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To Control Diabetes Using Machine Learning Algorithm and Calorie Measurement Technique

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Abstract: Because of the increasing workload, people are having several clinical examinations to determine their health status, resulting in limited time. Here, we present a healthful consuming device based on rule mining that can modify your parameter dependency and recommend the varieties of meals that will boost your fitness and assist you to avoid the types of meals that increase your risk for sicknesses. Using the meals database, the data mining technique is useful for gathering meal energy from breakfast, after breakfast, lunch, after lunch, dinner, after dinner, and bedtime for ninety days. The purpose of this study is to determine to mean random plasma glucose levels and h1bc levels using the Nathan, ADAG (A1C-derived average glucose), and DTTC (Dynamic Temporal and Tactile Cueing) methods. This system can identify and recognize food images, as well as keep track of the food items ingested by the user. Deep learning techniques are mostly utilized for picture recognition and categorization. The KNN (k-nearest neighbors algorithm) classification approach is used to determine if diabetes is normal, pre-diabetic, or chronic. This study employs deep learning and a smart camera app called "calorie mom" to track nutrition from meal photographs. In addition, the commonly used measures of divisions such as accuracy, sensitivity, uniqueness, and recalling diabetic dataset using Python 3 Jupyter Notebook were employed to evaluate the performance of a machine learning classifier.

Keywords: Data mining; random plasma glucose (RPM); calories; machine learning

1 Introduction

Data mining is the extraction of patterns from huge datasets to evaluate information and comprehend the nature of data. Data mining applications can be developed to evaluate the efficacy of medical treatments. By comparing and contrasting causes, symptoms, and treatment options, data mining can provide a study of which courses of action are effective. For example, the outcomes of patient groups treated with different drug regimens for the same disease or condition can be compared to determine which treatments work best and are the most cost-effective. United Health Care has looked at its treatment record data in this manner to determine if there are any ways to cut costs while still providing quality care. Despite the relevance of data mining in the use of technology for accurate and reliable food quality and safety evaluation and control, data mining techniques and methodologies have been employed in the food sector for analyzing hyperspectral pictures. Clinical profiles have also been developed to convey information about physicians' practice patterns to them. Diabetes is one of the world's most serious and quickly spreading diseases. In addition to heart difficulties, it raises the risk of kidney sickness, blindness, nerve damage, and blood vessel damage [1]. According to current statistics, more than 80% of diabetics die as a result of heart or blood vessel illness. Repalli et al. [2] attempt to anticipate a patient's diabetes by utilizing various data mining techniques and data analysis based on mining algorithms to generate predictions for patients. Diabetes mellitus can be managed by injecting insulin, changing dietary habits, and engaging in physical activities, however, there is a lack of a reliable monitoring system to visualize correct food intake. Diabetes should be identified in persons above the age of 30 according to doctors [3]. According to doctors, the majority of people are unaware that they have diabetes. As a result, experts suggest that diet and exercise are vital for sugar-free living. Kumar et al. [4] demonstrated the Fuzzy ID3 approach with diabetes data. The disease is estimated by the author using a computer, which collects data and uses classification methods to clustered data. Artificial intelligence, in particular, creates a sophisticated medical system for diagnosing diabetes patients [5]. When compared to other data mining techniques, the author's extended classifier system (XCS) produces higher accuracy. Fico et al. [6] developed a system that provides realistic treatment guidance for diabetic patients and prompt management of their blood sugar levels, but it lacks good meal recommendations. With the recent emphasis on food as a health concern, the food imaging system will most likely be utilized to record regular meals. The study by Dubey et al. [7] sought to ascertain the association between triglyceride levels and HbA1c. HbA1c levels were found to be strongly associated with fasting and two-hour postprandial levels. Despite this, it has a better connection at a two-hour postprandial level. Alotaibi et al. [8] developed a diabetes management system that sends SMS reminders to patients, as well as an interface for recording readings and an artificial intelligence unit that maintains the degree of health. Fuzzy logic Food intake monitoring is the technique of calculating or quantifying the number of calories consumed by examining a person's food intake throughout the day. As a result, the focus of this research is on effective methods for recognizing the type of food and its caloric value, as well as the calorie table [9]. Furthermore, it focuses on diabetes prognosis.

