HEALTH - BUDDY : PERSONALIZED HEALTH ADVISOR

PROJECT REPORT

21AD1513- INNOVATION PRACTICES LAB

Submitted by

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(An Autonomous Institution, Affiliated to Anna University,Chennai)

BONAFIDE CERTIFICATE

Certified that this project report titled "**HEALTH – BUDDY : PERSONALIZED HEALTH ADVISOR** " is the bonafide work of **S NITHYA (211422243226), SHINY ZERUBBA RAJIVE S (211422243305) and SUJITHA R (211422243322)**, who carried out the project work under my supervision. Certified further, that to the best of my knowledge the work reported herein does not form part of any other project report or dissertation on the basis of which a degree or award was conferred on an earlier occasion on this or any other candidate.

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INTERNAL EXAMINER **EXTERNAL EXAMINER**

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We S NITHYA [211422243226], SHINY ZERUBBA RAJIVE S [211422243305] and SUJITHA R [211422243322], hereby declare that this project report titled " **HEALTH – BUDDY : PERSONALIZED HEALTH ADVISOR** ", under the guidance of Shyamala P B.Teach, M.E, is the original work done by us and we have not plagiarized or submitted to any other degree in any university by us.

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I also take this opportunity to thank all the Faculty and Non-Teaching Staff Members of Department of Artificial Intelligence and Data Science for their constant support. Finally I thank each and every one who helped me to complete this project. At the outset we would like to express our gratitude to our beloved respected Chairman, **Dr.Jeppiaar M.A.,Ph.D,** Our beloved correspondent and Secretary **Mr.P.Chinnadurai M.A., M.Phil., Ph.D.,** and our esteemed director for their support.

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S NITHYA

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ABSTRACT

The "Health Buddy: Personalized Health Advisor" is an AI-powered digital health assistant developed to offer customized health recommendations for improved patient care. Utilizing a Random Forest algorithm, Health Buddy analyzes individual health data—including symptoms, medical history, and lifestyle habits—to generate personalized diet, exercise, and wellness plans. Through a user-friendly web interface, the system collects essential data points such as age, gender, BMI, and specific health conditions, allowing it to provide precise and relevant guidance for post-diagnosis care. Key features include a symptom checker to assess potential health issues, medication reminders to enhance adherence, and health tracking for monitoring vital signs and lifestyle activities. Health Buddy is designed to improve patient engagement and adherence by making health management both accessible and personalized. Planned enhancements include integration with wearable devices for real-time monitoring, improved data privacy measures, and potential telehealth capabilities, positioning Health Buddy as a scalable, comprehensive tool in personalized healthcare.

Keywords : personalized health advisor, AI-powered assistant, customized health recommendations, patient care, Random Forest, health data analysis, diet and exercise plans, wellness, user-friendly interface, post-diagnosis care, medication reminders, health tracking, vital signs, patient engagement, wearable integration, real-time monitoring, data privacy, telehealth, scalable healthcare.

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LIST OF ABBREVIATIONS

ABBREVIATIONS	MEANING
AI	Artificial Intelligence
ML	Machine Learning
BMI	Body Mass Index
TF-IDF	Term Frequency-Inverse Document Frequency
ROBERTA	Robustly Optimized BERT Approach
AUC	Area Under the Curve
NDCG	Normalized Discounted Cumulative Gain
RS	Recommendation System
API	Application Programming Interface
SYP	System for Your Personalized

CHAPTER 1

INTRODUCTION

1.1 THE EVOLUTION LANDSCAPE OF HEALTHCARE

The global healthcare landscape is undergoing a significant transformation. Rising healthcare costs, coupled with the increasing complexity of chronic diseases, pose significant challenges to individuals and healthcare systems alike. Moreover, geographical disparities in healthcare access limit many from receiving timely and effective care. To address these issues, there is a growing demand for personalized healthcare solutions that cater to the unique needs of each individual.

1.2 THE POWER OF TECHNOLOGY IN HEALTHCARE

Technological advancements, particularly in artificial intelligence (AI) and machine learning (ML), are revolutionizing the healthcare industry. Wearable devices, such as smartwatches and fitness trackers, enable continuous monitoring of vital health parameters, empowering individuals to take proactive steps towards better health.

Mobile health apps offer convenient access to health information, appointment scheduling, and telemedicine consultations, bridging geographical gaps and improving accessibility. Telemedicine, facilitated by video conferencing and remote monitoring technologies, allows healthcare providers to deliver quality care to patients remotely.

1.3 HEALTH BUDDY: PERSONALIZED HEALTH ADVISOR

To meet the growing demand for personalized healthcare, we propose **Health-Buddy**, an innovative digital health assistant designed to provide tailored health advice. This AI-powered chatbot leverages advanced algorithms to analyze user-provided data, such as symptoms, medical history, and lifestyle habits, to deliver accurate and relevant recommendations.

1.3.1 Key Features Of Health-Buddy Include:

(i) **Symptom Checker:** A sophisticated AI-powered tool that can identify potential health issues based on user-reported symptoms, providing initial guidance and suggesting necessary actions.

(ii) **Personalized Health Plans:** Tailored health plans that consider individual factors like age, gender, medical history, and lifestyle preferences. These plans may include dietary recommendations, exercise routines, and stress management techniques.

(iii) **Medication Reminders:** Timely alerts to ensure adherence to prescribed medication regimens, reducing the risk of medication errors and improving treatment outcomes.

(iv) **Health Tracking:** A comprehensive system for monitoring vital signs, such as heart rate, blood pressure, and blood glucose levels, as well as tracking lifestyle habits like sleep patterns and physical activity.

(v) **Mental Health Support:** Tools and resources to promote mental well-being, including stress management techniques, mindfulness exercises, and access to mental health professionals.

(vi) **Expert Consultations:** Virtual consultations with healthcare professionals to address complex health concerns and receive personalized advice.

1.4 PROJECT OBJECTIVES

The primary objectives of this project are:

1. **Developing an AI-powered chatbot:** Creating a conversational agent capable of understanding and responding to user queries in natural language, providing timely and accurate health information.

2. **Integrating with wearable devices:** Enabling seamless data exchange between Health-Buddy and wearable devices to collect real-time health data and generate personalized insights.
3. **Designing a user-friendly interface:** Developing an intuitive and visually appealing interface that can be easily accessed and used by individuals of all ages and technical backgrounds.
4. **Ensuring data privacy and security:** Implementing robust security measures to protect sensitive health information and adhering to relevant data privacy regulations.
5. **Evaluating the effectiveness of the system:** Conducting rigorous evaluations to assess the impact of Health-Buddy on user health outcomes, satisfaction, and adherence to recommended health behaviors.

