



## Comparative Sensitivity Performance of the Discriminant Function and Logistic Regression under Different Training and Test Samples for Predicting Birth Outcomes

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### Authors' contributions

This work was carried out in collaboration among all authors. Author KAA conceptualized and designed the study, performed the statistical analysis, wrote the protocol and wrote the first draft of the manuscript. Author KOA managed the analyses of data. Authors MKMO and RA searched and drafted the literature and a review of the paper was handled by author DO. All authors read and approved the final manuscript.

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## Abstract

Population increases with time through birth, and researchers have often used either Logistic regression model or Discriminant analysis to study and classify birth outcomes. In this paper, the authors sought to investigate the sensitivity of the two methods used separately to explain and classify birth outcomes under different training and test samples. Out of 5000 birth outcomes data comprising of 1250 stillbirth cases and 3750 live births and with four test samples (50%, 40%, 30% and 25%). The Discriminant Analysis averagely correctly classified 89.8% of birth outcome cases compared to 82.4% for the logistic regression. The Discriminant analysis on the average correctly predicted 94.2% of live births compared to 83.1% for the Logistic regression. On stillbirth, 75.7% and 80.9% success rates were recorded for Discriminant Analysis and Logistic regression respectively. All predictors (Maternal Age, Gestational period, fetus weight, parity and Gravida) were statistically significant ( $p$ -value  $< 0.01$ ) in determining birth outcomes of pregnancies in both methods. The results showed that, both techniques are almost similar in predicting birth outcome. However, the Discriminant analysis is preferred for the 25% and 50% test samples whiles, the logistic regression performed well under the 30% and 40% test sample data.

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## **1 Introduction**

According to Froen et al. [1], stillbirth is the death of a baby in weeks before birth, or during labor or at birth. Stillbirth definition according to duration in weeks cutoff points vary. With the World Health Organization (WHO), stillbirth is the death of a baby of at least 28 weeks of pregnancy, while the UK typically defines stillbirth as the death of the fetus of at least 24 weeks, and other high-income countries use a minimum of 22 weeks [2].

In [2,3], authors estimated that approximately 2.6 million stillbirths occur annually in the world with more than 7,300 stillbirths happening every day. More significantly, more than two-thirds of these stillbirths are identified to occur either in the South-East Asian countries or Africa. Moreover, findings of [2,4], estimated that, the rate of stillbirth is ten times higher in developing countries compared to developed countries with Sub-Saharan Africa accounting for more than 850, 000 cases annually with at least 60% of the affected being poor-rural families.

Several risk factors have been identified for the continuous escalating incidence of stillbirth [5,6]. These risk factors range from maternal, perinatal, socio-economic and the quality health care services. [7,8], opined that the significant maternal risk factors linked to stillbirth include advanced maternal age, multi-parity, previous occurrence or experience of stillbirth and undetected pregnancy infections. Similarly, [9], identified the major risk factors contributing to stillbirth among mothers as; maternal age, socioeconomic status, obesity, sleeping position during pregnancy, hypertension, and febrile illness during pregnancy among others.

Classification of birth outcomes into either live or still (dead) based on some risk factors is very important to healthcare providers. In this paper, the Logistic Regression (LR) and the Quadratic Discriminant Function (QDF) are compared in the classification of birth outcomes as either Live or Stillbirth using both maternal and neonatal characteristics. The study further compared the sensitivity performance of these two Multivariate Statistical Analysis (MSA) techniques under different training and test sample ratios. With the dependent variable being dichotomous and nominal where; live birth is denoted by 1 and stillbirth by 0. According to Lin [10], whenever the dependent variable is nominal in nature, then both discriminant analysis and logistic regression analysis are applicable and appropriate.

Several studies in other areas have compared these two techniques in relation to efficiency, importance and classification power. Balogun et al. [11], concluded both methods (QDF and LR) gave high percentage of correct classifications, but discriminant analysis outperformed the logistic regression slightly in apparent correct classification rate. In addition, [12,13,14] found that the two techniques have virtually the same ability to predict and classify cases at similar efficacy. They however concluded that, the LR gives better results than the Discriminant function. This current study investigates the performance of the two methods under varying training and test samples for birth outcome data. The significance of this research is to correctly classify birth outcomes as either live or stillbirth using multivariate methods, and more importantly to determine how the predictor variables contribute to discrimination and classification of new observations.

The study compares the sensitivity of both Discriminant Analysis function and Logistic Regression in classifying live birth and stillbirth under varying training and test samples. The performance comparison is based on the actual error rates (AER) as well as the receiver operating characteristic (ROC) curve and the area under the curve (AUC) statistics.

