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Food recommender system for Diabetes Type 2 patients.

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Declaration

I declare that this work has not been previously submitted and approved for the award of a degree by this or any other University. To the best of my knowledge and belief, the thesis contains no material previously published or written by another person except where due reference is made in the thesis itself.

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Approval

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Abstract

Diabetes mellitus is a chronic medical disorder that arises when the body does not produce enough insulin or when the body does not utilize the insulin produced effectively. Insulin is the hormone that regulates blood sugar in our bodies, when blood sugar is not regulated it leads to hyperglycemia which is excess blood sugar levels or hypoglycemia which is very low blood sugar levels. Due to urbanization that comes with very busy day to day schedules patients tend to pay little or no attention to their eating patterns leading them to opt for quick fixes such as fast foods, less balanced diets, and intake of a lot of processed food. The number of cases of diabetes patients has been steadily incrementing over the past few decades. Lack of proper diabetes management results in long-standing complications that end up using up on an individual's resources such as money and time spent seeking medical attention now and then. Diabetes management and control of blood sugar levels are usually done through pharmacotherapy which is the use of medication alongside nutritional therapy which involves eating healthy diets. For nutrition therapy to be effective, patients must consume nutrient-dense diets foods. Patients should take caution on their carbohydrate's intake, glycemic index, and glycemic load levels of foods they consume, this way they can control and maintain the blood glucose levels close to normal. Today, with the tremendous growth in technology we see an increase in the adoption and use of health recommender systems that are slowly becoming a close companion to an individual. A health recommender system can study the user, gather relevant information and recommend what suits the user best, hence making life easy. This study sought to develop a food recommender system expressly for diabetes Type 2 patients which will incorporate the use of a glucometer, a medical device used to assist patients and the caregivers monitor blood glucose levels and use that data to adjust nutritional therapy. Based on their sugar levels the recommender system will advise the patient on the appropriate foods they can consume at that time, ensuring the blood glucose target is attained hence reducing chances of sudden blood spikes and dips. Once the patient keys in the food they want to eat the model will respond by giving the patient the go-ahead to consume the food. In this study, we tested the Naïve Bayes algorithm with collaborative filtering to recommend food and achieved a prediction accuracy of 90.0%. The algorithm outperformed decision trees which gave an accuracy of 78% and the Support vector machine which had an accuracy of 75%.

Keywords: Diabetes mellitus, Insulin, hyperglycemia, hypoglycemia, glucometer.

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List of Abbreviations

ADA American Diabetes Association

BMI Body Mass Index

CSF Cerebrospinal Fluid

DIETOS DIET-Organizer System

DM Diabetes Mellitus

ERD Entity Relationship Diagram

EASD European Association for the study of Diabetes

GI Glycemic Index

GL Glycemic load

HbA1c Glycated hemoglobin

IDF International Diabetes Federation

IOM Institute of Medicine

KNN K nearest neighbor

NCD Non-communicable disease

NIDDK National Institute of Diabetes and Digestive and Kidney disease

RBC Red Blood Cells

RMSE Root Mean Square Error

SVM Support Vector Machine

TTM Trans theoretical Model

UML Unified Modelling Language

WBC White Blood Cells

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Dedication

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Chapter 1: Introduction

1.1 Background of the Study

In 2016, the World Health Organization (WHO) estimated 1.6 million deaths were directly caused by diabetes, another 2.2 million deaths were attributable to high blood glucose in WHO (2012). According to American Diabetes Association (ADA 2014) it has defined Diabetes mellitus (DM) as a chronic disease that affects how the human body turns food into glucose which is used as energy. The body produces little or no insulin, or the body does not utilize the insulin effectively. The prolonged hyperglycemia effects of diabetes are associated with long-term damages, dysfunction, and failure of different human body organs, such as neuropathy (nerve problems), retinopathy (eye problems), nephropathy (kidney problems), and macro vascular complications. These adverse impediments cause severe acute and chronic complications that can lead to kidney failure, adult-onset blindness, and lower-limb amputations.

There are different categories of diabetes mellitus, Type 1 diabetes, Type 2 diabetes, and gestational diabetes. The main types being diabetes Type 1 which was previously known as insulin-dependent that comprises 5–10% of diabetes patients. According to International diabetes federation (IDF, 2017) Type 1 diabetes is caused by an autoimmune reaction in which the body's immune system attacks the insulin-producing beta cells of the pancreas and causes the body to produce very little or no insulin; hence a diabetes patient is required to administer insulin on daily basis to maintain the recommended target blood glucose level. Type 2 which was formerly well-known as non-insulin-dependent, and which comprises 90–95% of diabetes patients is caused by the human's body inability to fully respond to insulin (IDF).

The global diabetes prevalence was projected to be 9.3% 463 million people, increasing to 10.2% 578 million by 2030 and 10.9% 700 million by 2045. The prevalence is greater in the urban area at 10.8% than the rural areas at 7.2% and in high-income by 10.4%) than low-income countries by 4.0% Pouya Saeedi et al., (2019). It is estimated that the ratio of 1:2, 50.1% of people living with diabetes are not aware that they have diabetes. DM negatively impacts the lives and well-being of individuals, families, and societies worldwide. According to a report by the (IDF), reports show that in 2017 the global health expenditure on diabetes was estimated to be USD 727 billion, given these statistics this calls for the immediate need to address the disease in terms of developing and employing multi-sectoral strategies to help improve diabetes management. The global increase in the number of Type 2 patients is related to rising rates of obesity, poor dietary habits, an increase in sedentary lifestyles, and rapid urbanization. Frank B. (2012)

Lifestyle changes characterized by increased intake of processed foods and physical inactivity appear to have together fostered overweight and obesity, which are strong risk factors for diabetes. J Tuomilehto et al., (2001) type 2 diabetes can be averted by a change in lifestyle for both men and women with high risk for DM by a decrease of 58% overall diabetes incidence. P Saeedi et al., (2019). Nutritional intake and lifestyle changes are the basis of diabetes Type 2 management. Constant education and support are also very essential to equip the patients with the skills, attitude knowledge, and motivation needed for effective daily diabetes management. According to ADA, (2014) and European Association for the study of Diabetes (EASD) emphasized on the emphasis in a patient-centered and personalized diabetes care. K Donsa et al., (2015) personalization of the patient’s diabetes treatment is possible at different levels. Personalizing the glycemic control targets is based on clinical parameters such as age, DM duration, and weight. Providing medication support and therapy control, which helps to correctly estimate an individual’s medication requirements and improve adherence to therapy goals. A personalized approach to the care of people living with diabetes provides a unique management plan for every individual S Subramanian et al., (2014).

The physical effect of Type 2 diabetes is well known, and its management has substantial effects on an individual, societal health, psychological well-being, and quality of life, as well as economic implications. It is argued that medical nutrition therapy is necessary for diabetes management to improve glycemic control and lower the risk of complications. Personalized care of Type 2 diabetes presents as a real-world approach, providing care that is responsive to individuals' specific, unique needs and preferences.

1.2 Problem Statement

According to WHO (2016) studies show that over the years the number of diabetic cases have been rapidly increasing in both developed and developing countries, making diabetes a key health priority globally. Most studies carried out show that the causes of the recent rapid increase in diabetes are associated with consumption of high-calorie dense-foods, increased intake of processed food, sedentary lifestyle coupled with the tremendous growth of urbanization cultures, unhealthy dietary intake patterns, tobacco and alcohol intake, genetic predisposition family and use of antiretroviral medications. According to V Thibault et al., (2016), the upsurge in the prevalence of diabetes could be justified by several factors some including individual-level and environmental risk factors, the detection effect, the evolution of the disease and global changes. According to ADA (2018) recommendations emphasizes that medical nutrition therapy ought to remain as part of the treatment plan after pharmacotherapy is initiated. The combination of these two therapies aids to keep blood glucose levels close to normal hence achieving an individual's goals. It is highly recommended that patients with pre-diabetes or new-onset diabetes ought to receive personalized medical nutrition therapy, preferably from a registered dietitian, as required to achieve treatment goals Franz et al., (2017).

Self-assessment of daily dietary intake by a diabetes Type 2 patient is deemed a critical part of nutritional therapy, it is important because the patient will eat foods according to their needs and guided by their blood glucose target values. As a first step to help manage diabetes through nutritional therapy, the food recommender system used alongside a glucometer which checks a patient's blood sugar levels. The recommender system uses the naïve Bayes algorithm to give personalized food recommendations to the patients based on their dietary needs. Elsweiler et al., (2015) food recommender systems are also considered as a possible means to support users to nurture themselves more health-wise. Adoption of the food recommender system will be part of a strategy for improving the eating behaviors of the patient.

1.3 Objectives

1.3.1 General Objective

The main objective of this study is to develop a food recommender system for diabetes type 2 patients based on their blood glucose levels.

1.3.2 Specific Objectives

i. To analyze dietary factors affecting diabetes Type 2 patients in Kenya,
ii. To evaluate techniques used for daily dietary self-assessment by diabetes Type 2,
iii. To develop a food recommender system for diabetes Type 2 patients in Kenya,
iv. To test the ability of the proposed model in giving food recommendations to diabetes Type 2 patients.

1.4 Research Questions

i. How do these factors affect daily appropriate dietary intake for diabetes Type 2 patients?
ii. What are the techniques used to self-assess daily dietary intake for diabetes Type 2?
iii. How can a food recommender system for diabetes Type 2 patients based on the Naïve Bayes algorithm be developed?
iv. How can the ability of a food recommender system for diabetes Type 2 patients be validated?

1.5 Justification

With the tremendous growth of urbanization and busy day to day schedules, it is easy to give little or no attention to the patients daily dietary intake. The proposed model will help the Diabetes type 2 patient self-assess their daily dietary intake by monitoring the glycemic index and glycemic load of foods they consume hence promoting healthy eating habits. This will help the patients maintain their target blood glucose level in addition to preventing the sudden spiking and dipping of sugar levels. The study will help researchers and students by adding value to the knowledge base in this area of health informatics. The model developed can be used by other application developers who may wish to improve their applications or for future researchers in food recommender systems for diabetic patients using machine learning techniques.

1.6 Scope and Limitation

This research work will focus on food recommendation to diabetes Type 2 patients, based on their glycaemia level. This study will only use the glycaemia level as the biomarker in guiding the model to recommend food to the patient. The model will not be suitable for type 2 patients with any existing conditions that require frequent use of medication as this can led to sudden dip and spike of blood sugar levels hence misguiding the food recommender model. Patients with existing conditions such as tuberculosis, hepatitis b, cancer and HIV/AIDS require continued evaluation by specialist because of the continued intake of drugs.

Chapter 2: Literature Review

2.1 Introduction

The purpose of this chapter was to conduct theoretical and empirical literature done on diabetes Type 2 and identify existing technological solutions for a food recommendation to diabetes Type 2 patients. It also illustrated a detailed description of the used machine learning models, algorithms, architecture, system, and the conceptual framework with the operationalized variables. Finally, it illustrated the existing research gaps in the literature that the study hoped to resolve.

2.2 Diabetes management

2.2.1 Global perspective of diabetes

National Institute of diabetes and digestive and kidney disease (NIDDK) defines Diabetes mellitus also known as diabetes as a chronic disease that occurs when blood glucose is too high. This occurs when the pancreas does not produce enough insulin or when the body cannot effectively utilize the insulin produced. Diabetes Type 1 causes the body to produce very little or no insulin; hence a diabetes patient is required to administer insulin on daily basis to maintain the glycaemia to the appropriate levels. Diabetes Type 1is mostly seen in children and adolescent. Diabetes Type 2 occurs when the body cannot properly utilize the produced insulin. Diabetes Type 2 is mostly seen in adults, but lately, the numbers are increasing in children and adolescents due to the increase of obesity cases, decrease in physical activity and unhealthy eating habits. The third one is Gestational diabetes which is hyperglycemia with glycaemia values seen to be above normal occurring during pregnancy, this can occur to a woman who has never been diagnosed with diabetes before. KJ Hunt et al., (2008) gestational diabetes affects close to 4% of all pregnant women in the world's population. According to IDF (2019), Type 2 diabetes is the most common type of diabetes covering 90% of the world's diabetes population. WHO, (2017) reported that the number of diabetes patients rose from 108 million in 1980 to 422 million in 2014, with an estimate of 1.6 million deaths in 2015 caused by diabetes. In 2016 diabetes was the direct cause of 1.6 million deaths. Between 2000 and 2016, there was a 5% increment in premature mortality from diabetes. According to IDF (2019), a report projected that by 2030 there will be 578.4 million, and by 2045, 700.2 million adults aged between 20-79 years will be diabetes patients. This is enough proof that diabetes is a major public health problem that calls for immediate action to help prevent and manage it. Fig 2.1 illustrates the Worldwide diabetes estimates and projections according to IDF.

At a glance	2019	2030	2045
Total world population	7.7 billion	8.6 billion	9.5 billion
Adult population (20-79 years)	5.0 billion	5.7 billion	6.4 billion
Diabetes (20-79 years)			
Global Prevalence	9.3%	10.2%	10.9%
Number of people with diabetes	463.0 million	578.4 million	700.2 million
Number of deaths due to diabetes	4.2 million	-	-
Total health expenditures for diabetes[i]	USD 760.3 billion	USD 824.7 billion	USD 845.0 billion
Hyperglycaemia in pregnancy (20-49 years)			
Proportion of live births affected	15.8%	14.0%[ii]	13.3%[ii]
Number of live births affected	20.4 million	18.3 million	18.0 million
Impaired glucose tolerance (20-79 years)			
Global prevalence	7.5%	8.0%	8.6%
Number of people with impaired glucose tolerance	373.9 million	453.8 million	548.4 million
Type 1 diabetes (0-19 years)			
Number of children and adolescents with type 1 diabetes	1,110,100	-	-
Number of newly diagnosed cases each year	128,900	-	-

Figure 2.1 Worldwide diabetes estimates and projections according to IDF 2019

	2019		2030		2045	
	Number of people with diabetes (millions)	**Prevalence (%)**	**Number of people with diabetes (millions)**	**Prevalence (%)**	**Number of people with diabetes (millions)**	**Prevalence (%)**
Men	240.1	9.6	296.7	10.4	357.7	11.1
Women	222.9	9.0	281.8	10.0	342.5	10.8

Figure 2.2 The total number diabetes men and women worldwide IDF(2019)

2.2.2 Diabetes in Africa

According to the IDF (2019), a report estimated that 19.4 million adults aged between 20-79 years in Africa are living with diabetes, with a regional predominance of 3.9%. Africa region currently records the lowest possible prevalence among all the IDF regions this is mainly caused by the lower levels of urbanization, under-reporting, and under-nutrition. Reports by IDF show that in 2019, Africa recorded 366,200 deaths, a 6.8% of all-cause mortality caused by diabetes with a 9.1% of all-cause mortality due to diabetes of adults aged between 30–39 years. Fig 2.3 illustrates Africa diabetes estimates and projections according to IDF.