1.5 ARCHITECTURE DESIGN

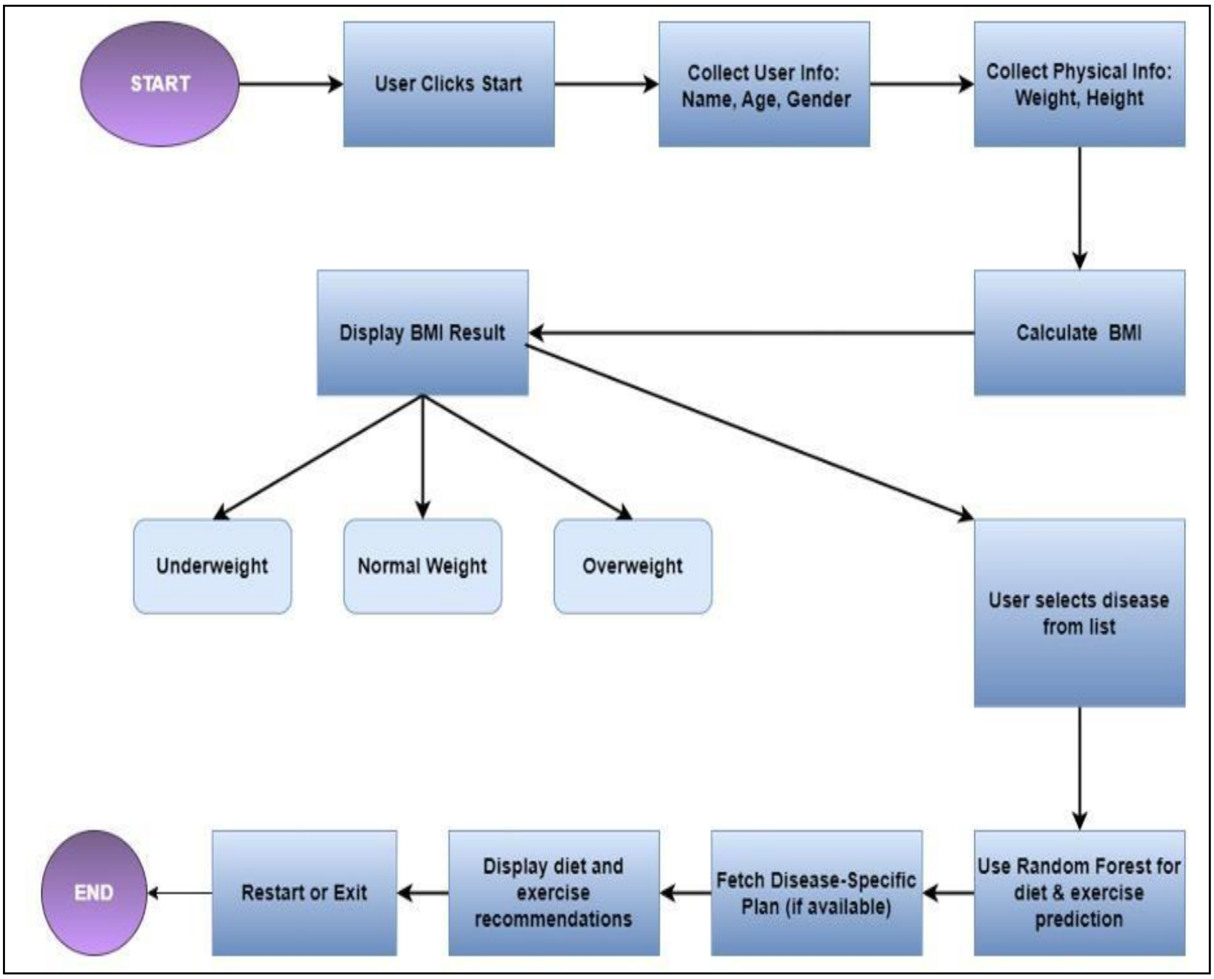


Figure 1.1 : Architecture Design

1.5.1 Initial Query

The system begins by asking the user a fundamental question: "Have you consulted a doctor recently?" This initial query serves as a gateway, directing the user towards appropriate health advice.

1.5.2 Medical Consultation

- **If No:** If the user has not consulted a doctor, the system will recommend seeking medical advice before proceeding.
- **If Yes:** The system will proceed to the next step.

1.5.3 User Information Collection

The system collects essential demographic information from the user, including:

- Name
- Age
- Gender
- Height
- Weight
- Disease

1.5.4 BMI Calculation and Weight Status Assessment

Using the collected height and weight data, the system calculates the user's Body Mass Index (BMI). The calculated BMI is then used to categorize the user's weight status into one of three categories: underweight, normal weight, or overweight.

1.5.5 Disease Input and Data Analysis

The user is prompted to input the recently diagnosed disease or health condition. The system then leverages a dataset containing information on various diseases, their associated dietary and exercise recommendations, and the Random Forest algorithm to analyze the input.

1.5.6 Personalized Recommendations

Based on the analyzed data and the Random Forest algorithm, the system generates personalized dietary and exercise recommendations tailored to the user's specific health condition. These recommendations are presented to the user in a clear and concise manner.

1.5.7 System Termination or Restart

The system concludes by offering the user two options:

- **Restart:** If the user wishes to input another disease or health condition.
- **Exit:** To terminate the system.

CHAPTER 2

LITERATURE REVIEW

In recent years, there has been a growing focus on personalized health technologies, particularly in the development of dietary and exercise recommendation systems. These systems aim to enhance individual health by offering tailored suggestions based on user preferences, health conditions, and activity levels. The literature on food and exercise recommendation systems highlights various approaches, from traditional machine learning techniques to deep learning and hybrid models.

Mehrdad Rostami et al. (2023) proposed a health-aware food recommendation system, combining time-aware collaborative filtering with content-based models to emphasize both user preferences and nutritional needs. Their system outperformed traditional methods, emphasizing the growing trend toward integrating health and nutrition in recommendation systems. In an earlier work (2022), Rostami's team leveraged deep learning and image clustering to provide visually explainable food recommendations, enhancing user transparency and trust.

Hybrid models have gained popularity for addressing challenges like cold start and time-sensitive recommendations. For example, G. Sekhar Babu et al. (2023) developed a hybrid recommendation system combining graph clustering and machine learning, which proved superior to traditional techniques. Similarly, Abolfazl Ajami et al. (2023) created a system for personalized dietary recommendations that integrated health factors such as basal metabolic rate, contributing to more tailored food suggestions.

In the domain of personalized diet and exercise, systems like SmartHealth (Kulkarni et al., 2024) have introduced advanced similarity modeling techniques like cosine similarity and Pearson correlation to provide customized plans for individuals with chronic conditions such as diabetes and hypertension. This approach demonstrated greater precision in aligning user preferences with optimal lifestyle recommendations compared to rule-based systems.

The integration of health management and machine learning is also evident in the work of Lakshmi et al. (2024), who combined disease prediction, life expectancy calculation, and personalized diet recommendations using machine learning techniques. Their system employed Gradient Boosting and Logistic Regression for disease prediction and K-Prototype clustering for diet recommendations, achieving high accuracy in both predictive and prescriptive tasks.

Content-based and collaborative filtering techniques continue to be foundational in recommendation systems. Singh and Dwivedi (2023) developed a food recommendation system using K-nearest neighbors to offer personalized food suggestions based on attributes like cuisine type and dietary preferences. The authors emphasized the importance of combining content-based features and collaborative filtering for more accurate and diverse recommendations.

Recent advancements have also focused on time-aware and nonparametric models. Rostami et al. (2022) presented a hybrid food recommender system using deep learning and graph clustering, incorporating time-awareness and trust networks to capture evolving user preferences. Yu et al. (2020) further explored nonparametric models for exercise medicine, addressing the limitations of parametric models in predicting dynamic physiological responses during irregular exercises.

Overall, the literature highlights the growing role of hybrid, deep learning, and machine learning approaches in developing personalized, health-conscious recommendation systems. These systems address key challenges such as cold start, time-sensitive recommendations, and user trust, paving the way for more accurate and user-centric health management solutions.

2.1 Food Recommendation Systems Based On Content-based and Collaborative Filtering Techniques

On the internet, numerous options are available for a specific type of product. It is tough to manually go through every product in a particular type when a user is trying to choose the best one. Because of this, manual searching is not very efficient. The recommendation system is crucial in recommending the best product in that situation. A food recommendation system is developed in this research paper using K-nearest neighbor's methods. The food data set is taken from Kaggle. We used Python programming language to implement the system. Our proposed recommendation system recommends food based on food name, food id, cuisine type, diet type like veg or non-veg in the case of content based filtering recommendation. For recommending the food with help of collaborative filtering we have used user id, food id and rating as an attributes.

AUTHOR : *Reetu Singh, Pragya Dwivedi*

YEAR : 2023

2.2 Fitness Guide: A Holistic Approach For Personalized Health And Wellness Recommendation System

In our fast-paced world, maintaining a healthy lifestyle is a challenge, with individuals often struggling to make informed decisions about their health. People have diverse needs, from fitness enthusiasts to those with specific health concerns, and finding personalized guidance can be overwhelming. This paper addresses this issue by creating a highly personalized Health and Wellness Recommendation System. When users enter the application, they provide essential information such as height, weight, and basic profile details. The key to our system lies in categorizing users into distinct health and fitness segments, accommodating varying user types, from fitness enthusiasts to those seeking guidance for occasional workouts, and even individuals with specific health concerns. This paper encompasses two primary features: 1. Strength Assessment: We leverage user- provided data and their chosen health and fitness category to calculate their physical strength. This strength assessment guides users on their fitness journey, providing valuable insights into their physical capabilities. 2. Diet Planning and Health Issue Management: In the diet planning feature, users input their meal preferences, and we employ the TF-IDF algorithm to generate tailored diet plans. Additionally, we address health issues by providing targeted exercise and dietary recommendations based on individual health conditions, ensuring a holistic approach to wellness. The system's versatility and adaptability cater to users' unique needs, offering them strength assessment, personalized diet plans, and health issue management in a seamless and user-friendly manner.

