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Machine Learning based Model for the Prediction of Fasting Blood Sugar Level towards Cardiovascular Disease Control for the Enhancement of Public Health

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ABSTRACT
Fasting Blood Sugar (FBS) levels reveal important information regarding a person's blood sugar management. There is a strong relationship between a person’s FBS level and cardiovascular disease (CVD) because uncontrolled long-term high FBS level can lead to CVD. Devising a means of predicting Fasting blood Sugar level of a patient will go a long way in proper management of diabetes and in turn help in cardiovascular disease control. Predicting the level of FBS for purposes of controlling CVD is the aim of this research. An all-inclusive review was first carried out on Fasting Blood Sugar, Blood Glucose Test, Diabetes, Cardiovascular disease and Machine Learning. Secondly, General Logistic Model (GLM) was adopted for the prediction of Fasting Blood Sugar levels based on the metrics used. Performance analysis results show effective prediction using the Confusion Matrix and AUC-ROC which gave 70% accuracy on the dataset used. Thirdly, the logistic regression model was deployed to Application Programming Interface (API) where each medical practitioner can adopt and used for predicting patient’s blood sugar level based on the metrics provided.

General Terms
Machine Learning

Keywords
Bio-inspired computing, Computer aided diagnosis, blood sugar, Cardiovascular disease, Machine Learning, Logistic Regression, public health.

1. INTRODUCTION
The body requires glucose for energy, and glucose is obtained from the food that is eaten. The body does not entirely use this glucose at the same time. Insulin allows glucose to be stored and released when it is needed. Fasting Blood Sugar (FBS) readings (levels) reveal important information regarding a person's blood sugar. An all-night fast is followed by a test to determine how often glucose (sugar) is found in a particular blood sample. When glucose levels are normal, it provides a valuable source of energy to all the cells in the body. Deviations from the usual range of blood glucose can result in severe short- and long-term health problems [1]. When the level is high, it acts as a slow poison which can harm blood vessels and neurons that control the heart in the long run. Serious health problems such as cardiovascular diseases, neuropathy, nephropathy, organ failures, and eye diseases, amongst many others, may develop if the blood sugar level is left untreated for a lengthy period of time. [2]. Early detection of certain diseases' signs, such as elevated blood sugar, can help avoid, manage, and even avert death.

Patients with diabetes also have a higher likelihood to experience unfavorable health effects including high blood pressure, where the blood flows through the arteries more forcefully and may injure the arterial walls. While high blood glucose levels that surpass the renal glucose re-absorption threshold led to glucose waste, low blood glucose levels can impair brain function. In addition, persistently high fasting blood sugar levels can have degenerative effects, such as harm to the heart, blood vessels, kidneys, nerves, eyes, and kidneys. [3, 4].Despite improvements in diabetes care, it is still one of the leading causes of death, new blindness, kidney failure, and a significant risk factor for heart disease, stroke, and congenital abnormalities [5]. Cardiovascular disease is so much more likely to impact diabetics. Any irregular heart condition is considered a CVD. This might be brought on by plague-lined heart blood vessels, which constrict the arteries and veins that deliver blood to and out of the heart. This condition prevents blood from flowing normally and could potentially end in clotting, which is likely to trigger a catastrophic stroke or heart attack. Blood pressure, poor nutrition, physical inactivity, high blood cholesterol, alcohol and cigarette use, obesity, and genetic mutations are risk factors for CVD. [6].

Diabetes and cardiovascular disease (CVD) have a close connection. CVD is the main cause of death among diabetics [7]. According to WHO, CVD ranks as the leading cause of mortality globally. Nearly 17.9 million deaths annually are attributed to CVD, which is thought to account for 31% of all fatalities worldwide [8]. In the United States, the mortality rate from cardiovascular disease is 1.7 times higher in people with diabetes mellitus (DM) than in people without it because of the increased likelihood of stroke and myocardial infarction (MI)[9]. Therefore, controlling fasting blood sugar for patients requires the involvement of medical experts, particularly doctors. Based on measurements taken from the patient, doctors consistently evaluate variations in blood glucose levels and adjust the dosage of medications being supplied as necessary. However, this approach is inefficient in part, because the number of diabetic medical experts is limited in comparison to the number of diabetic patients. Moreso, data collection mechanisms are being upgraded by technological advancements such as Internet of Things. These technologies can collect data from healthcare organizations on daily basis. Therefore, it is very hard for humans to compile millions of these data and draw conclusions about the disease of a specific patient. To detect the patterns in the data, machine learning techniques could be utilized as a prediction mechanism.

