# Application machine learning algorithms for identifying mothers who may mutilate their daughters.

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## ABSTRACT

Despite efforts aimed at eradicating female genital mutilation, this practice remains endemic in Nigeria and many parts of the world. Although, several studies have identified the correlates of female genital mutilation, recent advances in computational and social science research have provided new ways of identifying mothers who may mutilate their daughters. We used data from the Nigeria demographic and health survey (2013) to train five machine-learning algorithms to predict if a mother could mutilate their daughter. Our models comprised of Support Vector Machine (SVM), Classification Trees (CART), Naïve Bayes (NB), Linear Discriminant Analysis (LDA), and k-Nearest Neighbors (KNN). We externally validated the models in the 2016 Nigeria multiple indicator cluster survey. Our findings during external validation, suggests that the linear discriminant analysis gives the best accuracy (86%) while the k-Nearest neighbor model had the lowest accuracy (76%). The implications of these findings for policy and scholarship are discussed.

**Keywords:** Female genital mutilation, Nigeria, machine learning

## BACKGROUND

Female genital mutilation (FGM) is a tradition entrenched in Nigerian culture particularly in the southern region. This act is an abusive act towards girls and women with deleterious extensive health, social and economic implications. Although reduction in the prevalence of FGM has been reported in the country, much still need to be done to get rid of this practice in Nigeria particularly with regards to attitudes towards the practice.

Extensive research suggests that the implications of female genital mutilation for the health and wellbeing of women are diverse. Victims of FGM suffers trauma during the exercise, as they are subjected to cruel treatment such as being held down and cut with crude tools of questionable levels of sterility without any form of anaesthesia [7,8]. This practice often leaves the victims with feeling of incompleteness, less self-worth and psychological distress which can make them dread sex and childbirth; because of anticipated pain, becoming frigid and withdrawn which may result in marital conflict [9,10]. Other sequelae which are immediate includes excruciating pain, haemorrhage, shock, acute urinary retention, injury to adjacent tissues and death may occur immediately [11,12]. Some of the medium term and long-term consequences are urinary tract infection, pelvic inflammatory disease, chronic pelvic pain, infertility and ectopic pregnancy; low libido, vaginal fistulae, vaginal laceration during coitus, obstructed labour, genital tract laceration especially during vaginal delivery, postpartum haemorrhage [13,14]. Babies conceived by such women are at higher risk of still birth, early neonatal death and neurologic deficit from severe birth asphyxia [14].

Despite the efforts at the international, national and community level to eradicate female gender mutilation, this practice remains an endemic in Asia, Middle East and some part of Africa Nigeria inclusive. Among many other factors, social factors such as peer pressure, societal acceptance and parental pressure borne out of fear of ostracism and family shame are known to be contributing factors of FGM (Ekwueme, Ezegwui, & Ezeoke, 2010). FGM had been considered a restraint to the realization of the Millennium Development Goals and if care is not taken may restrict the actualization of the Sustainable Development Goals [17,18].

In this study we sought to use machine learning algorithms to identify mothers who may mutilate their daughters.

## METHODS

### *Study Design and Data Description:*

We used data from the 2013 demographic and health survey (DHS) of Nigeria to build a predictive model that could identify mother who may mutilate any of their daughters. We externally validated the model developed in an independent Nigeria multiple indicator cluster survey (MICS) conducted in 2016.

The DHS and MICS are nationally representative survey that monitors the demography and health of populations in developing countries. The survey's rich information on women's demographic behavior, including their marital status, fertility and behaviours make it a valuable resource for this study. In addition to the information collected from men, children, and households, the surveys also collect rich information about women's reproductive histories including the number of children ever born per woman, the number of daughters alive or dead, as well as well the number of daughters that have been mutilated. The women were also asked to give substantial information whether or not they have been mutilated, and if they have an accepting attitude to genital mutilation.

### *Study Population and Sample*

Eligible participants for this study were mothers age 15-49 years who have at least one daughter, had complete information on socio-demographic characteristics and participated in the female genital mutilation module of the surveys.

