Original Research Article

Sensitivity Analysis of the Quadratic Discriminant Function for Predicting Pregnancy Outcomes

ABSTRACT

The prevalence rate of stillbirth is ten times higher in developing countries relative to developed countries with a 2016 rate of 18 percent in Ghana. This study employed the Quadratic Discriminant Function for discriminating and classifying pregnancy outcomes based on some predictors. The study further examined the sensitivity of the Quadratic Discriminant Function in predicting pregnancy outcomes with variations in the training and test samples of deliveries recorded in a hospital in Accra, Ghana. The study considered the scenarios; 50:50, 60:40, 70:30 and 75:25 ratios of training sets to testing sets. Predictor variables on both maternal factors (maternal age, parity and gravida) and fetus variables (weight at birth and gestational period) were all statistically significant ($P < .01$) in discriminating between live birth and stillbirth. Results showed that maternal age had a negative effect on the live birth outcomes, while parity, gravida, gestational period and fetus weight recorded positive effects on live birth outcomes. The 75: 25 ratio outperformed the other ratios in discriminating between live and stillbirth based on the Actual Error Rate of 7.28% compared to 7.81%, 12.14% and 13.79% for the 50:50, 70:30 and 60:40 ratios respectively whereas, the receiver operating characteristic curve shows the 70:30 (AUC= 0.9233) ratio outperformed the others.

Keywords: Stillbirth, Discrimination, Performance, Errors, Sensitivity, Classification

1 Introduction

Stillbirth refers to the loss of a baby prior to the complete spontaneous vaginal delivery or extraction from its mother, the product of conception which weighs at least 1000g or has at least 35cm body length, whose maturity is at least twenty-eight (28) completed weeks of gestation [1, 2]. This is adopted in most countries, including Ghana as the working definition. The death of a baby whenever or, however, it occurs is seen as a deep loss, stillbirth is a somewhat unusual adverse outcome in the Western and advanced countries such as Sweden (3 per 1000 live births) but the reverse is the situation in developing countries. According to [3, 4], at least 7200 babies are stillborn around the world every day. An estimated total of 2.6 million stillbirths occurred globally in 2015 alone and there has been an insignificant decline of 1.1% per year over the previous years due to the little attention given to it. With the middle- and low-income countries accounting for approximately 98% of all stillbirth cases [5].

It is estimated that, the rate of stillbirth is ten times higher in developing countries relative to the developed countries with Sub- Saharan Africa recording more than 850, 000 cases annually with at least 60% of the affected been poor-rural families [5, 6, 7]. Moreover, [5] attributed 77% of the stillbirth cases recorded to Sub-Sahara Africa and Asia alone.

The contributory factors for the rising incidence of stillbirth are numerous [8, 9]. These risk factors range from maternal, perinatal, socio -economic and the quality of health care services. According to [10, 11], significant maternal risk factors associated with stillbirth include, among others, but not limited to, advanced age, multi-parity, previous occurrence or experience of stillbirth and undetected pregnancy infections. In this study, the factors considered include maternal age, birth weight, gestational age, parity and gravida extracted from the health facility. The definitions of these contributory factors are presented below (Table 1).

Table 1: Definition of Study variables

Variable	Definition
Response	
Pregnancy Outcome	Refers to the final result of fertilization (Live of stillborn)
Predictors	
Maternal Age	Age of the mother at time of delivery in years
Gestational period	This refers to the time between conception and delivery of a fetus whether alive or stillborn (in weeks)
Parity	It is the number of times that a woman has given birth to a fetus with a gestational age of 24 weeks or more, regardless of the outcome (live or stillborn)
Gravida	Refers to the number of times a woman has been pregnant
Birth Weight	Weight of fetus at birth (in Kg)

Gestational age of pregnancy is the most common perinatal risk factor for stillbirth. This can be classified under two distinct scenarios; an early gestational age, which causes early perinatal mortality (gestational age ≤ 23 weeks), and the late gestational age, resulting in late perinatal mortality (gestational age ≥ 40 weeks) [12].

