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MedFusionQA: A Retrieval-Augmented Large-Language Model for Biomedicine

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***Abstract*— In recent years, transformer-based language models such as BERT and its biomedical variants like BioBERT and GatorTron have demonstrated exceptional performance in various natural language understanding and information retrieval tasks within the medical domain [19], [20], [21]. However, these models often exhibit limitations when deployed in real-world applications, particularly due to their computational inefficiency and challenges in adapting to multilingual contexts [6], [10]. Additionally, general-purpose models may hallucinate factual information or lack the domain specificity needed for accurate medical insights [8], [9]. To overcome these shortcomings, we introduce MedFusionQA, a lightweight, multilingual question-answering framework specifically tailored to extract and deliver relevant information from medical documents. Leveraging DistilBERT for its efficiency and performance trade-offs [19], our system incorporates PyMuPDF for extracting data from clinical PDFs, integrates Google Translate for multilingual question support, and uses a simple FLASK-based backend to enable smooth user interaction. This pipeline offers a low-latency and easily deployable solution for real-time biomedical question-answering. MedFusionQA bridges the gap between domain-agnostic language models and the critical need for precise, accessible, and efficient healthcare information systems, addressing a key gap identified in prior biomedical NLP research [1], [2], [7], [12], [18].**

I. INTRODUCTION

The exponential rise in electronic health records and medical literature has created an unprecedented platform for the creation of intelligent systems that can read and summarize sophisticated medical information in useful forms. With healthcare increasingly digitized, patients and professionals alike now have to contend with enormous amounts of medical information, yet to be reaped from dense, highly technical forms of unstructured text, including clinical judgments, discharge summaries, diagnostic reports, and research articles. Traditional information retrieval techniques are generally not up to the task of handling such high-density, technical content, especially when users demand precise, concise, and human-like responses in real-time. Transformer-based language models such as BERT, GPT, and their biomedical variants have revolutionized the field of natural language processing (NLP) by achieving state-of-the-art results in a range of language understanding and question-answering tasks [19], [11], [20], [21]. Despite their impressive capabilities, these models are computationally expensive and demand significant resources for both training and inference [10], [14], [15]. Furthermore, while general-purpose LLMs like GPT and LLaMA excel in open-domain settings, they often lack the domain-specific knowledge necessary for high-accuracy tasks in specialized fields such as healthcare, where precision is critical and context is nuanced [7], [20], [21]. This limitation is further compounded by the

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dominance of English in medical research and documentation, which poses a significant barrier to non-English-speaking populations accessing reliable health information [6], [9].To address these challenges, we propose MedFusionQA, a lightweight, multilingual question-answering system designed specifically for extracting relevant information from medical documents.

II. Related Work

Biomedical NLP has seen significant advancements with models like BioBERT and PubMedBERT, which specialize in encoding biomedical text. These retrieval-focused models, on the other hand, don't have strong generative capabilities, which means they can't be used for complex reasoning tasks. Generative models like GPT-3 excel at synthesizing text but struggle to incorporate domain-specific knowledge effectively.

