Health-LLM: Personalized Retrieval-Augmented Disease Prediction Model

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Abstract

Artificial intelligence (AI) in healthcare has significantly advanced intelligent medical treatment. However, traditional intelligent healthcare is limited by static data and unified standards, preventing full integration with individual situations and other challenges. Hence, a more professional and detailed intelligent healthcare method is needed for development. To this end, we propose an innovative framework named Heath-LLM, which combines large-scale feature extraction and medical knowledge trade-off scoring. Compared to traditional health management methods, our approach has three main advantages. First, our method integrates health reports into a large model to provide detailed task information. Second, professional medical expertise is used to adjust the weighted scores of health characteristics. Third, we use a semi-automated feature extraction framework to enhance the analytical power of language models and incorporate expert insights to improve the accuracy of disease prediction. We have conducted disease prediction experiments on a large number of health reports to assess the effectiveness of Health-LLM. The results of the experiments indicate that the proposed method surpasses traditional methods and has the potential to revolutionize disease prediction and personalized health management. The code is available at https://github.com/jmyissb/HealthLLM.

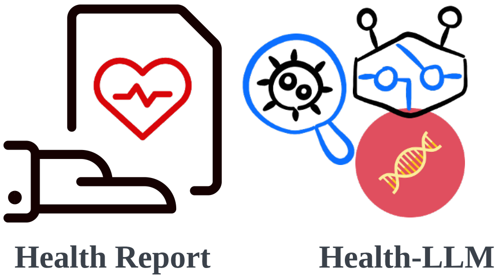

Figure 1: The overview of Health-LLM. A user presents their medical report to Health-LLM, an advanced AI health system. Health-LLM uses its algorithms to provide predictive insights and personalized health recommendations based on the data.

1 Introduction

The integration of AI into healthcare, notably through large language models (LLMs) such as GPT-3.5 (Rasmy et al., 2021) and GPT-4 (Achiam et al., 2023), has reshaped the field of health management. Recent studies highlight the crucial role of LLM in the use of machine learning to improve healthcare outcomes (Biswas, 2023; Singhal et al., 2022). Our focus lies on the Clinical Prediction with Large Language Models (CPLLM) approach (Wang et al., 2023), which showcases the superior predictive capabilities of LLMs fine-tuned on clinical data. Additionally, the COAD framework (Wang et al., 2023) addresses issues in previous automatic diagnosis methods, introducing a collaborative generation approach to mitigate challenges related to mismatches in the symptom sequence. Advancements in AI for healthcare demonstrate a significant shift towards models that handle complex medical data and offer improved precision. These advances are particularly important in addressing mismatches in symptom sequencing.

Nonetheless, traditional health management methods often struggle with the constraints imposed by static data and uniform standards, making them ill-equipped to fully meet individual needs (Uddin et al., 2019; López-Martínez et al., 2020; Beam and Kohane, 2018; Ghassemi et al., 2020). The health reports of the patients offer a wealth of data, including physiological indicators, lifestyle choices, medical backgrounds, and genetic traits. This information has the potential to predict future health issues and tailor health recommendations, but the difficulty lies in transforming this extensive data into practical insights.

Our current study aims to develop a new method that combines large-scale feature extraction, nuanced scoring of medical expertise, and machine learning techniques to effectively use patient health reports. Initially, we use advanced models to extract important features from patient health reports, including biomarkers, genetic data, lifestyle choices, and clinical indicators. We then work with medical professionals to assign varying weights and scores to these features, to better understand their impact on disease risk. Finally, we train a personalized classification model to make early predictions about disease occurrences and provide personalized health recommendations to individuals.

We propose an innovative approach named **Health-LLM**. Our research aims to provide the user with personalized health advice based on their potential health risks. We use data analysis, machine learning, and medical knowledge to develop a comprehensive health management methodology that can help predict and prevent future health complications. Our research involves detailed modelling and individual risk assessments to offer new perspectives for health management and disease prediction.

