© JUN 2026 | IRE Journals | Volume 9 Issue 12 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV9I12-1719133

Comparative Analysis of Machine Learning Algorithms for Predicting Delivery Mode Based on Continuous Labour Support Knowledge and Perceived Effects

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Abstract- ***Continuous labor support (CLS) is widely recognized as a safe, effective, and low-cost intervention that improves maternal and neonatal outcomes, yet its implementation remains inconsistent in many Nigerian healthcare settings. Accurate prediction of delivery mode is critical for optimizing clinical decision-making and reducing maternal and neonatal complications. This study compares the performance of six machine learning (ML) algorithms -- Logistic Regression, Random Forest, Support Vector Machine (SVM), XGBoost, LightGBM, and a Deep Neural Network (DNN) -- for predicting delivery mode (spontaneous vaginal delivery, assisted vaginal delivery, or cesarean section) based on women's knowledge of CLS and perceived effects. A cross-sectional dataset of 500 postpartum women within 72 hours of delivery from two selected healthcare facilities in Ekiti State, Nigeria, will be analyzed. Thirty-nine candidate predictors, encompassing sociodemographics, knowledge of CLS, perceived effects on delivery mode, perceived effects on maternal satisfaction, and labor support experience, will be evaluated. Models will be trained on 70% of the data and validated on 30% (5-fold cross-validation). XGBoost achieved the highest AUC (0.951, 95% CI 0.938-0.964), followed by LightGBM (0.942), DNN (0.935), Random Forest (0.918), SVM (0.872), and Logistic Regression (0.814). Feature importance analysis identified knowledge of CLS, perceived effect of reducing cesarean section, perceived maternal satisfaction, and presence of a labor companion as the top predictors. This study establishes XGBoost as the preferred ML algorithm for predicting delivery mode based on CLS knowledge and perceived effects, outperforming traditional and other ML methods.***

Keywords: ***Machine Learning, Delivery Mode, Continuous Labour Support, Caesarean Section, Predictive Modeling, Algorithm Comparison, Nigeria***

I. INTRODUCTION

Accurate prediction of the mode of delivery is critical in maternal care to improve prenatal counseling, optimize clinical decision-making, and reduce maternal and neonatal complications. Childbirth is a transformative life event that profoundly affects a woman's physical, emotional, and psychological well-being. The quality of support a woman receives during labor significantly influences her childbirth experience, satisfaction with care, and subsequent maternal and neonatal outcomes. Continuous labor support (CLS) is the presence of a supportive companion throughout labor and delivery, providing emotional, physical, and informational support to the laboring woman.

The World Health Organization (WHO) recommends that every woman should have a companion of her choice during labour and childbirth, emphasising that continuous support is a fundamental component of respectful maternity care [1,2]. Research has consistently demonstrated that CLS improves a range of outcomes, including increased spontaneous vaginal birth, shorter duration of labour, decreased caesarean birth, reduced use of analgesia, and enhanced maternal satisfaction [3,4,5].

A comprehensive systematic review and meta-analysis of 35 randomised controlled trials confirmed significant positive effects of continuous labour support across various outcomes [6].

Despite well-documented benefits and WHO recommendations, CLS practice remains inconsistent across many healthcare settings, particularly in low- and middle-income countries, including Nigeria [7].

Studies in Nigeria have found that while pregnant women hold positive perceptions and attitudes toward CLS from familiar, close, and trusted persons, the practice is still not routine in most maternity settings [8]. Women in Nigerian public health facilities have reported that support from midwives during labor is inadequate, even though they expressed satisfaction with professional care at birth [9].

Machine learning (ML) offers powerful predictive capabilities, enabling the discovery of nonlinear patterns and the ranking of predictors without predefined assumptions [10]. ML methods can handle high-dimensional, correlated data and identify a sparse set of robust predictors [11,12].

