A Food Recommender System for Patients with Diabetes and Hypertension

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A Food Recommender System for Patients with Diabetes and Hypertension

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Abstract

Diabetes and hypertension are examples of non-communicable diseases that are becoming a severe problem in the world today. A number of diseases have been connected to unhealthy eating habits. In this study, a recommender system that uses nutritional knowledge to suggest meals that are nutrient-dense to patients suffering from either ailments or one of it. The Study looked into computer models for tailored meal suggestions based on dietary data and user data in recent years. It examined physical traits, physiological data, and other personal information. A general framework for daily eating plan selections is presented in this article. The system used machine learning methodologies and techniques to generate recommendations for the necessary food items. K-means clustering and Random Forest classification technique were used which concentrates on providing meal recommendations that help the user maintain and enhance his or her health. The model was able to achieve an accuracy of 95% with 100 decision trees.

Keywords: *diabetes, hypertension, meal, prediction, k-means clustering, random forest, recommendation.*

1. Introduction

According to estimates from the International Diabetics Federation (IDF), 1 in 10 adults, or 537 million people, between the ages of 20 and 79 have diabetes. By 2030, it is expected to reach 643 million, and by 2045, it will reach 783 million. About three out of every four diabetic adults reside in low- and middle-income nations. In 2021, diabetes will be the cause of 6.7 million fatalities, or one every five seconds. Diabetes costs the healthcare system approximately USD 966 billion, a 316% rise over the past 15 years. Impaired glucose tolerance (IGT) affects 541 million adults, putting them at a significant risk of developing type 2 diabetes. One in twenty persons (24 million adults) in Africa have diabetes. By 2045, there will be 55 million people worldwide with diabetes, a 129% increase from the current level. 54% of patients with diabetes do not have a diagnosis. In 2021, diabetes will be the cause of 416,000 fatalities. In Nigeria, there will be 48,375 deaths due to diabetes between the ages of 20 and 79 in 2021 (IDF, 2023). According to the National Action on Sugar Reduction (NASR), Nigerians spend an estimated $4.5 billion annually on treating their diabetes.

IDF (2023) defines diabetes mellitus (DM) as a persistent condition that affects how the body breaks down food into glucose, which is utilized as energy. Either the body generates little to no insulin, or perhaps the body does not utilize the insulin efficiently, according to IDF's definition of DM. Long-term harm, dysfunction, and failure of various human body organs, including neuropathy (nerve difficulties), retinopathy (eye problems), nephropathy (kidney problems), and macro vascular consequences, are linked to the chronic hyperglycemia effects of diabetes. The severe acute and chronic problems brought on by these detrimental barriers might result in kidney failure, adult-onset blindness, and lower limb amputations. Diabetes comes in three different forms: type 1 diabetes, type 2 diabetes, and gestational diabetes. Kind 1, or insulin-dependent diabetes, affects 5–10% of adults with diabetes and is the most prevalent type (IDF, 2021).

Hypertension, sometimes referred to as High Blood Pressure (HBP), is a disorder when the pressure in the blood arteries is consistently elevated. The heart pumps blood through the vessels with each beat. The pressure of blood pushing against artery walls when it is pumped by the heart results in blood pressure (BP). The heart has to work more to pump blood when the pressure is higher. A significant medical condition called hypertension can raise your chance of developing heart, brain, kidney, and other problems. Over a billion individuals worldwide—roughly 1 in 4 men and 1 in 5 women—have the illness, it a significant cause of premature death. HBP is anticipated to result in 7.5 million deaths globally, or about 12.8% of all fatalities (WHO, 2021). WHO reported that 10,692 fatalities from hypertension, or 0.72% of all deaths, occurred in Nigeria in 2020. Nigeria is ranked 103 in the world due to its 16.07 per 100,000 people age-adjusted death rate (World Health Ranking, n.d). Numerous shared cause and risk factors exist for both diabetes and hypertension. A person who already has one ailment is more likely to develop the other. Similarly, a person with both ailments can discover that each condition makes the other worse. HBP frequently coexists with diabetes and obesity (Medical News Today, 2022). Diabetes doubles a person's risk of developing high blood pressure. In two out of three diabetic patients, HBP is either reported or treated with prescription medications (Johns Hopkins Medicine (2022).

Nutrition is an important part of a healthy lifestyle when you have diabetes. Your blood glucose, also known as blood sugar, can be kept within the desired range after a good meal. You must balance what you eat and drink in order to control your blood sugar. According to the National Institute of Diabetes and Digestive and Kidney Diseases, eating the right foods at the right times will help you maintain a healthy blood sugar level (NIH, 2022).

Dietary Approaches to Stop Hypertension is what the DASH diet stands for (Sacks et al., 2001). For those who want to cure or avoid developing hypertension, it is a healthy dietary strategy. The National Heart, Lung, and Blood Institute in the US supports it. The DASH diet's main objective is to lower a person's salt (sodium) intake. For non-hypertension individuals, the American Heart Association recommends a maximum daily salt intake of 2,300 mg, but for hypertensive individuals, the maximum daily sodium intake is 1,500 mg (Yancy et al., 2013).

Dietary consumption and lifestyle adjustments are a crucial part of managing diabetes and high blood pressure. It is asserted that nutrition therapy is crucial for the management of diabetes and high blood pressure in order to improve glycemic and salt control and lower the risk of complications (NIH, 2022; Yancy et al., 2013). Healthy diet, keeping a healthy weight, engaging in regular exercise, consuming alcohol in moderation, and giving up smoking are frequently effective ways to prevent or reduce HBP. Reduce your intake of salt and consume more fruits and vegetables to maintain a healthy diet for HBP patients. Blood pressure is increased by salt. The blood pressure increases as salt intake increases (NHS, 2022).

Healthcare systems that were previously difficult to analyze have now gotten simpler thanks to the application of machine learning techniques. In supervised learning, labelled datasets are used to train algorithms that accurately identify data or predict outcomes. Unsupervised learning makes use of data that has not been labeled, allowing hidden patterns to emerge (Jafari & Dorafshan, 2022). The urgent demand for computerized tools and services that would assist diabetic patients with carbohydrate (CHO) monitoring to control their glycemia was brought on by the widespread prevalence of diabetes.

The goal of this research is to create a diet recommendation system for diabetic and hypertensive patients that would suggest the right meal based on the patient's current level of sodium and glucose.

2. Related works

Basar et al. (2015) conducted a review that analyzed articles and the existing mobile apps that are currently available to support diabetes patient and based on the analysis described the opportunities for developing a mobile app that integrated most of the common features required for the self-management of a diabetic patient.

