Journal of Statistics, Computing and Interdisciplinary Research
ISSN (P): 2707-7101
J. Stat. Comp. & Interdis. Rese.
Volume 7(2) (2025), 269-284
http://scir.wum.edu.pk/index.php/ojs

Predictive Analysis of Diabetes using Logistic Regression (A Case Study from Sahiwal)

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Abstract

Diabetes mellitus is a long lasting metabolic disorder that is characterized by increased blood glucose levels, leading to serious complications if not diagnosed and managed at earliest. The prevalence of diabetes is increasing in Pakistan that highlights the need for effective prediction models to identify the individuals which are at high risk. The objective of this study is to predict the likelihood of diabetes among patients and highlight its significant factors. For this purpose, secondary data set of 809 patients collected by the DHQ Teaching Hospital, Sahiwal in 2024 were used. Descriptive statistics, graphical representation and binary logistic regression were applied to determine significant predictors. The analysis revealed that age, gender, hemoglobin A1c, dipsia and nephropathy were the statistically significant factors associated with diabetes. The findings demonstrate that logistic regression is an effective tool for predicting diabetes outcomes and identifying key risk factors. This study will help to highlight the importance of data-driven approaches in improving early diagnosis and supporting medical decision making in healthcare.

Keywords: *Diabetes Mellitus, Binary Logistic Regression, Predictive Modeling, Risk Factors, Statistical Analysis, Healthcare Prediction, Data Analysis.*

1. Introduction

Diabetes is one of the increasing and fastest rising public health issues which can cause a number of serious health complications. It is a carbohydrates metabolism disorder in which glucose level is chronically high due to insulin's impaired action or secretion. The prevalence of diabetes is increasing worldwide due to factors like physical activities, urbanization, aging factor, overweight, sedentary lifestyle and poor eating habits. It has two types of Type-1and Type-2. Type-1 diabetes can occur in childhood; usually mediated by immune mechanisms and it commonly occur in adults and younger person like aged 14-30. Type-2 diabetes can occurs later in life, especially with advancing age due to disease of the pancreases, it commonly occurs in older aged group. As the prevalence of diabetes and its associated mortality increasing, it highly impacts the emotional and economic burden on the diabetes patient. It is estimated that 49.7% of the people living with Type-2 diabetes and are undiagnosed. The average life expectancy of the patients with Type-2 diabetes is decreased by around 10 years.

Acute complications of diabetes that can become life-threatening include the Hyperosmolar Hyperglycemic State (HHS), a condition primarily seen in individuals with Type-2 diabetes. HHS occurs when blood sugar levels remain extremely high, typically above 600 milligrams per deciliter (mg/dL) for an extended period which can leads to severe dehydration, confusion, and in some cases, and loss of consciousness. This condition requires urgent medical intervention. Similarly, Hypoglycemia (low blood sugar) can also be dangerous if not treated promptly. It commonly affects people with diabetes who use insulin and is characterized by symptoms; such as blurred or confusion, seizures, double vision and clumsiness. Severe episodes demand immediate treatment with glucagon or emergency medical care.

In contrast, persistently elevated blood glucose levels can gradually inflict significant harm on the body's tissues and organs by damaging the blood vessels and nerves that support essential bodily functions. Over time, this deterioration can result in chronic complications such as cardiovascular diseases includes heart attack, coronary artery disease, stroke and atherosclerosis as well as nerve damage (neuropathy), kidney failure (nephropathy), vision impairment or blindness (retinopathy), foot ulcers, skin infections, amputations, and hearing loss. These acute and long-term complications emphasize the critical importance of maintaining optimal blood sugar control to protect overall health and minimize the risk of both immediate and progressive diabetes-related outcomes.

