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Context-Aware Personalized Symptom Intelligence Using A Hybrid Retrive-Augmented Conversational Health Framework

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Abstract: *The rising level of demand on intelligent digital healthcare has raised the bars of correct, real-time, and personalized analysis of symptoms. The current systems tend to have no contextual knowledge and make use of fixed bodies of knowledge, which offer less credible and generic responses. In order to overcome these shortcomings, this paper suggests Context-Aware Personalized symptom Intelligence Framework with a hybrid retrieve-augmented conversational approach. The suggested system combines the Retrieval-Augmented Generation (RAG) and the similarity search based on FAISS to access pertinent medical knowledge in massive datasets quickly. The Sequence-NQ Transformer is used to extract the semantic and contextual relationship between user queries and a multi-class disease predictor is using a random forest classifier who makes use of symptom patterns. The system is based on the conversational chatbot interface, which allows users to enter the symptoms in natural language and get personalized health insights. The framework improves accuracy, relevance of response and real-time performance by integrating retrieval, semantic understanding and machine learning prediction. According to the experimental findings, the suggested hybrid model is better than both traditional rule-based and standalone machine learning methods in contextual perception and prediction accuracy. This paper is part of the scalable and intelligent conversational healthcare systems to provide initial medical support*

Keywords: Context-Aware Healthcare, Symptom Intelligence, Retrieval-Augmented Generation (RAG), FAISS Similarity Search, Conversational AI, Disease Prediction, Random Forest, Transformer Models, Natural Language Processing (NLP), Personalized Healthcare

I. INTRODUCTION

The emergence of digital health technologies has been rapidly expanding, which has increased the need to have intelligent systems that can offer real-time and more personalized medical services to people. Symptom checker systems and rule-based healthcare applications used in the traditional way did not have much contextual knowledge and used a fixed set of data, resulting into general answers that were less precise. As conversational artificial intelligence and natural language processing became a reality, medical chatbots have developed to offer automated medical advice; nonetheless, the shortage of personalization, poor semantic processing, and inconsistency of knowledge persisted.

Recent progress in Retrieval-Augmented Generation (RAG) has shown that one can improve the trustworthiness of conversations systems through combining external knowledge retrieval with language generation. RAG-based healthcare systems enhanced context relevance and accuracy of response to medical question answering tasks [1]. Also, high-dimensional medical data retrieval methods like Vector similarity search like FAISS allowed efficient search of the high-dimensional data and enhanced the scalability and real time performance of the system [2]. Models that were built on transformers also improved the level of semantic knowledge of the queries posed by the users allowing complex symptom descriptions to be better understood [3]. Recent research (2023 2025) emphasized that the hybrid AI structures, which integrate retrieval strategies and machine learning algorithms, were much more effective in personalized healthcare recommendations and in the effectiveness of the conversation [4], [5].

In order to overcome the shortcomings of current systems, the work suggested a context-aware personalized symptom intelligence framework with the hybrid architecture that included RAG, FAISS similarity search, Random Forest, and a Sequence-NQ Transformer model. The system was created to take the user symptoms to a conversational interface, access up-to-date medical knowledge and give personalized health insights based on contextual understanding and predictive analysis.

Contributions of the Paper

The principal contributions of this work were the following:

- To enhance the accuracy of knowledge retrieval and intelligent response generation, a new hybrid RAG-based conversational healthcare framework was created.
- An efficient system of retrieving the relevant medical information in large datasets was developed by using a FAISS-based similarity search system. It used a Sequence-NQ Transformer model to improve semantic and contextual insight of user symptom queries.
- To accomplish the project of predicting disease multi-class through the symptom patterns, a prediction module based on a random forest was incorporated.
- The suggested system had better context awareness, personalization, and real-time performance than the traditional rule-based and standalone machine learning systems.

