NutriBuddy – A Diet Plan Recommendation System

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***Abstract*—This paper we are aiming to show how precisely we can analyze a disease with the help of symptoms and provide a diet plan for user with the data that is existing in research papers with the help of Large Language Models (LLM) and Retrieval Augmented Generation (RAG). A chatbot is created to help people to have conversation and provide answers to their queries, here we are focusing on the chronic diseases further narrowed them to heart disease, diabetes, and thyroid, conventional method of diet plan now is consulting a Personal Dietitian (PD) which often lack the accessibility and flexibility. We try to aim this and give personalized food instructions to all our users, and it is proven by [1] that AI can achieve it precisely compared with the human dietitians. Our application achieved 90% accuracy in providing accurate responses to the user queries.**

Index Terms*—*Large Language Models, Retrieval Augmented Generation, Chronic diseases, Personal Dietitian

I. Introduction

Food plays a pivotal role in our lives, exerting a profound impact on human health [2] and it is important to predict the disease before it gets serious, but many ignore to visit to doctor due to various reasons. Our Projects aims to solve this by creating an AI based chat bot that can predict the disease from the data given to it and capable of providing a diet plan to the analyzed disease. For this Paper we limit our diseases to chronic and narrow them to heart disease, diabetes and thyroid.

In addition to the traditional anticancer therapies, dietary interventions and nutritional supplements are added to the patient treatment and clinical trials were conducted, some of them have reported satisfactory clinical efficacy [3]. The study by Xiao focuses on how various kinds of metabolism and diet can affect chemotherapy and other related therapies. The World Health Organization revealed that approximately 30% of the global populace is affected by different diseases and malnutrition accounts for 60% of child deaths annually [4]. This demonstrates why recommendation systems should be easily accessible. In this paper, we are trying to help people make individual diets based on their health conditions using chatbot services. The system will be chronic diseases related and through an interaction the user will get the recommended diets for his/her certain conditions. Moreover, for those who are not willing to share their disease with other users, we have developed a bot to which they can provide symptoms and get diet plans.

II. Statement of the Problem

As the use of artificial intelligence increases, LLMs and retrieval-augmented generation have obtained keen interest across different fields. We are using this technology to build a chatbot that will combine the features of LLMs and RAG to automatically predict a disease and create a diet plan or to give a diet plan if the user knows about his diagnosis. With focus on the traditional diet planning approaches that involve human dieticians we encounter challenges such as accessibility to the dieticians, variation in dietician recommendations and lack of uniformity in the approaches used by the dieticians. The current research aims at improving the diet recommendation system's accessibility, consistency, and accuracy through AI. For this paper we are focusing on chronic disease that includes heart, diabetes and thyroid predicting and followed by providing food nutrition according to the user requests.

III. Review of Literature

A. Existing Methodology on Diet Plan

'Chatdiet – Personalized Nutrition-Oriented Recommender,' utilizes GPT Turbo with an orchestrator thus enabling the provision of customized diet advises to the users. This chatbot answers various questions related to diet and health: For instance: nutrition for deep sleep, increase in energy levels, or any generalised health issue. Using the language model from user's input, Chatdiet guarantees the recommended diet is as close as it can get to the personalized diet. An accurate evaluation of the applicability of the Chatdiet's model revealed a high percentage of its efficiency, which was estimated at 92%. This advanced tool is expected to revolutionize the future of health and can act as an alternative for human dieticians [2].

In a recent work, [1] wanted to improve nutritional support for such patients by employing a modified version of ChatGPT-4. Developed using the Chinese kidney diet recommendation for foods, this fine-tuned model will thus give dietary suggestion for an individual on the dialysis. The outcomes involved the evaluation of the effectiveness of the guidelines by analyzing the serum prealbumin, albumin as well as phosphate levels of patients. Participants took their regular food stuff choices from their personal dietitians before being put on the GPT based diet direction. Analysis showed that the study achieved worthwhile effects in regulating major nutritional biomarkers and these studies underlined the potential role of AI-based solutions of augmenting dietitian assistance for enhancing patient well-being.

Diet-Right is a form of web service food recommendation system, which aims at recommending food to patients that corresponds pathologically using their pathological reports. The system make use of the Ant Colony Optimization (ACO) algorithm to come up with customized, disease-associated nutritional meal plans. This demonstrates that the model uses cloud computing for a twelvefold speedup relative to single-node execution time and offers scalability. Experimental results show that increasing the number of ants enhances the system's accuracy. Diet-Right addresses the challenge of selecting appropriate diets in real time, particularly for patients with critical health conditions. The system is designed to prevent diseases with the help of balanced diet and trying to minimize the use of medicines. The AI and cloud architectures of the solution speak to its application in personalized eHealth solutions. This paper shows an example of how computational models may help in improving and optimizing the delivery of healthcare services, particularly in the planning of diet. [5].