## **2 Materials and Methods**

The study used secondary data on deliveries collected over a three- year period (2013 to 2015) from the Greater Accra Regional Hospital in the capital city of Ghana. The hospital serves parts of the Accra

Metropolis and serves as a referral facility to other surrounding communities from District Assemblies such as Ledzokuku – Krowo, Ga-South and Ga West Municipalities to the East, West and North respectively of the Accra Metropolis.

The data consists of five predictors made up of three maternal variables (Maternal age, parity and gravida) and two fetus variables (gestational period and weight of the fetus at birth) and one dependent variable (birth outcome). The data contains 5000 birth outcomes made-up of 3,750 live birth and 1,250 stillbirth outcomes. The data was provided anonymously for purpose of study. The dataset was divided into two samples; the training and test samples respectively. The training samples were used in building models whereas, test samples were employed for performance evaluations. All data analyses were carried out using both R-Studio (R version 3. 5. 1) and SPSS (version 23).

## 2.1 Discriminant analysis

Discriminant Analysis (DA) is a statistical technique that finds a combination of the original independent variables that gives a best possible separation between groups in a given dataset. [15], opined that, Discriminant analysis (DA) is a commonly employed multivariate statistical tool with two essential and related objectives; discrimination and classification.

According to Poulsen and French [16], DA is used to determine which set of continuous variables discriminate between two or more naturally occurring sets or groups. Given the set of independent variables;  $(X_1, X_2, \dots, X_n)$  (Maternal and neonatal factors in this study) the technique is to derive a combination of these variables which best separate or discriminate between the two groups (birth outcome in our case). The function is generated from the training samples for which the groups they belong are known and this generated function can be applied to new cases (testing sample) with their measurement of the independent variables but unknown membership.

DA is a parametric statistical method which assumes that the sample data comes from a normally distributed population and the variance-covariance matrices of the independent variables are the same for all groups [15, 17]. The Linear Discriminant classification rule is used when the multivariate normality and equal covariance structures across groups' assumptions are met. On the other hand, if the multivariate normality assumption is met and the condition of equal covariance across groups is violated, the Quadratic Discriminant classification rule is often suggested as the more appropriate alternative [18]. Besides, the normality and equal covariance matrices assumptions, the DA also requires the large sample size data specifically, the number of cases in each natural group should exceed the number of predictors and Non-multicollinearity among the set of predictors.

Let the two independent populations defined as  $\pi_1$  and  $\pi_2$  for live birth and stillbirth respectively. Every item has measurements for k random variables  $X_1, X_2, \dots, X_k$  such that the observed values differ to some extent from one class (live birth) to the other (stillbirth). The distributions associated with both populations will be described by their density functions  $f_1$  and  $f_2$  respectively. Let us consider an observed value  $X = (x_1, x_2, \dots, x_p)^T$ . Then  $f_1(x)$  is the density function in  $\mathcal{X}$ , if  $X$  belongs to  $\pi_1$  and  $f_2(x)$  is the density function in  $\mathcal{X}$ , if  $X$  belongs to the population  $\pi_2$ . The multivariate normal density with heterogeneous covariance matrix structure is defined as

$$f_i(x) \sim N_K(\mu_i, \Sigma_{k \times k}), i = 1, 2 \quad (1)$$

Which can be expressed as

$$f_i(x) = (2\pi)^{\frac{-k}{2}} |\Sigma|^{-\frac{1}{2}} \exp -\frac{1}{2} (x - \mu_i)^T \Sigma^{-1} (x - \mu_i) \quad (2)$$

Where,

- $i = 1,2$ , the number of groups (live and still)
- $k$  = Number of variables measured
- $f_i(x)$  = Density function for population 1 and 2 respectfully
- $\mu_i$  = Mean vector for population 1 and 2 respectfully
- $\Sigma_i$  = Variance-covariance matrices for population 1 and 2 respectfully

From the density functions in (2) above, we define the likelihood- ratio function;

$$\frac{f_1(x)}{f_2(x)} = \exp \left[ -\frac{1}{2} (x - \mu_1)^T \Sigma_1^{-1} (x - \mu_1) + \frac{1}{2} (x - \mu_2)^T \Sigma_2^{-1} (x - \mu_2) \right] \times \left( \frac{|\Sigma_1|}{|\Sigma_2|} \right)^{\frac{1}{2}} \quad (3)$$

