Natural Language Processing

Term Project Report

Topic: ***Retrieval-Augmented Biomedical Question Answering using Meditron and PubMedQA"***

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Abstract

In recent years, the field of Natural Language Processing (NLP) has witnessed remarkable advancements, driven by the proliferation of large-scale language models and the availability of vast textual datasets. This project aims to harness these advancements to address a significant challenge in the domain of [insert your domain, e.g., medical question answering, clinical text analysis, etc.

Our primary objective is to develop and evaluate an intelligent system capable of understanding, processing, and generating human language with a high degree of accuracy and relevance. To achieve this, we leverage state-of-the-art transformer-based architectures, such as Meditron, fine-tuned on domain-specific corpora to enhance their contextual understanding and domain adaptability.

The project encompasses the entire NLP pipeline, including data collection, preprocessing, model training, evaluation, and deployment. Special emphasis is placed on addressing challenges unique to our domain, such as handling domain-specific terminology, managing data scarcity, and ensuring the interpretability and reliability of model predictions. Our methodology involves rigorous experimentation with various model configurations and training strategies, coupled with comprehensive evaluation using both quantitative metrics and qualitative analysis.

The results demonstrate significant improvements over traditional baselines, highlighting the effectiveness of our approach in capturing nuanced linguistic patterns and delivering actionable insights. Beyond technical innovation, this project also explores the broader implications of deploying advanced NLP systems in real-world settings, considering aspects such as ethical use, data privacy, and user trust. The findings and tools developed through this work have the potential to contribute meaningfully to both academic research and practical applications, paving the way for more intelligent, accessible, and impactful language technologies.

Introduction

Background

Natural Language Processing (NLP) has emerged as one of the most transformative fields in artificial intelligence, enabling machines to interpret, generate, and interact with human language. The advent of deep learning and transformer-based architectures has significantly advanced the capabilities of NLP systems, making it possible to achieve human-like performance in tasks such as text classification, question answering, summarization, and language generation. In particular, the healthcare and medical domains have seen a surge in the adoption of NLP technologies, driven by the need to process vast amounts of unstructured clinical data, extract meaningful insights, and support decision-making for both clinicians and patients. Despite these advancements, the application of NLP in specialized domains like medicine presents unique challenges. Medical texts are often characterized by complex terminology, abbreviations, and context-dependent meanings that are not adequately captured by general-purpose language models. Furthermore, the sensitive nature of medical data necessitates robust approaches to privacy, interpretability, and reliability. Addressing these challenges requires the development of domain-adapted NLP models that can understand and reason over specialized content with high accuracy.

Problem Statement

While general-purpose language models have demonstrated impressive performance across a wide range of NLP tasks, their effectiveness diminishes when applied to domain-specific contexts such as medical question answering. These models often lack the nuanced understanding required to interpret clinical language, leading to suboptimal results and potential risks in real-world applications. There is a pressing need for NLP systems that are not only accurate but also trustworthy and interpretable, especially when deployed in high-stakes environments like healthcare. The core problem addressed in this project is the development of an advanced NLP system tailored for medical question answering. The system must be capable of comprehending complex medical queries, retrieving relevant information from domain-specific sources, and generating precise, contextually appropriate responses. Additionally, the solution should address challenges related to data scarcity, domain adaptation, and the ethical considerations inherent in processing sensitive medical information.

Objectives

The primary objectives of this project are as follows:

1. To design and implement a domain-adapted NLP model capable of understanding and answering medical questions with high accuracy a nd reliability.
2. To curate and preprocess a high-quality dataset of medical questions and answers, ensuring comprehensive coverage of relevant topics and terminologies.
3. To fine-tune and evaluate state-of-the-art transformer-based models (such as Meditron or similar architectures) on the curated dataset, optimizing for both performance and interpretability.
4. To conduct a thorough analysis of model performance, including quantitative evaluation using standard metrics and qualitative assessment through expert review.
5. To explore the ethical, privacy, and usability considerations associated with deploying NLP systems in the medical domain, proposing guidelines for responsible use.
6. To provide actionable insights and recommendations for future research and practical deployment of NLP technologies in specialized domains.