The Nigeria demographic and health survey comprised of 38,948 women aged 15-49 years who were resident in any of the 38,522 households selected for participation in the survey. The survey used a stratified three-stage cluster design consisting of 904 clusters, 372 in urban areas and 532 in rural areas. A fixed sample of 45 households were selected per cluster and all women age 15-49 who were either permanent residents of the households in the 2013 NDHS sample or visitors present in the households on the night before the survey were eligible to be interviewed. A minimum target of 943 completed interviews per state. We excluded about 62% of the women who have never had a girl child and did not participate in the female genital mutilation module of the dataset. The final analytic sample from this dataset of 14,853 mothers age 15-49 years who have at least one daughter, had complete information on socio-demographic characteristics and participated in the female genital mutilation module of the survey.

The Nigeria multiple indicator cluster survey was implemented jointly with the National Immunization Coverage Survey (NICS). The survey was designed to provide estimates for a large number of indicators on the situation of children (including vaccination coverage) and women at the national, rural/urban, states as well as the 6 geopolitical zones of Nigeria. The survey comprised of 36,176 women aged 15-49 years who were resident or visiting any of the 33,901 households which were included for participation in the survey. For this survey, we excluded about 76% of the women who have never had a girl child and did not participate in the female genital mutilation module of the dataset. The final analytic sample from this dataset of 8,827 mothers age 15-49 years who have at least one daughter, had complete information on socio-demographic characteristics and participated in the female genital mutilation module of the survey.

***Study Outcome variable:***

The outcome of interest for this study is the girl-child experience of female genital cutting. The variable was assessed from the information on the number of each woman's daughter that was/were genitally mutilated. Response to this question ranged from 0 (none) to 18 daughters. We recoded and classified the girl-child female genital mutilation experience as "circumcised" if any of their daughters were circumcised or "not circumcised" if any of the daughters was not circumcised.

***Features Selection***

We included in our model about ten predictors variables which have been identified to be significantly related to female genital mutilation in Nigeria and across the world. This comprised of women's age at first birth, marital status, region of residence, place of residence, maternal employment status, educational attainment, maternal experience of female genital cutting and maternal support for female genital mutilation. A detailed description and classification of each of the study variables is presented in the Table 1 below. Although a number of other features such as ownership of health insurance may be associated with genital mutilation, the unavailability of such variables in one of the datasets makes it unusable in the model.

***Model Building Development:***

We constructed and developed a series of model using the 10 predictive features identified in prior studies to train a machine learning algorithm to detect mothers who are likely to mutilate their girl children. We trained our prediction models using five commonly used classification techniques, comprising of linear discriminant analysis (LDA), classification and regression trees (CART), k-nearest neighbors (k-NN), support vector machines (SVM), random forest (RF), and naïve Bayes (NB). We examined all models with repeated ten-fold cross-validation (ten repeats), which partitions the original sample into ten disjoint subsets, uses nine of those subsets in the training process, and then makes predictions about the remaining subset. We selected optimum tuning parameters during cross-validation through an area under the receiver-operating curve (ROC)-maximisation process (comparing true positives to false positives). We used the best performing model in the training dataset to generate predictions in the independent validation set. We evaluate the performance of defect prediction models using 10 commonly-used performance measures, i.e., 3 threshold-independent (e.g., AUC) and 7 threshold-dependent (e.g., Precision, Recall, F-Measure) performance measures. We measured the significance of the model's accuracy with a one-tailed binomial test of model accuracy relative to the bigger class proportion (null-information rate). We also measured other relevant descriptions of model discrimination—including sensitivity, specificity, and area under curve (AUC)—at each stage.

For external validation, we applied the final model built using the 2013 demographic and health survey without modification to predict if a mother will mutilate her daughter's genitalia in the 2016 multiple indicator cluster survey. Figure 1 illustrates the analysis pipeline. All analyses were implemented in R (version 3.1.2). All R-code we developed for statistical modelling is available upon request.