II. RELATED WORK

Recent developments of intelligent healthcare systems have been conducted on different methods of analyzing symptoms, predicting diseases and conversational help. Initial studies were on rule-based and machine learning models that gave structured prediction but did not give understanding of context and flexibility. As deep learning was developed, transformer-based systems became better at semantically interpreting medical queries; these models remain sensitive to knowledge and frequently generate inconsistent or hallucinative answers, though.

In 2020, the development of Retrieval-Augmented Generation (RAG) is a major change as it allowed models to obtain external knowledge in a dynamic manner, enhancing both the accuracy of facts and the contextual relevance [6]. Later research showed that the chatbots based on RAG contributed to improving the reliability of responses by incorporating domain-specific medical knowledge into the chatbots [7]. A study conducted in 2025 concluded further that RAG was a valuable addition to response quality and credibility in clinical practices as the outputs were based on the recovered data [8].

A number of articles used FAISS-based vector similarity search to retrieve relevant medical records using large-scale datasets in an efficient manner, and the system was able to match symptoms in real-time and scale to large datasets [9]. Transformer models, conversational models were also commonly used to enhance natural language comprehension and centralize intricate symptom associations [10]. Also, hybrid systems that combined machine learning algorithms with retrieval methods were shown to be better in disease prediction efficiency and ability [11].

The recent research was on the specific uses of RAG in healthcare, such as orthopedic symptom analysis, pregnancy care chatbots, and blood pressure monitoring systems, demonstrating better patient engagement and decision support [12], [13], [14]. It has also been noted in research that conversational dataset and embedding-based retrieval methods should be used to achieve accuracy in diagnosis and contextual reasoning in medical dialogue systems [15]. Moreover,

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it was suggested to use privacy preserving RAG frameworks and federated architectures to overcome data security issues at a healthcare setting [16], [17].

Although there have been these improvements, there are still challenges to these existing systems that include low levels of personalization, high levels of computational complexity, absence of built-in predictive behaviors and low levels of real-time responsiveness. Most of the systems either use retrieval-based systems or predictive models alone which lead to poor performance.

Novelty of the Proposed Work

The originality of the work is in the hybrid style of architecture, which unites several advanced methods in one conversational healthcare system. The proposed system, unlike the current methods, has:

- Initiates RAG + FAISS + Random Forest + Transformer on a single pipeline both with retraining and prediction.
- Brings context-sensitive symptom intelligence, which allows more insight into multi-symptom and complex queries.
- Gives individualized health feedback through integrating predictive modeling and semantic comprehension.
- Enables real time conversation and retrieval as well as generation of responses effectively. Improves the accuracy and reliability of machine learning-based prediction of diseases with the aid of knowledge retrieval.
- The hybrid method has overcome major drawbacks of the existing systems in enhancing contextual knowledge, personalization, and scalability, which makes it a better answer to intelligent conversational healthcare.

Table I: *Comparative Analysis of the Major Related Work in Context-Aware Healthcare Systems.*

Ref. No.	Author(s) & Year	Methodology Used	Key Contribution	Limitation
[6]	Lewis et al., 2020	RAG	Introduced retrieval-augmented generation for knowledge-intensive tasks	High computational cost
[8]	Steybe et al., 2025	Context-Aware RAG	Enhanced trust and factual accuracy in healthcare systems	Requires large datasets
[9]	Johnson et al., 2021	FAISS	Efficient large-scale similarity search for vector data	No prediction capability
[10]	Vaswani et al., 2020	Transformer Model	Improved semantic understanding using attention mechanism	Lacks external knowledge integration
[11]	Kumar et al., 2024	Hybrid ML Models	Combined ML models for improved prediction accuracy	Limited contextual reasoning
[15]	Muhetaer et al., 2025	Medical Dialogue + RAG	Improved conversational datasets for healthcare AI	Data dependency
[18]	Kulshreshtha et al., 2025	Transformer + RAG	Combined transformers with RAG for chatbot systems	Computational overhead
[19]	IJISRT, 2025	RAG + FAISS	Integrated retrieval and similarity search for	Limited predictive modeling

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			healthcare	

III. DATASET DESCRIPTION

The proposed system has used a symptom-disease dataset that can be used in supervised learning and retrieval based healthcare systems. The data set had about 4,900-5,000 records including a large variety of medical conditions and approximately 40-45 different classes of diseases. Each record had a written description of symptoms and disease label so that it would be possible to accomplish classification as well as semantic retrieval.