The stresses and pressures at work, compounded by the shift to remote working, see people struggling to adhere to simple fitness and healing diets or remain healthy; therefore, suffering from obesity shortening their life spans. The present strategies do not work at times because people are busy and there is no organized way of implementing a new plan. To this end, recommending alternative diets and fitness solutions based on a user's schedule was proposed to be undertaken by a smartly designed chatbot named CHARLIE. Recommending meals and scores and rank the exercises and the entire daily plan based on time constraints as well as calorie intake is used by the CHARLIE platform. This tool could help users save time and make them want to stick to a healthier lifestyle without much planning [6].

To offer personalized dietary recommendation for diabetic patients, [7] developed a web based AI chatbot. To tackle the increasing societal burden of diabetes, which was 15.6% experienced by people aged 30 in 2020, the system relies on generative AI algorithms.An elderly chats with the chat bot about the dietary plans that it tailors for her and diverse social classes to help prevent diseases and promote healthy eating habits. From there, the AI model was fine tuned, cutting learning loss down to nearly zero thus ensuring that calories needs are known, along with seasonal availability of food, to return with the most precise dietary suggestions. It is a system designed to be adapted for varying health conditions and is made ergonomic falling in line with elderly use requirements. This groundbreaking concept illustrates chatbot capability to control diabetes and promote diabetes preventive care. These have been used to further its utility in supporting healthy eating and enhancing the quality of life of people with diabetes, and future research is needed to further enhance its utility.

B. Existing Methodology on Disease Prediction

An efficient AI based health advising and consulting chatbot HealthGuideBot which employs deep feedforward multilayer perceptron and NLP to generate responses to different queries related to diseases, treatments, and contacts of hospitals in the local area. The test accuracies measured for the system were 94.32% thus confirming the efficiency of the system. Intended for regions with few language-related interventions, HealthGuideBot offers significant improvements to the sector by focusing on providing relevant health information in those regions. It helps in pandemic control since it provides accurate health information on time thus is another instance of how AI has shifted into a new dimension and is helping people have easier access to health care services [8].

The DiseasePredictorBot designed by [9] is a machine learning based medical diagnostic tool designed to predict diseases based on symptoms and patient's age and gender. This system incorporates a database of more than 230 diseases and uses different ML techniques to make its forecast. This study has evaluated numerous algorithms and has discovered that the weighted K-Nearest Neighbors (KNN) algorithm is the most effective, surpassing 93.5% in terms of disease prediction. Indeed, this system suggests a best diagnosis in this field and provides a promising tool for early diagnosis and prescription based on needs of the patients.

Health-LLM, a model employing artificial intelligence that has an objective of improving the prediction of diseases and, individual's health status. It eradicates the flaws that come with traditional ways of solving health issues by focusing on stone age techniques of singling out data and applying it on everyone. The system incorporates health reports into a large scale language model for reporting task specific findings in detail. Drawing from medical knowledge trade-off scoring Health-LLM improves the weights of the health characteristics by engaging expert opinion. A semi-automated feature extraction helps language models to yield higher predictive accuracy of features. Tests prove that Health-LLM yields better predictability than conventional approaches to the problem. Its approach is personalized using an AI+ES system and integrates usage for handling numerous individual health concerns. This advanced system proves the capability of applying AI in improving the intelligent medical treatment and management system [10].

A medical chatbot and applies Natural Language Processing (NLP) and cosine similarity for solving a health query and disease detection. In this case, the chatbot matches the words of the user query with the words in a document and pulls out responses with the highest similarity to a given query at a rate of about 87% accuracy. This tool can be used by people who do not have opportunity to address such questions to healthcare consultants. Skilled stopword elimination and large training corpus tell how accurate the chatbot will be. Further improvements will further improve the precision of the results in addition to expanding on the results by including items such as the medications bought, recommended clinics, and recommended doctors when consultation at a deeper level is required [11].

The use of AI chatbots for disease prediction, which identified and reviewed 24 papers to evaluate the performance of the chatbots regarding early detection and management of diseases. Cognitive computing enabled by AI chatbots help to accelerate healthcare as they learn from patients' expressions by mimicking human conversation, can also help in patient segmentation and offering medical advice. Based on the research, there is a need to explore the AI chatbots as they are deemed helpful in enhancing the diagnosis speed and accuracy and assist the healthcare professionals in decision-making. However, to achieve much better results by the use of this technology, further studies are required for improving the functioning of AI chatbots. As as this technology evolves, could progress significantly in the management of care to patients, enhance specific treatment, and further the progression of disease management [12].

