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Assessment of Diabetic Patients Among Adults in Maiduguri, Using Multivariate Discriminant Model

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Abstract

This paper assesses the study that has carried out based on the broad objective of using the multivariate discriminant model for tackling diabetic patients among adults in Maiduguri, Borno state Nigeria. In this research work, data collected from the University of Maiduguri teaching hospital for ten (10) consecutive years from (2002-2011) of 987 patients. The data analyses were done using Fisher's method and Omnibus Chi-Square test. The Diabetic patient's responses categorized into two groups which include: Healthy ("0") and Diabetic ("1"). Various variables (predictors), i.e., Age, Sex, Weight, Blood sugar and Urine sugar are used based on discriminant analysis. Using Fisher's method of discriminant analysis, classification table that we got by selecting that option in the results obtained. The Overall % correctly classified = 88.2% for the male counterparts and 89.4% for the female counterparts. By relating actual groups to predicted groups percentage correct predictions without percentage accurate predictions and cross validation. In addition to that, the omnibus Chi-square test is a log-likelihood ratio test for investigating the Discriminant model coefficients (Age and Sex). The model coefficients are statistically significant as we reject H0 if $p<0.05$ at the 5% level of significance. The study concluded that Base on the analysis it shows female are mostly affected by the disease and the kinds of misclassification that took place. It also recommended that the Discriminant model built should be used for capable of tackling diabetes mellitus cases in (UMTH), Maiduguri, and Borno state [1-4].

Keywords: Discriminant analysis; Fisher's Method; Diabetes mellitus; Maiduguri

Introduction

Discriminant analysis was introduced by [5] as a statistical method for separating two groups of populations [4]. Extended this multivariate technique to multiple populations. At the basis of observations with known group membership–the training data–so-called discriminant functions are constructed aiming at separating the groups as much as possible. These discriminant functions can then used for classifying new observations to one of the populations. We distinguish linear and quadratic discriminant analysis, and this terminology refers to the discriminant function that is to build. In this case, we focus on Fisher's method (for two or more populations) leading to linear discriminant functions [6]. The problem can formulate as a simple eigenvector/Eigenvalues problem, and the plan is attractive and frequently used in practice. The discriminant analysis used in situations where the clusters are known a priori.

The discriminant analysis aims to classify an observation, or several views, into these known groups [7]. The discrimination rule has to organize the customer into one of the two existing groups, and the discriminant analysis should evaluate the risk of a possible "bad decision." Multivariate methods are relevant in virtually every branch of applied medicine, pharmacy, and public health [8]. They come into play either when we have a medical theory to test or when we have a relationship in mind that has some importance for medical decision or policy analysis in public health. According to [9], classification of observation into one of the several populations is discriminant analysis, while relating quantitative variables to other variables through a logistic (cumulative density function) function form is a logistic regression. The estimates generated from one of these methods often used in the other. However, the conditions for the application of both are not the same.

Discriminate function estimators have commonly been used in logistic regression in both theory and implementation [7] reported that when discriminant function estimators were compared empirically with maximum likelihood estimators for logistic regression; problems, they were found to be generally inferior, although not always by a substantial amount. According to [10], the issue of classification arises when an investigator makes some measurements on an individual and wishes to classify the individual into one of several categories by these measurements. The investigator cannot identify the individual with a group directly but must be used. In many cases, it can be assumed that there are a finite number of groups or population from which individual may have come, and each community characterized by a probability distribution of the measurements [10]. The discrimination problem is distinct from the logistic regression problem and, as might be expected, solutions generally proposed for the one are different from those for the other, although they are related. In some situations (such as when at least one variable is qualitative), the differences in solution become substantial [7].

