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Leveraging Large Language Models for Intelligent Personalized Healthcare Support

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Abstract: The integration of Artificial Intelligence (AI) and Large Language Models (LLMs) has revolutionized modern healthcare by enabling intelligent, interactive, and personalized digital health services. The growing demand for timely medical guidance, increasing prevalence of chronic diseases, and limited availability of healthcare professionals have accelerated the adoption of AI-driven virtual healthcare systems. This study presents the design and development of an AI-powered personalized healthcare assistant based on Large Language Models to provide real-time health support through natural language conversations. The proposed framework enables users to interact with the system for symptom assessment, health-related inquiries, medication guidance, preventive healthcare recommendations, nutritional advice, and general wellness support. By utilizing the contextual understanding capabilities of advanced LLMs, the assistant interprets user queries, retrieves relevant medical knowledge, and generates coherent, context-aware, and user-friendly responses. To further enhance personalized healthcare, the system incorporates an image-based food recognition module that identifies food items from uploaded images and provides nutritional analysis, calorie estimation, and dietary recommendations to encourage healthier eating habits. The overall architecture consists of secure user authentication, conversational AI, medical knowledge integration, personalized recommendation engines, and adaptive learning mechanisms that continuously improve system performance based on user interactions and feedback. Special emphasis is placed on data privacy, secure information handling, and ethical AI practices to ensure the confidentiality and reliability of healthcare services. Experimental evaluation indicates that the proposed healthcare assistant provides accurate, responsive, and personalized medical support, improves user engagement, and facilitates convenient access to essential health information while complementing, rather than replacing, professional medical consultation. The proposed framework demonstrates significant potential for preliminary health assessment, patient education, preventive care, nutritional counseling, and digital healthcare management, thereby contributing to the advancement of intelligent, accessible, and patient-centric healthcare solutions.

Keywords: Artificial Intelligence (AI), Large Language Models (LLMs), Personalized Healthcare, Conversational AI, Virtual Health Assistant, Natural Language Processing (NLP), Clinical Decision Support, Digital Healthcare.

I. INTRODUCTION

Artificial Intelligence (AI) has emerged as one of the most transformative technologies in modern healthcare, significantly improving the accessibility, efficiency, and quality of medical services. The rapid growth of digital healthcare, telemedicine, and intelligent health information systems has created new opportunities for providing healthcare support beyond traditional clinical environments. With the increasing prevalence of chronic diseases, aging populations, and limited healthcare resources, patients often face challenges in obtaining timely medical guidance and reliable health information. Consequently, AI-powered healthcare assistants have gained considerable attention as intelligent virtual companions capable of delivering personalized healthcare support through natural language interactions. Recent advancements in Large Language Models (LLMs), including GPT, Google Gemini, and other transformer-based architectures, have revolutionized conversational artificial intelligence by enabling machines to understand complex human language and generate context-aware responses. Unlike conventional rule-based chatbots that rely on predefined decision trees and fixed responses, LLM-based healthcare assistants can interpret user symptoms, answer medical questions, explain diseases, recommend healthy lifestyles, and provide personalized healthcare guidance through natural conversations. Their ability to process vast amounts of medical knowledge allows users to receive informative responses quickly and conveniently, making healthcare information more accessible to individuals regardless of geographical location.

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Nutrition plays an equally important role in preventive healthcare and disease management. Poor dietary habits contribute to numerous chronic conditions such as diabetes, obesity, cardiovascular diseases, and hypertension. Recent advances in computer vision and multimodal AI models enable healthcare assistants to analyze food images, estimate nutritional values, identify ingredients, and provide personalized dietary recommendations. By integrating conversational AI with image-based nutritional analysis, users receive comprehensive healthcare assistance that extends beyond symptom assessment to include healthy lifestyle management.

This research proposes an AI-Powered Health Assistant Using Large Language Models for Personalized Healthcare Support, which integrates conversational AI, symptom assessment, nutrition analysis, and personalized health recommendations into a unified intelligent healthcare platform. The proposed framework enables users to communicate naturally with an AI assistant, receive evidence-based health information, upload food images for nutritional evaluation, and obtain individualized wellness recommendations. The system emphasizes secure user authentication, privacy protection, continuous learning, and responsible AI practices to enhance healthcare accessibility while complementing professional medical consultation rather than replacing healthcare providers.