IDF Africa Region at a glance

	2019	2030	2045
Adult population (20–79 years)	501.3 million	703.9 million	1.1 billion
Diabetes (20-79 years)			
Regional prevalence	3.9% (2.1–7.1%)[i]	4.1% (2.3–7.5%)	4.4% (2.5–8.0%)
Age-adjusted comparative prevalence	4.7% (3.2–8.1%)	5.1% (3.4–8.8%)	5.2% (3.5–9.1%)
Number of people with diabetes	19.4 million (10.6–35.8 million)	28.6 million (16.0–53.1 million)	47.1 million (27.4–86.0 million)
Number of deaths due to diabetes	366,200 (200,054–627,374)	-	-
Diabetes-related health expenditure (20-79 years)			
Total health expenditure, USD	9.5 billion	12.7 billion	17.4 billion
Impaired glucose tolerance (20-79 years)			
Regional prevalence	9.0% (5.2–20.1%)	9.5% (5.6–21.0%)	10.3% (6.0–22.5%)
Age-adjusted comparative prevalence	10.1% (5.6–22.7%)	10.5% (5.7–24.1%)	10.7% (5.6–24.9%)
Number of people with impaired glucose tolerance	45.3 million (26.0–100.7 million)	66.8 million (39.1–147.7 million)	110.2 million (64.6–241.9 million)
Undiagnosed diabetes (20-79 years)			
Regional prevalence	59.7%	-	-
Number of people with undiagnosed diabetes	11.6 million (6.6–21.0 million)	-	-
Type 1 diabetes (0-19 years)			
Number of children and adolescents with type 1 diabetes	25,800	-	-
Number of newly diagnosed children and adolescents each year	10,300	-	-

Figure 2.3 Africa diabetes estimates and projections according to IDF 2019

2.2.3 Diabetes in Kenya

Prevalence in Kenya is 3.3%, according to the 2015 Stepwise survey carried out for non-communicable diseases. The report shows there is a possibility of underestimation since 60% of patients diagnosed with diabetes in Kenya are usually present in health care facilities with seemingly unrelated complaints. This means two-thirds of the people living with diabetes do not know they have diabetes IDF (2007). Majority of Kenyans living with diabetes, are diagnosed with diabetes Type2, which is largely manageable through eating healthy diets and regular physical.

2.3 Diabetes management

Management of diabetes differs depending on the type and severity of diabetes. For type 1 diabetes patients, insulin becomes part of an individual life, this is because it is a life-long treatment. It involves a wide variety of doses that include multiple dose injections or insulin pumps. Diabetes Management also incorporates monitoring glycemic control and to ensure this is achieved optimally one is required to self-monitor their glucose levels multiple times to modify insulin intake, diet, or physical activity as required. According to Povey& Carter (2007), consistency in diabetes self-management of diabetes is associated with the fulfilment of health outcomes in terms of good blood glucose control and fewer complications linked to diabetes, improved quality of life and a decline in diabetes-related death risks. Self-management refers to day to day activities an individual must undertake to reduce the impact of a disease on their health and wellbeing and as a result prevent further complications NM Clark et al., (1991 as cited in Mary D. Adu et al., 2019). Diabetes self-management will involve constant involvement in recommended behavioral activities such as healthy eating habits, physical activity, and daily blood glucose monitoring, which are all very crucial to successfully manage diabetes. According to ADA (2018) recommendations, it recognizes the integral role of nutritional therapy in overall diabetes management and has commended that each diabetes patient is actively engaged in self-management, education, and treatment planning with their health caregiver. Institute of Medicine (IOM) 1991 as cited in ADA (2013), published a report that showed evidence demonstrating that medical nutrition therapy (MNT) can improve clinical outcomes while cutting down the cost of general medicare for managing diabetes. Every diabetic patient has nutritional needs, and it is ideal for them to be referred to a registered dietitian or a credentialed nutrition professional for nutrition therapy at or soon after diagnosis.

2.4 Nutritional factors for diabetes management

Studies show that a mix of macronutrients produce the desired outcomes when it comes to diabetes management. Evidence indicates that there is not an ideal percentage of calories from carbohydrate, protein, and fat for all diabetic patients; therefore, macronutrient distribution should be based on an individualized assessment of current eating patterns, preferences, and metabolic goals (Institute of medicine, 2002).

2.4.1 Carbohydrates

The amount of carbohydrates intake and insulin availability may be the most important factor influencing glycemic response after eating and should be considered when developing an individual's eating plan. According to ADA (2014) carbohydrate intake monitoring whether by carbohydrate counting, food exchange or through experience-based estimation remains a crucial strategy in achieving glycemic control. To achieve good health diabetes patients are advised to consume carbohydrates from vegetables, fruits, whole grains, legumes, and low-fat dairy over other sources of carbohydrate such as added fats and sugars.

2.4.2 Glycemic index and Glycemic load

Through ADA guidelines it is highly recommended that individual patients ought to be educated on the Glycemic Index (GI) and Glycemic Load (GL) during the development of individualized eating plans. A study conducted by Yunsheng Ma et al. (2009) compared the ADA diet and the low-GI diet where the low-GI diet attained an equivalent control of HbA1c using less diabetic medication. Some studies that advocate for substituting high–glycemic load foods with low–glycemic load eating patterns have shown evidence demonstrating an A1C decrease of −0.2 to −0.5% this being a modest improvement in glycemic control. Thomas DE et al., (2011). GI is a ranking system that classifies carbohydrates containing foods by their effect on blood sugar levels (David Jenkins 1981 as cited by Thomas DE and Elliot EJ 2010). The GI value is calculated in a food laboratory using valid scientific methods, that classify different foods in 3 classes as low GI<55, medium Gi 56-69 and high GI>70. Glycemic load helps us know how high your blood sugar is likely to go when you eat a particular food item. Its formula is as shown:

Glycemic Load = Gi (%) x Carbohydrate (grams) content per portion ÷ 100.

Like the glycemic index, the glycemic load of a food is also classified as low GL <10g, medium GL11-19g and high GL>20g.For optimal good health, a patient is recommended to keep their daily glycemic load under 100.

2.4.3 Proteins and fats

According to Glycemic Index Foundation (GIF) eating proteins and fats have little effect on blood sugar levels, but this does not necessarily mean they will not affect blood glucose response when eaten with a rich carbohydrate food item. They tend to slow down digestion and the absorption rate of carbohydrate. Frank B et al., (2001) remarked that most nutritional recommendations do not protein and fats intake to diabetes Type 2 patients.

2.4.4 Dietary fibre and whole grains

Diabetes patients should consume at least the amount of fiber and whole grains recommended for the public; this is because little evidence shows that fiber significantly helps to improve glycemic control. One of the few studies conducted showed a reduction in HbA1c of 0.26% (95% CI, 0.02–0.51) Robert E et al., (2012). This recommends that increasing dietary fiber in the diet of patients with type 2 diabetes is beneficial and should be encouraged as a diabetes self-management strategy.

2.4.5 Transtheoretical model

It is a model associated with the likelihood of change in individual behavior and provides approaches to guide the individual. (Prochaska et al., 1970 as cited in Alison Hammond 2010). With diabetes management, a patient is encouraged to adopt new behaviors such as healthy eating habits and physical activity. A Diabetes type 2 patient attempting to adopt the new behavior must move through five stages, pre-contemplation, contemplation, preparation, action, and maintenance. In pre-contemplation stage information about the problem is shared illustrating the advantages of following a healthy lifestyle. In the Contemplation stage, the patient has begun to think about change, they start evaluating the benefits and barriers of change. In Preparation the stage there is clear goal setting which must be SMART. In the Action stage, the patient makes specific lifestyle behavior modifications. For example, always eating a balanced diet. Finally, in the maintenance stage, the person has adopted the new lifestyle for more than 6 months and are doing everything possible, not relapse. For example, they have managed to control their glycaemia to the recommended levels. A transtheoretical model is effective in changing the nutritional behavior in patients, Hashemzadeh M et al., (2019).DM type 2 is greatly influenced by the patients' lifestyle therefore the theory is a guideline to help them understand the process of change when it comes to adopting new behavior. It focuses on enhancing motivation to the patient to eat a healthy diet, adopt physical activity and monitor their blood glucose levels. After the patient is motivated to change behavior, they can maintain the new habit of living a healthy lifestyle.

2.5 Factors affecting nutritional dietary for diabetes Type 2 patients

A study conducted by Shamsi N et al., (2013) illustrates that improving dietary practice can help manage glycemic control and is likely to reduce glycosylated hemoglobin (HbA1c) by 1% to 2%. Nutritional therapy which is a crucial part of self-management of diabetes for diabetes Type 2 patients which should entail a detailed evaluation of their eating patterns, type, and the size of foods and the quantity of beverages consumed, the number of times they eat including meal and snack distribution throughout the day, macronutrient, and micronutrient intake. Not limited to weight history, body mass index (BMI) and target weight, glycaemia targets, knowledge on foods GI and GL and lastly review of the results of self-monitoring of blood glucose. According to Najla Shamsi et al. (2013), Diabetes patients find it challenging to remain consistent in adhering to their diabetic diet program. This is mostly influenced by food access/availability of healthful foods, tradition, cultural food systems, health beliefs, knowledge of foods that promote health and prevent disease, and economics/resources to buy health-promoting foods. A study by Shamsi N et., al (2013) reported that some of the factors that make the diabetes patients not to stick to their diet regime were, it takes effort to plan what to eat during every meal and to see it through. Edward Byers (2016) most diabetes type 2 patients are lack self-control in matters related to food and diet participants in the study said it was difficult for them to resist some of the foods that they enjoyed eating with restrictions before they were diagnosed with diabetes. Confusion and forgetfulness. Patients stated that sometimes it got confusing on what type of food to eat and the amount they should consume. Some patients said they forgot to check their blood glucose levels due to their daily schedules. Patients see diabetes as an inconvenience that interferes with their day-to-day social life. Y.M Demilew et al., (2019) dietary practice of type 2 diabetes patients is poor due to lack of nutrition education on diabetes diet management to the patients and families.

2.6 Machine learning techniques used in diabetes management

Machine learning is a data analytics technique that will teach a computer to do that which comes naturally to humans and animals. Machine learning techniques are classified into four categories, supervised learning, unsupervised learning, semi-supervised and reinforcement learning. Chen et.al (2019) machine learning techniques applied in the health informatics sector for instance healthcare and telemedicine, is playing a big role to the users who are clinicians, patients and their caregivers for better decision making in less time and very affordable.

2.6.1 Decision trees

Decision trees is a supervised learning method, which is used for solving classification problems. S. Sneha & Gangil, T (2019). The goal of the method is to predict the class value of the target variable. The decision tree will help to segregate the data set and build the decision model to predict the unknown class labels. A decision tree can be constructed to both binary and continuous variables. Decision tree optimally finds the root node based upon the highest entropy value. This gives the decision tree the advantage of choosing the most consistent hypothesis among the training datasets. An input to the decision tree is a dataset, consisting of several attributes and instances values and output will be the decision model. A study done by Ramezankhani A (2014) used decision tree analysis, using routine demographic, clinical, anthropometric and laboratory measurements to create a simple tool to predict individuals with low risk for type 2 diabetes.

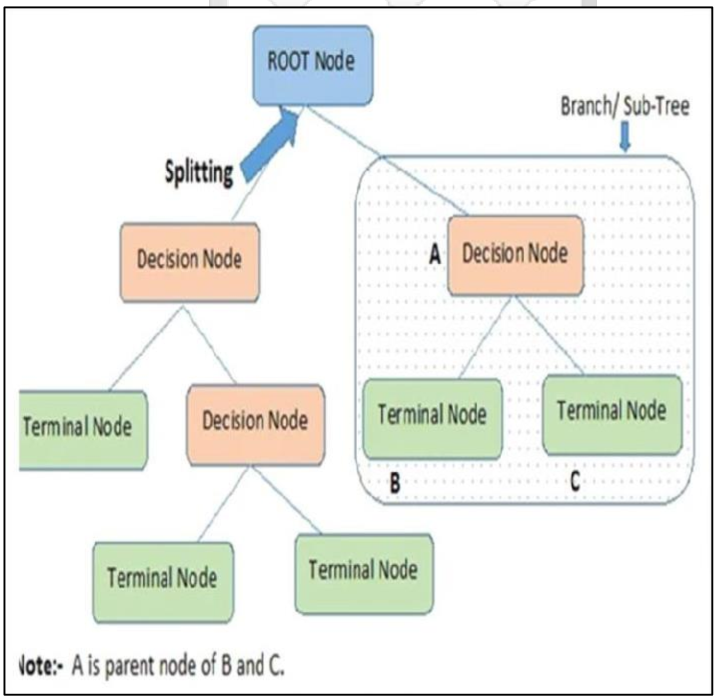


Figure 2.4 4 Decision tree S. Sneha & Gangil, T (2019)

2.6.2 Naïve bayes

Naive Bayes classifier is an approach based on a probability that works on each class label independently. It works on the Bayesian model of probability. Sneha & Gangil, T (2019) is a method that takes the dataset as input, performs analysis and predicts the class label using Bayes' Theorem. It is a classifier that gives results in a probabilistic character that is the probability of occurrence of a particular thing. Naïve Bayes works based on the conditional probability the algorithm brings the high classification accuracy when the size of the dataset is vast, it is a powerful classification technique suitable for large datasets. A.Sharmila, (2020) developed a prediction model using naïve bayes which tested the probability of a person has a risk of diabetes using attributes such as blood pressure, glucose, age and BMI. The Bayes Theorem formula calculates the posterior probability for each class using the shown formula.

p (Ca | Z) = p(Ca) p(Ca|Z) / p(Z)

Figure 2.5 Naive Bayes Gangil, T (2019)

where, p(Ca | Z) = posterior probability

p(Ca|Z) = Likelihood

p(Ca) = Class Prior Probability

p(Z) = Predictor Prior Probability

With the help of Bayesian probability terminology, the equation can be written as:

POSTERIOR=PRIOR*LIKELIHOOD/EVIDENCE

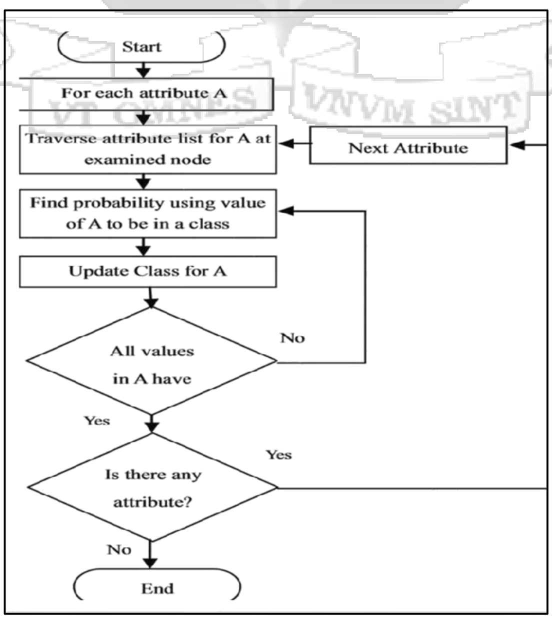


Figure 2.6 Naive bayes flowchart

2.6.3 Support vector machine

S. Sneha & Gangil, T (2019) SVM is a supervised learning, discriminative classification technique. This method can be used for both regression and classification. The logic behind the SVM is finding a hyper line between the dataset, which best divides the dataset into two classes. It includes 2 steps, Identifies the right or optimal hyper line in data space and mapping the objects to the boundaries specified. The SVM training algorithm builds a model that assigns new samples to one of the classes.

2.6.4 K nearest neighbour(KNN)

S. Sneha & Gangil, T (2019) is a classification technique which classifies the new sample based on similarity measure or distance measure. The measure includes 3 distance measures Euclidean distance, Manhattan, Minkowski. Steps used in KNN are training phase of the algorithm consists of only storing the feature sample and class label of the training sample. Classification phase: the user must define a "k" value for the classification of the undefined sample for the k number of the class labels, so the unlabeled sample can be classified into the defined class based on the feature similarity. Majority of voting classification occurs for unlabeled class. The value of the k can be selected by various techniques like heuristic technique.

2.7 Related works

Today with the use of machine learning techniques healthcare systems that were quite complex to evaluate, with emerging techniques it has become easier than before. M Mohri, (2012) supervised learning uses labelled datasets to train algorithms that classify data or used in predicting outcomes accurately. From a given corpus, you have you divide it into the training and the test datasets that contain both the input and the desired output to train the algorithm learn of any new cases that are fed into the predictive model and are required to give the correct output. Unsupervised learning uses unlabeled data leaving it to discover the hidden patterns. The global spread of diabetes led to the urgent need for automated tools and services that will support diabetes patients with carbohydrate (CHO) counting to control their glycaemia. The ease of availability for smartphones with enhanced capabilities alongside the latest advances allowed for the development of image analysis applications used for automatic assessment of food taken by a patient.