## RESULTS

### *Descriptive Profile of Study Sample*

The total sample for this study comprised of 14,853 (DHS) and 8,827 (MICS) mothers age 15-49 years who have at least one daughter, had complete information on socio-demographic characteristics and participated in the female genital mutilation module of the surveys. As presented in Table 1, about 20% of the mothers in both surveys reported that they mutilated at least one of them under 15-year-old daughters. About 40% of the sample were adolescents and young mothers as at the time of data collection while mothers aged 25-29 years accounted for about 24% of the sample in 2013. In 2016, most of the sample (57%) were adolescents and young mothers while middle aged and adult women accounted for about 14% of the sample. Single motherhood is not very common in the sample in 2013 (2%) and 2016 (2%). About 45% of the mothers reside in the northern part of the country in 2013 while compared to about 53% in 2016. Most of the mothers reside in the rural place of residence with a slight decline from 61% in 2013 to about 59% in 2016. More than half of the women reside in the richest quintile of household wealth in 2013 compared to only about 44% of the mothers in 2016. The majority of the mothers were unemployed in 2013 while more than three-quarters of the mothers reported to be currently working in 2016. In relation to female genital mutilation, about 41% of the mothers in 2013 reported that they were mutilated and about the same percentage of women in 2016 also reported being mutilated. Only about 71% of the mothers support the discontinuation of the practice compared to about 68% of the mothers in 2016.

### *Prevalence of Girl-Child FGM Experience.*

In Table 2, we examined the prevalence of Girl-Child FGM Experience across the 10 selected demographic and social features. In both years, we observed a statistically significant difference in the prevalence of girl-child female genital mutilation. We found that the prevalence is higher among women who were circumcised (40% - DHS, 2013; 43% - MICS 2016) and lowest among women who have never been circumcised (7% - DHS, 2013; 4% - MICS 2016). More than half of the women who support the continuation of female genital mutilation also had at least of one of their daughters mutilate in 2013 (53%) and in 2016 (64%). The Girl-Child FGM Experience was also more common among women in the poorest tertile of wealth in 2013 (26%) and (34%) compared to women in the richest tertile in both years. Close to one-third of the women in North-west Nigeria reported to have mutilated at least of one their daughters with a higher prevalence up to about half of the 2016 sample. Girl-Child FGM experience was also more common among women with no formal education in 2013 (24%) and in 2016 (34%) compared to women with tertiary or higher education in both years.

***Model Predictive Performance.***

In other to identify mothers who may mutilate their daughters, we built several predictive models using 10 features identified to be significant predictors of female genital mutilation. Table 3 contains performance measures of the model during internal cross-validation in the 20% test data from the 2013 dataset. Table 3 also contains performance measures of the models during external cross-validation in the 2016 multiple indicator cluster survey dataset. As indicated in the table, the linear discriminant analysis and random forest performed best during internal cross-validation with an accuracy of more than 78%. Although, both models were only able to correctly predict more than 92% the negative class (not mutilated), performed lower in accurately predicting women who circumcised at least one of their daughters with a positive predicted value of about 55%. The classification and regression tree (CART) model on the other hand was able to correctly identify 60% of mother who circumcised their daughters in the test dataset although with a lower overall accuracy of about 77%.

To confirm the model's external generalizability, we applied the 10-item model from the DHS dataset to women in the 2016 multiple indicator cluster survey. The results of the full model performance metrics are provided in the Table 3 and figure 1. The model showed significant improvement in accuracy during external validation. We observe that the linear discriminant analysis achieved the highest accuracy (86%) followed by support vector machine (SVM) model (85%) and the classification and regression tree (CART) model (84%). Overall, we observed that the random forest model (RF) achieved the best performance (PPV: 69%, NPV: 94%; AUC.PR: 0.847, AUC.ROC: 0.854, F1: 72%). The k-Nearest neighbor (KNN) model on the other hand achieved the least performance (PPV: 57%, NPV: 92%; AUC.PR: 0.843, AUC.ROC: 0.848, F1: 63%) compared to other models.

## CONCLUSION AND PLANS MOVING FORWARD

Overall, our findings suggest that machine learning techniques would be useful in identifying mothers who may mutilate their daughters. This could be crucial for targeted social and health interventions such as reorienting mothers who may circumcise their daughter(s) through education. As a crucial step towards disseminating our findings and ensuring its relevance for the local community, we intend to deploy our model via a shiny web-based app where women or the relevant stakeholders in Nigeria may self-examine their likelihood of circumcising their girl child(ren). Participants will also be invited to rate the app based on how accurate they perceive the models to be.