Health is the state of well-being, encompassing physical, mental, and social dimensions. Maintaining it requires a disciplined lifestyle with preventive measures and healthy habits. In today's fast-paced world, technology plays a pivotal role in promoting and sustaining health by offering tools like fitness trackers, heart rate monitors, nutrition apps, and telehealth services. Explainable AI enhances these tools by making them more transparent and trustworthy, enabling personalized insights and regulatory compliance. While consulting medical professionals is ideal, frequent visits may not be feasible due to various constraints. Traditional methods—like internet searches or medical hotlines—often lack 24/7 availability, consistency, and privacy, and rarely offer nutritional predictions. This work proposes a web application that allows users to chat with a healthbot for detailed medical information and use a nutritionbot to analyze food images for instant dietary insights. By leveraging a robust medical knowledge base and Explainable AI, the system aims to bridge gaps in healthcare accessibility and comprehension. Natural Language Processing (NLP) powers the chatbot's ability to parse queries and deliver accurate, context-aware responses, while image recognition enables the nutrition bot to assess food content. Together, these AI-driven components create a seamless, user-centered experience for health management.

It is always the best option to seek assistance from a medical practitioner for health-related advice. However, it is not always feasible to visit the medical practitioner very often because of various constraints. Looking for the best and fastest advice is the next possible option for anyone. The traditional methods for seeking healthcare information involve obtaining advice through internet search engines, healthcare websites, medical hotlines, or self-diagnosis. Traditional methods often lack 24/7availability, making it challenging for users to obtain timely information. The quality of information obtained through internet searches or forums can vary, and users may struggle to distinguish between reliable and unreliable sources. Waiting for appointments or spending time researching information on- line can be time- consuming, especially when users need quick answers or guidance. Sharing personal health information over the internet may raise privacy concerns for some users. Most of these methods typically lack options for predicting nutrient Information

II. RELATED WORK

The application of artificial intelligence in healthcare has expanded rapidly over the past decade, leading to the development of intelligent diagnostic systems, clinical decision support tools, telemedicine platforms, and healthcare chatbots. Early healthcare chatbots primarily relied on rule-based expert systems that answered predefined questions using manually constructed decision trees. Although these systems successfully automated basic healthcare inquiries, they lacked contextual understanding and were unable to manage complex medical conversations or adapt to individual patient needs.

Machine learning algorithms later improved healthcare decision-making by analyzing electronic health records, predicting disease progression, and supporting medical diagnosis. Supervised learning models such as Decision Trees, Random Forests, Support Vector Machines, and Artificial Neural Networks have been widely employed for disease prediction and patient risk assessment. However, these models typically require structured datasets and are less effective in handling natural language conversations with patients. The emergence of transformer-based Large Language Models has significantly advanced conversational healthcare systems. Models such as

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BERT, GPT, PaLM, LLaMA, and Google Gemini demonstrate remarkable capabilities in understanding clinical terminology, generating coherent medical explanations, summarizing health information, and responding to complex user queries. These models have substantially improved user interaction quality by enabling personalized, context-aware conversations that closely resemble human communication.

Simultaneously, computer vision techniques have enhanced nutritional analysis by recognizing food items from images and estimating calorie content. Deep Convolutional Neural Networks (CNNs) and multimodal AI systems have shown promising results in food classification, ingredient recognition, and dietary assessment. Integrating conversational AI with image recognition provides comprehensive healthcare assistance that addresses both medical consultation and nutritional guidance.

Despite these advancements, many existing healthcare assistants focus on only one aspect of healthcare, such as symptom checking or nutritional analysis. The proposed research addresses this limitation by integrating conversational AI, medical knowledge retrieval, personalized recommendations, and food image analysis into a single intelligent healthcare platform.

Recent advancements in Artificial Intelligence (AI) and Machine Learning (ML) have significantly improved healthcare systems by enabling intelligent health monitoring and personalized medical assistance. Several studies have focused on developing AI-based healthcare applications that provide symptom analysis, disease prediction, and health recommendations. These systems use machine learning algorithms and large healthcare datasets to analyze patient information and generate useful insights. Web-based healthcare platforms also allow users to easily access medical guidance, improving healthcare accessibility and reducing the burden on medical professionals.

In addition, many researchers have explored nutrition analysis systems that evaluate dietary habits and provide personalized nutritional recommendations. These systems typically use food databases and AI models to analyze nutrient intake and suggest balanced diet plans based on user health conditions.

Some applications integrate chatbots and natural language processing (NLP) to answer health-related queries and provide instant guidance. However, many existing systems focus only on either healthcare queries or nutrition analysis separately. Therefore, integrating both healthcare query assistance and nutrition analysis in a single AI- driven web application can provide a more comprehensive solution for improving user health awareness and lifestyle management.