Fig. 1 gives an idea that meals that contain carbohydrates begin to digest quickly [10]. Most carbohydrates digestion takes place in the small intestine, and dietary carbohydrates are delivered from the stomach to the small intestine. Broking down the carbohydrate content to monosaccharides for absorption in the liver is how glucose is extracted from meals. This glucose mixes with blood and travels to the brain and other bodily cells via muscles. Zheng et al. [11] proposed a general framework for a meal detection system, to properly monitor and evaluate the diet. But reporting a person's actual food intake is very difficult. Food artists also need to perform complex laboratory tests to accurately estimate food intake [12,13].

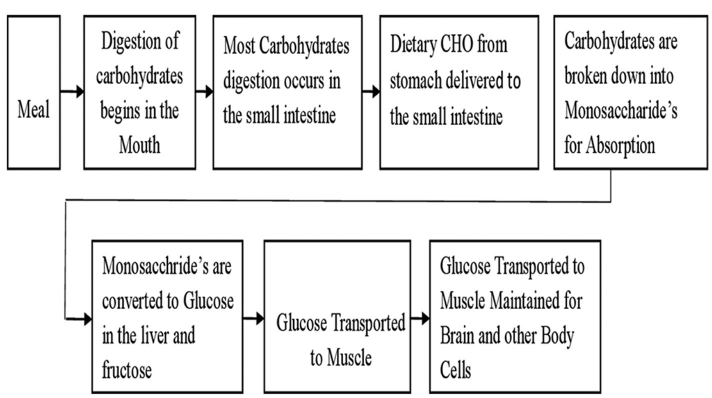


Figure 1: Conversion of meal into glucose

2 Proposed Methodology

The food calorie is a revolutionary computation procedure that presents a system for measuring calories [14]. As a result of uploading an image of the food item, the user will be able to determine the number of calories indicated in the supplied food image. There have been a few ways that are being preferred for identifying food images, estimating the calorie content of food items, and also measuring the number of calories consumed by a specific person through examining their daily dietary data [15].

2.1 Calorie Measuring System

Several other methods as well as algorithms have been implemented to the related works to calculate the same. This is a system that can be able to detect as well as recognize the food image and keep the track of food items consumed by the user. State-of-the-art deep learning techniques are mainly used for image recognition and classification. We use a smart camera app "calorie mama" that is excelled in deep learning to track nutrition from food images [16,17] "Calorie Mama App" is powered by our Food AI API [18]. Food AI API is found on the latest innovations in deep learning and image classification technology to identify food items quickly and accurately. Step by step procedure as follows:

Step 1: Click on the image of the user food item (using a mobile phone).

Step 2: Detach the unwanted area (background) of the image and select the target area.

Step 3: Images are provided for training purposes and that are being sent for testing.

Step 4: User clicked food image feature is sent for extraction purposes (shape, size, and color).

Step 5: Categorize the given images into their corresponding categories. Then the name of the given food item is predicted.

Step 6: The purpose of confirming the predicted food item by the User.

- In the case of an incorrect prediction, the user will state the type of food.
- In the case of correct prediction, the system will prompt the user to present the exact amount of predicted objects to be consumed by the user. By using that output, the system calculates and generates the number of calories.

Step 7: Some standard amounts of calories are stored in a CSV file.

Step 8: This program meticulously records the foods ingested and generates a weekly statistical analysis to assist the user in controlling his or her consumption, mostly to prevent obesity-related disorders.

The database is created from the dataset stored in text files if any cluster contains more than ten items. The above steps emulate each food database classified as each cluster database containing several sub-nutritionists. The Mass of food items using mathematical equation $M = \rho V$, where M is considered as the mass of food portion, ρ is density and V is the volume of food. Finally, the calorie of the given food item is estimated using a mass of food item and calorie value from Tab. 1 using the equation.