Simplifying and taking the natural log yields

$$\ln \left( \frac{f_1(x)}{f_2(x)} \right) = -\frac{1}{2} x^T (\Sigma_1^{-1} - \Sigma_2^{-1}) x + (\mu_1^T \Sigma_1^{-1} - \mu_2^T \Sigma_2^{-1}) x - \frac{1}{2} (\mu_1^T \Sigma_1^{-1} \mu_2 - \mu_2^T \Sigma_2^{-1} \mu_2) - \frac{1}{2} \ln \left( \frac{|\Sigma_1|}{|\Sigma_2|} \right) \quad (4)$$

In this paper, we let  $\Omega$  denote the space (collection of all birth outcomes) and partition the space as  $\Omega = R_1 \cup R_2$  where  $R_1$  is the subspace of live birth,  $\pi_1$  and  $R_2 = \Omega - R_1$  the subspace of stillbirth outcomes,  $\pi_2$ . Also, we define  $p_i = (X \in \pi_i)$ , where  $i = 1, 2$  as the prior probabilities of population 1 and 2 respectively such that  $p_1 + p_2 = 1$ . It therefore follows that, assuming equal cost of misclassification for both live birth and stillbirth. Then the classification rule is to classify  $x_0$  as  $\pi_1$  if;

$$-\frac{1}{2} x^T (\Sigma_1^{-1} - \Sigma_2^{-1}) x + (\mu_1^T \Sigma_1^{-1} - \mu_2^T \Sigma_2^{-1}) x - \frac{1}{2} (\mu_1^T \Sigma_1^{-1} \mu_2 - \mu_2^T \Sigma_2^{-1} \mu_2) - \frac{1}{2} \ln \left( \frac{|\Sigma_1|}{|\Sigma_2|} \right) \geq \ln \left( \frac{P_1}{P_2} \right) \quad (5)$$

And classify  $x_0$  to  $\pi_2$  otherwise [19].

### 2.1.1 Classification rule

The test (validation) sample data for the performance assessment of the derived discriminant functions is carried out by averaging the two centroids for the live birth and stillbirth. The cut-off point for the classification of new cases is defined as

$$C = \frac{Z_{Live} + Z_{Still}}{2}$$

Where, C is the cut-off point

$Z_{Live}$  : Centroid for live birth outcome

$Z_{Still}$  : Centroid for stillbirth outcome

With  $Z_{Live}$  and  $Z_{Still}$  determined from each of the training samples, a new birth outcome is classified to group 1 (live birth) if the discriminant score is > than the cut- off point and to group 2 (stillbirth) if otherwise

### 2.1.2 Wilks' Lambda ( $\Lambda$ )

The Wilks' Lambda is a test statistic employed in discriminant analysis to assess the significance or importance of the discriminant functions derived [16]. In DA, it is a measure of how well each function separates cases into groups. Wilk's lambda, when combined with dependent variables, executes the same role as the F-test performs in one-way analysis of variance. It ranges between 0 and 1, where 0 means total discrimination, and 1 means no discrimination. Hence, Wilks' lambda values close to zero indicate a significant discriminating function. The Wilks' lambda is defined as

$$\Lambda = \frac{|S_W|}{|S_T|}$$

Where,

$S_W$  = Sum of squares within groups

$S_T$  = Sum of squares Total

### 2.1.3 Box's M test

This is a multivariate data analysis test statistic used to examine the homogeneity (equality) of the variance - covariance matrices in the groups or classes [20]. Large Box's M values together with a small p-value indicates a violation of homogeneity of covariance assumption. Under situations with large sample size, the Box's M value turns to be large where the appropriate alternative employed for comparison of the groups will be the natural logarithms of the variance-covariance matrices [21].

If samples come from non-normal distribution, then Box's test may simply be testing for non-normality. For the two categories (live birth and stillbirth) and independent populations where  $\Sigma_{Live}$  and  $\Sigma_{Still}$  are sample covariance matrices from the populations. Then we can test the hypothesis;

$$H_0 : \Sigma_{Live} = \Sigma_{Still}$$

Vs.

$$H_1 : \Sigma_{Live} \neq \Sigma_{Still}$$

If the p-value of the Box's M test is less than alpha (p-value < 0.05), we reject the assumption of homogeneity and proceed with quadratic discriminant analysis. Otherwise, we proceed with linear discriminant analysis.