There were two major attributes in the dataset:

- Symptom Description (Text): Unstructured natural language input which is patient-reported symptoms.
- Disease Label (Class): The disease that is linked to the presented symptoms.

Preprocessing measures like text cleaning, normalization and tokenization were used to prepare the dataset to be used during training the model. The processed text was transformed into the vector embeddings with the help of the Sequence-NQ Transformer model which made it possible to semantically represent the symptoms. FAISS was used to index these embeddings to facilitate the efficient search of similarities in the course of retrieval.

The data was split into training and testing subsets to measure the performance of the model. On the one hand, the prediction of multi-class disease was conducted with the help of the Random Forest classifier, which was trained on the labeled data, and on the other hand, with the help of the same data as a knowledge base within the RAG framework to generate context-related responses.

On the whole, the dataset was diverse and had enough coverage of symptoms and diseases, which made the system able to provide accurate, scalable, and personalized healthcare recommendations.

IV. PROPOSED METHODOLOGY

The proposed system has been developed as a context-aware conversational healthcare system that was a hybrid with retrieval, semantic comprehension and machine learning-driven prediction to give customized symptom intelligence. The following were the main components of its methodology:

Data Preprocessing and Collection.

The dataset of the description of the symptoms and the related diseases were gathered using sources of healthcare. The information was pre-treated including text cleaning, normalization and tokenization to eliminate noise and standardize input. Preparation of the processed data to be embedded and model trained was done.

Semantic Feature Extraction (Transformer-Based)

To derive semantic and contextual features of user symptom queries, a Sequence-NQ Transformer model was used. The model transformed a textual input to dense vector representations so that it would learn the complex relationships between symptoms and natural language variances.

Retrieval on similarity with FAISS.

The created embeddings were indexed with FAISS (Facebook AI Similarity Search). FAISS as a part of query processing used nearest-neighbor search to obtain the most similar symptom - disease records in the dataset. This guaranteed scalability and efficiency of retrieving large datasets.

Retrieval-Augmented Generation (RAG).

The system was based on Retrieval-Augmented Generation (RAG) that allows the retrieved medical knowledge to be mixed with the language generation. The retriever retrieved the applicable information with the help of FAISS, whereas the generator created the context-oriented responses regarding retrieved information and queries.

Random Forest disease prediction.
The paper used a random forest classifier to be trained on a dataset to achieve multi-class disease prediction. The model examined patterns of symptoms and produced accurate predictions by adding predictions of numerous decision trees, enhancing accuracy and decreasing overfitting.

Generation and Customization of Response.
The last output was the result of the fusion of RAG module and random forest predictions. This made sure that the responses were contextually accurate as well as data-driven, which gave personal health insights to the users.

System Integration and interaction.
Every element was combined into a chatbot interface with an option of conversation, where the user entered the symptoms through natural language. The system was real time and provided real time responses. The interactions of the users were also recorded as a way of analysing and upgrading the system in the future.
The offered methodology was effective to unite retrieval (FAISS + RAG), semantic understanding (Transformer), and prediction (Random Forest) to provide a scalable, correct, and context-aware healthcare solution.