$$Estimated\ Calorie = Calorie\ from\ the\ table \times M$$

Table 1: Sample food item

S. no.	Types of food	Serving size	Calories	S. no.	Types of food	Serving size	Calories
1	Apples	1 medium (138 g)	72	25	Curd Rice	1 cup cooked	130
2	Spaghetti	1 cup (140 g)	220	26	Bisibela Bhat	1 cup 543 gram	199
3	Carrots	1 large (72 g)	30	27	Masala Papad	1 pc	424
4	Oranges	1 medium (131 g)	62	28	Onion Raitha	1 small bowl	150
5	Bananas	1 large (136 g)	121	29	Gulab Jamun	1 Piece	145
6	Potato chips	4oz (114 g)	620	30	Indian petha sweet	40 grams	250
7	Snickers bar	1 bar (113 g)	528	31	Sambar	1 cup	273
8	Brown rice	1 cup (195 g)	218	32	Rasam	100 ml	25
9	Honey	1 tbsp (21 g)	64	33	Broccoli	100 grams	34
10	Oatmeal	1 cup (234 g)	145	34	Chicken Stir Fry	100 grams	112
11	Ice cream	1 cup (49 g)	100	35	Aval upma	194 grams	360
12	Macaroni and cheese	1 seving (166 g)	290	36	Paneer Butter Masala	1 cup	37
13	Raisins	1 small box (43 g)	129	37	Halwa-Dry sweets	2 tsp	60
14	White rice	1 cup (186 g)	240	38	Milk Payaasam	100 grams	134.7
15	White bread	1 slice (30 g)	80	39	Vermicelli	1 cup cooked	220
16	Water melon	1 Cup (154 g g)	46	40	Fried rice	1 cup	333
17	Popcorn	2 cups (16 g)	160	41	Chicken fried rice	1 cup	329
18	Baked potato	1 medium (173 g)	161	42	Beef fried rice	1 cup	347
19	Glucose	50 g	194	43	Vegetable soup	1 cup	40
20	sweet potato	100 grams	86	44	Chinese Egg fried Rice	100 grams	164
21	bottle gourd (cooked)	100 grams	15	45	Chicken Biriyani	1 cup	348
22	Vegetable curry	100 grams	85	46	Mutton Biriyani	1 cup	387
23	Paneer Kalimirch	100 grams	265	47	Kadai Chicken	1 cup	400
24	Chapathi	3 pcs	205				

The above Tab. 1 flashes different sub-factors of food items. A sample record has been mentioned. In this study, a rule-based knowledge representation and reasoning are being followed. Next, we find day-wise average sum calories by using the following algorithm

Algorithm:

```
//input: food item (or food ingredients)
//output: To find out the calorie level in day today
Read food item (food ingredients);
data = pd.read_csv("../input/nutrition-food.csv")
def fooditem(request):
   breakfast = Category. Objects. filter(name = 'breakfast') [0]. fooditem_set.all()
   bcnt = breakfast. Count ()
   lunch = Category. Objects. filter(name = 'lunch') [0].fooditem_set.all()
   lcnt = lunch. Count ()
   dinner = Category. Objects. filter(name = 'dinner') [0].fooditem_set.all()
   dcnt = dinner.count()
   snacks = Category.objects. filter(name = 'snacks') [0].fooditem_set.all()
   scnt = snacks.count()
   context = {'breakfast': breakfast,
          'bcnt':bcnt,
          'lcnt':lcnt,
          'scnt':scnt,
          'dcnt':dcnt,
          'lunch':lunch,
          'dinner':dinner,
          'snacks':snacks,
         }
#Average menu calories for each categories
def menu_breakfast():
  print ('Average calories in breakfast:', menu_breakfast['Calories']. mean ())
  print ('Average calories in Beef & Pork:', menu_beefPork['Calories']. mean ())
  print ('Average calories in Chicken & Fish:', menu_chickenFish['Calories']. mean ())
  print ('Average calories in Salads:',menu_salads['Calories'].mean())
  print ('Average calories in Snacks & Sides:', menu_snacksSides['Calories']. mean ())
  print ('Average calories in Coffee & Tea:', menu_coffeeTea['Calories']. mean ())
  #Calculate Calories
def value_meal(items):
  arr = [0–2]
  j = 0
  for i in items:
```

(Continued)

Algorithm: (continued).

```
  item_calories = menu.loc[menu['Item'] == i]. Calories
  arr[j] = item_calories
  j = j + 1
  temp = arr [0]. append(arr [1]). append(arr [2])
  temp = temp.sum()
  return temp
for k in range (temp):
 k = 1800
 avgcalorie = (int ("enter the average calorie"))
 if (avgcalorie== 2000 or avgcalorie<2500):
  print ("calorie level as normal")
 elif(temp<2000):
  print ("calorie level as Low")
 else:
print ("calorie level as high")
```

In Tab. 2, the calorie level for food items should be calculated for 90 days, but it has been limited to 10 days due to space constraints. If breakfast, lunch, dinner, and snacks levels are satisfactory, the calorie level will be normal, and if they are good, the calorie level will be normal. If they are poor, the calorie level will be very low. If they are over calories, the calorie level is high. On the day if the Breakfast = Satisfied, Snacks 1 = poor, lunch = good, snacks 2 = S, Dinner = S, snacks 3 = good, then the calorie level is normal [19].

