (lr = 0.01); our training epoch is set to 50 epochs for efficient model convergence.

D. Model Evaluation Metrics

We know that evaluation metrics can objectively reflect the performance of the model. For this experiment, we use the accuracy and loss rate to evaluate our model. We use 80% of the dataset as training set and 20% as validation set. After training the model with the training set, apply it to the validation set to make predictions, and finally get the accuracy. We use accuracy as our evaluation metric. The formula for calculating the accuracy is as follows:

$$Accurancy = \frac{TP + TN}{TP + TN + FP + FN} \tag{13}$$

The model accuracy is shown in the fig4.

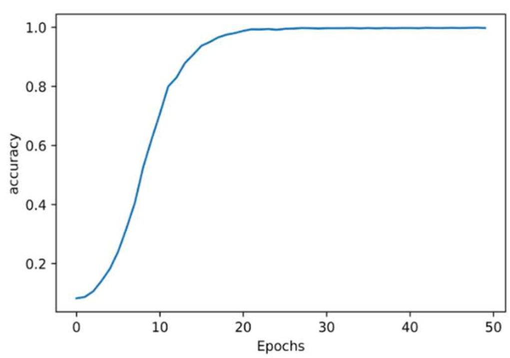

Fig. 4. Model accurancy

Form the Fig.4, our model accuracy is able to reach over 90% accuracy and tends to level off and approach 100%.

The model training loss is shown in the Fig 5. We can find that as the number of image-based training epochs increases, the training loss of the model converges to zero.

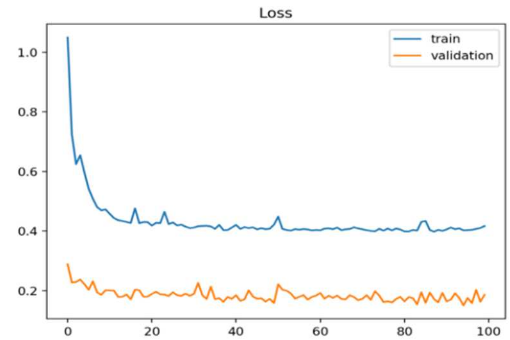

Fig. 5. Model training and validation loss

E. Examples of our model's text generation

Here is our text generation example, we compare the predictive generation using Chinese sentences without participle with Chinese sentences with participle, and the results are as follows.

From TABLE IV, the predicted generation of Chinese sentences without participles is as follows.

TABLE IV. CHINESE SENTENCES WITHOUT PARTICIPLES

User：“割双眼皮要多久恢复自然”
User：“How long does it take to recover naturally from double eyelid surgery”
Medical-chatbot：割双眼皮要多久恢复自然双眼皮手术可以只祛皮吗双眼皮手术可以只祛除皮肤，但要看个人的上睑条件。如果仅是上睑皮肤比较多，没有肌肉或者眶隔脂肪的多余，只祛除皮肤也能达到比较好的手术效果。
Medical-chatbot：How long does it take to recover naturally from double eyelid surgery? Can you remove just the skin? Double eyelid surgery can remove just the skin, but it depends on the condition of the individual's upper lid. If there is only a lot of skin on the upper lid and no excess muscle or orbital fat, you can achieve a better result by removing only the skin.

From TABLE V, the predictive generation of Chinese sentences with participles is as follows.

TABLE V. CHINESE SENTENCES WITH PARTICIPLES

User：“割 双眼皮 要 多久 恢复 自然”
User：“[How long] [does it take to] [recover] [naturally] [from double eyelid surgery]”
Medical-chatbot：割双眼皮要多久恢复自然不同患者间存在差异性，手术方式亦存在差异性，因此双眼皮手术后恢复自然的时间需视情况而定。造成双眼皮手术后出现肿胀的原因较多，不同人的诱发原因不同。一般而言，采用单纯埋线进行手术，7 天左右恢复自然，甚至术后 2 天即可恢复自然；采用小切口方式手术，恢复时间为半月至一个月；若采用全切方式进行手术，恢复时间可能延长至 3 个月。
Medical-chatbot：How long it takes to recover naturally from double eyelid surgery varies from patient to patient, as does the surgical procedure, so the time to recover naturally after double eyelid surgery depends on the situation. There are many reasons for the swelling after double eyelid surgery, and the triggering causes vary from person to person. Generally speaking, if the surgery is performed with a simple buried line, the recovery time is about 7 days, or even 2 days after the surgery; if the surgery is performed with a small incision, the recovery time is half a month to a month; if the surgery is performed with a full incision, the recovery time may be extended to 3 months.

In our experiments, we found that the model works better and produces more correct and useful responses when we input Chinese sequences that have been word-sorted in prediction than when we input Chinese sequences that have not been word-sorted.

F. Model Comparison

We use the model of GPT2 here for training our test data. The answer to our question of how long does it take to recover naturally from double eyelid surgery is as follows：

TABLE VI. ANSWERS TO QUESTIONS USING THE GPT2 MODEL

User： “割双眼皮要多久恢复自然”
User： “How long does it take to recover naturally from double eyelid surgery”
Medical-chatbot： 完全消肿需要 1~3 个月左右。因为每个人的身体情况不同，所以消肿的时间也会有所差异。做好相应护理工作可加快伤口的恢复速度。术后注意事项：一、保持伤口清洁，防止感染;二、术后 72 小时内可选择冰敷，对伤口消肿；三、术后建议勿食辛辣刺激性食物；四、术后一周内不要看电视、报纸等，卧床休息时最好半卧位(把枕头垫高)，以免眼睛过度疲劳或者头部位置过低而加重伤口肿胀。
Medical-chatbot： It takes about 1 to 3 months for the swelling to completely go down. Because each person's body condition is different, the time to reduce the swelling may also vary. Doing the corresponding care work can speed up the recovery of the wound. Postoperative precautions: First, keep the wound clean to prevent infection; second, ice packs can be chosen within 72 hours after surgery to reduce the swelling of the wound; third, it is recommended not to eat spicy and stimulating food after surgery; fourth, do not watch TV or newspapers for a week after surgery, and it is better to rest in bed in a semi-recumbent position (with a high pillow) to avoid aggravating the swelling of the wound due to excessive eye strain or low head position.

By comparing the models, we found that the answer obtained by the gpt2 model is how to reduce swelling and precautions after double eyelid surgery, and does not directly and accurately answer the question "How long does it take to recover from double eyelid surgery?" This question is not answered directly and precisely. In contrast, our proposed model has a better fit and can answer the question more accurately.

VI. SUMMARY

The thesis of this research is to explore the application of natural language processing in medical text generation and intelligent Q&A. Its significance and value is that it can alleviate the information asymmetry between doctors and patients due to professional knowledge to a certain extent, allocate medical resources to patients who need them more, and improve the utilization of medical resources. Our research involves the design of a language model based on the sequential framework for training text generation engines. Although this modeling framework has been addressed in other domains, its application in the medical domain is not yet mature. We experimentally demonstrate that the language model using TensorFlow's sequential framework can indeed be applied to an intelligent question and answer module in the medical domain. Our results show that it can generate medical text responses to eyelid-related questions in medical aesthetics based on the asked eyelid questions, with a good fit to the data we have trained. The current shortcoming of our study is that the unsegmented Chinese sequences are less effective in generation than the segmented Chinese sequences. This will be the direction of our further research in the future. Overall, the text generation model proposed in this project provides an improved direction for the exploration of intelligent question and answer and text generation in the medical field, promotes the development of intelligence in the medical field, and strengthens the contribution of NLP in the medical field.

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