

DISEASE DIAGNOSIS USING LLM





Team

- Asmina Nassar
- Nadeem Nazer
- Nandhish Thathanur Rajappa
- Vanessa Tojan
- Vidvath Krishna





Agenda

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- Problem Definition
- Objectives
- Literature review
- System Architecture
- Implementation
- Experimentation
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Introduction

- Disease diagnosis is critical for early intervention in healthcare.
- Advancements in Artificial Intelligence, especially Large Language Models (LLMs), offer promising prospects for improving disease prediction methods.
- This project introduces a disease prediction system specifically designed for the healthcare domain, leveraging LLM technology.



Problem Definition

- Challenges in Traditional Diagnostic methods
 - Manual review of patient data is time-consuming and relies heavily on medical expertise.
- Growing Healthcare Demands
 - Increasing demand for accessible and efficient disease prediction tools.
- Data Utilization
 - Abundant patient data is available.



Objectives

- Develop a Disease prediction system using large language models (LLMs).
- Enhance disease prediction accuracy by leveraging Retrieval-Augmented Generation (RAG) for contextually relevant responses.
- Conduct experiments to optimize various aspects of the system, including word embeddings, model architectures, and hyperparameters.
- Evaluate the system's performance using intrinsic metrics and human evaluation to ensure quality and relevance of outputs.



Literature review

- Overview: Introduction to the novel framework "Health-LLM" for enhancing AI in healthcare systems
 - Utilises retrieval augmented generation (RAG).
 - Delivers personalised health recommendations and disease forecasts.
 - LlamaIndex for feature extraction.
 - XGBoost for disease prediction.

Impact

- Emphasises Al's role in revolutionising healthcare management.
- Outperforms conventional model and prior AI technologies in accuracy and F1 score.
- Uses clinical data to enhance predictive power of LLMs.



Literature review

Clinical Applications

- Direct Preference Optimization (DPO) and its impact on model precision in medical contexts.
- Few-shot disease prediction using EHR and LLMs.

Technological Advances

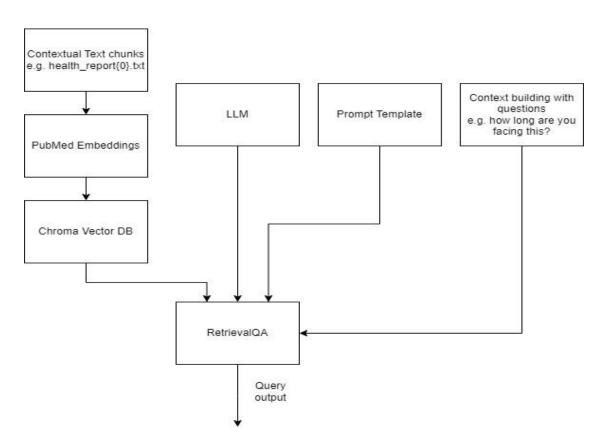
- Parameter-efficient Fine-tuning Techniques.
- Use of LoRA and quantization to improve computational efficiency.

Challenges and Future Research

- Managing data complexity and volume.
- Enhancing model generalization across diverse clinical settings.
- Aligning model outputs with expert medical preferences.



System Architecture







Implementation Details

Model around Langchain framework.

In context learning

RAG - 75 Health reports text documents are used.

Embeddings

- SentenceTransformerEmbeddings framework to use PUBMedBert-based-embeddings model.
- ChromaDB vector store for retrieval of vector embeddings.





Implementation Details

LLM

 Using BioMistral-7B-GGUF, quantized version of the BioMistral-7B, loaded using CTransformers API.

Retrieval chain

- The model, prompt with examples and retriever are set to the RetrievalQA Chain.
- More relevant information is fed to the retrieval chain by asking questions.





Experiment and Results

- Conducted a series of experiment focusing on 4 main factors:
- Models: Experimented on BioMistral-7B and Meditron-7B
- Embeddings: Experimented on BioClinicalBERT and PubMedBert-Base-Embeddings
- Model Specific Argument Selection
- Vector Database



