# PERSONALIZED DIET RECOMMENDATION SYSTEM FOR DIABETIC PATIENTS

Submitted in partial fulfillment of the requirements
of the degree of

**B. Tech. Computer Engineering**

By


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(Autonomous College Affiliated to the University of Mumbai)
NAAC Accredited with "A" Grade (CGPA : 3.18)


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# CERTIFICATE

This is to certify that the project entitled **"Personalized Diet Recommendation System for Diabetic Patients"** is a bonafide work of **Riya Shah (60004200118), Khushi Gupta (60004200136) and Riya Bihani (60004200139)** submitted to the University of Mumbai in partial fulfillment of the requirement for the award of the degree of B. Tech. in Computer Engineering

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## Project Report Approval for B.Tech.

This project report entitled ***Personalized Diet Recommendation System for Diabetic Patients*** by ***Riya Shah, Khushi Gupta and Riya Bihani*** is approved for the degree of ***B.Tech. in Computer Engineering.***

Examiners

1.--------------------------------------------

2.--------------------------------------------

Date:

Place:

# Declaration

I/We declare that this written submission represents my/our ideas in my/our own words and where others' ideas or words have been included, I/We have adequately cited and referenced the original sources. I/We also declare that I/We have adhered to all principles of academic honesty and integrity and have not misrepresented or fabricated or falsified any idea/data/fact/source in my/our submission. I/We understand that any violation of the above will be cause for disciplinary action by the Institute and can also evoke penal action from the sources which have thus not been properly cited or from whom proper permission has not been taken when needed.

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# Abstract

Diabetes, a pervasive chronic condition, demands meticulous management, particularly in the realm of diet, to mitigate its impact on health. The challenges faced by individuals with diabetes, such as the need for a balanced and diabetes-friendly diet, are further complicated by the integration of personalized exercise suggestions. To address these complexities, a personalized diet recommendation system emerges as a vital tool to empower individuals in effectively managing diabetes.

This comprehensive project report delves into the multifaceted landscape of diabetes management. It begins with an exploration of the challenges faced by diabetes patients, emphasizing the crucial role of diet regulation and the added complexities of maintaining a consistent and healthy lifestyle. The motivation behind the project lies in addressing these challenges by offering a personalized solution that provides tailored diet plans, exercise recommendations, and an AI-driven chatbot for real-time guidance.

The proposed solution involves a systematic approach, encompassing data collection, preprocessing, feature engineering, model design, training, and integration of essential components. Key steps include the development of an intelligent chatbot using Natural Language Processing (NLP) techniques, the creation of personalized diet plans and exercise recommendations based on deep learning models, and the design of a user-friendly web app interface. The report outlines the literature review, functionality, requirements, and future scope of the project, emphasizing its potential to revolutionize diabetes management.

This project aims not only to offer a practical solution to the challenges faced by individuals with diabetes but also to pave the way for a dynamic, user-centric platform that stays ahead of technological advancements in diabetes care.

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# List of Abbreviations

| Sr. No. | Abbreviation | Expanded form |
|---|---|---|
| 1. | AI | Artificial Intelligence |
| 2. | RAG | Retrieval Augmented Generation |
| 3. | LLM | Large Language Model |
| 4. | RFE | Recursive Feature Elimination |
| 5. | KNN | K-Nearest Neighbors |
| 6. | SVM | Support Vector Machine |
| 7. | BMI | Body Mass Index |

# Chapter 1

# INTRODUCTION

## 1.1 Description

Diabetes, a prevalent chronic condition, necessitates careful management to mitigate its impact on health. Diet plays a pivotal role in regulating blood sugar levels, making personalized nutritional guidance crucial for individuals with diabetes. Achieving a balanced and diabetes-friendly diet is challenging, requiring tailored plans that align with specific nutritional guidelines [1]. Effective health management involves not only dietary considerations but also the integration of customized exercise suggestions to foster a holistic well-being approach. Recognizing the significance of these aspects, a personalized diet recommendation system emerges as a crucial tool to empower individuals in their journey to effectively manage diabetes.

The project is an application designed to empower individuals with diabetes. Offering meticulously crafted diet plans and curated recipes aligned with diabetes-specific nutritional guidelines, the platform aims to foster healthier eating habits and enhance blood sugar management. Beyond traditional dietary guidance, the system includes personalized exercise suggestions tailored to each user's health condition, promoting a holistic approach to well-being. An integral component is the AI-driven chatbot—a personalized diet assistant using natural language processing. Seamlessly integrated, these features create a user-friendly interface, empowering individuals to make informed lifestyle choices and actively participate in their ongoing health journey.

## 1.2 Problem Formulation

Diabetes patients often face a multitude of challenges related to their diet and overall health. One significant issue is the need for meticulous dietary management to regulate blood sugar levels. Balancing carbohydrate intake, choosing foods with a low glycemic index, and monitoring portion sizes become critical tasks. This can lead to feelings of restriction and frustration, as individuals may find it challenging to enjoy a varied and satisfying diet while adhering to these stringent guidelines. Additionally, the constant awareness and decision-making required can contribute to stress and anxiety surrounding food choices.

Another common problem is the struggle to maintain a consistent and healthy lifestyle. Diabetes management requires not only careful attention to diet but also regular physical activity. Finding the motivation and suitable exercise routines that align with individual health conditions can be a hurdle. Moreover, the emotional impact of living with a chronic condition may contribute to issues such as emotional eating or difficulty in adhering to long-term lifestyle changes. The constant need for self-monitoring, medication adherence, and regular medical check-ups adds to the complexity of managing diabetes, impacting the overall well-being and quality of life for individuals facing this health challenge.

## 1.3 Motivation

The personalized diabetes recommendation system [2] addresses the challenges faced by diabetes patients by offering tailored solutions for effective health management. Firstly, the system provides a meticulously crafted diet plan that considers individual preferences and nutritional requirements while adhering to diabetes-specific guidelines. The inclusion of diverse and delicious recipes ensures that users can enjoy a satisfying and varied diet without compromising their health. This not only addresses the challenge of dietary restrictions but also promotes a positive relationship with food.

Moreover, the system integrates personalized exercise suggestions, accounting for individual health conditions and preferences. Tailored workout routines cater to the unique needs of diabetes patients, making physical activity more accessible and enjoyable. Additionally, the inclusion of a personalized diet assistant chatbot serves as a valuable support system. Users can engage in real-time conversations to seek advice, receive instant information on suitable food choices, and find motivation for maintaining a consistent lifestyle.

A distinctive feature that sets this personalized diabetes recommendation system apart from existing apps is its commitment to providing all premium features free of cost. Unlike other applications such as HealthifyMe, MyFitnessPal, etc. that require a subscription for access to advanced functionalities, this system ensures that every user, regardless of financial constraints, can benefit from the full spectrum of features. This inclusivity enhances accessibility and affordability, making comprehensive diabetes management support available to a wider audience. By democratizing access to premium features, the personalized recommendation system aims to create a more equitable and supportive environment for individuals facing the challenges of diabetes.

## 1.4 Proposed Solution

The proposed solution for the project is a personalized diabetes recommendation system designed to tackle the challenges encountered by diabetes patients, providing tailored solutions for effective health management. Here's an elaboration:

Predictive Health Assessment:
The system starts by analyzing various health indicators to predict the likelihood of diabetes. By leveraging data such as blood sugar levels, BMI, family history, and other relevant factors, it provides users with a personalized risk assessment.

Customized Diet Plan:
Once the risk assessment is complete, the system generates a meticulously crafted diet plan. This plan takes into account not only the individual's nutritional requirements but also their preferences. By tailoring the diet to each user's tastes, it ensures that they can adhere to it more easily, promoting long-term compliance.

Adherence to Guidelines:
The diet plan adheres strictly to diabetes-specific guidelines, ensuring that users consume foods that won't negatively impact their health. This includes monitoring carbohydrate intake, controlling portion sizes, and emphasizing nutrient-dense foods.

Diverse and Delicious Recipes:

A key feature of the system is the inclusion of a wide range of diverse and delicious recipes. This variety ensures that users can enjoy a satisfying and varied diet without feeling restricted or deprived. By providing enjoyable food options, it helps to foster a positive relationship with food, which is crucial for long-term adherence to dietary changes.

Diet Assistant Chatbot:

To provide ongoing support, the system incorporates a diet assistant chatbot specifically designed for diabetic patients. This chatbot allows users to engage in real-time conversations, providing them with advice, information on suitable food choices, and motivation to maintain a consistent lifestyle. Users can ask questions, seek clarification, or simply receive encouragement whenever needed.

In summary, the personalized diabetes recommendation system offers a holistic approach to diabetes management by combining predictive health assessment, customized diet planning, adherence to guidelines, diverse recipes, and a supportive chatbot. By addressing the challenges of dietary restrictions, promoting a positive relationship with food, and providing ongoing support, it aims to empower users to take control of their health and lead fulfilling lives despite their condition.

## 1.5 Scope of the Project

The current personalized diet system focuses on aiding individuals with diabetes through a web app with features like tailored diet plans, curated recipes, and exercise suggestions for a balanced lifestyle. Users access and follow personalized meal plans, fostering healthier habits and improved blood sugar management. The system includes a personalized chatbot utilizing natural language processing, offering instant responses and guidance on diabetes, nutrition, and exercise, enhancing user engagement and support in diabetes management.