Our key contributions can be summarized as follows:

- We propose to use LLMs to evaluate health reports with a novel feature extraction method.
- We use the RAG to retrieve knowledge from professional knowledge.
- We employ an AutoML feature engineering approach to train a linear classifier for final disease prediction.

In this article, we detail our approach, experimental results, and potential implications for the healthcare field.

2 Related Work

2.1 AI for Health Management

AI is revolutionizing healthcare, using machine learning and other computational methods to enhance healthcare outcomes. This evolution is significantly driven by the emergence of LLMs, as seen in studies like (Biswas, 2023; Singhal et al., 2022; Rasmy et al., 2021). These models are vital in clinical applications, including disease prediction and diagnosis. The intersection of AI and healthcare has seen notable progress, fueled by the availability of extensive health datasets and the advancement of sophisticated language models. Recent research, such as (Wang et al., 2023), demonstrates the immense potential of LLMs in the healthcare sector, where they are used to understand and generate health reports and evaluate various health situations.

A key development in this field is the Clinical Prediction with Large Language Models (CPLLM), which highlights the potential of LLMs fine-tuned on clinical data (Wang et al., 2023). CPLLM, using historical diagnosis records, has shown superiority over traditional models such as logistic regression and even advanced models such as Med-BERT in predicting future disease diagnoses. Another significant advancement in AI for health is the COAD framework, which addresses the limitations of previous Transformer-based automatic diagnosis (AD) methods (Wang et al., 2023). Earlier models faced challenges due to mismatches in symptom sequences and the influence of symptom order on disease prediction. COAD introduces a disease and symptom collaborative generation framework, aligning sentence-level disease labels with symptom inquiry steps and expanding symptom labels to reduce the order effect. These advancements indicate a trend in AI for health, shifting towards models that effectively manage the complexity and subtleties of medical data. The progress made by CPLLM and COAD underscores the transformative impact these technologies can have on healthcare, enhancing precision, efficiency, and personalization in patient care.

In our investigation, we used the GPT-3.5 Turbo model (Rasmy et al., 2021), known for its lower cost and faster speed compared to GPT-4.0 (OpenAI, 2023). This model, being the most capable in the GPT-3.5 series, offers a balance between performance and practicality for healthcare applications.

2.2 AutoML

In the evolving landscape of automated machine learning (AutoML), significant strides have been made in optimizing the data science workflow, specifically in areas like model selection, training, and scoring. The "State of Data Science" report by Anaconda highlights that these aspects constitute only a small portion of a data scientist's responsibilities. The majority of their time is still dedicated to data engineering and cleaning tasks, areas where

AutoML's impact is currently limited (He et al., 2021). To bridge this gap, recent developments have focused on integrating LLMs with AutoML. This integration aims to extend the AutoML functionality to more complex domains that require extensive domain expertise (De Bie et al., 2022). However, challenges such as limited interpretability and consistency in LLMs persist. The CAAFE framework represents a notable advancement in this direction. It combines the robustness of classical ML with the domain knowledge capabilities of LLMs, facilitating the generation of interpretable Python code for feature engineering. This innovation significantly refines the AutoML pipeline (Hollmann et al., 2023). Building on CAAFE's semi-automated approach, we further enhanced it into a fully automated system, particularly in the feature engineering process, thereby advancing AutoML's capabilities and efficiency.

2.3 Information Retrieval

Information Retrieval (IR) is an essential field of computer science that focuses on retrieving pertinent information from vast amounts of data (Mitra and Chaudhuri, 2000). Its main goal is to locate information relevant to a user's query from various document collections, such as text, images, audio, and more. The process usually involves two main steps: parsing the user query and finding matching information in the dataset. Web search engines, such as Google and Bing, are the classic applications of information retrieval, which use complex algorithms to assess the relevance of information and rank the most relevant results first (Li et al., 2020). Information retrieval encompasses various techniques and methods, including text, image, and audio retrieval, cross-language retrieval, and other theoretical models, such as asset-based models, algebraic models, probabilistic models, and feature-based retrieval models.