The factors linked to a specific sickness are investigated and used to forecast the likelihood of individuals developing such illnesses using machine learning techniques. Methodologies for machine learning can analyze vast amounts of data and spot trends that might not be obvious to humans [28]. It often improves the accuracy and efficiency of the processing of increasing amounts of data. Additionally, it permits immediate adaptability without human intervention [6]. This research goal is to employ a Machine Learning (ML) model, Regression, to predict patient's Fasting Blood sugar level towards cardiovascular disease control. Section 2 of this work reviews related work; section 3 outlines the research methodology. Description of key components of the proposed system and the model design are reported in sections 4 and 5 respectively. Section 6 explains the data and analyses the results of the work. The work is concluded in section 7.

2. LITERATURE REVIEW

There are several ML approaches to predict cardiovascular disease. [10] employed ML approaches to predict the rate of hospitalization and death due to heart failure using 5 methods: Logistic Regression, Support Vector Machine, Gradient Descent, Random Forest.[11] used ML to know the level of CVD in patients undergoing dialysis. [12] developed a process to get missing values in clinical datasets in order to correctly predict CVD using Naïve Bayes, Support Vector Machine, Decision Tree, Logistic Regression and Random Forest algorithms. [13] used techniques from Random Forest, Logistic Regression, Neural Networks, and Gradient Boosting to apply ML practices to anticipate CVD in routine clinical data.

ML techniques have also been adopted to predict blood sugar level in patients. Plis et al. [1] adopted ML approaches for general diabetic management. Eiger, Nagy and Kovacs [14] introduced the development of Real-time patient data is used in a machine learning (ML) approach to predict imminent blood sugar levels with an emphasis on supporting conservative therapy. Ramalinggam, Pandium, Manikandam and Roobanvaikundaraja [2] examined six classifiers (K-Nearest Neighbor, Naive Bayes, Decision Tree, Support Vector Machine, Classification and Regression Tree, and C5) to see which one predicted blood sugar the most accurately and consistently across distinct clinical datasets. Huang, Zhou and Sun [15] built a mobile application to collect patients' diet pattern and predict blood sugar level. Once sufficient data is collected, the system trains the ML model using linear, polynomial and Gaussian process regressions and predicts the patient's blood sugar level based on diet.

In this work blood sugar level is predicted using logistic regression and applied for the control of CVD to enhance public health. This is yet to be done in those literature.

2.1 Overview of Fasting Blood Sugar (FBS)

The measurement of sugar levels on an empty stomach is known as fasting blood glucose, and it is a extensively used concept. This phrase, which is directly connected to the level of the body's insulin, is a result of a blood test. Fasting is the abstinence from food or any other fluid apart from water for an eight-hour period. The period of fasting is a good period to check glucose levels. Monitoring one's blood glucose levels is crucial. Observations from blood glucose measurement can help someone make crucial decisions about their diet, exercise, and medications. As per [6,] the typical range for fasting blood glucose levels is between 70 mg/dL (3.9 mmol/L) and 100 mg/dL (5.6 mmol/L). Glycemia supervision and lifestyle changes are advised when the levels are between 100 and 125 mg/dL (5.6 and 6.9 mmol/L). When two independent tests reveal fasting blood glucose levels of 126 mg/dL (7 mmol/L) or higher, diabetes is suspected. Dizziness, sweating, palpitations, blurred vision, and other signs of hypoglycemia, or low fasting blood sugar level, have all been reported. High fasting blood sugar levels, or hyperglycemia, indicate a higher chance of developing diabetes. A person's fasting blood plasma glucose (FBG) may be within the standard parameters if they do not have diabetes or if they receive the proper treatment with glucose-lowering medications if they do. Mean FBS is utilized as a stand-in for both national diabetes treatment and promotion of good eating and lifestyle choices. Checking blood sugar levels enables medical professionals to determine if the overall glucose objectives are met, protect individuals from long-term problems of diabetes and preventing the unpleasant side effects of high and low blood sugar.