Table 2: Average sum calories per day

Day	Person name: A. Bhanupriya, Age: 24						Total calories	Calories level
	Node 1, food calories							
	Breakfast	Snack 1	Lunch	Snack 2	Dinner	Snack 3		
Day 1	S	P	G	S	S	G	2036	Normal
Day 2	P	G	Oc	Oc	G	G	2564	High
Day 3	Oc	P	S	P	S	S	1909	Low
Day 4	Oc	P	S	G	Oc	Oc	2752	High
Day 5	Oc	P	S	P	G	S	2083	Normal
Day 6	Oc	G	Oc	P	G	S	2521	High
Day 7	P	G	P	P	P	G	1358	Very low
Day 8	P	G	P	G	S	Oc	1635	Very low
Day 9	P	P	G	Oc	Oc	S	2139	Normal
Day 10	G	P	Oc	S	G	Oc	2590	Normal

Where, S – Satisfactory, P – Poor, G – Good, OC - Over Calories, H – High.

2.2 Machine Learning Techniques

Machine learning, like artificial intelligence, is recognized for practicing distributing ideas from other connected domains. There has recently been an upsurge in the number of experiments and studies in the field of food classification that use machine learning/deep learning approaches. Aizawa et al. proposed a Bayesian framework-based incremental learning strategy for food image recognition and estimate. Bossard et al. employed Random Forest to achieve a classification accuracy of 50.67 percent on the Food-101 test set by mining discriminative components. The random forest model is used to cluster the superpixels in the training dataset. The field's main focus is learning, i.e., attaining skills or knowledge from experience. Rajesh et al. involved various methods of algorithms such as ID3, C4.5, LDA. Now Pace, K-NN to diagnose diabetes for a given database. The author concludes that C4.5 with a lower error rate of 0.0938 and higher accuracy is the best algorithm 91%. Robert et al. preferred a framework concentrated mainly on the diabetes management problem into sub-goals: Developing a Tensor flow neural network model for food categorization. This approach will allow users to input a specific food image to prompt whether the selected meal is suggested or encouraged for eating, as well as it will apply the KNN algorithm for recommended meals. Raising diabetes inquiries with the help of cognitive sciences and an answer chatbot, tracing user activity, user location, and recorded blood sugar level measurements [20,21]. Machine learning algorithms have also been used to diagnose other types of chronic diseases. The study uses machine learning algorithms to predict treatment efficacy in diabetic patients. Based on drug use, the study predicted treatment results in patients with mild to severe diabetes. Most commonly it is the integration of useful feedback from historical data. Some of the Machine learning algorithms are given below:

Some of the Machine learning algorithms are given below:

2.2.1 Naive Bayesian (NB)

The naive Bayesian technique takes the dataset as input and, using Bayes' theorem, performs the analysis as well as forecasts the class label. It estimates a probability of class based on the supplied input data and assists in predicting the unknown data sample of the class. It is a considerable classification strategy that is well-suited to massive datasets.

2.2.2 Support Vector Machine (SVM)

The supervised learning method is utilized in the discriminative classification technique. This approach can be used for both regression and classification. The sole rationale behind the SVM, which will be divided into two classes, is determining a hyper line between the datasets. There are two processes to identifying the proper or ideal hyper line in data space and carefully mapping the items to the given bounds.

2.2.3 Random Forest (RF)

The random forest's main reason for being is a bagging approach for developing random sample attributes. Furthermore, the process for locating the root node and splitting the feature node that receives access randomly distinguishes the decision tree algorithm from the random forest algorithm.

2.2.4 K Nearest Neighbour (KNN)

This classification technique was utilized to distinguish the new sample, which was based on a similarity or distance metric.

2.2.5 Decision Tree (DT)

It is a supervised learning technique that has certain advantages for both classification and regression issues, but it is generally preferred for classification problems. This classifier is also tree-structured, with the inner nodes representing database features, the branches representing end rules, and each leaf node representing the end.