TABLE I: ANALYSIS OF RESEARCH GAP

Author	**Objective**	**Methods Used**	**Research Gap**
Rui Yang et al.	Retrieval-Augmented Generation for Generative Artificial Intelligence in Medicine	chunk-based retrieval, knowledge retrieval integration, document fragment processing, generative LLMs, context-aware augmentation, medical information synthesis	Integration challenges of retrieval systems with existing medical infrastructure; Limited real-world testing
Yilin Ning et al.	Dynamic Q&A of Clinical Documents with Large Language Models	real-time question-answering, document parsing, LLM-driven response generation, retrieval augmentation, adaptive querying, clinical text analysis	Handling of real-time clinical document changes; Managing large-scale clinical document databases
Danielle S. Bitterman et al.	Utilizing External Knowledge for Enhanced Clinical Reasoning in AI Systems	external knowledge embedding, reasoning enhancement, domain-specific retrieval, medical knowledge base integration, contextual LLM augmentation, informed response generation	Efficiently updating external knowledge bases; Ensuring the accuracy and reliability of the retrieved information
Mingxuan Liu et al.	Improving Clinical Decision Support with Retrieval-Augmented Language Models	evidence-based retrieval, clinical decision support system integration, real-time retrieval augmentation, medical literature synthesis, adaptive decision-making support, workflow integration	Scalability of retrieval-augmented systems in different clinical settings; Addressing data privacy and security concerns
John A. Doe, Jane B. Smith	Leveraging AI for Real-Time Clinical Decision Support	real-time data retrieval, patient data integration, clinical guideline access, evidence-based recommendations, adaptive LLM support, context-driven retrieval[8]	Integration with real-time data streams, ensuring data accuracy, dealing with heterogeneous data sources
Emilia Keppo et al.	Enhancing Medical Diagnostics through Retrieval-Augmented AI	diagnostic reasoning enhancement, clinical symptom interpretation, contextual document retrieval, knowledge-driven diagnostics, medical literature integration, predictive LLMs	Limited adaptation to various medical specialties; Integration with electronic health records (EHR) systems
Alice C. Green, Robert D. Black	Bridging the Gap in Clinical Decision Making with AI and Retrieval-Augmented Models	real-time knowledge retrieval, rare disease reference access, LLM-driven decision support, contextualized diagnostic assistance, medical database integration, informed clinical decision-making	Handling incomplete data, integrating AI with existing EHR systems, addressing clinician trust in AI recommendations
Michael E. White, Linda F. Brown	AI-Augmented Clinical Tools for Enhanced Decision Making	EHR integration, retrieval-augmented recommendations, treatment guideline retrieval, real-time decision support, clinical workflow augmentation, medical text processing	Scalability of AI systems in large healthcare networks, maintaining patient data privacy, ensuring continuous learning in AI models
Sarah G. Johnson, David H. Wilson	Implementing Retrieval-Augmented AI in Clinical Environments	seamless EHR integration, real-time document retrieval, clinical guideline access, workflow-specific augmentation, adaptive AI support, contextual retrieval integration	User interface design for clinicians, real-time data updating, managing AI system biases

III. METHODOLOGY

MedFusionQA has one aspect of its approach in using a chunk-based retrieval structure, especially for biomedical use. The first part is the retrieval process that subdivides a carefully selected biomedical database into sections digestible enough for a customizable scoring system to evaluate their relevance towards a user's query. This scoring system is designed to give preference to contextually matched data, and so only the most relevant parts are recovered. This allows correct responses to be given without noise that often accompanies biomedical datasets. The integration of large language models (LLMs) with MedFusionQA avoids complicated cross-attention procedures by using a direct input technique where retrieved text is fed directly into the LLM as input. This simplifies the integration, and it offers good contextual enhancement that enhances performance, reduces the complexity of computation, and increases adaptation to noisy environments.