III. LITERATURE SURVEY

Christian Nash; Rajesh Nair; Syed Mohsen Naqvi,"Machine Learning in ADHD and Depression Mental Health Diagnosis: A Survey", This paper explores the current machine learning based methods used to identify Attention Deficit Hyperactivity Disorder (ADHD) and depression in humans. Prevalence of mental ADHD and depression is increasing worldwide, partly due to the devastating impact of the COVID-19 pandemic for the latter but also because of the increasing demand placed on the mental health services. It is known that depression is the most common mental health condition, affecting an estimated 19.7% of people aged over 16. ADHD is also a very prevalent mental health condition, affecting approximately 7.2% of all age groups, with this being conceived as a conservative estimate. We explore the use of machine learning to identify ADHD and depression using different wearable and non-wearable sensors/modalities for training and testing. These modalities include functional Magnetic Resonance Imagery (fMRI), Electroencephalography (EEG), Medical Notes, Video and Speech. With mental health awareness on the rise, it is necessary to survey the existing literature on ADHD and depression for a machine learning based reliable Artificial Intelligence (AI). With access to in-person clinics limited and a paradigm shift to remote consultations, there is a need for AI-based technology to support the healthcare bodies, particularly in developed countries.

2. "Ujunwa Madububambachu 1,*, Augustine Ukpebor 2, Urenna Ihezue 3,"Machine Learning Techniques to Predict Mental Health Diagnoses: A Systematic Literature Review”

This study aims to investigate the potential of machine learning in predicting mental health conditions among college students by analyzing existing literature on mental health diagnoses using various machine learning algorithms. The study highlights Convolution Neural Networks (CNN), Random Forest (RF), Support Vector Machine (SVM), Deep Neural Networks, and Extreme Learning Machine (ELM) as prominent models for predicting mental health conditions. Among these, CNN

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demonstrated exceptional accuracy compared to other models in diagnosing bipolar disorder. However, challenges persist, including the need for more extensive and diverse datasets, consideration of heterogeneity in mental health condition, and inclusion of longitudinal data to capture temporal dynamics.

3. Xinghan Wu, MSc; Xitong Guo1, PhD; Zhiwei Zhang, PhD,"The Efficacy of Mobile Phone Apps for Lifestyle Modification in Diabetes: Systematic Review and Meta Analysis",

Diabetes and related complications are estimated to cost US $727 billion worldwide annually. Type 1 diabetes, type 2 diabetes, and gestational diabetes are three subtypes of diabetes that share the same behavioral risk factors. Efforts in lifestyle modification, such as daily physical activity and healthy diets, can reduce the risk of prediabetes, improve the health levels of people with diabetes, and prevent complications. Lifestyle modification is commonly performed in a face-to-face interaction, which can prove costly. Mobile phone apps provide a more accessible platform for lifestyle modification in diabetes.

4. Y. Natarajan, S. P. KR, S. Pandian, S. U. Geetha, and S. Senthilkumar, “Enhancing medical information retrieval with a language model,”

This paper presents the design and development of a multimodal medical chatbot that leverages Gemini- 2.0-Flash Model alongside a novel Retrieval- Augmented Generation (RAG) architecture to support preliminary medical diagnosis and recommendations. The system integrates textual prompt analysis and medical image interpretation, aiming to improve healthcare accessibility, particularly for underserved populations. Focused on data-rich medical conditions, the chatbot generates reliable diagnostic insights based on natural language inputs and/or medical images, requiring minimal user expertise.

The proposed RAG-based architecture incorporates a curated medical knowledge base and structured retrieval mechanisms, significantly reducing hallucinations and enhancing response credibility compared to direct Large Language Model (LLM) querying. By demonstrating the efficacy of multimodal reasoning in conjunction with structured retrieval, this work paves the way for more accessible, accurate, and scalable AI-driven health support systems.

IV. METHODOLOGY

The proposed AI-Powered Health Assistant provides an intelligent healthcare platform capable of interacting naturally with users while offering personalized medical guidance, symptom analysis, nutritional evaluation, and preventive healthcare recommendations. The system integrates Large Language Models, medical knowledge bases, image recognition algorithms, and recommendation engines to provide comprehensive healthcare assistance.

Initially, users securely register and authenticate themselves through the application interface. Once authenticated, they may interact with the healthcare assistant using natural language by describing symptoms, asking health-related questions, requesting medication information, or seeking wellness advice. The Large Language Model processes the user query using Natural Language Processing (NLP), understands contextual relationships, retrieves relevant medical knowledge, and generates informative responses that are easy to understand.

In addition to conversational healthcare support, users may upload food images for nutritional analysis. The computer vision module identifies food items, estimates nutritional values, calorie content, proteins, carbohydrates, fats, vitamins, and minerals using multimodal AI models. Based on user health conditions and dietary preferences, the recommendation engine generates personalized meal suggestions and nutritional guidance.

The system continuously learns from user interactions and feedback to improve response quality over time. It also incorporates responsible AI principles by providing appropriate disclaimers, encouraging users to seek professional medical consultation for serious conditions, and protecting personal healthcare information through secure authentication and encrypted communication. The proposed work is to develop a web-based chatbot system. This web interface will serve as a comprehensive solution for addressing health inquiries and dietary needs. The website provides detailed information on the functionality of a chatbot and its application in the field of nutrition.