3 Methodology

3.1 In-context learning for feature generation

In the initial phase of our methodology, we systematically extract symptom features from a range of diseases by harnessing the in-context learning capabilities of advanced large-scale language models. We prime the model with a series of exemplars, such as 'Symptoms: Cold—Symptoms: Runny or stuffy nose, sore or stinging throat, cough, sneezing', to teach it the pattern of symptom feature

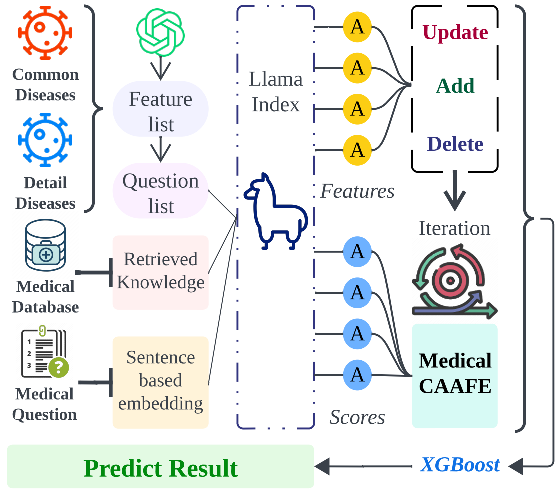

Figure 2: The workflow of the Health-LLM.

generation. Leveraging this in-context learning paradigm, our system is then poised to efficiently produce symptom descriptors for a diverse array of diseases in a batch processing mode.

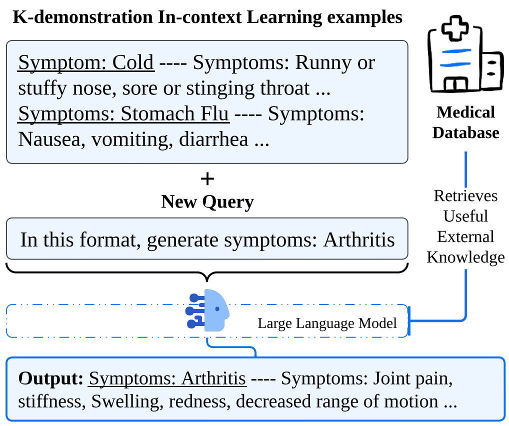

Figure 3: In-context learning workflow of Health-LLM

To enhance the precision of this generative process, we integrate a supplementary knowledge base, employing a RAG mechanism for enriched knowledge retrieval, a process that will be elaborated upon in the subsequent section. This integration enables our system to correlate and validate the generated symptoms against a repository of medical knowledge, ensuring a high degree of accuracy and relevance. Consequently, our approach facilitates the mass production of symptom features, effectively laying the foundation for the subsequent stages of disease prediction and analysis within our study.

In in-context learning, the initial step involves the formulation of training examples (x_i, y_i) in a format that maps input to labels using intuitive templates (Brown et al., 2020). These examples are then combined into a sequence using the following equations.

$$P = \pi \{x_1, y_1\} \otimes \pi \{x_2, y_2\} \otimes \cdots \otimes \{x_{|\Lambda|}, y_{|\Lambda|}\} \otimes \pi \{x_{\text{test}}, *\}, \tag{1}$$

In which π signifies a template-based transformation and $\otimes$ represents the operation of concatenation.

3.2 Health Report Document Embedding

To extract pertinent information from health documents and answer specific questions, it is vital to pinpoint and utilize the relevant sections within the document. These chosen segments serve as a foundation for the larger model to generate answers. To achieve this goal, we need to assess the similarity between the questions and document fragments. Typically, cosine similarity is used to calculate vector representations, known as embeddings, based on the query and document segments. These embeddings encode information into fixed-size vectors, effectively capturing the document's semantics in a high-dimensional space.

For the text embedding method, we choose Massive Text Embedding Benchmark (MTEB) (Muennighoff et al., 2022) as a benchmark to evaluate the performance of various text embedding models. Among these models, the all-mpnet-base-v2 (Reimers and Gurevych, 2019) model stands out for its robust MTEB score and efficient processing speed. Hence, we opt for the all-mpnet-base-v2 model for text embedding. Then, in order to save these embedding text within a vector database ChromaDB.