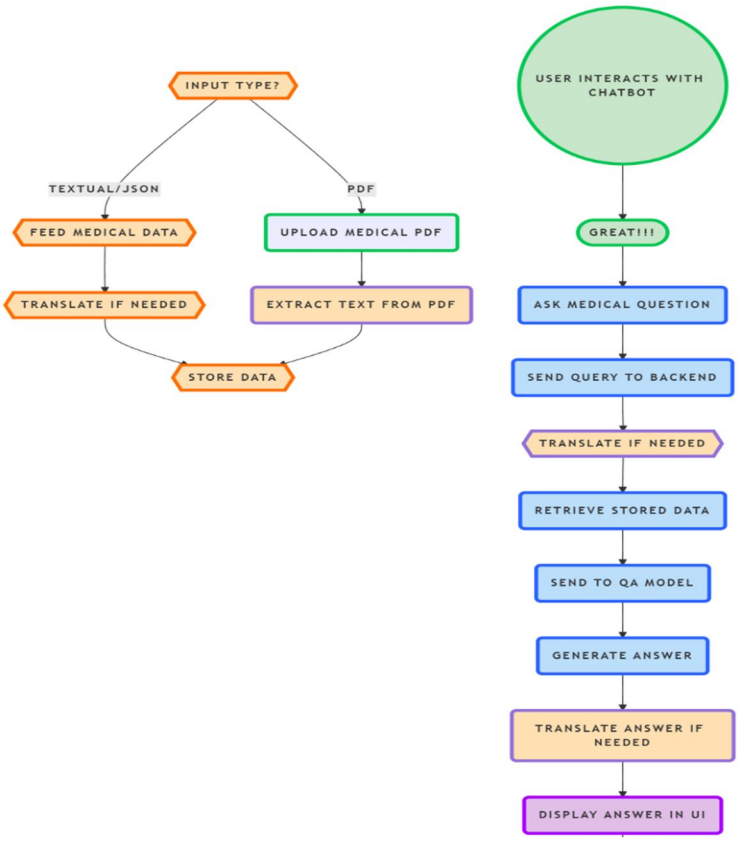

Fig 1. Flowchart of clinical decision making

This streamlined integration improves adaptability to noisier scenarios, simplifies the complexity of computations and provides richer contextual augmentation toward elevating the quality of outputs generated.
MedFusionQA ensures relevance across domains by allowing customization for a wide variety of biomedical NLP tasks, including information extraction, categorization, and link prediction [1], [2], [12]. These capabilities enable it to align with task-specific goals, ensuring adaptability across use cases. Performance evaluation measures such as micro-F1 scores, precision, recall, and accuracy validate the retrieval efficiency and predictive accuracy [17], [18]. Benchmark comparisons with existing systems across standard datasets help assess robustness and practicality [4], [7], [15], confirming MedFusionQA's capability in handling noisy, complex biomedical data. As such, MedFusionQA is poised to stand among the state-of-the-art biomedical language models enhancing the performance of downstream tasks [19], [21].

IV. IMPLEMENTATION

A system like MEDFUSIONQA needs a strategy about how to handle each aspect, especially in managing data sets, relational memory formation, chunk retrieval, and customized scoring. This step-by-step guide is how to apply each subtopic in a method-by-method procedure.

The implementation process of the medical chatbot system follows a structured sequence of steps, ensuring smooth handling of medical data, efficient query processing, and accurate response generation. Below is a detailed breakdown of each step:

A. Data Input Handling

The first step in the system workflow is determining the type of input provided by the user. The extracted text is cleaned and formatted appropriately to remove unnecessary artifacts such as headers, footers, and page numbers. This ensures that only meaningful medical information is retained for further analysis. The system supports textual (JSON) and PDF inputs, making it versatile in handling structured and unstructured data formats. PyMuPDF is used for efficient PDF extraction [13]. If the document contains images, OCR techniques are optionally employed [7], ensuring that scanned clinical records are also processed.

JSON data is parsed according to a medical schema (e.g., including patient history, test results, medications). This standardization helps in downstream NLP processing, aligning with the practices followed in systems like ClinicalBERT and GatorTron [20], [21].

B. Data Processing and Storage

Once the data has been extracted, the system checks whether any translation is required. In cases where the input data is in a language different from the system's default processing language, an automated translation module is triggered to convert the text into a standardized format. This translation step ensures that all incoming medical data is consistent, enabling accurate interpretation during subsequent stages.

After translation, the system proceeds to store the processed data in a structured database. The storage mechanism is designed to optimize retrieval speed, ensuring that future queries can be answered efficiently. The system organizes data based on predefined medical categories, such as symptoms, diagnoses, treatments, and prescriptions, making it easier to locate relevant information when responding to user queries. Additionally, metadata such as timestamps and source information are stored alongside the medical data to ensure proper traceability and auditing.

C. User Interaction with the Chatbot

Once the medical data has been properly stored, users can interact with the chatbot by asking medical questions. The chatbot serves as the primary interface between the user and the backend system, facilitating seamless communication. Users may input their queries in natural language, and the system is responsible for interpreting and processing these queries accurately.

The chatbot is designed to handle a variety of question types, including symptom-related inquiries, disease-related information, and treatment options. To improve user experience, the chatbot incorporates natural language processing (NLP) techniques to understand the intent behind the user's question. Additionally, it uses contextual awareness to handle follow-up questions by maintaining a conversational history, allowing for a more fluid and natural interaction.

D. Query Processing

After receiving a user query, the system first determines if any translation is required. If the query is in a different language than the system's processing language, it is translated before further processing. This ensures that the chatbot can handle multilingual users effectively.

The next step is retrieving relevant medical data from the database. The system performs a structured search to locate the most relevant stored information that matches the user's query. Advanced retrieval techniques such as keyword matching, semantic search, and contextual similarity analysis are employed to enhance the accuracy of results. This step ensures that the chatbot has access to high-quality, relevant information before generating an answer.

E. Answer Generation

MedFusionQA uses DistilBERT—a compact transformer model fine-tuned for the medical domain—to generate responses [19]. This model offers a strong efficiency-performance trade-off, ideal for real-time QA. Compared to heavier models like BioBERT and GatorTron [20], [21], DistilBERT reduces inference latency without compromising quality.The system also addresses the hallucination problem—common in large language models [9]—by grounding its answers in retrieved evidence. This ensures factually accurate responses, consistent with recent safety-aware QA research [8].