## REFERENCES


1. NBS, UNICEF. Multiple Indicator Cluster Survey 2016-17, Survey Findings Report. Abuja, Nigeria. National Bureau of Statistics (NBS) and United Nations Children's Fund (UNICEF); 2017.

2. NPC, ICF. Nigeria Demographic and Health Survey 2013. Abuja, Nigeria, and Rockville, Maryland, USA. National Population Commission (NPC) [Nigeria] and ICF International. 2014; 2014.

3. UNICEF. Female genital mutilation/cutting: A global concern [Internet]. United Nations Children's Fund; 2016. Available: https://www.unicef.org/media/files/FGMC_2016_brochure_final_UNICEF_SPREAD.pdf

4. Garba I, Muhammed Z, Abubakar I, Yakasai I. Prevalence of female genital mutilation among female infants in Kano, Northern Nigeria. Arch Gynecol Obstet. 2012;286: 423–428.

5. PRB. Female Genital Mutilation/ Cutting: Data and Trends. Population Reference Bureau; 2014.

6. Onuh S, Igberase G, Umeora J, Okogbenin S, Otoide V, Gharoro E. Female genital mutilation: knowledge, attitude and practice among nurses. J Natl Med Asso. 2006;98: 409–414.

7. Nour M. Female Genital Cutting: A persisting practice. Reviews in Obstetrics and Gynaecology. 2008;1: 135–139.

8. WHO. Understanding and addressing violence against women. Female genital mutilation. Geneva, Switzerland: World Health Organization, Pan American Health Organization; 2012.

9. Ezenyeaku C, Okeke T, Chigbu C, Ikeako L. Survey of women's opinions on female genital mutilation in South East Nigeria: Study of patients attending antenatal clinic. Ann Med Health Sci Res. 2011;1: 15–20.

10. Odoi A. Female genital mutilation. Comprehensive Gynaecology in the Tropics. 1st ed. Accra: Graphic Packaging Ltd; 2005. pp. 268–78.

11. Berg R, Underland V, Odgaard-Jensen J, Fretheim A, Vist G. Effects of female genital cutting on physical health outcomes: a systematic review and meta-analysis. BMJ Open. 2014; doi:10.1136

12. Serour G. Medicalization of female genital mutilation/cutting. Afr J Urol. 2013;19: 145–9.

13. Adekunle A, Fakokunde F, Odukogbe A, Fawole A. Female genital mutilation - postcircumcision vulval complications in Nigerians. J Obstet Gynaecol. 1999;19: 632–5. doi:10.1080/01443619963914

14. Banks E, Meirik O, Farley T, Akande O, Bathija H, Ali M. Female genital mutilation and obstetric outcome: WHO collaborative prospective study in six African countries. 2006;367: 1835–41.

15. Gamal Eldin A, Babike S, Sabahelzain M, Eltayeb M. "FGM/C Decision-Making Process and the Role of Gender Power Relations in Sudan." Evidence to End FGM/C: Research to Help Women Thrive. [Internet]. New York: Population Council.; 2018. Available: https://www.researchgate.net/publication/328654878

16. Abolfotouh S, Ebrahim A, Abolfotouh M. Awareness and predictors of female genital mutilation/cutting among young health advocates. International Journal of Women's Health. 2015;7: 259–269.

17. Epundu U, Ilika A, Ibeh C, Nwabueze A, Emelumadu O, Nnebue C. The Epidemiology of Female Genital Mutilation in Nigeria - A Twelve Year Review. Afrimedic Journal. 2018;6: 1–10.

18. WHO. Global strategy to stop health-care providers from performing female genital mutilation. Geneva, Switzerland: UNAIDS, UNDP, UNFPA, UNICEF, UNHCR, UNIFEM, WHO, FIGO, ICN, IOM, WCPT, WMA, MWIA; 2010.

19. Shell-Duncan B, Hernlund Y, Wander K, Moreau A. Contingency and change in the practice of female genital cutting: dynamics of decision making in Senegambia. Summary Report. 2010.