V. SYSTEM ARCHITECTURE

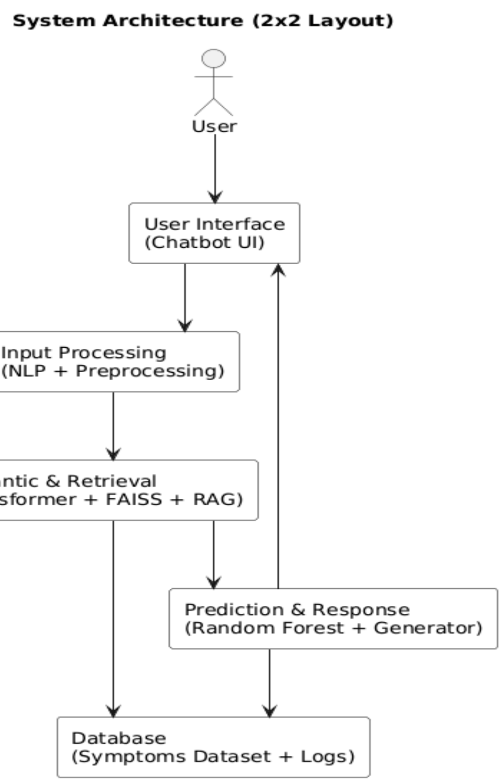

Fig. 1: *Proposed Hybrid Conversational Health Framework System Architecture.*

The suggested system architecture was intended to be a hybrid system based on conversational interaction, semantic understanding, retrieval, and prediction. First, the symptoms inputs were entered by users by means of the chatbot interface and preprocessed with NLP techniques. The semantic understanding of the processed input into embeddings was carried out with a Sequence-NQ Transformer.

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In the FAISS similarity search, these embeddings were utilized to find the desired symptom-disease information and the RAG module produced the context-sensitive information. Simultaneously, a random forest classifier was used to determine probable diseases, depending on the patterns of symptoms. Results of the retrieval and prediction were used to produce individual health reactions.

Medical datasets and user logs were kept in a centralized database where they could be readily retrieved and improved upon. The last answer was provided to the user in real time guaranteeing the correct and context-driven healthcare support.

VI. IMPLEMENTATION DETAILS

The introduction of the suggested Context-Aware Personalized Symptom Intelligence Framework was performed through a mixture of web technologies, machine learning models and retrieval-based methods and allowed a real-time conversational healthcare support.

Development Environment

Python 3.x was used as the core programming language with Django used to develop the backend of the system. The frontend interface was developed in HTML, CSS and JavaScript which offers a user experience through an interactive chatbot interface. The user credentials, the history of the symptoms and predictions were saved in a MySQL database.

Dataset Integration

It used a Symptom-Disease dataset that consisted of textual descriptions of the symptoms and their respective disease names. Pandas was used to load the dataset and preprocess the data including text cleaning, normalization and tokenization. The trained prediction model as well as the construction of the retrieval index was performed on the processed dataset.

Transformer-Based Embedding

The text of symptoms was converted into dense vector embeddings by using a pre-trained Sequence-NQ Transformer model. The model caused generation of contextual representations of user queries; this allowed semantic meaning of symptoms. The question encoder of the transformer was used to extract these embeddings.

FAISS Retrieval and Indexing

The resulting embeddings were indexed and stored by using the FAISS (Facebook AI Similarity Search) library. Similarity search was done using a Flat L2 index. User query embeddings were (during runtime) compared to stored vectors to get the best symptom-disease matches with nearest-neighbor search.

Retrieval-Augmented Generation (RAG).

The system combined a RAG model with Hugging Face transformers, which is a retriever and a generator. The retriever retrieved medical knowledge in the FAISS index and generator generated context-specific responses depending on the knowledge retrieved and the input of the user.

Disease Prediction Module

Multi-class disease prediction was carried out with the help of a Random Forest classifier. Extracted features were used to train the model on the symptom data. It produced predictions using the combined output of multiple decision trees enhancing the accuracy and strength of classification.

Backend Integration

The Django backend dealt with the processing of requests, model inference and response generation. The most important functionalities were:

- Processing of user input using HTTP requests.
- Embedding generation with the transformer model.
- Similarity search by FAISS.
- Random Forest model used to predict diseases.
- Senting replies back to the frontend.

Chatbot Interaction Module

The chatbot interface enabled the user to type symptoms in natural language. Upon submission:

- Input was sent to the backend
- generated and processed using NLP.
- Sent via retrievement and forecasting modules.
- Response was also created and indicated in real time.