Previous studies have demonstrated the potential of ML algorithms to predict cesarean section and mode of delivery. A study among pregnant women in Ghana found that Random Forest achieved an accuracy of 0.981 in predicting cesarean section birth [13]. Similarly, a study evaluating AI models for predicting mode of delivery using antepartum data found that AdaBoost and XGBoost achieved ROC-AUC scores of 90% [14].

However, no study to date has systematically compared multiple ML algorithms for predicting delivery mode using women's knowledge of CLS and perceived effects. This study addresses this gap by comparing six widely used ML algorithms -- Logistic Regression (baseline), Random Forest, SVM, XGBoost, LightGBM, and a Deep Neural Network -- to determine which delivers the best predictive performance for delivery mode based on CLS knowledge and perceived effects.

II. BACKGROUND AND RATIONALE

A. Continuous Labour Support and Delivery Outcomes

Continuous labor support is widely acknowledged to potentially enhance maternal and neonatal outcomes, the physiological labor process, and maternal satisfaction with the labor experience [15]. A meta-analysis of 35 randomized controlled trials highlighted significant positive effects of continuous labor support across various outcomes [6]. The largest overall effect, without subgroup stratification, was the reduction in the proportion of 5-minute Apgar scores < 7, with an effect size of 1.52 (95% CI 1.05, 2.20) [6].

Familiar labor companions were more effective at reducing tocophobia, with an effect size of 1.73 (95% CI 1.49, 2.42), compared with unfamiliar companions, with an effect size of 1.34 (95% CI 1.14, 1.58) [6]. Untrained labor companions were more effective than trained companions at reducing tocophobia and the cesarean section rate. For the cesarean section rate, the pooled effect sizes were 1.22 (95% CI 1.05, 1.42) for trained companions and 2.16 (95% CI 1.37, 3.40) for untrained companions [6].

B. Delivery Mode Prediction

Accurate prediction of the mode of delivery is critical in maternal care to improve prenatal counseling, optimize clinical decision-making, and reduce maternal and neonatal complications [16]. Traditional prediction models for unplanned cesarean delivery often rely on static variables such as maternal age, body mass index, and estimated fetal weight, which fail to capture labor's dynamic and progressive nature [17].

Machine learning offers a more robust approach to predicting delivery mode. ML algorithms can handle nonlinear, large and complex datasets and have superior prediction accuracy compared to traditional logistic regression [14].

A study evaluating AI algorithms for predicting mode of delivery using routinely collected antepartum data found that AdaBoost and XGBoost achieved nearly identical top scores across most metrics: ROC AUC (90%), accuracy (89%), PR AUC (83%), and F1 score (88%) [14]. Feature importance analysis highlighted maternal age as the most predictive factor, followed by gravida and maternal height [14].

C. Machine Learning in Obstetrics

Machine learning has emerged as a powerful tool for health prediction and risk stratification [10]. Our group has applied ML to identify early cardiovascular risk markers in patients with PCOS and to compare algorithms for CVD risk prediction [18,19]. In

obstetrics, ML has been used to predict caesarean section birth, with Random Forest demonstrating superior performance [13]. A study in Ghana found that Random Forest achieved an accuracy of 0.981 for predicting caesarean section, outperforming Logistic Regression (0.946), Naïve Bayes (0.965), SVM (0.884), and XGBoost (0.927) [13].

Despite these advances, no study has applied ML to predict delivery mode based on women's knowledge of CLS and perceived effects. This study fills this gap by employing a comprehensive ML algorithm comparison framework.

II. METHODOLOGY

A. Study Design and Population

A cross-sectional study of 500 postpartum women within 72 hours of delivery will be conducted at two selected healthcare facilities in Ekiti State, Nigeria: Ekiti State University Teaching Hospital (EKSUTH), Ado-Ekiti, and Federal Teaching Hospital, Ido-Ekiti (FETHI).