2.7.1 GOCARB system a smartphone application

Anthimopoulos M et.al (2015) developed GoCARB system a smartphone application designed to support diabetes Type 1 patient used computer vision to estimate the amount of carbohydrates in meals. The method used to develop GOCARB system was computer vison which was used to train the model interpret and understand the visual images. The patients take 2 pictures using their smartphone the plate is detected and the foods segmented, the food volumes are calculated, and the CHO content is estimated. The limitation of computer vison is more information was needed from the patient when it comes to complex foods that are mixed together or covered in sauces.

2.7.2 DIET-Organizer system

G. Agapito et al.2016 propose a web-based recommender system called DIETOS (DIET-Organizer System) to improve the quality of life of individuals affected by chronic diet-related diseases. DIETOS system could recommend foods with personalized nutritional related suggestions based on the user health profile. DIETOS was an expert system that did not use statistical or data mining algorithms to classify users, because the system implicitly used guidelines furnished by the medical specialist. This system used health profiling which was based on the answers the patients gave to recommend food to the patient. One limitation of the system was the recommendations were not based on the patient's dietary needs at the moment. Another limitation was DIETOS did not advise users on diets compatible with their health status.

2.7.3 A snack recommender system

S Norouzi et al., (2018) developed a knowledge-based smart phone application which was a snack recommender system that integrated artificial intelligence techniques via knowledge base according to the guidelines posted by the ADA (2014). The methods used were a combination of constraint-based reasoning and roulette wheel algorithm used during the development of the model to rank snacks and choose what fits the patient best according to their health status. Physical activity level was crucial because the snack recommendation was based on their calorie requirement. The BMI made the recommender system less sensitive to personal interests to suggest what was beneficial for one's health. One limitation of the recommender system was it during evaluation phase it did not include main meals what was included were snacks. Another limitation was the recommender system did not use precise algorithms to improve on the recommendation.

2.7.4 Diet-right a smart food recommender system

F Rehman, et.al (2017), proposed a model that recommended various foods to people based on their pathological test reports. The method used to develop the system was Root Mean Square Error (RMSE) to select globally best solution. The normal ranges of the indicators are given in the test reports this way, the patient can identify the abnormalities after comparing with the normal ranges. The system gathers the data of normal ranges for the tests that were conducted. The system is trained on various types of age groups and their respective ranges of parameters allowing the system to suggest diets as per the needs of the patient. The ranges of the same component may differ based on gender, age groups, and fasting or no fasting. One limitation of the system was it did not breakdown for different timings of the day, such as breakfast, lunch, and dinner considering the amount of nutrition in different food items at different timings and daily needs of the patients.

2.8 Summary of literature review

Table 2.1 Summary of the reviewed literature

Description of the variables	**Measures**	**Techniques used**	**Gaps**	**Source**
Food recommender systems	DIETOS-Web-based food recommender system	Expert system	The food recommendation was done based on the user's profile.	G.Agapito et al. (2016)
	DIET RIGHT A Smart Food Recommendation System	Root Mean Square Error Ant Colony Optimization	Th recommender system is based on pathological test reports.	Faisal Rehman, et.al 2017
	GoCARB system is a smartphone application.	Computer vision	More information was needed for complex foods that are mixed together or covered in sauces.	Anthimopoulos M et.al (2015)
	A snack recommender system	An expert system that used roulette wheel algorithm	The recommender system included just snacks	S Norouzi et al., (2018)

2.9 Gaps identified

The food recommender systems in the related works did not address the issue of blood glucose monitoring in real-time, the recommender systems used pathological tests previously done by the patient or the information shared on their profiles. This is a gap because diabetes self-management demands for continuous Glucose Monitoring since the levels of an individual’s blood glucose may vary hourly in different situations hence the food recommendations will also vary accordingly. Other systems failed to address the issue of the nutrition factors to balance the diet of the user according to their needs. The proposed prototype will recommend food to the patient based on their blood glucose levels. The model will classify different foods as either high GI, medium GI or low GI, through this it will recommend food to the patient that are not likely to spike or dip their sugar levels. Monitoring the blood sugar levels will guide which food the model will recommend to the patient.

2.10 Conceptual framework

Based on the literature review and the various gaps identified, this study proposed a conceptual model that will use the patients' glycaemia levels which is real-time to recommend food they can eat to manage their blood sugar levels. Foods from the international glycemic index were used to create the corpus necessary for training the model. The foods will be annotated as low GI, medium GI, and high GI, naïve Bayes algorithm will be used to now classify which foods should be eaten when depending on their blood glucose readings. The model's performance will be evaluated based on the metrics of precision and accuracy. A user will key in their blood glucose measurements the data will be preprocessed in the food construction module to check for the appropriate food to recommend. Figure 2.7 illustrates the conceptual model of the proposed prototype.

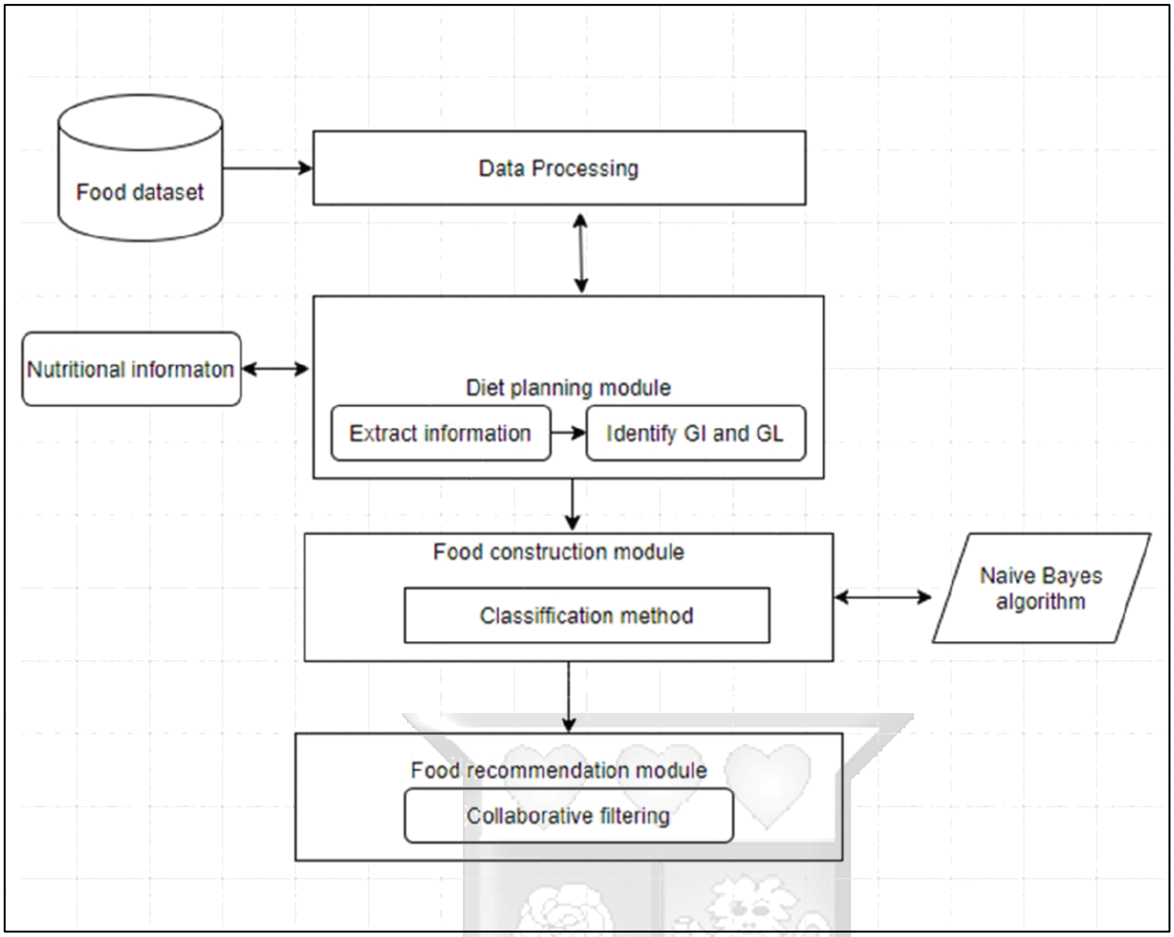


Figure 2.7 Conceptual framework

Chapter 3: Research methodology

3.1 Introduction

Research methodology is the process of solving problems systematically. Bhatnagar & singh, (2013). This section will describe the research design, data collection techniques and the methodology adopted for the development of the food recommender system for diabetes type 2 patients. The study was greatly influenced by the objectives that were intended to be achieved by the end of the research study.

3.2 Research design

This study took an experimental design approach due to the processes involved, a hypothesis, a variable that can be manipulated by the researcher, and variables that can be measured, calculated, and compared. This study determined the relationship between two variables, the dependent variable which is the patient's glycaemia levels and the independent variable which is the food item recommended to the patient. Building the food recommender system as a proof of concept and validation of the model using several experiments to ensure the best performance is achieved.

3.3 Agile development system methodology

Agile development methodology approach employs continual planning, learning and improvement. This approach was adopted for this study because of its ability to incorporate iteration to enable continued feedback during development to refine and deliver successively. The iterations involved continuous planning, continuous testing, continuous integration, and continuous evolution. The interactions in Agile methodology were necessary for the development of the food recommender model to ensure its accuracy since some of the variables are unique for every diabetes patient. This methodology helped to add and remove features when need be during the development process. Figure 3.1 is an overview of the stages of Agile development that were followed to achieve the set objectives. The phases involved are planning, requirements analysis, design, building and testing.

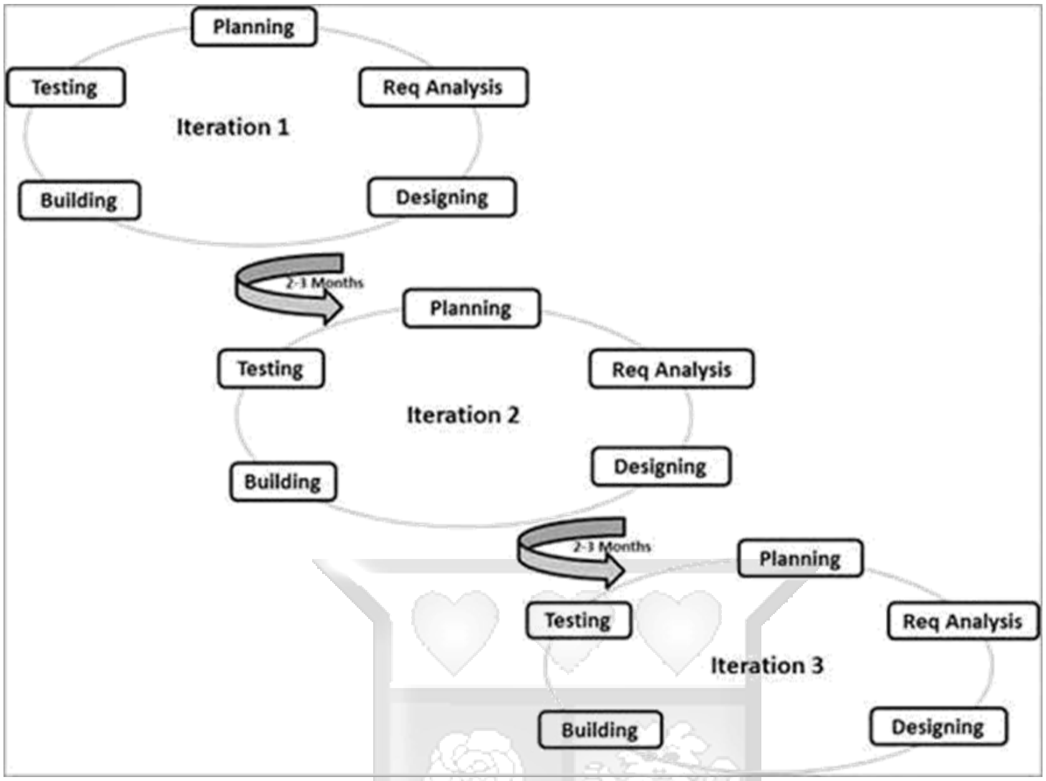


Figure 3.1 Overview of the stages of Agile development steljes (2012)

3.3.1 Planing phase

This is the initial stage where the planning of how the development process was done. This stage was very fundamental because it identified all the resources needed to build the food recommender system. This entailed sourcing for both the secondary and primary data that was used.

3.3.2 Requirement analysis phase

This phase captured the user specifications that the system is required to meet. Guided by the first objective, I was able to collect and analyze the entire system's functional and nonfunctional requirements ensuring they are all defined. This involved defining more details of the system inputs, processes, outputs and interfaces.

3.3.3 Design phase

This stage involved creating rough mock-ups of the user interface illustrating how the diabetes patients would interact with the system. During this stage, requirements were mapped into the system architecture. The several created mock-ups of the user interface were used to ensure the results of this phase were complete and precise meeting all the non-functional requirements.

3.3.4 Building

This stage was the backbone of the entire process as it involved writing the code and converting design documentation into the actual software.

3.3.5 Testing

This stage was spent conducting a series of tests to ensure the code was clean and that the system met its set objectives.

3.4 Data collection and collection methods

The technique used for data collection for this study included both primary data and secondary data. Primary data was the questionnaires and interviews conducted to the diabetes Type 2 patients to give insights that guided in achieving the first research objectives. A total of 20 patients were approached and enrolled (11 women and 9 men) they were included as research participants. Secondary data which was also used, was sourced from existing databases and dataset. The data of different foods and their nutritional value was sourced from the International Table of Glycemic Index and Glycemic load value Fiona S. Atkinson et al., 2008 (see appendix A). A sample of the GI &GL is depicted as shown.

	Food Number and Item	GI[2] (Glucose = 100)	GI[2] (Bread = 100)	Subjects (type & number)	Reference food & time period	Ref.	Serve Size	Avail. carbo-hydrate	GL[3] per serve
							g	g/serve	
	BAKERY PRODUCTS								
	Cakes								
1	Banana cake, made with sugar	47±8	67	Normal, 8	Bread, 2h	1	60	29	14
2	Banana cake, made without sugar	55±10	79	Normal, 7	Bread, 2h	1	60	22	12
3	Carrot cake, prepared with coconut flour (Philippines)	36	52±3	Normal, 10	Bread, 2h	2	60	23	8
4	Chocolate cake made from packet mix with chocolate frosting (Betty Crocker, General Mills Inc., Minneapolis, USA)	38±3	54	Normal, 10	Glucose, 2h	UO[4]	111	52	20
5	Cupcake, strawberry-iced (Squiggles, Farmland, Grocery Holdings, Tooronga, Australia)	73±12	104	Normal, 10	Glucose, 2h	UO[4]	38	26	19

Figure 3.2 Sample of GI and GL in foods Fiona S. Atkison et al., (2008)

3.5 Target population and sampling

A population is the total number of units in a study environment from which a sample may be selected Bryman, (2012). The 1000 foods in the international Glycemic index dataset were chosen as the population for this study. Classification techniques were applied in the study, the population was divided into sub-groups of high GI, medium GI, and Low GI, which were selected to be in the study to guide the model in recommending food to the patient. The study used simple random sampling this form of sampling agrees with the law of statistical regularity which simply means that if a simple random sample is chosen, it carries the same characteristics as the population Kothari, (2004).

3.6 Data analysis and model development

The data analysis approach adopted for this study was classification techniques. Classification of the attributes and labels was done using inference statistical analysis methods. The goal of classification was to accurately classify the class labels of instances whose contextual attribute are known, but class values are unknown J, Kamber et al., (2011). Java programming language was used to build the Android application on the other hand python was used to come up with the model that was used to make food recommendations to the patients.

3.7 Food recommnedation model development

The development of the food recommender model underwent the following steps:

3.7.1 Data importing

The food dataset was imported.

3.7.2 Data cleaning

The data was cleaned to eliminate noise and any irrelevant data from the large data set, cleaning the data entailed removing any redundant record, extra data fields and any null records.