In Ghana, stillbirth prevails at a rate of 18 per1000 live births [3] which is high relative to then MDGs target 12 per 1000 live births, hence it is imperative that efforts be made to unravel the primary causes of stillbirth and find possible remedies to this nagging problem since it causes great emotional suffering for the mother and the family at large. Stillbirth remains an essential pointer of accessible quality antenatal and delivery care services. Stillbirth to some extent an avoidable disorder and can be reduced if there is an increased effort in the creation of awareness among women and communities at large about the importance of regular ante-natal care and intra-natal care during pregnancy and the role it plays in the management and reduction of stillbirths. In a study involving health-care professionals and parents, results showed that most stillborn are not recorded. Hence, the silence surrounding stillbirths hides the problem and impedes needed investment [9].

The occurrence of stillbirth constitute a great and obscure loss of life and a major public health issue that must be addressed. Although numerous measures are put in place by Ghanaian government such as Free Maternal Health Care, Free Delivery Care Program (FDCP) for pregnant women among other measures in order to meet the then Millennium Development Goals Four and Five (MDGs 4& 5) which eventually expired in September, 2015 with an unachieved target of 12 per 1000 live births. However, though the newly adopted Sustainable Development Goals (SDGs) is silent on stillbirth, it has an ambitious target of 10 per 1000 live births of perinatal loss to be achieved by all countries by 2030 of which stillbirth forms part.

The problem of stillbirths continues to prevail in most developing countries not excluding Ghana is still very alarming. Although the proportion of stillbirth worldwide dropped by 14% between 1995 and 2015 representing a decline of 1.1% per year but this decline was not substantial, whiles the rate of decline in the sub-region including Ghana was just 0.7% but, declined by 3.8% in the western pacific region [5].

The incidence of stillbirth is also influenced by smoking during pregnancy and smoke from cooking with firewood or other forms of smoke biomass due to the nicotine and carbon monoxide exposure to both the fetus and the mother [13]. Antenatal and Obstetric care during pregnancy are very important in preventing stillbirth and other complications associated with pregnancies [2].

Although several studies have been undertaken to identify determinants of stillbirth outcomes among pregnancy women in sub – Sahara Africa by using some multivariate tools, this study used the Quadratic Discriminant function (QDF) to separate stillbirth from live birth and to further evaluate its performance sensitivity under varying training and testing samples.

2 Methodology

2.1 Study setting and design

This retrospective study was carried out using ante-natal and delivery registry data spanning from January, 2013 to December, 2015 of a regional hospital located in the Accra Metropolis of the Greater Accra region. The health facility serves parts of the Accra Metropolis with a population over 1.5 million inhabitants [25]. It also serves communities from surrounding District or Municipal Assemblies such as Ledzokuku – Krowo, Ga-South and Ga West Municipalities to the East, West and North respectively of the Accra Metropolis. The study focused on all singleton deliveries within the three-year period under consideration in the hospital.

2.2 Data Collection Method

The study extracted secondary data from the hospital's computerized records department responsible for collecting information from all pregnant women who are put to bed at the obstetrics and gynaecology unit in the hospital from 2013 to 2015. Data are collected within 24 hours after delivery or later on as mothers have recovered in case of complicated deliveries. In all, a total of 25,042 deliveries were recorded in the period of study. Data captured on the mothers include maternal age, gravidity and parity. While, on the babies, information such as weight at birth, gestational age, mode of delivery (either SVD or CS) and the pregnancy outcome were recorded.

2.3 Quadratic Discriminant Analysis (QDA)

Quadratic Discriminant Analysis (QDA) is a classification technique in which one observes two groups based on multivariate normal observations with heterogeneous covariance matrices structure. We assume;

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

With a density function defined by;

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

Where;

$i=1,2$ The number of groups

$p=$ The 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 function in equation (2) above, the likelihood- ratio function is expressed as

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

Simplifying and taking the natural log yields,

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

Where, $|\Sigma|$ denotes the determinant of the matrix, Σ. Equation (4) can be is expressed in the quadratic form as

$$Q(x) = x^T Ax + B^T x + C \qquad (5)$$

Where;

$$A = -\frac{1}{2}\left(\Sigma_1^{-1} - \Sigma_2^{-1}\right)$$

$$B = \left(\Sigma_1^{-1}\mu_1 - \Sigma_2^{-1}\mu_2\right)$$

$$C = -\frac{1}{2}\left(\mu_1^T \Sigma_1^{-1}\mu_1 - \mu_2^T \Sigma_2^{-1}\mu_2\right) - \frac{1}{2} In\left(\frac{|\Sigma_1|}{|\Sigma_2|}\right)$$

The function, *Q(x)* is known as the quadratic discriminant function (QDF) and can be used to classify future observations based on the rule that: if $Q(x) \geq \tau$, where τ is the pre-determined cut -off value, then assign *x* to the first group otherwise, assign to the second group. Where τ is defined as the product of the cost ratio and the prior probability ratio. We let p_1 denote the prior probability that an item to be assigned will be generated by the first distribution, and set $p_1 = 1 - p_2$.