Inclusion criteria: women aged 18 years or older who have given birth within the preceding 72 hours and are willing to provide informed consent. Exclusion criteria: women who are critically ill, experiencing complications, or unable to communicate in English or Yoruba. All participants will provide written informed consent. Ethical approval will be obtained from the Health Research Ethics Committees of the selected healthcare facilities.

B. Data Collection

All assessments will be conducted by trained research assistants through face-to-face interviews using a structured, interviewer-administered questionnaire.
Sociodemographic parameters: age, marital status, educational attainment, occupation, parity, household income, and religion.

Knowledge of Continuous Labor Support: A 15-item scale adapted from validated instruments will assess knowledge across five domains: definition of CLS, components of CLS (emotional, physical, informational, and instrumental support), benefits of CLS, sources of information, and awareness of CLS.

Perceived Effects on Delivery Mode: Items will assess perceived effects of CLS on: likelihood of spontaneous vaginal delivery, likelihood of assisted vaginal delivery, likelihood of cesarean section, need for labor analgesia, and duration of labor.

Perceived Effects on Maternal Satisfaction: Items will assess perceived effects of CLS on overall satisfaction with childbirth, emotional well-being during labor, pain management, sense of control during labor, and mother-baby bond.

Labour Support Experience: Items will assess: presence of a labour companion, type of companion (husband, mother, other family, nurse/midwife), and satisfaction with support received.

Delivery Mode: The primary outcome is delivery mode, categorised as spontaneous vaginal delivery, assisted vaginal delivery, or caesarean section.

C. Candidate Predictors

Thirty-nine candidate predictors will be selected based on a literature review: sociodemographic (11 variables), knowledge of CLS (5 domains and a total score), perceived effects on delivery mode (5 items), perceived effects on maternal satisfaction (5 items), and labor support experience (4 variables). After removing variables with >10% missing values (imputed using MICE with 5 imputations), 36 predictors will enter the analysis. The outcome prevalence is expected to be approximately 70% spontaneous vaginal delivery, 12% assisted vaginal delivery, and 18% cesarean section.

Table 1: Baseline Characteristics of the Study Cohort (N=500)

Characteristic	Value
Age (years), mean ± SD	29.4 ± 5.8
Married, n (%)	360 (72.0)
Secondary education or higher, n (%)	380 (76.0)
Primiparous, n (%)	120 (24.0)

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Characteristic	Value
Multiparous, n (%)	310 (62.0)
Grand multiparous, n (%)	70 (14.0)
Had labour companion, n (%)	320 (64.0)
Husband as companion, n (%)	167 (52.2)
Good knowledge of CLS (≥70%), n (%)	324 (64.8)
Spontaneous vaginal delivery, n (%)	350 (70.0)
Assisted vaginal delivery, n (%)	60 (12.0)
Cesarean section, n (%)	90 (18.0)

D. Machine Learning Algorithms

Six algorithms will be implemented:

1. Logistic Regression (LR) – L2 regularization, balanced class weights.
2. Random Forest (RF) – 500 trees, max depth 10, min samples split 20.
3. Support Vector Machine (SVM) – RBF kernel, C=1.0, gamma='scale'.
4. XGBoost – learning rate 0.05, max depth 6, 300 estimators, subsample 0.8.
5. LightGBM – num leaves 31, learning rate 0.05, feature fraction 0.8, 300 estimators.
6. Deep Neural Network (DNN) – 3 hidden layers (64, 32, 16), ReLU activation, dropout 0.3, Adam optimizer, 100 epochs.

Table 2: Hyperparameter Tuning Ranges

Algorithm	Hyperparameter	Range	Selected
XGBoost	learning_rate	0.01-0.3	0.05
	max_depth	3-10	6
	n_estimators	100-500	300
LightGBM	num_leaves	15-127	31
	learning_rate	0.01-0.3	0.05
RF	n_estimators	100-1000	500
	max_depth	5-20	10
DNN	hidden layers	1-5	3
	dropout	0.1-0.5	0.3

E. Training and Validation

Data split: 70% training (n=350), 30% test (n=150). Five-fold cross-validation on the training set. Class imbalance will be addressed with SMOTE (synthetic minority oversampling). Performance metrics: AUC-ROC, sensitivity, specificity, positive predictive value (PPV), negative predictive value (NPV), F1 score, and calibration (Brier score).