2.2 Blood Glucose Test

Using a blood test, you can figure out how much glucose is in your blood. Foods with high in carbohydrates supply glucose. It serves as the body's natural energy source. A hormone called insulin helps the body's cells utilize glucose. Insulin is produced in the pancreas and released into the circulatory system as blood glucose levels rise. Usually, blood glucose levels increase a little bit after eating. In response to this surge, the pancreas releases insulin to prevent excessive blood sugar increases. The eyes, kidneys, nerves, and blood arteries can all suffer damage from persistently high blood glucose levels. There are several ways to measure blood glucose, including;

i. **Fasting blood sugar (FBS)**: is a test that evaluates blood sugar levels after at least 8 hours have elapsed before eating. It often serves as the initial evaluation for diabetes and pre-diabetes.

ii. **RBS (random blood sugar):**is a test that measures blood sugar levels without taking your most recent meal into account. It's possible to take numerous arbitrary readings during the day. Random testing is successful because glucose levels in healthy patients do not dramatically change through the day. Frequent fluctuations in blood glucose levels could be a sign of trouble. Some other name for this test is a routine blood glucose test.

iii. Two hours after you start eating, your blood sugar is checked using a 2-hour postprandial blood sugar test. This test will most likely be performed at home if you suffer from diabetes. It can verify that you'll be taking the appropriate dosage of insulin along with your meals.

iv. The hemoglobin A1c test and the oral glucose tolerance test are other ways to monitor blood sugar levels (OGTT). You can compute your normal blood sugar level over the last two to three months with the A1c test. Pregnant women who have diabetes can be diagnosed with the OGTT (gestational diabetes).

The American Diabetes Association asserts that it is normal for blood sugar levels to increase after eating. When blood glucose is anticipated to peak after eating, 1-2 hours after the start of the meal, the objective is to keep it under 180mg/dL [15]. Depending on a patient's demands or risk of hypoglycemia, these objectives may need to be modified. When blood sugar levels drop below 70 mg/dL, low blood sugar, also referred to as hypoglycemia, occurs. When blood sugar levels exceed 180 mg/dL, hyperglycemia, often known as high blood sugar, occurs [16]. Therefore, checking your blood sugar levels could assist you in determining whether you're meeting your glucose objectives and prevent long-term diabetic complications as well as the uncomfortable signs of high and low blood sugar.

2.3 Diabetes

Diabetes is a disorder in which the body has trouble using sugar (glucose) as an energy source inside its cells. As a result, extra sugar accumulates in the body system. Uncontrolled diabetes can have disastrous consequences, including harm to a number of body organs and tissues, such as the heart, kidneys, eyes, and nerves. The body won't be able to handle and use glucose from food properly if a person has diabetes. There are numerous types of diabetes, each with a unique set of symptoms, but they are all characterized by an excessive amount of glucose in the blood. The illness is managed with the help of medications like insulin. Some kinds of diabetes may be prevented by leading a healthy lifestyle. The many forms of diabetes are described below;

i. **Type 1 diabetes:** Since this condition is immunological, the body is battling itself. Your pancreas suffers from damage to the cells that make insulin in this circumstance. Up to 10% of diabetic patients have type 1 diabetes. Despite the fact that it primarily impacts children and young people, it can manifest at any age. Diabetes also goes by the name "juvenile." Insulin must be taken daily by those with Type 1 diabetes. Due to this, it is also referred to as insulin-dependent diabetes.

ii. **Type 2 diabetes**: This form of diabetes develops whenever your tissues do not react to insulin effectively or when your body does not create enough insulin. The disease's most prevalent type is diabetes mellitus. Up to 95% of diabetics have type 2 diabetes. People in thier forties and later are most affected. Other names for type 2 diabetes include insulin-resistant diabetes and adult-onset diabetes. Your parents or grandparents likely referred to it as "having a touch of sugar." In this study, type 2 diabetes is used to predict the Fasting Blood Sugar level for cardiovascular disease.

iii. **Pre-diabete**s: This form of diabetes is the precursor to Type 2 diabetes. Although your blood glucose levels are higher than usual, Type 2 diabetes has not yet been identified in you.

iv. **Gestational diabetes**: is a kind of diabetes that might appear in some pregnant women. However, if you have gestational diabetes, you are much more likely to eventually acquire Type 2 diabetes.