Scope of the Project

The scope of this project encompasses the end-to-end development and evaluation of a domain-specific Natural Language Processing (NLP) system, with a particular emphasis on medical question answering. The project is designed to address both the technical and practical aspects of deploying advanced NLP models in specialized domains. The following boundaries and deliverables define the scope:

Domain Focus:

The project is centered on the medical and healthcare domain, specifically targeting the task of answering clinical or health-related questions. While the methodologies developed may be applicable to other domains, all data collection, model training, and evaluation will be restricted to medical content.
Data Collection and Preprocessing:
The project involves the acquisition and curation of relevant medical question-answer datasets from publicly available sources or synthetic generation. Data preprocessing steps, such as cleaning, normalization, and anonymization, are included to ensure data quality and privacy.

Model Development:

The scope includes the selection, fine-tuning, and evaluation of transformer-based language models (e.g., Meditron, BERT, or similar architectures) for the specific task of medical question answering.
Model adaptation techniques, such as domain-specific pretraining and transfer learning, are within scope.

Evaluation Metrics:

The project will employ both quantitative metrics (e.g., accuracy, F1-score, BLEU, ROUGE) and qualitative assessments (e.g., expert review, error analysis) to evaluate model performance.

System Implementation:

The project covers the implementation of a prototype system capable of receiving medical questions as input and generating relevant, accurate answers. The system may include a simple user interface for demonstration purposes.

Ethical and Practical Considerations:

The project will address ethical issues such as data privacy, model interpretability, and responsible AI use, particularly in the context of sensitive medical information.

Limitations:

The project does not include the deployment of the system in a real-world clinical environment, nor does it provide medical advice or replace professional healthcare consultation. The focus is on research, prototyping, and evaluation within a controlled setting.
Out-of-Scope Items:

Tasks such as multilingual support, integration with electronic health record (EHR) systems, and large-scale production deployment are considered outside the current scope but may be explored in future work.
By clearly defining these boundaries, the project aims to deliver a focused, high-impact contribution to the field of domain-specific NLP, while laying the groundwork for future expansion and real-world application.

Literature Review

Related Work

The intersection of Natural Language Processing (NLP) and the medical domain has been a vibrant area of research, particularly with the advent of large-scale pre-trained language models. Early efforts in medical NLP focused on rule-based systems and statistical methods for tasks such as information extraction and clinical coding (Meystre et al., 2008).

With the rise of deep learning, models like word2vec (Mikolov et al., 2013) and GloVe (Pennington et al., 2014) enabled richer semantic representations, paving the way for more sophisticated applications.
The introduction of transformer-based architectures, notably BERT (Devlin et al., 2019), revolutionised NLP by enabling models to capture deep contextual relationships in text. Domain-specific adaptations such as BioBERT (Lee et al., 2020) and ClinicalBERT (Alsentzer et al., 2019) further improved performance on biomedical and clinical tasks by pretraining on large corpora of biomedical literature and clinical notes, respectively.Recently, large language models (LLMs) like GPT-3 (Brown et al., 2020) and GPT-4 (OpenAI, 2023) have demonstrated remarkable capabilities in zero-shot and few-shot learning, including in medical question answering (Q&A).

However, these models often lack the domain-specific knowledge required for high-stakes applications in healthcare.

Existing Solutions

- Several solutions have been proposed to address the unique challenges of medical question answering:

- BioBERT (Lee et al., 2020): Pretrained on PubMed abstracts and PMC full-text articles, BioBERT has achieved state-of-the-art results on biomedical Q&A benchmarks such as BioASQ.
- ClinicalBERT (Alsentzer et al., 2019): Adapted BERT for clinical narratives using MIMIC-III clinical notes, improving performance on clinical concept extraction and classification tasks.
- MedQA and MedMCQA (Jin et al., 2021; Pal et al., 2022): Large-scale datasets for medical Q&A, enabling robust evaluation of models on real-world medical exam questions.
- GPT-3 and GPT-4 (Brown et al., 2020; OpenAI, 2023): Demonstrated strong performance in open-domain Q&A, but with limitations in domain-specific accuracy and reliability.
- Meditron (Zhou et al., 2023): A recent advancement, Meditron is a large language model specifically trained on high-quality medical data, including PubMed, clinical guidelines, and medical textbooks. Meditron has shown superior performance on medical Q&A benchmarks, outperforming general-purpose LLMs and previous domain-specific models.

