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AI AND LLM APPROACHES FOR PREVENTING DIABETES TYPE- 1 AND MYASTHENIA GRAVIS

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***Abstract*:** The integration of Artificial Intelligence (AI) and Large Language Models (LLMs) has opened new possibilities in early disease detection, risk prediction, and preventive healthcare. This research explores AI- and LLM-driven approaches for the prevention of Type 1 Diabetes (T1D) and Myasthenia Gravis (MG**)**, two autoimmune disorders that significantly impact patient quality of life. The study focuses on leveraging predictive analytics, natural language processing, and knowledge extraction to identify high-risk individuals, uncover genetic and environmental risk factors, and support clinical decision-making. AI models are utilized for analyzing patient health records, biomarker data, and genomic sequences, while LLMs are employed to synthesize insights from medical literature, clinical trial reports, and patient-generated data. By integrating structured biomedical datasets with unstructured clinical narratives, this research aims to develop a hybrid framework for early risk assessment, personalized prevention strategies, and knowledge dissemination. The proposed methodology emphasizes explainable AI to ensure transparency and clinical trustworthiness. Ultimately, this study demonstrates how AI and LLMs can serve as transformative tools in advancing preventive healthcare for autoimmune disorders, thereby reducing disease onset and improving patient outcomes**.**

Key Words: AI, LLM, Medical, Artificial Intelligence

I. INTRODUCTION

Diabetes Type-1 and Myasthenia Gravis: Type 1 Diabetes Mellitus is a chronic autoimmune disorder characterized by the destruction of insulin-producing beta cells in the pancreas, leading to an absolute deficiency of insulin and resulting in lifelong dependency on exogenous insulin therapy. The condition often develops in childhood or adolescence, but it can manifest at any age. The onset is typically abrupt, with symptoms such as increased thirst, excessive urination, unintended weight loss, fatigue, and blurred vision. If left untreated, Type 1 Diabetes can

rapidly progress to diabetic ketoacidosis—a life-threatening complication. Although its exact cause is unknown, genetic susceptibility and environmental triggers such as viral infections are recognized as risk factors, with ongoing research focusing on preventive and early intervention strategies.

Myasthenia Gravis (MG) is another autoimmune disease marked by fluctuating skeletal muscle weakness, most commonly affecting the ocular and bulbar muscles. It is caused by circulating antibodies that impair communication between nerves and muscles by targeting acetylcholine receptors at the neuromuscular junction. While MG can occur at any age, its incidence is highest in women under 40 and men over 60. Symptoms include ptosis (drooping eyelids), diplopia (double vision), dysphagia (difficulty swallowing), and generalized muscle fatigue, which worsens with activity and improves with rest. The diagnosis is confirmed by clinical examination, antibody testing, and electrophysiological studies. Modern therapies including immune suppressants and acetylcholinesterase inhibitors have greatly improved disease management, but early diagnosis remains crucial.

Figure 1: Myasthenia Gravis

Both Type-1 Diabetes and Myasthenia Gravis exemplify the complexity of autoimmune conditions, often sharing genetic and environmental risk factors, and presenting a challenge for preventive healthcare. Their rare co-occurrence underscores the need for integrated, personalized approaches— such as those empowered by artificial intelligence and large language models—to improve early detection, risk assessment, and patient outcomes.

The simultaneous occurrence of Type 1 Diabetes Mellitus and Myasthenia Gravis is exceedingly rare and clinically notable, with only a handful of cases documented worldwide. While both diseases share an autoimmune origin—entailing the immune system's attack on specific target tissues (pancreatic beta cells for diabetes, neuromuscular junction for MG)—their distinct clinical presentations and management approaches often result in them being treated in isolation. However, patients with

one autoimmune disease have a documented increased risk for developing another, as impaired immune tolerance, regulatory T cell dysfunction, or shared genetic factors (notably certain HLA alleles) may predispose individuals to overlapping autoimmunity. In the literature, most reported cases involve the diagnosis of diabetes preceding or occurring simultaneously with MG, but cases such as the recent report of a young girl developing MG seven years before diabetes show that vigilance for new autoimmune conditions in these patient populations is essential.