Approximately 37.3 million individuals representing nearly 11% of the total population were currently affected by diabetes in the United States. According to the International Diabetes Federation (IDF), 537 million people estimated across worldwide were living with diabetes in 2021. This figure is projected and found to increase 643 million in 2030 and 783 million in 2045. Globally, diabetes accounted for approximately 1.6 million deaths in 2015 and around 6.7 million adults aged between 20 to 79 years were probable to have died as a result of diabetes-related complications in 2021. Diabetes considerably elevates the risk of multiple health complications, including cardiovascular and vascular diseases, kidney and eye disorders, and nerve damage (neuropathy). The escalating prevalence and complications of diabetes has emerged as a critical public health concern in Pakistan, adversely affecting the health, productivity, and quality of life of the individuals and families. Therefore, the identification of significant risk factors and the early diagnosis of diabetes are imperative for effective prevention, time management, and reduction of its long-term adverse outcomes.

2. Literature Review

Heydari, I., et al., (2010) investigated the chronic problems of diabetes mellitus in newly diagnosed patients. 200 consecutive diagnosed patients were evaluated in this study. Their screening tests for neuropathy, retinopathy, hypertension, nephropathy and hyperlipidemia were undertaken. The percentage of frequency for the positive screening tests was found to be 73.5% (hyperlipidemia), 58.5% (hypertension), 52% (neuropathy), 10% (nephropathy), and 6% (retinopathy).

Goyal, R., & Jialal, I. (2018) described the type 2 diabetes mellitus. It is a chronic metabolic disorder characterized by persistent hyperglycemia, leading to the development of disabling and life-threatening health complications and a microvascular complication increased the risk of cardiovascular diseases. Diabetes mellitus was considered to be a global public burden as this number is expected to rise to 200million by 2040. This study highlighted the risk factors, life complication and management strategies of diabetes mellitus.

Mohajan, D., & Mohajan, H. K. (2023) defined diabetes mellitus as a chronic, non-contagious metabolic disorder arising from absolute and relative insulin deficiency, which can lead to elevated blood glucose levels and impaired carbohydrate metabolism. The condition shortens life expectancy, makes small blood vessels less healthy, and makes life less enjoyable. If not treated, it can hurt the heart, blood vessels, eyes, kidneys, and nerves. There are different ways to avoid problems, and treatment plans that could help patients' mental and physical health.

Tomic, D. et al., (2025) described type 1 diabetes mellitus (T1DM). The study summarized the evidence regarding the epidemiology (prevalence, incidence, and excess mortality) of type 1 diabetes mellitus in older adults (ages ≥ 60), as well as reviewed the genetics, immunology, and diagnostic challenges associated with type 1 diabetes mellitus in this population. Several studies indicate an incidence peak of type 1 diabetes mellitus in older adults, sometimes exceeding that in children, and the population prevalence generally increases with age.

Recent studies have used different models to understand the risk factors of diabetes, but many of them included only a limited number of variables. In this study, logistic regression is used with 13 predictor variables related to some demographic, clinical, and biochemical characteristics to better understand the causes of diabetes. The target variable, called "Outcome," is coded as 0 for non-diabetic and 1 for diabetic, which helps in clearly identifying each case. The significance of this study is that we used many predictors that have not been commonly used before. By adding these variables, the study aims to highlight important factors linked to diabetes and improve the accuracy of prediction. The results of this research can help in early detection, prevention, and better management of diabetes in the population.

3. Material and Method

3.1. Data Collection Method

The secondary data set is used for this study, which was originally created by Dr. Muhammad Shoaib and one of his research students Aysha Qamar in 2024. The dataset was collected from 809 patients that were present in the District Headquarter Teaching Hospital (DHQTH), Sahiwal, Pakistan and the study was supervised by Dr. Sarfaraz Ahamd Khan, Senior Registrar and Specialists. We use and download this data that is available on the kaggle website which is a public data-sharing platform for academic and research purpose. The following variables like Diabetes Outcome, Age, Gender, Region, Weight, BMI (Body Mass Index), Diabetes Insipidus, Family History of Diabetes, Hemoglobin A1c (HbA1c), Blood Sugar Random (BSR), Exercise, Dipsia (Excessive thirst), Nephropathy and High-Density Lipoprotein (HDL) are used in this study. The target variable called 'Diabetes Outcome', which is categorized as 0 for non-diabetic and 1 for diabetic. This dataset is valuable as it is collected from a hospital in Sahiwal and is useful for performing diabetes prediction through various statistical techniques. Binary Logistic Regression is used for modeling the relationship between variables.