In order to recommend meals, encourage exercise, and remind users to take action, Fico et al. (2016) presented a system that builds three ontologies for activity, meals, and user data and integrates them. The additional domains are imported into the integrated ontology, which also establishes their connections. This approach permits prompt blood sugar level maintenance for diabetic patients and provides them with useful treatment advice, but it does not provide them with useful meal recommendations for HBP. For managing diabetes, Mougiakakou et al. (2010) presented the SMARTDIAB platform. It integrates cutting-edge techniques in data mining, communications, simulation algorithms, and database (DB) technology for controlling Type 1 diabetes. It included both hardware and software elements for the proper treatment of diabetes, but it is deficient in an efficient meal recommender for diabetics with high blood pressure.

El-Sappagh et al. (2019) conducted a comprehensive survey of Mobile Health (MH) research on diabetes management articles published between 2011 and 27 September 2017. In the survey, current challenges in MH, along with research gaps, opportunities, and trends were discussed. The literature review searched three academic databases (ScienceDirect, IEEE Xplore, and SpringerLink). A total of 60 articles were analyzed, with 30% from ScienceDirect, 38% from IEEE Xplore, and 32% from SpringerLink. MH was analyzed in the context of the electronic health record (EHR) ecosystem. The paper provided a critical analysis of challenges that have not been fully met, and highlights directions for future research that could improve MH applicability.

By integrating users' ontological profiles with general clinical diabetes recommendations and guidelines, Alian et al. (2018) presented a recommendation system to support diabetes self-management for American Indians, but it lacks the useful meal recommendation for diabetes patients with HBP.

Alotaibi et al. (2014) created a diabetes management system using Java for Android, Objective C for iPhone, and PHP and MySQL for the online application. The system included a reminder module that sent SMS notifications to patients to remind them to take readings, a reading log interface, and an artificial intelligence unit that uses fuzzy logic to assess the patient's health. Although the system mentioned above offers a great platform for keeping doctors informed about patient status, it is missing a module for tracking food and activity. That is a limitation given how important food and activity tracking are for treating diabetes and high blood pressure.

A research study was undertaken by Zheng et al. in 2019 to evaluate the efficacy of a straightforward outpatient diabetes self-management education program. In the trial, the control group and the intervention group were evenly distributed among 60 patients with type 2 diabetes mellitus. This study did not include a meal recommendation system.

Phanich et al., (2010) used clustering algorithms and self-organizing, categorized foods according to their nutritional value. Foods that are scarce, common, and avoidable were divided into these categories. Instead of recommending meals, their recommender system offers wholesome substitutions for foods in avoidable food groups. Despite the fact that the system they devised enables diabetics to avoid eating unhealthy meals, it does not cater for the user's specific needs. Due to the fact that everyone's body type, level of exercise, and BMI vary, this could be a drawback (BMI).

A personalized nutrient-based meal recommender system called Yum-me was proposed by Yang et al. in 2017 to accommodate people's dietary needs, dietary restrictions, and fine-grained food preferences. With the help of pairwise and item-wise visual comparisons, Yum-innovative me's online learning architecture teaches users how they prefer certain foods. Yum-me increases the acceptance rate of recommendations by 42.63%, however it doesn't provide diabetic patients with high blood pressure with a useful meal recommendation.

Toledo et al, (2019) general's framework for daily meal plan suggestions, which integrates the management of nutritional-aware and preference-aware information simultaneously. It has a prefiltering stage where foods that are inappropriate for the user's attributes are removed using the multicriteria decision analysis tool AHPSort. Although this advancement offers good meal suggestions based on the user's nutritional awareness and preference awareness at the same time, it does not offer the most useful meal suggestions for diabetics with high blood pressure.

A mobile-based diabetes Q&A and early warning system called Dia-AID was created by Xie et al. (2018) to help diabetes patients and communities at high risk. Three elements make up the Dia-AID system: a large-scale, multilingual diabetic FAQ repository; a multimode fusion Q&A framework; and a health data management module. Meal suggestions, food identification, and medication reminder notifications on cellphones are all missing from this system.

In accordance with the ADA's established standards, Norouzi et al. (2018) created a knowledge-based smart phone application that included a snack recommender system that combined artificial intelligence techniques via knowledge base (2022). In order to rate snacks and select the one that best suits the patient based on their health status, a combination of constraint-based reasoning and the roulette wheel algorithm was applied. Because the snack recommendation was based on their calorie needs, physical activity level was important. The recommender system became less attentive to personal interests to propose what was best for one's health as a result of the BMI. The recommender approach had the drawback of only including snacks during the evaluation period rather than big meals. It lacks the practical meal advice for diabetics with high blood pressure.

A model was put up by Rehman et al. (2017) that suggested different diets to patients depending on the results of their pathology test results. Root Mean Square Error (RMSE) was the method utilized to construct the system in order to choose the best solution globally. In order for the patient to recognize abnormalities after comparing them to the normal ranges, the normal variations of the indicators are provided in the test reports. The system collects information about the test results' typical ranges. The system is trained on a variety of age groups and their associated parameter ranges, enabling it to recommend diets in accordance with the patient's demands. Depending on the gender, age group, and whether or not a person is fasting, the limits of the same element may vary. Its absence of an efficient meal advice for diabetics with high blood pressure is one of its drawbacks.

Individuals who are at risk for coronary heart disease were given a personalized diet recommendation by Kim et al. in 2009. It has a Nutrient Extraction Module that uses an algorithm based on the user's vital signs and basal metabolic rate to determine the necessary nutrients. A vital sign recorder takes the user's vital signs and transmits the information to the server. Additionally, the system has a Preference Configuration Module that saves user food preferences and suggests diets based on them. Additionally, it suggests diets based on a person's personal information, health status, family history, amount of food consumed, amount of energy expended, and level of activity. The system does not recommend a reduced salt (sodium) diet, unlike in the case of HBP sufferers.

Roy et al. (2022) proposed an expert system that recommends a weight loss diet to patients with non-communicable diseases. An open dataset was used as input for the machine learning algorithm. The dataset consisted of various commonly used food items with their nutrition values including fats, calories, iron, vitamins etc. K-means clustering and random forest techniques was used for the expert's system but the system was targeted at recommending weigh loss diet to patients or users' weight and cholesterol level not considering if the patient has issue such as diabetes and high blood pressure which certain weight loss diet code be very detrimental to them if consumed. Hence this research seeks to fill the gap.