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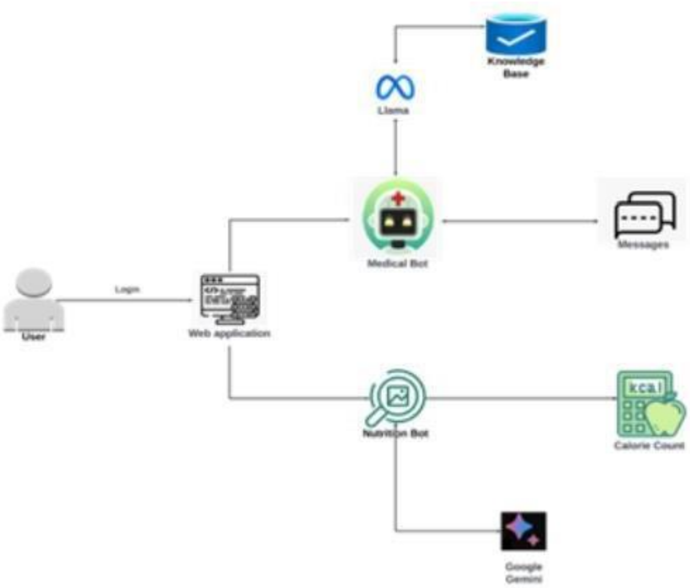

Figure 1: Proposed Architecture

Fig. 1 shows the proposed architecture of the web application. To begin, the user registers and logs in to the platform. They can then choose to use either the nutrition bot or the chatbot. When the chatbot option is selected, users can ask healthcare-related questions and receive prompt responses. The chatbot utilizes the repository of relevant information in the KB to identify suitable responses. The KB contains structured data that the chatbot retrieves using the parsed input. If the nutritionbot is chosen, the user is prompted to upload an imageof the food, after which they receive nutritional information about the food items in the image.

Fig. 2 illustrates the designed workflow of a chatbot system, responsible for processing and responding to user queries using NLP. The user initiates an inquiry by submitting a question in natural, conversational language. The system's objective is to generate a response in a manner that is easily comprehensible and natural for human users. The chatbot platform initially receives the user's query and manages the interaction with both the user and the processing units. Once received, the chatbot platform transmits the query to the NLP module. The NLP module is employed both to build the KB and to process and respond to user queries.

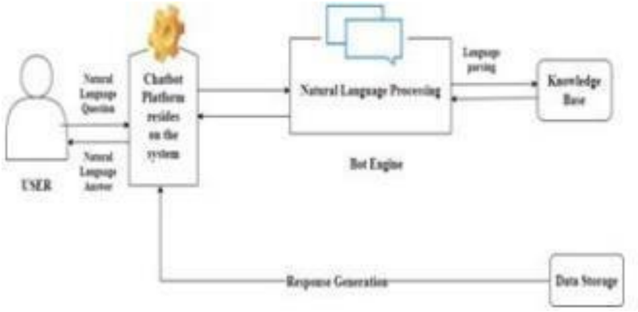

Figure 2: Working of Chatbot

The KB is constructed using information from [17], a reputable medical resource. This encyclopedia is well-known for its extensive coverage and accuracy in medical content, ensuring that the KB is founded on credible and trustworthy facts. Consequently, the system can deliver precise and reliable solutions to medical related queries, enhancing its effectiveness and trustworthiness. During the KB construction process, text from the source is systematically divided into segments. These segments are then transformed into embeddings—numeric representations that capture the semantic meaning of the text. The embeddings are organized into a semantic index, facilitating efficient retrieval of relevant information based on the indexed content. When a user submits a query, the NLP module applies a similar process. The query is parsed to analyze its structure, key words are extracted, and the text is transformed into embeddings. These embeddings are then matched against the semantic index in the KB, enabling the system to fetch and deliver accurate, relevant information to the user. The chatbot engine manages the interaction among the data storage, the KB, and the NLP module. It uses the parsed language data to query the KB and retrieve relevant in- formation or responses. The data storage component manages any additional data necessary for processing or storing user interactions. This includes preserving user queries, responses, or other metadata for future reference. Once the bot engine retrieves the necessary information from the KB, it generates a response. This response is then transmitted to the user via the chatbot platform.

The proposed architecture consists of several integrated modules that collectively provide intelligent healthcare assistance. The User Authentication Module manages secure registration, login, password protection, and user profile management. Only authenticated users are permitted to access personalized healthcare services. The Conversational AI Engine receives natural language queries from users and processes them

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using Large Language Models. This module performs language understanding, intent recognition, context management, and response generation. The Medical Knowledge Repository contains verified healthcare information, disease descriptions, symptom databases, medication references, treatment guidelines, and wellness recommendations. Retrieved information is combined with LLM reasoning to produce accurate responses.