3.2. Binary Logistic Regression (BLR)

Binary logistic regression (BLR) was employed in this study to examine the relationship between the Diabetes Outcome (dependent variable) and a set of variables like Age, Gender etc. (independent variables). The dependent variable, referred to as "Outcome," is binary in nature and coded as 0 for non-diabetic and 1 for diabetic individuals. This method is appropriate for situations where the response variable has two possible outcomes.

The BLR model estimates the probability of an event (diabetes) occurring as a function of several independent or predictor variables. In this study, thirteen independent variables related to demographic, clinical, and biochemical characteristics were included in the model. The logit function is used to transform the linear combination of independent variables or predictors into probabilities ranging from 0 to 1. The model for the BLR is expressed as:

$$logit\ (p) = \ln\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_k X_K$$

where (p) denotes the probability of being diabetic,

(β_0) is the intercept,

and (β_i's) are the coefficients corresponding to each predictor variable (X_i).

The coefficients of the model were estimated by using the Maximum Likelihood Estimation (MLE) method by using the sample data. The significance of the variables was assessed using the Wald test, while the adequacy of overall model fit was evaluated using measures such as the Hosmer–Lemeshow goodness-of-fit test, Likelihood Ratio Test and the model classification accuracy. Odds ratios were also calculated to interpret the effect of each predictor on the likelihood of diabetes occurrence.

4. Results and Discussion

Table 1: Descriptive Statistics for the Continuous Variables of the Study

Variables	**n**	**Minimum**	**Maximum**	**Mean**	**Standard Deviation**	**Variance**
Age	809	16	70	35.37	13.425	180.225
Weight	809	36	102	68.94	11.884	141.229
BMI	809	14	37	25.13	4.138	17.127
Diabetes Insipidus	809	40	115	81.72	11.306	127.827
Hemoglobin A1c	809	4	12	6.65	2.081	4.329
Blood Sugar Random	809	71	354	155.74	75.841	5751.78
High Density Lipoprotein (HDL)	809	30	62	46.30	6.784	46.028

Table 1 presents descriptive statistics for continuous variables, such as age, weight, BMI, diabetes insipidus, hemoglobin A1c, random blood sugar, and high-density lipoprotein. The most pertinent average values for each variable are shown in this table, including the average age of 35.37 years, the average weight of 68.94 pounds, and the average BMI of 25.13. The lowest and maximum values for each variable are also displayed in this table. Ages range from 16 to 70 years, and hemoglobin A1c values range from 4 to 1. BMI has a relatively small variance of 17.127, whereas Blood Sugar Random has a huge variance of 5751.78.

4.1. Bar Chart for Discrete Variables

In Figure 1, bar chart visually represents the distribution by “Diabetes Outcome” categorized as: “Yes” and “No”. The chart shows that the number of patients without diabete and those with diabete are nearly equal, with a slightly higher count observed in the non-diabetic group.

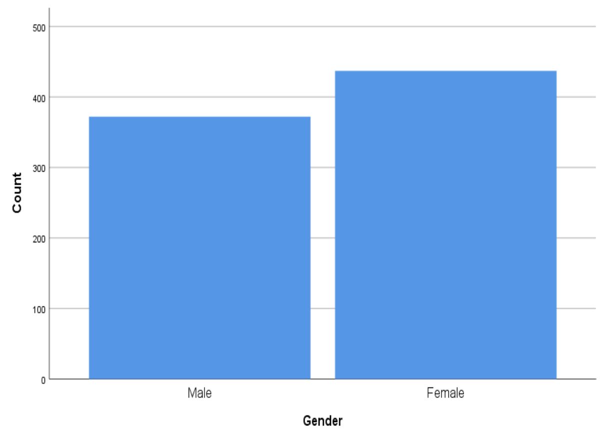

Figure 1: Bar Chart Showing the Classification Diabetes Outcome

In Figure 2, bar chart visually represents the distribution by “Gender” category: “Male” and “Female.” In this figure, the chart illustrates that there are more females than males in the observed population.

