DIABETES PREDICTION USING MACHINE LEARNING ALGORITHMS

C.Vijayalakshmi¹, Hema.B², Athira¹

¹Department of Statistics and Applied Mathematics Central University of Tamil Nadu, Thiruvarur ²Department of Corporate Secretaryship Kumararani Meena Muthiah College of Arts and Science, Chennai

ABSTRACT

Diabetes is a chronic disease. Diabetes rate is increasing day by day. Even the youngster of this generation face this disease. Diabetes occurs because of high sugar in blood. It destroys the life of human by this disease worldwide. One can study huge datasets by using big data analytics. It helps to find more informative knowledge to predict the data's outcome, hidden information and pattern regarding the datasets. When the sugar content in blood is high it produces many symptoms. Diabetes can also cause many other diseases like blindness, kidney failure, amputations, heart failure and stroke. Machine learning is a method of learning machine's language by emerging scientific data science fields in many ways. A diabetes prediction model is combined by overall result in this. It has few factors like Glucose, BMI, Age, Insulin etc. for this interpretation of the data. Comparative analysis also carried out to know about the accuracy rate.

KEYWORDS: Diabetes prediction; machine learning; networks;

INTRODUCTION

Diabetes is a common disease. It affects people of all age groups. First comprehend what occurs in the body without diabetes in order to comprehend diabetes and how it develops. It is caused by high sugar levels in blood. Carbohydrates that consume is sugar. Energy source of body is Carbohydrate meals and it must be consumed by all. Foods are broken down into glucose by the body and eat them. In the stream of the blood, circulation of glucose is happening in the body. Glucose may transport to brain, where it helps in performing and thinking process. Hyperglycemia is a typical complication of untreated diabetes that damages many organs, including neurons and blood vessels, over time. Diabetes is spread across the world, according to International Diabetes Federation a study was conducted and analyzed that millions of people suffer from diabetes. In 2014 and above 8.5 percent persons affected diabetes. Diabetes was the reason for 1.5 million deaths in 2019. All diabetes – related deaths were 48 percent and it was under the age of 70. By 2045, an estimated 700 million will have diabetes across the world, according to the International Diabetes Federation. With 1.5 million deaths projected in 2019, diabetes is the main causes of death worldwide. Due to a lack of effective treatment choices, diabetes more than doubles the risk of dying early in many parts of the world. The Western Pacific has the highest amount of deaths, with over 717,000 people succumbing to the disease in 2021. The most important indicator of

diabetes progression is Obesity. The International Diabetes Federation believes that in certain wealthy nations, the number of newly diagnosed diabetes patients is actually decreasing. However, diabetes is rising as people's living situations improve. Because of the changing lifestyle, many people are suffering from this disease. The organization also sees the lack of diabetes diagnosis as a persistent issue. The cause of diabetes is unknown, but lifestyle and genetic factors have a significant impact. Diabetes patients are at risk of having many problems like heart disease and damage of nerve.

LITERATURE SURVEY

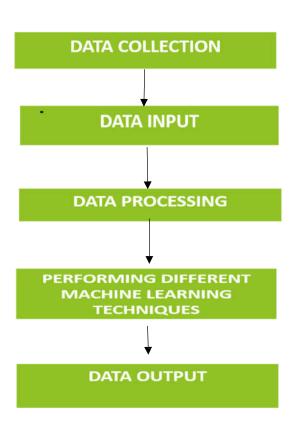
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METHODOLOGY

Various machine learning strategies used for predicting diabetes. Accurate outcome will be determined for each approach. Various strategies are employed in this instance. The accuracy measurements of the machine learning models are the output. As a result, the diabetes model can be forecasted.

MODEL FORMULATION



DATASET DESCRIPTION

	Pregnancies	Glucose	Insulin	BMI	Diabetes	Age	Outcome
					Pedigree		
					Function		
1	6	148	0	33.6	0.627	50	1
2	1	85	0	26.6	0.351	31	0
3	8	183	0	23.3	0.672	32	1
4	1	89	94	28.1	0.167	21	0
5	0	137	168	43.1	2.288	33	1
6	5	116	0	25.6	0.201	30	0

The trait to predict with 0 and 1 is the outcome. It denotes the absence of diabetes for 0 and the presence of diabetes for 1.

<u>INFERENCE</u>: The dataset comprised 768 samples before outliers were removed. The dataset currently has 636 samples after outliers were removed.