AUTHOR : *Sathya A, Vignesh A, Akash M, Gokulakrishnan S, Narendran.M*

YEAR : 2024

2.3 Nonparametric Model Prediction for Intelligent Regulation of Human Cardiorespiratory System to Prescribed Exercise Medicine

Intelligent regulation for human exercise behaviors becomes significantly necessary for exercise medicine after the COVID-19 epidemic. The key issue of exercise regulation and its potential development for intelligent exercise is to describe human exercise physiological behaviors in a more accurate and sufficient manner. Here, a non-parametric modeling method with kernel-based regularization is presented to estimate cardiorespiratory biomarkers (i.e., oxygen uptake (VP O2) and carbon dioxide output (VP CO2) by merely non-invasively monitoring the indicator of exercise intensity (e.g., walking speed). Using the kernel-based non-parametric modeling, we show that VP O2 and VP CO2 behaviors in response to continuous and diversied exercise intensity stimulations can be quantitatively described. Furthermore, the dataset from the stairs experiment with a proper protocol is applied in the kernel parameter selection, and this selection approach is compared with the numerical simulation approach. The comparison results illustrate an improvement of 4:18% for oxygen uptake and 7:63% for carbon dioxide output in a half period, and 11:00% for oxygen uptake and 12:60% for carbon dioxide output in one period when using the kernel parameter selected from the stairs exercise. Moreover, the advantages of using the non-parametric model, the necessity of suffcient stimulation for identification and the importance of the kernel regularization term are also addressed in this paper. This method provides fundamental work for the practice of intelligent exercise.

AUTHOR : HAIRONG Y, YI ZHANG, LIN YE, HAMZAH M. ALQUDAH, KAIRUI GUO, AHMADREZA ARGHA, BRANKO G. CELLER, RONG SONG, STEVEN SU

YEAR : December 2020

2.4 A Physical Activity Recommender System for Patients With Arterial Hypertension

Recommender systems have been applied in several areas, including e-Health systems, which refers to information and health services enhanced through technology. However, most studies aim at imposing rules to improve lifestyle, rather than recommending nutrition and physical activities. In this context, this study aims to develop a system for recommending physical activities for hypertensive patients to create opportunities for the patients so they can search for and create a healthy lifestyle. To achieve this goal, we elaborated on a hypertensive user profile model, called HyperModel2PAR, and a physical activity recommender system for hypertensive patients, called HyperRecSysPA. The model resulting from this study is composed of 32 elements divided into three groups, which were used in the modeling of user profiles within the system for generating HyperRecSysPA recommendations. The developed system was validated by physicians who answered a speci_c questionnaire. As a result, _ 75% of the recommendations generated were approved. Therefore, this study has prospective contributions to the literature, since both models obtained conclusive results in the assessments performed.

AUTHOR : LUCIANO RODRIGO FERRETTO, ERICLES ANDREI BELLEI, DAIANA BIDUSKI, LUIZ CARLOS PEREIRA BIN, MIRELLA MOURA MORO, CRISTIANO ROBERTO CERVI, ANA CAROLINA BERTOLETTI DE MARCHI.

YEAR : APRIL, 2020

2.5 An Advanced Deep Learning Approach for Dietary Recommendations using ROBERTA

This project introduces a novel Food Recommendation System empowered by the Roberta model, a state-of-the-art transformer-based architecture in natural language processing. Leveraging Roberta’s advanced language understanding capabilities, our system aims to revolutionize the domain of dietary recommendations by providing personalized and context-aware suggestions to users. The Roberta model plays a pivotal role in capturing intricate textual nuances related to nutritional content, dietary preferences, and individual health profiles, thereby enhancing the accuracy and relevance of the recommendations. The methodology involves the integration of Roberta into the recommendation system, detailing the fine tuning process and adaptation of the model to the unique challenges posed by dietary recommendation tasks. We explore the incorporation of relevant nutritional databases, ensuring that the Roberta model is well-versed in the domain-specific knowledge required for effective food suggestions. The system's performance is evaluated through various metrics, showcasing its ability to outperform traditional rule-based and machine learning-based approaches in providing tailored dietary advice.

Furthermore, this project presents insightful curves and analyses derived from the model's training process, illustrating the learning trajectory, and highlighting key milestones in its proficiency. The experimental results demonstrate the system's effectiveness in adapting to diverse user preferences and evolving dietary trends, establishing its potential to positively impact users' health and well-being. Ultimately, our Food Recommendation System, driven by the Roberta model, signifies a significant advancement in the fusion of deep learning and nutritional science. The methodology curves presented herein offer a comprehensive understanding of the model's learning dynamics, emphasizing its role in revolutionizing the landscape of personalized dietary recommendations. The promising results obtained pave the way for future research and applications, underscoring the potential of advanced language models in enhancing the precision and efficacy of food recommendation systems.

AUTHOR: Bajjuri Usha Rani, Terli Joshnavalli, Betha Srikanth Reddy, Atluri Sreelaasya
YEAR : June 2024

2.6 A Novel Time-Aware Food Recommender-System Based on Deep Learning and Graph Clustering

Food recommender-systems are considered an effective tool to help users adjust their eating habits and achieve a healthier diet. This paper aims to develop a new hybrid food recommender-system to overcome the shortcomings of previous systems, such as ignoring food ingredients, time factor, cold start users, cold start food items and community aspects. The proposed method involves two phases: food content-based recommendation and user-based recommendation. Graph clustering is used in the rst phase, and a deep-learning based approach is used in the second phase to cluster both users and food items. Besides a holistic-like approach is employed to account for time and user-community related issues in a way that improves the quality of the recommendation provided to the user. We compared our model with a set of state-of-the-art recommender-systems using ve distinct performance metrics: Precision, Recall, F1, AUC and NDCG. Experiments using dataset extracted from Allrecipes.com demonstrated that the developed food recommender-system performed best.

AUTHOR: MEHRDAD ROSTAMI, MOURADOUSSALAH, VAHID FARRAHI

YEAR : May 2022

2.7 An Overview of Recommendation Techniques and Their Applications in Healthcare

With the increasing amount of information on the internet, recommendation system (RS) has been utilized in a variety of fields as an efficient tool to overcome information overload. In recent years, the application of RS for health has become a growing research topic due to its tremendous advantages in providing appropriate recommendations and helping people make the right decisions relating to their health. This paper aims at presenting a comprehensive review of typical recommendation techniques and their applications in the field of healthcare. More concretely, an overview is provided on three famous recommendation techniques, namely, content-based, collaborative filtering (CF)-based, and hybrid methods. Next, we provide a snapshot of five application scenarios about health RS, which are dietary recommendation, lifestyle recommendation, training recommendation, decision-making for patients and physicians, and disease-related prediction. Finally, some key challenges are given with clear justifications to this new and booming field. Recommendation systems Categories E-commerce E-commerce Music Video Recommendation systems

Categories E-commerce Movie Social network News Music Music Video Movie Social network News.

AUTHOR: Wenbin Yue, Zidong Wang, Jieyu Zhang, and Xiaohui Liu

YEAR : April 2021

2.8 Diet Plan and Home Exercise Recommendation system using Smart Watch

Obesity and sedentary lifestyles have become significant health concerns globally. To solve these issues, this system presents a Diet Plan and Home Exercise Recommendation System (SYP) that utilizes users' smartwatch data and pathological information to generate personalized diet plans and exercise recommendations. The proposed SYP system leverages the capabilities of modern smartwatches, which are equipped with various sensors to collect comprehensive health data. Additionally, it incorporates users' pathological data obtained through medical tests. By integrating these diverse datasets, the system can provide tailored recommendations based on an individual's specific health profile. The SYP system operates in two main phases: data collection and recommendation generation. During the data collection phase, the system collects and analyzes data from users' smartwatches and pathological records, such as heart rate, sleep patterns, blood pressure, glucose levels, and body mass index. The collected data is then processed to extract relevant features and construct a comprehensive health profile for each user. In the recommendation generation phase, the SYP system employs machine learning algorithms to analyze the user's health profile and generate personalized diet plans and home exercise recommendations. The generated recommendations are designed to be practical, feasible, and aligned with the user's health objectives.

AUTHOR : Shreeraj Gaikwad, Pratik Awatade, Yadnesh Sirdeshmukh, Prof. Chandan Prasad

YEAR : *2023*

2.9 Life Expectancy Prediction And Diet Recommendation System for Cardiovascular and Diabetes Disease Using Machine Learning

In the current era, people face many health issues and diseases due to inadequate and inappropriate food intake. People rely on medicine rather than having a proper dietary plan due to a lack of concise information on a proper diet. The diverse options in food components and people's preferences with underlying health conditions make it difficult to perform real-time nutrition selection that fulfills a proper dietary plan. This problem is addressed through the implementation of a machine learning algorithm that effectively detects diseases and calculates life expectancy, enabling the formulation of suitable diet plans to mitigate their impact. The proposed work focuses on two common diseases: Diabetes and Cardiovascular Disease.A supervised classification algorithm has been used for predicting diseases and an unsupervised clustering algorithm has been used for diet recommendation. The objective is to facilitate convenient disease prediction at home and offer personalized, healthy diet recommendations. By motivating users to adopt a healthy lifestyle, the proposed work aims to prevent or reduce the influence of diseases.