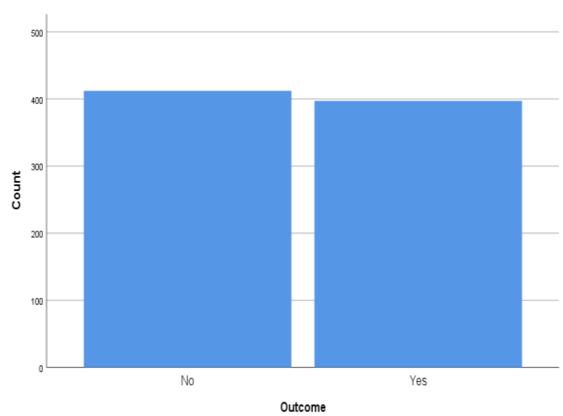

Figure 2: Bar Chart Showing Gender Distribution

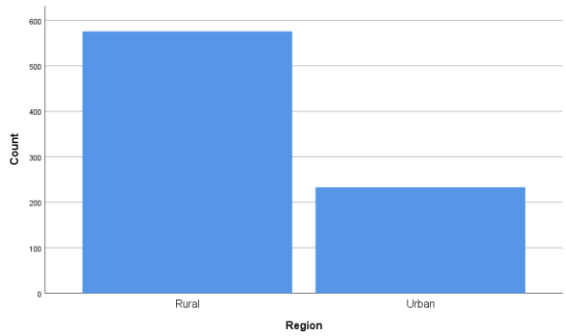

Figure 3: Bar Chart Showing Regional Distribution.

In Figure 3, bar chart displays the count of individuals across “Region” categories: “Rural” and “Urban.” The figure shows that many more people had been diagnosed with diabetes in rural regions than in urban areas.

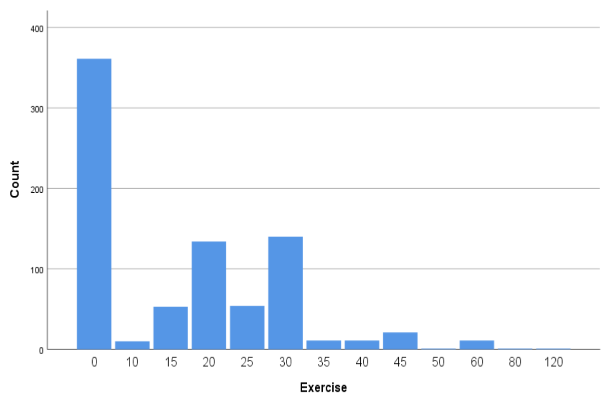

Figure 4: Bar Chart Displaying Distribution of Exercise

In Figure 4, bar chart shows the number of people across "Exercise." Diabetes patients should exercise for more than 0 minutes. This graph shows that people with diabetes are more likely to be inactive than people without diabetes.

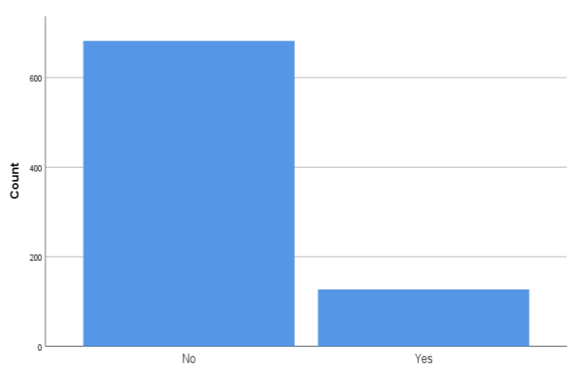

Figure 5: Bar Chart Showing Distribution of Nephropathy

In Figure 5, bar chart shows the count distribution of diabetic patients across the "Nephropathy" categories ("Yes" or "No"). In this graph, "Yes" represents patients who have had kidney disease, and "No" represents diabetic patients without kidney disease. In this graph many diabetic patients fall in the "No" category as compared to the "Yes" category.