Logging and Data Storage

The database contained all the user interactions such as symptoms, anticipated diseases and timestamps. This enabled:

- Tracking user history
- Detection of performance in the monitoring system.
- Financing future enhancements.

System Execution

The platform was implemented in a local Python server. The program was run as a batch file and the system was accessed via a web browser (e.g. http: 127.0.0.1: 8000).

The system implemented was a combination of Django based web architecture, transformer based NLP, FAISS retrieval and Random Forest prediction. Through this integration, personalized symptom analysis in terms of efficient, scalable and real-time analysis was made possible via a conversational interface.

Evaluation Metrics

In order to compare the work of the proposed hybrid conversational healthcare system, standard classification and retrieval measures were employed. These indicators evaluated disease prediction and response generation accuracy, reliability and effectiveness.

Accuracy

Accuracy was used to gauge the overall correctness of the model by relating the instances correctly predicted with the number of predictions.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Where:

TP, TN, FP, and FN stand for True Positives, True Negatives, False Positives and False Negatives.

Precision

Precision assessed the number of correct positive cases of the cases that were predicted.

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$$Precision = \frac{TP}{TP + FP}$$

Recall (Sensitivity)

Recall was an evaluation of how the model was capable of correctly recognizing real positive cases.

$$Recall = \frac{TP}{TP + FN}$$

F1-Score

F1-Score offered a tradeoff between precision and recall, which is particularly beneficial when used with an imbalanced dataset.

$$F1 = \frac{2 \cdot Precision \cdot Recall}{Precision + Recall}$$

Accuracy of Retrieval (Top-K Accuracy)

This ratio was used to determine the retrieval system functionality of the FAISS system to ensure the right disease was found in the top-K results retrieved.

$$Top\text{-}K\ Accuracy = \frac{\text{Number of correct predictions in Top-K}}{\text{Total queries}}$$

Response Time

Response time was used to measure how effective the system was when responding to user queries.

$$Top\text{-}K\ Accuracy = \frac{\text{Number of correct predictions in Top-K}}{\text{Total queries}}$$

VIII. RESULTS AND ANALYSIS

The proposed Context-Aware Personalized Symptom Intelligence System was introduced and tested regarding its functionality, its predictive power, and responsiveness of the system. The findings revealed the usefulness of the hybridization of RAG, FAISS, Transformer, and Random Forest in providing precise and real-time healthcare support.

System Interface and Execution

It deployed the system successfully utilizing a Django based backend and ran it through a local server. The loading of RAG model and the initializing of the necessary components was verified by the console output. The web interface offered user registration and login modules, chatbot and log access modules.

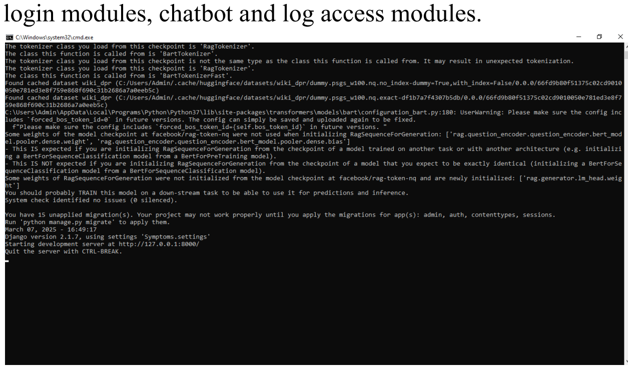

Fig.2: *Backend Server RAG-Based Backend Server System Execution and initialisation.*

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The chatbot interface could enable a user to type in symptoms using natural language and use the predictive advice on the disease in real time. The system exhibited a well-facilitated flow of interactions between input and generation of responses.