In the future, the personalized diet recommendation system aims to integrate wearable devices to track real-time health metrics, and foster a supportive community within the app. Collaboration with healthcare providers and the integration of medical records will provide a more comprehensive health solution. The inclusion of multilingual support will ensure accessibility for a diverse user base, while continuous user feedback incorporation will drive iterative improvements in the user interface, features, and overall user experience. The future scope envisions a dynamic and user-centric platform that stays ahead of technological advancements, addressing evolving user needs in diabetes care.

# Chapter 2

# REVIEW OF LITERATURE

The following paragraphs and table describe the literature survey, covering the ideas in the different papers and applications examined for the project.

## 2.1 Papers related to Diet Recommendation system

David M Williams et al. [1] highlight the significance of personalized management in Type 2 Diabetes (T2D), emphasizing patient factors like life expectancy, age, treatment preference, diabetes duration, and psychosocial aspects. Personalized strategies prove more cost-effective and enhance medication adherence, patient satisfaction, and overall quality of life. Recent guidance stresses the consideration of medical factors and comorbidities. The paper explores the nuanced factors influencing physicians' decisions in diabetes management, signaling a shift towards more tailored and patient-centric care.

Omisore et al. [2] introduce a system for diabetes diagnosis and management, featuring a multimodal adaptive neuro-fuzzy inference model and a knowledge-based diets recommender. Trained and validated with Pima Indians and Schorling diabetes datasets, the diagnosis model achieved high accuracies, extending its robust performance to a private dataset from Nigeria. The recommender model, combining diagnoses with eating formulae, generates personalized weekly food plans. Evaluation results demonstrate the system's efficacy, outperforming baseline models and existing machine learning methods. The proposed system holds potential to significantly reduce global morbidity and mortality rates associated with diabetes mellitus.

Nadia Tabassum et al. [3], introduced the Nutrition Diet Expert System designed for doctors to calculate daily calorie requirements and recommend tailored diet plans for diabetic patients. The system aims to help individuals achieve a healthy body weight, control diabetes, and prevent complications. Utilizing fuzzy logic within a recommender system, the model factors in individual dietary requirements at micro and macro nutrient levels. Results indicate the system's efficacy in providing personalized diet plans. The paper proposes an expert agent system with adaptive learning features for improved functionality. Taking into account factors like gender, age group, diabetes type, activity level, BMI, and caloric needs, the system employs fuzzy logic to suggest precise diet plans.

Yera et al. [4] utilized the PRISMA 2020 framework, surveyed 34 relevant papers on food recommender systems for diabetic patients, classifying them into Semantic-based, Optimization-based, Rule-based, and Interaction-based approaches. The analysis identifies strengths and weaknesses, focusing on dataset issues, proposal evaluation, integration, and untapped research potential. Future directions stress the need for a consolidated research framework, enhanced knowledge domain exploitation, and improved personalization. The paper acknowledges areas for further exploration, including distinctions between recommendation approaches for type-1 and type-2 diabetes, aiming to contribute to advancing research in effective food recommender systems for diabetic patients.

Mandar Kulkarni et al. [5] have shown a RAG-based chatbot that uses FAQ data to address credit card-related inquiries. It demonstrates the accuracy and OOD query detection advantages of an internal retrieval embedding model over its public equivalent. It also finds situations in which context that has already been obtained is sufficient to generate responses, suggesting chances for cost and token optimisation. An external policy-based model is suggested to optimise token usage in the RAG pipeline using Reinforcement Learning, which leads to notable cost savings (~31%) and marginal accuracy increases. Although a credit card FAQ chatbot is the main emphasis, the suggested RL technique may be used in many RAG pipelines.

In order to compare Retrieval-Augmented Generation (RAG) versus conventional Language Models (LLMs) utilising hallucination-inducing prompts, Philip Feldman et al.[6] investigates how RAG can solve hallucinations by combining external knowledge with prompts. RAG can still be tricked by contradicting cues, even if it can sometimes increase accuracy. This emphasises the need for more reliable solutions. We address the implications for building trustworthy LLMs and offer helpful suggestions for implementing RAG. Furthermore, our results highlight how important context is for improving response accuracy with RAG, exposing different kinds of errors even in cases where the context is correct and providing guidance for improving RAG systems.

Jiawei Chen et al. [7] methodically examine how RAG affects LLMs, emphasising four key functionalities: counterfactual resilience, information integration, negative rejection, and noise robustness. The study assesses six representative LLMs using the Retrieval-Augmented Generation Benchmark (RGB), a corpus created for evaluating RAG in both English and Chinese. The results show that although LLMs show some resilience to noise, they have serious problems with information integration, negative rejection, and managing incorrect information. These findings highlight the continued challenges of using RAG with LLMs and the need for additional development to guarantee accurate and consistent replies.

Megh Shah et al. [8], published a paper where the challenge of providing personalized diet recommendations is addressed by comparing the performance of multiple algorithms. The researchers implement and evaluate multiple machine learning algorithms, such as decision trees, SVM, random forests, and K-NN, to generate diet recommendations based on individual health data.

Muhammad Exell Febrian et al.[9] used a dataset with a variety of health variables to compare two k-Nearest Neighbour algorithms and the Naive Bayes algorithm for diabetes prediction. The results of Confusion Matrix assessment and supervised machine learning revealed that the Naive Bayes algorithm performed better than KNN. Average accuracy for Naive Bayes was 76.07%, average precision was 73.37%, and average recall was 71.37%. Average accuracy for KNN was 73.33%, average precision was 70.25%, and average recall was 69.37%. Based on the Pima Indians dataset, the study concludes that Naive Bayes is the more advantageous algorithm for diabetes prediction. In order to further improve accuracy and precision, further studies may involve incorporating new algorithms, such as neural networks, and using strategies, such as Particle Swarm Optimisation. The creation of application programmes may also make it easier to put these discoveries into practice.

Isfafuzzaman Tasin et al. [10] presented an automated strategy for predicting diabetes using several machine learning techniques. It includes both a proprietary dataset of Bangladeshi female patients and the publicly accessible Pima Indian dataset. SMOTE and ADASYN preprocessing techniques are used to alleviate class imbalance. AUC, F1 score, precision, recall, accuracy, and other metrics are included in performance evaluation for many machine learning and ensemble approaches. When combined with the ADASYN method, the XGBoost classifier performs best, obtaining an accuracy of 81%. Techniques for domain adaptation further highlight the system's flexibility. Then, a smartphone application and a website are combined with the refined XGBoost framework to provide real-time diabetes prediction. Future research directions include obtaining larger private datasets to improve predictive power and investigating hybrid systems that combine optimisation and fuzzy logic with machine learning.

## 2.2 Existing Apps

Table 1. Existing Apps

| Apps | Features |
| --- | --- |
| Lifesum Healthy Eating and Diet [11] | 1. Utilize an application designed to assist you in improving your diet, ensuring essential nutrient intake, and maintaining hydration levels.<br>2. The app provides a calorie tracking feature for those interested in monitoring calorie intake and enables you to keep tabs on your daily water consumption, ensuring optimal hydration.<br>3. Lifesum boasts an extensive database encompassing foods and beverages from various brands, facilitating quick logging of meals and snacks. Users can also add custom products to their daily meal diary and log exercise activities to track calorie expenditure.<br>4. Presenting the "Life Score," a numerical depiction of your holistic well-being. Respond to 41 questions regarding your dietary choices and exercise routines to generate this score, with a higher value indicating a healthier way of life.<br>5. Although Lifesum provides certain features at no cost, access to advanced |

| | |
|---|---|
| | functionalities requires a premium subscription. By opting for Lifesum Premium, available at $22.00 for three months, $30 for six months, or $45 for a year, users unlock additional features including personalized diet plans, recipes, health tips, and comprehensive macro and carb tracking. |
| Noom [12] | 1. Personalized Plans - Noom offers personalized weight loss and wellness plans tailored to individual goals and health profiles.<br>2. Food Logging - Users can easily log their meals and snacks to track calorie intake and develop awareness of their eating habits.<br>3. Exercise Tracking - The app allows users to log their physical activities and workouts, helping them monitor their fitness progress.<br>4. Coaching and Support - Noom connects users with certified health coaches who provide guidance and motivation through in-app messaging.<br>5. Behavioral Change Techniques - Noom employs behavior change techniques to help users develop healthier habits and make sustainable lifestyle changes.<br>6. Noom employs a color-coded system, classifying foods as "green," "yellow," or "red" according to their nutritional value. This system simplifies the process for users to make healthier food choices.<br>7. Harnessing technology, Noom utilizes machine learning to assist individuals in cultivating healthy habits. Additionally, it incorporates online clustering algorithms to match users with their optimal support groups and provides various other functionalities. |
| HealthifyMe [13] | 1. Track your food intake and daily activities effortlessly with the app, maintaining a comprehensive record of your daily routine.<br>2. Benefit from an AI Nutritionist feature that offers real-time motivation and addresses your inquiries promptly.<br>3. Connect with a team of in-house dieticians, nutritionists, and fitness coaches for expert guidance and support.<br>4. Enhance your understanding of wellness and health with regularly updated |

| | |
|---|---|
| | articles available within the app.<br>5. Explore a variety of healthy and delightful recipes tailored to your preferences.<br>6. Engage in live workout sessions led by fitness experts, allowing you to exercise conveniently from the comfort of your home. |
| MyFitnessPal [14] | 1. Calorie and Nutrition Tracking - MyFitnessPal allows you to log your daily food intake, including calories, macronutrients, micronutrients. You can manually enter food items, scan barcodes, or choose from a large database of pre-existing entries.Also track daily water intake.<br>2. Barcode Scanner - Easily log packaged food items by scanning barcodes.<br>3. Goal Setting - Set personal goals and determine your daily calorie and nutrient targets based on your goals.<br>4. Exercise Logging: Record your physical activities and estimate calories burned.<br>5. Nutrition Reports: Access detailed reports on your nutritional intake.<br>6. Recipe Importing: You can import and save recipes from the web or manually enter your own recipes. The app will calculate the nutritional information for the entire recipe and each serving.<br>7. Community and Social Features: Connect with friends and join fitness groups.<br>8. Integration with Fitness Devices: Sync with wearable fitness devices.<br>9. Weight Tracking: Log and visualize your weight loss or gain progress. |

The literature review presents a thorough analysis of current methodologies and technologies in personalized diabetes management and dietary recommendation systems. It underscores the importance of personalized approaches in diabetes care and explores various machine learning techniques employed for diabetes prediction and dietary guidance. Notably, the project introduces an innovative approach that integrates predictive analytics, personalized meal planning, and AI-driven support through an intuitive chatbot interface built using the RAG model. This novel solution addresses the necessity for tailored diabetes management by offering real-time assistance on meal planning, lifestyle modifications, and health advice specific to diabetes, thus providing a holistic and scalable platform for individuals managing diabetes.