STATISTICAL ANALYSIS

	Pregnancies	Glucose	Insulin	BMI	Diabetes	Age	Outcome
					Pedigree		
					Function		
Min.	0.000	0.0	0.00	0.00	0.0780	21.00	0:500
1 st Qu	1.000	99.0	0.00	27.30	0.2437	24.00	1:268
Median	3.000	117.0	30.5	32.00	0.3725	29.00	
Mean	3.845	120.9	79.8	31.99	0.4719	33.24	
3 rd Qu	6.000	140.2	127.2	36.60	0.6262	41.00	
Max	17.000	199.0	846.0	67.10	2.4200	81.00	

INFERENCE

The minimum value is the data's lowest value. The minimal value is for pregnancies, glucose, insulin, and BMI. The first quartile (Q1), which means the (n+1)/4th term. Insulin is at its lowest in the first quarter, while age is at its highest.

The data's midpoint is represented by the median. With the median, it represent a large number of data points with just one.

Median =
$$\left(\frac{n+1}{2}\right)^{th}$$
 observation
n is even,

Median = $\left(\frac{n}{2}\right)^{th} + \left(\frac{n}{2} + 1\right)^{th}$ observation

For glucose, the median is high, while for diabetes pedigree function, it is low.

The average of all the data is used in the mean formula.

The third quartile(Q3) is given as:

Third quartile (Q3) = (3(n+1)/4th term, also known as the upper quartile.

Third quarter is minimum for diabetes pedigree function and the maximum for glucose.

The maximum is the highest value of the data.

Age has the maximum value

	Minimum	Maximum	Mean	Std Dev	Range
Pregnancies	0	17	3.845	3.37	17
Glucose	0	199	120.895	31.973	199
Blood Pressure	0	122	69.105	19.356	122
Skin Thickness	0	99	20.536	15.952	99
Insulin	0	846	79.799	115.244	846
BMI	0	67.1	31.993	7.884	67.1
Diabetes Pedigree Function	0.078	2.42	0.472	0.331	2.342
Age	21	81	33.241	11.76	60
Outcome	0	1	0.349	0.477	1

INFERENCE

Dataset's maximum and minimum values are both relatively simple metrics. The difference between the greatest and least value of the data is the range of the data.

Max Value – Min Value = Range

Highest range is for the glucose.

Highest mean is for glucose.

Highest Standard deviation is for Insulin.

MACHINE LEARNING TECHNIQUES

Instances	768
Attributes	9
Test mode	10-fold cross-validation

In the context of the model, K is the specific value chosen. The value of K is ten in this case. As a result, 10-fold cross-validation is used.

Machine learning models employ cross validation to estimate previously unknown data.

Classifier model (full training set)

Cross-validation

Correlation coefficient	-0.0908
Mean absolute error	0.4548
Root mean squared error	0.4771
Relative absolute error	100 %

Root relative squared error	100 %
Total Number of Instances	768

INFERENCE

The coefficient of correlation is negative. It describes how far two variables are moving in different directions.

In statistics, MAE is the amount of the deviation between a prediction and its true value.

Mean absolute =
$$\frac{Sum \ of \ all \ absolute \ errors}{No \ of \ errors \ (n)}$$

$$= \sum_{i=1}^{n} \frac{X_i - X}{n}$$

MAE = mean absolute error

Xi = predictionX = true value

n = total number of data points

The model will try to reduce the inaccuracy as much as possible. The mean absolute error is minimal in this case.

The RMSE is calculated using the root of the square mean of squared deviation between actual and predicted outcomes.

RMSE =
$$\sqrt{\frac{1}{n} \sum_{i=1}^{n} (Y_i - \hat{Y}_i)^2}$$

RMSE = root mean square error

Yi = prediction

 $Y_i = true \ value$

n = total number of data points

The root mean square error is abbreviated as RMSE. Because RMSE is low in this case, it is a better-fitting model. When compared to MSE, RMSE will always have more or equivalent mistakes. The greater the gap between them, the greater the variance in the sample's individual errors.