3.3 Retrieval-Augmented Generation for External Knowledge

The Retrieval Augmented Generation (RAG) (Lewis et al., 2020) method is a natural language processing model that combines retrieval and generation components to handle knowledge-intensive tasks. The method consists of two stages: Retrieval and Generation. During the retrieval phase, RAG employs the Dense Passage Retrieval (DPR) system to retrieve the most relevant documents from a large-scale document database that answers the input question. The input question is encoded as a vector, which is then compared with the document vectors in the database to locate the most relevant documents. During the generation phase, RAG uses a Transformer-based sequence-to-sequence model (such as BART or T5) to generate answers that consider both the input and the retrieved document content. The main idea behind this method is to use a large-scale document collection to enhance the generation model's ability and improve the model's efficiency in dealing with complex and knowledge-dependent problems.

Our approach builds key-value memory from knowledge presentation by adding additional healthcare knowledge to the original large model with the help of the RAG method. In the Retrieval phase, we use Dense Passage Retrieval (DPR) to generate the information base retrieval structure. The details are shown below,

$$\begin{aligned} &\mathbf{d}(z) = \mathrm{BERT}_d(z), \quad \mathbf{q}(x) = \mathrm{BERT}_q(x), \\ &p_\eta(z \mid x) \propto \exp\left(\mathbf{d}(z)^\top \mathbf{q}(x)\right), \end{aligned} \tag{2}$$

where $d(z)$ is a dense representation of a document produced by a $BERT_{BASE}$ document encoder (Devlin et al., 2018), and $q(x)$ is a query representation produced by a query encoder also based on $BERT_{BASE}$. Calculating top-k $(p_\eta(\cdot \mid x))$, the list of k documents z with the highest prior probability $p_\eta(z \mid x)$, is a Maximum Inner Product Search (MIPS) problem, which can be approximately solved in sub-linear time (Johnson et al., 2019).

In the generator, we pick $p_\theta(y_i \mid x, z, y_{1:i-1})$ as a generator component that could be modelled using any encoder-decoder. BART-large (Karpukhin et al., 2020) is used to generate the final content. This pre-trained model seq2seq transformer with 400M parameters. To generate information using BART, we concatenate input x with retrieved content z. BART is a pre-trained model with diverse noising functions, achieving superior results and outperforming T5. We call the BART generator parameters θ the parametric memory.

3.4 Assigning the Score by Llama Index

In this study, we adopt OpenAI's GPT-3.5-Turbo (Ray, 2023) as our LLM. To integrate LLM models from different sources, we adopt the Llama Index framework (Liu, 2022), which simplifies the integration process, facilitates the call of large models and can be used to ask questions about health reports. This choice of approach allows us to take full advantage of advanced natural language processing models to extract features, a key step in our

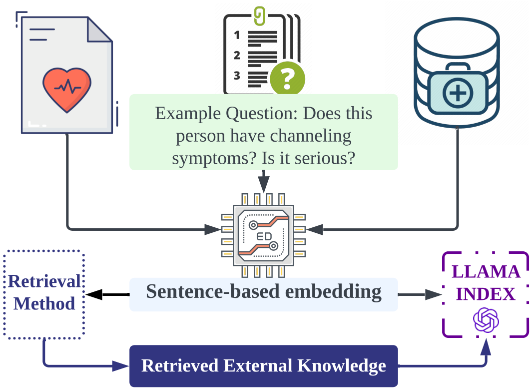

Figure 4: LLM for Feature Generation

ability to predict disease and provide health advice. This framework will not only improve the accuracy of predictions but also bring more innovation and improvements to the future of healthcare.

For feature generation, we take a systematic approach by asking LLMs specific questions about an individual's health status. Our contextual information for these questions is provided to LLM in embedded form. Through the guidance of system prompts, LLM is asked to answer the questions. When answering questions, large language models actually lack very specialized knowledge in medicine, so our system comes with some expertise in various fields. We utilize advanced Retrieval Augmented Generation technology to synchronize our queries with the knowledge base. Whenever a question is asked, RAG is employed to identify and retrieve the three most relevant pieces of information that are in line with the symptoms mentioned in the question. These selected pieces of information are then extracted and seamlessly integrated to enrich the input prompts for the models.