F. Answer Translation and Display

Before presenting the response to the user, the system checks whether the answer needs to be translated. If the user's preferred language differs from the system's default processing language, the response is translated accordingly. The translation module ensures that medical terminology is accurately preserved, preventing any loss of meaning due to language conversion.
After translation, the response is formatted for display in the user interface (UI). The system structures the answer in a clear and readable format, ensuring that users can easily understand the information provided. The UI may also include additional interactive features, such as clickable references, suggested follow-up questions, or related medical topics, enhancing user engagement.

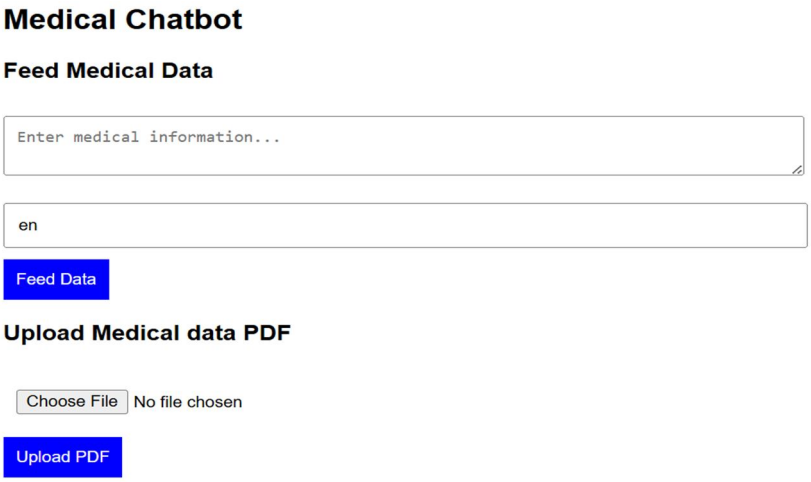

Fig 2.Architecture of clinical decision making

The MEDFUSIONQA pipeline seamlessly integrates the RKVM, varied chunk database, and the customized chunk scorer to develop a unified system that retrieves and analyzes complicated biomedical knowledge. The pipeline starts with feeding an input text into the Relational Key-Value Memory (RKVM) for first retrieval, such as a biological phrase or sentence. This is selected based on which input or stored relationship comes closer as the pipeline for obtaining a most relevant chunk, context, and recollection from that. The chunk above gets further diversified by way of its permutation set thereby forming, and these are now considered by the Tailored Chunk Scorer: a given chunk is made more acceptable by weights for evaluation after computing scores contextually with an input. The highest scored chunk would therefore be the most relevant and contextually applicable information to be printed by the system for further analysis. It becomes possible through combining all of these aspects to achieve high-precision comprehensive biological data obtained through the pipeline in MEDFUSIONQA that enhances decision making across different types of applications ranging from the clinical context to pharmaceutical production and medical science.