IV. Objective of the Study

The goal of this project is to create a chatbot which is AI integrated trained LLM and RAG to forecast diabetes, heart disease, thyroid as well as to suggest diet regimens for clients to enhance their health condition. The idea is to improve the personalization factor for each query or for each condition of the user and we are focusing on the flexibility this bot helps to improve the users convenience in getting the food nutrition information. Assess the chatbot's efficiency in providing the right health prediction and adequate individualized dietary advice at every session, by proving that an AI-based health advisory system can perform as well or even better than an actual dietitian.

V. Data Collection

The datasets for this project are research papers which have symptoms and diet plans for each disease. These papers are collected from Google Scholar. We collected many papers with symptoms and diet plans for each disease. Then we filtered out five papers in each category. These papers mainly cover the symptoms and diet plan for each disease. The dataset for this project includes all the papers from [13]–[42] in References section. Some of the papers with symptoms for each disease include review of common symptoms of thyroid [13], and heart disease [18], diabetes [24].The diet plan papers include dietary advice for diabetes [39],nutrition resource guide [33],and nutrition management of hypothyroidism [28].

VI. Data Preprocessing and Storage

The disease and diet plan papers are categorized into Thyroid, Diabetes, and Heart disease folders. These research papers contain unstructured data in PDF format. These data are split into chunks of size 512 and converted into vector embeddings, which are machine-understandable formats. We have used the Hugging face embedding sentence transformer all-mpnet-base-v2 to create embeddings for text in chunks. This model is a small powerful model. It can be helpful in semantic understanding and handles diverse queries. Figure 1 shows the data preprocessing process for storing research papers in vector database.

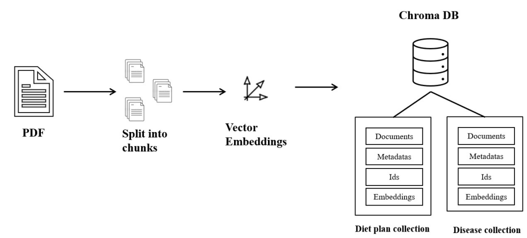

Fig. 1. Data Preprocessing(vector Database)

These chunks are stored in a vector database. We chose Chroma DB as the vector database for this project. Chroma DB is simple, opensource and provides strong metadata support. We created two collections separately for disease and diet plan. The documents in the collection contain text chunks, metadata, id, and vector embeddings. We have also created a folder element in metadata, that stores which disease this file belongs to. The vectors are stored in local persistent directory storage/chroma.

Food data central nutrition data zip file contains multiple CSV files for each year. We used only food, food nutrition and nutrition file. The food file contains food names, food nutrition file contains nutrition information of those foods and nutrition file contains the nutrition name and unit of those amounts. These files are combined using foreign and primary key in each file. We also combined 2023 and 2024 files into a single file. Then, we removed null values and duplicate values from the combined dataset. After all preprocessing, there are approximately 7000 foundation food items. We created a database in Postgres. Then, we saved the final data frame into the database psycop2 driver. Foundation food data table contains the final dataset. Figure 2 shows the top 5 records of final merged foundation food data in Postgres database.

	fdc_id bigint	food_name text	amount double precision	nutrient text	unit_name text
1	2258587	Carrots, baby, raw	38.250983	Energy (Atwater Specific Factors)	KCAL
2	2258587	Carrots, baby, raw	40.7723	Energy (Atwater General Factors)	KCAL
3	2258587	Carrots, baby, raw	9.0787	Carbohydrate, by difference	G
4	2258587	Carrots, baby, raw	0.805	Protein	G
5	2258587	Carrots, baby, raw	0	Selenium, Se	UG
6	2258587	Carrots, baby, raw	0.09288	Manganese, Mn	MG

Fig. 2. Top 5 rows of foundation food data table

VII. Methodology

We have created a Flask web application. Internally, Llama 3.1 8b LLM is used in the chatbot to generate diet plans for users. Llama3.1 is an opensource model released by Meta. We chose this model because it requires less hardware requirements, and light weight when compared to other large models. We downloaded the model from Ollama and ran locally in the system. We have used Langchain framework to work with llama model in Python. We created prompts to invoke LLM with RAG (Context) and generate responses. We have used Postgres for Food data central nutrition data and Chroma DB for storing research papers in the form of vectors. Figure 3 shows the working of this project.