# Chapter 3

# SYSTEM ANALYSIS

## 3.1 Functional Requirements

- **Maintaining records**

  The system should be able to maintain records and data of the users with all the factors and tuples.

- **Pre-processing**

  The data received has to be modified for effective use. The process begins with filling the empty spaces if any. The next step is to convert the data into the required form. The data is converted to binary, boolean, numerical as required. The third and final step is to integrate the data collected.

- **Managing authenticity, reliability, and integrity**

  The system should be capable enough to maintain the authenticity, reliability, and integrity of the dataset. It should be able to do this regardless of the maintenance activities or other user actions.

- **Feature selection**

  The system should be efficient enough to select the required feature and eliminate irrelevant or useless features. The system uses a recursive feature selection technique to achieve the goal of reducing the factors to relevant ones.

- **Displaying results**

  The system is expected to display results efficiently without any difficulty or error in the display. The final output should be clear and precise, not ambiguous. The display should be clear to read and understand.

- **Interactive chatbot**

  The user can communicate with the personalized chatbot. It functions to create tailored diet plans based on user profiles, offering real-time interaction, nutritional information, and meal suggestions.

## 3.2 Non functional Requirements

- **Performance and Scalability**

  The system should maintain quick response times to user queries for personalized diet recommendations, ensuring a seamless and efficient user experience.

  It should be scalable to accommodate a growing user base and increased data volume, maintaining performance levels even during peak usage.

- **Security and Privacy**

  The system must prioritize data security, implementing robust measures to safeguard user health data, dietary preferences, and personally identifiable information.

  Secure communication protocols should be in place to protect user interactions with the chatbot, preventing unauthorized access and data interception.

- **User Experience and Personalization**

  The system's interface should be user-friendly, providing an intuitive experience for users interacting with the chatbot and accessing personalized diet recommendations.

  Personalization features should consider individual preferences, dietary restrictions, and health goals to enhance the relevance and effectiveness of diet recommendations.

- **Interoperability and Maintainability**

  The system should seamlessly integrate with external health data sources, wearables, or fitness apps to gather relevant information for accurate diet recommendations.

  It should be designed with a modular architecture to ensure ease of maintenance, updates, and future enhancements, allowing for the integration of new guidelines or features over time.

## 3.3 Specific Requirements

The application reads categorical as well as boolean values. Hence, to process the information provided there are certain system requirements to be met which shall ensure smooth and efficient performance.

1. **Software Requirements**
    - Python
    - Anaconda
    - Google Colab

- Operating System: Windows 10
- IDE: Jupyter/Spyder

**2. Hardware Requirements**

- RAM: 4GB and Above
- Intel Core i5 processor
- Laptop

### 3.4 Use Case Diagrams and description

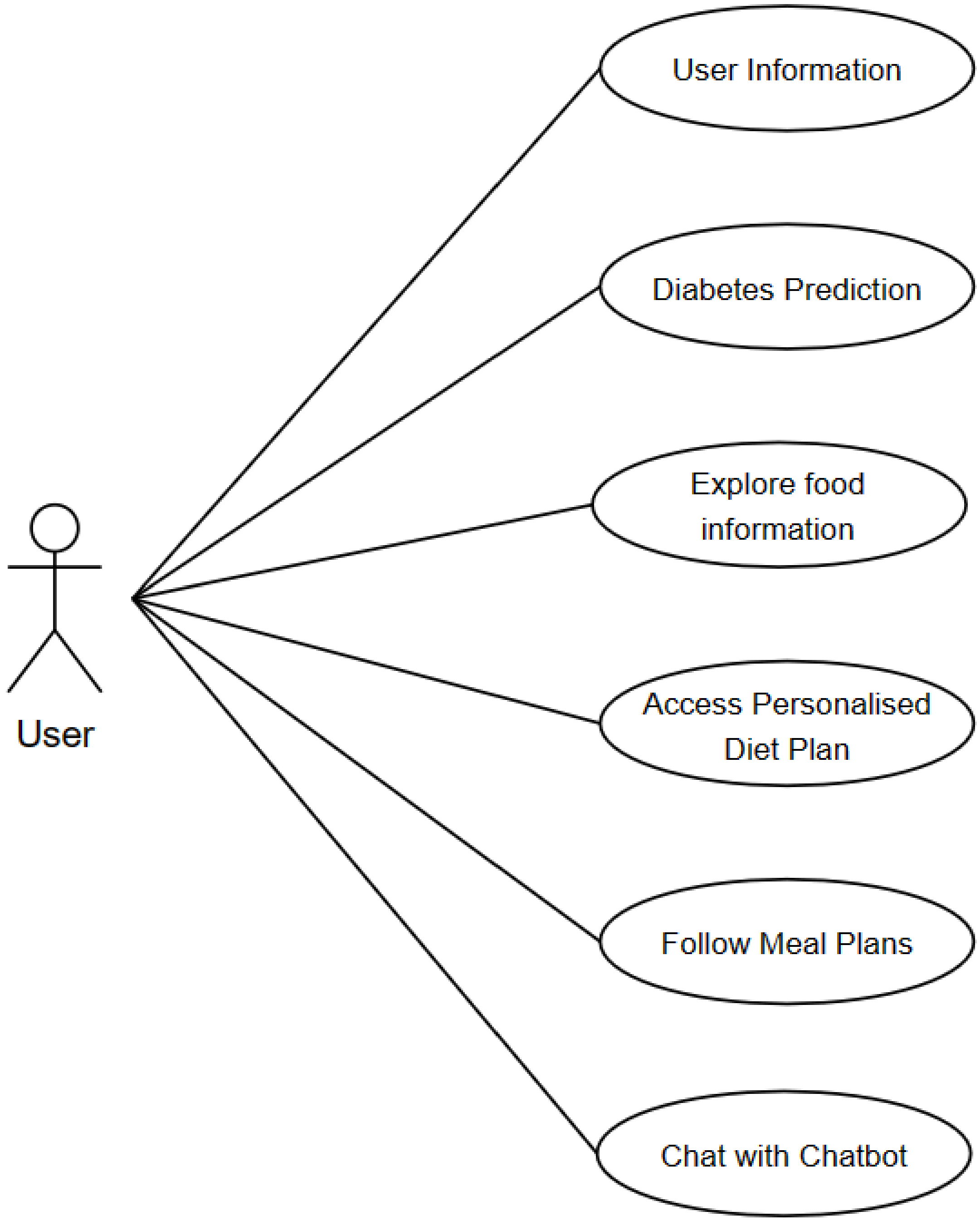



Fig. 3.4 Use Case Diagram

The use case diagram illustrates the key functionalities of a Personalized Diet Recommendation System designed specifically for diabetic patients. The primary actor in the system is the "User," representing individuals seeking personalized dietary guidance for managing their diabetes. The diagram outlines various processes that cater to the user's needs and contribute to an effective and user-friendly experience.

- User Information- The system allows users to provide or update their personal information, including health-related data and preferences, to tailor the recommendations accordingly.
- Diabetes Prediction: Based on the data provided by the user, the system predicts whether the patient is diabetic or not.
- Explore Food Information - Users can explore detailed information about different food items, including nutritional content, to make informed decisions about their dietary choices.
- Access Personalized Diet Plan - Based on the user's profile and health information, the system generates a personalized diet plan, considering the specific needs and restrictions associated with diabetes.
- Follow Meal Plans - Users have the option to follow the generated meal plans, helping them adhere to a structured and diabetes-friendly diet.
- Chat with Chatbot for Personalized Diet Recommendations - The system incorporates a chatbot feature, allowing users to engage in real-time conversations for immediate assistance and personalized diet recommendations. The chatbot utilizes user data and preferences to offer tailored advice and support.

# Chapter 4

# ANALYSIS MODELING

## 4.1 Activity Diagrams/ Class Diagrams

The system includes crucial classes like "User," "DietaryData", "DiabetesPrediction" and "DietRecommendation" for managing user information and providing personalized diet recommendations. Operations in "UserInterface" handle user input and display recommendations. The "UserManager" validates and stores user data, while the "DietaryDataManager" manages dietary information. Together, they ensure efficient processing and management of user-specific dietary data.