3. Materials and Method

Research methodology is the process of solving problems systematically. Bhatnagar & Singh, (2013). This section will describe the conceptual framework of the model, data description, the methodology adopted for the development of the food recommender system for patients with diabetes and HBP. K-means clustering and Random Forest classification methods was used as a combined clustering and classification technique in this paper.

Figure 1 shows the diagram of the flow of the proposed conceptual model that used the patients' blood glucose level and BP reading which is real-time to recommend food they can eat to manage their blood sugar and

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BP levels. Food and nutrition datasets from the USDA were used to create the corpus necessary for training the model. The foods are annotated as sodium level and Glycemic Index (GI), K-means cluster algorithm was used to cluster the food dataset on the sodium content and GI according to calories and Random Forest algorithm classifies the food items and predict which food should be eaten depending on their blood glucose level and BP level given. The user will enter their Age, Vegetarian or non-vegetarian status, blood glucose level and BP measurements into the system and the data will be preprocessed in the food classification module to check for the appropriate food to recommend.

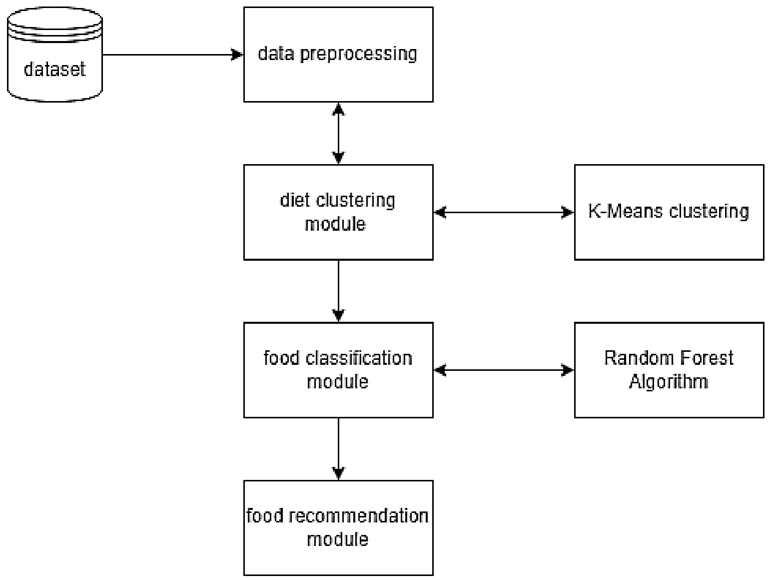
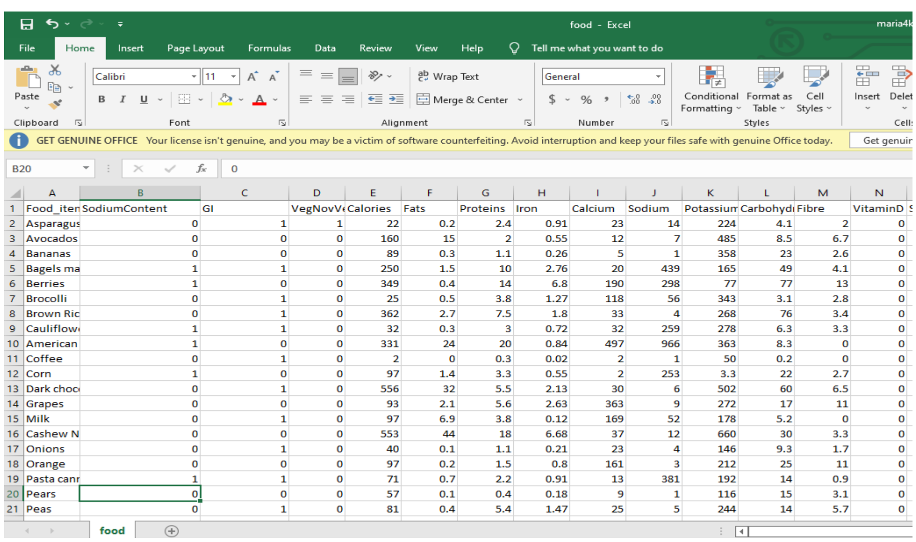


Figure. 1: Conceptual framework

3.1 Dataset description

The USDA food and nutrition datasets used for this research is in Comma Separated Value (CSV) format and the first one has 90 rows and 15 columns which contains the food items and their sodium and GI level. The sodium content is in low and high and it is depicted as 0 and 1 respectively while the GI is in low and high and it is depicted by 1 and 0 respectively. The other dataset is with 90 rows and 11 columns which contains just the nutritional details of the food items. Figure 2 and Figure 3 shows the datasets viewed on excel. The dataset was divided in an 80:20 percent for both training and testing of the random forest model.



Food_iten	SodiumContent	GI	VegNovVe	Calories	Fats	Proteins	Iron	Calcium	Sodium	Potassium	Carbohydi	Fibre	VitaminD
Asparagus	0	1	1	22	0.2	2.4	0.91	23	14	224	4.1	2	0
Avocados	0	0	0	160	15	2	0.55	12	7	485	8.5	6.7	0
Bananas	0	0	0	89	0.3	1.1	0.26	5	1	358	23	2.6	0
Bagels ma	1	1	0	250	1.5	10	2.76	20	439	165	49	4.1	0
Berries	1	0	0	349	0.4	14	6.8	190	298	77	77	13	0
Brocolli	0	1	0	25	0.5	3.8	1.27	118	56	343	3.1	2.8	0
Brown Ric	0	1	0	362	2.7	7.5	1.8	33	4	268	76	3.4	0
Cauliflow	1	1	0	32	0.3	3	0.72	32	259	278	6.3	3.3	0
American	1	0	0	331	24	20	0.84	497	966	363	8.3	0	0
Coffee	0	1	0	2	0	0.3	0.02	2	1	50	0.2	0	0
Corn	1	0	0	97	1.4	3.3	0.55	2	253	3.3	22	2.7	0
Dark choc	0	1	0	556	32	5.5	2.13	30	6	502	60	6.5	0
Grapes	0	0	0	93	2.1	5.6	2.63	363	9	272	17	11	0
Milk	0	1	0	97	6.9	3.8	0.12	169	52	178	5.2	0	0
Cashew N	0	0	0	553	44	18	6.68	37	12	660	30	3.3	0
Onions	0	1	0	40	0.1	1.1	0.21	23	4	146	9.3	1.7	0
Orange	0	0	0	97	0.2	1.5	0.8	161	3	212	25	11	0
Pasta canr	1	1	0	71	0.7	2.2	0.91	13	381	192	14	0.9	0
Pears	0	0	0	57	0.1	0.4	0.18	9	1	116	15	3.1	0
Peas	0	1	0	81	0.4	5.4	1.47	25	5	244	14	5.7	0