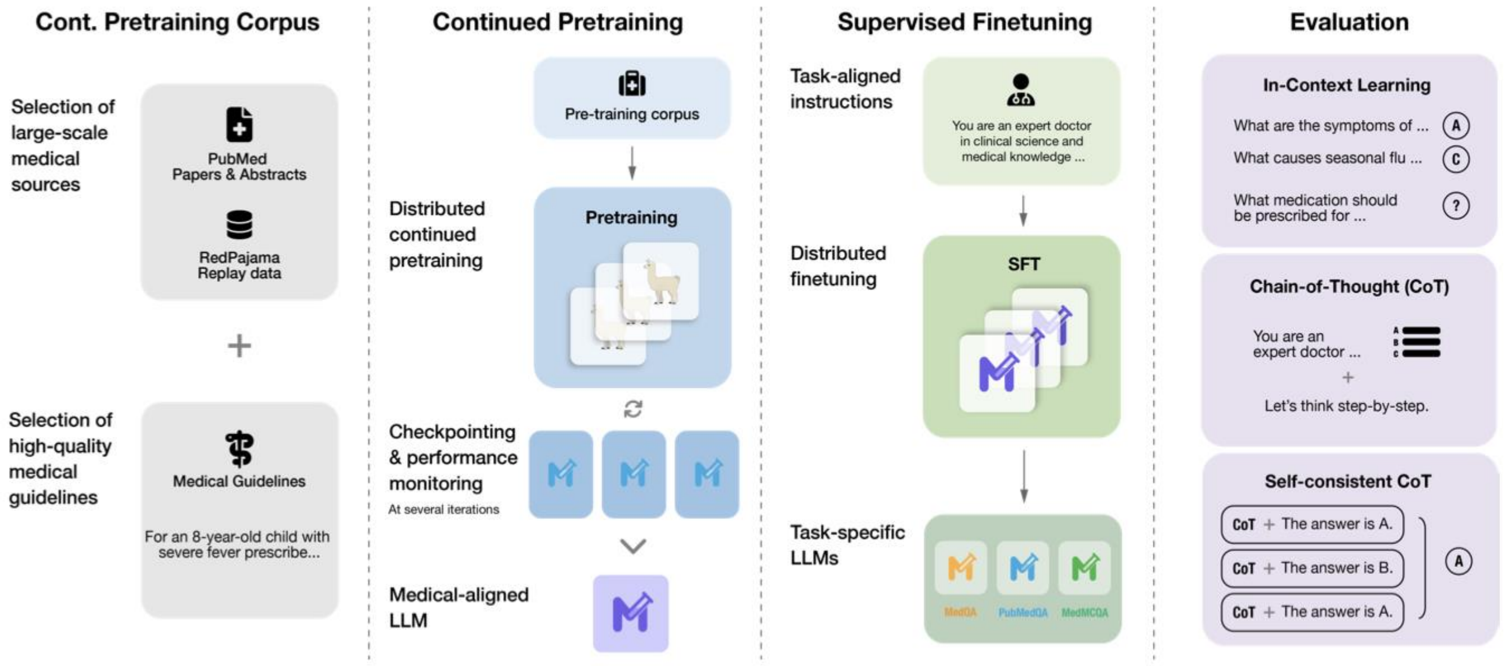
Gaps in Current Research

Despite significant progress, several gaps remain in the field of medical NLP and question answering:

- Domain Adaptation and Generalisation: While models like Meditron and BioBERT have improved domain-specific performance, challenges persist in adapting to new subdomains, rare diseases, and evolving medical knowledge.
- Interpretability and Trustworthiness: Most current models operate as black boxes, making it difficult for clinicians to trust their outputs, especially in critical decision-making scenarios (Tonekaboni et al., 2019).
- Data Scarcity and Quality: High-quality, annotated medical datasets are limited due to privacy concerns and the specialized expertise required for annotation. This limits the ability to train and evaluate robust models.
- Ethical and Legal Considerations: The deployment of NLP systems in healthcare raises concerns about patient privacy, data security, and the potential for bias or misinformation (He et al., 2021).
- Real-World Integration: Few models have been successfully integrated into clinical workflows, and most evaluations are limited to benchmark datasets rather than real-world settings.