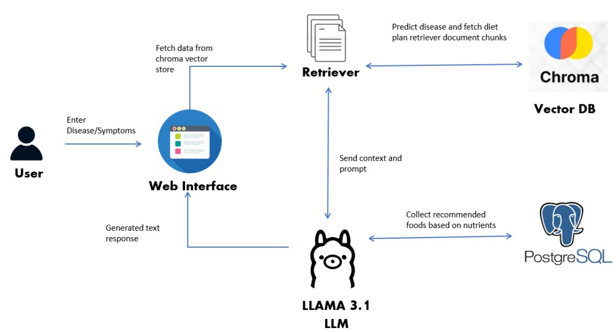

Fig. 3. Project flow chart

The user can choose to provide disease directly or symptoms if they don't know the disease. If a user chooses disease, we will prompt them with Thyroid, Diabetes and Heart disease options. They can choose any one of them to generate diet plans.

If they choose symptoms, they can provide symptoms in the input box provided. Internally, we will collect context from disease collection in vector database. The retriever will be created to collect 10 chunks with 0.3 similarity score. Then, the prompt to predict disease, context, and symptoms is sent to LLM. The LLM is directed to predict only with context and generate one word disease as a response. If not found in context, LLM will return None. In those cases, we will inform the user that there is no cause for concern.

Once we get the disease, we will collect context from diet plan collection in vector database. The retriever will be created to collect 10 chunks with 0.3 similarity score. Then, the prompt to create diet plan, context, and user query is sent to LLM. Then, LLM will create a JSON with diet plan summary, nutrient recommendations, and list of foods to avoid.

We will extract the nutrients list from JSON response. Then, call the Postgres with SQL query to fetch food items with list of nutrients as provided. Once we get the food items we will aggregate diet plan summary, list of food recommendations, and list of foods avoid. We will send all these to LLM to generate a proper text in human understandable format.

The user can also ask follow-up questions for the diet plan provided. The chat between LLM and user is stored in a session variable. If users ask any questions, internally we will create a retriever with diet plan context, prompt with chat history and send it to LLM to generate responses. The LLM is directed to generate response from context. If not found in context, it will generate responses from its own knowledge only related to health care and dietitian industry. The session variable with chat history is reset every time user refreshes the page.

VIII. Hypothesis for the Study

The hypothesis testing for this project is to check the system is consistent in providing same responses for semantically similar input. We tested the chatbot for different inputs for Thyroid disease. We provided disease for a few cases and semantically similar symptoms for some cases as input. The response generated is semantically consistent most of the time. The sentences are rephrased every time because of LLM, but the output is the same. The recommended food might vary because we are fetching five food items randomly from Postgres database. Figure 4 and Figure 5 show the sample responses for the same Diabetes disease.

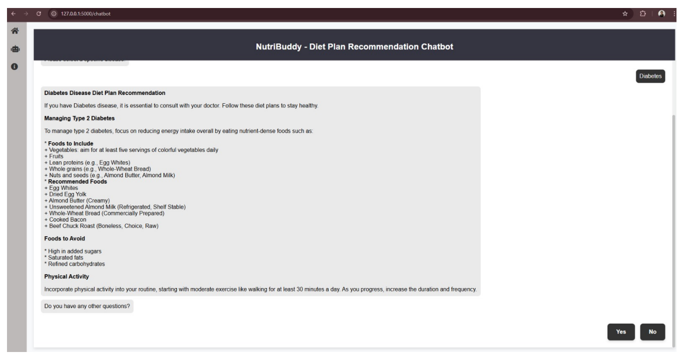

Fig. 4. Response 1

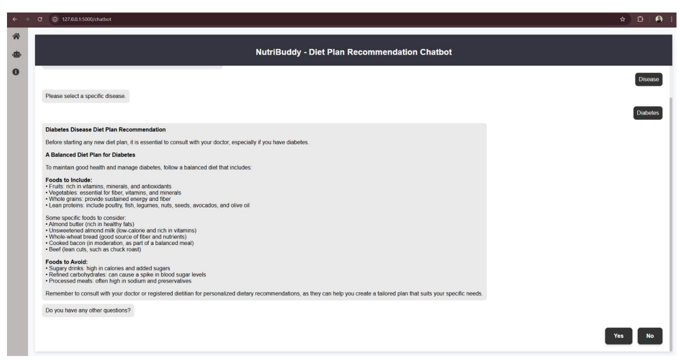

Fig. 5. Response 2

IX. Results

This chatbot is evaluated based on accuracy, relevance, and ability to not hallucinate responses. Since chatbot generates text-based responses, there are no predefined set of evaluation methods. We did manual testing to check the correctness of response. Figure 6 shows normal response case for Thyroid disease option.