2.3.1 Classification Using the Quadratic Rule

Given the density functions of the two populations π_1 and π_2 as given in (2) such that both populations π_1 and π_2 have multivariate normal densities with mean vectors and covariance matrices μ_1, Σ_1 and μ_2, Σ_2 respectively, then the classification rule becomes; Classify x_0 as π_1 if;

$$-\frac{1}{2}x^T\left(\Sigma_1^{-1} - \Sigma_2^{-1}\right)x + \left(\mu_1^T\Sigma_1^{-1} - \mu_2^T\Sigma_2^{-1}\right)x - \frac{1}{2}\left(\mu_1^T\Sigma_1^{-1}\mu_2 - \mu_2^T\Sigma_2^{-1}\mu_2\right) - \frac{1}{2}\ln\left(\frac{|\Sigma_1|}{|\Sigma_2|}\right) \geq 0 \qquad (6)$$

And classify x_0 to π_2 otherwise. The classification regions are defined by quadratic functions of x [14].

2.3.2 Wilks' Lambda

The Wilks' Lambda is mostly employed in discriminant analysis to assess the relevance or importance of the discriminant functions derived [15]. It ranges between 0 and 1. With lambda values close to zero indicating significant discriminating function.

2.3.3 Box's M Test

This is a multivariate data analysis test statistic used to examine the equality of variance - covariance matrices in the categories [16]. Where large Box's M values accompanied with a small *p-value* indicates violation of equality of covariance assumption. On the other hand, with large size, the Box's M value turns to be large. In these circumstances, the appropriate alternative employed for comparison of the groups will be the natural logarithms of the variance-covariance matrices [17].

2.5 Performance Evaluation

The performance of discriminant functions derived for the study is assessed by determining the misclassification error rates for utilizing such functions for classifying new cases or observations. The most widely used [14] error rates are;

2.5.1 Apparent Error Rate (APER)

The APER refers to the fraction of cases belonging to sample that are misclassified by the classification rule. Let n_{1M} and n_{2M} be the number of objects misclassified as π_1 and π_2 respectively then,

$$APER = \frac{n_{1M} + n_{2M}}{n_1 + n_2} \tag{7}$$

The APER is relatively easy to calculate. However, it occasionally underestimates the actual error rate (AER) when classifying new observations. To find a more accurate value for AER we most often choose an independent "test sample" of new cases whose true populations are known. Where a good estimate of the AER is given as

$$AER = \frac{n_{1M}^T + n_{2M}^T}{n_1 + n_2} \tag{8}$$

Where n_{1M}^T and n_{2M}^T are the test sample observations misclassified as misclassified as π_1 and π_2 respectively.

2.5.2 Balanced Error Rate (BER)

The Balanced Error Rate (BER) statistics is the mean of the misclassified rates on samples drawn from the two known populations (represented by π_1 and π_2 respectively) as shown in the table below.

Table 2: Confusion Matrix for two populations

		Prediction	
		π_1	π_2
True Population	π_1	a	b
	π_2	c	d

Where a, b, c and d are elements in the confusion matrix. The Balanced Error Rate can be given mathematically as

$$BER = \frac{1}{2}\left(\frac{b}{a+b} + \frac{c}{c+d}\right) \tag{9}$$

Where b and c are the number of misclassified in the two populations π_1 and π_2 .

3 Results

3.1 Preliminary Analysis

In this section, we present summary of data used for the study and also examine the characteristics of predictor variables and their contribution to the discrimination and classification of birth outcome cases into their respective groups (Live or Stillbirth). From the 25,042 deliveries over the period understudy, 23792 (95.0%) were live birth with 1250(5%) been stillbirth outcomes. The results further show that, averagely 5% of all deliveries in the hospital are stillbirth with 4.9%, 5.2% and 4.9% in 2013, 2014 and 2015 respectively (Table 3).