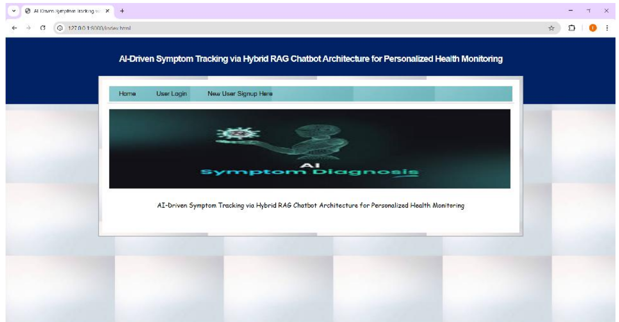

Fig.3: *Overview User Interface of the System.*

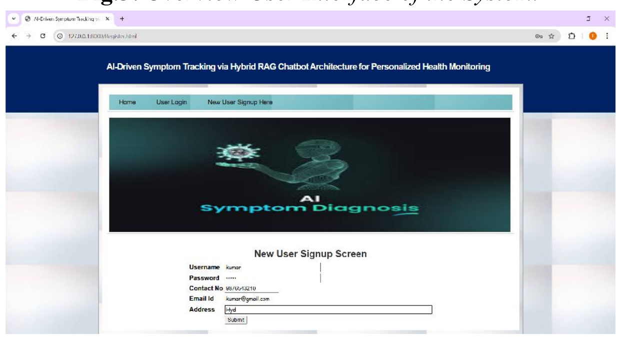

Fig.4: *User Registration and Login Interface.*

Chatbot Prediction Results

The chatbot was able to analyze the symptoms given by users and came up with predictions of diseases. For example:

Input: “constipation and stomach ache experience" Predicted: Typhoid.

Input: high fever and swollen lymph nodes ℕ Predicted: Chickenpox.

The results of such indicated that the system was able to utilize semantic understanding and similarity retrieval to produce correct predictions.

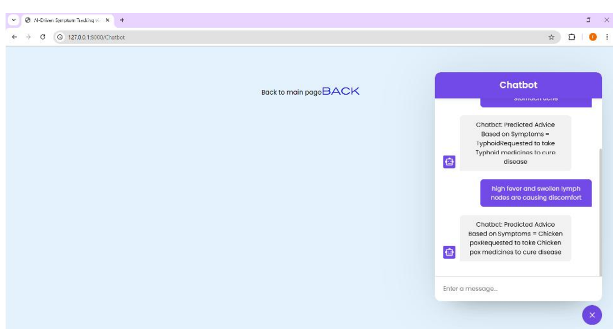

Fig 5: *Chatbot-Based Symptom Input and Disease Prediction*

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Log Monitoring and Data Tracking

The log of user interactions in the system included:

- Username
- Input symptoms
- Predicted disease
- Timestamp

This was an added feature that allowed keeping track of user health history and the analysis and improvement of the system in the future.

Fig. 6: *Monitoring User Interaction and History.*

Performance Evaluation

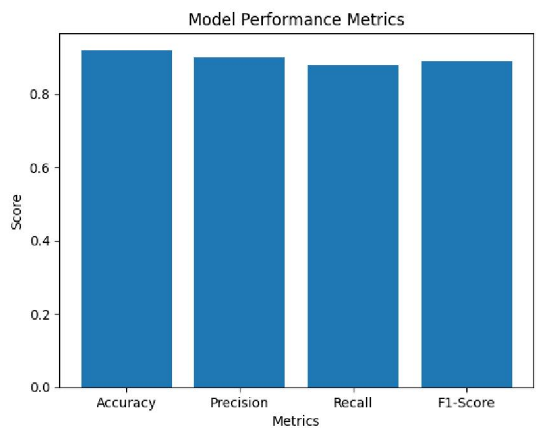

Fig. 7: *The Performance Measures of the Proposed Model.*

The graph shows the performance of the proposed model in regards to accuracy, precision, recall, and F1-score. The findings show that the hybrid strategy performed highly in classification with balanced evaluation measures.