3.7.3 Data splitting

The data was split into two 80% training at and 20% for testing.

3.7.4 Selection of the machine learning algorithm

The Algorithm chosen for the implementation of this project was Naive Bayes Classifier. It is a classifier that gives results in a probabilistic character that is the probability of occurrence of a particular thing. In this work, the role of Naive Bayes classifier was chosen to be used on the data used collected from various patients depicting their blood sugar levels and the type of meals they took. This was used to calculate the individual probability hence give the prediction to other patients who had similar blood sugar levels in recommending the food. Naive Bayes played an important role in classifying the blood sugar levels and the foods taken and hence calculating the probability of each patient individually. Based on probability results, the classifier predicted the food a patient should eat based on the sugar levels of the patient.To fit the Naïve Bayes to the recommender train GaussianNB classifier was used.

3.7.5 Model training and testing

In this implementation, the data taken was categorized into training data and test data. The training data was the one where details of the patients and the food they ate with the predicted result indicating if the food caused spiking or dipping of blood sugar levels. The test data is where implementation works and hence predicts the food a patient should eat. Test data was also data through which the implementation of the project was checked. The trained model was tested with 20 % of the training dataset of 80% to determine the model's accuracy.

3.7.6 Model validation

The validation of the model was done on the 20% testing dataset. The confusion matrix was used in the implementation of this phase due to check for the accuracy of the classifier used

Table 3.1 Confusion matrix

N=1000	Predicted: No	Predicted: Yes
Actual: No	30	50
Actual: Yes	20	900

Table 3.2 Confusion matrix naive bayes

N=1000	Predicted: No	Predicted: Yes	
	TN=30	FP=50	80
	FN=20	TP=900	920
	50	950	

3.8 System analysis

3.8.1 System requirement specification

The system analysis will involve the system requirements analysis and the representation of the identified system requirements using the various system analysis tools. The method that will be used in requirements gathering will be a document review approach. The system requirements will be categorized into functional and non-functional requirements.

3.8.2 System hardware analysis

The model was developed using a Hp core i7 ProBook 430 G4 laptop which has 8G Ram and 1TB SSD. These were sufficient resources required to develop the prototype.

3.8.3 System software analysis

The model was developed using Naïve Bayes algorithm the problem at hand required supervised learning. The advantage of Naïve Bayes being is it is easy to implement and its scalability.

3.9 System and design

The system design approach that was adopted for this study was object-oriented programming. The output of this was the UML (Unified Modelling Language), ERD (entity-relationship diagrams, use-case, class diagrams, and sequence diagram. The UML syntax provides the flexibility of representing system components which applies various approaches to the synthesis of models Giese, (2018).

ERD (entity relationship diagrams) were applied in the study during database design to show entities, attributes, and relationships.

Use-case diagrams were used to illustrate the interaction of the actors and the system processes.

Class diagrams were used in the study to construct and visualize object-oriented systems.

Sequence diagrams were used to show object interactions arranged in time sequence.

3.9.1 System implementation

The food recommender system will be built in this phase. The development environment will be Windows 10 64-bit. The implementation procedure followed a series of steps as listed

1. Installation of Anaconda for the development environment.
2. Installation of python.
3. Collecting and organizing the dataset
4. Develop the model using Naïve Bayes algorithm.

5. Test and validate the model.

3.10 Research quatity aspect validity

The validity of the study is ensuring that the needed functionalities are meeting the set research objectives. The aspect of validity used for this research was content validity. Choudrie and Dwivedi, 2005 cited in Taherdoost (2016). Contrastingly, a quantitative approach may allow researchers to send content validity questionnaires to experts working at different locations, whereby distance is not a limitation.

3.10.1 Reliability

Testing for reliability is significant as it refers to the consistency across the parts of the model. (Huck, 2007cited in Taherdoost 2016). Cronbach Alpha coefficient will be used to measure the reliability of the research. It will be the most appropriate when using the Likert scales for the questionnaires sent to the experts to help scale the responses.

3.10.2 Dissemination of the study rsults

After series of evaluations and careful planning, writing up results from the study will be communicated to target audiences. These results will be presented in organizations that deal in health informatics especially in diabetes management such as the Kenya diabetes and management Centre.

3.10.3 Utilization of the study results

The study results will be shared in centers that help patients manage diabetes like Kenya Diabetes management Centre and pharmacy.

3.10.4 Ethical consideration

The research subjects who agree to take part in the study were required to read and understand the consent form before signing it. All previous research works used in developing this study were cited appropriately giving due acknowledgement to the respective authors.

Chapter 4: System analysis and architechure

4.1 Introduction

This chapter discussed the architecture and the detailed design of the proposed food recommender system by incorporating the identified system requirements that are the functional and non-functional requirements. The chapter highlighted the system design diagrams and system architecture adopted in the development of the proposed system.

4.2 System analysis

The study aimed to develop a food recommender system that would recommend food to diabetes type, 2 patients, after analyzing their glycemic levels against the categorized food items in the model based on the research objectives this section outlined the system requirements of the proposed system.

4.2.1 Requirement gathering

The method adopted for requirement gathering was the document review approach. The system requirements were divided into functional and non-functional requirements.

4.2.2 Functional requiremnents

The functional requirements are the basic processes and functions that the system is expected to perform to achieve the system's objective.

1. The system should allow users to register their details.
2. The system should allow the users to update their profile and check their history.
3. The system should allow the users to enter their glycaemia levels which will be used as parameters to guide the model to give food recommendations.
4. The system should fetch food items that match their nutritional requirements upon user request.
5. The system should display to the user different foods with their caloric value.

4.2.3 Non functional requirements

The non-functional requirements will explain the performance characteristics of the system that will enable the developed system to perform optimally.

Ease of use

The intended users of the prototype will be diabetes patients. The interaction between the prototype and the users shall be easy to allow them to operate it with minimum or no training. The user will easily key in their blood sugar levels which will be displayed on the screen, then click on food recommendation or custom meal tab. The tabs are straight forward hence making food recommendation easy.

Reliability

The system shall provide consistent and reliable information to the users this is because it is dealing with human health. All the food information shared to the users were advised by expertise such as dieticians and nutritionists. The food list used to guide the glycemic index and load was extracted from the international tables of glycemic index and glycemic load.

Maintainability

Development of the prototype used Agile methodology which entails frequent modifications. The application shall go through the modifications with a fair degree of effortlessness.

Persistent storage

The system shall ensure permanent storage of food items for easy retrieval when a user needs to. It will be responsible of managing the food and users lists.

Availability

The system's components shall be operational and accessible when required for use. The system will be available to end users 99.999% of the time.

System performance

The system shall have high performance with the in-built capability of serving high traffic with a low response time.

4.3 System architechure

The system architecture demonstrates how the food recommender system prototype, and its components are made up as illustrated in Fig 4.1. The food recommendation process will start after the user tests their glycaemia levels, the user will feed in the results on their mobile application.

The glycaemia readings module collector will receive the readings and run them through the Naïve Bayes algorithm module to match them to the food item the users can eat to manage their blood sugar levels. The most suitable food item for the patient to consume is sent to them

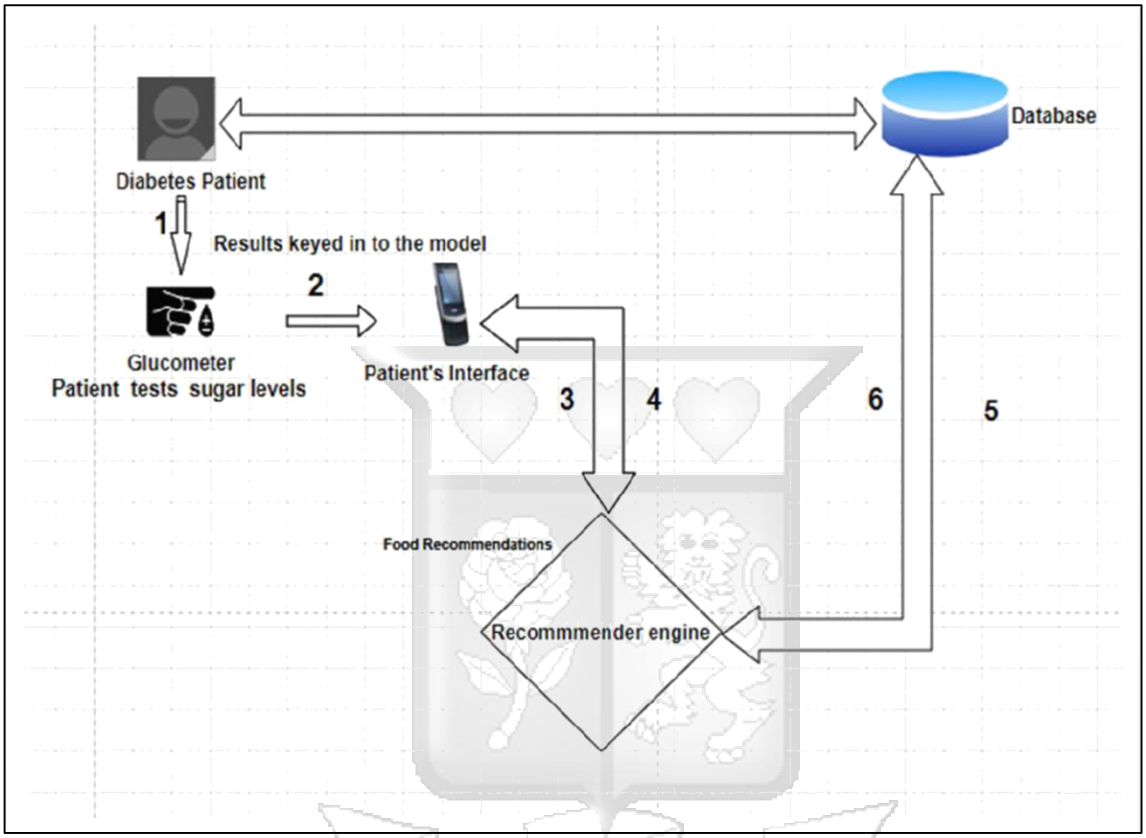


Table 4.1 System architechure

4.4 System design

4.4.1 Usecase diagram

Use cases were used to illustrate a collection of related success and failure scenarios during the interaction of the actors and the system processes. Fig 4.2 illustrates how the actors will interact with the proposed food recommendation prototype for diabetic patients.

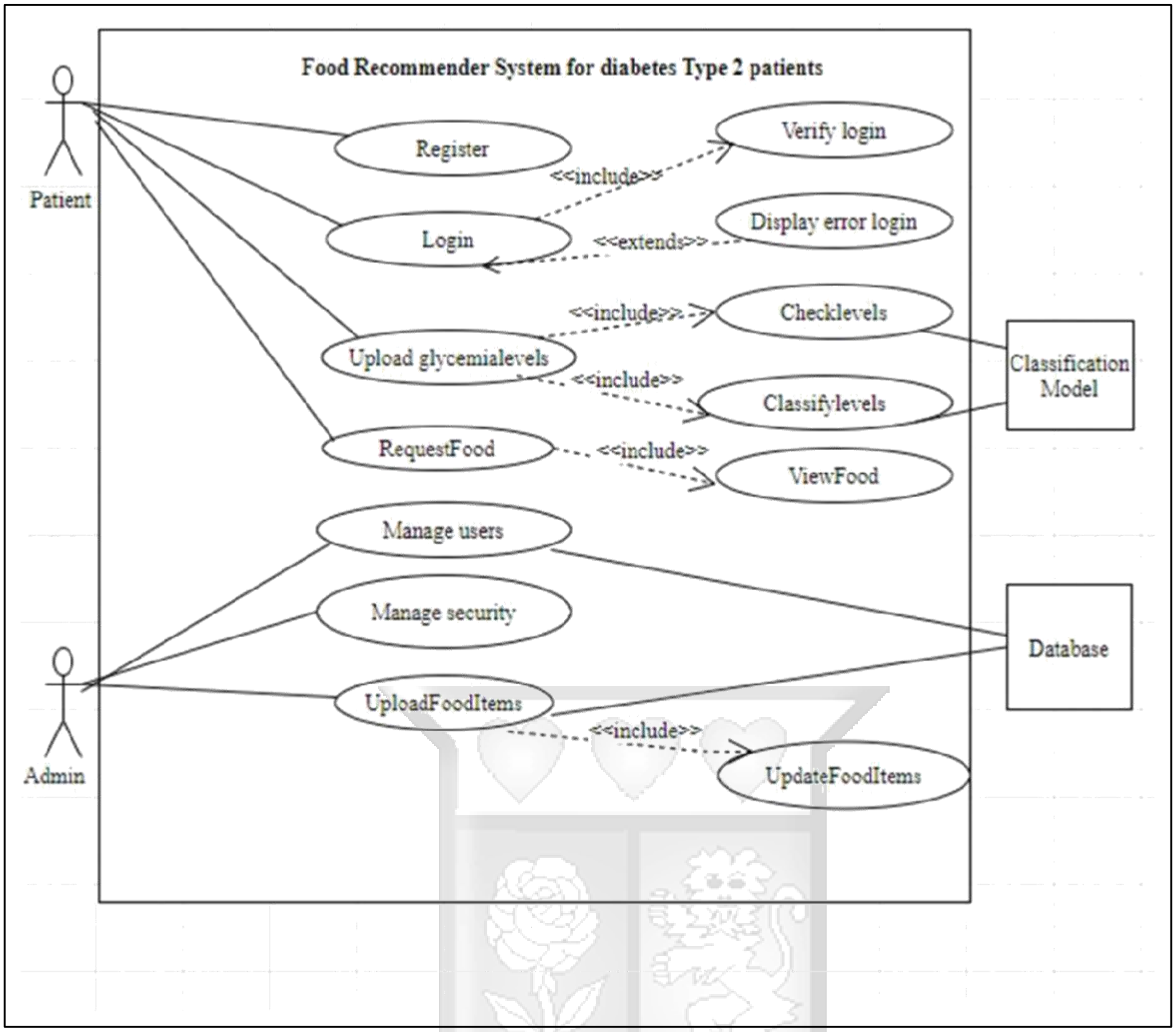


Table 4.2 Use case diagram

4.4.2 Detailed use case description

This section will give an elaborate description of the use cases In Fig 4.2 written in a fully dressed format.

Use Case UC1: Register Patient

Preconditions: Application is installed

Main Success Scenario

1. Patient enters their details on the system to register.
2. Patient saves their details.
3. System records patient's details.
4. System presents patient with patient detail summary.

Extensions

At any time, the system fails to support recovery and correct data entry, ensuring all registration state and events can be recovered from any part of the scenario.

1. Patients reload the system, and request recovery or prior state.
2. System reconstructs prior state.

2a. System detects anomalies preventing recovery.

- System signals error to the patient records the error and enters a clean state.
- Patient starts a new registration.

Special Requirements

- Account creation response within 5min 90% of the time

Use Case UC2: Classify glycaemia levels.

Preconditions: Patient is identified and authenticated.

Post condition: Patient has fed the glycaemia levels to the system.

Main Success Scenario

1. Patient uploads the glycaemia levels to the system.
2. System records the glycaemia levels.
3. System presents the patient with the recommended food item.
4. Patient logs out.

Extensions

At any time, the system fails to present the user with the recommended food.

- Ensure there is internet connectivity.
- Restart the system.

Special Requirements

- Food recommendation response time should be within 5min 90% of the time.

Use Case UC3: Request food

Preconditions: Patient is registered on the system

Post condition: Patient details are saved.

Main Success Scenario

1. Patient logs in the system.
2. Patient uploads the glycaemia levels to the system.
3. System records the glycaemia levels.
4. System presents the patient with the recommended food item.
5. Patient logs out.

Extensions

At any time, the system fails-to present the user with the recommended food.

- Ensure there is internet connectivity.
- Restart the system.

Special Requirements

- Food recommendation response time should be within 5min 90% of the time.