Table 3: Pregnancy Outcomes incidence by year

	Pregnancy Outcome		
Year	Stillbirth	Live birth	Total
2013	357(4.9%)	6918(95.1%)	7275
2014	482(5.2%)	8834(94.8%)	9316
2015	411(4.9%)	8040 (95.1%)	8451
Total	1250 (5.0%)	23792 (95.0%)	25042

Due to the wide disparity in proportions between the live birth and stillbirth outcomes and for the validity of the analysis, the study made use of all stillbirth (1,250) cases and a random sample of 3,750 live birth cases with complete information on all predictor variables considered.
Presented in Table 4 are the group statistics (Mean (SD)) for the two groups. The results show that all predictor variables considered are different for the birth outcome categories. We further present results testing for the significant difference between the birth outcomes on these predictor variables. The test results (Table 5) indicate that all predictor variables are significantly (*P < .01*) different for the birth outcomes. Which indicates that these variables are significant determinants of birth outcomes.

Table 4: Group Statistics

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

Table 5: Tests for Equality of Group Means

Predictors	Wilks' Lambda	F	Sig.
Maternal Age	0.876	462.338	< .01
Parity	0.621	1991.690	< .01
Gravida	0.461	3815.624	< .01
Gestational period	0.895	382.477	< .01
Weight of fetus	0.898	369.393	< .01

The Box's M test is employed in the study to assess the appropriateness of the Quadratic Discriminant Analysis (QDA). With test statistic of 2587.967 and a corresponding *P < .01* (Table 6), confirms that the QDA is suitable and adequate for the study.

Table 6: Box's Test of Equality of Covariance Matrices

Box's M	2587.967
F Approx.	172.209
Sig.	< .01

3.2 Model Results

In this section, we fit the quadratic discriminant function models to the dataset under varying training and testing sample ratios to assess the performance of the models in differentiating between stillbirth and live birth outcomes among pregnant women.

Presented below (Table 7) are the parameter estimates for the quadratic discriminant function under different scenarios of the training and test samples and the combined data. For the different scenarios under consideration, we partition both stillbirth and live birth pregnancy outcomes into 50% training and 50% testing for the first scenario and then proceed with the 60%:40%, 70%:30% and the 75%:25% training and testing samples respectively. Also, in Table 7 are the group centroids for the respective scenarios.

We observe from the parameter estimates that, with the exception of maternal age of women and the constant which are negative, the other variables (parity, gravida, gestational period and fetus weight at birth) are positive. The negative coefficient for maternal age implies that, increase in age of women reduces the chance for live birth where on the contrast, those with positive coefficients indicate that, an increase in these variables increases the chances of having live birth.

Table 7: Parameter estimates for Quadratic functions

		50:50	60:40	70:30	75:25
Predictors	Maternal Age (Years)	-0.0065	-0.009	-0.009	-0.008
	Parity	0.2368	0.2628	0.2497	0.229
	Gravida	0.9326	0.9135	0.914	0.9265
	Gestation (Weeks)	0.0931	0.0875	0.0851	0.0869
	Fetus Weight (Kg)	0.0964	0.1232	0.1376	0.131
	Constant	-7.9887	-7.746	-7.646	-7.725
Group Centroids	Stillbirth	-1.5439	-1.573	-1.564	-1.561
	Live birth	0.8239	0.8417	0.8458	0.8521

Model Statistics for the various scenarios of training and testing samples are presented below (Table 8). All scenarios produced QDF's with eigenvalues greater than one (1) and Wilk's lambda values all less than one (1). Moreover, the significant (*P < .01*) canonical correlations for each scenario is at least 0.72 which shows that, the quadratic discriminant functions (QDFs) are significant in explaining the variations in the pregnancy outcomes among women.

Performance of each scenario was assessed by the use of the average of the group centroids to classify the test sample cases. Birth outcomes were classified as live birth if the quadratic discriminant score for the case is ≥ the average of the centroids otherwise, it is classified as stillbirth birth outcome.

The performance of each QDF is assessed with the test samples for each scenario by means of the actual error rates (AER) and the balanced error rates (BER) since the apparent error rates are believed to underestimate the errors associated with these functions. Based on these error rates, the QDF with the least error rate is considered the best discriminating function.