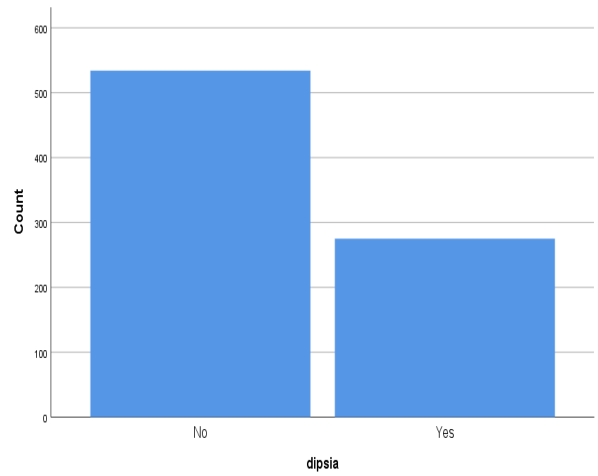

Figure 6: Bar Chart Showing Distribution of Dipsia

In Figure 6, bar chart shows the count distribution of diabetic patients across the "Dipsia" categories ("Yes" or "No"). In this graph, "Yes" represents diabetic patients who have felt like they have excess thirst, and "No" means diabetic patients who have not felt like they have excess thirst. In this graph many diabetic patients fall in the "No" category as compared to the "Yes" category.

4.2. Box Plot for Continuous Variables

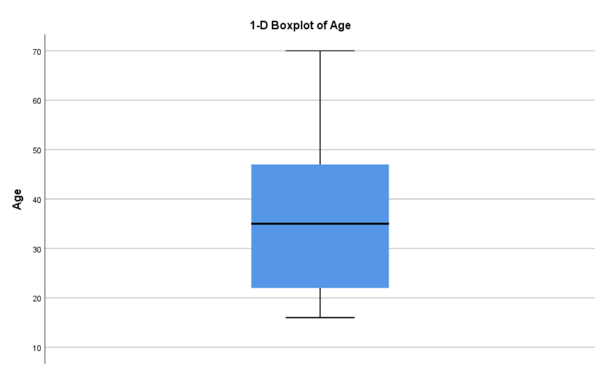

Figure 7: Box Plot Showing Age Distribution

In Figure 7, box plot highlights the distribution of "Age." In the box plot, the median age of diabetic patients is around 35. The central 50% of diabetic patients' ages range from approximately 22 (1st quartile) to 47 (3rd quartile). The minimum age of diabetic patients is around 16, and the maximum age is around 70, and there is no outlier within the data set.

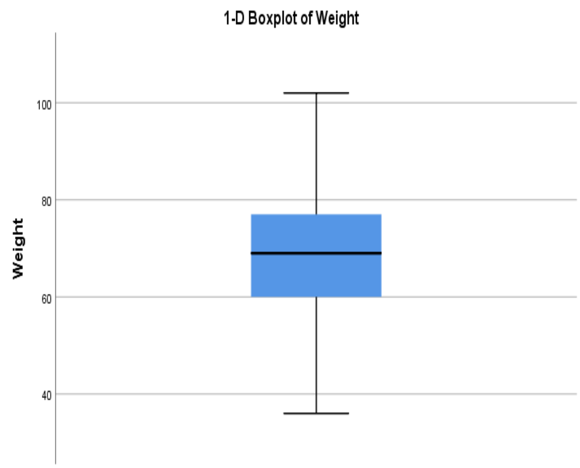

Figure 8: Box Plot Showing Weight Distribution

In Figure 8, box plot highlights the distribution of "Weight." In the box plot, the median weight of diabetic patients is around 69 units. The central 50% of patients' weight falls from roughly 60 units (1st quartile) to 78 units (3rd quartile). The minimum weight of diabetic patients is around 36 units, and the maximum weight of diabetic patients is around 102 units. There is no outlier in this dataset.