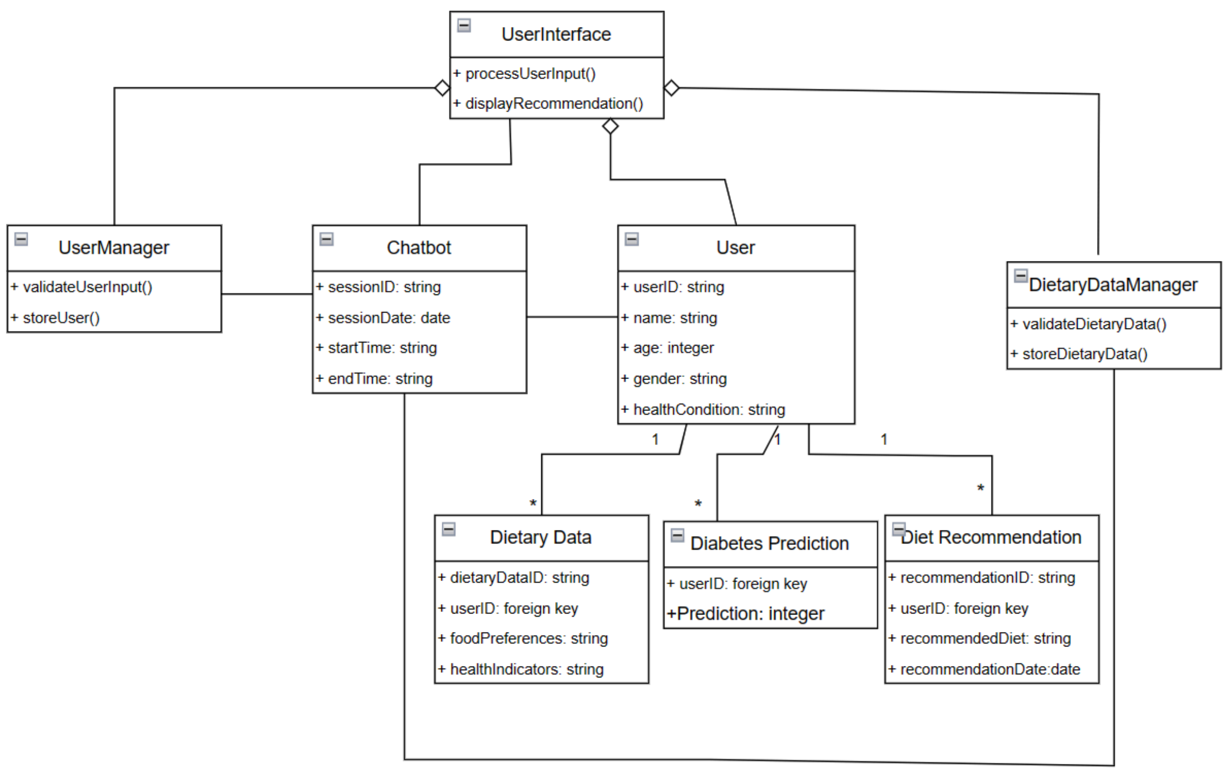



Fig 4.1 Class Diagram

## 4.2 Functional Modeling

The Level 0 Data Flow Diagram illustrates the "Personalized Diet Recommendation System for Diabetes." This system includes two external entities: "Users" who interact with the system, and a

"Database" for storing user information and dietary data. Data flows consist of "User Input" from Users to the system, conveying dietary preferences and health details. In return, the system provides "Diet Recommendation" data flows to Users.

The Level 1 Data Flow Diagram outlines three key modules in the "Personalized Diet Recommendation System for Diabetes." The "User Interface Module" manages user input and displays recommendations, while the "User Data Management Module" oversees user data storage. Simultaneously, the "Dietary Data Management Module" oversees dietary data and stores recommendations, contributing to the effective functioning of the system.