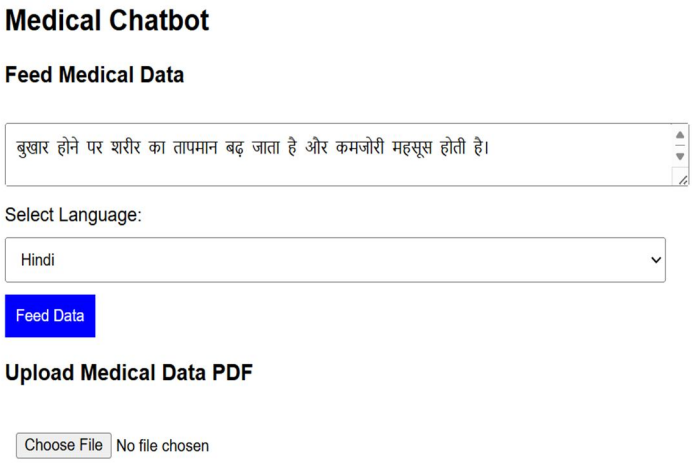

Fig 3. Input Sample

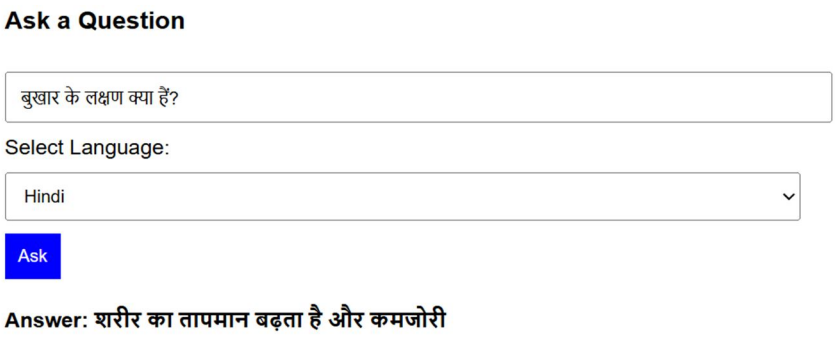

Fig 4.Output Sample

The training procedure for MEDFUSIONQA is very well designed to bring about an optimal biomedical relationship extraction process through several well-thought-out stages, involving major data preprocessing and augmentation with high-quality input. Normalized texts remove all unnecessary symbols, adjust for proper casing, and remove stop words, so that the model is able to concentrate only on biomedical language. The tools of biomedical entity recognition annotate critical terms such as genes, proteins, diseases, and drugs as unique categories for relationship extraction. The dataset is expanded using augmentation techniques, such as replacing biomedical terms with synonyms and generating synthetic relationship triples by adjusting known pairs.
This combination of the components enables the MEDFUSIONQA pipeline to get accurate and holistic biological data, thus forming a better decision-making range of tasks in the clinical field, pharmaceutical development, and biomedical research. The output from the system for further processing is the most pertinent and contextually aligned information represented by the chunk with the highest score.

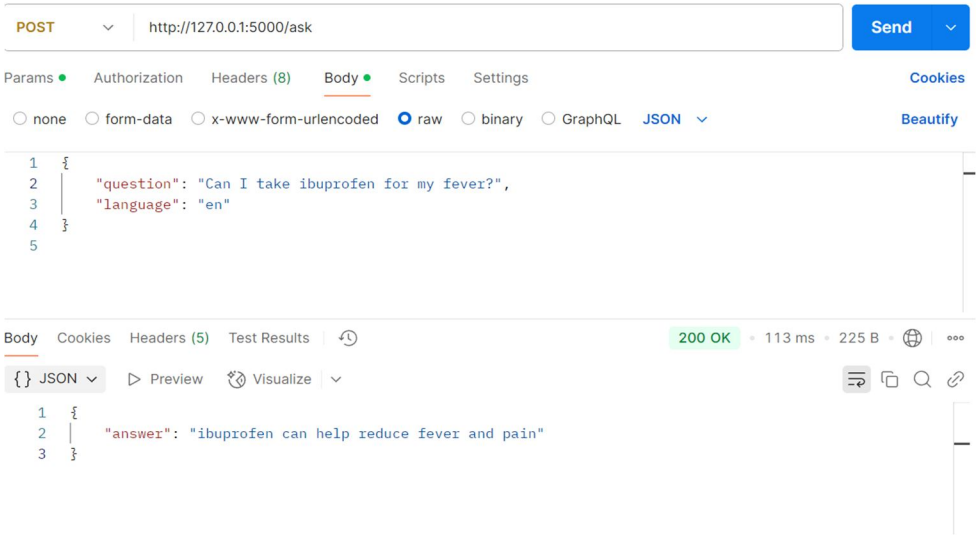

Fig 5.Output using Postman API

A neural network called the Tailored Chunk Scorer is trained on a triplet loss function. The chunks are ranked with the most relevant ones coming on top according to the context of the query. Such training improves the ranking capability of the neural network. With domain-specific loss and batch-wise gradient updates, further optimization is achieved in the performance of the model. The model is trained on a set of biological relationship data both before validation and after undergoing that process in an iterative procedure to identify any shortcoming, especially with complex or rare types of relationship. Hyperparameter tuning along with specific modifications such as generation of synthetic data help establish the model's durability, flexibility, and better generalize across different biological interactions.

V. Conclusion

MedFusionQA represents a substantial leap forward in the use of retrieval-augmented generation for biomedical NLP applications. By streamlining the retrieval process, enhancing model efficiency, and implementing a

dynamic, LLM-supervised feedback loop, we have developed a system that not only meets the stringent demands of the healthcare sector but also sets a new benchmark for future research. The comprehensive evaluation of MedFusionQA demonstrates its potential to transform clinical data analysis, support accurate and reliable decision-making, and ultimately improve patient care through advanced, AI-powered tools. This work serves as a robust foundation for the next generation of biomedical AI systems—systems that are not only technically sound but also deeply attuned to the critical needs of healthcare practitioners and researchers alike.

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