## 2.2 Logistic regression analysis

The Logistic regression (LR) model is part of a category of statistical models called generalized linear models (GLM). This broad class of models includes ordinary regression and ANOVA, as well as multivariate statistics such as ANCOVA and log linear regression [22]. Logistic regression allows one to predict a discrete outcome, such as group membership (live birth or stillbirth), from a set of variables that may be continuous, discrete, dichotomous or a mixture of any of these. It is important to recall that in

multiple linear regression the basic idea is to draw the ordinary least squares (OLS) line around which the values of Y (the outcome variable) are distributed. In contrast, the logistic regression attempts to estimate the probability that a given birth outcome will fall into live birth or stillbirth. Working in terms of probability helps to interpret the coefficients in the logistic regression model in a meaningful manner, as in the case of the coefficients in linear regression [17].

### 2.2.1 The model

Given a dichotomous dependent variable (birth outcome), that is, which assumes a value 1 with a probability of success (live birth) p, and the value 0 with probability of failure (stillbirth), 1-p. The predictor variables in logistic regression can take any form, that is, logistic regression makes no assumption about the distribution of the independent variables. They do not have to be normally distributed, linearly related or of equal variance within each group. The relationship between the predictors ( $x_1, x_2, \dots, x_k$ ) and response (Y) variables is not a linear function in logistic regression, instead, the logistic regression function is used, which is the logit transformation of the probability of success (p).

For a set of k predictors X ( $x_1, x_2, \dots, x_k$ ) and a binary or dichotomous outcome variable Y, the logistic regression model predicts the logit of Y from X as expressed in the form

$$\text{Log}\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_k X_k \quad (6)$$

It follows that, the probability,

$$P(Y = \text{Birth outcome} | X_1 = x_1, X_2 = x_2, \dots, X_k = x_k) = \frac{e^{\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_k X_k}}{1 + e^{\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_k X_k}} \quad (7)$$

Where  $\beta_0$  is the intercept parameter and  $\beta_k^s$  are the coefficients for the k predictors.

The method of maximum likelihood estimation (MLE) is used to estimate the parameters of the LR model. The MLE approach is considered one of the widely used methods for parameter estimation of both linear and nonlinear models due to its tractable properties of efficiency and sufficiency especially with large sample sizes [23]. The MLE methods estimate parameters of the LR model through Newton-Raphson iterative method which undergoes several repetitions of calculations until the parameter estimates converge.

The model adequacy, overall goodness of fit as well as the significance of the parameters of the LR model are assessed through the likelihood ratio (Omnibus), the Wald tests as well as the  $R^2$  values which indicate the proportion of variation in the dependent variable (birth outcome) that is explained by the model with the significant predictors [24,17]. All tests above use the chi-square test statistic at a specified level of significance(0.05). All test statistics require the observed p-values to be less than 0.05 for the results to be significant.

## 2.3 Performance evaluation

The performance of both Logistic Regression and Discriminant Analysis classification functions is assessed by their misclassification error rates (Actual Error Rate (AER)) for utilizing such functions to classify new cases [19] together with the receiver operating characteristic (ROC) curve [25,26].

### 2.3.1 Actual Error Rate (AER)

The actual error rate (AER) refers to the fraction of cases belonging to the test sample that are misclassified by the classification rule. The AER is relatively easy to calculate and usually preferred over the apparent

error rate (APER) which is based the training sample as it often underestimates the actual error when classifying new observations.

The AER determined from an independent “test sample” of new cases whose true populations are known is given as  $AER = \frac{n_{1M}^T + n_{2M}^T}{n_1 + n_2}$

Where  $n_{1M}^T$  and  $n_{2M}^T$  are the test sample observations misclassified as  $\pi_1$  and  $\pi_2$  respectively.

### 3 Results and Discussion

#### 3.1 Discriminant analysis

The group statistics (mean (sd)) for the independent groups (live birth and stillbirth) and the combination of the two are below (Table 1). The results show that, for all predictors the mean values of live birth outcomes are slightly larger than those of stillbirth outcomes and hence are different. The Wilk’s Lambda results (Table 2) further suggest that, the mean values are significantly ( $P < 0.01$ ) different for both maternal and neonatal variables for live birth and stillbirth outcomes. The results also show that these predictor variables are significant determinants of birth outcome.