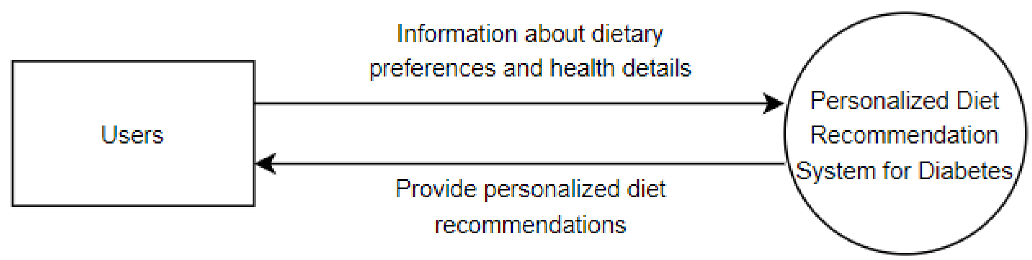



Fig. 4.2 DFD Level 0

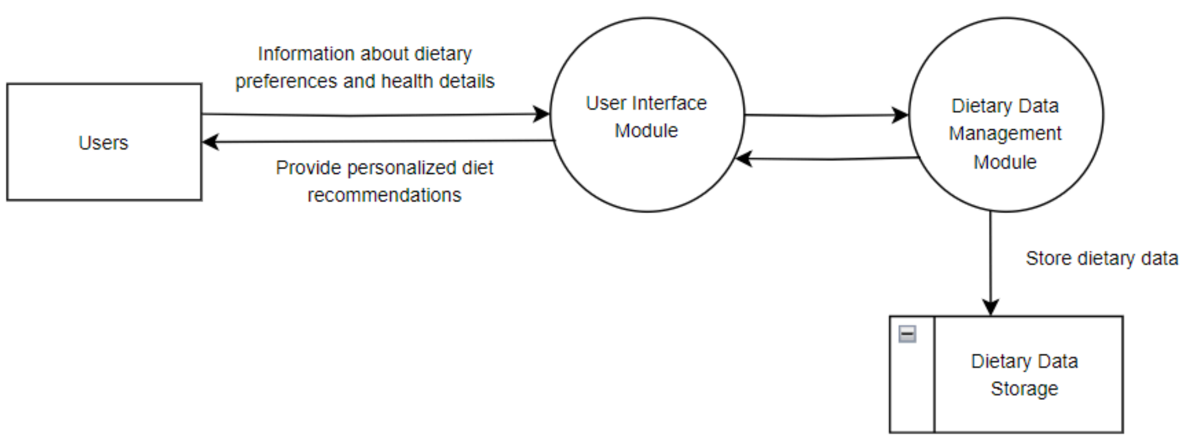



Fig. 4.3 DFD Level 1

## 4.3 Timeline chart

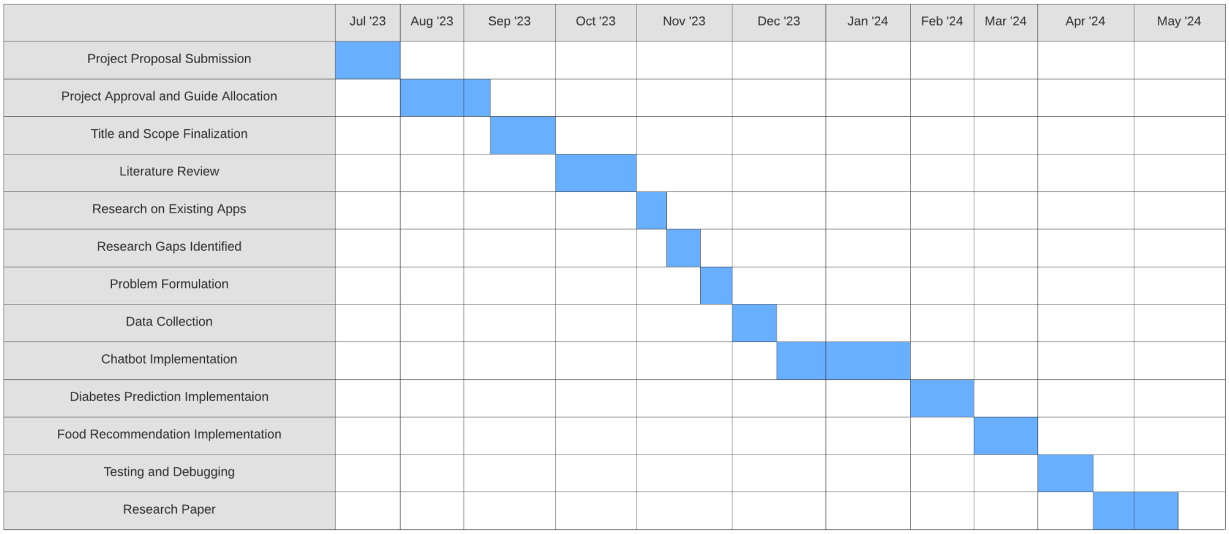



Fig. 4.4 Timeline chart of the project

# Chapter 5

# DESIGN

## 5.1 Architectural Design

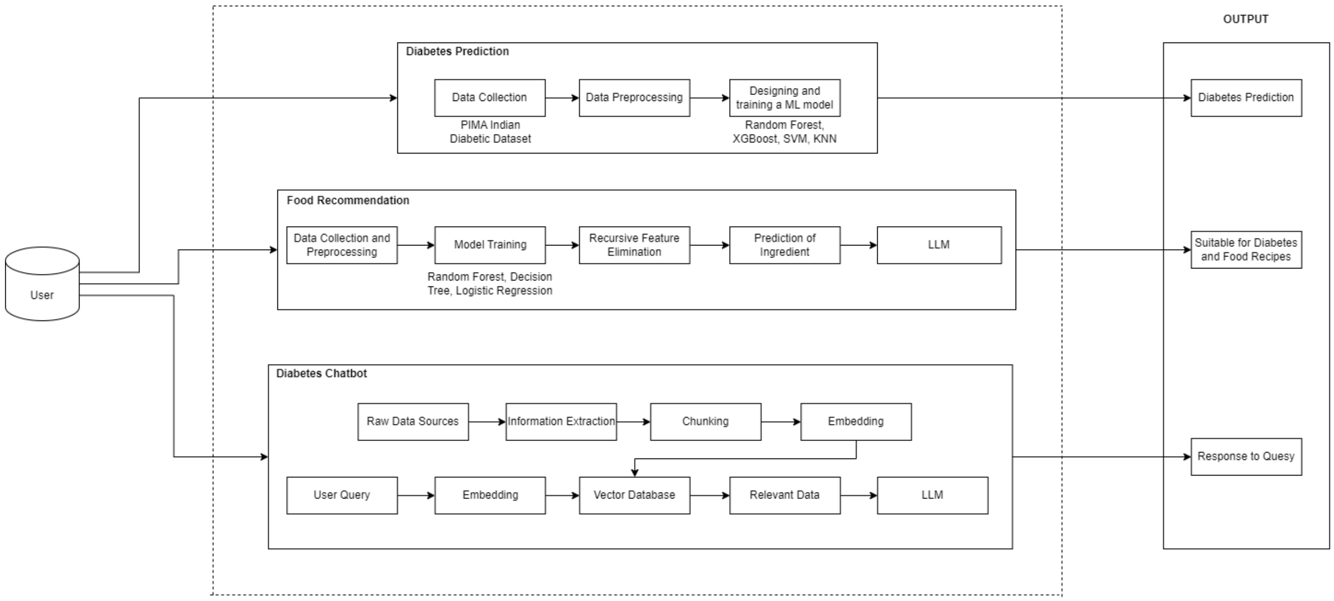
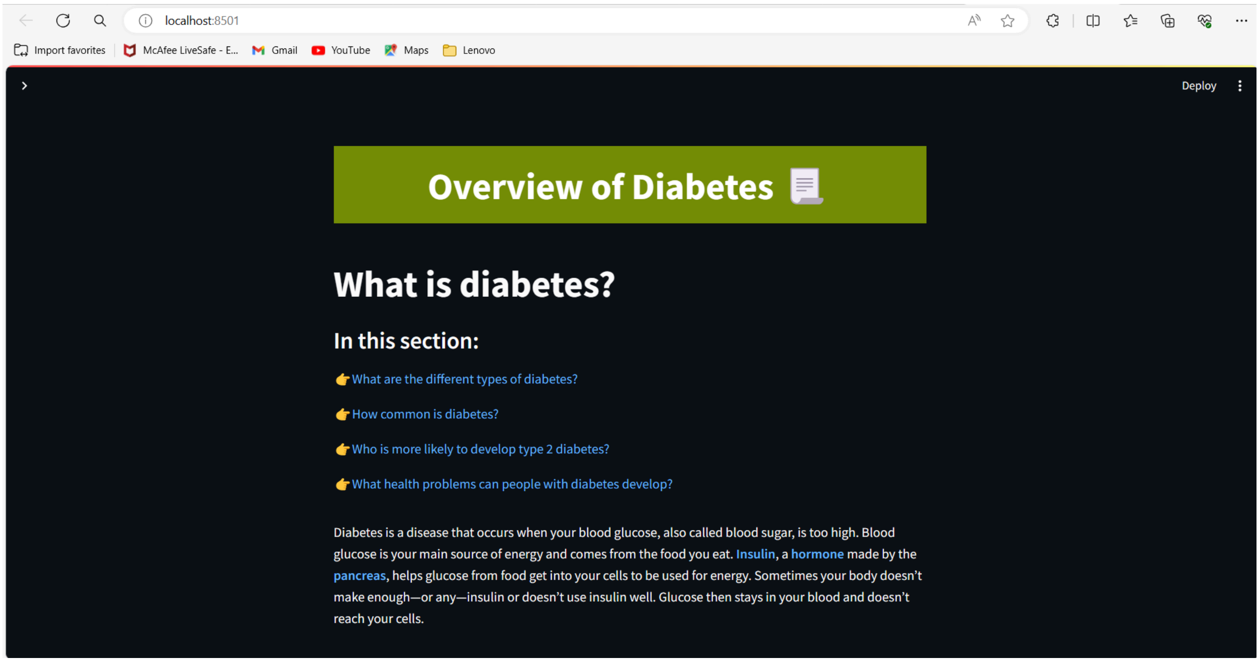


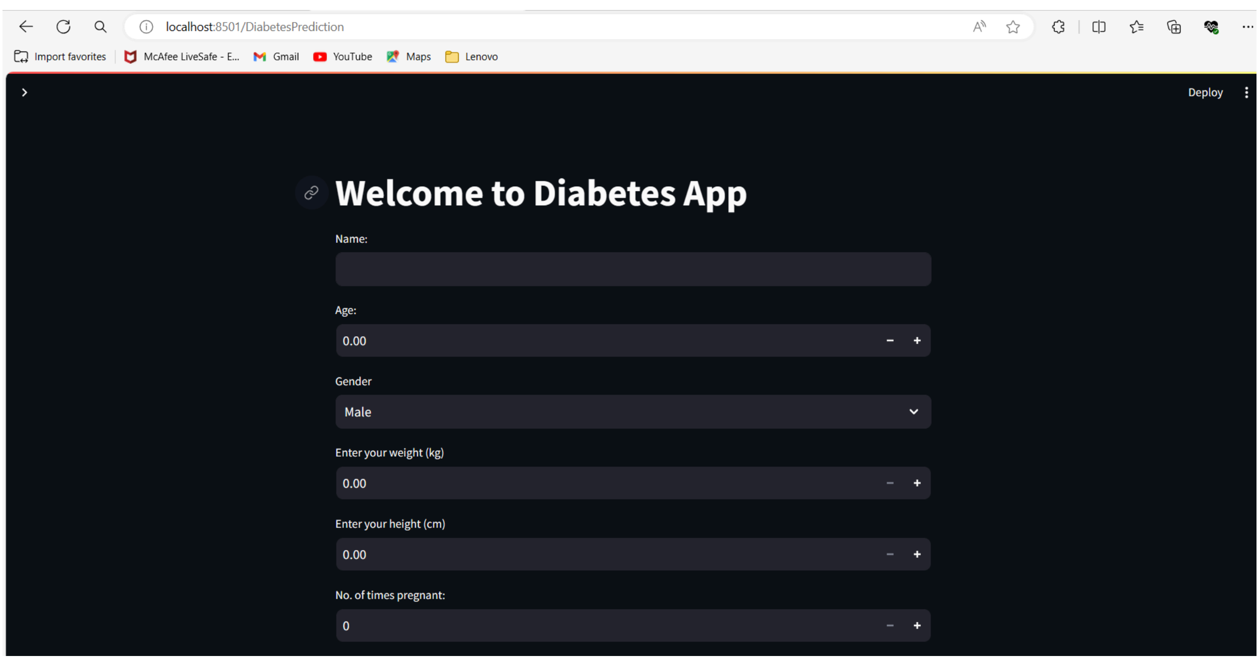

Fig. 5.1 Architectural Design

The project utilizes machine learning for accurate prediction of diabetes onset based on health indicators and historical data. It generates tailored meal plans considering individual dietary preferences, medical history, and nutritional requirements while adhering to diabetes management guidelines. The project also offers real-time assistance on meal planning, lifestyle modifications, and health advice specific to diabetes through an intuitive AI chatbot interface built using the RAG model. It seamlessly integrates predictive analytics, personalized meal planning, and AI-driven support to provide a comprehensive diabetes management solution on a scalable and adaptable platform.

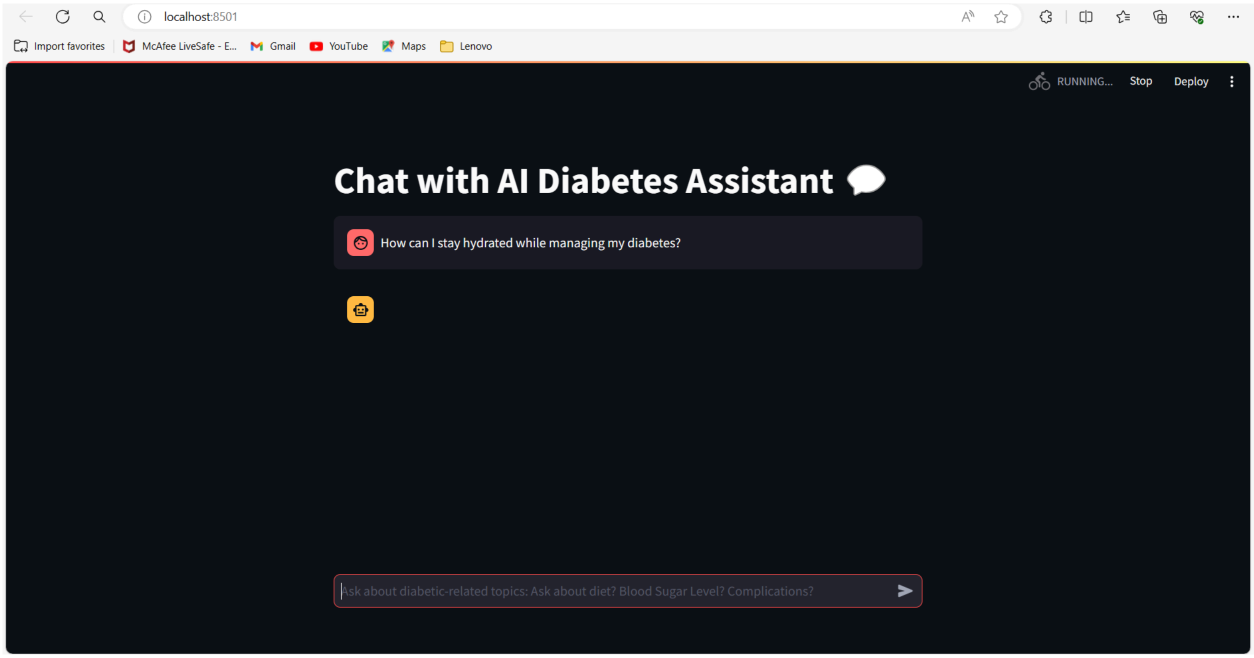
## 5.2 User Interface Design




( a )




( b )




( c )

Fig. 5.2 User Interface Design

# Chapter 6

# IMPLEMENTATION

## 6.1 Algorithms / Methods Used

### Diabetes Prediction

The PIMA Indians Diabetes Dataset has been used which aims to determine if a patient has diabetes. The dataset is restricted to female Pima Indians who are 21 years of age or older. Along with the target variable, outcome, it includes a variety of medical parameters, including age, BMI, insulin levels, and the number of pregnancies.