Based on the errors (AER and BER) of these functions, the 75:25 training and testing sample recorded the least errors of 7.28% and 12.76% respectively making it the best function. The 50%: 50% scenario followed with actual and balanced errors of 7.18% and 14.35% whiles on the contrary, the 60%:40% produced the relatively largest actual and balanced errors of 13.79% and 18.03% respectively. Results on the eigenvalues, canonical correlations and the error values all confirm the 75%:25% scenario as the best for predicting pregnancy outcomes.

Table 8: Models Performance Statistics

Ratios (Training: Test)	Eigenvalue	Wilk's lambda	Canonical correlation	Chi-Square Statistic	df	Sig.	AER	BER	APER
All	1.381	0.420	0.762	2829.160	5	< .01			10.20
50:50	1.274	0.440	0.748	1344.168	5	< .01	7.81	14.35	9.70
60:40	1.325	0.430	0.755	1649.098	5	< .01	13.79	18.03	9.60
70:30	1.324	0.430	0.755	1932.109	5	< .01	12.14	15.02	9.70

75:25	1.331	0.429	0.756	2085.533	5	< .01	7.28	12.76	9.80

The ROC curves together with AUC values for the respective training and testing samples are presented in below (Figure 1). The figure show that all training and testing samples recorded AUC values above 0.85 indicating excellent discrimination and classification of birth outcomes using the quadratic discriminant function (QDF)[18]. The 70% training versus 30% testing ratio as the best discriminatory ratio than the others with the largest AUC value of 0.9233 followed by the 50:50 ratio with AUC value of 0.9179.