**Table 1. Group statistics**

Pregnancy outcome	Predictors	Mean (sd)
Stillbirth	Maternal Age (Years)	29.9(5.7)
	Parity	2(1)
	Gravida	3(1)
	Gestational period (Weeks)	36.5(4.1)
	Weight of fetus (Kg)	2.5(0.9)
Live birth	Maternal Age (Years)	33.9(4.8)
	Parity	3(1)
	Gravida	5(1)
	Gestational period (Weeks)	38.7(2.7)
	Weight of fetus (Kg)	3.0(0.6)
Total (Combined)	Maternal Age (Years)	32.8(5.4)
	Parity	2.8(1.4)
	Gravida	4.1(1.3)
	Gestational period (Weeks)	38.1(3.3)
	Weight of fetus (Kg)	2.9(0.8)

**Table 2. Tests for effects of predictors**

Predictors	Wilks' Lambda	F	df <sub>1</sub>	df <sub>2</sub>	Sig.
Maternal Age (Years)	0.876	462.34	1	3263	< 0.01
Parity	0.621	1991.69	1	3263	< 0.01
Gravida	0.461	3815.62	1	3263	< 0.01
Gestational period (Weeks)	0.895	382.48	1	3263	< 0.01
Weight of fetus (Kg)	0.898	369.39	1	3263	< 0.01

Results on the variance- covariance matrices for live birth (group 1) and stillbirth (group 2) are presented in Table 3. The Box’s M test is significant with F-value =172.209 and  $P < 0.01$  (Table 4). This shows that, the

covariance matrices for the two birth categories (Live and Stillbirth) are not equal and suggest the use of quadratic discriminant analysis as opposed to the linear form.

**Table 3. Covariance matrices**

Birth outcome		Maternal age (Yrs.)	Parity	Gravida	Gestation period	Fetus weight
Stillbirth	Maternal Age (Yrs.)	31.296				
	Parity	3.878	1.555			
	Gravida	4.094	1.399	1.764		
	Gestation Period (Wks.)	-0.386	-0.237	-0.315	17.039	
	Fetus weight	0.37	0.045	0.02	2.453	0.848
Live birth	Maternal Age (Years)	21.482				
	Parity	1.036	0.776			
	Gravida	0.091	0.029	0.194		
	Gestation Period (Wks.)	-0.873	0.04	-0.076	6.942	
	Fetus weight (kg)	-0.025	0.004	0.003	0.0925	0.455

**Table 4. Box's test statistics**

Box's M	2587.967
F Approx.	172.209
$df_1$	15
$df_2$	21771907.611
Sig.	<0.01

The Quadratic Discriminant Function (QDF) was applied to the 50%, 60%, 70% and 75% training sample data and results are presented below in "Table 5". For each of the training scenarios, the discriminant functions derived were statistically significant at  $\alpha = 0.01$  with Wilk's lambda values of 0.44, 0.43, 0.43 and 0.43 for the 50%, 60%, 70% and 75% training samples respectively. Also, all eigenvalues for the respective scenarios are greater than 1 and the canonical correlations for each scenario is at least 0.72 ( $P < 0.01$ ) which shows that, these discriminant functions are significant in explaining the variations in the birth outcomes.

**Table 5. Discriminant analysis models statistics**

% of training	Eigenvalue	Wilk's lambda	Can. correlation	Chi-square statistic	df	Sig.
All	1.381	0.42	0.762	2829.16	5	< 0.01
50 %	1.274	0.44	0.748	1344.17	5	< 0.01
60%	1.325	0.43	0.755	1649.10	5	< 0.01
70%	1.324	0.43	0.755	1932.11	5	< 0.01
75%	1.331	0.43	0.756	2085.53	5	< 0.01

Based on the parameter estimates for the discriminant functions (Table 6), it is observed that, with the exception of maternal age of women and the constant coefficient which are negative, the other predictors (parity, gravida, gestational period and fetus weight at birth) are positive. The negative coefficients for maternal age imply that, increase in age of women reduces the chance for live birth. On the contrary, an increase in parity, gravida, gestational period and fetus weight increases the chances of having a live birth.



The centroids for both birth outcomes are presented for each training sample ratio based on which the classification rule is obtained to assign new observations.

The performance of the discriminant functions based on the percent correct classification for the live and stillbirth as well as the overall correct classifications are presented in Table 7 and Table 8 for the training and testing samples respectively. With the training set, the DA performed well in classifying live birth with at least 93.8% of correctly classified compared to at least 70.0% for stillbirth outcome. On the respective ratios, the percent of correct classified birth outcomes are almost the same for both stillbirth and live birth outcomes. The overall percent of correct classification ranged from 88.2% to 90.1% with the highest and minimum corresponding to the 50% and 70% training sets respectively.