3 Results and Discussion

The learning models are executed in Jupyter Notebook. Knowledge here occurs is represented in the mode of condition-action pairs: IF this condition happens, THEN some action will happen. The below Fig. 2 shows the training database is given as input and the testing database is finding calories using rules to detect intake of calories.

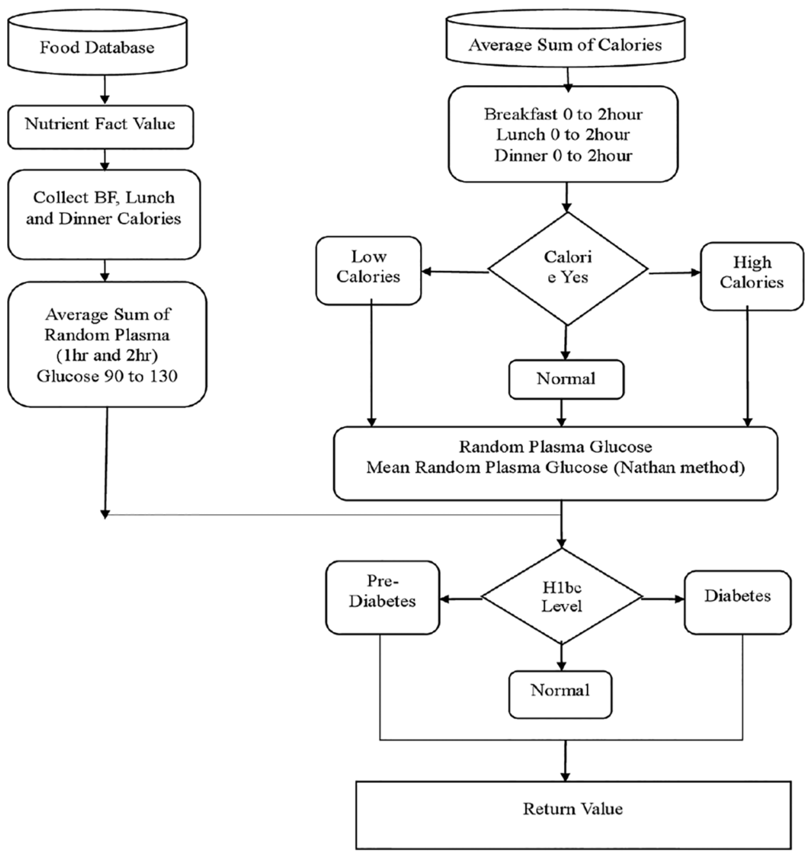


Figure 2: Random plasma glucose flow chart

Fig. 2 shows the flow chart for mean random plasma glucose level from the food database containing several sub-nutritionists which classify the food items within dairy, Beverage, Eggs, Meat, and Poultry, Snacks groups based on nutrients. The measuring level is based on calories of food intake. The user eats a meal 3 or >3 times (breakfast, lunch, dinner, etc.) and the associated nutritional values are recorded or stored in the user profile from day 1 to 90. Man's daily caloric requirement varies from person to person. A baby needs 1,000 calories a day, while an active male between the ages of 16 and 18 needs up to 3,200 calories. For a woman, the daily caloric requirement can range from 200 to 2300 depending on the woman's physical activity.

Calculate the average total calories for those days using a value from the user database and the calorie level determined by the above criteria. Calculate mean random plasma glucose level using zero, one, and two hour rpm, and then use Nathan, ADAG, and DTTC formulas to obtain h1bc level.

3.1 Developing a Theoretical Model for a Human's Blood Glucose Level

To obtain the blood glucose level G(t) blatantly, solve the differential equations $\frac{dc}{dt} = k_1 C$ and obtain an expression for C(t).

$$\int \frac{dc}{dt} = \int -k_1 C$$

$$\int \frac{dc}{C} = \int -k_1 dt$$

$$\log_e C = -k_1 \mathrm{t} + \mathrm{d}$$

$$C(t) = A_0 e^{-k_1 t} \tag{1}$$

Let us consider another differential equation

$$\frac{dG}{dt} = -k_1 \mathrm{C} - k_2 (\mathrm{G} - G_0) \tag{2}$$

where, C represents the attention of carbohydrates, and G represents the awareness of glucose inside the blood. When time is zero, the bottom price of the glucose rate is zero. The initial conditions are C (0). = A_0 and G (0) = G_0. The first-order linear differential equation is:

$$\frac{dy(t)}{dt} + p(t).y(t) = q(t) \tag{3}$$

$$\mathrm{y} = e^{-\int p(t)d(t)} \left[\int q(t) e^{\int p(t)dt} dt + c \right]$$