Model Selection

Fact Based Selection

	MMLU										
	Clinical KG	Medical Genetics	Anatomy	Pro Medicine	College Biology	College Medicine	MedQA	MedQA 5 opts	PubMedQA	MedMCQA	Avg.
BioMistral 7B	60.9 ±1.5	61.7 ±2.1	49.6 ±1.2	55.1 ±1.3	56.9 ±1.0	55,5 ±1.7	44.4 ±0.2	37.4 ±0,4	37.6 ±1.5	43.9 ±0.3	50.3
Mistral 7B Instruct	57.0 ±0.8	56.7 ±0.5	46.9 ±0.3	51.0 ±1.1	58.6 ±0.9	50.1 ±1.0	42.3 ±0.3	34.5 ±0.5	72.2 ±0.5	42.8 ±0.5	51.2
BioMistral 7B Ensemble	62.8 ±0.5	62.7 ±1.7	46.9 ±0.3	57.0 ±0.6	60.6 ±0.9	56.3 ±0.3	$44.7{\scriptstyle~\pm0.4}$	37.1 ±0.6	$68.0{\scriptstyle~\pm 0.4}$	44.8 ±0.3	54.
BioMistral 7B DARE	61.3 ±0.4	61.0 ±2.8	49.9 ±0.9	55.3 ±0.7	64.4 ±0.9	53.9 ±1.4	47.0 ±0.5	38.8 ±0.7	70.0 ±0.7	44.9 ±0.2	54.0
BioMistral 7B TIES	62.3 ±0.5	61.3 ±1.9	48.1 ±2.2	55.8 ±0.8	57.2 ±0.7	<u>56.5</u> ±1.5	$44.0{\scriptstyle~\pm 0.4}$	37.7 ±0.4	44.3 ±0.8	44.0 ±0.3	51.
BioMistral 7B SLERP	63.1 ±1.6	63.3 ±0.9	49.9 ±1.9	57.4 ±0.3	63.4 ±0.9	57.8 ±0.9	46.6 ±0.2	38.9 ±0.4	68.1 ±1.4	45.7 ±0.7	55.4
MedAlpaca 7B	49.1 ±1.3	49.0 ±5.7	$48.4_{\pm 1.9}$	63.8 ±0.8	47.2 ±0.6	43.5 ±1.8	35.4 ± 0.3	30.4 ±0.6	56.0 ±0.9	31.2 ±0.2	45.4
PMC-LLaMA 7B	25.3 ±1.5	26.0 ±3.7	31.9 ±1.8	16.9 ±0.5	28.0 ±2.4	24.9 ±1.2	27.6 ±0.8	21.1 ±0.8	53.3 ±0.6	23.5 ±0.3	27.8
MediTron-7B	37.9 ±1.5	47.0 ±3.7	39.3 ±1.6	34.2 ±1.0	42.6 ±1.4	30.4 ±0.7	34.8 ±0.6	26.3 ±0.5	55.9 ±1.0	33.6 ±0.2	38.2
BioMedGPT-LM-7B	50.1 ±1.0	52.0 ±0.8	46.2 ±1.8	47.3 ±1.7	47.9 ±2.5	45.5 ±0.7	39.3 ±1.2	34.9 ±0.4	58.6 ±0.3	34.9 ±0.5	45.
GPT-3.5 Turbo 1106	74.71 ±0.3	74.00 ±2.2	65.92 ±0.6	72.79 ±1.6	72.91 ±1.7	64.73 ±2.9	57.71 ±0.3	50.82 ±0.7	72.66 ±1.0	53.79 ±0.2	66.

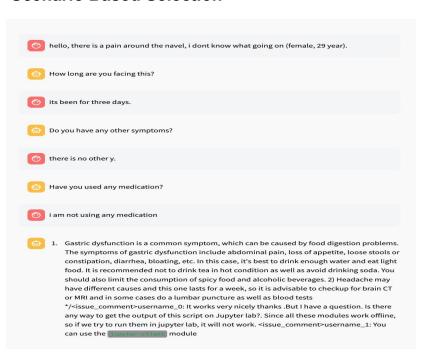
Performance of BioMistral 7B with 3 shot in context learning[6]





Model Selection

Scenario Based Selection



Medical Chatbot

How may I help you today?

Hello, there is a pain around the navel, I don't know what's going on (female, 29 years old). .

How long are you facing this?

lt has been there for three days. .

Do you have any other symptoms?

There are no other symptoms.

Have you used any medication?

l have not used any medication.

The pain in the navel area could be related to gastric dysfunction. Gastric dysfunction is a common symptom, which can be caused by food digestion problems. The symptoms of gastric dysfunction include abdominal pain, loss of appetite, loose stools or constipation, diarrhea, bloating, etc. In this case, it's best to drink enough water and eat light food. It is recommended not to drink tea in hot condition as well as avoid drinking soda. You should also limit the consumption of spicy food and alcoholic beverages.

Meditron 7B

Biomistral 7B



Embedding Selection

Compared the performance of BioMistral-7B when utilizing mainly 2 distinct embedding models

- BioClinicalBERT: fusion of BioBERT and Clinical BERT which is trained on MIMIC corpus
- Pubmedbert-base-embeddings: PubMedBERT variant using sentence-transformers which was trained on PubMed dataset.
- Why Pubmedbert-base-embedding
 - trained on a massive dataset of PubMed abstract whereas MIMIC contains notes from a single healthcare institution (BIDMC)
 - Pubmedbert-base-embeddings utilizes a sentence-transformer architecture
 - Enables dynamic embedding sizes from 64 to a full size of 768

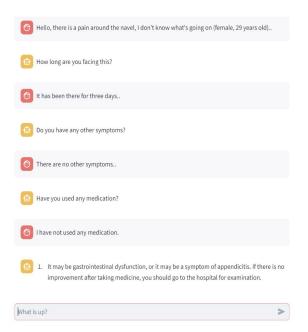




Embedding Selection

Scenario Based Selection





Pubmedbert-base-embeddings

BioClinicalBERT





Model Specific Argument Selection

- Retriever parameter *k*
- C Transformer parameter like temperature, max token
 - Automated with Optuna
 - Manually worked on a range of values
 - temperature=0.7
 - k=3 is optimum





Vector Database

- Qdrant
 - Had dependency with Docker
- Opted for Chroma DB



Evaluation

- Evaluated using intrinsic metrics.
 - ROGUE-L Longest common subsequence between reference and response.
- Evaluated using manual human assessment.
 - Helpfulness
 - Fluency
 - Relevance

Model Name	Helpfulness	Fluency	Relevance	ROGUE-L	
Meditron 7B	3.56	4.12	3.68	0.33	
Bio-Mistral 7B	3.77	4.32	4.17	0.3	

Table 1. Evaluation of our System



Conclusion

- Using In-context learning and RAG, system was able to generate tailored response.
- Biomistral 7B performed better in our case compared to Meditron 7B Quantized versions.
- Lack of medical related telecommunication data leads to poor performance in certain scenarios.
- Further improvement can be done using multimodal system.



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DEMO







THANK YOU