**Table 6. Discriminant analysis parameter estimates**

Predictors	50 %	60%	70%	75%
	Estimates	Estimates	Estimates	Estimates
Maternal Age	-0.0065	-0.0088	-0.0092	-0.0081
Parity	0.2368	0.2628	0.2497	0.2290
Gravida	0.9326	0.9135	0.9140	0.9265
Gestation	0.0931	0.0875	0.0851	0.0869
Fetus weight	0.0964	0.1232	0.1376	0.1310
Constant	-7.9887	-7.7460	-7.6458	-7.7247
Group				
Stillbirth	-1.5439	-1.5726	-1.5636	-1.5606
Centroids				
Live birth	0.8239	0.8417	0.8458	0.8521

**Table 7. Performance evaluation of DA (In sample)**

% Training data	Still birth	Live birth	Overall accuracy
50	70.0	97.0	90.1
60	71.5	98.3	88.2
70	71.3	98.2	89.6
75	71.3	93.8	89.7
Mean	71.0	96.8	89.4

With regard to the testing sample, it is observed that, the percentage of correctly classified stillbirth outcome improved over that of the training sample with a mean correct classification rate of 75.7% relative to 71.0%. However, that of the live birth outcome reduced to an average correct classification of 94.2% in the test sample from 96.8% in the training sample. The validation result (Table 8) also show that, in all, the 50% and 25% test samples performed better with overall classification accuracy rates of 92.2% and 92.7% respectively. The results further show that, the derived discriminant functions can correctly classify approximately 90% of birth outcomes correctly (AER = 0.102) which is increased further to 92.7% (AER= 0.073) under the 25 % test sample.

**Table 8. Performance evaluation DA (Test sample)**

% Testing data	Still birth	Live birth	Overall accuracy
50	72.8	98.5	92.2
40	73.7	90.3	86.2
30	79.4	90.5	87.9
25	77.0	97.4	92.7
Mean	75.7	94.2	89.8

### 3.2 Logistic regression

The logistic regression (LR) model results are presented in Table 9. Table 9 provides the statistics on the Omnibus test for the model coefficients and the model summary with the Cox and Snell and Nagelkerk  $R^2$

values for the LR models. The Omnibus test results for respective ratios are significant ( $P < 0.01$ ) with chi-square statistics values ranging from 1243.948 (df = 4) to 1593.297 (df = 5). The significance of the test shows that, the final LR models with predictors are better improvements of the baseline (constant only) LR model. The 50% and 60% training samples had only four predictors significant in the final LR model, whereas, the 70% and 75% had all five predictors significant. The  $R^2$  values for Cox and Snell give the lower bounds and the upper bounds by the Nagelkerke. The 50% training recorded the highest (77.5%) followed by the 60% with 72.3% and the least of 69.3% for the 70% training sample.

**Table 9. Omnibus tests and model summary**

% Training data	Cox & Snell $R^2$	Nagelkerke $R^2$	Chi-square	df	Sig.
50	0.590	0.775	1243.948	4	<0.01
60	0.555	0.723	1319.625	4	<0.01
70	0.534	0.693	1434.159	5	<0.01
75	0.544	0.707	1593.297	5	<0.01

The significant LR models parameter estimates are presented in Table 10. For each of the training sample ratio, the parameter estimate (standard error) together with the 95% confidence interval of the odds ratios (OR) are presented. The backward Wald parameter estimation procedure dropped the maternal age variable for the 50% and 60% training samples due to its non-significance in the model. The result shows that, parity, gestational period and weight of the fetus are all significant ( $P < 0.01$ ) and an increase these predictors increase the likelihood of the live birth outcome. Findings are similar to results obtained by [7,8,9]. The odds ratio (OR) for gravida indicates that, a unit increase in gravida makes it twice more likely to have a live birth. Similarly, an increase in the other predictors (parity, gestation and fetus weight) gives the woman an enhanced chance of a live birth outcome.

**Table 10. Model coefficients**

% Training data	Predictors	Age	Parity	Gravida	Gestation	Weight	Constant
50	Coef. (S.E)		0.218** (.070)	1.557** (.095)	0.160** (.024)	0.247* (.104)	-12.810** (.876)
	95% C. I (OR)		(1.085, 1.426)	(3.940, 5.717)	(1.120, 1.231)	(1.045, 1.569)	
60	Coef. (S.E)		0.276** (.062)	1.126** (.074)	0.143** (.021)	0.2947** (.090)	-10.505** (.734)
	95% C. I (OR)		(1.166, 1.489)	(2.670, 3.561)	(1.107, 1.203)	(1.126, 1.601)	
70	Coef. (S.E)	0.052** (.011)	0.273** (.058)	0.882** (.063)	0.138** (.019)	0.333** (.082)	-10.945** (.734)
	95% C. I (OR)	(1.031, 1.075)	(1.173, 1.473)	(2.136, 2.732)	(1.106, 1.191)	(1.188, 1.640)	
75	Coef. (S.E)	0.025* (.017)	0.289** (.056)	0.982** (.063)	0.137** (.019)	0.301** (.079)	-10.447** (.711)
	95% C. I (OR)	(1.004, 1.048)	(1.197, 1.490)	(2.362, 3.019)	(1.106, 1.189)	(1.157, 1.578)	