Diabetes Mellitus is a group of metabolic conditions characterized by high blood sugar or hyperglycemia, and by both under-and-over secretion of insulin, the hormone that transports glucose across cell membranes [2,11]. It is a chronic disorder of carbohydrate metabolism resulting from insufficient production of insulin or the inadequate utilization of this hormone by the body's cells. Diabetes is a significant health matter globally. There is a need for planning to reduce the threat of this disease. Change in lifestyle and using balanced food can reduce the rate and danger of diabetes in patients [12]. This disease disturbed not only the economy of third world countries, yet a list of more advanced nations are expanding a more significant amount of their budget for preventing and curing against this disease. Complications from diabetes include blindness, renal disease, high B.P and stress, CHD, high or low cholesterol level in blood, damage of nerves, arterial affected problems, and stroke therefore, there is a need for advertising, consulting and liaison with adults above 40 years of age, so as to know the implication, cause, and prevention and control the disease. Within this framework, the paper seeks to achieve this study aims to develop discriminant models that are capable of tackling diabetes mellitus patients among adults based on weight, age, gender, blood and urine sugar levels and the following objectives. The scope of this research is concentrated on following three significant predictions;

a) To determine the number of patients that are correctly classified using Fisher's method.

b) To identify if other variables apart from the significant variables selected are substantial.

c) Assess the dependence of the discriminant functions (Age and sex) in a group separation.

Materials and Methodology

In this research design, we have considered all the factors which involved in; the simple random sampling is the chosen sampling design. The five (5) selected predictor variables which are capable of characterizing a Diabetic patient have analyzed [13]. The experience and records of medical practice, these variables are also believed to vary significantly between normal healthy (π_1) and people with diabetes (π_2). The following vectors are required for the Euclidean distance; we need the mean vectors and the covariance matrices of a sample of both normal healthy (π_1) and people with diabetes (π_2).

X_1 =Sex, where x_2 is coded as 1 for male and 2 for female.

X_2 = Age

X_3 = Weight (kg)

X_4 = Blood sugar (mill moles per liter)

X_5 = Urine sugar (mill moles per liter)

For normal healthy patients,

$$\overline{X_1} = \begin{pmatrix} \overline{X_{11}} \\ \overline{X_{12}} \\ \overline{X_{13}} \\ \overline{X_{14}} \\ \overline{X_{15}} \end{pmatrix} \qquad S_1 = \begin{pmatrix} S_{111} & S_{112} & S_{113} & S_{114} & S_{115} \\ S_{121} & S_{122} & S_{123} & S_{124} & S_{125} \\ S_{31} & S_{132} & S_{133} & S_{134} & S_{135} \\ S_{141} & S_{142} & S_{143} & S_{144} & S_{145} \\ S_{151} & S_{152} & S_{153} & S_{154} & S_{155} \end{pmatrix}$$

For Diabetic patients

$$\overline{X_2} = \begin{pmatrix} \overline{X_{21}} \\ \overline{X_{22}} \\ \overline{X_{23}} \\ \overline{X_{24}} \\ \overline{X_{25}} \end{pmatrix} \qquad S_1 = \begin{pmatrix} S_{211} & S_{212} & S_{213} & S_{214} & S_{215} \\ S_{221} & S_{222} & S_{223} & S_{224} & S_{225} \\ S_{231} & S_{232} & S_{233} & S_{234} & S_{235} \\ S_{241} & S_{242} & S_{243} & S_{244} & S_{245} \\ S_{251} & S_{252} & S_{253} & S_{254} & S_{255} \end{pmatrix}$$

The Euclidean distance of the population of normal healthy (π_1) is

$$\hat{l}_1 = \overline{X_1'}S_p^{-1}\left(\overline{X_1} - \overline{X_2}\right)$$

S_p is the pooled covariance matrix. The mean Euclidean distance is given by [12]. Similarly, the Euclidean distance of the population of diabetic (π_2) is

The discriminant function, therefore, obtained as follows:

$$\hat{l}_2 = \overline{X_2'}S_p^{-1}\left(\overline{X_1} - \overline{X_2}\right) \qquad \hat{Y} = X'S_p^{-1}\left(\overline{X_1} - \overline{X_2}\right)$$