AUTHOR : Dr.Lakshmi K, Dr. Deeba K, Vani Harave, Sneha Bharti

YEAR : 2024

2.10 SmartHealth: Personalized Diet and Exercise Plans Using Similarity Modeling

Due to the growing prevalence of chronic diseases stemming from unhealthy lifestyles, a personalized approach to patient care is crucial. This paper delves into a system that utilizes cosine similarity and Pearson correlation to generate tailored diet and exercise plans, effectively managing chronic diseases. The system focuses on common chronic conditions like diabetes, hypertension, and thyroid disorders. Through sophisticated similarity modeling for diet and exercise, the proposed system provides integrated and personalized lifestyle recommendations, outperforming non personalized or basic rule-based systems.

AUTHOR : Kiran S Kulkarni, Kiran S Kulkarni, Darvesh Bansal, Ashaq Hussain Ganie

YEAR : March 2024

CHAPTER 3

SYSTEM DESIGN

3.1 SYSTEM ARCHITECTURE DIAGRAM

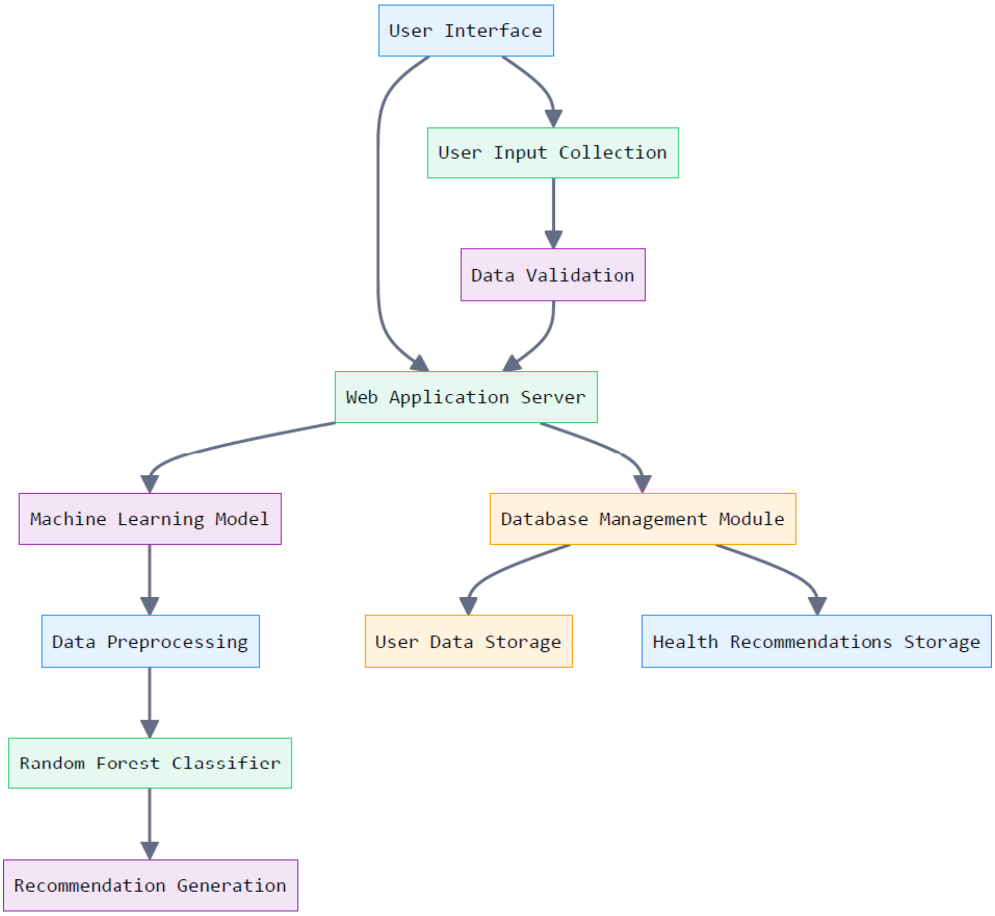


Figure3.1: System Architecture Diagram

The Health Buddy system follows a three-tier architecture: presentation layer, application layer, and data layer. The presentation layer consists of a webinterface where users input their health data and view recommendations. The application layer contains the core ML model (Random Forest), recommendationengine, and data processing modules. The data layer manages two databases - onefor user profiles and health data, another for the medical knowledge base containing conditions and recommendations. The system uses RESTful APIs for communication between layers, with separate modules for data validation, authentication, and recommendation generation.

3.2 CLASS DIAGRAM

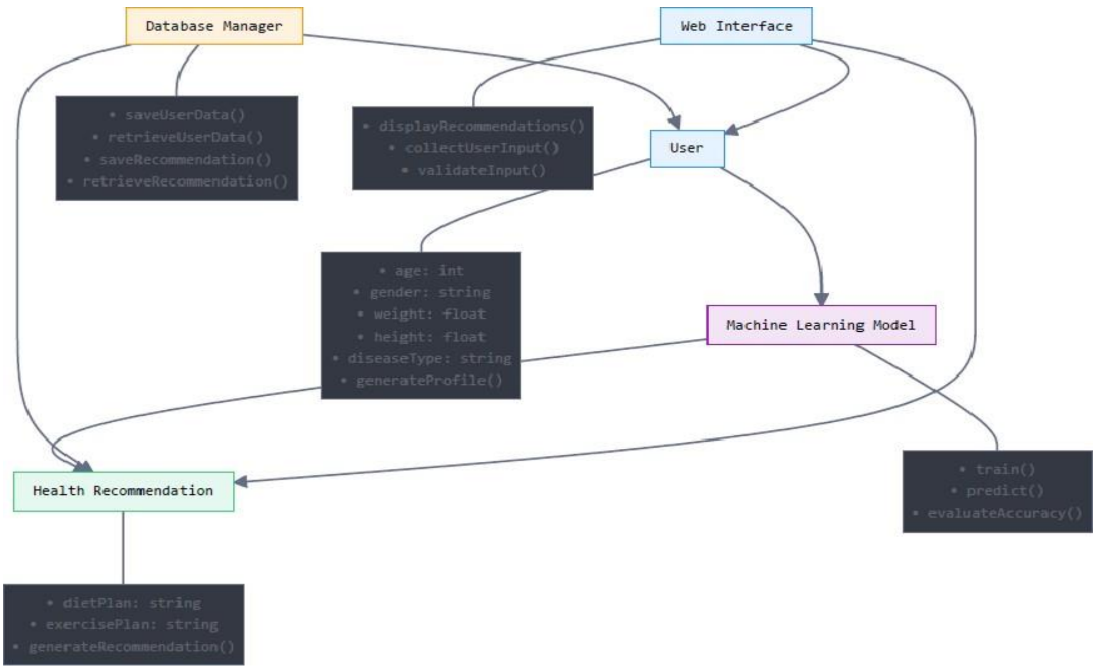


Figure 3.2: Class Diagram

The core classes include: User (manages user profiles with attributes like age, weight, height), HealthData (stores medical conditions and measurements), RecommendationEngine (generates personalized advice using ML model), MLModel (implements Random Forest algorithm), Database (handles data persistence), and UserInterface (manages web interactions). Key relationships include User having one-to-many HealthData records, RecommendationEngine using MLModel for predictions, and Database serving both User and HealthData storage needs. Classes implement methods for data validation, recommendation generation, and profile management.

3.3 ACTIVITY DIAGRAM

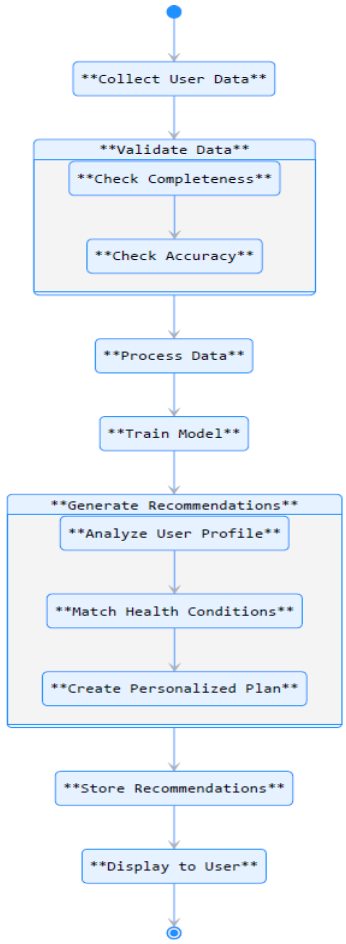


Figure 3.3: Activity Diagram

The workflow begins with user registration/login, followed by health data input. The system validates input data and processes it through the ML model. Based on analysis, the system generates personalized recommendations. Users can view, save, or modify recommendations. The system continuously monitors user feedback and updates recommendations accordingly. Alternative flows include data validation failures, system alerts for concerning health patterns, and periodic recommendation updates based on new user data.