Figure 2: Food dataset description

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	A	B	C	D	E	F	G	H	I	J	K
1	0Calories	1Fats (gm)	2Proteins(g)	3Iron(mg)	4Calcium(mg)	5Sodium(mg)	6Potassium(mg)	7Carbohydrates (gm)	8Fibre (gm)	9Vitamin D (mcg)	10Sugars (gm)
2	160	15	2	0.55	12	7	485	8.5	6.7	0	0.7
3	89	0.3	1.1	0.26	5	1	358	8.5	2.6	0	12
4	349	0.4	14	6.8	190	298	77	8.5	13	0	46
5	331	24	20	0.84	497	966	363	8.5	0	0	0
6	2	0	0.3	0.02	2	1	50	8.5	0	0	0
7	97	1.4	3.3	0.55	2	253	3.3	8.5	2.7	0	7.7
8	93	2.1	5.6	2.63	2	9	272	8.5	11	0	6.3
9	97	6.9	3.8	0.12	2	52	178	8.5	0	0	0
10	553	44	18	6.68	2	12	660	8.5	3.3	0	5.9
11	97	0.2	1.5	0.8	2	3	212	8.5	11	0	0
12	57	0.1	0.4	0.18	2	1	116	8.5	3.1	0	9.8
13	411	17	46	8.57	2	329	1129	8.5	7.1	200	5.7
14	381	1.4	2	0.8	2	286	110	8.5	2.5	0	65
15	429	9.5	13	2.28	2	490	241	8.5	14	0	0.5
16	168	3.7	4.5	8	2	94	76	8.5	0.9	0	0.1
17	156	1.7	5	17.2	2	207	63	8.5	2.1	0	0.74
18	130	1.5	2.6	3.16	2	201	117	8.5	1.1	0	0.5
19	16	0.2	1.2	0.47	2	42	212	8.5	0.9	0	2.63
20	60	4	3.1	0.08	2	70	234	8.5	0	1	7
21	407	6.2	4.4	3.81	2	457	51	8.5	2.9	0	55
22	188	7.2	4.4	24	2	522	91	8.5	2.2	0	0.24
23	151	2.4	9	37.4	2	438	180	8.5	1	0	1.35

Figure 3: Nutrition dataset

3.2 K-means clustering

Unsupervised learning algorithm K-Means Clustering divides the unlabeled dataset into various clusters. Here, K specifies how many pre-defined clusters must be produced as part of the process; for example, if K=2, there will be two clusters, if K=3, there will be three clusters, and so on. It gives us the ability to divide the data into various groups and provides a practical method for automatically identifying the groups in the unlabeled dataset without any need for training. Each cluster has a centroid assigned to it because the algorithm is centroid-based. This algorithm's primary goal is to reduce the total distances between each data point and its corresponding clusters (JavaTpoint, 2022). K-Means clustering was utilized in this study to group foods based on their low sodium level, GI, and calorie content.

3.3 Random Forest

Supervised machine learning algorithms like random forest are frequently employed in classification and regression issues. On various samples, it constructs decision trees and uses their average for classification and majority vote for regression. The Random Forest Algorithm's ability to handle data sets with both continuous variables, as in regression, and categorical variables, as in classification, is one of its most crucial qualities. It produces superior outcomes for categorization issues (Analytic Vidhya, 2022). The description of the random forest is shown in Figure 4. In this study, 80% of the dataset was used to train the Random Forest algorithm, and 20% of the dataset was used to evaluate the trained model. As shown in the nutritional dataset, the target vector for training and testing was food that was already clustered and low in sodium and GI. The feature were the nutrition data of the food items, which are encoded numbers that represent calories, fats, proteins, iron, calcium, potassium, carbohydrate, fiber, and vitamins. Using the patients' entered blood glucose and blood pressure levels, the trained model was then utilized to forecast which food the patients should eat.

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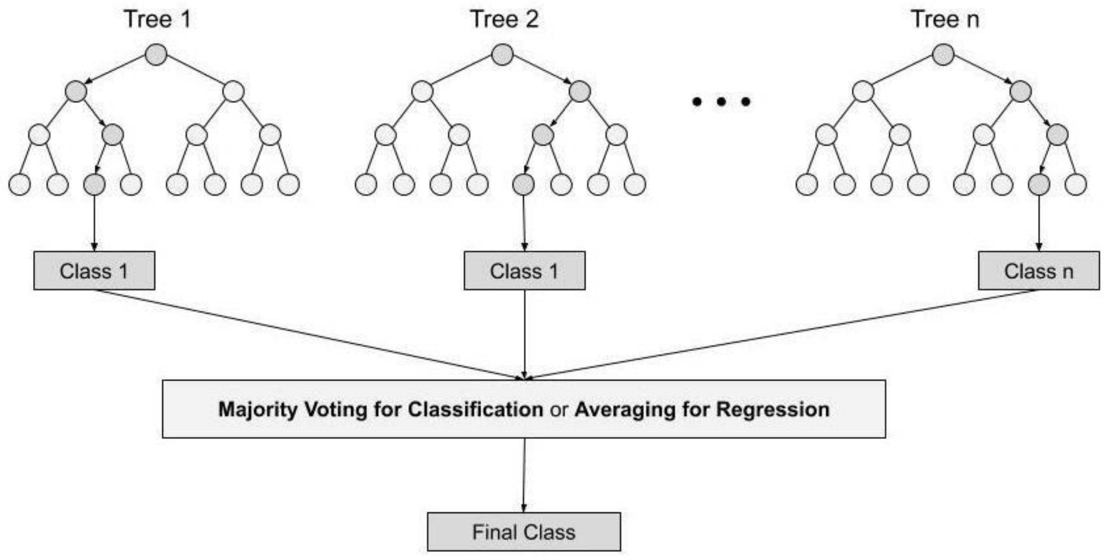

Figure 4: Random Forest (source: Analytic Vidhya, 2022)

3.4 Tkinter package

Python provides a variety of choices for GUI development (Graphical User Interface). Tkinter is the approach used the most frequently among all GUI approaches. It is a typical Python interface for the Python-supplied Tk GUI toolkit. The fastest and simplest approach to construct GUI apps is with Python and Tkinter. Tkinter makes building a GUI a simple process. The Tk GUI toolkit's sophisticated object-oriented interface is provided by Tkinter (Tutorialpoint, 2022). Figure 5 depicts how the tkinter GUI appears. The recommender system's user interface was created using the tkinter programming language.