The mean Euclidean distance for populations (π_1) and (π_2) is given by $\hat{M} = \frac{1}{2}\left(\hat{l}_1 + \hat{l}_1\right)$

The discrimination function can get by $\hat{Y} = X'S_p^{-1}\left(\overline{X_1} - \overline{X_2}\right)$

Making use of some empirical data, the classification rule for the person with diabetes (π_2) if otherwise, and the patient is standard (π_1) can be categorized as $\hat{Y} \geq \hat{M}$ is a diabetic (π_2) otherwise normal (π_1)

The following table exemplified in the following for the health status of a diabetic or healthy person [14].

Omnibus chi-square test

The omnibus Chi-square test is a log-likelihood ratio test for investigating the Discriminant model coefficients for the given Hypothesis

H_0: The model coefficients are not statistically significant

H_1: The model coefficients are statistically significant

Test statistic

$$\chi^2 = 2\left[\sum_{i=1}^{r}\sum_{j=1}^{c} O_{ij}\mathrm{In}O_{ij} - \sum_{i=1}^{r} R_i\mathrm{In}R_i - \sum_{j=1}^{r} C_j\mathrm{In}C_j - n\mathrm{In}n\right]$$

Or

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$$\chi^2 = 2\left[\sum_{i=1}^{r}\sum_{j=1}^{c} O_{ij}\ln\left(\frac{O_{ij}}{e_{ij}}\right)\right]$$

Where

O_{ij}, R_i, e_{ij} are observed value, row total, column total and expected values respectively.

Decision rule

Reject H_0 if $p < 0.05$ otherwise accept H_0 at the 5% level of significance. The primary importance of the model coefficient is in the Discriminant model. Hence, the Omnibus test is applied.

Plans and methods of data collection

Secondary means of data collection employed through a suitable design clinical survey, and the study conducted in Maiduguri with data obtained from University Of Maiduguri Teaching Hospital, (UMTH) Maiduguri. The age, sex, blood sugar level, urine sugar level, and weight were recorded, collected and tabulated for diabetics' patients respectively. Statistical package for social sciences (SPSS) version 17 employed for the analysis based on recorded data of (987) Diabetic patients at the University of Maiduguri Teaching Hospital, (UMTH) from the year (2002-2011) [15,16].

Results and Discussion

Interpreting the printout results

Table 1: Table for a diabetic or normal person for assessment $\hat{Y} \geq \hat{M}$.

S/NO	Outcome	Criterion	Health Status
1	$\hat{Y}_1$	$\hat{Y}_1 \geq \hat{M}$	Diabetic patient
2	$\hat{Y}_2$	$\hat{Y}_2 \geq \hat{M}$	Normal healthy
3	$\hat{Y}_3$	$\hat{Y}_3 \geq \hat{M}$	Normal healthy
4	$\hat{Y}_4$	$\hat{Y}_4 \geq \hat{M}$	Diabetic patient
5	$\hat{Y}_5$	$\hat{Y}_5 \geq \hat{M}$	Normal healthy

In the discriminant analysis we are trying to predict group membership, so firstly we examine whether there are any significant differences between groups on each of the independent variables using group means and ANOVA results data. Table 1 test of equality of group means the results of univariate ANOVA's carried out for each independent variable are highly significant they differ (Sig.=.000) (Table 2). The Pooled Within-Group Matrices also supports the use of these IV's as covariance, Age and Weight are highly significant while intercorrelations are moderately good.