Use expertise in the corresponding problem area as a prompt when asking a question, and assign a confidence score to the answer result, which ranges from 0 to 1. This score is considered a feature of the machine learning model. By asking multiple relevant questions about people's health status, we can generate multiple features. For example, one of the following questions could be asked: "Does this person have good sleeping habits? Does he have any bad behaviour at night?" In theory, multiple similar questions could be asked and the resulting scores used as the basis for building a machine learning model one of the characteristics. This approach allows us to take a more complete look at an individual's health and provides more information to predict possible diseases. This process not only provides a structured approach to feature generation but also provides important input for subsequent machine learning models.

The Llama index serves to streamline document-based QA through a strategic 'search-then-synthesize' approach. The process unfolds as follows: Initially, health report documents are curated and formatted into plain text. These documents are then segmented into smaller manageable text blocks. Each block is processed through a text-embedding interface, transforming it into a vector representation that is subsequently stored within a vector database; here, OpenAI's embeddings can be utilized for this transformation.

When the system poses a question, it is converted into a vector to facilitate a search within the vector database, aiming to identify the most relevant text block(s). The identified text block is then amalgamated with the query to formulate a refined request. This newly crafted request is dispatched to the OpenAI API for processing. For this paper, a list of

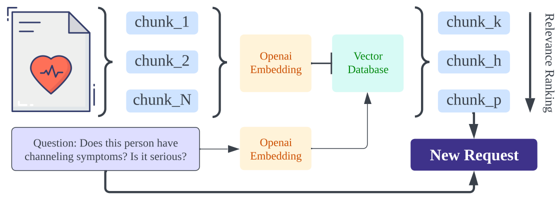

Figure 5: LLM for Feature Generation

152 questions and an area knowledge database was created. The question is generated automatically by symptoms generated by in-context learning. The scores for answering specified questions under the large model supported by professional knowledge will be used as features to enter the downstream machine learning model. For example: Sleep: 0.6, which means that his sleep condition is alright.

3.5 Prediction Model

In our quest to develop a robust disease classification system, we have established a comprehensive framework that encompasses 61 disease labels, ranging from common ailments such as insomnia and indigestion to more complex conditions like endocrine disorders. Within this system, we employ a binary classification scheme: '0' signifies the absence of the respective disease, while '1' indicates its presence. Additionally, we have introduced a finer level of granularity for certain diseases, such as fatty liver. In this context, '1' corresponds to a mild fatty liver and '2' denotes a severe fatty liver. It is important to note that if an individual is diagnosed with mild fatty liver, they are not simultaneously diagnosed with severe fatty liver, and vice versa.

In our quest to improve disease prediction through AutoML, the significance of domain-specific knowledge incorporation has become clear. Addressing this, we use Context-Aware Automated Feature Engineering (CAAFE), which utilizes the prowess of LLMs (Hollmann et al., 2023) to generate features iteratively with semantic relevance informed by the dataset's context. We have evolved from a semi-automated system to a fully automated one. We now use large models to autonomously craft feature and dataset descriptions, thereby streamlining the feature engineering process and enriching our models with contextually meaningful data.

3.6 Health Analysis

In our system, when identifying a potential disease that an individual may be at risk of, we employ a large external medical knowledge database curated by healthcare professionals to access relevant prevention and treatment methods. Subsequently, we communicate this information to the individual seeking consultation. As the individual may have further queries and concerns, our system is designed to engage in an ongoing dialogue, providing responses and recording these interactions in an electronic medical record. This meticulous record-keeping ensures the efficiency and accuracy of each response, thereby facilitating a more personalized and effective exchange of information.