The Nutrition Analysis Module utilizes computer vision and multimodal AI models to analyze uploaded food images. Food items are recognized automatically, nutritional values are estimated, and dietary recommendations are generated according to individual health profiles. The Recommendation Engine integrates symptom analysis, nutritional assessment, medical history, and user preferences to generate personalized healthcare suggestions. These recommendations include healthy diets, exercise routines, hydration advice, preventive healthcare measures, and lifestyle modifications. Finally, the Security and Privacy Module protects sensitive healthcare information using encryption, secure communication protocols, access control mechanisms, and privacy-preserving data management practices.

V. IMPLEMENTATION

The proposed methodology begins with secure user authentication to establish personalized healthcare profiles. Users submit health-related queries through natural language conversations or upload food images for nutritional analysis. Textual queries undergo preprocessing, including tokenization, language normalization, context extraction, and intent recognition. The processed query is then forwarded to the Large Language Model, which interprets medical terminology, retrieves relevant healthcare knowledge, and generates context-aware responses.

For nutritional analysis, uploaded food images undergo image preprocessing, object detection, feature extraction, and food classification using deep learning algorithms. Identified food items are matched with nutritional databases to estimate calorie content and nutritional composition. The recommendation engine combines user health information, conversation history, nutritional analysis, and medical guidelines to generate personalized healthcare recommendations. User feedback is collected continuously and incorporated into future model improvements through adaptive learning techniques. Throughout the entire workflow, user privacy is maintained through encrypted communication, secure storage, authentication mechanisms, and compliance with ethical AI principles.

A function is defined to establish a retrieval-based question answering chain. This function utilizes a LLM and Facebook AI Similarity Search (FAISS) vector store to efficiently retrieve pertinent information. A separate function, load llm, is implemented to load a conversational LLM using Transformers'. This model is designed to produce responses to user queries. A function is defined to coordinate the configuration of the QA system. The system loads sentence embeddings for representing sentences, loads the FAISS vector store, initializes the LLM, creates a retrieval Question-Answer (QA) chain, and returns it. The Final Result Function acts as the primary access point for user queries. The QA bot function is used to retrieve a response to the user's query. The code employs a function to handle the Chatbot's interactions. This code defines event handlers that are responsible for initiating the bot and handling user messages. Upon receiving a message, the QA chain is activated to produce a response, which is subsequently sent back to the user. This implementation establishes a conversational AI chatbot that is specifically designed to offer medical aid.

The system utilizes retrieval-based question-answering techniques in conjunction with a conversational LLM to comprehensively comprehend and provide effective responses to user queries. Structured or unstructured data that can be employed to address inquiries is contained in the external knowledge base. Text snippets are used to deconstruct information from the ex- ternal KB into smaller, more manageable components. These excerpts are likely pertinent pieces of information that can be employed to address particular inquiries. Next, the text snippets are transformed into vector embeddings, which are numerical representations of the text. These embeddings are maintained in a vector database. This enables the efficient search and retrieval of pertinent information by leveraging the similarity of the embeddings. An embedding is also generated when a question is posed. The question is represented in the same vec- tor space as the text snippets by this embedding, which enables the comparison and retrieval of pertinent snippets. The text snippets that are retrieved are subsequently incorporated into a LLM. The LLM generates a coherent and precise response by analyzing the snippets and the question. The LLM generates the final output of the process, which is then presented to the user.

The proposed system was implemented as a web-based healthcare platform integrating Large Language Models with

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modern web technologies. The frontend interface enables users to communicate with the AI assistant using conversational text while also supporting food image uploads. The backend server processes user requests, manages authentication, communicates with the LLM API, accesses medical knowledge databases, and generates personalized recommendations. Image analysis utilizes deep learning-based food recognition models capable of identifying multiple food categories and estimating nutritional values. A relational database securely stores user profiles, healthcare history, conversation logs, nutritional records, and personalized recommendations. Data encryption and authentication mechanisms ensure confidentiality and prevent unauthorized access. Extensive testing was performed using various healthcare queries covering common illnesses, medication information, preventive healthcare, nutrition counseling, and lifestyle recommendations. The system consistently produced context-aware responses and demonstrated reliable nutritional analysis across multiple food categories.