**Table 1:** Descriptive Characteristics of the Study Population

| Characteristics | DHS | | MICS | |
|---|---|---|---|---|
| | Sample n = 14,853 | Percentage % | Sample n = 8,827 | Percentage % |
| **Age at First Birth** | | | | |
| < 20 | 8531 | 57.4% | 3579 | 40.5% |
| 20 - 24 | 4315 | 29.1% | 3144 | 35.6% |
| 25 - 29 | 1574 | 10.6% | 1553 | 17.6% |
| 30+ | 433 | 2.9% | 551 | 6.2% |
| **Marital Status** | | | | |
| Never Married | 264 | 1.8% | 188 | 2.1% |
| Ever Married | 14589 | 98.2% | 8639 | 97.9% |
| **Region of Residence** | | | | |
| North Central | 1356 | 9.1% | 1494 | 16.9% |
| North East | 2122 | 14.3% | 651 | 7.4% |
| North West | 4405 | 29.7% | 1792 | 20.3% |
| South East | 1902 | 12.8% | 1263 | 14.3% |
| South South | 2471 | 16.6% | 1868 | 21.2% |
| South West | 2597 | 17.5% | 1759 | 19.9% |
| **Place of Residence** | | | | |
| Urban | 6152 | 41.4% | 3443 | 39.0% |
| Rural | 8701 | 58.6% | 5384 | 61.0% |
| **Wealth Status** | | | | |
| Poorest | 2667 | 18.0% | 830 | 9.4% |
| Poorer | 2801 | 18.9% | 1320 | 15.0% |
| Middle | 2890 | 19.5% | 1710 | 19.4% |
| Richer | 3329 | 22.4% | 2270 | 25.7% |
| Richest | 3166 | 21.3% | 2697 | 30.6% |
| **Employment Status** | | | | |
| Unemployed | 3247 | 21.9% | 4909 | 55.6% |
| Employed | 11606 | 78.1% | 3918 | 44.4% |
| **Educational Attainment** | | | | |
| No Education | 5878 | 39.6% | 2354 | 26.7% |
| Primary | 3457 | 23.3% | 1868 | 21.2% |
| Secondary | 4208 | 28.3% | 3374 | 38.2% |
| Higher | 1310 | 8.8% | 1231 | 13.9% |
| **Girl-Child FGM Experience** | | | | |
| Circumcised | 3034 | 20.4% | 1744 | 19.8% |
| Not Circumcised | 11819 | 79.6% | 7083 | 80.2% |
| **Support for FGM** | | | | |
| Continued | 3496 | 23.5% | 1920 | 21.8% |
| Depends | 1204 | 8.1% | 611 | 6.9% |
| Stopped | 10153 | 68.4% | 6296 | 71.3% |
| **Maternal FGM Experience** | | | | |
| Circumcised | 6080 | 40.9% | 3626 | 41.1% |
| Not Circumcised | 8773 | 59.1% | 5201 | 58.9% |