Table 3 Provides an index of the importance of each predictor like the standardized regression coefficients (beta's) did in multiple regression. The sign indicates the direction of the relationship. Blood sugar was the strongest predictor while Urine sugar was next in importance as a predictor. These two variables with large coefficients stand out as those that strongly predict allocation to the Diabetic or Healthy group. Age, absence from work and Weight were less successful as predictors. These "discriminant function coefficients" work just like the beta-weights in regression. Based on these, we can write out the equation for the discriminant function:

$$DF = 0.080X_{2i} + 0.202X_{3i} + 0.631X_{4i} + 0.615X_{5i}$$

Using this equation, given the Diabetic variables on Age, Weight, Blood sugar, and Urine sugar, we can calculate their score on the discriminant function. The standardized canonical discriminant function coefficients table. The interpretation of the discriminant coefficients (or weights) is like that in multiple regressions.

Table 2: Tests of equality of group means.

Wilks' Lambda	F	df1	df2	Sig.	
Age	0.958	23.846	1	539	0
Weight	0.863	85.285	1	539	0
Blood sugar	0.571	404.158	1	539	0
Urine sugar	0.566	413.316	1	539	0

Table 3: Pooled within-groups matrices.

		Age	Weight	Blood sugar	Urine sugar
Covariance	Age	259.082	56.321	.888	2.77
	Weight	56.321	179.359	1.838	5.901
	Blood sugar	.888	1.838	9.420	1.430
	Urine sugar	2.770	5.901	1.430	10.049
Correlation	Age	1.000	.261	.018	.054
	Weight	.261	1.000	.045	.139
	Blood sugar	.018	.045	1.000	.147
	Urine sugar	.054	.139	.147	1.000

Group centroids

Table 4: Standardized canonical discriminant function coefficients.

	Function
	1
Age	.08
Weight	.202
Blood sugar	.631
Urine sugar	.615

A further way of interpreting discriminant analysis results is to describe each group regarding its profile, using the group means of the predictor variables. These group means are called centroids.

These display in the Group Centroids table (Table 4). Healthy patients have a mean of -1.200 while Diabetic patient produces an average of 1.161. Cases with scores near to centroids predicted as belonging to that group.

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Unstandardized Canonical Discriminant Functions Evaluated At Group Means. Here are the group centroids. If someone's response on the discriminant function is closer to −1.200, then the data came for is patient is healthy "response (0)". If the reaction on the DF is closer to 1.161, then the data probably came from a Diabetic patient. In practical terms, we usually figure out which group a person is in by calculating a cut score halfway between the two centroids:

Cut Score = $\hat{M}=\frac{1}{2}\left(\hat{i}_1+\hat{i}_2\right)=\frac{1}{2}(-1.200+1.161)=0.0195$

If an individual patient on the DF (calculated by plugging in their scores on Age, Weight, and Blood sugar and Urine sugar to the DF equation we wrote out above) is above 0.0195, then they were probably Diabetic patients. If their DF score is below 0.0195, then they were perhaps healthy patients (Table 5).

Table 5: Functions at group centroids.

Diabetic	Function
	1
0	-1.2
1	1.161

Fisher's linear discriminant functions

The Fishers linear discriminant model for each group is computed as follows:

Normal healthy: $\pi_1: \; Y_1 = X'S^{-1}\left(\bar{X}_2 - \bar{X}_1\right)$

$$Y = -15.543 + .114X_{2i} + .285X_{3i} + .283X_{4i} + .633X_{5i}$$

Diabetic patients $\pi_2: \; Y_2 = X'S^{-1}\left(\bar{X}_2 - \bar{X}_1\right)$

$$Y = -27.138 + .125X_{2i} + .320X_{3i} + .769X_{4i} + 1.091X_{5i}$$

The classification rule is to substitute into the Fishers linear discriminant model for each group evaluate; then classified into the group whose model produced the higher discrimination score. This criterion is entirely equivalent to the standardized linear discriminant model (Table 6).

a) 2% of selected original grouped cases correctly classified.

b) 88.5% of unselected original grouped cases correctly classified.

Here's the classification table that we got by selecting that option in the SPSS dialog box. It gives information about actual group membership vs. predicted group membership. Overall % correctly classified = 88.2%. This part of the table shows you what kinds of misclassification took place. By relating actual groups to predicted groups Percentage correct predictions without percentage correct predictions without cross-validation.