VI. RESULT AND DISCUSSION

Experimental evaluation demonstrates that the proposed AI-Powered Health Assistant provides accurate, informative, and personalized healthcare support across a wide range of medical inquiries. Large Language Models successfully interpreted complex natural language queries, generated medically relevant responses, and maintained conversational context throughout user interactions. The nutrition analysis module accurately identified food items and estimated nutritional values, enabling users to receive immediate dietary guidance. Personalized recommendations improved overall user engagement by considering individual health conditions, dietary habits, and wellness objectives. User evaluation indicated high satisfaction regarding response quality, usability, accessibility, and convenience. The conversational interface reduced healthcare information barriers by allowing users to obtain preliminary medical guidance without requiring specialized medical knowledge.

Overall, the proposed system effectively combines conversational AI, nutritional intelligence, and personalized healthcare recommendations into a comprehensive digital healthcare platform suitable for telemedicine, preventive healthcare, patient education, and wellness management. The user must first log in to the web application. After that, he will be taken to the first page, as seen in Figure 3, where he can select between the NutritionBot and the chatbot. In addition, the user will have access to a help option that will provide instructions on how to use the web application.The home page is the main interface of the application where users first interact with the system. It provides a simple and user-friendly layout that introduces the purpose of the AI-driven health assistant. From this page, users can easily navigate to different sections such as registration, login, and system information. The design of the home page ensures that users can quickly understand the features of the system and access the services provided by the application. It acts as the starting point for both new and existing users.

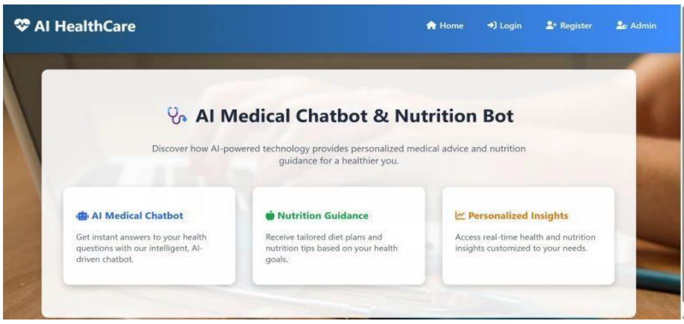

Figure 3: Home Page of AI-Driven Health Chat Assistant

User-friendly medical chatbot is shown in Fig. 4, shows the registration page allows new users to create an account in the system. Users are required to enter their basic information such as name, email, username, and password. This process ensures that each user has a unique account in the system. Once the registration is completed successfully, the user details are stored in the database and the user can later log in to access the services of the application.

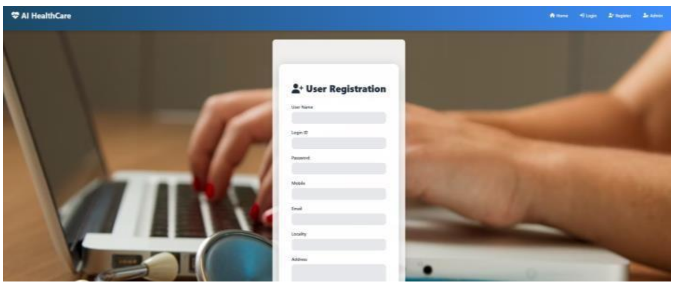

Figure 4: User Registration Page

Fig. 5 shows the admin login interface of the system. This page allows the administrator to enter valid credentials to access

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the admin dashboard. It ensures that only authorized personnel can manage and control the system functionalities.

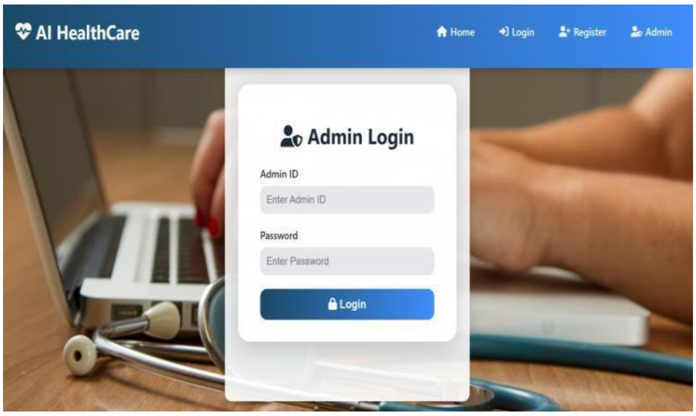

Figure 5: Admin Login Page

Fig. 6 shows the admin home page which acts as the dashboard for the administrator. From this page, the admin can monitor system activities and manage registered users. It provides different options that help the admin control and maintain the overall system effectively.