In addition, the following are some of common kinds of diabetes:

i. Monogenic diabetes abnormalities, which make up 4% of all cases of the disease, are rare genetic causes of diabetes. Examples of this kind of diabetes include neonatal and young-onset diabetes.

ii. Diabetes that is caused by cystic fibrosis only harms those who suffer from the disorder.

iii. Diabetes caused by drugs or chemicals: This kind of diabetes can develop as a consequence of glucocorticoid steroid use, organ transplantation, HIV/AIDS treatment, or other conditions.

2.4 Cardiovascular Disease (CVD)

Cardiovascular diseases (CVDs) are a range of heart and blood vessel problems [17].The most significant behavioral risk factors for cardiovascular disease and stroke are poor diet, inactivity, smoking, and excessive alcohol use. Complications such as obesity, high blood lipids, high blood pressure, and excessive blood sugar are possible [17]. These "intermediary risk factors" can be identified in primary care environments and indicate an increased risk of heart disease, stroke, and other undesired events. There is a close connection between Diabetes Mellitus (DM) and cardiovascular disease (CVD) [15], devising a means of predicting Fasting blood Sugar level of a patient will go a long way in proper management of diabetes and in turn help in cardiovascular disease control. Furthermore, adults with diabetes have incidences of heart disease and stroke leading to death that are two to four times greater than those without diabetes [18]. The risk of coronary heart disease (CHD) is almost the same for type 2 diabetics (T2D) who haven't previously experienced a myocardial infarction as it is for non-diabetics who have [19]. However, it is still debatable if the cardiovascular risk that diabetes brings is comparable to the risk that a prior myocardial infarction poses. [20]. Patients with diabetes are likely to have other co-morbidities such as obesity, dyslipidemia and hypertension all of which contribute to an increased risk of CVD [21].The fundamental mechanisms that induce accelerated coronary heart disease and, as a result, an increased prevalence of cardiovascular disease in diabetic patients are unknown. The goal of this research article is to model and deploy a machine Learning System for prediction of Fasting blood sugar level towards Cardiovascular disease control.

2.5 Machine Learning in Healthcare

In today's age of Information technology, medical records are regularly digitalized, and a variety of sensors have been developed to capture vital signals. As a result, artificial intelligence (AI) is gaining popularity as a data-driven computational technique for clinical decision-making in data analytics [23]. In a variety of medical applications, AI techniques like machine learning (ML), data mining, and deep learning (DL) have shown potential. Only a few instances include data exploration of novel genotypes in cardiovascular illness [26], pattern recognition on an electrocardiogram (ECG) for atrial fibrillation identification [24], and breast cancer screening utilizing image processing [24]. Digital technologies such as artificial intelligence (AI), cloud computing, mobile computing, and mobile computing are accelerating the aspect based of the health sector. Currently, artificial intelligence (AI) is a hot topic in research and a potential technical progress [27].

3. RESEARCH METHODOLOGY

In this research, Logistic Regression model is adopted for predicting Fasting Blood Sugar level based on identified metrics aided by the trained data. Linear classification is a method for classifying data using a linear predictor function that combines weights and dependent variable values. This procedure could include non-linear operations. This means that given a set of data (X, Y), where X is a matrix of values with m samples and n features and Y is a vector with m examples, the goal is to train the model to correctly anticipate which class future values will belong to. A weight matrix with a random start is primarily generated. Then, as stated in equation (1), it is multiplied by the characteristics.