3.4 SEQUENCE DIAGRAM

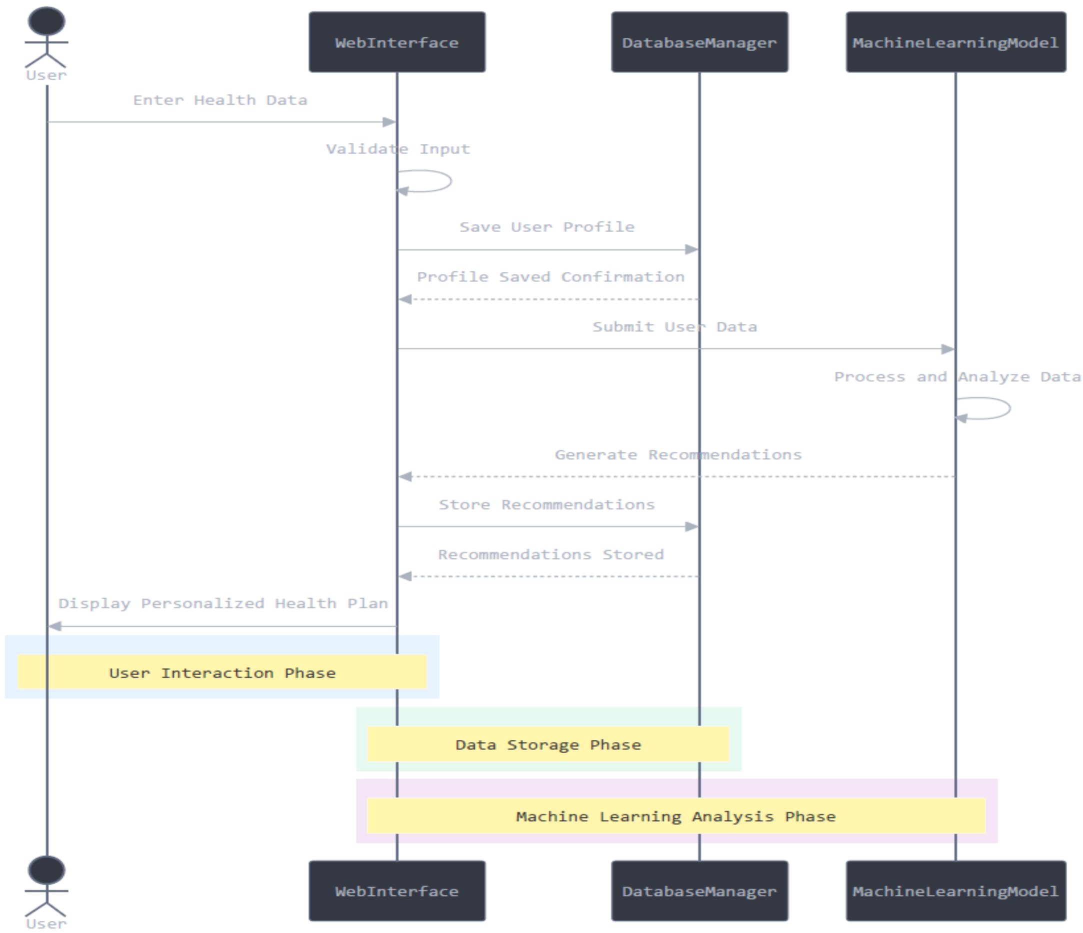


Figure 3.4: Sequence Diagram

The interaction sequence starts with user authentication, followed by health data submission to the interface. The interface forwards data to the recommendation engine, which requests user history from the database. The ML model processes combined data to generate recommendations. Results are stored in the database and returned to the interface for display. Error handling sequences include validation failures and data retrieval issues. The system maintains session state throughout interactions.

3.5 DATA FLOW DIAGRAM

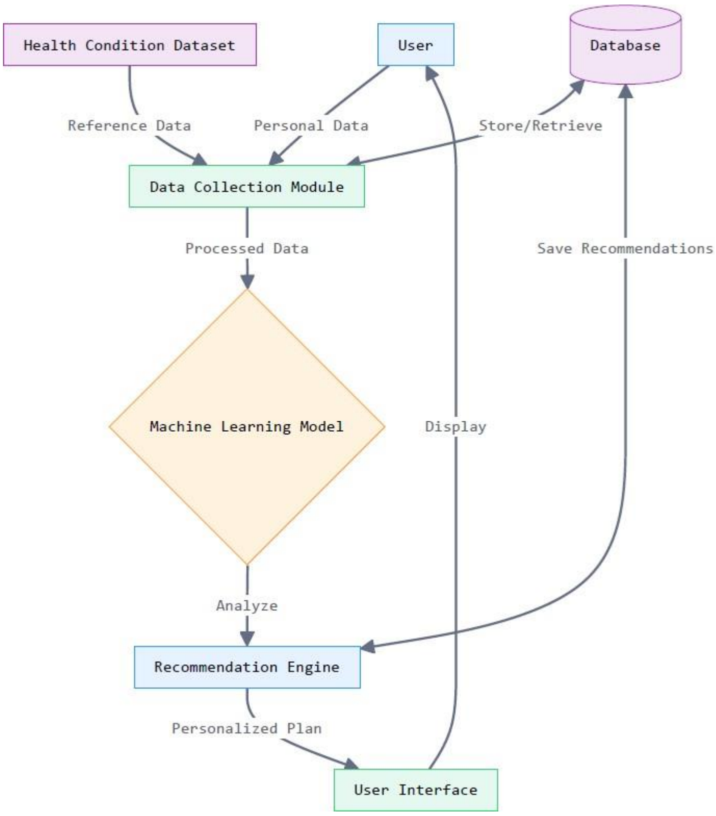


Figure 3.5: Dataflow diagram

Data flows from user input through validation processes to the central database. The ML model receives processed data from multiple sources: user input, medical knowledge base, and historical records. Recommendations flow through the recommendation engine to user interface. External data flows include healthcare provider inputs and system updates. Data transformations occur at validation, analysis, and recommendation generation stages. The system maintains separate flows for personal data and anonymized analytics

CHAPTER 4

EXISTING SYSTEM: MyFitnessPal

4.1 INTRODUCTION

MyFitnessPal is a popular fitness and nutrition tracking app that empowers users to monitor their daily food intake and exercise routines. It offers a comprehensive platform for individuals to set personalized health goals, track progress, and make informed lifestyle choices.

4.2 CORE FEATURES AND FUNCTIONALITIES

4.2.1 Food Tracking*:*

- Extensive food database with nutritional information.
- Barcode scanning for quick food entry.
- Customizable meal plans and recipes.
- Calorie tracking and macronutrient breakdown.

4.2.2 Exercise Tracking:

- Built-in exercise library with various activities.
- Manual exercise entry with custom workouts.
- Integration with wearable devices for automatic exercise tracking.

4.2.3 Community and Social Features:

- Forums and social groups for support and motivation.
- Friend connections and challenges.

- Sharing progress and achievements.

4.2.4 Personalized Insights and Coaching:

- Customized meal plans and workout routines.
- Progress tracking and goal setting.
- Personalized nutrition advice.

4.3 STRENGTHS AND WEAKNESS

4.3.1 Strengths:

- User-friendly interface and intuitive design.
- Comprehensive food and exercise database.
- Strong community and social features.
- Integration with wearable devices.
- Personalized recommendations and coaching**.**

4.3.2 Weaknesses:

- Limited customization options for advanced users.
- Reliance on user input for accurate data.
- Potential for data privacy concerns.
- Subscription-based premium features.

4.4 POTENTIAL AREAS FOR IMPROVEMENT

1. **Enhanced AI and Machine Learning:**

    - Improve food recognition accuracy through advanced image analysis.

- Develop personalized workout plans based on individual fitness levels and goals.
- Utilize AI to provide more accurate calorie and macronutrient estimations.

2. **Expanded Social Features:**

- Introduce real-time chat and video features for better community interaction.
- Facilitate group challenges and competitions.
- Offer virtual fitness classes and group workouts.

3. **Integration with Healthcare Providers:**

- Allow users to share their health data with healthcare professionals.
- Collaborate with healthcare providers to develop personalized health plans.

4. **Mental Health Integration:**

- Incorporate mindfulness and meditation exercises.
- Offer tools for stress management and emotional well-being.

5. **Data Privacy and Security:**

- Strengthen data encryption and security measures.
- Provide clear privacy policies and user controls.

CHAPTER 5

PROPOSED SYSTEM

5.1 MODULES

The project consists of Four modules. They are as follows,

1. User Interface Module
2. Data Input Module
3. Recommendation Engine Module
4. Dataset Management Module

5.1.1 User Interface Module

The User Interface Module serves as the front-end component of the application, providing users with a web-based platform to interact with it. Through this interface, users can easily input essential details such as age, gender, and disease type using well-structured forms and buttons. The design emphasizes user-friendliness, allowing individuals with varying levels of technical knowledge to navigate the application seamlessly. For instance, users can select their disease from a dropdown list, enter their age, and provide health metrics like weight and height. This web interface not only facilitates efficient data entry but also enhances user engagement by making the experience intuitive and accessible.