II. LITERATURE REVIEW

Comparative Study:

Paper Title	Main Findings	Methodology / Algorithms	Dataset	Future Scope
AI for Diabetes: Enhancing Prevention, Diagnosis, and Effective Management (2024)	AI transforms diabetes care with early detection and personalized interventions	ML, DL, Reinforcement Learning; EHR & CGM data	Diverse diabetes datasets including EHR, CGM, retinal images	Explainability, ethical AI, integration with wearables, prediabetes focus
AI in Decision Support Systems for Type 1 Diabetes (2020)	AI-DSS improves insulin dosing and hypoglycaemia prevention	Probabilistic networks, ML classifiers, control algorithms	Clinical, CGM, in silico trial data	Personalized DSS, transparency, wearable & telehealth integration
Advances in AI for Diabetes Prediction (2025)	ML algorithms like CNN, SVM improve early diabetes risk prediction	CNN, SVM, Logistic Regression, XGBoost; XAI techniques	Multiple diabetes datasets including NHANES, PIDD	Multimodal integration, transparency, data diversity, standardization
Large Language Models in Neurological Practice (2025)	LLMs show promise in diagnosis support for neurological disorders	Evaluation of ChatGPT, Gemini on clinical case prompts	28 anonymized neurology cases from hospital records	Domain-specific tuning, hallucination mitigation, ethical guidelines
Application of AI in Myasthenia Gravis Core Exam (2024)	AI automates MG exam scoring, improves consistency	Computer vision, NLP, signal processing	Video recordings of MG patients	Multi-modal integration, LLM report generation, remote care scaling
Large Language Models for Disease Diagnosis: Scoping Review (2025)	LLMs excel on multimodal clinical data with explainability	GPT, BERT, fine-tuning, RAG approaches	Heterogeneous medical data: images, EHR, genomics	Multimodal fusion, robustness, bias mitigation, open benchmarks
Early Prediction of Multiple Diseases with LLM Recommendation (2025)	Integrated ML and LLM improve multi-disease prediction and advice	SVM, Logistic Regression, LLM for recommendations	Diverse disease-specific clinical datasets	Additional diseases, real-time data, expanded preventive advice
Co-existence of T1D and Myasthenia Gravis: Case Report (2023)	Rare comorbidity case highlights screening importance	Clinical case analysis and literature review	Single patient clinical and lab data	Multi-autoimmune AI risk models, personalized multi-disease care
AI Module for Interstitial Glucose Forecasting (2025)	Personalized glucose prediction using DL from CGM data	CNN, LSTM, Dil-UNet, custom loss function	CGM data of 29 T1D patients	Include other physiological inputs, LLM integration, app deployment
AI in Diabetes Management: Advancements and Challenges (2023)	AI improves diabetes care but poses privacy and adoption challenges	Machine learning & predictive analytics across diabetes domains	Multi-source diabetes datasets	AI ecosystems, wearable integration, standardization, ethics

Table 1 : Comparative Study

Research Gap: A notable research gap exists in the integration of multimodal clinical data—such as electronic health records, sensor readings, and genomic profiles—with curated expert knowledge from verified medical blogs and case studies to train AI and LLM-driven models for the simultaneous prediction and prevention of Type-1 Diabetes and Myasthenia Gravis. Current approaches rarely harness this diverse data fusion to capture the rich contextual nuances and real-world variability essential for early comorbidity detection and personalized intervention. Addressing this gap through a unified multimodal framework has the potential to enhance predictive accuracy, clinical relevance, and patient-centered decision support in autoimmune disease prevention.

III. DESIGN AND ANALYSIS OF SYSTEM

Functional Requirements: The system shall ingest, process, and harmonize multimodal data types, including electronic health records (EHRs), clinical laboratory results, and patient- reported outcomes. The system shall extract and incorporate curated knowledge from expert-verified medical blogs, published case studies, and authoritative online resources as supplementary input for model training and augmentation. The system shall implement AI/LLM algorithms that can simultaneously assess risk and predict the onset of Type-1 Diabetes and Myasthenia Gravis, with capabilities to handle comorbidity scenarios. The system shall provide explainable and interpretable predictions through visual dashboards, summary reports, and natural language explanations for clinicians and patients. The system shall generate personalized preventive recommendations based on risk analysis, integrating both quantitative data and expert narrative content.