Clustering
Test mode: evaluate on training data

Clustering model (full training set)

Number of clusters sel	ected by cross	2		
validation	20.000			
Number of iterations p	performed	2		
Attribute	1 (0.38)		0 (0.62)	
Pregnancies				
mean	4.8483		3.2241	
std. dev.	3.768		2.926	
Glucose				
mean	142.7926		107.3415	
std. dev.	31.308		23.7835	
Blood Pressure			I	
mean	71.6206		67.5488	
std. dev.	20.6869		18.2902	
Skin Thickness				
mean	22.7605		19.1599	
std. dev.	17.4576		14.7598	
Insulin				
mean	118.3012		55.9702	
std. dev.	155.4014		71.0018	
BMI	<u> </u>			
mean	35.3693		29.9027	

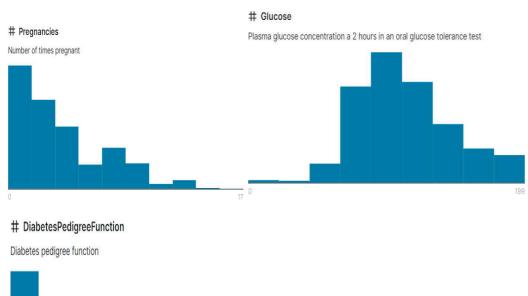
std. dev.	7.0256	7.6503
Diabetes Pedigree Function		
mean	0.579	0.4056
std. dev.	0.4037	0.2552
Age		
mean	37.2137	30.7821
std. dev.	11.3178	11.3365
Outcome	,	
mean	0.8872	0.0158
std. dev.	0.3163	0.1247

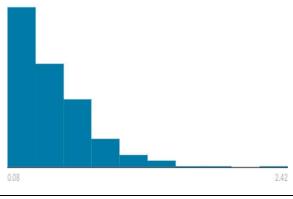
Model and evaluation on training set

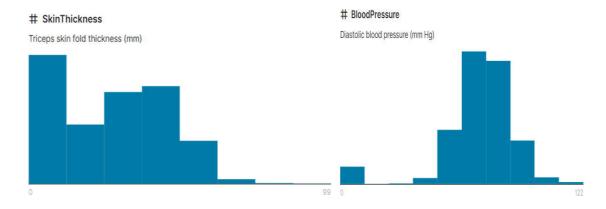
Clustered Instances

0	289 (38%)
1	479 (62%)
Log likelihood	-29.34631

GRAPHICAL REPRESENTATION





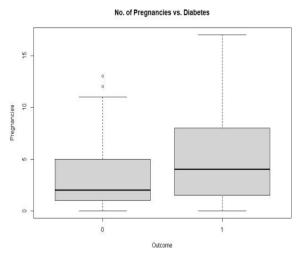


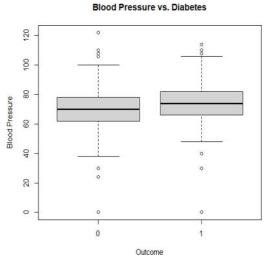
Age Age (years)

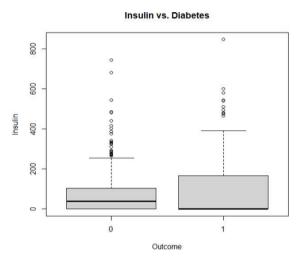
Outcome

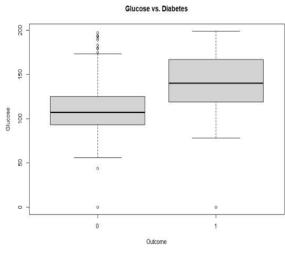
Class variable (0 or 1) 268 of 768 are 1, the others are 0