5.1.2 Data Input Module

The Data Input Module is responsible for capturing the necessary user information required for generating personalized health recommendations. This module collects key details such as age, gender, disease type, weight, and height.

For example, a user might input their age (35), select their gender (male), choose their disease (Typhoid), and provide their weight (75 kg) and height (175 cm). To ensure the integrity of the data collected, this module incorporates validation techniques that check the accuracy and acceptability of inputs, preventing erroneous data entries. This robust validation process guarantees that all collected data is reliable and suitable for subsequent analysis.

5.1.3 Dataset Management Module

Given the absence of existing datasets for this specific application, the Dataset Management Module is tasked with creating and maintaining a custom dataset. This dataset consists of vital attributes, including Patient ID, Age, Weight, Height, Gender, Disease, Dietary Recommendations, and Exercise Guidance. It encompasses a variety of common and chronic conditions, such as Typhoid, Cholera, and COVID-19, and features diverse patient profiles to ensure a comprehensive training foundation for the machine learning model. Thismodule also manages data storage through a database system, allowing for securestorage, efficient retrieval, and timely updates of patient information as new data is collected through user interactions.

5.1.4 Recommendation Engine Module

The Recommendation Engine Module serves as the analytical core of the application, implementing a Random Forest machine learning algorithm to analyze user data and generate personalized health recommendations. Initially, this module prepares and preprocesses the dataset to enhance its quality for training. The Random Forest model then learns to identify patterns and relationships between various patient attributes and their corresponding dietary and exercise recommendations during the training phase. Recommendations are fine-tuned based on individual factors such as Body Mass Index (BMI), gender, and age. For instance, users with a higher BMI may receive tailored advices emphasizing weight management and low-impact exercises, while gender-specific nutritional needs are considered as well. Ultimately, this module equips the application with the capability to provide users with targeted advice, such as suggesting low-calorie diets and moderate exercises for older adults with elevated BMIs, thereby ensuring that recommendations are aligned with each user's unique health profile.

5.2 FUTURE ENHANCEMENT

- **Enhanced Interactivity:**

  To provide a more personalized and engaging experience, the app can incorporate features like interactive tutorials, gamification elements, and real-time chat support with healthcare professionals.
- **Utilization of Medical Database:**

  By leveraging a comprehensive medical database, the app can offer accurate disease diagnosis, evidence-based recommendations, drug interaction checks, and personalized treatment plans.
- **Real-time Monitoring:**

  Real-time monitoring of vital signs and health parameters, coupled with early warning systems and remote patient monitoring, can significantly improve health outcomes.
- **Timely Reminders for Medication:**

  The app can send personalized medication reminders, integrate with smart devices, and provide support for adherence to medication schedules.
- **Healthcare Professional Intervention:**

  Telehealth consultations, collaborative care, and emergency response features can enhance the accessibility and quality of healthcare services.

CHAPTER 6

RANDOM FOREST ALGORITHM

6.1 INTRODUCTION

Random Forest is a versatile machine learning algorithm that belongs to the ensemble learning family. It combines multiple decision trees to make accurate predictions. By aggregating the decisions of individual trees, Random Forest reduces overfitting and improves generalization performance.

6.2 HOW RANDOM FOREST WORKS

6.2.1 Random Selection of Features:

For each decision tree, a random subset of features is selected from the entire feature set. This randomness helps to reduce correlation between trees and improves the model's overall performance.

6.2.2 Construction of Decision Trees:

Each decision tree is constructed using a subset of the training data and the randomly selected features. The trees are grown deep, without pruning, to maximize their diversity.

6.2.3 Prediction:

To make a prediction for a new data point, each decision tree in the forest casts a vote. The most frequent prediction among the trees is considered the final prediction.

6.3 ADVANTAGES OF RANDOM FOREST:

High Accuracy: Random Forest often achieves high accuracy due to its ensemble nature.

Robustness to Overfitting: By averaging the predictions of multiple trees, the model is less prone to overfitting.

Feature Importance: Random Forest can be used to assess the importance of different features in the dataset.

Handles Missing Values: The algorithm can handle missing values effectively.

Versatility: It can be applied to both classification and regression problems.

6.4 DISADVANTAGES OF RANDOM FOREST:

Complexity: Random Forest can be computationally expensive, especially for large datasets.

Interpretability: While individual decision trees are interpretable, the ensemble nature of Random Forest can make it difficult to understand the model's decision-making process.

6.5 USAGE OF RANDOM FOREST IN HEALTH BUDDY PROJECT:

Analyze patient data: Identify patterns and correlations between patient characteristics and disease outcomes.

Predict disease risk: Use patient data to predict the likelihood of developing specific diseases.

Personalize treatment plans: Tailor treatment recommendations based on individual patient factors.

Optimize healthcare resource allocation: Identify high-risk patients and allocate resources accordingly.

CHAPTER 7
CONCLUSION

In conclusion, The Personalized Health Advisor project showcases the potential of machine learning in providing tailored health recommendations. By combining user-friendly interfaces with advanced algorithms, it offers a scalable solution for post-diagnosis care. While the system shows promise in supporting patient health management, it's important to note its limitations and the need for continued development and medical professional involvement. This project lays the groundwork for more advanced, AI-driven personalized healthcare solutions in the future.

APPENDICES

A1. MAIN APPLICATION CODE

app.py

```
from flask import Flask, request, render_template
import pandas as pd
import os
import pickle
import psycopg2
from psycopg2 import sql

app = Flask(__name__)

# Set the full path to your CSV file
CSV_FILE =
'C:\\Users\\zerub\\OneDrive\\Desktop\\new\\data\\patient_data.csv'
MODEL_FILE =
'C:\\Users\\zerub\\OneDrive\\Desktop\\new\\data\\model.pkl' # Path to your
trained model

# Database connection details
DB_HOST = 'localhost' # e.g., 'localhost' or your database server
DB_NAME = 'health_buddy'
DB_USER = 'postgres'
DB_PASS = ''

def get_db_connection():
    conn = psycopg2.connect(
        host=DB_HOST,
        database=DB_NAME,
        user=DB_USER,
        password=DB_PASS
    )
    return conn

def load_disease_recommendations():
    if not os.path.exists(CSV_FILE):
        raise FileNotFoundError(f"CSV file not found at {CSV_FILE}")
```

```
    try:
        df = pd.read_csv(CSV_FILE, encoding='ISO-8859-1')
    except UnicodeDecodeError as e:
        print(f"Error reading the file due to encoding: {e}")
        return None

    disease_recommendations = {}

    for _, row in df.iterrows():
        disease = row['Disease'].lower()
        if disease not in disease_recommendations:
            disease_recommendations[disease] = {
                "food_recommended": [],
                "food_to_avoid": [],
                "exercise": []
            }

        if pd.notna(row['Food Recomended']):
                    disease_recommendations[disease]['food_recommended'].append(
          row['Food Recomended'])
        if pd.notna(row['Food to be avoided']):
            disease_recommendations[disease]['food_to_avoid'].append(row['Food
to be avoided'])
        if pd.notna(row['Exercise']):
            disease_recommendations[disease]['exercise'].append(row['Exercise'])

    return disease_recommendations

disease_recommendations = load_disease_recommendations()

def load_model():
    with open(MODEL_FILE, 'rb') as file:
        model = pickle.load(file)
    return model

model = load_model()
```

```
@app.route('/')
def home():
    return render_template('screen1.html')

@app.route('/dietary_recommendations', methods=['POST'])
def dietary_recommendations():
    patient_id = request.form['patient_id']
    age = request.form['age']
    weight = request.form['weight']
    height = request.form['height']
    gender = request.form['gender']
    disease = request.form['disease'].lower()

    diet_recommendations = generate_dietary_recommendations(disease)
    exercise_recommendations = generate_exercise_recommendations(disease)

    # Store patient info and recommendations in the database
    store_patient_data(patient_id, age, weight, height, gender, disease,
diet_recommendations, exercise_recommendations)

    return render_template('screen2.html',
                           diet_recommendations=diet_recommendations,
                           patient_id=patient_id,
                           age=age,
                           weight=weight,
                           height=height,
                           gender=gender,
                           disease=disease)

@app.route('/exercise_recommendations', methods=['POST'])
def exercise_recommendations():
    disease = request.form['disease'].lower()
    exercise_recommendations = generate_exercise_recommendations(disease)

    return render_template('screen3.html',
                           exercise_recommendations=exercise_recommendations,
                           disease=disease)
```

```
def generate_dietary_recommendations(disease):
    if disease in disease_recommendations:
        # Remove duplicates by converting to a set and back to list
        food_recommended =
list(set(disease_recommendations[disease]["food_recommended"]))
        food_to_avoid =
list(set(disease_recommendations[disease]["food_to_avoid"]))

        return {
            "food_recommended": " | ".join(food_recommended),
            "food_to_avoid": " | ".join(food_to_avoid)
        }
    else:
        return {"food_recommended": "No specific recommendations",
"food_to_avoid": "No specific avoidances"}

def generate_exercise_recommendations(disease):
    if disease in disease_recommendations:
        # Remove duplicates from exercise recommendations
        exercise_recommendations =
list(set(disease_recommendations[disease]["exercise"]))
        if exercise_recommendations:
            return " | ".join(exercise_recommendations)

    return "No specific exercise recommendations available for this disease."

def store_patient_data(patient_id, age, weight, height, gender, disease,
diet_recommendations, exercise_recommendations):
    conn = get_db_connection()
    cursor = conn.cursor()

    # Insert patient data and dietary and exercise recommendations into the
database
    insert_query = sql.SQL("""
        INSERT INTO patient_data (patient_id, age, weight, height, gender,
disease, food_recommended, food_to_avoid, exercise_recommendations)
```

```
        VALUES (%s, %s, %s, %s, %s, %s, %s, %s, %s)
    """)

    cursor.execute(insert_query, (
        patient_id,
        age,
        weight,
        height,
        gender,
        disease,
        diet_recommendations["food_recommended"],
        diet_recommendations["food_to_avoid"],
        exercise_recommendations
    ))

    conn.commit()
    cursor.close()
    conn.close()

if __name__ == '__main__':
    app.run(debug=True)
```