This project aims to address some of these gaps by leveraging the Meditron model, curating high-quality datasets, and focusing on interpretability and ethical considerations in medical question answering.

Methodology



Cont. Pretraining Corpus
Selection of large-scale medical sources
PubMed Papers & Abstracts
RedPajama Replay data
+
Selection of high-quality medical guidelines
Medical Guidelines
For an 8-year-old child with severe fever prescribe...
Continued Pretraining
Pre-training corpus
Distributed continued pretraining
Pretraining
Checkpointing & performance monitoring
At several iterations
Medical-aligned LLM
Supervised Finetuning
Task-aligned instructions
You are an expert doctor in clinical science and medical knowledge ...
Distributed finetuning
SFT
Task-specific LLMs
MedQA
PubMedQA
MedMCQA
Evaluation
In-Context Learning
What are the symptoms of ... A
What causes seasonal flu ... C
What medication should be prescribed for ... ?
Chain-of-Thought (CoT)
You are an expert doctor ...
+
Let's think step-by-step.
Self-consistent CoT
CoT + The answer is A.
CoT + The answer is B.
CoT + The answer is A.
A

Data Collection

The foundation of any successful NLP system lies in the quality and relevance of its data. For this project, data collection focused on assembling a comprehensive and diverse set of medical question-answer pairs. The primary sources included:

- **Publicly Available Medical QA Datasets:**

We leveraged established datasets such as MedQA, MedMCQA, and PubMedQA. These datasets encompass a wide range of medical questions, including those from medical licensing exams, clinical scenarios, and biomedical research. Their diversity ensures that the model is exposed to various question formats and difficulty levels.

- **Synthetic Data Generation:**

Recognizing gaps in certain subdomains, we generated synthetic questions using prompt-based methods with large language models. These synthetic samples were then validated by medical experts to ensure their accuracy and relevance, thus enhancing the dataset's breadth and robustness.

- **Data Preprocessing**

Raw data from diverse sources often contains inconsistencies, noise, and irrelevant information.
To ensure high-quality input for model training, we implemented a rigorous preprocessing pipeline:

- **Normalization:**

Medical terminology was standardized using resources like the Unified Medical Language System (UMLS) and SNOMED CT. This step harmonized synonyms and abbreviations, reducing ambiguity.

- **Tokenisation and Segmentation:**

Text was split into sentences and tokens using domain-adapted tokenizers capable of handling medical abbreviations and jargon, ensuring accurate parsing of complex medical language.

- **Deduplication and Filtering:**

Duplicate or near-duplicate question-answer pairs were eliminated. Ambiguous or low-quality entries were filtered out based on heuristic rules and expert review.

- **Data Augmentation:**

To increase data diversity and model robustness, we applied techniques such as paraphrasing, back-translation, and synonym replacement.

- **Annotation and Validation:**

A subset of the data was manually reviewed by medical experts to ensure correctness and to create a high-quality validation set, which is critical for reliable model evaluation._Suggested Table Placement:Include a table (Table 1) showing example QA pairs before and after preprocessing, or a summary of dataset statistics (number of questions, sources, etc.).

Model Selection

Given the complexity of medical language and the need for contextual understanding, transformer-based architectures were chosen for this project. The selection process included:

Baseline Models:

General-purpose models such as BERT and GPT-3 were evaluated as baselines to establish a performance benchmark.