In the initial data exploration, preprocessing techniques like Missing Observation Analysis, Outlier Observation Analysis and Local Outlier Factor (LOF) were performed to remove missing values and determine outliers.

For training and testing, predictive models such as Random Forest, K Nearest Neighbor (KNN), XGBoost and SVM Classifier have been utilized for diabetes prediction.

### Food Recommendation

The proposed methodology revolves around personalized food recommendations tailored for individuals with diabetes. The approach begins by soliciting ingredient inputs from users, subsequently scrutinizing each ingredient's compatibility with diabetic dietary requirements. To accomplish this, three distinct models are trained: Logistic Regression, Decision Tree, and Random Forest. Notably, here, Random Forest exhibited superior performance, boasting an impressive accuracy of 96%. After training, Recursive Feature Elimination (RFE) is applied to each model to select the most relevant features for prediction. Remarkably, Logistic Regression, after undergoing RFE, emerged with the highest accuracy of 97%. Decision Tree and Random Forest also demonstrated competitive performances, with accuracies of 94% and 95%, respectively. This refined approach not only ensures accurate predictions but also enhances interpretability by focusing on the most influential features, thereby facilitating more effective personalized food recommendations for individuals managing diabetes.

The dataset utilized encompasses a comprehensive array of features for each ingredient, encompassing critical nutritional aspects such as Glycemic Index, Calories, Carbohydrates, Protein, Fat, Sodium Content, Potassium Content, Magnesium Content, Calcium Content, and Fiber Content. Leveraging this rich feature set, the model endeavors to forecast the suitability of food items for individuals managing diabetes.

Initially, the methodology checks if the queried ingredient exists within the precompiled list, promptly returning its suitability status. In cases where the ingredient is absent from the list, the model leverages all available features to formulate a prediction regarding its diabetic-friendliness. Following the determination of a food item's appropriateness for diabetic consumption, users are afforded the option of soliciting a corresponding recipe. This function is facilitated by a Retrieval Augmented Generative model, with the specific implementation being Llama-2-7b-chat-hf, an openly accessible model. This model seamlessly integrates retrieval mechanisms with generative capabilities, thereby enabling the provision of tailored recipes aligned with the dietary needs of individuals managing diabetes. The dataset used for this includes a corpus of documents containing recipes fit for diabetic patients. The model learns from this corpus and generates recipes accordingly, ensuring that the recommendations align with dietary guidelines and restrictions for diabetes management.

### Diabetes Chatbot

The proposed methodology revolves around using the Retrieval-Augmented Generation (RAG) system along with the open source LLama2 model LLama Index framework. This system combines information retrieval and text generation techniques to effectively handle PDF documents, create an index for document retrieval, and use LLama2 to respond to user queries.
Initially essential libraries such as PyPDF, Langchain, bitsandbytes, Sentence Transformers, Llama-index, llama-index-embeddings-langchain, llama-index-llms-huggingface are installed. Nutrition in Diabetes by Peter Pribis and Hana Kahleova and Textbook of Diabetes edited by RICHARD I.G. HOLT, CLIVE S. COCKRAM and others are the pdf documents utilized for pdf processing. The next step involves setting up the LLM model which involves initializing Hugging face LLM and using Sentence Transformers to create sentence embeddings for both

documents and user queries. After that a query engine is created to generate responses using ServiceContext.from_defaults and VectorStoreIndex.from_document.

## 6.2 Working of the project

In this phase, the diet recommendation system is translated into practical code, and specific modules are implemented to bring the envisioned features to life.

### Diabetes Prediction

```
#svm classifier
classifier=svm.SVC(kernel='linear')
classifier.fit(X_train,y_train)
X_train_prediction=classifier.predict(X_train)
training_data_accuracy_score=accuracy_score(y_train,X_train_prediction)
print(f"Accuracy Score of training data : {training_data_accuracy_score * 100} %")
X_test_prediction=classifier.predict(X_test)
testing_data_accuracy_score=accuracy_score(y_test,X_test_prediction)
print(f"Accuracy Score of testing data : {testing_data_accuracy_score * 100} %")

#Random Forest
classifier_rf = RandomForestClassifier(random_state=123)
classifier_rf.fit(X_train, y_train)
y_test_pred_rf = classifier_rf.predict(X_test)
testing_accuracy_rf = accuracy_score(y_test, y_test_pred_rf)
print(f"Accuracy Score on testing data: {testing_accuracy_rf * 100:.2f}%")
```

Fig. 6.1 Testing SVM Classifier and Random Forest Models for Diabetes Prediction

```
#KNN
classifier_knn = KNeighborsClassifier()
classifier_knn.fit(X_train, y_train)
y_train_pred_knn = classifier_knn.predict(X_train)
training_accuracy_knn = accuracy_score(y_train, y_train_pred_knn)
print(f"Accuracy Score on training data: {training_accuracy_knn * 100:.2f}%")
y_test_pred_knn = classifier_knn.predict(X_test)
testing_accuracy_knn = accuracy_score(y_test, y_test_pred_knn)
print(f"Accuracy Score on testing data: {testing_accuracy_knn * 100:.2f}%")

#XGBoost
classifier_xgb = xgb.XGBClassifier()
classifier_xgb.fit(X_train, y_train)
y_test_pred_xgb = classifier_xgb.predict(X_test)
testing_accuracy_xgb = accuracy_score(y_test, y_test_pred_xgb)
print(f"Accuracy Score on testing data: {testing_accuracy_xgb * 100:.2f}%")
```

Fig. 6.2 Testing KNN and XGBoost Models for Diabetes Prediction

## Food Recommendation

```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix

features = ['Glycemic Index', 'Calories', 'Carbohydrates', 'Protein', 'Fat',
       'Sodium Content', 'Potassium Content', 'Magnesium Content',
       'Calcium Content', 'Fiber Content']

X = dataset[features]
y_diabetes = dataset['Suitable for Diabetes']

X_train_diabetes, X_test_diabetes, y_train_diabetes, y_test_diabetes = train_test_split(X, y_diabetes, test_size=0.2, random_state=42)

logistic_regression = LogisticRegression(random_state=42)
decision_tree = DecisionTreeClassifier(random_state=42)
random_forest = RandomForestClassifier(random_state=42)

logistic_regression.fit(X_train_diabetes, y_train_diabetes)
decision_tree.fit(X_train_diabetes, y_train_diabetes)
random_forest.fit(X_train_diabetes, y_train_diabetes)

y_pred_logreg = logistic_regression.predict(X_test_diabetes)
y_pred_dt = decision_tree.predict(X_test_diabetes)
y_pred_rf = random_forest.predict(X_test_diabetes)

print("Logistic Regression:")
print(classification_report(y_test_diabetes, y_pred_logreg))
print("Decision Tree:")
print(classification_report(y_test_diabetes, y_pred_dt))
print("Random Forest:")
print(classification_report(y_test_diabetes, y_pred_rf))
```

Fig. 6.3 Initial Training of the Models used for Food Recommendation

```python
from sklearn.feature_selection import RFE
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier

models = {
    'Logistic Regression': LogisticRegression(),
    'Decision Tree': DecisionTreeClassifier(),
    'Random Forest': RandomForestClassifier()
}

rfe = RFE(estimator=LogisticRegression(), n_features_to_select=5, step=1)

rfe.fit(X, y_diabetes)

selected_features = X.columns[rfe.support_]

X_selected = dataset[selected_features]

X_train_selected, X_test_selected, y_train_diabetes, y_test_diabetes = train_test_split(X_selected, y_diabetes, test_size=0.2, random_state=42)

for model_name, model in models.items():
    # Train the model
    model.fit(X_train_selected, y_train_diabetes)

    y_pred_selected = model.predict(X_test_selected)

    print(f"Classification Report for {model_name} with selected features:")
    print(classification_report(y_test_diabetes, y_pred_selected))
```

Fig. 6.4 Recursive Feature Elimination on the models

## Diabetes Chatbot

```python
import torch

llm = HuggingFaceLLM(
    context_window=4096,
    max_new_tokens=256,
    generate_kwargs={"temperature": 0.0, "do_sample": False},
    system_prompt=system_prompt,
    query_wrapper_prompt=query_wrapper_prompt,
    tokenizer_name="meta-llama/Llama-2-7b-chat-hf",
    model_name="meta-llama/Llama-2-7b-chat-hf",
    device_map="auto",
    model_kwargs={"torch_dtype": torch.float16 , "load_in_8bit":True}
)
```

Fig. 6.5 LLM model for Diabetes Chatbot

```python
service_context=ServiceContext.from_defaults(
    chunk_size=1024,
    llm=llm,
    embed_model=embed_model
)
```

Fig. 6.6 Creation of Query Engine for Diabetes Chatbot

# Chapter 7

# TESTING

## 7.1. Test Cases

a) **Pipeline Flow Testing:** End to End Testing of the System, right from attribute collection to prediction of the life expectancy of the patient.

b) **Interface Testing:** User interaction and interaction ability testing to look out for glitches and loopholes in the system.