From Eq. (2)

$$\frac{dG}{dt} + k_2\, G(t) = k_1\, A_0\, e^{-k_1 t} - k_2 G_0 \tag{4}$$

$$G(t) = e^{-\int e^{-K_2 t}} \left[\int (K_1 A_0 e^{-K_0 t} + K_2 G_0) \right] e^{-\int e^{-K_2 t} dt} + C$$

$$G(t) = A_0 \frac{K_1}{(K_2 - K_1)} (e^{-K_1 t} - e^{-K_2 t}) + G_0 \tag{5}$$

The parameters $A_0 = 121.7,\ G_0 = 90, \acute{K}_1 = 0.0453$ and $K_2 = 0.0224$ (6)

Therefore,

$$G(t) = 90 - 240.74\ (e^{-0.0453\ t} - e^{-0.0224\ t}) + G_0 \tag{7}$$

For calculating the random plasma glucose zero-hour, one hour and two hours are

$$(\mathrm{C/B}) + (90 - 240.7438*(\exp(-0.0453*0) - \exp(-0.0224*0)) \tag{8}$$

$$(C/B) + (90 - 240.7438 * (\exp(-0.0453 * 120) - \exp(-0.0224 * 120)) \quad (9)$$

$$(C/B) + (90 - 240.7438 * (\exp(-0.0453 * 180) - \exp(-0.0224 * 180)) \quad (10)$$

where C represents calorie and B represents Age. Tab. 3 shows the human's random blood glucose level based on food calories.

Table 3: Human's random blood glucose level based on food calories

S. no.	Age	Calorie	BF 0 h	BF + 1 h	BF + 2 h	Calorie	LF 0 h	LF + 1 h	BF + 2 h	Calorie	Dinner 0 h	Dinner + 1 h	Dinner + 2 h
1	57	68	101	147	116	169	116	163	132	79	102	149	118
2	25	45	106	153	121	90	122	169	137	68	114	161	129
3	18	39	109	156	125	84	132	179	147	39	109	156	125
4	19	45	111	158	126	90	132	179	147	45	111	158	126
5	27	44	105	152	120	71	113	160	129	35	102	149	117
-	-	-	-	-	-	-	-	-	-	-	-	-	-
-	-	-	-	-	-	-	-	-	-	-	-	-	-
-	-	-	-	-	-	-	-	-	-	-	-	-	-

Next, we find the h1bc level by Nathan, DTTC, and ADAG formulas.

$$\textit{Nathan Formula} = \frac{(\textit{Mean Random Plasma Glucose} + 86)}{33.3} \quad (11)$$

$$\textit{Diabetes Control and Complications Triai (DTTC)} = \frac{(\textit{Mean Random Plasma Glucose} + 77.3)}{35.6} \quad (12)$$

$$\textit{A1c Derived Average Glucose (ADAG)Formula} = \frac{(\textit{Mean Random Plasma Glucose} + 46.7)}{28.7} \quad (13)$$

If the h1bc level is less than 5.7 then the health condition is "Normal", If the h1bc level is between 5.7 and 6.4 then the health condition is moved to "Pre-diabetes" and If the h1bc level is greater than 6.4 then the health condition moves to diabetes level. Tab. 4 shows the comparison of age and diabetes.