Figure 5: Tkinter GUI (source: Tutorialpoint, 2022)

4. Results and Discussion

The python tkinter library was imported for the development of the graphical user interface of the proposed food recommender system. The code snippet used on the jupyter notebook to create the interface is shown in Figure 6.

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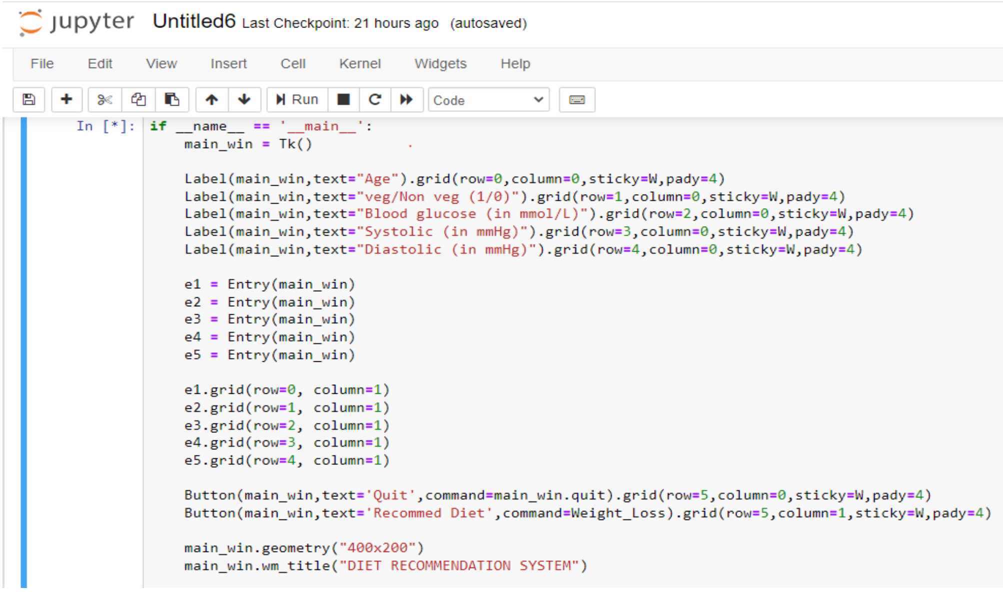


```
if __name__ == '__main__':
    main_win = Tk()

    Label(main_win,text="Age").grid(row=0,column=0,sticky=W,pady=4)
    Label(main_win,text="veg/Non veg (1/0)").grid(row=1,column=0,sticky=W,pady=4)
    Label(main_win,text="Blood glucose (in mmol/L)").grid(row=2,column=0,sticky=W,pady=4)
    Label(main_win,text="Systolic (in mmHg)").grid(row=3,column=0,sticky=W,pady=4)
    Label(main_win,text="Diastolic (in mmHg)").grid(row=4,column=0,sticky=W,pady=4)

    e1 = Entry(main_win)
    e2 = Entry(main_win)
    e3 = Entry(main_win)
    e4 = Entry(main_win)
    e5 = Entry(main_win)

    e1.grid(row=0, column=1)
    e2.grid(row=1, column=1)
    e3.grid(row=2, column=1)
    e4.grid(row=3, column=1)
    e5.grid(row=4, column=1)

    Button(main_win,text='Quit',command=main_win.quit).grid(row=5,column=0,sticky=W,pady=4)
    Button(main_win,text='Recommed Diet',command=Weight_Loss).grid(row=5,column=1,sticky=W,pady=4)

    main_win.geometry("400x200")
    main_win.wm_title("DIET RECOMMENDATION SYSTEM")
```

Figure 6: Tkinter code for the development of the user interface (source: Author, 2022)

4.1 System implementation

Once the code in figure 6 is run, the user interface pops up. The graphical user interface of the food recommender system allows the user to enter Age, vegetarian and non-vegetarian status, blood glucose level, systolic and diastolic blood pressure level details into the provided fields. There is also the button the user can click to submit which then recommend food after entering the details above and also a button to quit and launch a new window. Figure 7 shows the user interface of the food recommender system when launched.

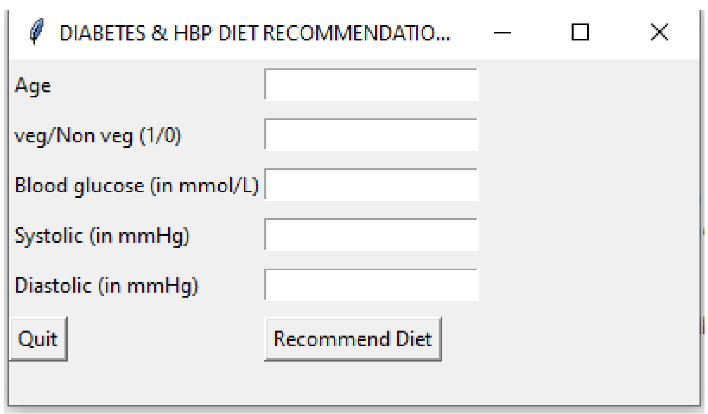

Figure 7: User interface of the recommender system

4.2 Applying K-Means for clustering on Sodium Content and GI

Figure 8 shows the code used for the k-means clustering of the sodium content and GI of the food items according to calories content 0 was used to show food low in sodium while 1 was used to indicate foods with low GI. The foods with low sodium and low GI are clustered once the details are entered and submitted.

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```
Datacalorie=SodiumContentfoodseparatedIDdata[1:,1:len(SodiumContentfoodseparatedIDdata)]

X = np.array(Datacalorie)
kmeans = KMeans(n_clusters=2, random_state=0).fit(X)

XValu=np.arange(0,len(kmeans.labels_))
# fig,axs=plt.subplots(1,1,figsize=(15,5))
# plt.bar(XValu,kmeans.labels_)
dnrlbl=kmeans.labels_
# plt.title("Predicted Low-High Weigted Calorie Foods")

Datacalorie=GIfoodseparatedIDdata[1:,1:len(GIfoodseparatedIDdata)]

X = np.array(Datacalorie)
kmeans = KMeans(n_clusters=2, random_state=0).fit(X)
#print ('## Prediction Result ##')
#print(kmeans.labels_)
XValu=np.arange(0,len(kmeans.labels_))
# fig,axs=plt.subplots(1,1,figsize=(15,5))
# plt.bar(XValu,kmeans.labels_)
lnchlbl=kmeans.labels_
# plt.title("Predicted Low-High Weigted Calorie Foods")
```

Figure 8: K-means clustering (source: Author, 2022)

4.3 Applying Random Forest Classifier

After the clustering is completed, the random forest trained on 80% data with target feature as the food items from the dataset was used to classify the food item based on the given data input using the code as shown in Figure 9. After the training, the model can then recommend food item to the user pending what detail the user supplied through the form loaded. The model was able to achieve an accuracy of 95% with 100 decision trees.