4.4.3 Sequence diagram

The sequence diagram illustrated in Fig 4.3 demonstrates the sequence of interactions between the user of the proposed system and the interactions between the components of the system illustrating the to and from flow of requests and feedbacks of the system. The patient will enter their details through the installed mobile application, once the system retrieves the user's details it will ask the user to upload their glycemic levels upon receiving the levels, they are passed on to the classification module to determine which food items the system should recommend to the patient. The system gives feedback to the patient in form of the food they should eat.

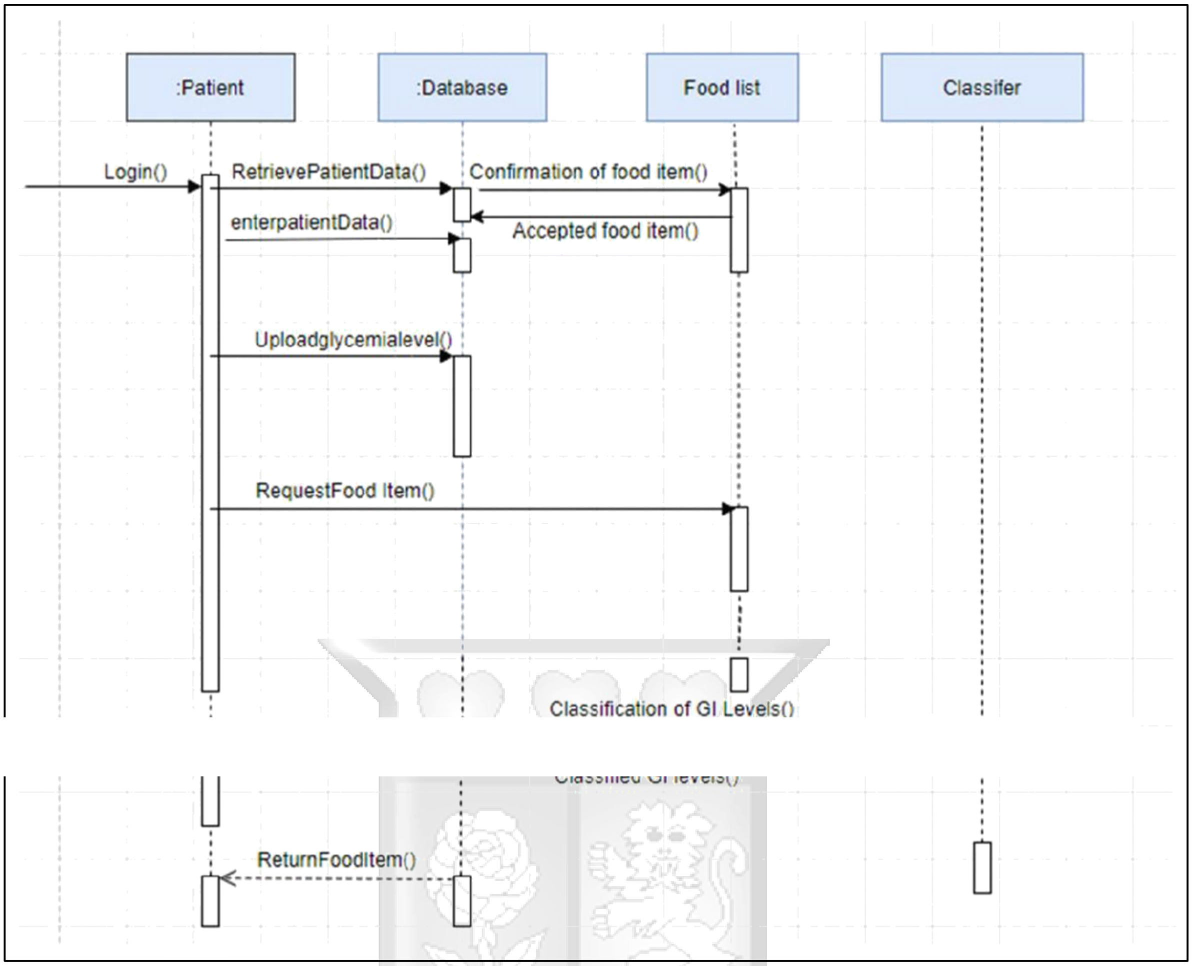


Figure 4.1Sequence diagram

4.4.4 Entity relationship diagram

Entity-relationship diagram (ERD)is used to represent the conceptual data model of the proposed system. It depicts how the database will be constructed. It also shows the interaction between the different entities in the system. Fig 4.4 shows the ERD for the proposed system after normalization.

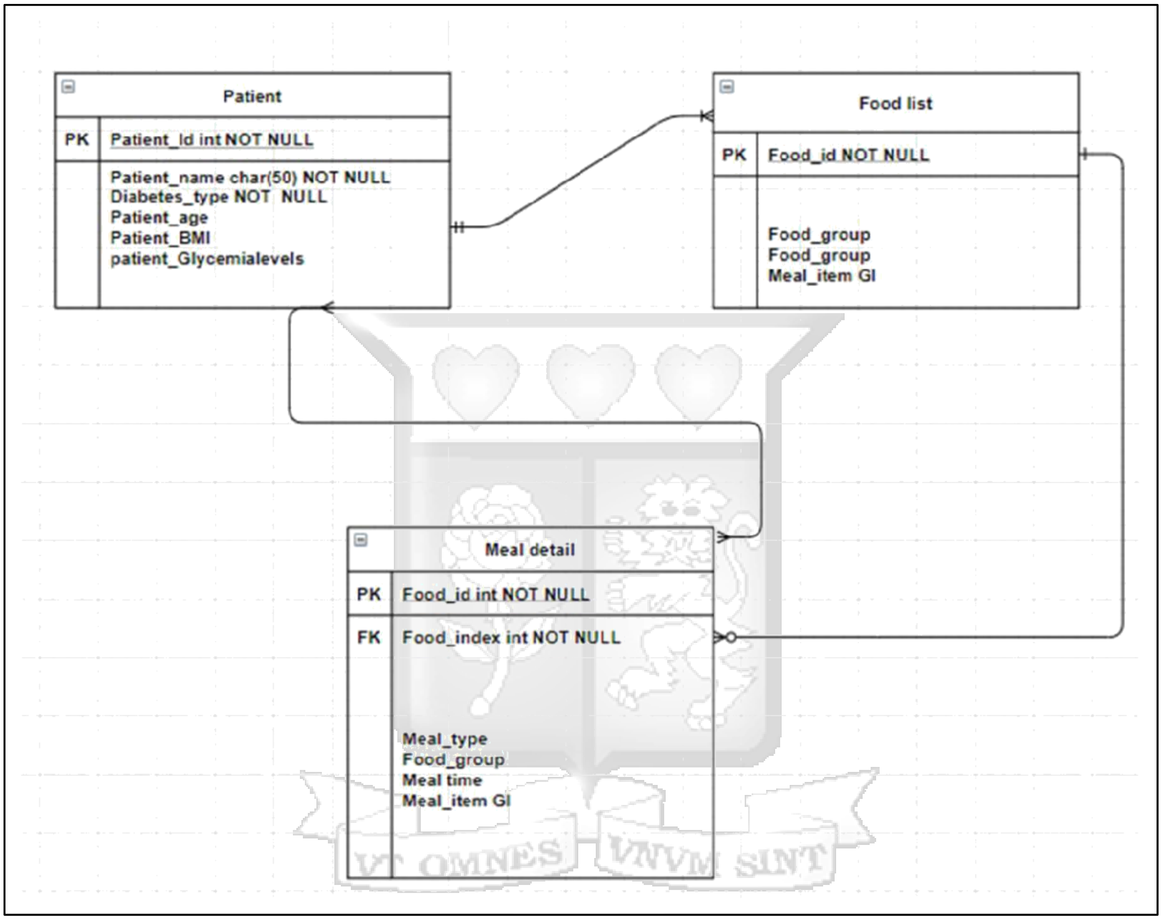


Figure 4.2 Entity relationship diagram

4.4.5 Class diagrams

Class diagrams are used to demonstrate the structure of a system by showing all interactions of the system's classes and their corresponding attributes, operations, and relationships among objects. Fig 4.5 illustrates the class diagram.

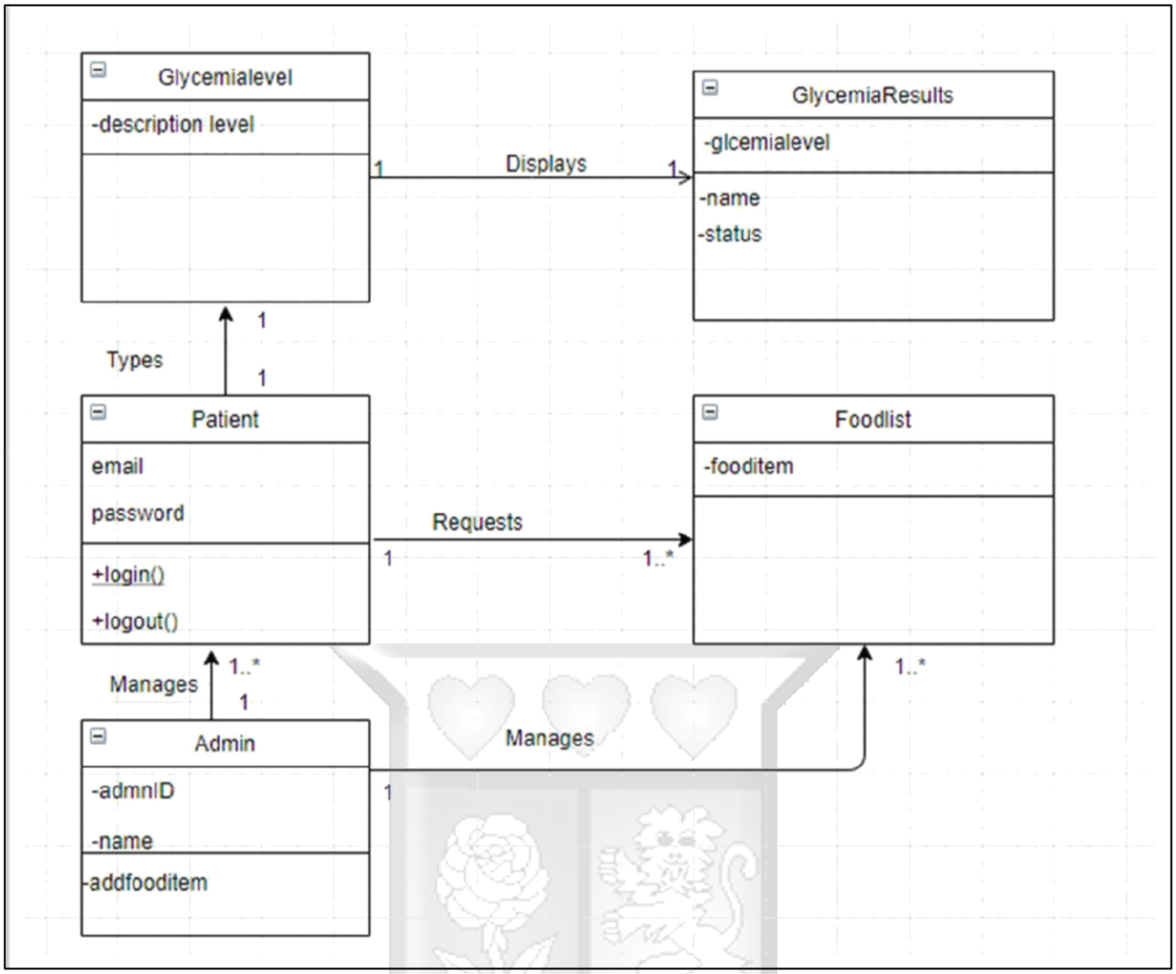


Figure 4.3 Class diagram

4.4.6 Mobile application wireframe

The following figures are the various wireframe designs for the mobile application.

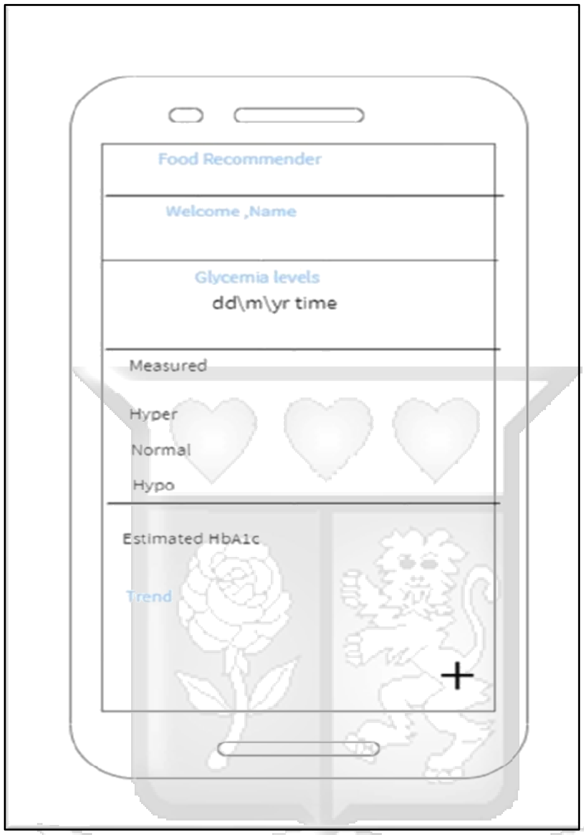


Figure 4.4 Input glycemia levels wireframe

Figure 4.5 Check food item wireframe

Figure 4.6 Food recommendation

Chapter 5: System implementation and testing

5.1 Introduction

This section centered on how the prototype of the proposed system was built, tested, and validated. The implementation phase involved exploring the various modules of the system, how the development was done and how it functions. Testing and validation involved functional testing and usability testing to check if the system fulfilled the set objectives.

5.2 System implementation

Agile software development methodology was used in this study and during the development phase of the prototype. Its continuous iteration ability helped in the modifications of different versions of the system to meet the study's objectives. The food recommender system for diabetes type 2 patients is an Android mobile application that was developed using Android studio and Java. The database used was Firebase and SQlite. For the patient to use the application effectively they are needed to incorporate a glucometer, which is a medical device used by diabetes patients to monitor their blood sugar levels as part of diabetes self-management. In this application, the Android application is the client-side which the patients interact with by keying in their sugar levels on the application and to do this there is need for internet connectivity. The application validates with the central database to confirm the status of the patient's glycaemia levels whether they are high, medium, or low. From this feedback, the application can recommend food to the patient, or the patient can check whether the food they want to consume is suitable for their blood sugar levels. For instance, if the sugar levels are high and the patient wants to eat a meal with high a GI the application will warn the patient to choose another food item with a low GI to avoid spiking the glycaemia to very high levels.

Loading the CSV file

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt

dataframe=pd.read_csv("recommended_train.csv")
df1=dataframe.dropna(axis=1,how='all')
```

Figure 5.1 Load csv file

Cleaning of the data

```
df=df1.drop('Unnamed: 12',axis=1)
df = le.fit_transform(df.astype(str))
```

Figure 5.2 Cleaning of the data

Training and testing

```
:=features
'=labels
! from sklearn.cross_validation import train_test_split
'rom sklearn.model_selection import train_test_split
_train, X_test, y_train, y_test = train_test_split(x, y, test_size=0.2,random_state=109) # 80% training and 20% test
```

Figure 5.3 Training and testing

Visualizing the training set results

```
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test, y_pred)

# Visualising the Training set results
from matplotlib.colors import ListedColormap
x_set, y_set = x_train, y_train
X1, X2 = nm.meshgrid(nm.arange(start = x_set[:, 0].min() - 1, stop = x_set[:, 0].max() + 1, step = 0.01),
                     nm.arange(start = x_set[:, 1].min() - 1, stop = x_set[:, 1].max() + 1, step = 0.01))
mtp.contourf(X1, X2, classifier.predict(nm.array([X1.ravel(), X2.ravel()]).T).reshape(X1.shape),
             alpha = 0.75, cmap = ListedColormap(('purple', 'green')))
mtp.xlim(X1.min(), X1.max())
mtp.ylim(X2.min(), X2.max())
for i, j in enumerate(nm.unique(y_set)):
    mtp.scatter(x_set[y_set == j, 0], x_set[y_set == j, 1],
                c = ListedColormap(('purple', 'green'))(i), label = j)
mtp.title('Food Recommender (Training set)')
mtp.xlabel('Blood Sugar')
mtp.ylabel('recommended_foods')
mtp.legend()
mtp.show()
```

Figure 5.4 Visualizing of training set results

Visualizing of testing set results.