## 7.2. Types of Testing Used

a) **Component Testing:** Most of the time, developers carry it out after unit testing is finished. The goal of component testing, which involves testing several components as a single code, is to find any defects that may arise from connecting the various functionalities to one another.

b) **End-to-End Testing:** Similar to system testing, end-to-end testing entails evaluating the complete application environment in a scenario that resembles actual use, like utilising network connectivity, interfacing with other hardware, apps, or systems as needed.

c) **Functional Testing:** Functional testing solely looks at the output to determine whether or whether it complies with the provided requirements, ignoring any internal components. It is a technique for black box testing. It is modified to meet an application's functional requirements.

d) **Graphical User Interface (GUI) Testing:** Validating the GUI in accordance with the stated business requirements is the primary goal of testing the GUI. Typically, the Detailed Design Document and GUI mockup screens specify the application's graphical user interface (GUI) that the developer expects. The GUI testing includes checking the text and content in the tables, the size of the buttons and input field that are visible on the screen, and the alignment of every table.

# Chapter 8

# RESULTS AND DISCUSSIONS

## 8.1 Results

In this phase, results of various modules are discussed below.

## Diabetes Prediction

```
1D Data : [  2.  110.   70.   25.   80.   25.    0.3  30. ]

2D Data : [[  2.  110.   70.   25.   80.   25.    0.3  30. ]]

Predicted Value: [0]
This person is Non-Diabetic
```

(a)

```
1D Data : [  5.    130.     72.     35.     80.     33.6     0.627   50.    ]

2D Data : [[  5.    130.     72.     35.     80.     33.6     0.627   50.    ]]

Predicted Value: [1]
This person is Diabetic
```

(b)

```
1D Data : [  3.    150.     70.     30.     90.     25.5     0.45   35.   ]

2D Data : [[  3.    150.     70.     30.     90.     25.5     0.45   35.   ]]

Predicted Value: [1]
This person is Diabetic
```

(c)

Fig. 8.1 Predictions on Sample Data

## Food Recommendation

```
List the ingredients that you have : chia seeds
List the ingredients that you have : stop
['chia seeds']
```

```
Yes, chia seeds is suitable for diabetes.
['chia seeds']
```

```
What meal do you want: 1. Breakfast 2. Lunch 3. Snack 4. Dinner 5. No - breakfast
Are you : 1. Vegetarian 2. Non-vegetarian - 1
1. Chia Seed Breakfast Pudding
Ingredients:
- 1/4 cup chia seeds
- 1 cup unsweetened almond milk
- 1 tsp vanilla extract
- 1 tbsp honey
- 1/4 cup fresh berries
- 1 tbsp unsalted chopped almonds
- Optional: 1 tsp ground cinnamon

Instructions:
1. In a bowl, combine the chia seeds, almond milk, vanilla extract, and honey.
2. Mix well and let it sit in the fridge for at least 2 hours or overnight.
3. Once thick and pudding-like, top with fresh berries and chopped almonds.
4. Optional: sprinkle with ground cinnamon for added flavor.
5. Serve for a nutrient-packed, low sugar breakfast option.

2. Chia Seed Oats Breakfast Bowl
Ingredients:
- 1/4 cup chia seeds
- 1/2 cup rolled oats
- 1 cup unsweetened almond milk
- 1 tsp vanilla extract
- 1/4 cup fresh blueberries
- 1 tbsp unsalted chopped walnuts
- Optional: 1 tsp maple syrup

Instructions:
1. In a bowl, mix together the chia seeds, rolled oats, almond milk, and vanilla extract.
2. Let the mixture sit in the fridge for at least 30 minutes or overnight.
3. Top with fresh blueberries and chopped walnuts.
4. Optional: drizzle with maple syrup for added sweetness.
5. This hearty and nutritious breakfast is packed with fiber, protein, and healthy fats to keep you full and satisfied.
```

(a)

```
List the ingredients that you have : gulab jamun
List the ingredients that you have : stop
['gulab jamun']

No, gulab jamun is not suitable for diabetes.
```

(b)

```
List the ingredients that you have : tomato
List the ingredients that you have : onion
List the ingredients that you have : potato
List the ingredients that you have : black quinoa
List the ingredients that you have : stop
['tomato', 'onion', 'potato', 'black quinoa']
```

```
Yes, tomato is suitable for diabetes.
Yes, onion is suitable for diabetes.
No, potato is not suitable for diabetes.
Yes, black quinoa is suitable for diabetes.
['tomato', 'onion', 'black quinoa']
```

```
What meal do you want: 1. Breakfast 2. Lunch 3. Snack 4. Dinner 5. No - lunch
Are you : 1. Vegetarian 2. Non-vegetarian - 1
1. Quinoa and Black Bean Stuffed Tomato:
- 4 large tomatoes
- 1 cup cooked black quinoa
- 1/2 cup black beans, drained and rinsed
- 1/4 cup finely chopped onion
- 1/4 cup diced bell pepper
- 1/4 cup diced zucchini
- 1 garlic clove, minced
- 1 teaspoon olive oil
- Salt and pepper to taste
Instructions:
1. Preheat the oven to 375°F.
2. Cut off the top of the tomatoes and scoop out the seeds and pulp.
3. In a pan, sauté onions, bell pepper, zucchini, and garlic in olive oil until softened.
4. Add black beans and cooked quinoa to the pan and season with salt and pepper.
5. Stuff the tomatoes with the quinoa and black bean mixture.
6. Place the stuffed tomatoes in a baking dish and bake for 20 minutes.
7. Serve hot as a main dish for lunch.

2. Quinoa and Vegetable Salad:
- 1 cup cooked black quinoa
- 1 small onion, finely chopped
- 1 large tomato, diced
- 1 bell pepper, diced
- 1/2 cucumber, diced
- Handful of fresh parsley, chopped
- 2 tablespoons lemon juice
- 2 tablespoons olive oil
- 1 teaspoon honey
- Salt and pepper to taste
Instructions:
1. In a large bowl, mix together the cooked quinoa, onion, tomato, bell pepper, cucumber, and parsley.
2. In a small bowl, whisk together the lemon juice, olive oil, honey, and salt and pepper.
3. Pour the dressing over the quinoa and vegetable mixture and toss well.
4. Serve the salad cold as a nutritious and filling lunch for diabetics.
```

(c)

Fig 8.2 Sample instances for food recommendation

# Diabetes Chatbot

```
response = query_engine.query("What are some easy and healthy snack options for people with diabetes?")
```

```
print(response)
```

```
Some easy and healthy snack options for people with diabetes include dried fruits such as raisins, prunes, and apricots, which have been shown to have a beneficial effect on postprandial glucose regulation
```

(a)

```
response = query_engine.query("How can I manage cravings for sugary foods and drinks?")
```

```
print(response)
```

```
There are several strategies you can use to manage cravings for sugary foods and drinks:

1. Stay hydrated: Sometimes, thirst can be mistaken for hunger or cravings for sweets. Drinking water or other low-calorie drinks can help curb your appetite and reduce cravings.
2. Eat regular meals: Skipping meals or going too long without eating can lead to increased cravings for unhealthy snacks. Eating regular, balanced meals throughout the day can help keep your hunger and cr
3. Choose complex carbohydrates: Eating complex carbohydrates, such as whole grains, fruits, and vegetables, can help slow the release of sugar into your bloodstream, reducing cravings for sugary foods.
4. Get enough sleep: Lack of sleep can increase levels of the hunger hormone ghrelin and decrease levels of the fullness hormone leptin, leading to increased cravings for unhealthy foods. Aim for 7-9 hours
```

(b)

```
response = query_engine.query("I'm interested in trying intermittent fasting, is it safe for someone with diabetes?")
```

```
print(response)
```

```
Intermittent fasting can be a challenging and potentially dangerous approach for individuals with diabetes, as it may cause significant fluctuations in blood glucose levels. The American Diabetes Ass

It is essential to consult with a healthcare provider before starting any new diet or fasting regimen, especially if you have diabetes. They can help you determine the best approach based on your ind

In summary, while intermittent fasting may have potential health benefits for some individuals, it is not recommended for individuals with diabetes without proper medical supervision and monitoring.
```

(c)

Fig. 8.3 Chatbot responses

## 8.2 Experimentation

### Diabetes Prediction

For diabetes prediction four models SVM Classifier, Random Forest, K Nearest Neighbor and XGBoost are utilized. XGBoost outperforms others with an accuracy of 88.82%. Random Forest and KNN show comparative accuracies of 86% and 87%, whereas SVM Classifier has the last accuracy of 82%.

```
Accuracy Score on testing data: 88.82%
```