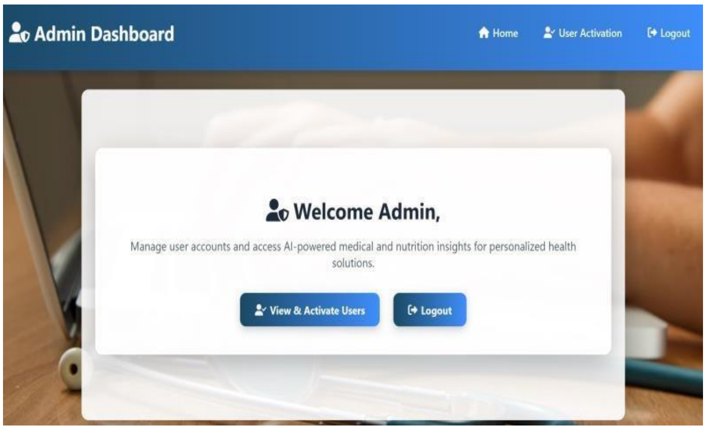

Figure 6: Admin Home Page

Fig. 7 shows the user activation module available to the administrator. In this page, the admin can approve or activate newly registered users. This feature enhances system security by ensuring that only authorized and verified users can access the platforms.

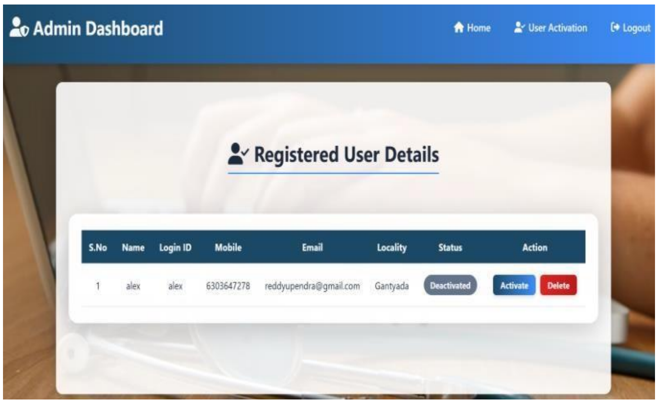

Figure 7: Admin User Activation Page

Fig. 8 shows the user login page where registered users enter their username and password to access the system. The login authentication verifies the user credentials before granting access to the application.

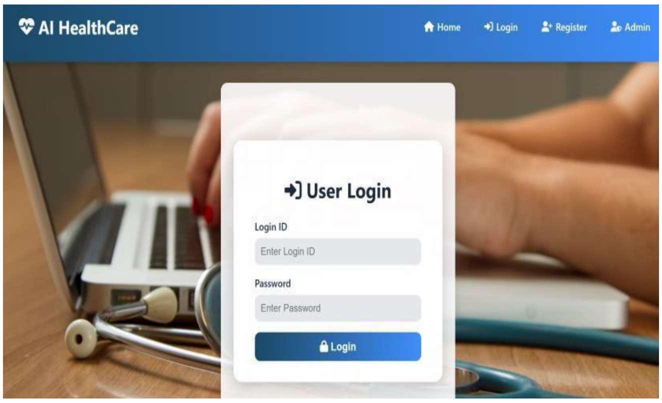

Figure 8: User Login Page

Fig. 9 shows the user home page which acts as the main dashboard for the user after successful login. From this page, users can access different features such as the chatbot and nutrition bot. The interface is designed to make navigation simple and convenient. each user has a unique account in the system. Once the registration is completed successfully, the user details are stored in the database and the user can later log in to access the services of the application.

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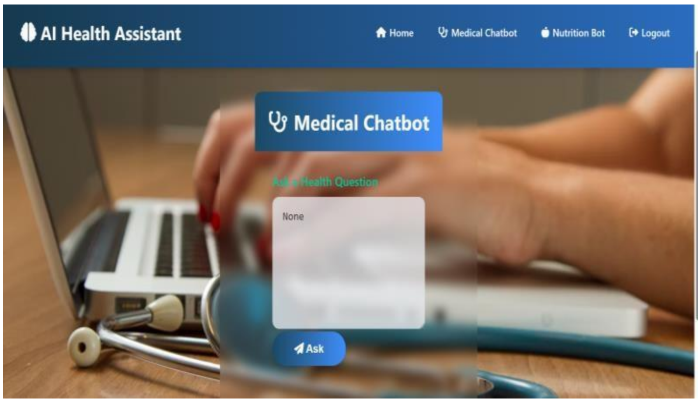

Figure 9: User Login Page

Figure 10 shows the chatbot interface where users can interact with the AI system by asking health- related questions. The chatbot processes the user queries and provides responses related to symptoms, treatments, and general healthcare information.