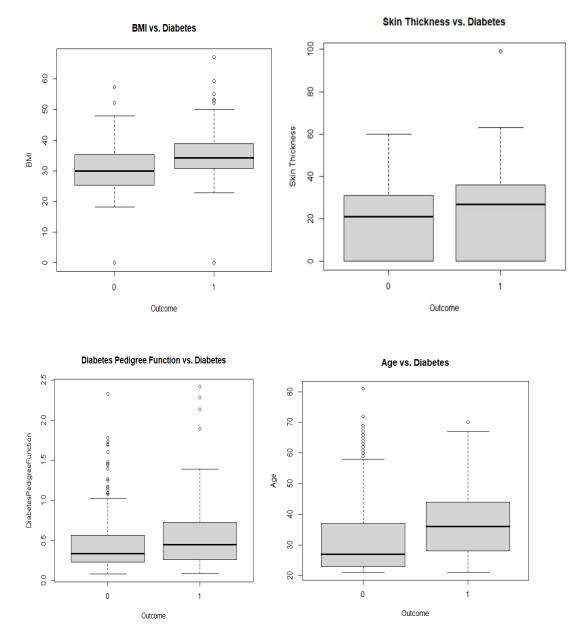






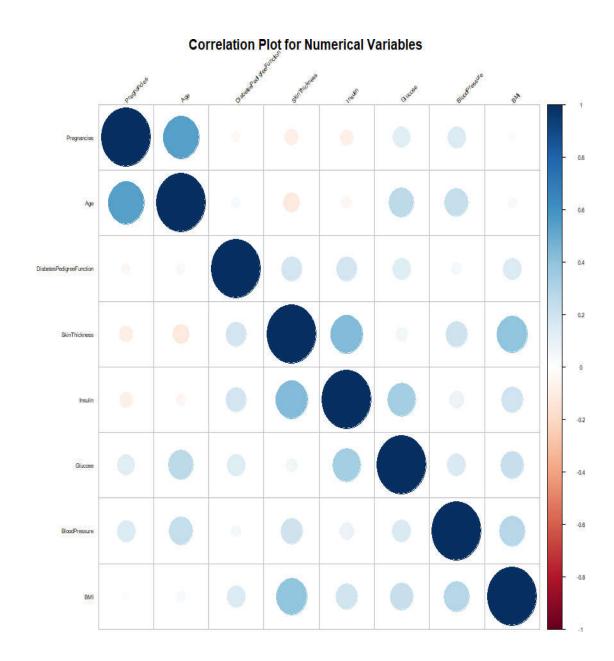






INFERENCE

Above graphs show that the data is biased towards data points having an outcome value of 0. The data is skewed towards data points with an outcome value of 0, which indicates that there is no diabetes present. No. of Pregnancies vs Diabetes graph is positively skewed. Glucose vs Diabetes, Blood Pressure vs Diabetes, BMI vs Diabetes are graphs in which both sides are nearly same. Insulin vs Diabetes, Skin Thickness vs Diabetes, Diabetes Pedigree Function vs Diabetes, Age vs Diabetes graphs are negatively skewed.



INFERENCE

In this data is represented using a dot-representation, positive correlation represents blue and negative correlation represents red. The greater the dot, the stronger the link. Because it shows the correlation of each variable the matrix is symmetrical and that the diagonal is perfectly positively correlated. Unfortunately, there is no correlation between any of the variables.

CORRELATION MATRIX

	Pregnan cies	Gluco se	Blood Pressure	Skin Thicknes s	Ins ulin	BM I	Diabetes Pedigre e Function	Age
Pregnancies	1.00000	0.129 45867	0.14128198	- 0.0816717 7	- 0.0 735 346 1	0.0 176 830 9	-0.03352267	0.5443 4123
Glucose	0.12945 867	1.000 00000	0.15258959	0.0573278 9	0.3 313 571 1	0.2 210 710 7	0.13733730	0.2635 1432
Blood Pressure	0.14128 198	0.152 58959	1.00000000	0.2073705 4	0.0 889 333 8	0.2 818 052 9	0.04126495	0.2395 2795
Skin Thickness	- 0.08167 177	0.057 32789	0.20737054	1.0000000	0.4 367 825 7	0.3 925 732 0	0.18392757	- 0.1139 7026
Insulin	- 0.07353 461	0.331 35711	0.08893338	0.4367825 7	1.0 000 000 0	0.1 978 5	0.18507093	- 0.0421 6295
BMI	0.01768 309	0.221 07107	0.28180529	0.3925732	0.1 978 590 6	1.0 000 000 0	0.14064695	0.0362 4187
Diabetes Pedigree Function	- 0.03352 267	0.137 33730	0.04126495	0.1839275	0.1 850 709 3	0.1 406 469 5	1.00000000	0.0335 6131
Age	0.54434 123	0.263 51432	0.23952795	- 0.1139702 6	- 0.0 421 629 5	0.0 362 418 7	0.03356131	1.0000

INFERENCE

The correlation matrix is entirely symmetrical in this case. There is no single attribute that has a strong relationship with the outcome value. Some traits have a negative association with the outcome value, whereas others have a positive link. The correlation between Pregnancies and Age is highly correlated. The correlation between Pregnancies and Diabetes Pedigree Function is least correlated.

Logistic Regression

Model	Estimate	Std.Error	Z Value	<i>Pr(> Z)</i>
Intercept	-8.4169989	0.7106686	-11.844	2*10^16
Glucose	0.0345879	0.0036653	9.436	2*10^16
Blood Pressure	-0.0122052	0.0052309	-2.333	0.0196
Skin Thickness	0.0008423	0.0069023	0.122	0.9029
Insulin	-0.0013691	0.0009118	-1.502	0.1332
BMI	0.0878755	0.0148520	5.917	3.28*10^09
Diabetes Pedigree	0.8904459	0.2957255	3.011	0.0026
Function				
Age	0.0326696	0.0081094	4.029	5.16*10^05

INFERENCE

The logistic regression coefficient is 0.734375.