```
X_test=np.zeros((len(weightlosscat),6),dtype=np.float32)

print('##################')

#randomforest
for jj in range(len(weightlosscat)):
    valloc=list(weightlosscat[jj])
    valloc.append(agecl)
    valloc.append(clbmi)
    X_test[jj]=np.array(valloc)*ti

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.20, random_state =

# instantiate the classifier with n_estimators = 100

clf = RandomForestClassifier(n_estimators=100, random_state=0)

# fit the model to the training set

clf.fit(X_train, y_train)

# Predict on the test set results

y_pred = clf.predict(X_test)
```

Figure 9: Random Forest code for food classification

Figure 10 shows the confusion matrix of the trained model that was obtained using the test data which is 20% of the dataset. It shows how the model classified and misclassified the various food items. Since 0 represents low sodium foods and 1 represents low GI foods. From the confusion matrix there is only one misclassification. other performance metrics of the model was measured such as the precision, recall, F1-score and support values are as shown in table 1.

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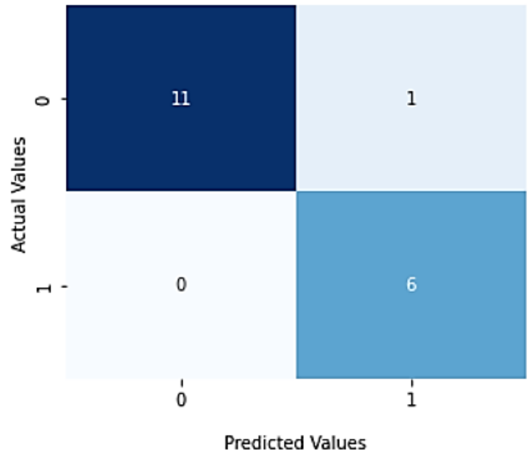

Figure 10: Confusion matrix

Table 1: Performance metrics of the model using the test dataset

Analysis	Precision	Recall	F1-score	Support
0	1.00	0.91	0.95	12
1	0.86	1.00	0.96	6
Accuracy			0.94	18
Macro avg	0.93	0.95	0.94	18
Weighted avg	0.95	0.94	0.94	18

4.4 Predicting Food Items for Diabetes with HBP

Figure 11 and Figure 12 shows the window of the predicted food items based on the information supplied by the user to the system.

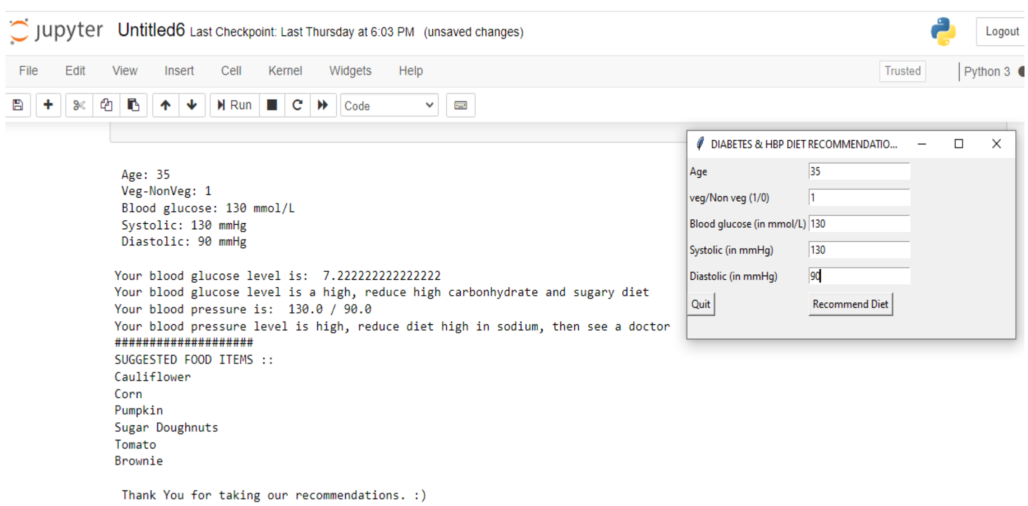

Figure 11: Complete Recommender System (source: Author, 2022)

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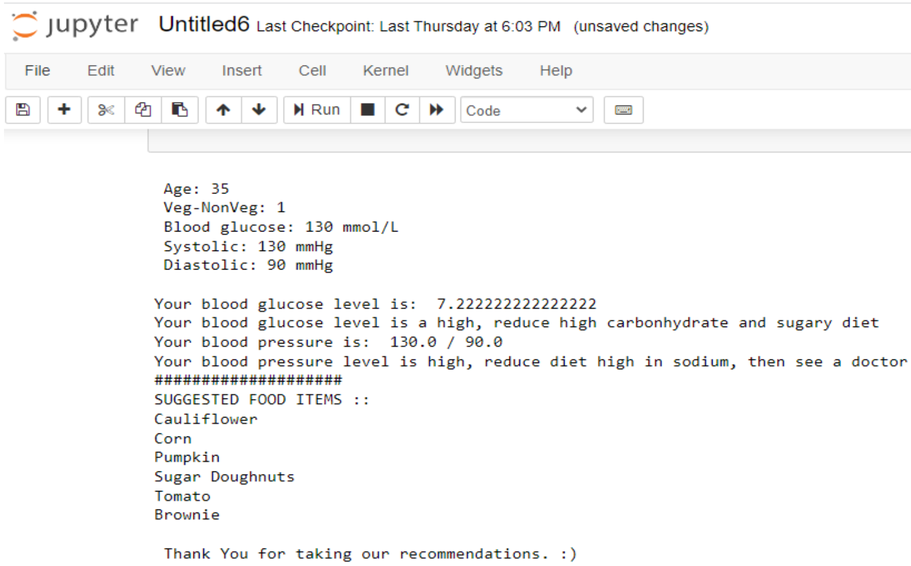

Figure 12: Recommended Food Item

5. Conclusion

Based on the available dataset, random forest was able to categorize and predict dietary items for the patients. The model and system both produced good results. The meal recommender system will be a useful tool for enhancing nutrition and encouraging a healthy lifestyle provided it was properly created, put into practice, and assessed. The nutrition informatics specialists who were needed to create the food recommender system can benefit from the knowledge provided by this study.

References

Addo, J., Amoah, A. G., & Koram, K. A. (2006). The changing patterns of hypertension in Ghana: a study of four rural communities in the Ga District. *Ethnicity & disease*, 16(4), 894-899

Alian, S., Li, J., & Pandey, V. (2018). A Personalized Recommendation System to Support Diabetes Self-Management for American Indians. IEEE Access, 6, 73041-73051

Alian, S., Li, J., & Pandey, V. (2018). A Personalized Recommendation System to Support Diabetes Self-Management for American Indians. IEEE Access, 6, 73041-73051

Alotaibi, M. M., Istepanian, R. S., Sungoor, A., & Philip, N. (2014, June). An intelligent mobile diabetes management and educational system for Saudi Arabia: System architecture. In IEEE-EMBS International Conference on Biomedical and Health Informatics (BHI) (pp. 29-32). IEEE

Analytic Vidhya, (2022). Understanding Random Forest. https://www.analyticsvidhya.com/blog/2021/06/understanding-random-forest/

Anthimopoulos M., Dehais J., Shevchik S., Ransford B. H., Duke D., Diem P, & Mougiakakou, S. (2015). Computer vision-based carbohydrate estimation for type 1 patients with diabetes using smartphones. Journal of diabetes science and technology, 9(3), 507–515

Appel, L. J., Moore, T. J., Obarzanek, E., Vollmer, W. M., Svetkey, L. P., Sacks, F. M., Bray, G. A., Vogt, T. M., Cutler, J. A., Windhauser, M. M., Lin, P. H., & Karanja, N. (1997). A clinical trial of the effects of dietary patterns on blood pressure. DASH Collaborative Research Group. The New England journal of medicine, 336(16), 1117–1124. https://doi.org/10.1056/NEJM199704173361601

Appel, L. J., Sacks, F. M., Carey, V. J., Obarzanek, E., Swain, J. F., Miller, E. R., 3rd, Conlin, P. R., Erlinger, T. P., Rosner, B. A., Laranjo, N. M., Charleston, J., McCarron, P., Bishop, L. M., & OmniHeart Collaborative Research Group (2005). Effects of protein, monounsaturated fat, and carbohydrate intake on blood

Online ISSN: 2736-0903
Print ISSN: 2736-089X
www.slujst.edu.ng