A2. SAMPLE SCREENSHOTS

A2.1 When the patient have consulted the doctor

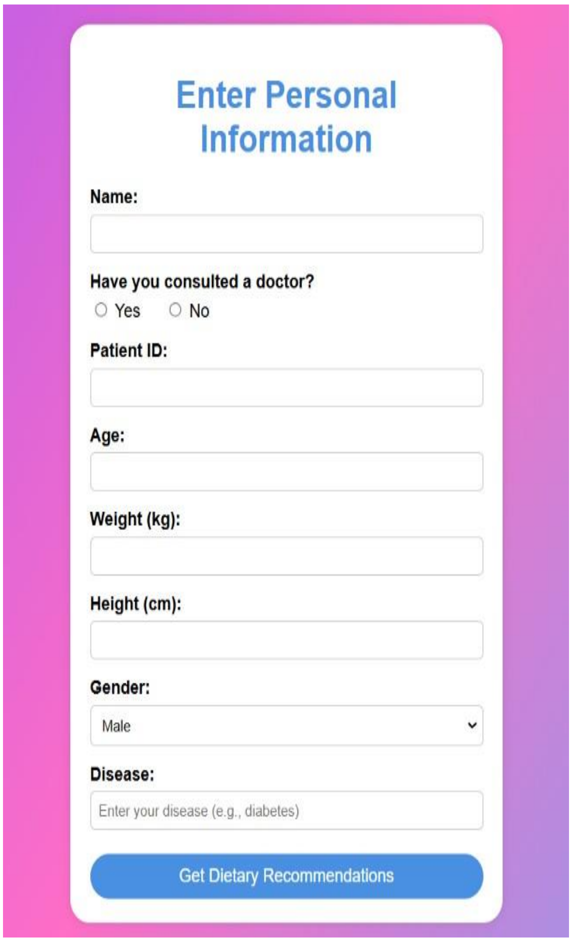


Figure A.1: Data input screen

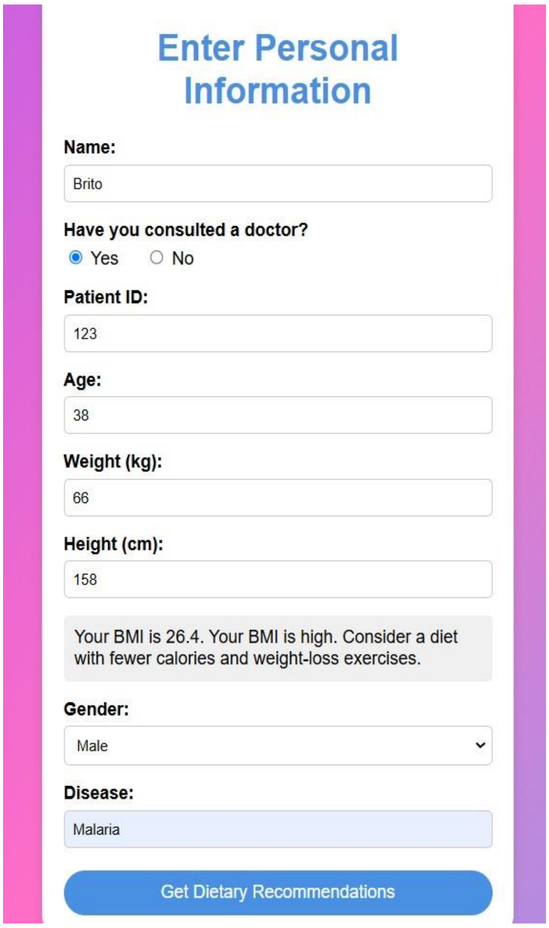


Figure A.2 : Sample user inputs

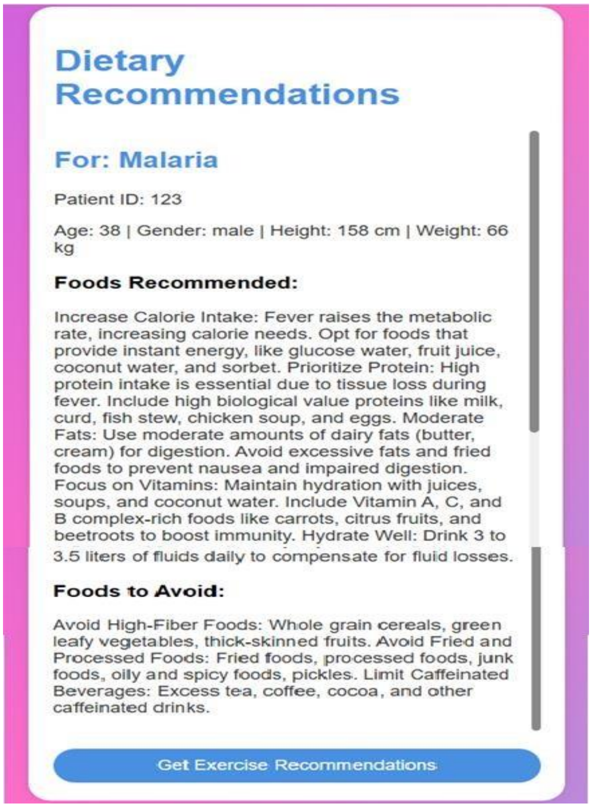


Figure A.3: Dietary recommendations for malaria

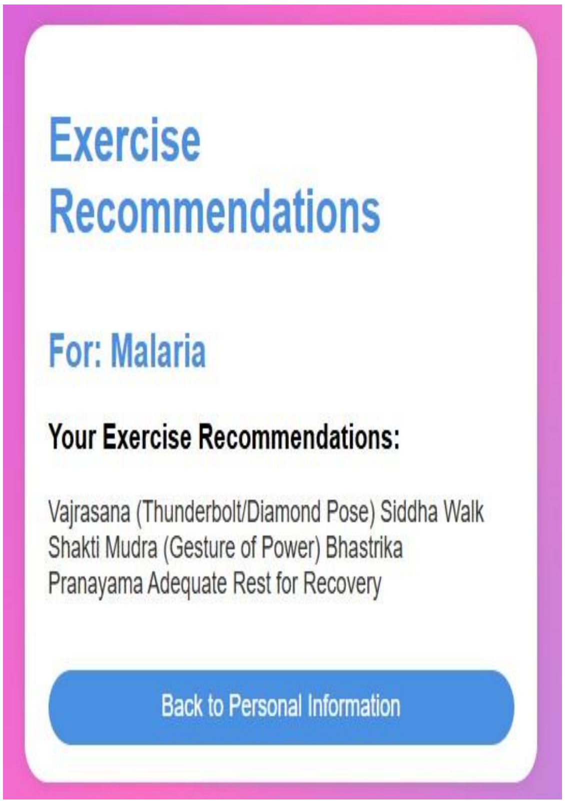
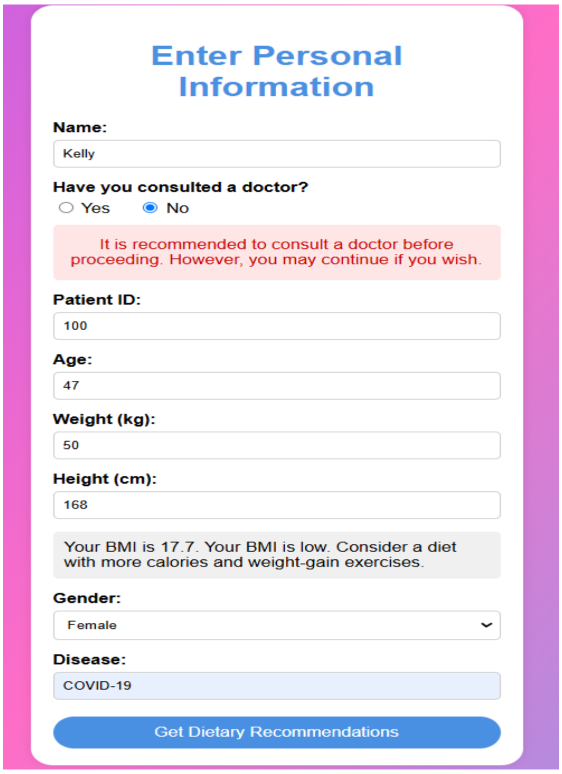
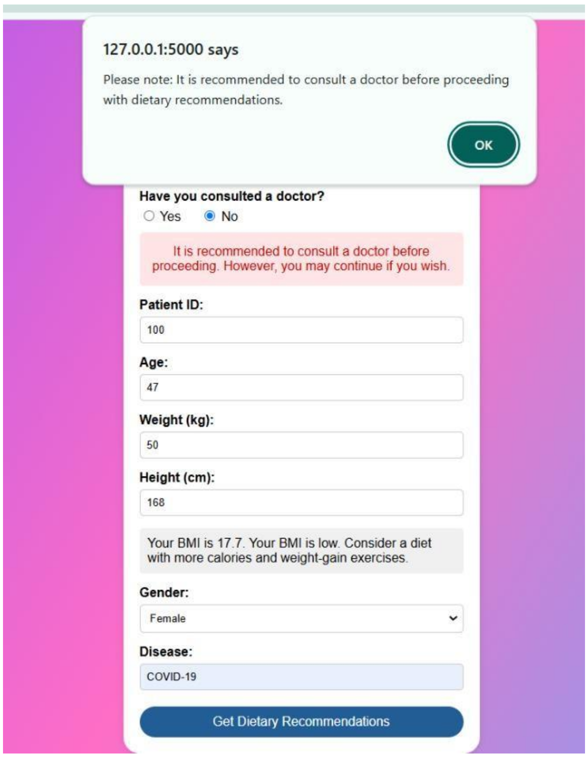


Fig A.4: Exercise recommendation for malaria