The p-value (Pr (>|Z|)) column represents z-value column. It is statistically significant for the predictor variable in connection to the response variable in the model if the value of p is less than 0.05. Here, the p-values for *glucose*, *blood pressure*, *BMI*, *diabetes pedigree function*, and *age* are less than 0.05. As a result, the model's response variable has a statistical link with all of them.

Null deviance	993.48 on 767 degrees of freedom
Residual deviance	738.68 on 760 degrees of freedom
AIC	754.68

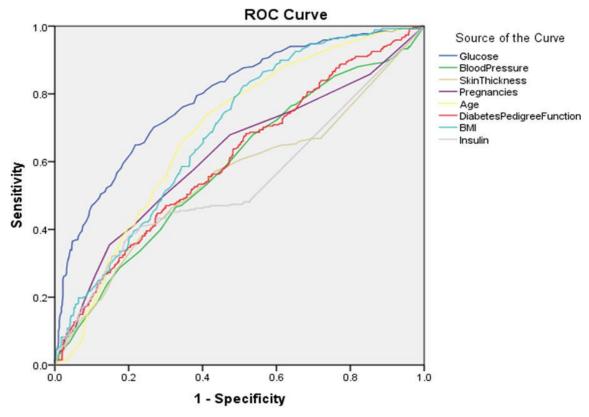
A good match for the model is shown by the deviance between Null Deviance and Residual Deviance. Larger disparity, the more accurate the model is. A null deviance occurs when an equation has just one intercept and has no variables, but a residual deviance occurs when all variables are considered. If the difference is significant enough, the model should be considered good. Because the difference between null and residual deviation isn't large in this case, the model doesn't fit well.

Because the AIC score is so high in this case, the model will not be a better-fit model.

Case Processing Summary

Outcome	Valid N (listwise)
Positive	268
Negative	500

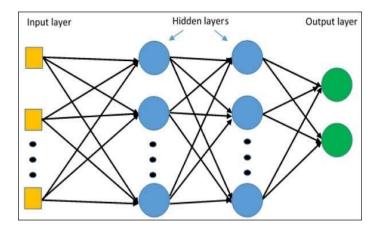
The test result variable(s) with higher values suggest more evidence of a positive actual state. Positive-The actual positive state is 1.



Diagonal segments are produced by ties.

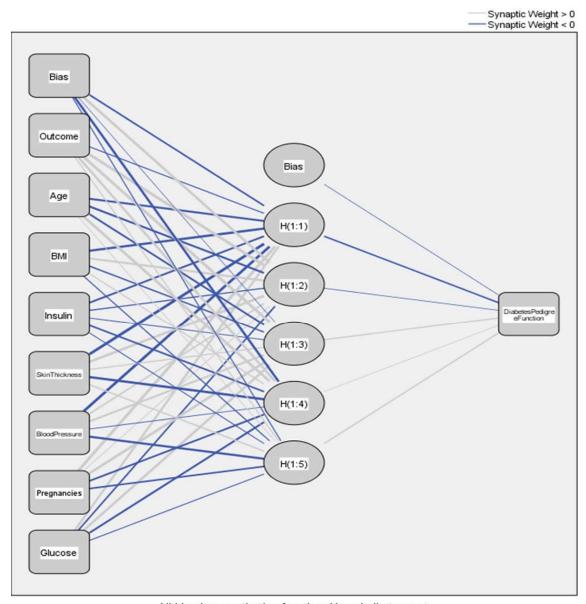
MultilayerPerceptron

- MLP is a type of feed forward ANN that is fully connected ANN.
- It consists of: input layer, hidden layer and output layer.



<u>ANN</u>

ANNs or SNNs underpins deep learning. It enables trainees to improve their accuracy over time by learning and improving their accuracy.



Hidden layer activation function: Hyperbolic tangent Output layer activation function: Identity

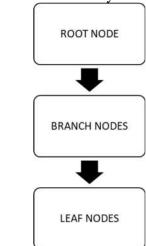
Classification

Sampled Observation	Predicted		
	0	1	Percent correct
Training			
0	290	55	84.1%
1	64	117	646%
Overall Percent	67.3%	32.7%	77.4%
Testing			
0	133	22	85.8%
1	30	57	65.5%
Overall Percent	67.4%	32.6%	78.5%

Dependent Variable : outcome

Decision Tree

- A popular way of representing and visualizing prediction models and algorithms.
- It visually defines the rules for easy interpretation and comprehension.