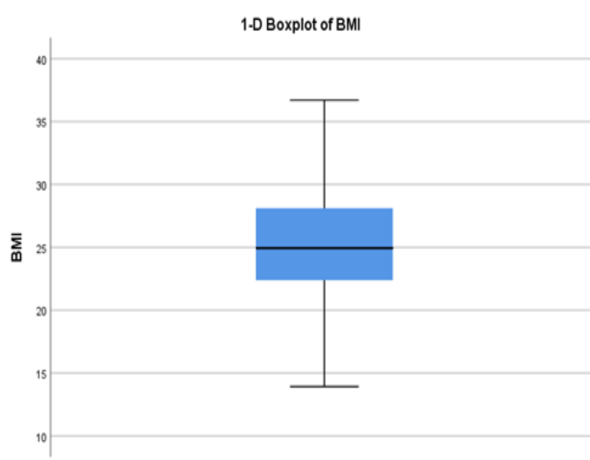

Figure 9: Box Plot Showing BMI Distribution

In Figure 9, box plot highlights the distribution of "BMI." In this box plot, the median BMI of diabetic patients is approximately 25. The central 50% of patients' BMI range falls from roughly 22.5 value (1st quartile) to 28.5 value (3rd quartile). The minimum BMI of patients is around 14, and the maximum BMI is approximately 36.5, and there is no outlier in this data set.

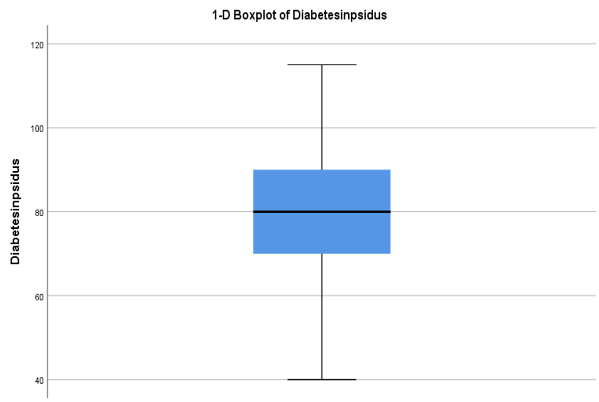

Figure 10: Box Plot Showing Diabetes Insipidus Distribution

In Figure 10, box plot highlights the distribution of "Diabetes insipidus." In this box plot, the median diabetes insipidus of diabetic patients is approximately 80. The central 50% of patients' diabetes insipidus range spans from roughly 70 (1st quartile) to 90 (3rd quartile). The minimum observed value is around 40, and the maximum value is approximately 117, and there is no outlier in this data set

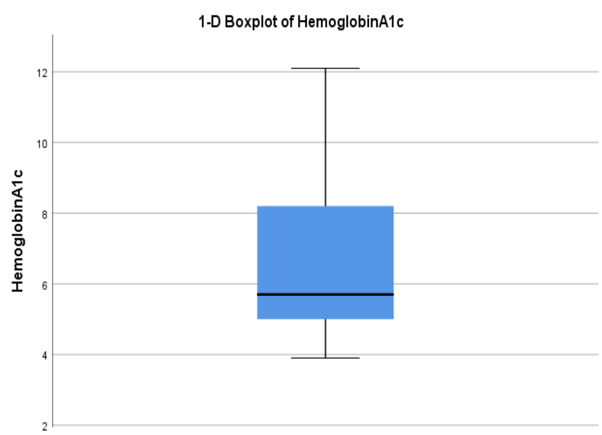

Figure 11: Box Plot Showing Hemoglobin A1c Distribution

In Figure 11, box plot illustrates the distribution of "Hemoglobin A1c" values. The median hemoglobin A1c level is approximately 5.7. The central 50% of the data spans roughly from 5.2 (1st quartile) to 8.29 (3rd quartile). The highest observed hemoglobin A1c value is approximately 12.1, and the lowest observed value is around 3.8, and there is no outlier in this data set.