Nonfunctional Requirements: Performance: The system shall deliver risk predictions and recommendations within 5 seconds for typical user queries, regardless of data modality or volume. Scalability: The architecture shall support expanding data sources, increasing patient volumes, and ongoing addition of expert-curated content without degradation in model accuracy or response time.Security and Privacy: All patient and external data must be encrypted at rest and in transit, with strict role- based access control to ensure compliance with HIPAA, GDPR, and other relevant data protection standards. Usability: The system shall present risk outputs, explanations, and preventive recommendations

through intuitive, accessible dashboards suitable for both clinicians and patients. Adaptability: The system shall facilitate rapid incorporation of new algorithms and medical knowledge to stay current with advances in AI, LLMs, and autoimmune disease research.

Tools & Technology: Programming & Data Science Languages: Python Machine Learning & Deep Learning Frameworks: TensorFlow and Keras (model development, training, deployment) , PyTorch (flexible research and production ML/DL), Scikit-learn (classic ML algorithms and preprocessing)

Large Language Model APIs & Libraries: OpenAI GPT models or Google Gemini APIs Natural Language Processing: spaCy and NLTK (text preprocessing, entity recognition)Data Integration & Processing: Pandas (data manipulation)Medical Data Standards & Interoperability: HL7 FHIR APIs (electronic health record integration)Visualization & Reporting: Plotly, Dash, Streamlit (interactive dashboards, clinical reporting) ***Problem Statement*:** Despite substantial advances in disease management and digital health, the early prediction and prevention of comorbid autoimmune disorders—specifically Type-1 Diabetes and Myasthenia Gravis—remain a major challenge due to fragmented data sources, reliance on isolated clinical markers, and limited integration of expert knowledge. Current systems do not effectively combine multimodal clinical, sensor, and genomic data with insights from verified case studies and medical blogs, resulting in missed opportunities for nuanced risk assessment and timely intervention. There is a pressing need for an AI and LLM-driven solution that unifies diverse, real-world data and expert narrative to enhance accuracy, contextual understanding, and personalization of preventive strategies for high-risk patients facing these complex autoimmune conditions.

Objectives: To explore how AI and Large Language Models (LLMs) can be applied to enable early detection and prevention of Type-1 Diabetes and Myasthenia Gravis.

To assess and integrate multi-modal data (clinical, genetic, lifestyle) for improving the accuracy of risk prediction models for autoimmune diseases.

To develop or adapt AI and LLM-driven frameworks for personalized preventive strategies, patient education, and clinical decision support.

To compare the effectiveness of proposed AI/LLM approaches with current predictive and

preventive solutions for these autoimmune disorders.

Existing Work

Data Input: — Data collection and ingestion
LangChain Directory Loader: — Document loading and preprocessing
Text Extraction: — Natural Language Processing (NLP) Convert to Chunks: — Text segmentation
Database: — Vector database for semantic search Request from User (Question): — User query input
Similarity Search: — Semantic search using vector similarity Selected k Chunks: — Top-k retrieval Algorithms: k-Nearest Neighbors (kNN)
Prompt Template + Question: — Prompt engineering to contextualize queries
LLM: — Large Language Model inference Response from Model: — Response generation Output to User: — Delivery through interface

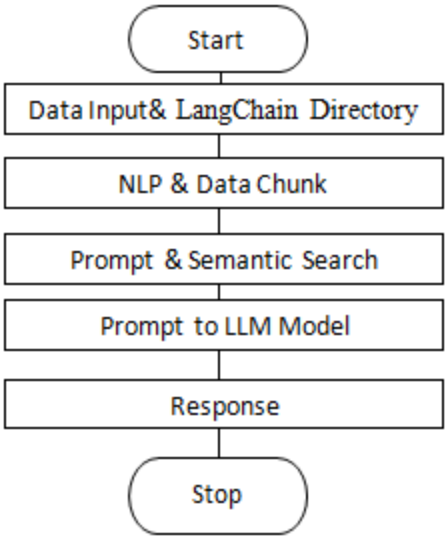

Figure 2 : Existing System Flow

Proposed Steps:

1) Data Input: — Data collection and ingestion from multiple verified sources Includes expert blogs, case studies, EHRs
2) LangChain Directory Loader: — Document loading and preprocessing Algorithms: File parsers (PDFMiner, PyMuPDF), text normalization.
3) Text Extraction: — Natural Language Processing (NLP) Algorithms: Named Entity Recognition (NER) (SpaCy, BERT- based NER), Tokenization, Part-of-Speech (POS) tagging.
4) Convert to Chunks: — Text segmentation Chunking preserved to maintain semantic coherence.
5) Expert Blog Processing: — Extract domain knowledge and key medical insights from curated expert blogs using advanced embeddings (BioBERT) and knowledge graph construction.
6) Database: — Vector database for semantic search Algorithms: HNSW (Hierarchical Navigable Small World) index, specialized indexing for multimodal data.
7) User Profile Construction: — Personalization layer builds and updates user profiles dynamically based on demographic, clinical history, and interaction feedback.