Table 6: Classification function coefficients.

	Diabetic	
	0	1
Age	.114	.125
Weight	.285	.32
Blood sugar	.283	.769
Urine sugar	.633	1.091
(Constant)	-15.543	-27.138

The classification rule that is as follows:

- Classify as Group 0 (Normal Healthy) if $Y < 0.0195$
- Classify as Group 1 (Diabetic patient) if $Y \geq 0.0195$

$$DF = 0.080X_{2i} + .202X_{3i} + .631X_{4i} + .615X_{5i}$$

The model also tested for goodness of fit and classificatory power for new observations. The discriminant model has some few patients with the misclassified case for UMTH, Maiduguri which proves to be very good. This model is used to analyze the date which could be collected from other hospitals and other regions of the country. The predictions will be helpful for a cure for other patient and will be in welfare or Nigerian society.

Discriminant analysis on female responses

Table 7: Classification results.

			Diabetic	Predicted Group Membership		Total
				0	1	
Cases Selected	Original	Count	0	243	23	266
			1	41	234	275
		%	0	91.4	8.6	100
			1	14.9	85.1	100
Cases Not Selected	Original	Count	0	206	28	234
			1	23	188	211
			Ungrouped cases	0	1	1
		%	0	88	12	100
			1	10.9	89.1	100
			Ungrouped cases	0	100	100

The Table 7 shows the means that we asked for it gives means on each variable for people in each sub-group, and also the overall mean on each variable. A rough idea of variables that may be significant can obtained by inspecting the group means and Standard

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deviations. The mean differences between Weight and Age depicted in to suggest that these may be good discriminators as the separations are large in Table 7 above 'test of equality of group means the results of univariate ANOVA's carried out for each independent variable are highly significant, they differ (Sig.=.000) (Table 8). The covariance matrix has 443 degrees of freedom. Table 9 gives us the standardized coefficients for each discriminant function.

Table 8: Tests of equality of Group mean.

	Wilks' Lambda	F	df1	df2	Sig.
Age	0.948	24.099	1	443	0
Weight	0.894	52.463	1	443	0
Blood sugar	0.565	341.642	1	443	0
Urine sugar	0.579	321.719	1	443	0

Table 9: Pooled within-groups matrices.

		Age	Weight	Blood sugar	Urine sugar
Covariance	Age	213.370	55.333	.326	1.403
	Weight	55.333	188.606	.307	5.53
	Blood sugar	.326	.307	9.873	2.332
	Urine sugar	1.403	5.530	2.332	11.125
Correlation	Age	1.000	.276	.007	.029
	Weight	0.276	1.000	.007	.121
	Blood sugar	0.007	0.007	1.000	.223
	Urine sugar	0.029	0.121	.223	1.000

These "discriminant function coefficients" work just like the beta-weights in regression. Based on these, we can write out the equation for the discriminant function:

Using this equation, given the Diabetic variables on Age, Weight, Blood sugar, and Urine sugar. We can calculate their score on the discriminant function. To figure out what that DF score means, look at the group centroids, below

$$DF = .130X_{2i} + .191X_{3i} + .636X_{4i} + .576X_{5i}$$

Unstandardized canonical discriminant functions evaluated at group means.

Table 10: Standardized canonical discriminant function coefficients.