pressure and serum lipids: results of the Omni Heart randomized trial. JAMA, 294(19), 2455–2464. https://doi.org/10.1001/jama.294.19.2455

Ataklte, F., Erqou, S., Kaptoge, S., Taye, B., Echouffo-Tcheugui, J. B., & Kengne, A. P. (2015). Burden of undiagnosed hypertension in sub-saharan Africa: a systematic review and meta-analysis. Hypertension, 65(2), 291-298

Awuah, R. B., Anarfi, J. K., Agyemang, C., Ogedegbe, G., & Aikins, A. D. G. (2014). Prevalence, awareness, treatment and control of hypertension in urban poor communities in Accra, Ghana. Journal of Hypertension, 32(6), 1203-1210

Basar, M.A., Alvi, H.N., Bokul, G.N., Khan, M.S., Anowar, F., Huda, M.N., & Al Mamun, K.A. (2015). A review on diabetes patient lifestyle management using mobile application. 2015 18th International Conference on Computer and Information Technology (ICCIT), 379-385

Bhatnagar, M., & Singh, P. (2013). Research Methodology as SDLC Process in Image Processing. International Journal of Computer Applications, 77, 43-45

El-Sappagh, S., Ali, F., El-Masri, S., Kim, K., Ali, A., & Kwak, K.S. (2019). Mobile Health Technologies for Diabetes Mellitus: Current State and Future Challenges. IEEE Access, 7, 21917-21947

Etyang, A. O., & Gerard Scott, J. A. (2013). Medical causes of admissions to hospital among adults in Africa: a systematic review. Global health action, 6(1), 19090

Fico, G., Fioravanti, A., Arredondo, M.T., Gorman, J., Diazzi, C., Arcuri, G., Conti, C., & Pirini, G. (2016). Integration of Personalized Healthcare Pathways in an ICT Platform for Diabetes Managements: A Small-Scale Exploratory Study. IEEE Journal of Biomedical and Health Informatics, 20, 29-38

IDF, (2023). About Diabetics. https://www.idf.org/aboutdiabetes/what-is-diabetes.html

IDF, (2023). Deaths attributable to diabetes. https://diabetesatlas.org/data/en/indicators/7/

IDF, (2023). IDF Diabetes Atlas. https://diabetesatlas.org/#:~:text=Diabetes%20around%20the%20world%20in%202021%3A&text=Over%203%20in%204%20adults,over%20the%20last%2015%20years

International Diabetes Federation (IDF), (2019) Diabetes Atlas. Epidemiology and Mobidity. In: International Diabetes Federation

JavaTpoint, (2022). K-Means Clustering Algorithm. https://www.javatpoint.com/k-means-clustering-algorithm-in-machine-learning

Johns Hopkins Medicine, (2022). Diabetes and High Blood Pressure. https://www.hopkinsmedicine.org/health/conditions-and-diseases/diabetes/diabetes-and-high-blood-pressure

Kim, J., Lee, J., Park, J., Lee, Y., & Rim, K.W. (2009). Design of Diet Recommendation System for Healthcare Service Based on User Information. 2009 Fourth International Conference on Computer Sciences and Convergence Information Technology, 516-518

Medical news today, (2022, March 30). The link between diabetes and hypertension. https://www.medicalnewstoday.com/articles/317220

Mougiakakou, S.G., Bartsocas, C.S., Bozas, E., Chaniotakis, N.A., Iliopoulou, D., Kouris, I.N., Pavlopoulos, S.A., Prountzou, A., Skevofilakas, M., Tsoukalis, A., Varotsis, K., Vazeou, A., Zarkogianni, K., & Nikita, K.S. (2010). SMARTDIAB: A Communication and Information Technology Approach for the Intelligent Monitoring, Management and Follow-up of Type 1 Diabetes Patients. IEEE Transactions on Information Technology in Biomedicine, 14, 622-633

Nduka, C., Sarki, A., Uthman, O., & Stranges, S. (2015). Impact of antiretroviral therapy on serum lipoprotein levels and dyslipidemias: a systematic review and meta-analysis. International Journal of Cardiology, 199, 307-318

NHS, (2022). Prevention High blood pressure (hypertension). https://www.nhs.uk/conditions/high-blood-pressurehypertension/prevention/#:~:text=The%20more%20salt%20you%20eat,which%20is%20about%20a%20teaspoonful.&text=Eating%20a%20low%2Dfat%20diet,also%20helps%20lower%20blood%20pressure

SLUJST
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https://doi.org/10.56471/slujst.v7i.341
Online ISSN: 2736-0903
Print ISSN: 2736-089X
www.slujst.edu.ng

NIH, (2022). Diabetes Diet, Eating, & Physical Activity. https://www.niddk.nih.gov/health-information/diabetes/overview/diet-eating-physical-activity

Norouzi, S., Kamel Ghalibaf, A., Sistani, S., Banazadeh, V., Keykhaei, F., Zareishargh, P., Amiri, F., Nematy, M., & Etminani, K. (2018). A Mobile Application for Managing Diabetic Patients' Nutrition: A Food Recommender System. Archives of Iranian medicine, 21(10), 466–472