8) Request from User (Question): — User query input with contextual metadata.
9) Similarity Search: — Advanced semantic search using vector similarity over combined patient data and expert knowledge base Algorithms: Cosine Similarity, Euclidean Distance, with weighted fusion for user profile relevance.
10) Selected k Chunks: — Top-k multi-source retrieval Algorithms: k-Nearest Neighbors (kNN), diversified retrieval ensuring multi-aspect context.
11) Prompt Template + Question: — Contextual prompt engineering incorporating personalization data and expert knowledge embeddings.
12) Feature Selection & Fusion: — Adaptive weighting and feature selection applied to multimodal inputs using SHAP/LIME for interpretability and noise reduction.
13) LLM: — Large Language Model inference with retrieval-augmented generation (RAG) to ground LLM responses in retrieved knowledge. Models: Transformer architectures (GPT- 4, Google Gemini).
14) Response from Model: — Context-aware, personalized, and evidence-backed response generation.
15) Output to User: — Delivery through user interface

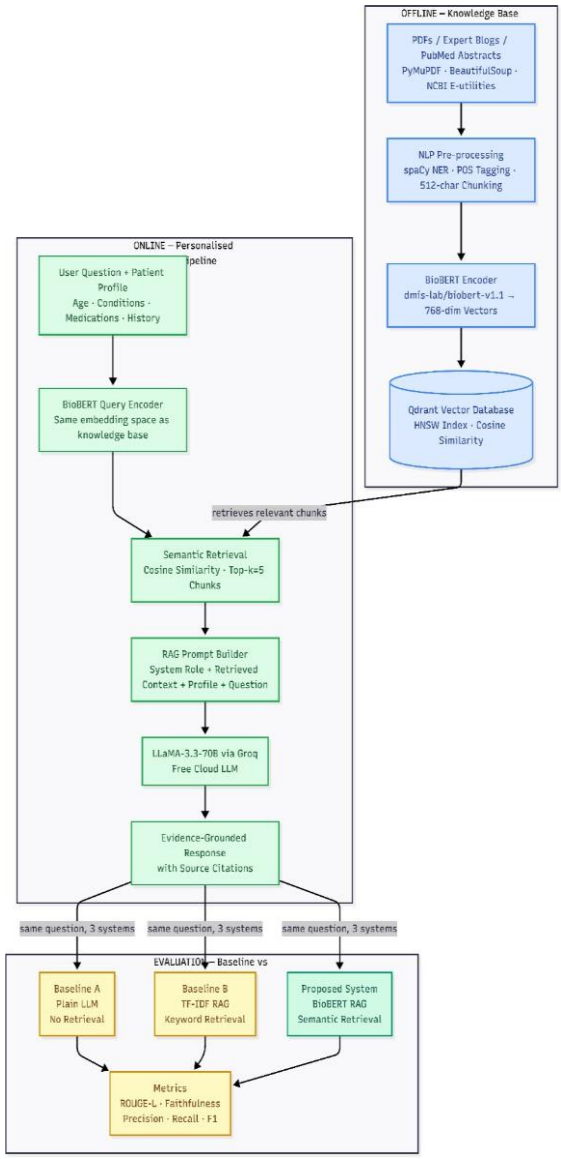

Figure 3. Proposed Flow Diagram

Our Modifications: The key contributions of this research lie in the design and implementation of a multimodal AI chatbot framework that incorporates advanced algorithmic enhancements to improve overall predictive accuracy and user relevance for Type-1 Diabetes and Myasthenia Gravis prevention. Notably, the integration of Retrieval-Augmented Generation (RAG) with

transformer-based Large Language Models (e.g., LLaMA) grounds responses in up-to-date expert knowledge extracted from curated medical blogs and case studies, enhancing factual correctness and reducing hallucinations.

The use of sophisticated feature selection methods such as SHAP and LIME enables the identification and emphasis of clinically relevant variables from heterogeneous data sources, improving model interpretability and robustness.