```
from matplotlib.colors import ListedColormap
x_set, y_set = x_test, y_test
X1, X2 = nm.meshgrid(nm.arange(start = x_set[:, 0].min() - 1, stop = x_set[:, 0].max() + 1, step = 0.01),
                     nm.arange(start = x_set[:, 1].min() - 1, stop = x_set[:, 1].max() + 1, step = 0.01))
mtp.contourf(X1, X2, classifier.predict(nm.array([X1.ravel(), X2.ravel()]).T).reshape(X1.shape),
             alpha = 0.75, cmap = ListedColormap(('purple', 'green')))
mtp.xlim(X1.min(), X1.max())
mtp.ylim(X2.min(), X2.max())
for i, j in enumerate(nm.unique(y_set)):
    mtp.scatter(x_set[y_set == j, 0], x_set[y_set == j, 1],
                c = ListedColormap(('purple', 'green'))(i), label = j)
mtp.title('Food recommender Test set')
mtp.xlabel('Blood Sugar')
mtp.ylabel('recommended_foods')
mtp.legend()
mtp.show()
```

Figure 5.5 Visualizing of training set results

5.2.1 Food recommender system

The application is designed to run on Android mobile phones and requires internet connectivity. Several food preferences of other diabetic patients were collected, and the predictions of the food items were done using collaborative filtering based on Naive Bayes algorithm.

5.2.2 Android mobile application

Figure 5.6 represents the first interface the patient gets after installing the application. The patient is required to register on the application.

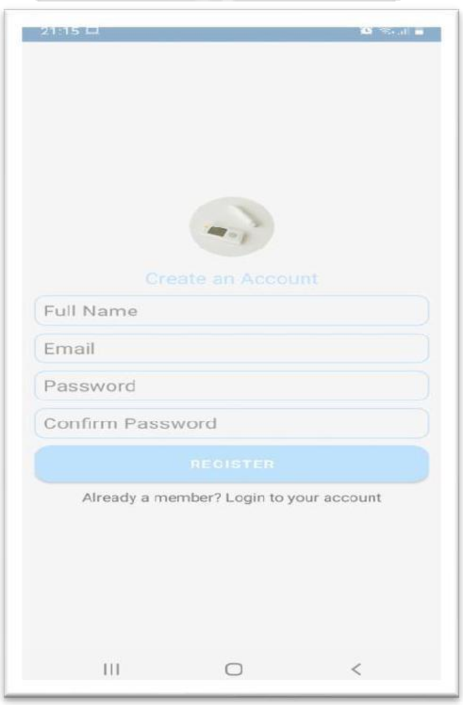


Figure 5.6 Registration page

```java
private void registerUser() {

    name=edtName.getText().toString().trim();
    email=edtEmail.getText().toString().trim();
    password=edtPassword.getText().toString().trim();
    confirm=edtConfirm.getText().toString().trim();

    if (TextUtils.isEmpty(name)){
        Toast.makeText( context: this,  text: "Please enter your name!!", Toast.LENGTH_SHORT).show();
        return;
    }else if (TextUtils.isEmpty(email)){
        Toast.makeText( context: this,  text: "Please enter your email", Toast.LENGTH_SHORT).show();
        return;
    }else if (TextUtils.isEmpty(password)){
        Toast.makeText( context: this,  text: "Please enter your password!!", Toast.LENGTH_SHORT).show();
        return;
    }else if (TextUtils.isEmpty(confirm)){
        Toast.makeText( context: this,  text: "Please confirm your password!!", Toast.LENGTH_SHORT).show();
        return;
    }else if (!password.equals(confirm)){
        Toast.makeText( context: this,  text: "Passwords do not match!!", Toast.LENGTH_SHORT).show();
        return;
```

Figure 5.7 Registration code

After registration, a verification email is sent to the patient's email address for them to verify the email.

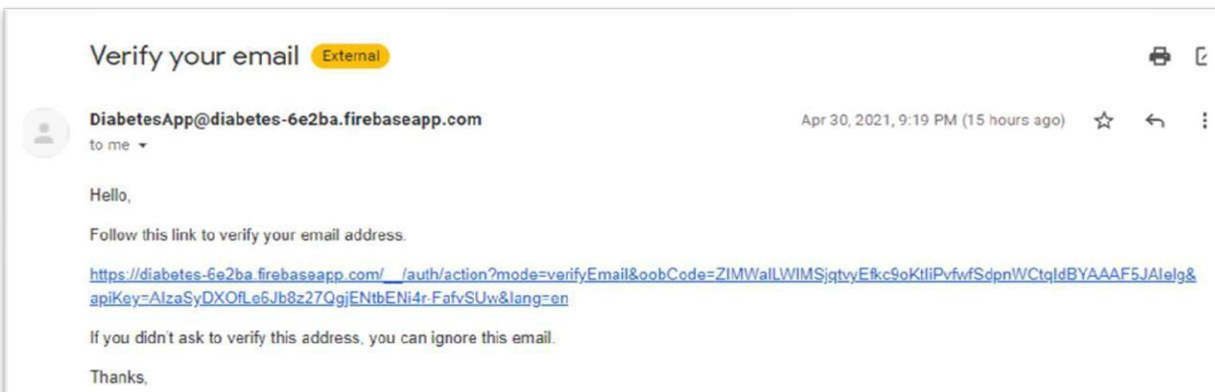


Figure 5.8 Email verification

After the email is verified, the patient is redirected to the login page. Fig 5.9 represents the login page.

Figure 5.9 Login page

After a successful login, the patient is requested to update their profile. Fig 5.10 represents the profile page.

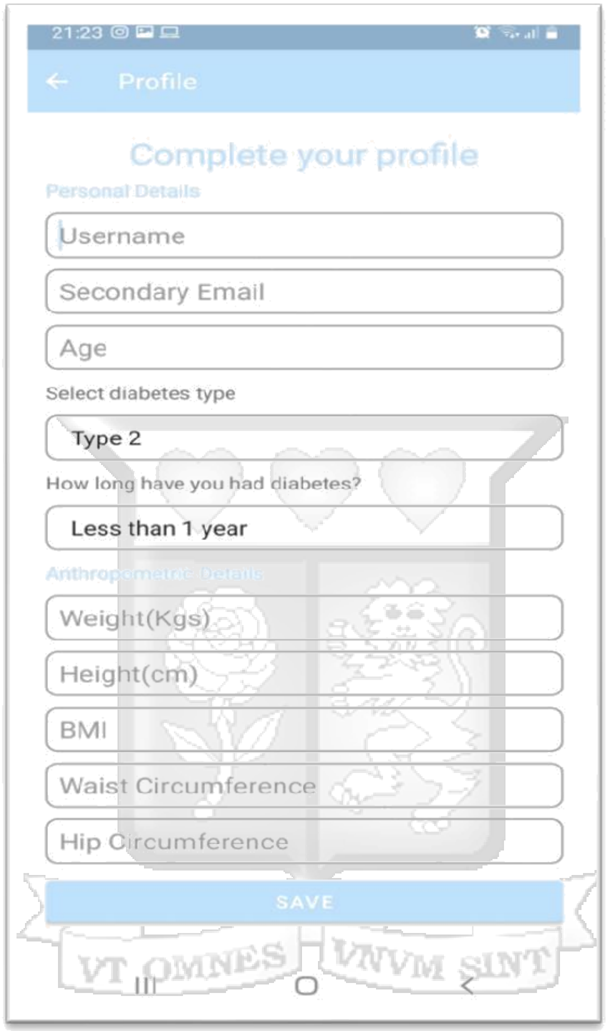
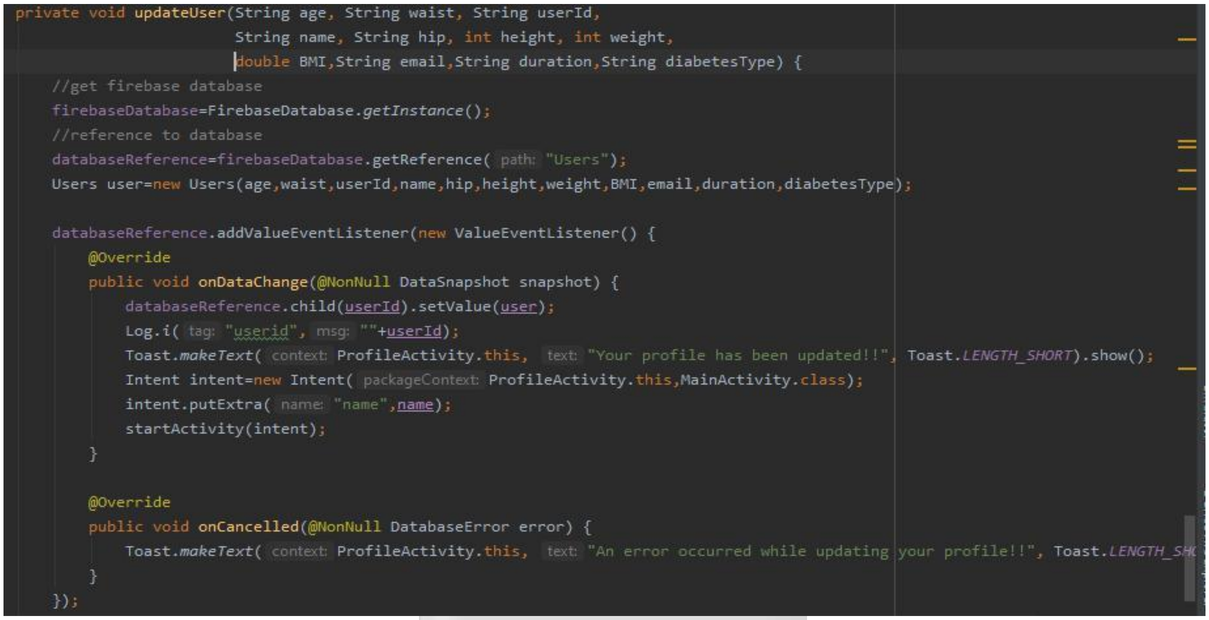


Figure 5.10 Login page

Figure 5.11 illustrates the profile page code



```
private void updateUser(String age, String waist, String userId,
                        String name, String hip, int height, int weight,
                        double BMI,String email,String duration,String diabetesType) {
    //get firebase database
    firebaseDatabase=FirebaseDatabase.getInstance();
    //reference to database
    databaseReference=firebaseDatabase.getReference( path: "Users");
    Users user=new Users(age,waist,userId,name,hip,height,weight,BMI,email,duration,diabetesType);

    databaseReference.addValueEventListener(new ValueEventListener() {
        @Override
        public void onDataChange(@NonNull DataSnapshot snapshot) {
            databaseReference.child(userId).setValue(user);
            Log.i( tag: "userid", msg: ""+userId);
            Toast.makeText( context: ProfileActivity.this, text: "Your profile has been updated!!", Toast.LENGTH_SHORT).show();
            Intent intent=new Intent( packageContext: ProfileActivity.this,MainActivity.class);
            intent.putExtra( name: "name",name);
            startActivity(intent);
        }