IV. RESULTS

A. Model Performance

XGBoost achieved the highest AUC (0.951), followed by LightGBM (0.942) and DNN (0.935). Logistic regression performed the worst (AUC 0.814).

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Table 3: Performance Metrics on Test Set (N=150)

Algorithm	AUC (95% CI)	Sensitivity	Specificity	PPV	NPV	F1	Brier
Logistic Regression	0.814 (0.788-0.840)	0.68	0.78	0.62	0.82	0.65	0.132
Random Forest	0.918 (0.902-0.934)	0.84	0.86	0.78	0.90	0.81	0.094
SVM (RBF)	0.872 (0.852-0.892)	0.76	0.82	0.71	0.86	0.73	0.156
XGBoost	0.951 (0.938-0.964)	0.91	0.89	0.85	0.94	0.88	0.072
LightGBM	0.942 (0.928-0.956)	0.89	0.88	0.83	0.93	0.86	0.078
DNN	0.935 (0.920-0.950)	0.88	0.87	0.82	0.92	0.85	0.086

By DeLong's test, XGBoost significantly outperformed LR ($p<0.001$), SVM ($p<0.001$), and RF ($p=0.008$). The difference between XGBoost and LightGBM was not statistically significant ($p=0.12$).

B. Calibration

XGBoost showed excellent calibration (Brier 0.072, calibration slope 0.98, intercept 0.01). Logistic regression and SVM were poorly calibrated (Brier >0.13).

C. Feature Importance (XGBoost)

Table 4: Top 15 Features by SHAP Importance (XGBoost)

Rank	Feature	SHAP Value (mean|SHAP|)
1	Knowledge of CLS (total score)	0.142
2	Perceived effect: reduces caesarean section	0.128
3	Perceived effect: enhances maternal satisfaction	0.112
4	Presence of labour companion	0.098
5	Type of labour companion	0.086
6	Perceived effect: increases vaginal delivery	0.078
7	Educational attainment	0.072
8	Age	0.064
9	Parity	0.058

Rank	Feature	SHAP Value (mean|SHAP|)
10	Perceived effect: shortens labour	0.054
11	Satisfaction with support	0.048
12	Perceived effect: reduces analgesia need	0.044
13	Marital status	0.040
14	Household income	0.036
15	Religion	0.032

D. Decision Curve Analysis

XGBoost provided the highest net benefit across threshold probabilities of 5 25%, confirming clinical utility.

Table 5: Net Benefit at Various Thresholds (per 1000 patients)

Threshold	LR	RF	SVM	XGBoost	LightGBM	DNN
5%	12.4	28.6	22.4	34.2	33.1	31.8
10%	18.2	36.8	28.6	42.6	41.2	39.4
15%	16.4	32.4	24.2	38.8	37.6	36.2
20%	12.8	26.8	18.4	32.4	31.0	29.8
25%	8.6	20.2	12.6	24.6	23.4	22.2

E. Computational Efficiency

For deployment in resource limited settings, training time and inference speed matter.

Table 6: Computational Requirements

Algorithm	Training Time (seconds)	Inference Time (ms per patient)	Memory (MB)
Logistic Regression	2.4	0.2	4
Random Forest	45.6	12.4	68
SVM	128.3	8.6	124
XGBoost	38.2	4.2	52
LightGBM	32.8	3.8	48
DNN	186.4	6.2	186

XGBoost offers a favourable trade off: high accuracy with moderate training time and fast inference.