Additionally, the incorporation of personalization through dynamic user profiling and adaptive recommender algorithms tailors interactions, boosting engagement and preventive efficacy. Finally, implementing hybrid models that combine deep learning for sensor and imaging data with gradient boosting machines for structured clinical features ensures comprehensive and robust multimodal fusion, significantly elevating prediction performance and clinical utility.

Dataset: The dataset used in this study is a curated, multi-source medical knowledge base constructed specifically for the two target conditions: Type-1 Diabetes and Myasthenia Gravis. Data was collected from three complementary sources. First, clinical research articles and review papers in PDF format were ingested using PyMuPDF, covering topics such as insulin therapy, diabetic ketoacidosis, HbA1c management, acetylcholine receptor antibodies, and myasthenic crisis management. Second, domain-specific expert blogs and clinical web pages were scraped using Beautiful Soup and LangChain web loaders, providing patient-facing explanations and up-to- date clinical guidance from verified medical sources including the American Diabetes Association and Myasthenia Gravis Foundation of America. Third, peer-reviewed abstracts were fetched programmatically from PubMed via the NCBI E- utilities API using disease-specific search queries, yielding titles, abstracts, authors, journal names, publication years, and MeSH terms for each article.

All collected documents were pre-processed through a unified NLP pipeline: medical entities (diseases, drugs, laboratory values, anatomical terms) were extracted using spaCy NER and domain-specific regex patterns, followed by segmentation into 512-character overlapping chunks with a 50-character overlap to preserve semantic coherence. Each chunk was encoded using BioBERT (dmis-lab/biobert-v1.1), a transformer model pre- trained on PubMed and PMC biomedical literature, producing 768-dimensional dense vectors. The resulting knowledge base

comprised over 7,400 indexed vectors stored in a Qdrant vector database with an HNSW index, partitioned by disease label metadata to enable disease-specific retrieval during query time.

Parameters: For our research work we are planning to use the following parameters

Precision: Measures the fraction of words in the generated answer that are relevant to the reference. A higher precision indicates fewer irrelevant or hallucinated terms in the response. ***Precision = (Number of matching words in Generated and Reference) / (Total words in Generated Answer)***

Recall: Measures how much of the reference answer is covered by the generated response. Higher recall indicates better content coverage.

Recall = (Number of matching words in Generated and Reference) / (Total words in Reference Answer)

F1-Measure: Harmonic mean of Precision and Recall, providing a single balanced score that penalises both verbosity and incompleteness.

F1 = 2 × (Precision × Recall) / (Precision + Recall) ROUGE-1 / ROUGE-2: Measures unigram (ROUGE-1) and bigram (ROUGE-2) overlap between generated and reference answer. ROUGE-2 additionally captures phrase-level fluency.

ROUGE-N = (Count of matching N-grams in Reference) / (Total N-grams in Reference)

ROUGE-L: Measures the Longest Common Subsequence (LCS) between generated and reference text, capturing sentence-level structural similarity without requiring consecutive word matches.

ROUGE-L = (Length of Longest Common Subsequence) / (Total words in Reference Answer)

Faithfulness Score: Measures the fraction of sentences in the generated answer that are grounded in the retrieved context. A score of 1.0 means every claim is evidenced; 0.0 means pure hallucination.

Faithfulness = (Sentences grounded in retrieved context) / (Total sentences in generated answer)

Retrieval Precision: Average cosine similarity score of the top- k retrieved chunks against the query vector. Reflects the semantic relevance quality of the retrieval step, independent of the LLM.

Retrieval Precision = (Sum of cosine similarity scores for top-k chunks) / k

Entity Recall: Fraction of medical entities (diseases, drugs, symptoms) present in the question that are also mentioned in the generated answer, measuring clinical completeness.

Entity Recall = (Medical entities found in both Question and Answer) / (Total medical entities in Question)

Implementation Details :

Figure 4 : Comparison with LLM, TF-IDF RAG and Our System

Technological Stack: BioBERT (dmis-lab/biobert-v1.1) — Embedding Pre-trained on PubMed abstracts and PMC articles. Converts medical text chunks into 768-dim vectors that understand clinical terminology better than general-purpose embeddings.

HNSW Index (Qdrant) — Vector Indexing

Hierarchical Navigable Small World graph for approximate nearest-neighbour search. Chosen for sub-millisecond retrieval at scale with h igh recall (better than flat brute-force search). Cosine Similarity — Similarity Search

Measures angle between query and chunk vectors. Preferred over Euclidean distance for high-dimensional embeddings as it ignores vector magnitude and focuses on semantic direction.