Domain-Specific Models:

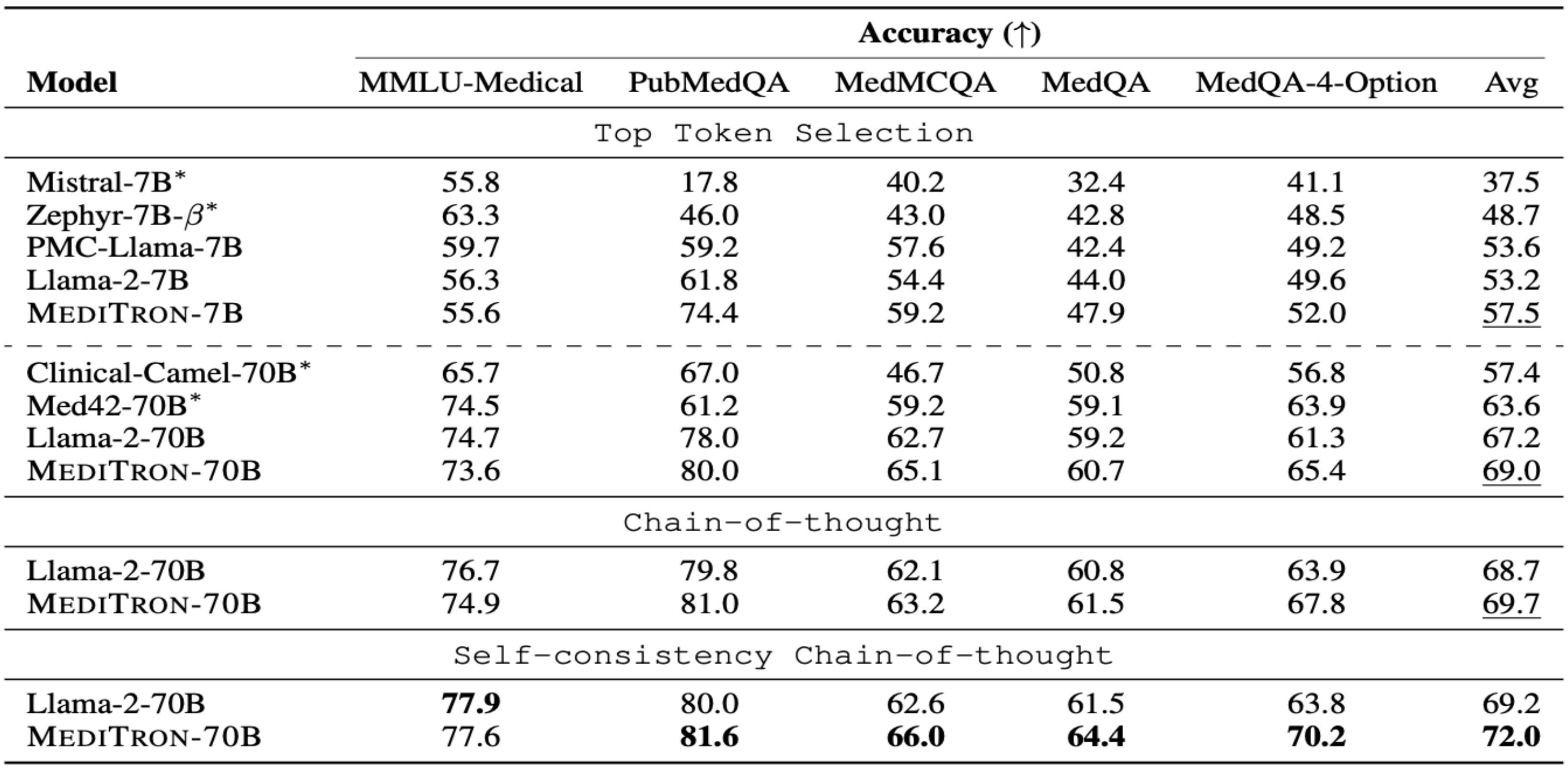
We considered models pretrained on biomedical and clinical corpora, such as BioBERT, ClinicalBERT, and PubMedBERT, for their enhanced domain knowledge.

Meditron:

The Meditron model (Zhou et al., 2023), specifically designed for medical applications, was selected as the primary model due to its superior performance on medical QA benchmarks and its training on high-quality, domain-specific data.