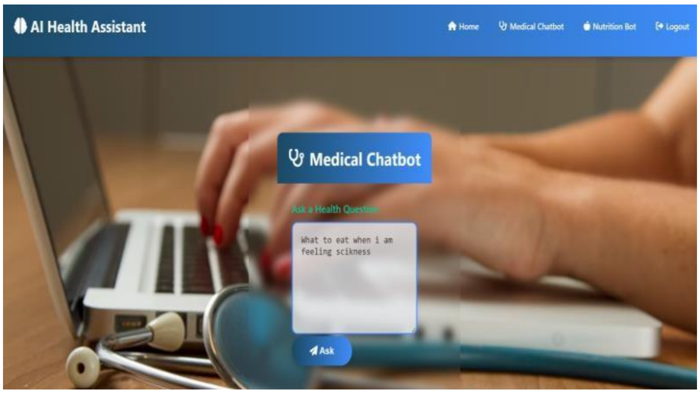

Figure 10: Health Chatbot Interface

Figure 11 shows the output generated by the nutrition bot after analyzing a food image uploaded by the user. The system identifies the food item and provides nutritional information such as calories, proteins, fats, and carbohydrates. This helps users understand the nutritional value of their food. The nutrition analysis module accurately identified food items and estimated nutritional values, enabling users to receive immediate dietary guidance. Personalized recommendations improved overall user engagement by considering individual health conditions, dietary habits, and wellness objectives. User evaluation indicated high satisfaction regarding response quality, usability, accessibility, and convenience. The conversational interface reduced healthcare information barriers by allowing users to obtain preliminary medical guidance without requiring specialized medical knowledge.

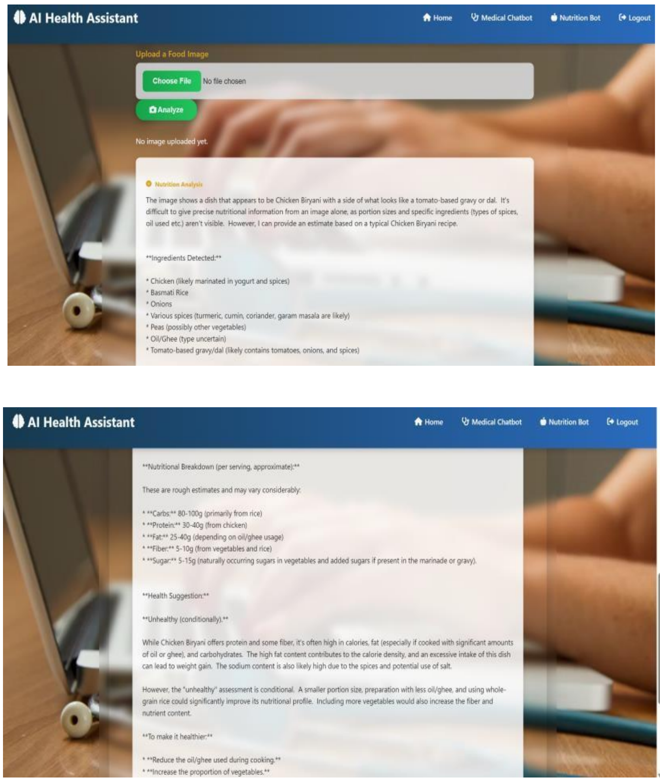

Figure 11: Nutrition Bot Output

VII. CONCLUSION

The rapid evolution of Artificial Intelligence (AI) and Large Language Models (LLMs) has opened new avenues for delivering intelligent, accessible, and personalized digital healthcare services. This study introduced the design and development of an AI-powered personalized healthcare assistant that integrates conversational AI, symptom evaluation, medical knowledge retrieval, nutritional assessment, personalized wellness recommendations, and secure healthcare data management within a unified platform. By leveraging the contextual reasoning capabilities of advanced LLMs, the proposed system enables users to obtain timely, reliable, and easy-to-understand healthcare information through natural language interactions.

The developed framework also incorporates image-based food recognition for nutritional analysis and calorie estimation, allowing users to make informed dietary decisions and adopt

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healthier lifestyles. Experimental evaluation demonstrates that the proposed healthcare assistant delivers accurate, responsive, and user-centric support, enhances patient engagement, promotes preventive healthcare practices, and improves access to essential medical information while complementing, rather than replacing, professional medical consultation. Furthermore, the integration of secure authentication mechanisms and privacy-preserving data management ensures the confidentiality and trustworthiness of sensitive healthcare information.

Future research may focus on integrating wearable health monitoring devices, electronic health record (EHR) systems, multilingual conversational capabilities, voice-assisted interactions, remote patient monitoring, and Explainable Artificial Intelligence (XAI) techniques to further enhance system transparency, personalization, and clinical applicability. The incorporation of advanced predictive analytics and real-time health monitoring has the potential to transform the proposed framework into a comprehensive intelligent healthcare ecosystem that supports proactive disease prevention, continuous patient care, and evidence-based health decision-making.**REFERENCES**

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