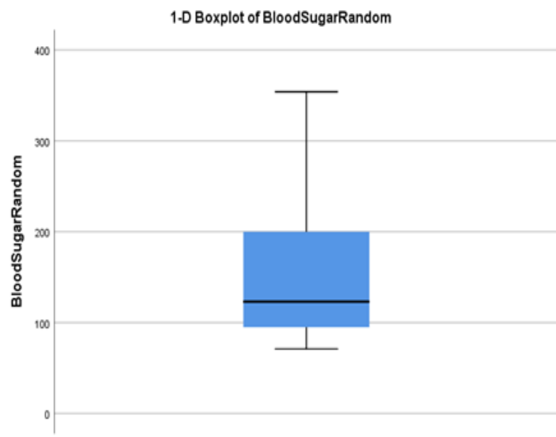

Figure 12: Box Plot Displaying the Distribution of Blood Random Sugar

In Figure 12, box plot illustrates the distribution of “Blood Random Sugar” values. The median random blood sugar level is approximately 125. The central 50% of the data spans roughly from 100 (1st quartile) to 200 (3rd quartile). The highest observed random blood sugar value is 360, and the lowest observed value is around 70, and there is no outlier in this data set.

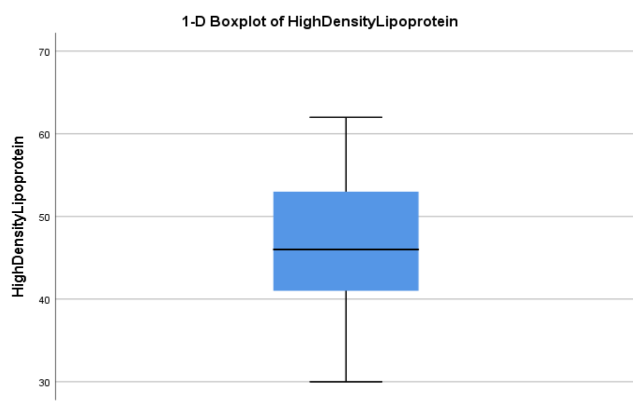

Figure 13: Box Plot Showing the Distribution of High-Density Lipoprotein

In Figure 13, box plot illustrates the distribution of “High Density Lipoprotein” values. The median high-density lipoprotein level is around 45. The central 50% of the data spans roughly from 41 (1st quartile) to 53 (3rd quartile). The highest observed high-density lipoprotein value is 30, and the lowest observed value is around 62, and there is no outlier in this data set.

4.3. Results of Binary Logistic Regression (BLR)

Table 2: Model Summary of the Fitted Model

Step	-2 Log Likelihood	Cox & Snell R Square	Nagelkerke R Square
1	57.760a	0.731	0.975

Estimation terminated at iteration number 11 because parameter estimates changed by less than .001

Table 2 shows the model summary of the binary logistic regression. It shows that the BLR model got a -2-log likelihood of 57.760 at step 1. After 11 iterations, the estimation process successfully converged because the estimates of parameter changed by less than 0.001. The value of the Cox & Snell R Square is .731 and the value of the Nagelkerke R Square is 0.975 shows that the model explains the data very well. The Nagelkerke R Square shows that an about 97.5% change in the dependent variable is explained by the predictors or independent variables in the model, which means that the model fits very well.