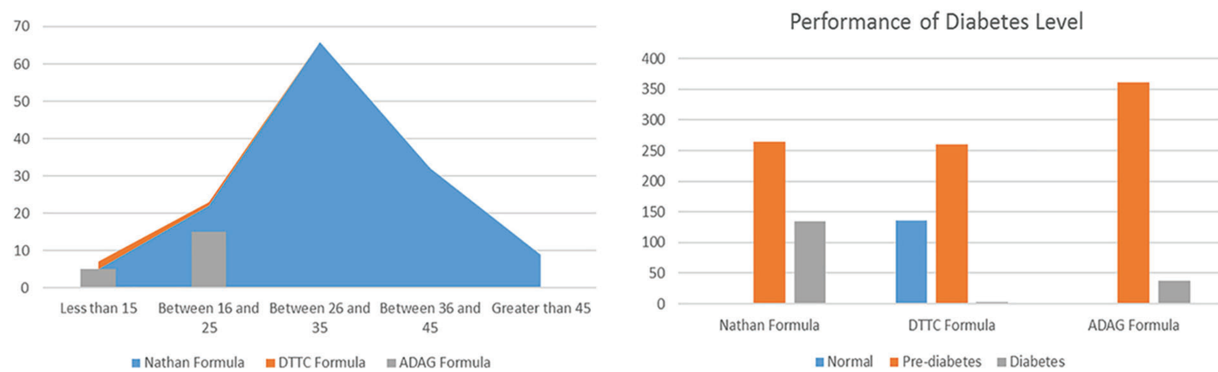
Table 4: Comparison of age and diabetes

Age	Nathan formula	DTTC formula	ADAG formula
Less than 15	5	2	5
Between 16 and 25	22	1	15
Between 26 and 35	66	0	0
Between 36 and 45	32	0	0
Greater than 45	9	0	0

3.2 Comparison of the Proposed Methodologies Based on Age and Diabetic Level

Nathan's formula performs effectively in predicting several diabetes cases, as shown in Figs. 3a and 3b. As a result, the Nathan formula outperforms the ADAG and DTTC formulae. The widely used metrics of stratification measures including accuracy, sensitivity, and uniqueness, as well as the recall diabetes dataset, are utilized to analyze the execution of a classifier based on machine learning. The classification models were analyzed and compared to obtain the optimal model for prediction of the diabetes diseases. Here, Accuracy is the ratio of precisely classified events to the total events, mathematically:

$$Accuracy = \frac{(TP + TN)}{(TP + TN + FP + FN)} \tag{14}$$



(a) (b)

Figure 3: (a) Comparison of age and diabetes, b) Performance of diabetes level

Sensitivity (or) Recall is also called TN rate. It indicates that the precisely classified negative cases can be determined by:

$$Specificity = \frac{TP}{(TP + FN)} \tag{15}$$

Specificity is also called TP rate that indicates the precisely identified positive cases, it can be determined by:

$$Specificity = \frac{TN}{(TN + FP)} \tag{16}$$

Precision is the proportion of accurately predicted positive cases and it can be determined by:

$$Precision = \frac{TP}{(TP + FP)} \tag{17}$$

The error rate is also called misclassification rate that projects the incorrect classified cases, and it can be determined by:

$$Error\ Rate = \frac{(FP + RN)}{(TP + TN + FP + FN)} \tag{18}$$

$$F_1 - Score = \frac{(2 \times Recall \times Precision)}{(Recall \times Precision)} \tag{19}$$

This model will be estimated by using a confusing matrix, which presents the number of correct and incorrect predictions.

4 Experimental Result

The experiments are implemented instantaneously in Jupyter Notebook and it is proven that this magnificent environment strikes out the barriers of elevating the environment for implementing machine algorithms that are written in Python. It applies tensor flow back end. The results in Tab. 5 show that the machine learning algorithms do a good job of classifying the dataset. The Nathan formula only predicts an increase in diabetes cases. As a result, the Nathan formula outperforms the ADAG and DTTC formulas (s). Random Forest (92%) and Decision Tree (91%) ensembles are found to perform exceptionally well, greatly boosting accuracy without and with cross-validation (CV).

Table 5: Performance analysis of machine learning algorithms

Classification	Accuracy without CV (%)	Accuracy with CV (%)
Random forest	92	90
Naive bayes	88	80
Decision tree	86	91
K-nearest neighbor	83	85
SVM	80	76

5 Conclusion

Diabetes is a lifestyle disease that influences millions of human beings worldwide each year. But their inability to access their diet accurately raised the development of this system. Prediction of diabetes level is implemented using classification-based association rule mining algorithms. The application of machine learning thus enhances vigorously in all domains. As a result, it is discovered that the healthcare sector is not an exception. Random Forest (92%) and Decision Tree (91%) ensembles are found to perform extremely well and improve the accuracy without and with cross-validation significantly.

This work can be expanded to engage actual time medical information gathered from various cancer centers and transformed into desktop applications, thus the doctors can make use of this as an aiding tool in their diagnosis.

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