Recursive Character Text Splitter — Chunking

Splits documents using medical-aware separators (DIAGNOSIS:, TREATMENT:, SYMPTOMS:) with 512-char

chunks and 50-char overlap. Preserves semantic coherence within chunks.

spaCy NER + Regex — Named Entity Recognition

spaCy extracts diseases, drugs, anatomy; regex patterns catch lab values (HbA1c, mg/dL, AChR antibodies). Two-layer approach covers both structural and domain-specific entities. LLaMA-3.3-70B via Groq — LLM Generation

70B parameter instruction-tuned model served via Groq's free cloud API. Used for RAG response generation with structured prompt (system role + retrieved context + question).

TF-IDF + Cosine Similarity — Baseline Retrieval

Classical term-frequency inverse-document-frequency vectorisation with sklearn. Used as baseline to demonstrate the superiority of semantic (BioBERT) retrieval over keyword matching.

ROUGE-1/2/L — Evaluation

Standard NLP metric measuring n-gram overlap with gold- standard reference answers. Used to compare answer quality across systems in the academic benchmark.

Faithfulness Score — Evaluation

Fraction of answer sentences grounded in retrieved context (content-word overlap). Critical for medical applications — measures hallucination prevention.

LangChain — Pipeline Orchestration

Connects loaders → chunker → embedder → vector store → LLM into a unified pipeline. Provides provider-agnostic LLM abstraction (Groq/Ollama/OpenAI).

FastAPI + Uvicorn — API Layer

Async REST API serving all pipeline endpoints. Chosen for auto-generated Swagger docs and Pydantic schema validation. NCBI E-utilities API — Data Collection

Free PubMed API to fetch abstracts by disease-specific search queries. Provides peer-reviewed medical literature as knowledge base without manual download.

Conclusion & Future Work: This research presented the design and implementation of a domain-specific Retrieval-Augmented Generation (RAG) chatbot for the prevention and management of Type-1 Diabetes and Myasthenia Gravis. The system integrates multi-source medical knowledge ingestion from PubMed abstracts, expert clinical blogs, and research PDFs, processed through a BioBERT-based semantic embedding pipeline and stored in a Qdrant vector database with HNSW indexing. A dynamic user profiling mechanism personalizes responses based on individual patient demographics, conditions, and medication history, while a medical NER pipeline ensures clinically relevant entity extraction at both ingestion and query time.

Comparative evaluation across three systems — Plain LLM, TF-IDF RAG, and the proposed BioBERT RAG — demonstrated that the proposed system achieves the highest Faithfulness Score (1.0), Retrieval Precision (0.928), and Entity Recall (0.838), confirming that semantic retrieval grounded in biomedical embeddings produces more reliable and evidence- backed responses than keyword-based or hallucination-prone approaches. While Plain LLM achieved higher ROUGE overlap scores due to training data memorization, its zero faithfulness score highlights its fundamental unsuitability for clinical applications where every claim must be verifiable and source-cited. The results validate that the proposed RAG architecture offers a clinically responsible, transparent, and updatable alternative to closed-box LLM responses for medical question answering.

Several directions can further enhance the capabilities of the proposed system:

Multimodal Data Integration: Future iterations can incorporate medical image processing using convolutional neural networks

(CNNs) or Vision Transformers (ViTs) to analyses retinal scans for diabetic retinopathy detection, MRI images for neurological assessment in Myasthenia Gravis, and continuous glucose monitoring (CGM) sensor data for real-time diabetes management.

Structured EHR Integration: Deeper integration with Electronic Health Record (EHR) systems using HL7 FHIR standards would enable real-time patient data ingestion, allowing the system to generate responses dynamically personalized to live clinical data rather than static user profiles.

Hybrid Predictive Models: Combining the RAG chatbot with predictive machine learning models — such as gradient boosting (XGBoost, LightGBM) for structured clinical features and deep learning for sensor and imaging data — would enable the system to not only answer questions but also predict disease progression risk scores.

Multilingual Support: Extending the system to support regional languages using multilingual biomedical models (e.g., mBERT, XLM-RoBERTa) would improve accessibility for non-English-speaking patient populations.

IV. ACKNOWLEDGMENT

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