**Table 2:** Prevalence of Girl-Child Genital Mutilation among Mothers in Nigeria.

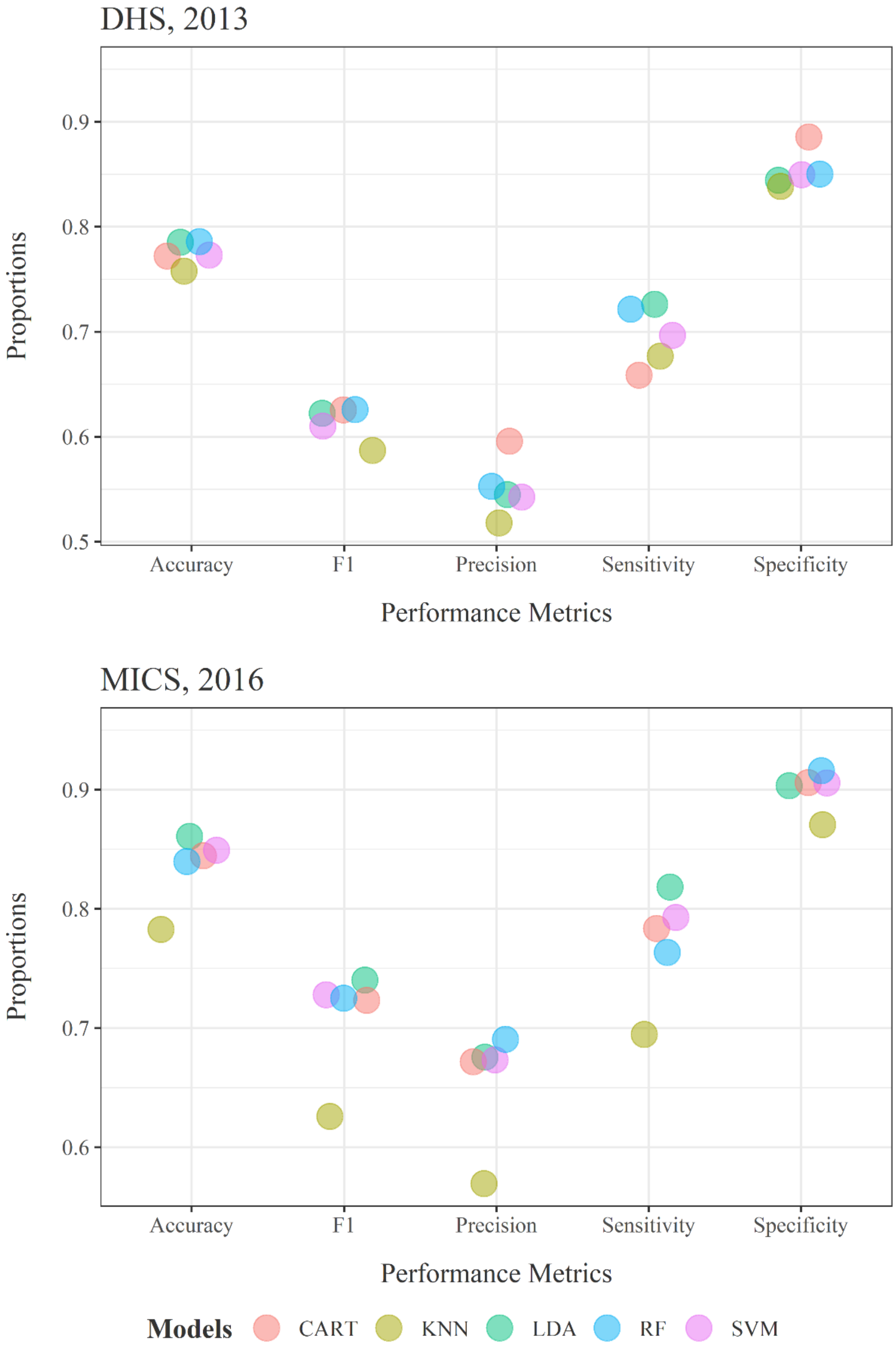
| | DHS | | | MICS | | |
|---|---|---|---|---|---|---|
| | Number | Percentage | p-value | Number | Percentage | p-value |
| **Maternal FGM Experience** | | | | | | |
| Circumcised | 2411 | 39.7% | < 0.001 | 1553 | 42.8% | < 0.001 |
| Not Circumcised | 623 | 7.1% | | 191 | 3.7% | |
| **Support for FGM** | | | | | | |
| Continued | 1848 | 52.9% | | 1226 | 63.9% | |
| Depends | 272 | 22.6% | < 0.001 | 145 | 23.7% | < 0.001 |
| Stopped | 914 | 9.0% | | 373 | 5.92% | |
| **Place of Residence** | | | | | | |
| Urban | 1214 | 19.7% | 0.082 | 616 | 17.9% | < 0.001 |
| Rural | 1820 | 20.9% | | 1128 | 21.0% | |
| **Wealth Status** | | | | | | |
| Poorest | 685 | 25.7% | | 280 | 33.7% | |
| Poorer | 671 | 24.0% | | 385 | 29.2% | |
| Middle | 560 | 19.4% | < 0.001 | 356 | 20.8% | < 0.001 |
| Richer | 643 | 19.3% | | 388 | 17.1% | |
| Richest | 475 | 15.0% | | 335 | 12.4% | |
| **Region of Residence** | | | | | | |
| North Central | 192 | 14.2% | | 190 | 12.7% | |
| North East | 168 | 7.9% | | 15 | 2.30% | |
| North West | 1354 | 30.7% | < 0.001 | 902 | 50.3% | < 0.001 |
| South East | 408 | 21.5% | | 154 | 12.2% | |
| South South | 179 | 7.2% | | 132 | 7.07% | |
| South West | 733 | 28.2% | | 351 | 20.0% | |
| **Employment Status** | | | | | | |
| Unemployed | 617 | 19.0% | 0.024 | 1200 | 24.4% | < 0.001 |
| Employed | 2417 | 20.8% | | 544 | 13.9% | |
| **Educational Attainment** | | | | | | |
| No Education | 1431 | 24.3% | | 805 | 34.2% | |
| Primary | 700 | 20.2% | < 0.001 | 322 | 17.2% | < 0.001 |
| Secondary | 767 | 18.2% | | 508 | 15.1% | |
| Higher | 136 | 10.4% | | 109 | 8.85% | |
| **Marital Status** | | | | | | |
| Never Married | 25 | 9.5% | < 0.001 | 9 | 4.8% | < 0.001 |
| Ever Married | 3009 | 20.6% | | 1735 | 20.1% | |
| **Age at First Birth** | | | | | | |
| < 20 | 1769 | 20.7% | | 872 | 24.4% | |
| 20 - 24 | 887 | 20.6% | 0.014 | 554 | 17.6% | < 0.001 |
| 25 - 29 | 316 | 20.1% | | 240 | 15.5% | |