        @Override
        public void onCancelled(@NonNull DatabaseError error) {
            Toast.makeText( context: ProfileActivity.this, text: "An error occurred while updating your profile!!", Toast.LENGTH_SHO
        }
    });
```

Figure 5.11 Profile page code

Once the patient has saved their profile, the system is ready for use. Fig 5.12 represents the application's overview. On this interface, the patient enters their blood sugar levels.

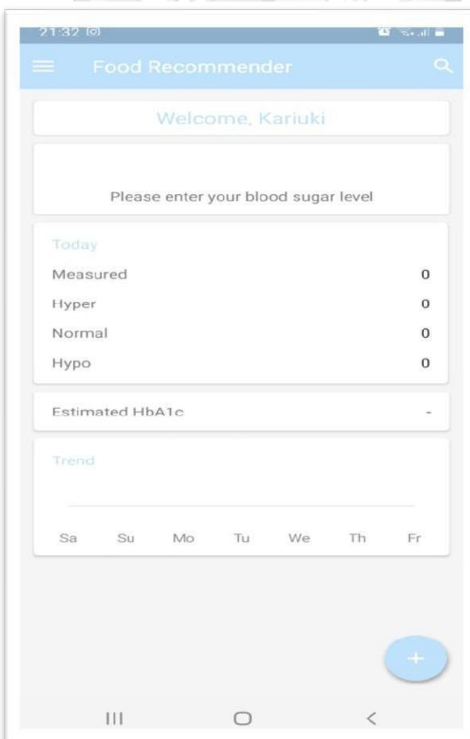


Figure 5.12 Application overview

Once the patient has checked their blood sugar level using a glucometer, they can enter the records on the model. Fig 5.13 represents the blood sugar page.

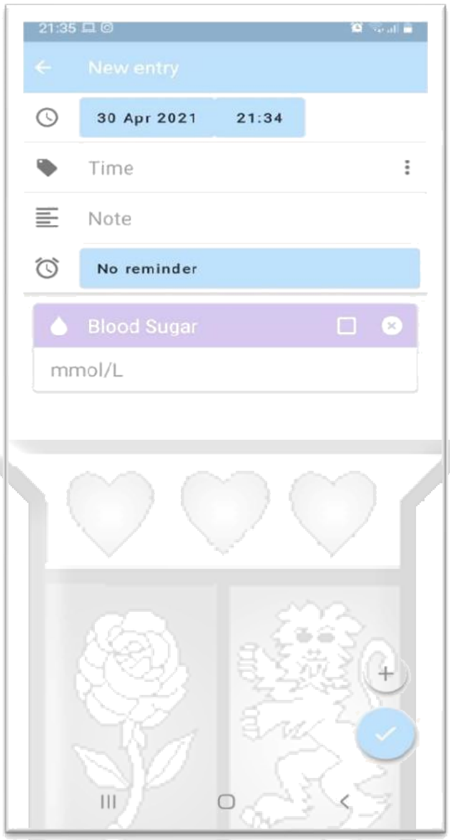


Figure 5.13 Blood sugar page

After keying the blood sugar levels, the application responds with the status of the blood sugar levels as either high, medium, or low. Fig 5.14 represents the blood sugar status.

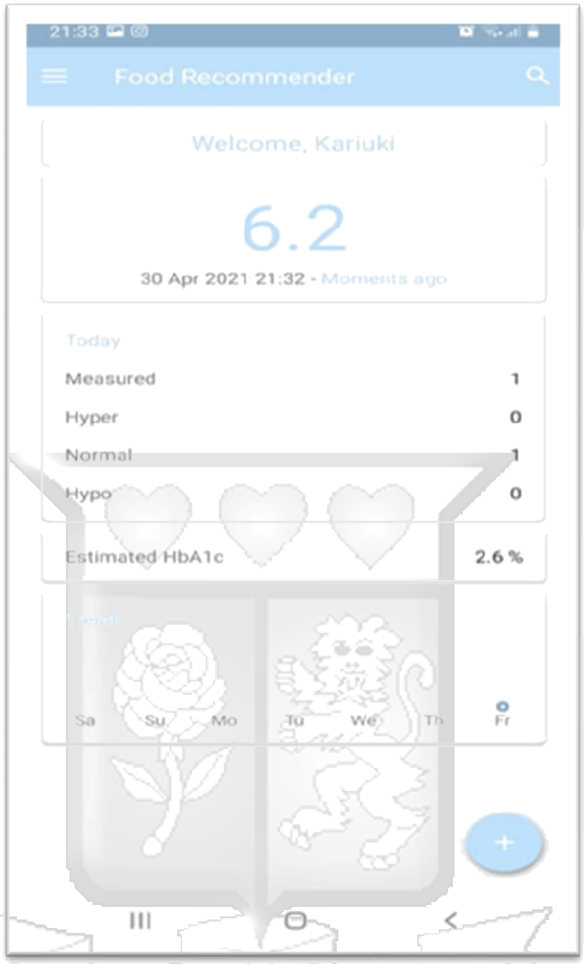


Figure 5.14 Blood sugar level status

After confirmation of the blood sugar level status, the patient can check recommendations on the most suitable foods to eat based their glycemia levels. Fig 5.15 shows the food recommendation page displaying lunch and dinner option.

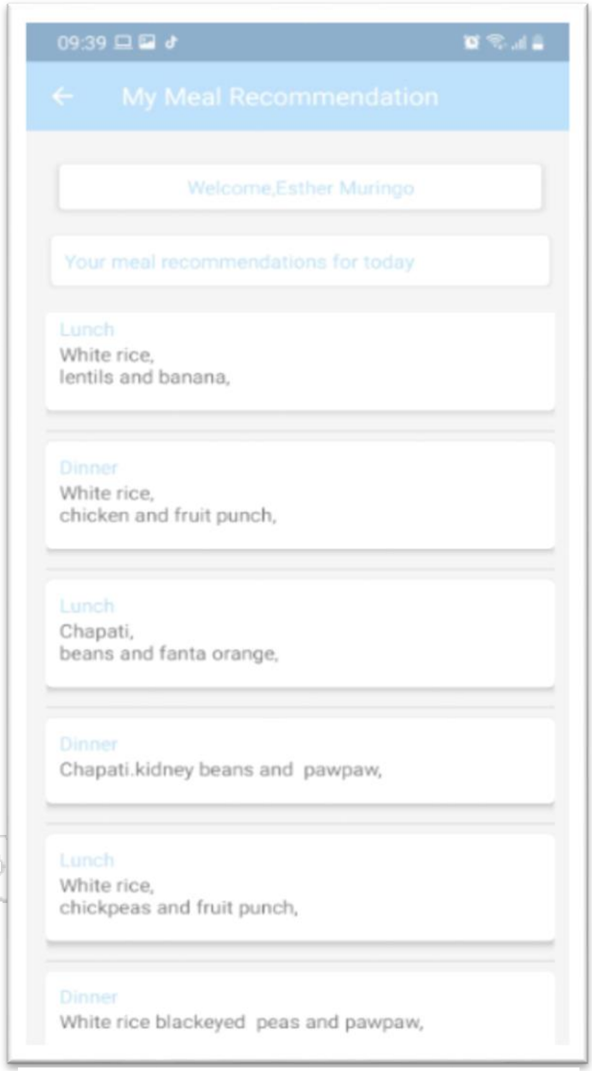


Figure 5.15 Food recommendation page

Fig 5.16 shows the food recommendation displaying breakfast options

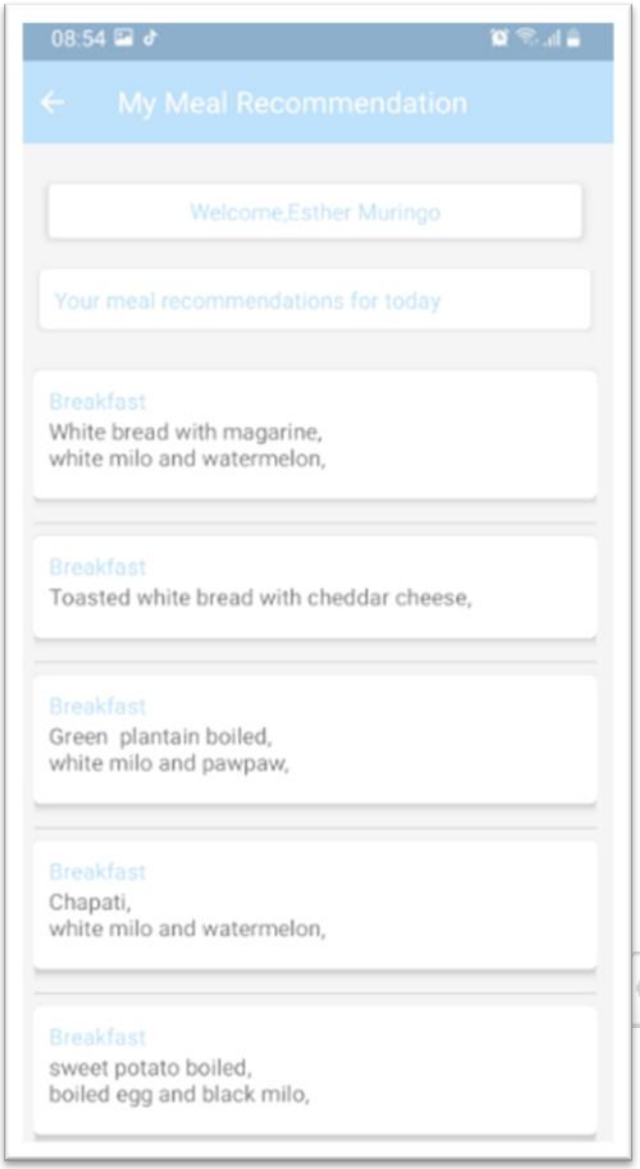


Figure 5.16 Food recommendation page breakfast option

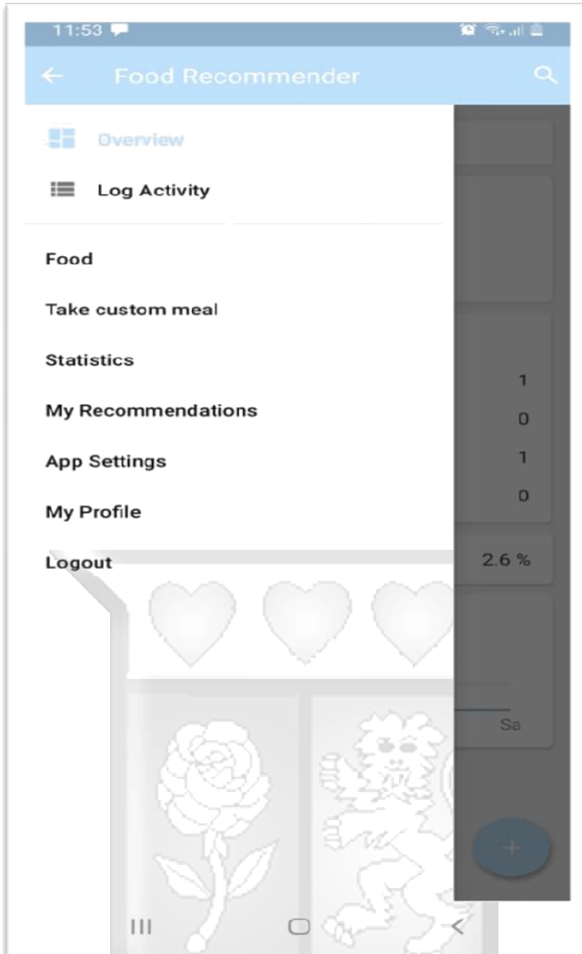


Figure 5.17 Recommendation overview

From the recommendation overview the patient can select the meals they want to eat and thereafter the model give feedback on whether the food is suitable for them based on their blood sugar levels. Fig 5.18 represent the custom meals tab.

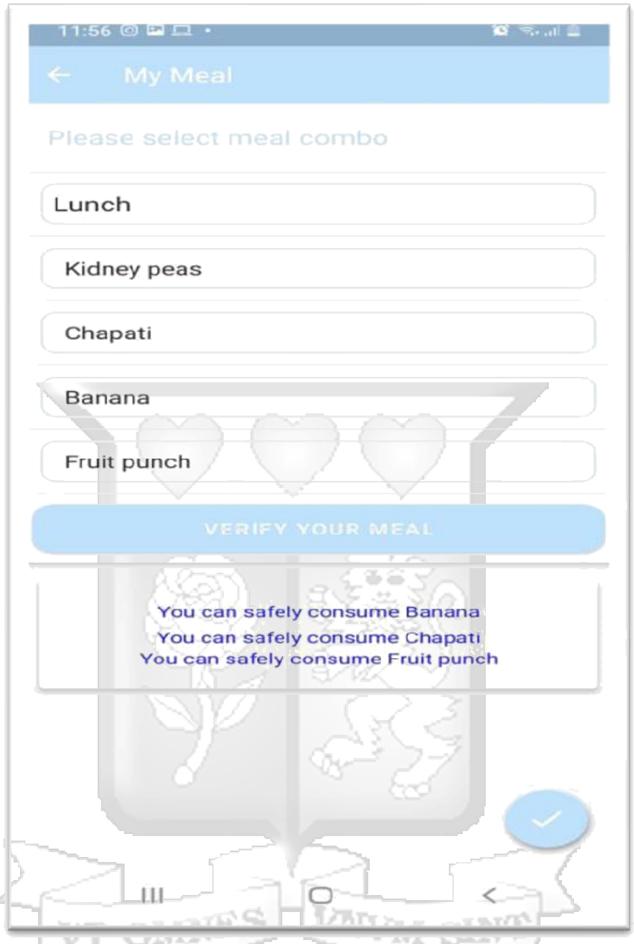


Figure 5.18 Custom meal tab

```java
public ViewHolder onCreateViewHolder(@NonNull ViewGroup parent, int viewType) {
    View view=LayoutInflater.from(parent.getContext()).inflate(R.layout.food_item,parent, attachToRoot: false)
    return new ViewHolder(view);
}

    @Override
    public void onDataChanged() {
        super.onDataChanged();
        if (getItemCount() ==0){
            list_empty.setVisibility(View.VISIBLE);
        }
    }
    @Override
protected void onBindViewHolder(ViewHolder viewHolder, int i, Recommendations recommendations) {

         progressDialog.dismiss();
        viewHolder.setMealType(recommendations.getMealTime());
        String s = recommendations.getRecommended_foods();
        String strings[] = s.split( regex: ",");
        for (int a = 0; a < strings.length; a++) {...}
        s = "";