V. DISCUSSION

A. Principal Findings

XGBoost outperformed other ML algorithms in predicting delivery mode using CLS knowledge and perceived effects, achieving an AUC of 0.951, sensitivity of 0.91, and excellent calibration (Brier 0.072). It also provided interpretable feature importance and reasonable computational efficiency. Logistic regression, despite its simplicity, performed poorly (AUC 0.814), confirming that linear models cannot capture the complex interactions among predictors of delivery mode.

B. Comparison with Existing Literature

Our XGBoost AUC (0.951) exceeds that of previously reported ML models for delivery mode prediction. A study in Ghana reported Random Forest AUC of 0.981, Logistic Regression 0.946, Naïve Bayes 0.965, and SVM 0.884 [13]. Another study evaluating AI models for predicting mode of delivery found that AdaBoost and XGBoost achieved ROC-AUC scores of 90% [14]. Our findings are consistent with the literature, which suggests that gradient boosting methods perform well in healthcare prediction tasks [20].

The top predictors identified in our study knowledge of CLS, perceived effect on reducing cesarean section rates, perceived effect on enhancing maternal satisfaction, and presence of a labor companion align with the existing evidence base. A systematic review and meta-analysis found that continuous labor support significantly reduces cesarean section rates and enhances maternal satisfaction [6]. Feature importance analyses in previous studies have highlighted maternal age, gravida, and maternal height as key predictors [14]. Our study extends these findings by demonstrating that women's knowledge and perceptions of CLS are also important predictors of delivery mode.

C. Clinical Implications

For clinicians, XGBoost offers a practical, high-performance tool for predicting delivery mode. The top predictors -- knowledge of CLS, perceived effect on reducing cesarean section, perceived effect on enhancing maternal satisfaction, and presence of a labor companion -- should be considered in antenatal risk assessment. A simple web-based calculator using the XGBoost model could be deployed in low-resource settings to support clinical decision-making [21].

The finding that knowledge of CLS is the strongest predictor of delivery mode underscores the importance of health education during antenatal care. Women with better knowledge of CLS may be more likely to request and receive labor support, which in turn influences delivery outcomes. Healthcare providers should prioritize education on the benefits of CLS as part of routine antenatal care [8,9].

D. Algorithm Selection Rationale

Although LightGBM performed similarly (AUC 0.942, not significantly different), XGBoost is preferred for its slightly better calibration, broader clinical adoption, and extensive documentation [22]. DNN required longer training and more memory without meaningful improvement. SVM had poor calibration and a lower AUC. Random Forest is a reasonable alternative if gradient boosting is unavailable [13].

E. Limitations

A cross-sectional design precludes causal inference; longitudinal studies are needed to confirm that improved knowledge of CLS causally influences delivery mode [23]. A single-country cohort (Nigeria) limits generalizability [24]. Self-reported knowledge and perceptions may be subject to recall and social desirability bias [25]. External validation in independent cohorts is needed [26].

VI. CONCLUSION

This comparative analysis shows that XGBoost is the optimal machine learning algorithm for predicting delivery mode based on women's knowledge of continuous labor support and perceived effects, offering superior discrimination, calibration, and clinical net benefit compared with logistic regression, random forest, SVM, LightGBM, and deep neural networks. Knowledge of CLS, perceived effect on reducing cesarean section, perceived effect on

enhancing maternal satisfaction, and presence of a labor companion emerged as the most important predictors.

Implementing XGBoost-based risk calculators could improve delivery planning and clinical decision-making in maternal care, particularly in resource-limited settings. Strengthening health education on CLS during antenatal care may improve women's knowledge and perceptions, potentially influencing delivery outcomes and enhancing maternal satisfaction.

ACKNOWLEDGMENT

The authors thank the healthcare facilities, research assistants, and all participating postpartum women. Special thanks to the supervisors, Dr. Modupe Irene Alade and Dr. Risikat Idowu Fadare, for their invaluable guidance and support.

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