| | | | | |
|---|---|---|---|---|
| 30+ | 62 | 14.3% | 78 | 14.2% |

**Figure 1:** Predictive performances of the five machine learning algorithms

**Table 3:** Predictive performances of the five machine learning algorithms.

| | ALGORITHMS | | | | |
|---|---|---|---|---|---|
| | LDA | CART | KNN | SVM | RF |
| **DHS, 2013** | | | | | |
| Accuracy | 0.785 | 0.772 | 0.757 | 0.773 | 0.786 |
| Accuracy *[ACC > NIR]* | <0.000 | <0.000 | 0.105 | 0.001 | <0.000 |
| Kappa | 0.507 | 0.523 | 0.462 | 0.494 | 0.513 |
| McNemar's Test *[P-value]* | <0.000 | 0.004 | <0.000 | <0.000 | <0.000 |
| Positive Predicted Value | 0.545 | 0.596 | 0.518 | 0.542 | 0.552 |
| Negative Prediction Value | 0.923 | 0.91 | 0.91 | 0.916 | 0.922 |
| AUC.PR | 0.779 | 0.83 | 0.809 | 0.72 | 0.821 |
| AUC.ROC | 0.774 | 0.808 | 0.814 | 0.759 | 0.821 |
| **MICS, 2016** | | | | | |
| Accuracy | 0.861 | 0.844 | 0.782 | 0.849 | 0.839 |
| Accuracy *[ACC > NIR]* | <0.000 | <0.000 | <0.000 | <0.000 | <0.000 |
| Kappa | 0.668 | 0.648 | 0.522 | 0.654 | 0.653 |
| McNemar's Test *[P-value]* | <0.000 | <0.000 | <0.000 | <0.000 | <0.000 |
| Positive Predicted Value | 0.675 | 0.672 | 0.569 | 0.673 | 0.69 |
| Negative Prediction Value | 0.953 | 0.944 | 0.92 | 0.947 | 0.94 |
| AUC.PR | 0.83 | 0.849 | 0.843 | 0.774 | 0.847 |
| AUC.ROC | 0.822 | 0.828 | 0.848 | 0.804 | 0.854 |


DHS, 2013
Proportions
0.9
0.8
0.7
0.6
0.5
Accuracy
F1
Precision
Sensitivity
Specificity
Performance Metrics
MICS, 2016
Proportions
0.9
0.8
0.7
0.6
Accuracy
F1
Precision
Sensitivity
Specificity
Performance Metrics
Models
CART
KNN
LDA
RF
SVM