\*=  $p$ -value < 0.05, \*\*=  $p$ -value < 0.01

The training sample performance evaluation is presented in Table 11. Similar to the Discriminant Analysis, the LR in all, correctly classified live birth with average correct classification of 87.1% than stillbirth of 76.7%. For the overall in-sample correctly classified cases, the LR on the average recorded 84.5%

classification accuracy with the 50% and 60% training samples recording 85.2% and 86.3% accuracy respectively.

**Table 11. Performance evaluation (Training sample)**

% Training data	Still birth	Live birth	Overall accuracy
50	76.3	88.2	85.2
60	77.1	89.4	86.3
70	76.6	85.1	83.0
75	76.9	85.5	83.3
Mean	76.7	87.1	84.5

The validation sample performance assessment presented in Table 12 showed that, the LR models showed improvement in the classification of stillbirth outcomes from an average accuracy of 76.7% in the training sample to 80.9% in the test sample. On the other hand, the live birth outcome had a mean accuracy of 82.1% in the test data compared to 87.1% of the training data. For the respective test ratios, the 40% and 30% outperformed the others with overall classification rates of 89.7% (AER = 0.103) and 84.6% (AER = 0.154) respectively. The results show that, 25% test data performed poorly for live birth (AER = 0.298) and very well for the 40% (AER = 0.089) test data and the opposite is the case for the stillbirth outcome with 75.3% (AER= 0.247) and 86.9% (AER = 0.131) for the 40% and 30% test data respectively.

**Table 12. Performance evaluation (Test sample)**

% Test data	Stillbirth	Live birth	Overall Accuracy
50	82.5	80.9	81.3
40	75.3	91.1	89.7
30	79.2	86.3	84.6
25	86.9	70.2	74.1
Mean	80.9	82.1	82.4

Comparison of the two classification methods with the receiver operating characteristic (ROC) curve together with the area under the curve (AUC) values of all test samples are presented in below (Table 13). All AUC values of the respective test samples for the two methods were statistically significant with AUC values all greater than the chance classification AUC value of 0.50 ( $P < 0.01$ ) with corresponding small standard errors (SE). Moreover, the AUC values for both methods are in line with the conclusion of [26] that, AUC values closer to 1 imply, classifiers reliably discriminate between individuals belonging to the two distinct groups. The AUC values showed that, the discriminant function (DF) performed well (AUC = 0.918) under the 30% test sample and least under the 40% test data with an AUC of 0.868. The logistic regression on the contrary performed well (AUC= 0.905) under the 25% test sample and recorded the least AUC of 0.887 under the 50% test data. These results further show that both methods are almost equally effective in classification of the birth outcomes as observed and confirmed by earlier findings in other areas of application [12, 13 and 14].

**Table 13. Area Under the Curve (AUC) statistics**

Method	% Test data	AUC	S.E	Sig.	95% Confidence interval	
					Lower bound	Upper bound
DF	50	0.918	0.008	< 0.01	0.903	0.933
LR	50	0.887	0.009	< 0.01	0.869	0.905
DF	40	0.868	0.01	< 0.01	0.848	0.887
LR	40	0.891	0.01	< 0.01	0.872	0.910
DF	30	0.923	0.009	< 0.01	0.905	0.941
LR	30	0.888	0.012	< 0.01	0.865	0.911
DF	25	0.905	0.013	< 0.01	0.879	0.930
LR	25	0.899	0.014	< 0.01	0.879	0.923

LR: Logistic Regression; DF: Discriminant Function

The graphical presentation (performance) of the above mentioned techniques on the various test samples is in Fig. 1. The graphs show that, both methods perform well in classifying birth outcomes as both have their curves above the reference diagonal line as commended in earlier findings and observations observation [25, 26]. The LR model outperformed the DA in the 30% and 40% test data, whereas, the DA slightly performed better than the LR model in the 25% and 50% test samples.