Table 3: Results of Omnibus Test for Binary Logistic Regression

Chi-Square		**Df**	**Sig.**
Step	1063.474	13	0.000
Block	1063.474	13	0.000
Model	1063.474	13	0.000

In Table 3, the Chi-square value for Step 1 is 1063.474, and there are 13 degrees of freedom. The p-value, which shows how important the result is, is .000, which is less than the usual alpha level of 0.05. This very important result shows that the independent variables in the model, as a whole, make the prediction of the dependent variable much better than a model with no predictors or independent variables. The model, in short, is statistically significant and fits the data much better than a null model.

Table 4: Observed and Predicted Classification of Diabetes Outcome

		Predicted		
		Outcome		**Percentage Correct**
Observed		**No**	**Yes**	
Outcome	**No**	408	4	99.0
	Yes	8	389	98.0
Overall Percentage				98.5

Table 4 shows the observed and predicted classification of diabetes outcome which compares what actually happened to what was predicted to happen in order to show the results of a classification model. The model correctly predicted 408 cases of "No" and incorrectly predicted 4 cases of "Yes," which means it was 99.0% of the time. The model correctly predicted 389 "Yes" answers and incorrectly predicted 8 "No" answers, giving it a 98.9% correct prediction rate. The classification model was able to predict with 98.5% accuracy, which is very good.

Table 5: Estimated Coefficients of the Fitted Binary Logistics Regression Model

Predictors	B	S.E.	Wald	Df	Sig.	Exp (β)
Age	0.66	.028	5.433	1	.020	1.068
Gender	2.203	1.102	3.992	1	.046	9.050
Region	-1.541	1.128	1.864	1	.172	.214
Weight	0.023	0.042	.293	1	.589	1.023
BMI(Body Mass Index)	0.168	0.120	1.945	1	.163	1.183
Diabetes inpsidus	0.082	0.046	3.169	1	.075	1.085
Family History	0.005	0.779	0.000	1	.995	1.005
HemoglobinA1c	3.903	0.997	15.314	1	.000	49.551
Blood Sugar Random (B.S.R)	0.055	0.024	5.258	1	.022	1.056
Exercise	-0.015	0.030	0.253	1	.615	.985
Dipsia	2.557	1.044	6.003	1	.014	12.900
Nephropathy	3.587	1.789	4.019	1	.045	36.108
High Density Lipoprotein	-0.114	0.081	1.996	1	.158	.892
Constant	-41.014	10.232	16.067	1	.000	.000

The results from a logistic regression analysis used to predict diabetes are shown in Table 5. Major factors like hemoglobin A1c and dipsia have statistically significant correlations with the prediction of diabetes, as evidenced by their high Exp (B) values (49.551 and 12.900) and low "Sig" (p-value) values (0.000 and 0.014, respectively), indicating that they are good predictors. This model suggests that factors like family history and exercise are not significant predictors, but other variables like age, gender, and blood sugar random also exhibit some predictive power, based on this model.

5. Conclusion

After the analysis of the data, the study concluded that binary logistic regression is a useful tool for identifying and measuring the impact of different clinical, demographic and biochemical factors in the prediction of diabetes. The bar chart shows that the number of patients without diabetes and those with diabetes are nearly equal, with a slightly higher count observed in the non-diabetic group. The results of the BLR model show that age, gender, hemoglobin A1c, dipsia and nephropathy are the significant factors of diabetes. The results highlighted that the patients have regularly checked their hemoglobin A1c and be aware of the symptoms and treat them at earliest. Furthermore, by adding more variables such as diet, socioeconomic status etc. and using advanced statistical techniques that could improve future research.

6. Future Recommendation

For future research, large diverse and multicenter datasets should be used to enhance and generalize the studies. More variables should be added like lifestyle, behavior and environmental factors that could make stronger predictions. In addition, more advanced statistical models and machine learning techniques should be adopted for modeling. A long-term study design could also be used. The findings of this study will help to develop a digital risk assessment tool or application that assists healthcare practitioners in detecting and managing diabetes at the early stage.

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