4 Experimental Studies

4.1 Dataset Details and Evaluation Metrics

The data set used in our experiments is IMCS-21(Chen et al., 2023). To the best of our knowledge, IMCS-21 is currently the only dataset on telemedicine consultation in China. The data set contains a total of 4116 annotated samples with 164 731 utterances, which covers 10 pediatric diseases: *bronchitis*, *fever*, *diarrhea*, *upper respiratory infection*, *dyspepsia*, *cold*, *cough*, *jaundice*, *constipation* and *bronchopneumonia*. Each dialogue contains an average of 40 utterances, 523 Chinese characters (580 characters if including self-report) and 26 entities. To evaluate the quality of our model prediction, we employ three metrics: ACC(Accuracy), AUC(Area Under The Curve) and F1(Macro F1-score)

4.2 Comparative experiment

4.2.1 Health-LLM diagnostic test

Our comparative analysis involves two open-source models, GPT-3.5 and GPT-4. Initially, we'll deploy these models in a zero-shot setting to diagnose cases. Following this, we'll transition to a few-shot context, providing each model with a selection of prior predictions to enhance their diagnostic capabilities. Subsequently, we will integrate supplementary medical knowledge into the larger models to refine their predictions further. The culmination of this process will involve leveraging the dataset we use in Health-LLM to fine-tune LLaMA-2, with the objective of observing the impact on its performance. Health-LLM achieves SOTA compared to direct inference using other large models

Table 1: The result of the Health-LLM diagnostic test on the dataset compared with other models.

Models	Accuracy	F1
GPT-3.5(zero-shot)	0.333	0.361
GPT-3.5(few shot)	0.381	0.349
GPT-3.5(few shot with information retrieval)	0.451	0.451
GPT-4(zero-shot)	0.390	0.312
GPT-4(few shot)	0.620	0.671
GPT-4(few shot with information retrieval)	0.680	0.718
Fintuned-LLama2-7B	0.710	0.593
Fintuned-LLama2-13B	0.730	0.671
Health-LLM	**0.833**	0.762

4.3 Ablation Study

In this section, we compare our External Medical Knowledge Retrieval, AutoML and Reach-augmented Generation are used to perform ablation studies, which are used to verify the effectiveness of each structure of our Health-LLM.

4.3.1 Ablation Study on External Medical Knowledge Retrieval

For the ablation experiments, we aim to confirm the impact of External Medical Knowledge retrieval. We carried out experiments on our dataset, consisting of two groups: one with the complete Health-LLM, and the other with Health-LLM, where we removed our professional medical knowledge retrieval. We need to verify whether our retrieval of professional external knowledge can be achieved using only the llama index. Here, our experimental group directly bypassed the RAG process and directly input the extracted features into the Lima-index framework we used to test the necessity of RAG in our Health-LLM. We used these two models to conduct tests. The results are presented in Table 2.

Table 2: The result of Health-LLM diagnostic test on MedQA dataset.

Model	ACC
Health-LLMs without Retrieval	0.78
Health-LLMs	0.83

The experimental results show that we must index professional healthcare data to ensure the accuracy of diagnostic reasoning. Our diagnostic reasoning accuracy has improved significantly in the group with indexed professional healthcare knowledge.

4.3.2 Ablation Study on AutoML feature Pre-processing

In these ablation experiments, we aim to confirm if the feature preprocessing of AutoML has a positive impact on the inference of the entire Health-LLM. We have prepared two sets of experiments, differing only in the original feature used and the feature preprocessed by AutoML. The results of the experiments are presented in Table 3,

Table 3: The result of Health-LLM diagnostic test

Models	ACC
Health-LLMs without AutoML	0.77
Health-LLMs	0.83

From the experimental results, we have some necessity to use AutoML for data set preprocessing, and the experimental results are slightly improved in the three groups of experiments. Therefore, we believe that our data processing and feature extraction with AutoML is effective, but this link still needs further iteration to achieve a better performance assistance effect.

5 Conclusion

In this study, we present a new method that combines large-scale feature extraction, precise scoring of medical knowledge, and machine learning techniques to make better use of patient health reports. Our approach can predict potential future diseases ahead of time and provide customized health advice to individuals. This will lead to significant improvements in the field of health management and healthcare.

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