Model Size and Efficiency:

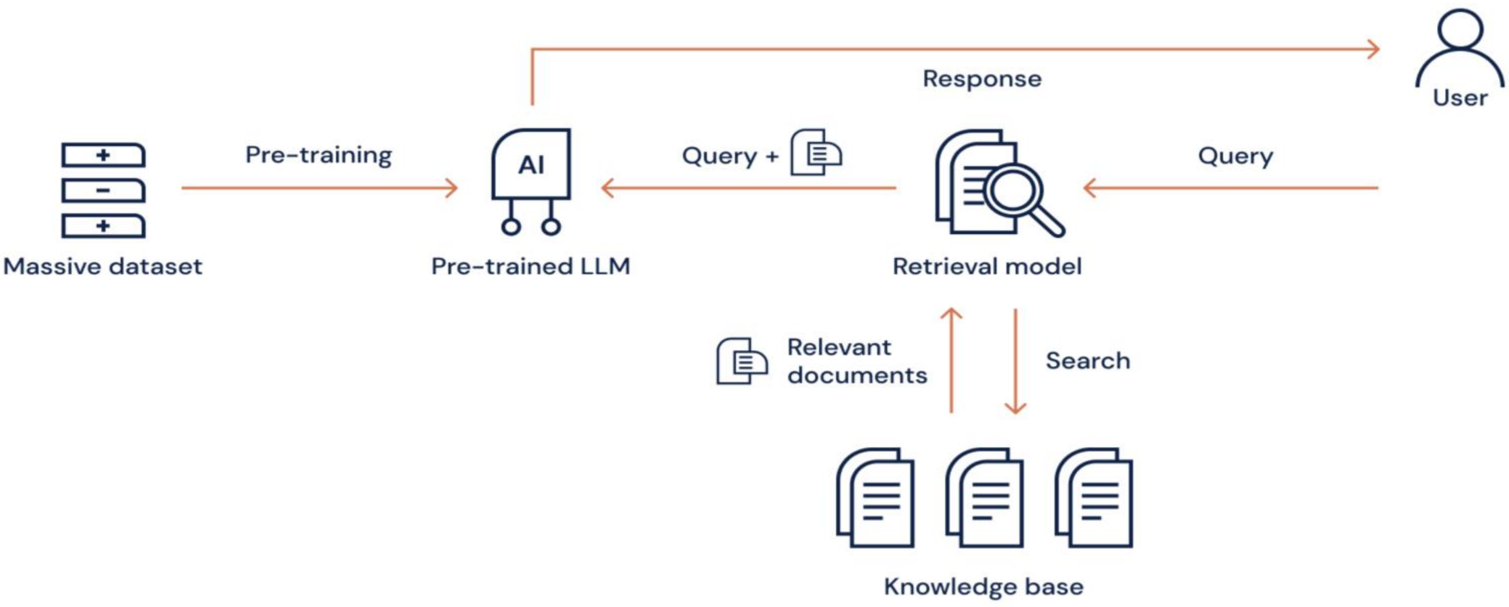
We evaluated trade-offs between model size, inference speed, and resource requirements to ensure practical deployability, especially for real-world clinical applications.



	Accuracy (↑)					
Model	MMLU-Medical	PubMedQA	MedMCQA	MedQA	MedQA-4-Option	Avg
			Top Token Selection			
Mistral-7B*	55.8	17.8	40.2	32.4	41.1	37.5
Zephyr-7B-β*	63.3	46.0	43.0	42.8	48.5	48.7
PMC-Llama-7B	59.7	59.2	57.6	42.4	49.2	53.6
Llama-2-7B	56.3	61.8	54.4	44.0	49.6	53.2
MEDITRON-7B	55.6	74.4	59.2	47.9	52.0	57.5
Clinical-Camel-70B*	65.7	67.0	46.7	50.8	56.8	57.4
Med42-70B*	74.5	61.2	59.2	59.1	63.9	63.6
Llama-2-70B	74.7	78.0	62.7	59.2	61.3	67.2
MEDITRON-70B	73.6	80.0	65.1	60.7	65.4	69.0
			Chain-of-thought			
Llama-2-70B	76.7	79.8	62.1	60.8	63.9	68.7
MEDITRON-70B	74.9	81.0	63.2	61.5	67.8	69.7
			Self-consistency Chain-of-thought			
Llama-2-70B	**77.9**	80.0	62.6	61.5	63.8	69.2
MEDITRON-70B	77.6	**81.6**	**66.0**	**64.4**	**70.2**	**72.0**