Phanich, M., Pholkul, P., & Phimoltares, S. (2010). Food Recommendation System Using Clustering Analysis for Diabetic Patients. 2010 International Conference on Information Science and Applications, 1-8

Povey, R. C., & Clark-Carter, D. (2007). Diabetes and healthy eating: a systematic review of the literature. The Diabetes educator, 33(6), 931–961. https://doi.org/10.1177/0145721707308408

Rahimi, A., Hashemzadeh, M., Zare-Farashbandi, F., Alavi Naeini, A. M., & Hasanzadeh, A. (2018). The effect of nutrition education course on awareness of obese and overweight female 1st-year High School students of Isfahan based on transtheoretical model of behavioral change. Journal of education and health promotion, 7, 76. https://doi.org/10.4103/jehp.jehp_120_17

Ramezankhani, A., Pournik, O., Shahrabi, J., Khalili, D., Azizi, F., & Hadaegh, F. (2014). Applying decision tree for identification of a low risk population for type 2 diabetes. Tehran Lipid and Glucose Study. Diabetes research and clinical practice, 105(3), 391–398. https://doi.org/10.1016/j.diabres.2014.07.003

Sacks, F. Svetkey, L., Vollmer, W., Appel, L., Bray, G., Harsha, D., Obarzanek, E., Conlin, P., Miller, E., Simons-Morton, D., Karanja, N., Lin, P., Aickin, M., Most-Windhauser, M., Moore, T., Proschan M. & Cutler, J. (2001). Effects on Blood Pressure of Reduced Dietary Sodium and the Dietary Approaches to Stop Hypertension (DASH) Diet. New England Journal of Medicine, 344(1), 3-10

Sharmila A. &, Saraswathi E. (2020). Analyzing Diabetic Data Using Naive-Bayes Classifier. European Journal of Molecular & Clinical Medicine, 7(4), 2687-2699

The Guardian, (2022). 76.2m Nigerians are hypertensive but only 23 million on treatment. https://guardian.ng/features/76-2m-nigerians-are-hypertensive-but-only-23-million-on-treatment/

Tutorialpoint (2022). *Python - GUI Programming (Tkinter)*. https://www.tutorialspoint.com/python/python_gui_programming.htm

Udogadi, N. S., Onyenibe, N. S. & Abdullahi, M. K. (2019). Dietary Management of Diabetes Mellitus with Focus on Nigeria. International Journal of Diabetes Research, 2(1), 26-32

Vasan, R. S., Beiser, A., Seshadri, S., Larson, M. G., Kannel, W. B., D'Agostino, R. B., & Levy, D. (2002). Residual lifetime risk for developing hypertension in middle-aged women and men: The Framingham Heart Study. Jama, 287(8), 1003-1010

WebMD, (2022). DASH Diet and High Blood Pressure. https://www.webmd.com/hypertension-high-blood-pressure/guide/dash-diet#:~:text=Dietary%20Approaches%20to%20Stop%20Hypertension%20(DASH)%20is%20an%20eating%20plan,calcium%2C%20fiber%2C%20and%20protein

WHO (2021, August 25). Hypertension. https://www.who.int/news-room/fact-sheets/detail/hypertension

World health ranking (n.d). Nigeria: Hypertension. https://www.worldlifeexpectancy.com/nigeria-hypertension

Yancy, C.W., Jessup, M., Bozkurt, B., Butler, J., Casey, D. E., Drazner, M. H., Fonarow, G. C., Geraci, S.A., Horwich, T., Januzzi J. L. & Johnson, M.R. (2013), ACCF/AHA guideline for the management of heart failure: a report of the American College of Cardiology Foundation/American Heart Association Task Force on Practice Guidelines. Journal of the American College of Cardiology, 62(16), e147-e239

Yang, L., Hsieh, A., Yang, H., Pollak, J., Dell, N., Belongie, S., Cole, C. & Estrin, D. (2017). Yum-me: a personalized nutrient-based meal recommender system. ACM Transactions on Information Systems (TOIS), 36(1), 1-31

Yera Toledo, R., Alzahrani, A.A., & Martínez, L. (2019). A Food Recommender System Considering Nutritional Information and User Preferences. IEEE Access, 7, 96695-96711

Zheng, F., Liu, S., Liu, Y., & Deng, L. (2019). Effects of an Outpatient Diabetes Self-Management Education on Patients with Type 2 Diabetes in China: A Randomized Controlled Trial. Journal of Diabetes Research, 3(2)

SLUJST
Sule Lamido University Journal of Science & Technology Vol. 7 No. 1 [June, 2023], pp. 83-96
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Online ISSN: 2736-0903
Print ISSN: 2736-089X
www.slujst.edu.ng

Jafari, F., & Dorafshan, S. (2022). Comparison between Supervised and Unsupervised Learning for Autonomous Delamination Detection Using Impact Echo. *Remote Sensing*, *14*(24), 6307.

Roy, F., Shaji, A., Sherimon, V., and Amri, M. M. S. A., (2022). Stay-Healthy: An expert system to suggest a healthy diet. *International Journal of Engineering Science Technologies, 6(1)*, 11-17.doi: 10.29121/IJOEST.v6.i1.2022.262