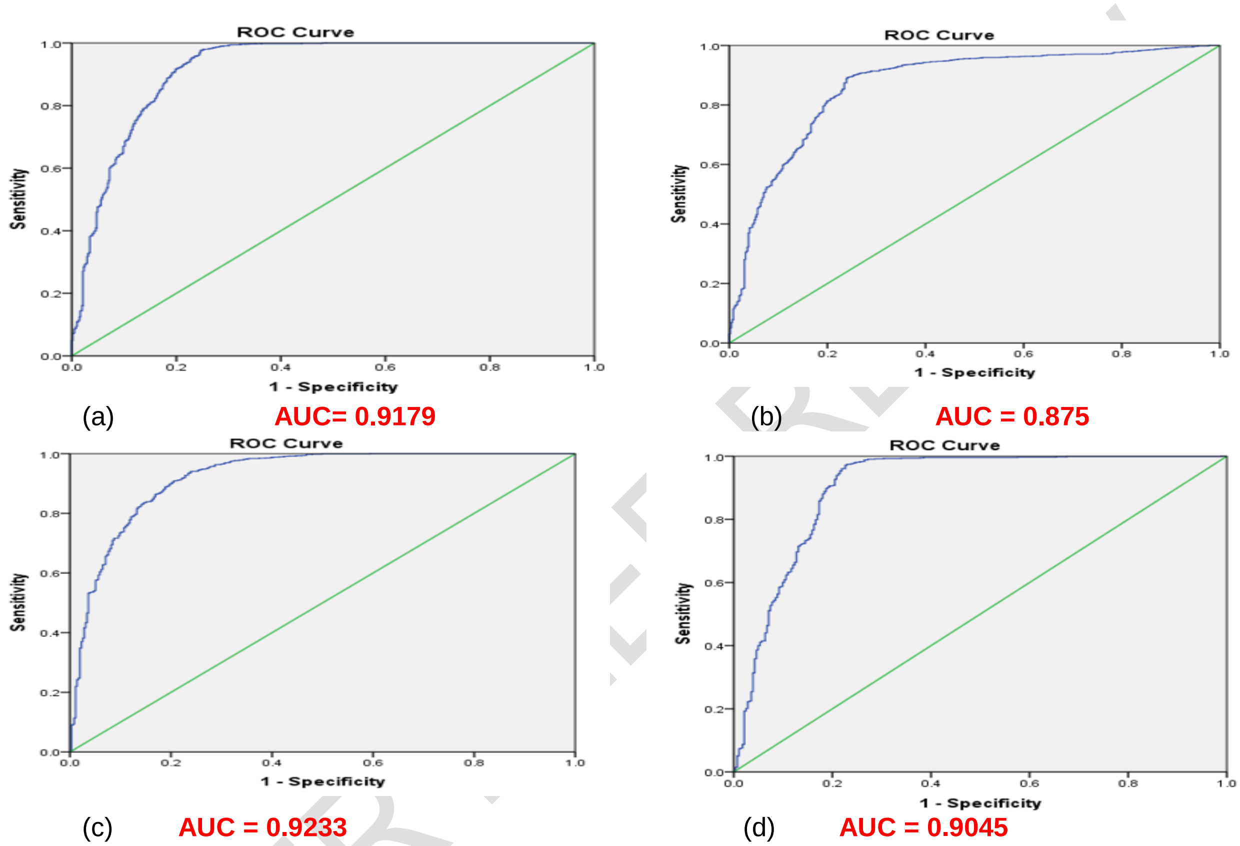

Figure 1: Receiver Operating Characteristic Curves for the Four Ratios with Area under Curve (AUC) Values.
(a) 50:50. (b) 60: 40. (c) 70: 30. (d) 75:25

4 Discussion

The still birth incidence for this study for the three year period (2013-2015) was 5.0% which translates to 50 stillbirth per 1000 deliveries. This rate is comparatively high to that of other developing country in the African continent. For instance, in Tanzania, the stillbirth rate was observed at 42 per 1000 [11] and much lower in Nigeria where it was 22 per 1000 [20]. On the contrary, the observed stillbirth rate in Ghana was also lower than that of 56 per 1000 in Zimbabwe [21], 80 per 1000 in Ethiopia [22] and 156 per 1000 recorded in Gambia [23]. It is also worth noting that, the stillbirth incidence rate in Ghana alone is five times the targeted perinatal loss of 10 per 1000 to be achieved by the year 2030 as part of the SDG's.
The observed high stillbirth incidence could be attributed to referrals of complicated cases from health facilities outside the capital, lack of knowledge on mental health healthcare services, lack of transportation services (ambulances) at health facilities outside the capital and most importantly, delay in seeking and receiving care increases the risk of stillbirth as observed in earlier studies [22].
The quadratic discriminant function (QDF) employed in this paper to identify significant predictors for discriminating and classifying deliveries or pregnancy outcomes. The QDF model was appropriate for the data with significant ($P < .01$) Box's M test results (Table 6). The predictors were all significant ($P < .01$)

based on the Wilk's Lambda results (Table 5) and important in discriminating between stillbirth and live birth outcomes. The model results (Table 8) show that all the quadratic discriminant functions for the various scenarios were appropriate with each having eigenvalues greater than one (1), canonical correlations > 0.70 and Wilk's Lambda values > 1 as discussed in [15].

The model results for all scenarios of training and testing sample showed that, among the five (5) predictors, maternal age had negative effect on the live birth outcomes. Thus, increase in age of women increased the risk of stillbirth. This finding was also observed by [9, 10 and 24]. Whilst on the other hand, parity, gravida, gestational period and fetus weight recorded positive effects on live birth outcomes. Which implied that, increase in these predictors will reduce the risk of stillbirth outcomes. The effect of parity on stillbirth observed in this study is however contrary to the findings of [10] and [24] where multiparty of women increases the risk of stillbirth outcomes.

The performance of functions under each of the scenarios was generally good and acceptable. However, based on the error rates, the 75%: 25% training and testing samples outperformed the other scenarios with the lowest AER and BER values of 7.28% and 12.76% respectively (Table 8). Whilst, with respect to the receiver operating characteristic (ROC) curve, the 70:30 ratio performed best (AUC = 0.9233) followed by the 50:50 ratio with AUC value of 0.9179.

5 Conclusions

The stillbirth incidence in the setting of this study is very high and is 5 times the targeted SDGs of 10 per 1000 of all perinatal losses by 2030. The results obtained show that all variables considered were statistically significant for discriminating and classifying pregnancy outcomes. The best training and testing samples for the QDF was 75% training to 25% test samples based on the actual and balanced error rates and 70 % training versus 30% testing according to the ROC curves and the area under curve (AUC) values. The findings of the study recommend the use of either 70:30 or 75:25 training to testing sample ratio for discrimination and classification purposes. To establish the superiority of the best training and testing samples, further research using other statistical techniques with additional socio-economic variables could be investigated.

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