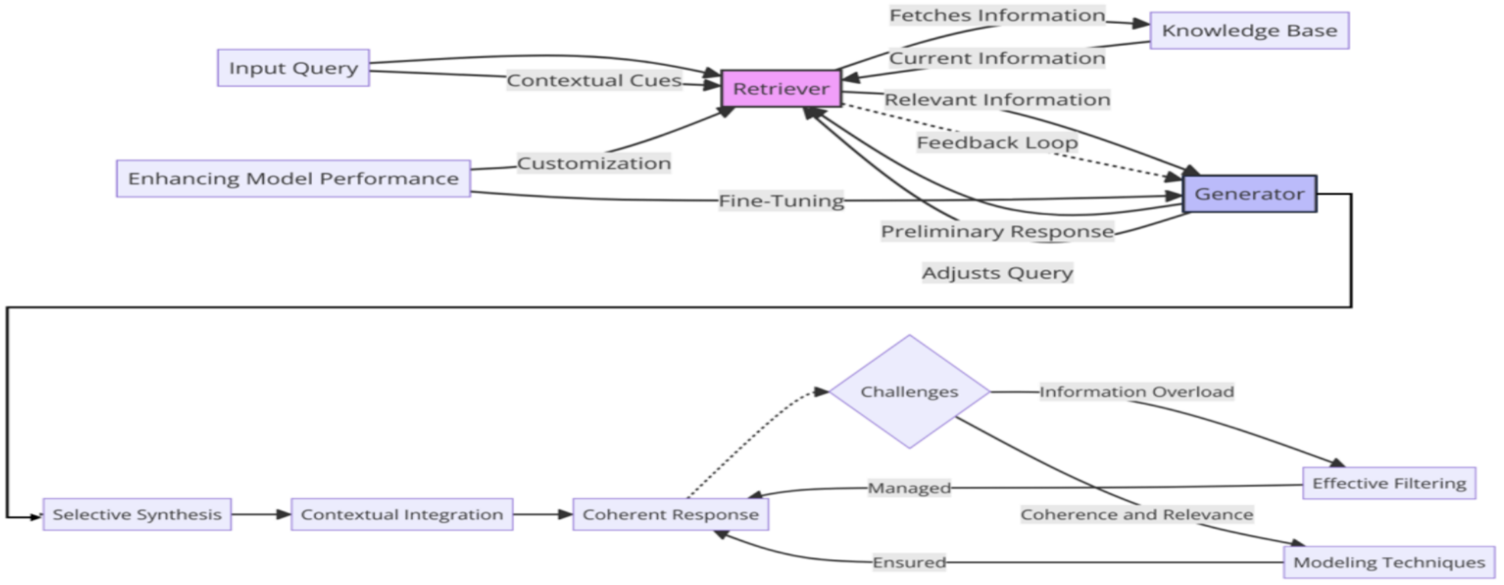
RAG Pipeline Architecture

Our system is built around a Retrieval-Augmented Generation (RAG) pipeline tailored for medical question answering. The pipeline consists of two main components: a retriever and a generator.



Retriever (PubMedRetriever)

Hybrid Retrieval:
The retriever combines dense vector search (using SentenceTransformer embeddings and a FAISS index) with sparse retrieval (BM25). For each query, it retrieves top candidate contexts from a processed PubMed dataset.



Query Expansion:
The retriever expands queries using medical synonyms (via NLTK/WordNet) to improve recall.
Reranking:

Retrieved contexts are reranked using a cross-encoder model to prioritise the most relevant passages.