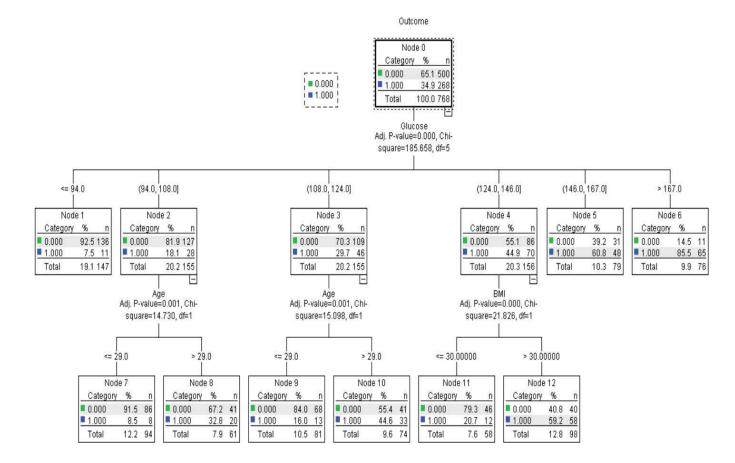
Tree pred	0	1
0	121	29
1	29	49

Tree prediction	0.745614

Classification Tree:

Observed	Predicted		
	0	1	Percent
			Correct
0	418	82	83.6%
1	97	171	63.8%
Overall Percentage	67.1%	32.9%	76.7%

Classification



K-Nearest Neighbor Analysis

- K-Nearest Neighbor predicts the classification of a new sample point by identifying data points that are segregated into numerous groups.
- It is known as the LAZY algorithm.
- It uses a similarity metric to classify new data points.

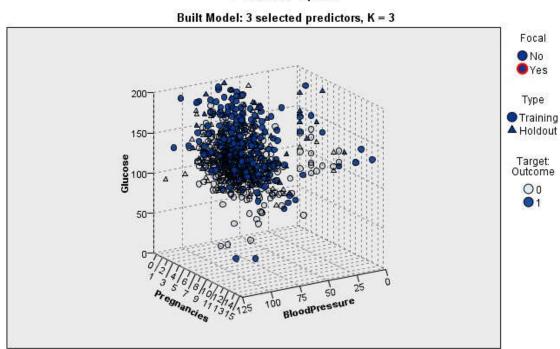
Case Processing Summary

ouse 11 occusing summary			
		N	Percent
Sample	Trainin g	541	70.5%
	Holdout	226	29.5%
Valid		767	100.0%
Exclude	d	1	
Total		768	

K- Nearest Neighbor Analysis - Algorithm

- 1) Import data from .xls or.csv file.
- 2) Set K to zero (nearest neighbors).
- 3) Calculate the distance between query and current points for each sample in the training set. To an ordered collection, add distance and an example of index.
- 4) From small to large, sort ordered collection of distances and indexes.
- 5) Choose first K values from sorted collection.
- 6) Have labels for K values you selected.
- 7) Return mode of K labels.

Predictor Space



Select points to use as focal records

This chart is a lower-dimensional projection of the predictor space, which contains a total of 8 predictors.

Results

NON-DAIBETES PATIENTS	500
DIABETES PATIENTS	268

Out of 768, we concluded that 500 patients do not have diabetes.

ALRITHM	ACCURACY
Logistic Regression	73%
Decision Tree	74%
Perceptron	67%
KNN	75%

COMPARATIVE ANALYSIS

Comparing the dataset with 'Diabetes Prediction Using Pipeline'.

Algorithms	Accuracy (Dataset used in this	Accuracy (Dataset of Diabetes
	paper)	Prediction Using Pipeline)
Logistic Regression	73%	69%
Decision Tree	74%	62%
Perceptron	67%	54%
KNN	75%	68%

CONCLUSION

After analyzing the data by different machine learning techniques, it leads to the result that accuracy is obtained based on decision tree algorithm. In this various machine learning techniques are performed like logistic regression, decision tree, perceptron and KNN. This method helps the patients to find out the blood sugar content in body and predict whether the patient has diabetes or not at the earliest stage.

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