Fig. 8.4 Accuracy of XGBoost Model

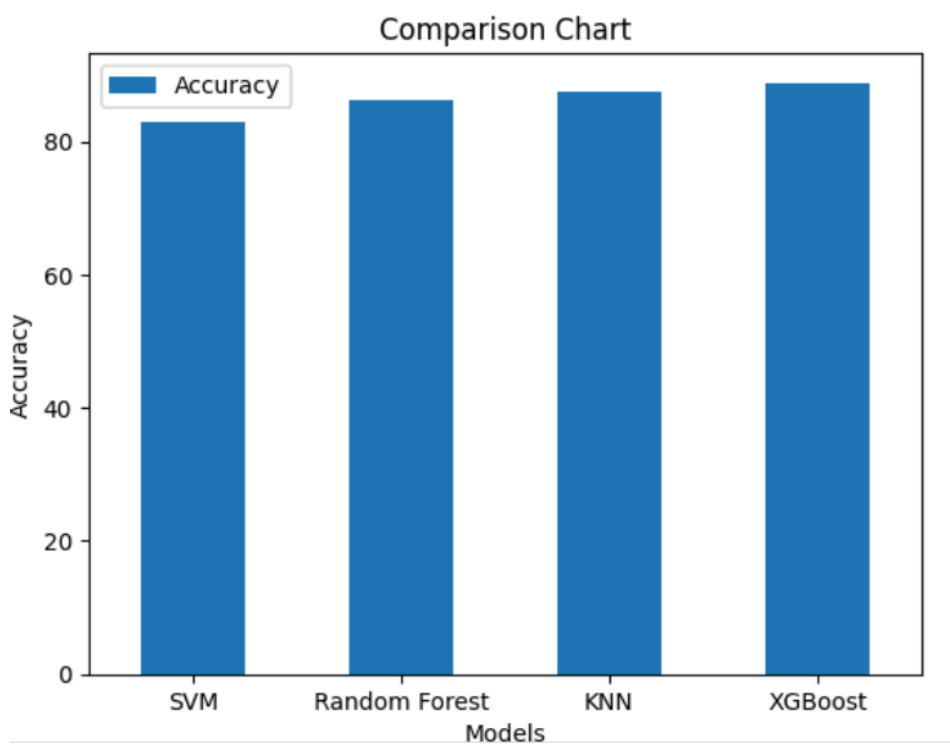



Fig. 8.5 Comparison of used Models

### Food Recommendation

For food recommendation, three separate models—Random Forest, Decision Tree, and Logistic Regression—are trained. Random Forest performed better in this instance, with an astounding accuracy of 96%. Each model is subjected to Recursive Feature Elimination (RFE) after training in order to identify the most pertinent features for prediction. Surprisingly, after undergoing RFE, Logistic Regression showed the greatest accuracy of 97%. Moreover, Decision Tree and Random Forest showed competitive results, with 94% and 95% accuracy, respectively.

Logistic Regression:

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| 0 | 0.67 | 0.36 | 0.47 | 11 |
| 1 | 0.93 | 0.98 | 0.95 | 90 |
| accuracy | | | 0.91 | 101 |
| macro avg | 0.80 | 0.67 | 0.71 | 101 |
| weighted avg | 0.90 | 0.91 | 0.90 | 101 |

Decision Tree:

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| 0 | 0.69 | 0.82 | 0.75 | 11 |
| 1 | 0.98 | 0.96 | 0.97 | 90 |
| accuracy | | | 0.94 | 101 |
| macro avg | 0.83 | 0.89 | 0.86 | 101 |
| weighted avg | 0.95 | 0.94 | 0.94 | 101 |

Random Forest:

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| 0 | 0.89 | 0.73 | 0.80 | 11 |
| 1 | 0.97 | 0.99 | 0.98 | 90 |
| accuracy | | | 0.96 | 101 |
| macro avg | 0.93 | 0.86 | 0.89 | 101 |
| weighted avg | 0.96 | 0.96 | 0.96 | 101 |

Fig. 8.6 Accuracy after initial training of the Models

Classification Report for Logistic Regression with selected features:

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| 0 | 1.00 | 0.73 | 0.84 | 11 |
| 1 | 0.97 | 1.00 | 0.98 | 90 |
| accuracy | | | 0.97 | 101 |
| macro avg | 0.98 | 0.86 | 0.91 | 101 |
| weighted avg | 0.97 | 0.97 | 0.97 | 101 |

Classification Report for Decision Tree with selected features:

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| 0 | 0.73 | 0.73 | 0.73 | 11 |
| 1 | 0.97 | 0.97 | 0.97 | 90 |
| accuracy | | | 0.94 | 101 |
| macro avg | 0.85 | 0.85 | 0.85 | 101 |
| weighted avg | 0.94 | 0.94 | 0.94 | 101 |

Classification Report for Random Forest with selected features:

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| 0 | 0.80 | 0.73 | 0.76 | 11 |
| 1 | 0.97 | 0.98 | 0.97 | 90 |
| accuracy | | | 0.95 | 101 |
| macro avg | 0.88 | 0.85 | 0.87 | 101 |
| weighted avg | 0.95 | 0.95 | 0.95 | 101 |

Fig. 8.7 Accuracy after Recursive Feature Elimination on the models

## Diabetes Chatbot

The responses provided by the chatbot are authenticated by seven medical professionals who then evaluate and rate their accuracy on a range of one to five. Overall, the answers are rated four on a scale of five by 57% of the medical professionals, which proves the validity of the answers provided by the chatbot.

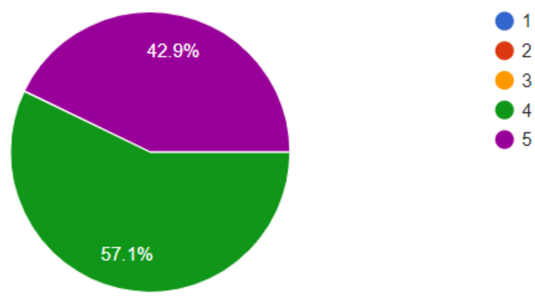



Fig. 8.8 Rating of response provided by chatbot for Fig. 7.3 (a)

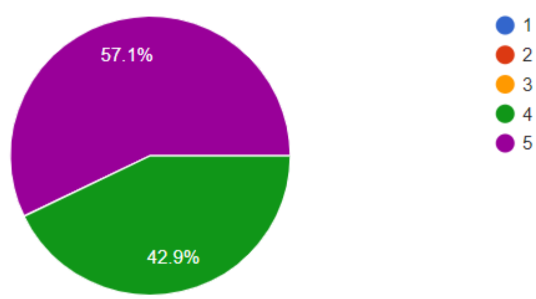



Fig. 8.9 Rating of response provided by chatbot for Fig. 7.3 (b)

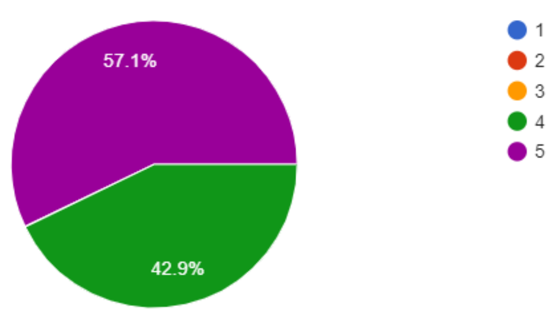



Fig. 8.10 Rating of response provided by chatbot for Fig. 7.3 (c)

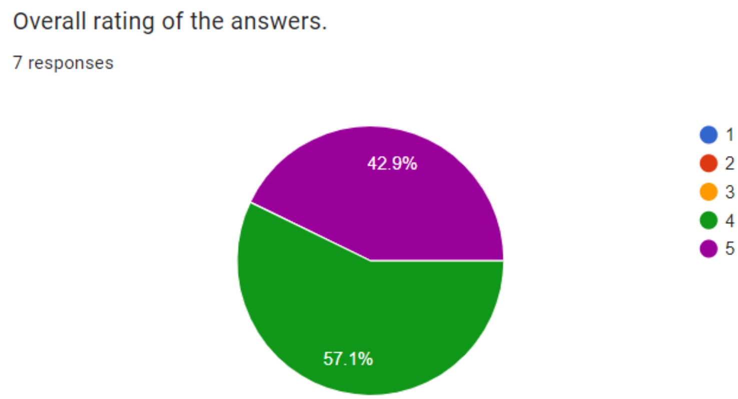



Fig. 8.11 Overall Rating of responses provided by chatbot

# Chapter 9

# CONCLUSION AND FUTURE SCOPE

In conclusion, the personalized diet recommendation system offers a promising solution to address the critical need for effective health management in individuals with diabetes. The project acknowledges the importance of meticulous attention to dietary choices and regular physical activity in diabetes management. The user-friendly web app interface enhances accessibility, enabling users to input preferences and health conditions for a personalized experience. Notably, the system provides inclusive access to premium functionalities free of cost, distinguishing it from existing applications that often require subscriptions for advanced features. This commitment to inclusivity aims to create a more equitable and supportive environment for individuals managing diabetes.

Looking to the future, there are several areas for improvement and expansion. Firstly, addressing the limitations of the chatbot model, such as occasional truncation of responses, would enhance the user experience. Providing more personalized meal plans based on users' preferences, dietary restrictions, and health goals would also be beneficial. Furthermore, incorporating wearable devices for continuous monitoring could revolutionize the system by providing real-time data on users' physical activity, blood glucose levels, and other relevant metrics. This integration would allow for more dynamic and personalized recommendations, adapting to users' changing health needs and behaviors.

Overall, the personalized diet recommendation system serves as a promising tool to empower individuals in managing their health effectively, making informed lifestyle choices, and actively participating in their ongoing health journey. With continued development and innovation, it has the potential to significantly improve the quality of life for individuals with diabetes.

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