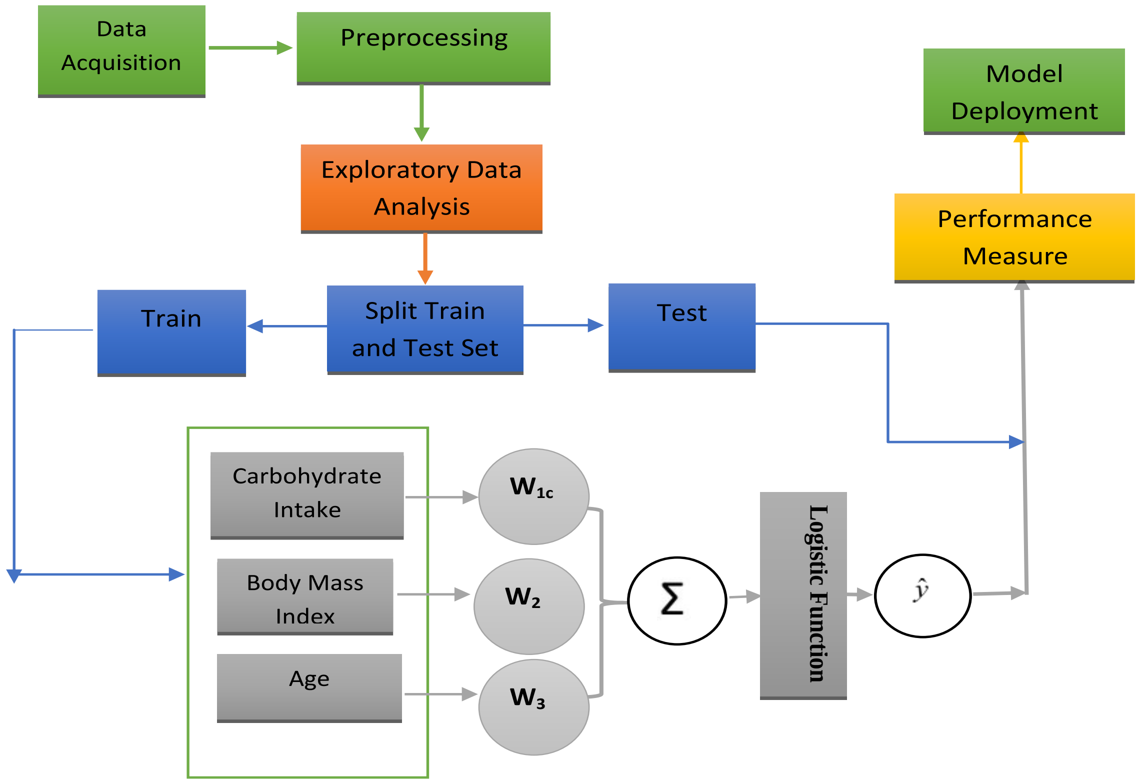

Fig 1: Architecture of the proposed system

$$a = w_0 + w_1x_1 + w_2x_2 + w_3x_3 + \cdots \ w_nx_n \qquad (1)$$

The output of equation 1 is then passed to a link function. shown in equation 2.

$$yi^{\wedge} = {}^{1}/_{(1+e^{-a})} \qquad (2)$$

This is followed by calculating the cost for that iteration whose formula is

$$cost(\omega) = (-\frac{1}{m})\sum_{i=1}^{i=m} y_i \log(y_i^{\wedge}) + (1 - y_i)\log(1 - y_i^{\wedge}) \qquad (3)$$

Then the derivate of this cost function now the gradient in equation 4.

$$dw_j = \sum_{i=1}^{i=n} (y^i - y)x_j^i \qquad (4)$$

and the update now becomes

$$w_i = w_j - (a * dw_j) \qquad (5)$$

Description of Key phases in the proposed System

1. **Data Preprocessing:** The process of converting unprocessed data into an understandable format is known as data preparation. Before using machine learning techniques, the data must be is of high quality.
2. **Logistic Regression:** is a Machine Learning method for resolving classification issues. It is a predictive analytical method that is founded on the idea of probability.
3. **Prediction**: Prediction is the outcome of an algorithm after it has been trained on a prior dataset and applied to new data when predicting the probability of a certain result.
4. **Exploratory data analysis**: is a straightforward categorization approach typically carried out by visual means. It is a method for decomposing large data sets into their key features. In order to confirm whether or not the data makes sense. Every machine learning issue is solved via EDA. It is most likely among the crucial elements of a machine learning project. Figure 1 shows the components mentioned above.
5. **Model Deployment**: Machine learning deployment is indeed the method of setting up a machine learning model in a real-world setting. The model is often integrated with apps utilizing an API and can be utilized in a variety of contexts. One of the most important steps in an organization's machine learning strategy is deployment.