        for (int b = 0; b < strings.length; b++)
            s += strings[b];
        viewHolder.setRecommendedFoods(s);
}
```

Figure 5.19 Recommendation code

The mobile application can track the patients' blood glucose and have the statistic incase the patient need to do a follow up with a specialist. Fig 5.19 represents the statistics page.

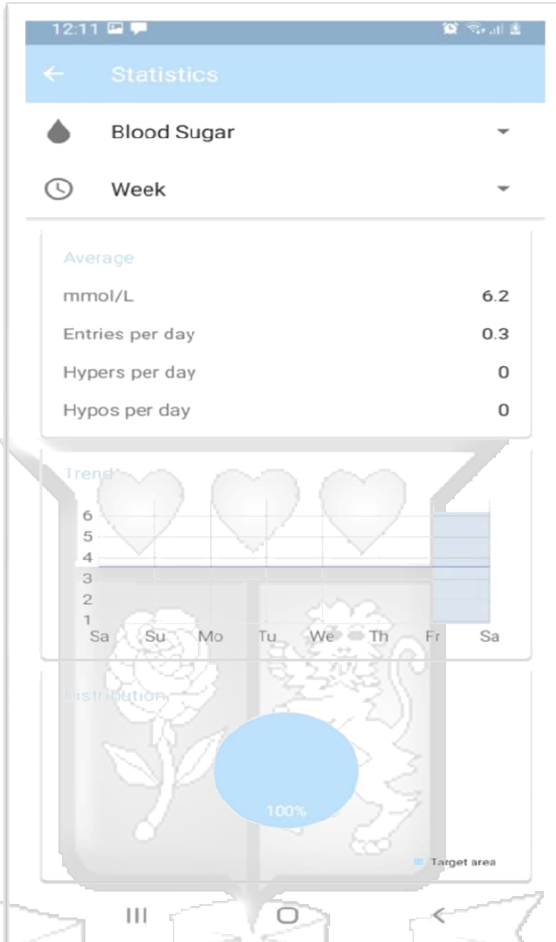


Figure 5.20 Statistics page

5.3 System Testing

The mobile application was developed using Agile software development methodology which allows for continuous iterations at different phases. Continuous testing was done to test performance and bugs issues. Functional testing was conducted to assess the compliance of the developed prototype with the specified functional requirements.

5.3.1 Testing on model accuracy

During the tests invalid inputs were used to test where the system would detect errors. For the registration process to be successful the patient must verify their email. This was represented in fig 5.21.

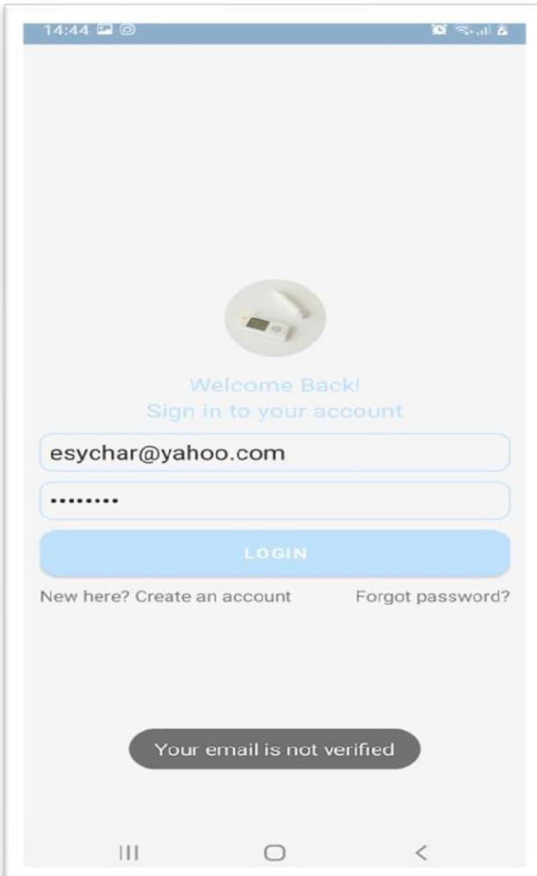


Figure 5.21 Email verification error

The application can detect a wrong username or password, this is represented in fig 5.22.

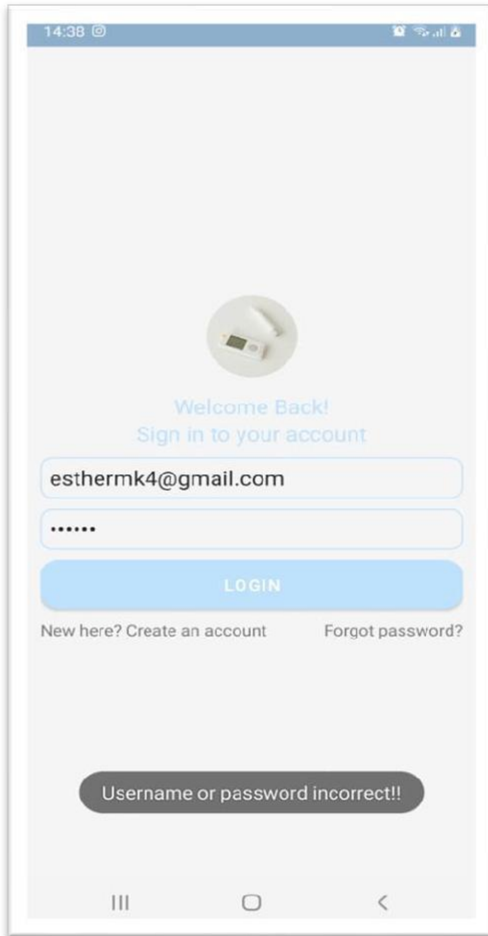


Figure 5.22 Incorrect credentials error

5.4 System validation

A compatibility test was conducted to make sure the mobile application aligned with the real business environment where it was deployed. Android platform compatibility testing was done against existing Android versions. Table 5.1 illustrates the compatibility test done.

Table 5.1 Compatibility Test

Name	**Android version**	**Compatibility**
Oreo	8.1	Yes
Pie	9	Yes
Android 10	10	Yes
Android 11	11	Yes

5.4.1 Usability test results

The usability and validation questionnaire were prepared using google forms and distributed to 11 respondents via email. All the participants were able to respond. All the participants were able to install the application as shown in fig 5.23.

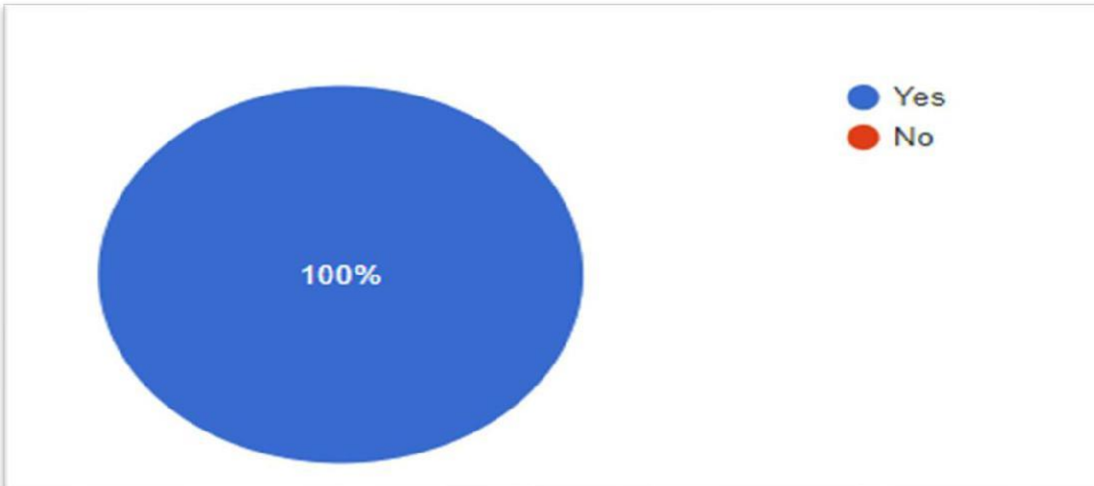


Figure 5.23 Usability results

None of the participants encountered any problems during installation, registration and recommendations result as shown in fig 5.24.


none

No challenge

Useful application. This is great

No problem encountered

NONE

none

Figure 5.24 Problems encountered

The respondents stated some of the features that they thought were interesting as shown in fig 5.25.

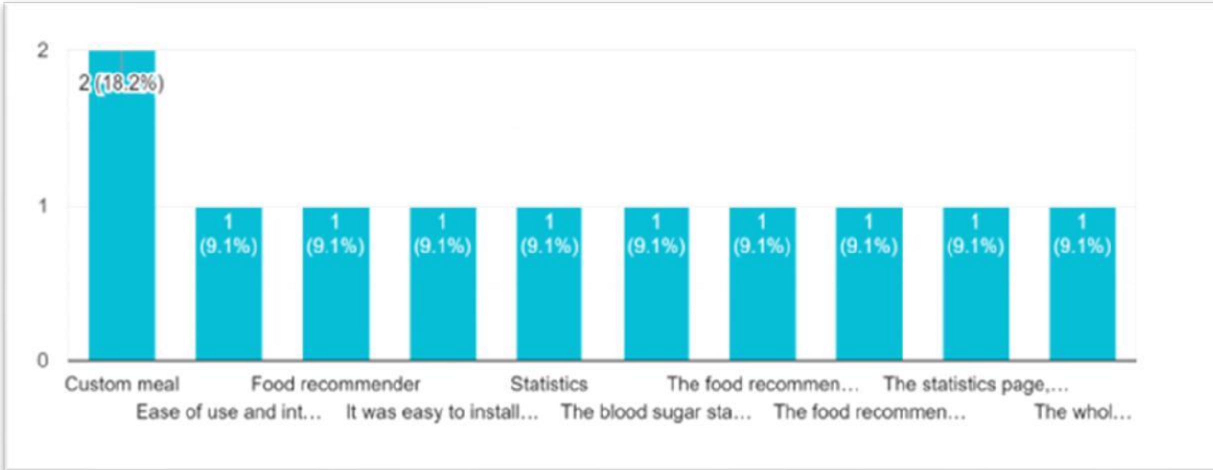


Figure 5.25 Interesting features

All the participants confirmed they would recommend the application to other diabetes patients to help with self-diabetes management as shown in fig 5.25.

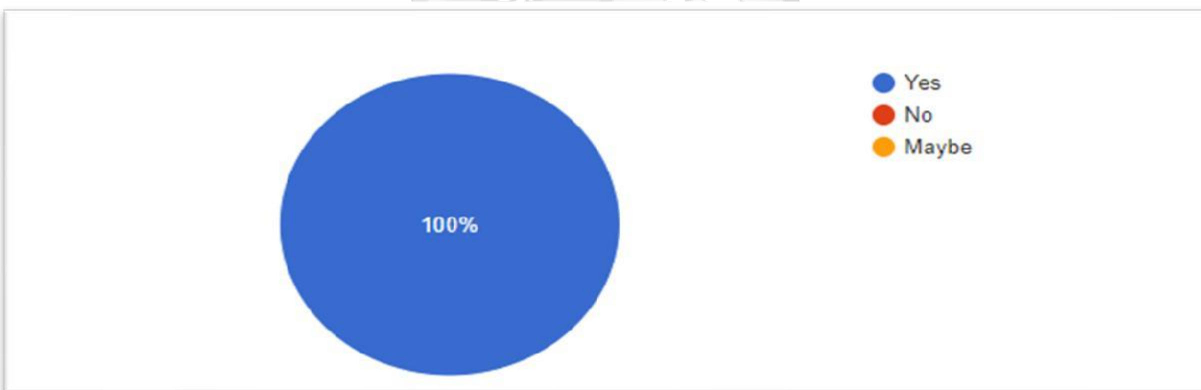


Figure 5.26 Application acceptability

5.4.2 Conclusions

The requirements identified during requirements analysis acted as a guide during the implementation phase. The system design gave information on how the system development was done. The research objectives were the cornerstones used during the development of the system to ensure it met the research objectives.

Chapter 6: Discussions

6.1 Introduction

This chapter explains the research conclusions, achievements, and reviews how the research objectives were realized not limited to mentioning the application's advantages and limitations. A food recommender system was developed using naïve Bayes and its performance was tested using the test set. The outcomes obtained from this study formed the basis on which an Android mobile application for food recommendation for diabetes type 2 patients was developed.

6.2 Review of research objectives

To reference section 1.3 the first objective of the study was to analyze the dietary factors that affecting diabetes Type 2 patients, according to the findings it was seen that busy schedules, lack of self-control, forgetfulness and a lot of effort are some of the dietary factors that affect diabetes patients. These findings are in line with the literature review as discussed in section 2.2. In the reviewed literature, nutritional therapy plays an important role when it comes to diabetes self-management. The glycemic index and glycemic load of foods greatly influence the levels of our blood sugars levels after consumption.

The second objective was to explore the current technologies used for food recommendations to patients. To develop a suitable solution, the research findings were used to help identify the most appropriate technology. The literature review explored different technologies that support food recommendations to patients this including support vector machine, computer vision, decision trees nearest neighbor and Ant colony optimization. The study established that machine learning techniques used in the health informatics sector are playing a key role in tasks such as classification, analyzing, association and predictions. The technology used naïve Bayes algorithm is in line with tasks the technologies discussed in section 2.4 perform.

The third objective was to design and develop the food recommender system for diabetes type 2 patients. According to the research finding patients wanted a food recommender system that would help them with the self-management of diabetes. The application developed can guide the patients on what to consume based on their blood sugar levels as part of their nutritional therapy.

The fourth object was to test the ability of the prototype. The usability testing and validation questionnaire in Appendix B was used to test the performance of the prototype and all the participants did not face any problems interacting with the system. Easy to find core functionality, responsiveness and usefulness were appraised excellent.

6.3 Advantages of the application

The developed application helps the diabetes patient monitor the food they consume; they can eat food based on their blood glucose levels taking caution of how high or low the GI level of the food they consume is. This guides them to know the likelihood of their blood glucose spiking, dipping, or maintaining it close to normal.

6.4 Limitations of the application

The application requires internet access for it to be used, this might limit the users who do not have access to internet connection. The application is not suitable to diabetes patients who have other existing conditions. Patients with existing conditions such as tuberculosis, hepatitis b, cancer and HIV/AIDS require continued evaluation by a specialist because of the continued intake of drugs. In some scenarios, you find these drugs may cause a sudden dip or spike in the sugar levels. The application only uses blood glucose to give food recommendations.

Chapter 7: Conclusion and recommendation

7.1 Introduction

In this chapter, conclusions, recommendations, and future work are discussed. As for the conclusions, all the objectives are reviewed briefly by looking at how the research questions were answered. In recommendation, the researcher gives some recommendations to users and stakeholders of the system. Future work entails something that was not implemented in the system but can be implemented in the future.

7.2 Conclusions

From the study it was established that nutritional therapy is very important when it comes to self-assessment in diabetes management. It is important for patients to know the effect the food they eat has on their blood glucose levels. The recommender system analyzes the glycaemia index of different foods and recommend the most suitable food to the patient based on their blood glucose level. For instance, if the patient's blood glucose is high, they are recommended to eat foods with a low GI. The study advocates substituting high– glycemic load foods with low–glycemic load eating patterns and has shown evidence demonstrating an A1C decrease of −0.2 to −0.5%. A review of the approaches currently used and the technologies in use food recommendation is based on pathological test done to the patient or the information the patient gave on their profiles. Recommendations done are not based on real time needs of the patient showing the status of their blood glucose levels, meaning whatever they consume influences their glycaemia levels.

The main objective of the study was to develop food recommender system for diabetes type 2 patients based on Naïve Bayes algorithm. The dataset was collected, preprocessed, labelled using ADA guidelines and further split into training and test sets.

To test the developed prototype usability testing was done using questionnaires that were distributed.to 11 respondents. Feedback received showed that the prototype passed the usability test.

7.3 Recommendations

This study showed that Naïve Bayes algorithm can be used in a food recommender system. This study notes that better classification results would have been obtained if a large data set had been used. A total of 1000 foods were collected but only 150 foods were used. Most of the foods in the dataset were not locally available and the prototype would not be effective enough if it recommended food items that were not available. The researcher recommends that the size of the training data to be increased by collecting and labelling more foods that are locally available to improve the performance of the classifier.

7.4 Future work

The researcher saw that the proposed prototype has the potential to be expanded in the future and proposed, to expand the market to more users, the same application be developed for other platforms like iOS and Windows. For future work on the application could analyze local foods and develop a local food dataset using the local dialects.

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Appendices

Appendix A:Sample of food list

meal_category	Food_item	Glycemic index	Glycemic load
Bakery prdts			
	Banana cake, made with sugar	47	14
	Banana cake, made without sugar	55	12
	Fruit and cinnamon bread	71	11
	White flour bread	71	10
	Banana oat and honey muffin	65	17
	Blueberry muffin	50	15
	Chocolate butterscotch muffin	53	15
	Chocolate chip muffin	52	17
	Muffin, plain made from wheat flour	46	11
	Pancakes prepared from wheat flour	80	16
Beverage			
	Coca cola, soft drink	53	14
	Fanta, orange soft drink	68	23
	Fruit punch	67	19
	Lemonade schweppes, lemon soft drink	54	15
	Smoothie, banana	30	8
	smoothie, banana and strawberry	44	11
	smoothie, mango	32	9
	Black milo	55	9
	White milo	35	9
	Carrot juice, freshly made	43	10
	Apple and Mango juices, pure, unsweetened	47	16
	Apple, pineapple, and passion fruit juice unsweetened	48	16
	Orange juice	46	12
	Tomato juice, no added sugar	33	3
	Porridge (wholemeal wheat, oat, rice & wheat flou	51	15
Carbohydrates			
	Green plantain boiled	65	17
	Green banana fried	35	11
	Green banana boiled	37	10
	Ripe plantain fried	90	26
	Ripe plantain boiled	66	13
	Chapati	59	16
	Butternut pumpkin boiled	51	3
	Sweet corn	48	14
	White potato boiled	82	21
	sweet potato boiled	44	11
	Sweet potato fried	76	34
	Yam roasted	80	28
	Yam boiled	74	28
	Mashed potato	71	14
	Instant two minute noodle	46	11
	Brown rice	55	23

Appendix B: Usability Questionnaire

A food recommender system for Diabetes Type 2 patients

Section A: Usability Testing

A1. Was the application easy to install? (Choose ONE) *

Mark only one oval.

Yes

No

A2. Was it easy to register yourself (Choose ONE) *

Mark only one oval.

Yes

No

A3. Did you receive a verification email after registering? (Choose ONE)*

Mark only one oval.

Yes

No

A4. If any of your answer above is ‘No’ please list the problems, you encountered? *

A5. How would you rate the food recommender system? (Choose ONE)*

Mark only one oval.

⬭ Great

⬭ Very Good

⬭ Good

⬭ Fair

⬭ Poor

A6. What feature interested you most? *

A7. Any comments, suggestions, or improvements about this application?

A8. Would you recommend the application to anyone (Choose ONE) *

Mark only one oval.

◯Yes

◯ No

◯Maybe

A9. How would you rate the food recommender system? (Choose ONE)*

Mark only one Oval

◯ Great

◯ Very Good

◯ Good

◯ Fair

◯ Poor

A10. What feature interested you most? *

A11.Would you recommend the application to anyone.

Mark only one Oval

◯ Yes

◯ No

◯ Maybe

Appendix C: Nutritional and eating habit questionnaire

Nutrition and Eating Habits Questionnaire

PATIENT'S NAME:

BIRTH DATE:

AGE:

BMI:

DIABETES TYPE:

1.What would you like to gain from this interaction?

☐ Improve blood glucose ☐ Improve eating habits ☐ what to eat levels

☐How much to eat ☐ Meal planning

2. Would you describe your appetite? ☐ Good ☐ fair ☐ poor

3. Do you have any eating or digestion problems such as

☐ Chewing ☐ Diarrhea ☐ Gas ☐ Swallowing ☐Indigestion ☐ Other

4. Do you drink alcoholic beverages? ☐ Beer ☐ wine ☐ liquor

If yes, how often? How much?

5. Do you use any meal replacement products such as: (Ensure,Boost,Glucerna)

☐ Yes ☐ No

If yes, which ones and how often?

6. What time do you eat?

Breakfast Lunch Dinner Snacks

7. Do these times change on weekends? ☐ Yes ☐ No

8. Have you had diet counseling before? ☐ Yes ☐ No

9. Do you have a meal plan? ☐ Yes ☐ No

If yes, how many calories?

10. What food planning method do you use?

☐ None ☐ Carbohydrate Counting. ☐ Calorie Counting ☐ Exchange Lists. ☐ Healthy Eating Using the Food Pyramid.

11. How much of the time are you able to follow it?

☐ 0%-25% ☐ 25%-50% ☐ 50%-75% ☐ 75%-100%

12. Have you been told to follow any other diet restrictions? ☐ Yes ☐ No

If yes, what are they?

13. Has your weight changed in the past year? ☐ No Gained ☐ Lost

14.What is your recommended weight?

15. Do you exercise now? ☐ Yes ☐ No

16. If recommended, would it be hard for you to make changes in your eating habits?

☐ Yes ☐ No

.17. How often do you glucose levels go high

☐ Every now and then ☐ Not often ☐ rarely

18. Would you want a model that would recommend food to eat? ☐ Yes ☐ No

Appendix D:Similarity report

Ouriginal

Document Information

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Analyzed document	(D103697969)
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W	URL: https://www.hindawi.com/journals/ijta/2020/8870141/ Fetched: 11/13/2020 3:49:34 AM	4
SA	**RPS_2_Rohini_V1.docx** Document RPS_2_Rohini_V1.docx (D95778458)	1
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