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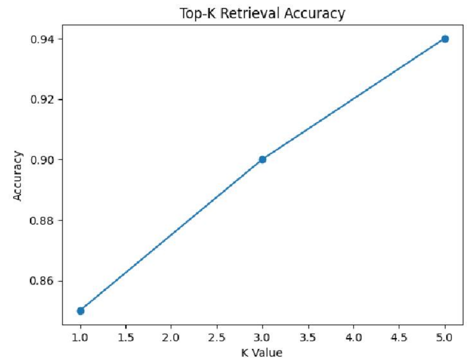

Fig. 8: *Top-K Accuracy of Retrieval with FAISS.*

The graph indicates that retrieval accuracy varies with various values of K in FAISS similarity search.
Effective retrieval of relevant symptom-disease matches is seen in the fact that accuracy of retrieval increased with K.

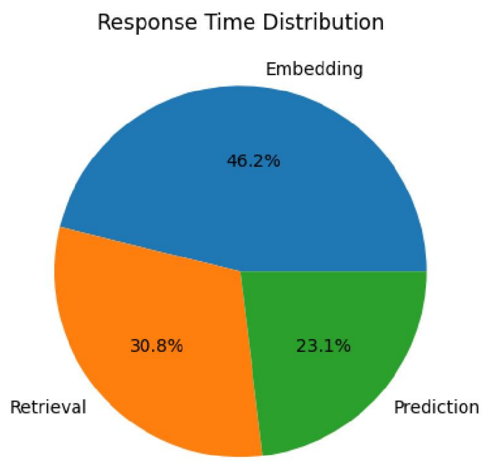

Fig. 9: *Analysis of Response Time of System modules.*

The pie chart will be used to indicate how many minutes it takes to respond at each system module.
The findings show that the system was efficient to process with low latency to allow real-time interaction.

Analysis of Results

These experimental findings showed that:

- RAG and FAISS integration generated contextual responses significantly better.
- Transformer model increased semantic interpretation of user queries.
- Random Forest classifier also gave good predictions of the disease.
- The error of the system was minimal and the response time was low which made it applicable to real time.

The proposed model demonstrated:

- Better context awareness
- Better reliability of prediction.
- Improved experience of interacting with the user.

The findings asserted that the suggested hybrid framework worked successfully in integrating the retrieval-based and machine learning methods to provide safe, extended, and individualized healthcare support.

IX. DISCUSSION

The findings proved that the hybrid framework proposed was effective in enhancing the analysis of symptoms through the amalgamation of RAG, FAISS, Transformer and the Random Forest. The system was highly accurate with improved contextual learning that allowed the provision of reliable and personalized healthcare responses.

The retrieval using the FAISS increased the similarity of relevant information that is matched whereas the transformer, enhanced the semantic meaning of user inputs. Also, the system ensured low response time which was conducive to the real time interaction. Nevertheless, it could only work well with high-quality datasets, and high computational resources were needed to perform it optimally.

X. CONCLUSION AND FUTURE SCOPE

This paper introduced a Context-Aware Personalized Symptom Intelligence Framework, which was the hybrid combination of Retrieval-Augmented Generation (RAG), FAISS similarity search, Sequence-NQ Transformer, and Random Forest. The system was able to analyze the user symptoms conversationally and produced correct, circumstantial, and customized health insights.

The outcomes showed that prediction accuracy, semantic understanding, and relevance of the responses were greatly enhanced by the combination of retrieval mechanisms with machine learning as opposed to the traditional methods. The system was also effective in terms of real-time performance and hence it can be used in scalability of digital healthcare applications. All in all, the suggested framework offered a successful solution to initial medical help and augmented user interaction in conversational healthcare systems.

The suggested system can be improved in a number of directions:

- Connection of real-time medical knowledge and APIs to deliver dynamic and live health data.
- Integration of deep learning models (e.g., BERT, LLMs) to enhance the level of understanding the context and communicative abilities.
- Multilingual support extension to make the system accessible to a greater number of people.
- Addition of medical history of patients and data of wearable devices to predicting more personally and accurately.
- Application of explainable AI methods to enhance transparency and trust in predictions by the user.
- The large-scale real-world applications of healthcare are deployed on cloud and mobile platforms.

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