A2.2 When the patient have not consulted the doctor



FigureA.5(a): When patient did not consult doctor



FigureA.5(b): Notification for patient

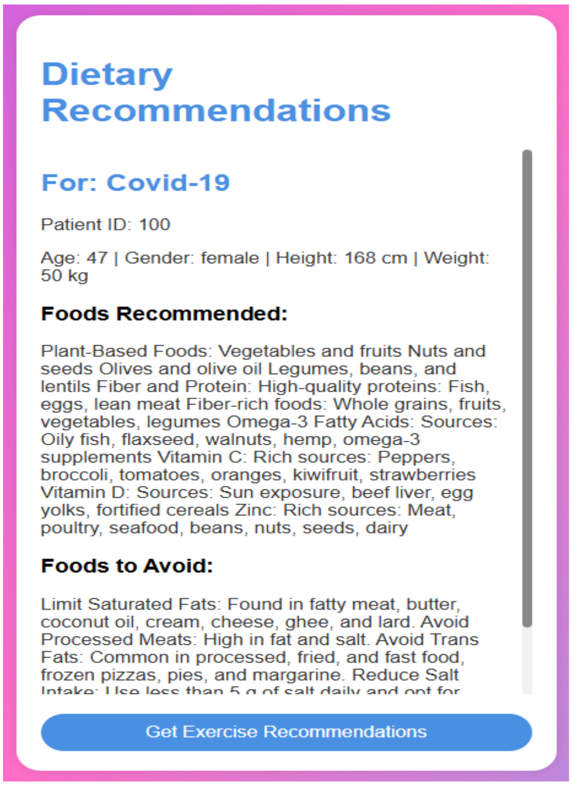
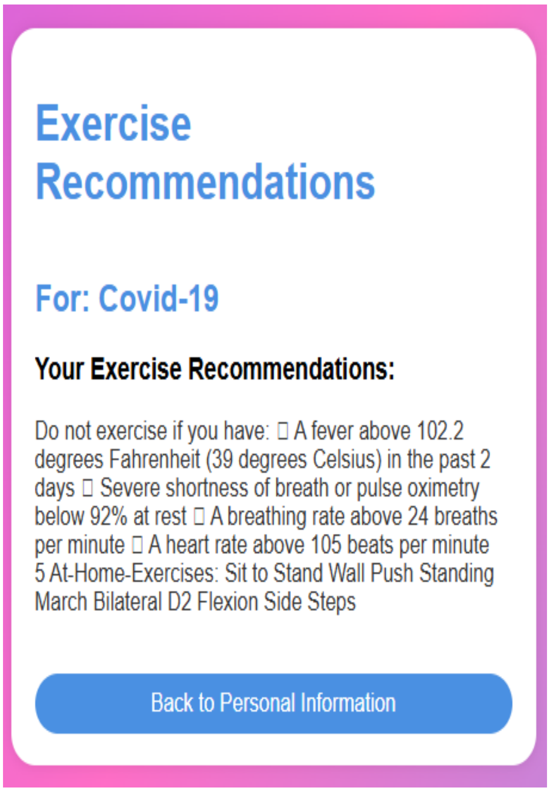


Fig A.6: Dietary recommendations for Covid19



FigA.7:Exercise recommendations for Covid19

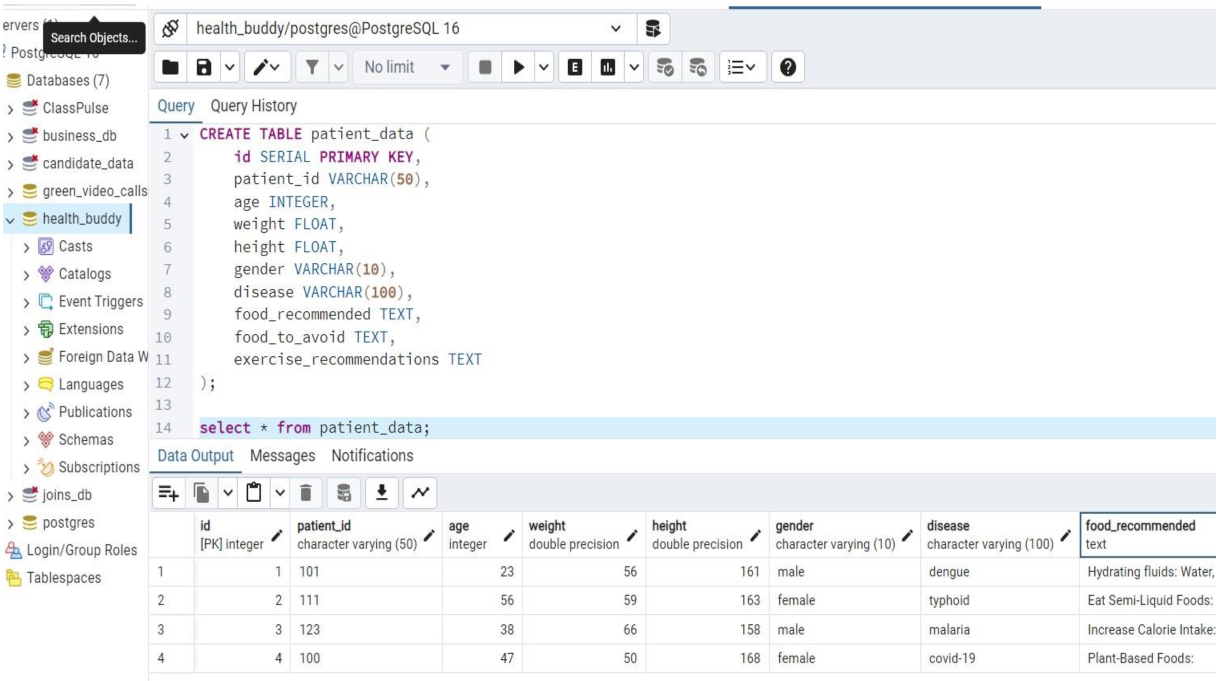


Figure A.8: Postgres Database storing patient data

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