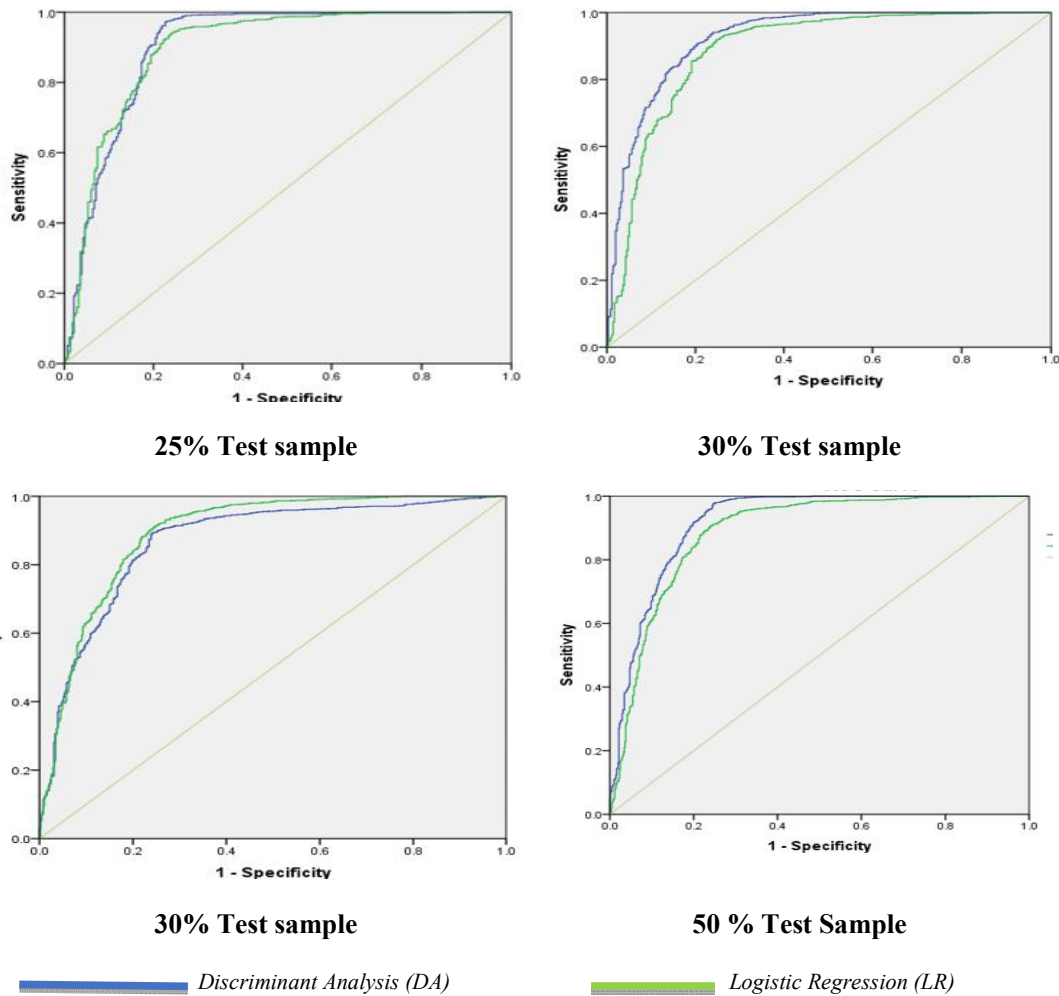


Fig. 1. Receiver Operating Characteristic (ROC) curves for the four test samples

## 4 Conclusion

In this study, two (2) classification techniques were compared and evaluated in classifying birth outcomes into either live birth or stillbirth with some maternal variables (maternal age, parity and gravida) and fetus factors (gestation period and fetus weight). The test sample classification results show that, the DA performed relatively better (Overall accuracy = 89.8% (AER = 0.102)) compared to the LR (Overall accuracy = 82.4% (AER = 0.176)) which confirms the findings of [13] and however, contrary to findings of [14] which favor the LR analysis. Both methods performed better in classifying live birth than a stillbirth. Moreover, both methods showed that gestation period, parity, gravida and fetus weight had a similar effect on birth outcomes which were also observed by Gordon et al. [8].

The results of this study are helpful for predicting birth outcomes of pregnant or expectant women as both methods performed well in classifying birth outcomes. Further research with other classification methods together with more predictors are needed to ascertain the robust and appropriate method or technique for application in classification of birth outcomes.

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## **Competing Interests**

Authors have declared that no competing interests exist.

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