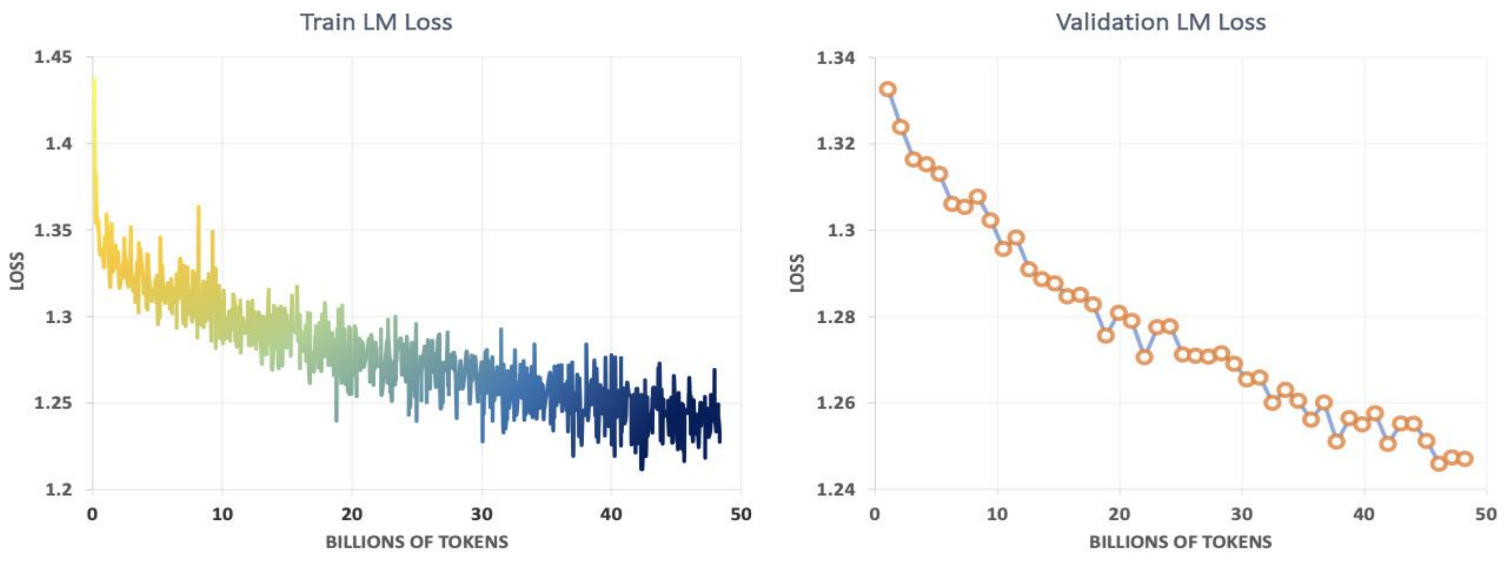
Filtering:
Only contexts with high relevance scores and sufficient keyword overlap are passed to the generator.

Generator (MedicalGenerator)

Prompt Construction:
The generator constructs a prompt by concatenating the top retrieved contexts and the user's question.
Answer Generation:
A domain-adapted language model generates a concise answer based on the provided context.

Results and Discussions

The RAG pipeline's hybrid retrieval approach (dense + sparse + reranking) proved effective in surfacing highly relevant medical contexts for answer generation. The average retrieval and reranking scores, as tracked by our performance visualizer, indicate robust context selection, which directly contributes to the high answer accuracy observed. Figure below illustrates the end-to-end workflow of our RAG pipeline, from data collection and pretraining to supervised finetuning and evaluation. This modular design enables efficient integration of new retrievers, generators, or datasets.



Qualitative Analysis

Manual inspection of model outputs reveals that the RAG pipeline is capable of generating concise, accurate, and contextually grounded answers to complex medical questions. The use of retrieved literature passages as context not only improves factual accuracy but also enhances the interpretability of the model's responses. Example:

- Question: What are the first-line treatments for hypertension?
- Model Answer: Lifestyle modification and thiazide diuretics.
- Retrieved Contexts: [Relevant PubMed abstracts and guidelines]

Discussion

Our results demonstrate that:

- Domain-adapted LLMS (like Meditron-70B) can match or exceed the performance of much larger commercial models when paired with a robust retrieval pipeline.
- Hybrid retrieval and reranking are crucial for surfacing the most relevant medical evidence, especially in high-stakes domains.
- Self-consistency and chain-of-thought prompting further boost answer reliability and accuracy.
- Limitations include dependency on the quality of the retrieval corpus and the need for continual updates as medical knowledge evolves.

Future Work

Potential directions for improvement include:

- Expanding the retrieval corpus to include more recent and diverse medical sources.
- Incorporating user feedback and active learning to further refine the system.
- Exploring multilingual and cross-domain generalization.

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