3.1 Model Design

The Following steps were taken to design the Logistic Regression model of the proposed System.

i. Pre-process the data set.

ii. Examine the dataset for outliers and irregularities.

iii. Segment data set into training and test set in the ratio of 70: 30%

iv. Use a logistic function in the trained set

v. apply the test set on the trained model

vi. use a confusion matrix to evaluate the performance of the model.

vii. deploy the model to an interactive web application.

Furthermore, the dataset obtained from the University of Uyo Teaching Hospital is as contained in table 1.

Table 1: Dataset

Weekly Carbohydrate intake	Body Mass Index	Age	FBS Level (1-High, 0-Low)
4	33.21	43	1
1	28.58	21	0
2	24.97	25	1
2	17.36	42	0
3	24	57	0
1	27.55	29	0
2	40.46	23	1
3	29.82	59	0
1	24.17	48	1
2	29.96	63	0
1	23.59	29	1
3	20.94	37	0
1	24.34	57	0
3	43.72	60	1
2	23.59	58	1
1	26.45	71	1
2	20.2	22	0
4	27.47	32	0
3	31.43	57	0
1	29.59	18	0
4	21.56	45	0
1	55.74	78	0
3	51.02	65	1
1	19.51	54	0
2	76.98	28	0
1	71.66	79	1
3	27.89	45	0
1	64.63	56	1
2	23.53	67	0
1	29	53	0
3	32.01	60	1
1	27.11	56	0
2	21.97	43	0
1	23.42	32	0
3	29.96	70	0
1	31.16	34	0
4	37.31	81	1
1	34.35	32	1
1	27.06	45	0
2	23.36	42	1
1	27.59	23	0
2	23.94	45	0
2	24.38	50	0

4. EXPLORATORY DATA ANALYSIS AND RESULT

Exploratory data analysis is a classification technique that is usually accomplished using visual means. It is a method of examining data sets in order to highlight their most important properties. In order to determine whether or not the data good to be used. EDA is used to solve every machine learning problem. It is, without a doubt, one of the most crucial aspects of a machine learning research. As the market expands, so does the amount of data available. It becomes more difficult for businesses to make decisions without first conducting thorough research. With the use of charts and graphs, one can make sense of the data and determine whether or not there is a relationship. As a result, any conclusions are reached using these numerous graphs. This study used a Logistic Regression model to predict Fasting Blood Sugar level of a patient for risk of being High or Low as it relates to risk of being prone to cardiovascular disease. Figure 2, figure 3 and figure 4are graph that shows inputs which are Body mass index, Age, and Carbohydrate intake respectively contained in the dataset