	Function
	1
Age	.130
Weight	.191
Blood sugar	.636
Urine sugar	.576

Table 10 tells us the correlation between each item and the discriminant function. Those come from the table called "standardized canonical discriminant function coefficients." Here are the group centroids. If someone's response on the discriminant function is closer to –1.085, then the data came for is patient is healthy "response (0)". If the response on the DF is closer to 1.23, then the data probably came from a Diabetic patient. In practical terms, we usually figure out which group a person is in by calculating a cut score halfway between the two centroids:

Cut score $\left(\hat{M}\right) = \hat{M} = \frac{1}{2}\left(\hat{I}_1 + \hat{I}_2\right) = \frac{1}{2}(-1.085 + 1.203) = 0.059$

If an individual patient on the DF (calculated by plugging in their scores on Age, Weight, and Blood sugar and Urine sugar to the DF equation we wrote out above) is above 0.059, then they were probably Diabetic patients. If their DF score is below 0.059, then they were perhaps healthy patients (Table 11).

Table 11: Functions at group centroids.

Diabetic	Function
	1
0	-1.085
1	1.203

Fisher's linear discriminant functions

Table 12: Classification function coefficients.

	Diabetic	
	0	1
Age	.121	0.141
Weight	.281	0.313
Blood sugar	.284	0.748
Urine sugar	.576	0.971
(Constant)	-15.254	-26.193

The Fishers linear discriminant model for each group is computed as follows:

Normal healthy π_1

$$Y_1 = X'S^{-1}\left(\bar{X}_2 - \bar{X}_1\right)$$

$$Y_1 = -15.254 + 0.121X_{2i} + 0.281X_{3i} + 0.281X_{4i} + 0.576X_{5i}$$

Diabetic patients π_2

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$$Y_2 = X'S^{-1}\left(\bar{X}_2 - \bar{X}_1\right)$$

$$Y_2 = -26.193 + 0.141X_{2i} + 0.313X_{3i} + 0.748X_{4i} + 0.971X_{5i}$$

The classification rule is to substitute into the Fishers linear discriminant model for each group and evaluate; then classified into the group whose model produced the higher discriminant score. This criterion is equivalent to the standardized linear discriminant mode (Table 12).

a. 89.4% of selected original grouped cases correctly classified

b. 88.4% of unselected original grouped cases correctly classified

Non-parametric tests

(Table 13)

Table 13: Classification results.

			Diabetic	Predicted Group Membership		
				0	1	Total
Cases Selected	Original	Count	0	213	21	234
			1	26	185	211
			Ungrouped cases	0	1	1
		%	0	91	9	100.0
			1	12.3	87.7	100.0
			Ungrouped cases	.0	100	100.0
Cases Not Selected	Original	Count	0	243	23	266
			1	40	235	275
		%	0	91.4	8.6	100.0
			1	14.5	85.5	100.0

Chi-square test frequencies

a. 0 cells (.0%) have expected frequencies less than 5. The minimum expected cell frequency is 493.5.

b. 0 cells (.0%) have expected frequencies less than 5. The minimum expected cell frequency is 12.3 (Table 14-16).

Table 14: Descriptive statistics.

	N	Mean	Std. Deviation	Minimum	Maximum
Sex	987	1.45	0.498	1	2
Age	987	48.45	16.013	1	95

Table 15: Sex.

	Observed N	Expected N	Residual
1	541	493.5	47.5
2	446	493.5	-47.5
Total	987		

Table 16: Age.

S. No.	Observed N	Expected N	Residual	S. No.	Observed N	Expected N	Residual
1	10	12.3	-2.3	49	10	12.3	-2.3
2	6	12.3	-6.3	50	83	12.3	70.7
3	1	12.3	-11.3	51	12	12.3	-0.3
4	2	12.3	-10.3	52	22	12.3	9.7
5	1	12.3	-11.3	53	17	12.3	4.7
8	2	12.3	-10.3	54	15	12.3	2.7
9	3	12.3	-9.3	55	44	12.3	31.7
12	3	12.3	-9.3	56	24	12.3	11.7
13	3	12.3	-9.3	57	9	12.3	-3.3
14	5	12.3	-7.3	58	15	12.3	2.7
15	2	12.3	-10.3	59	11	12.3	-1.3
16	1	12.3	-11.3	60	75	12.3	62.7
17	4	12.3	-8.3	61	6	12.3	-6.3