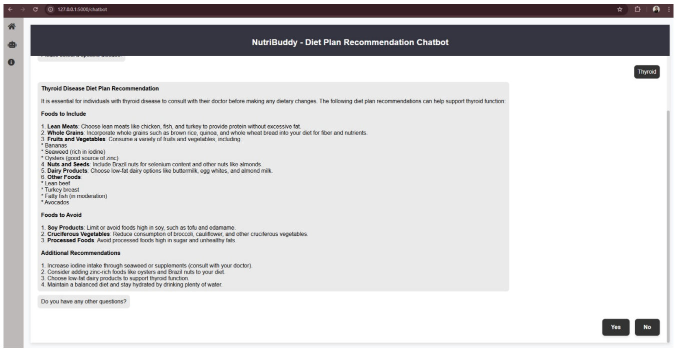

Fig. 6. Normal Response (Disease case - Thyroid)

Figure 7 shows the symptoms case for Diabetes. The provided symptoms “fatigue, dry mouth and itching” match with Diabetes disease. The chatbot predicted it correctly and provided diet plans to the user.

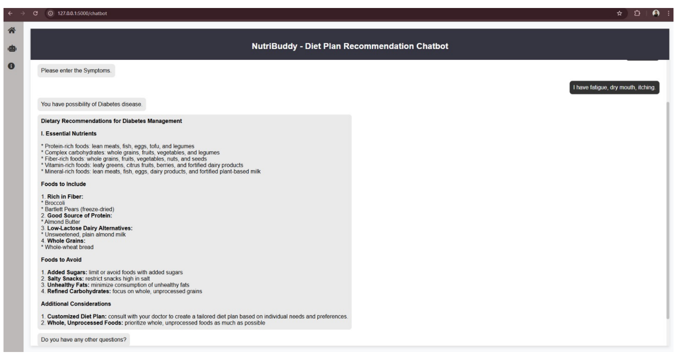

Fig. 7. Normal Response (Symptoms case - Diabetes)

Figure 8 shows the corner case where user has no matching disease from our context. So, the chatbot responded with no concerns message.

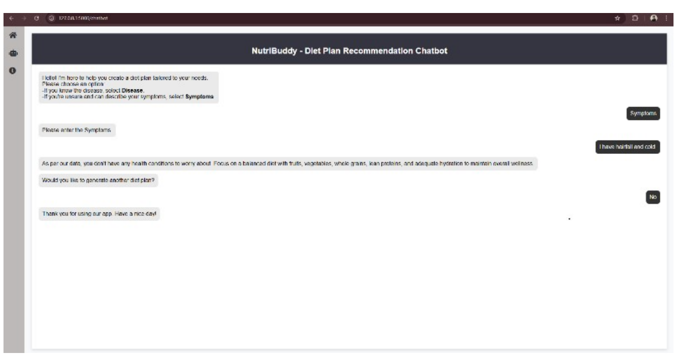

Fig. 8. No Disease Response

The chatbot responds with semantically similar responses every time. Also, it fetches the same set of chunks in most cases for the same disease or similar symptoms. The chatbot does not hallucinate in most cases. The accuracy of this bot is 90%. Since it provides similar responses for semantically similar inputs 90% of the time in 40 test cases.

X. Conclusion

In this project, a chatbot was created to predict chronic health conditions including diabetes, heart stroke and thyroid disorders using LLMs and RAG. The system also provided diet plans with the intention of ensuring a healthy lifestyle. In the evaluation task, once we carried out around 35-40 queries Nutribuddy achieved accuracy rate of 90% meaning that it provided the potential health risks and the dietary advice properly in terms of how it is answering user query and fetching the documents where the information is provided.

Such results suggest that AI solutions could act as supportive agent to conventional health-care practices by delivering constant, accessible, and individualized health info. Future development can involve enlarging the current set of data that the model uses, incorporation of real-time health information and call for opinions from healthcare experts on the correct use of the proposed system.

XI. Future Enhancements

This chatbot can be further enhanced by adding data from professional nutritionists to provide calorie level food recommendations for the users. The USDA Food data central foundation foods data have detailed nutrition level information with amount. This could be combined with nutrition data to give users detailed calorie managed diet plans. Then, collecting additional information such as age, height, and weight of user to provide more user specific diet plans. Also, voice-based chat functionality could be a great addition to make it more user friendly.

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