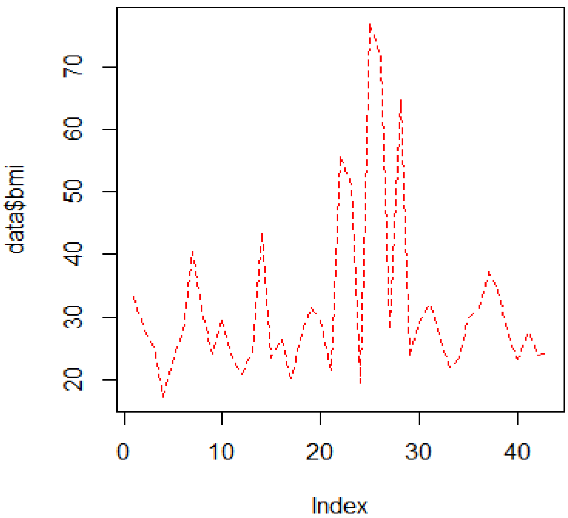

Fig 2: Body mass index

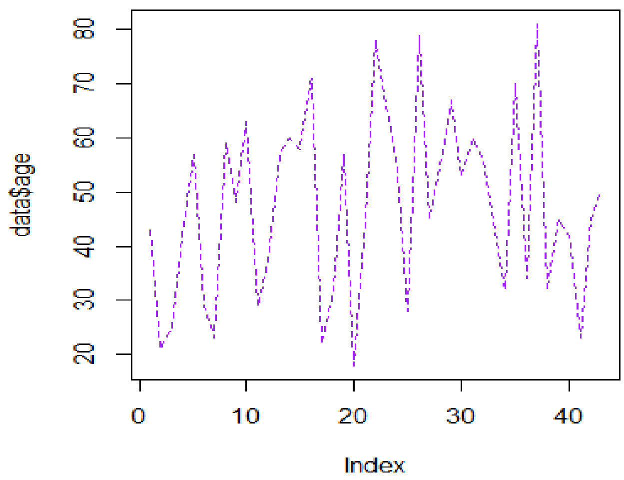

Fig 3: Age

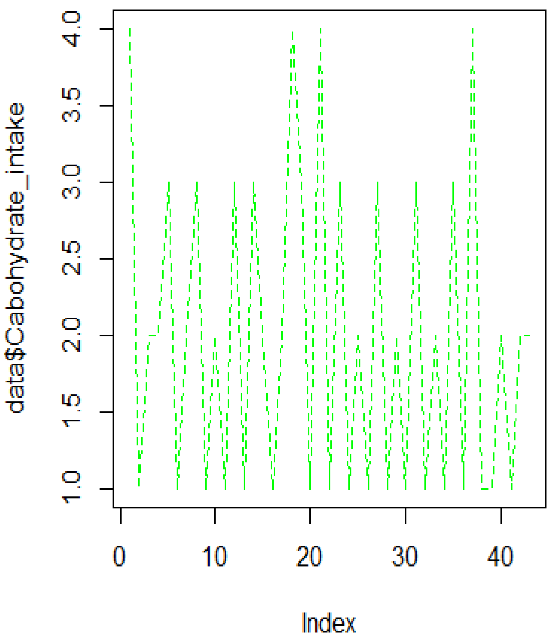

Fig 4: Carbohydrate Intake

The general logistic model was trained using the dataset, the result shows how the data fits in to logistic regression model depicted in figure 5 which shows how the logistic model fits into the data set.

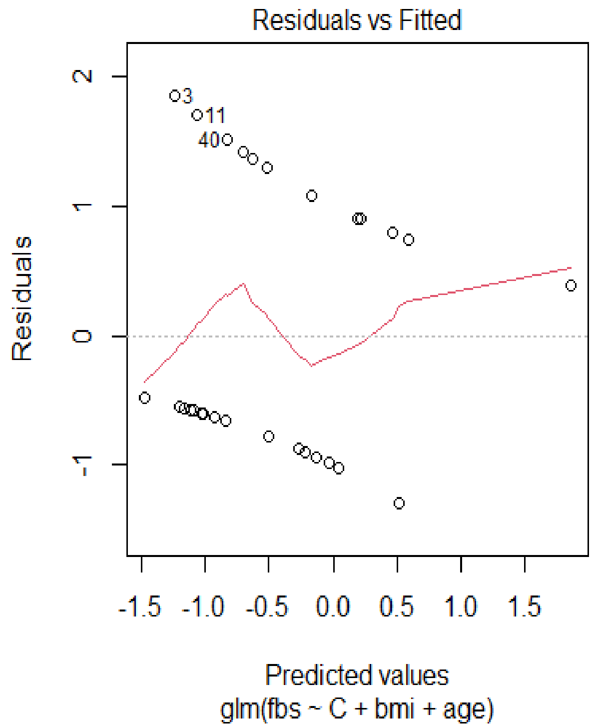

Fig 5: Logistic model

Additionally, the confusion matrix is shown in table 2;