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18	4	12.3	-8.3	62	11	12.3	-1.3
19	7	12.3	-5.3	63	11	12.3	-1.3
20	2	12.3	-10.3	64	7	12.3	-5.3
22	2	12.3	-10.3	65	35	12.3	22.7
23	1	12.3	-11.3	66	9	12.3	-3.3
24	5	12.3	-7.3	67	4	12.3	-8.3
25	11	12.3	-1.3	68	10	12.3	-2.3
26	5	12.3	-7.3	70	43	12.3	30.7
27	5	12.3	-7.3	71	3	12.3	-9.3
28	7	12.3	-5.3	72	2	12.3	-10.3
29	11	12.3	-1.3	73	8	12.3	-4.3
30	22	12.3	9.7	74	1	12.3	-11.3
31	8	12.3	-4.3	75	15	12.3	2.7
32	16	12.3	3.7	76	2	12.3	-10.3
33	4	12.3	-8.3	77	3	12.3	-9.3
34	4	12.3	-8.3	78	5	12.3	-7.3
35	33	12.3	20.7	80	9	12.3	-3.3
36	7	12.3	-5.3	81	3	12.3	-9.3
37	5	12.3	-7.3	84	1	12.3	-11.3
38	28	12.3	15.7	85	1	12.3	-11.3
39	17	12.3	4.7	88	1	12.3	-11.3
40	54	12.3	41.7	90	1	12.3	-11.3
41	3	12.3	-9.3	92	1	12.3	-11.3
46	11	12.3	-1.3	95	1	12.3	-11.3
47	17	12.3	4.7	**Total**	**987**		
48	16	12.3	3.7				

Conclusion

The consistent high hit rates for all the analysis on the Diabetic Mellitus responses. The overall percentage of correct classifications which is 88.2 and 89.4%, as seen in the classification results for this study (Tables 6 and 12), which is a measure of predictive ability shows that discriminant analysis can be used to predict the patient's knowledge or disability the diabetic responses of the variable(s) that have a relationship with cause of the disease. This study tends to illustrate the logicality and wisdom in examining related statistical technique used for prediction. The use of discriminant analysis in this manner that is, conducting discriminant analysis for predictive purpose enables us to identify the patient's condition either he/she is healthy ("0" response), or diabetic ("1" response) termed at risk; as well as brought to light the difficulty in understanding its concept. Therefore, there is a need for instructional intervention.

In conclusion, this study shows that discriminant analysis provides results that are both more interpretable and statistically sound, in addition to being a statistically correct procedure for prediction purpose than traditional measures. Discriminant analysis classification is found to be vital and useful for diagnoses in any hospital. A multivariate normal distribution assumption holds for the response variables. This means that each of the dependent variables is generally distributed within groups, that any linear combination of the dependent variables normally distributed, and that all subsets of the variables must be multivariate normal.

I. Each group must have a sufficiently large number of cases.

II. Different classification methods may be used depending on whether the variance-covariance matrices are equal (or very similar) across groups.

III. Non-parametric discriminant function analysis, called kth nearest neighbor, can also be performed.

Recommendations

As this study focused on collected data from varies sources and analysis predicts the recommendations which would be beneficial for Doctors and hospitals in other part of country in African commitment we have following recommendations. The present analysis leads suggestion for the investigator working in health sector to control diseases named Diabetes.

i. In the light of the above, it recommended that Doctors and Clinics should adopt the use of the models built by this research to detect the prevalence of Diabetics among adults so that adequate measures for prevention and control of Diabetics can take early enough to alert the danger of the full manifestation of the disease.

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It is also recommended that the Discriminant model built should be used for capable of tackling diabetes mellitus cases in (UMTH), Maiduguri, and Borno state.

Table 17: Test statistics.

	Sex	Age
Chi-Square	9.144[a]	1696.931[b]
Df	1	79
Asymp. Sig.	0.002	0

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