Table 2: predicted value vs actual value

	Actual value	
Predicted Value	0	1
0	16	2
1	7	5

The confusion matrix shows that, of the 30 observations in the training set, 16 correctly identified patients with low blood glucose levels, 7 incorrectly identified patients with high glucose levels, 5 correctly identified patients with high glucose levels, and 2 incorrectly identified patients with high glucose levels. By summing the confusion matrix's diagonals and dividing it by the total number of observations, or (sum (diagonals (confusion matrix) / sum (confusion matrix)), the accuracy is calculated and yielded a result of 0.7~70% accuracy. As a graphical representation of a binary classifier system's diagnostic accuracy as its bias threshold is changed, the receiver operating characteristic (ROC) curve, also known as a ROC curve or graph, is another crucial method or metric for performance evaluation or analysis of a model. Figure 6's ROC graph and area under the curve (AUC) highlight the effectiveness of the approach.

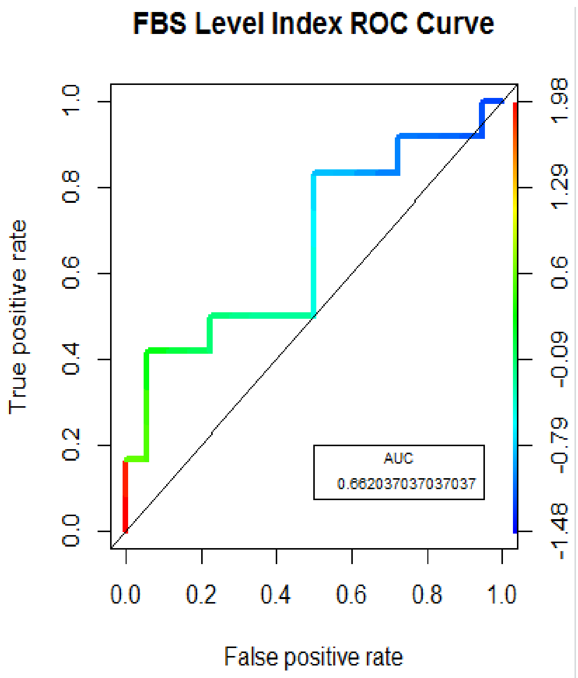

Fig 6: ROC graph

Furthermore, a user interface that relies on this developed model is developed. This is for ease of use by medical practitioners for the prediction of each individual sugar level with the aim of controlling Diabetics and in general reduce Cardiovascular Disease as shown in Figure 7.

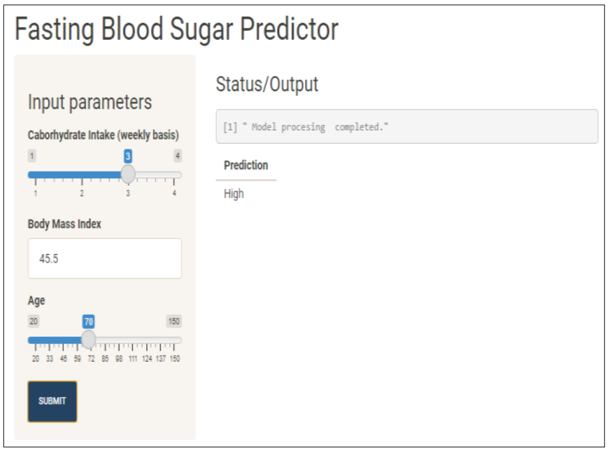

Fig 7: User interface for predicting Fasting Blood Sugar Level

5. CONCLUSION

Keeping track of blood sugar level can assist individuals and medical practitioners in developing a management strategy for this illness. High blood sugar can pose serious threats to public health and such include but not limited to; diabetes, heart disease (i.e cardiovascular disease), stroke, renal disease, blindness. These consequences can be delayed or prevented adequate health base on prior knowledge of the causative factors and adequate lifestyle adjustments. With this information, health-care practitioners can decide on the optimal diabetes treatment plan for each individual and in turn reduce the chance of an individual risk of cardiovascular disease. Thus, using the metrics found in the dataset as a foundation, this research implemented a machine learning framework to predict the fasting blood sugar level. Additionally, performance analysis was performed on the model to assess its accuracy using confusion matrix and Area Under Curve (AUC) ROC graph, two crucial metrics in performance analysis of machine learning models. The results have proven effective and efficient, with both methods providing an accuracy of 70% on the dataset used.

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