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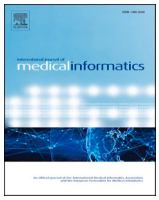

Machine learning prediction of kangaroo mother care in Sierra Leone: a comparative study of feature selection techniques and classification algorithms

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ABSTRACT

Background: Kangaroo Mother Care (KMC) is a critical intervention for improving neonatal outcomes, particularly for low-birth-weight infants. Identifying predictors of KMC practice remains essential for targeted health interventions and policy development.
Objective: This study utilizes data from the 2019 Sierra Leone demographic and health survey to identify predictors of KMC using different feature selection techniques and classification algorithms.
Methods: We analyzed 7,377 maternal and child health records from the 2019 Sierra Leone demographic and health survey, applying three feature selection techniques and seven classification algorithms. Data preprocessing included class balancing and cross-validation. Three feature selection techniques employed were: Adaptive Ant Colony Optimization (ACO), Recursive Feature Elimination (RFE), and Backward Feature Selection. Seven machine learning algorithms implemented were: Logistic Regression, Support Vector Machine variants, K-Nearest Neighbours, Random Forest, XGBoost, Stacking Ensemble, and Voting Ensemble. Data preprocessing included SMOTE for class imbalance, 5-fold and 10-fold cross-validation, and hyperparameter optimization using GridSearchCV.
Results: Random Forest and XGBoost consistently achieved the highest performance across all feature selection methods. Using consensus features from multiple selection techniques, Random Forest achieved an accuracy of 0.72, F1-score of 0.78, and ROC-AUC of 0.7689, whilst XGBoost demonstrated similar performance (accuracy: 0.72, F1-score: 0.78, ROC-AUC: 0.7685). Backward Feature Selection and ACO outperformed RFE in identifying discriminative features. Ensemble methods showed robust generalization capabilities.
Conclusion: Machine learning models, particularly ensemble methods combined with comprehensive feature selection techniques, demonstrate strong predictive capability for KMC practice, offering valuable insights for maternal and child health interventions in Sierra Leone.

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1. Introduction

Kangaroo Mother Care (KMC) represents one of the most effective, evidence-based interventions for improving survival rates and health outcomes among low-birth-weight infants, particularly in resource-limited settings [1]. This practice, which involves skin-to-skin contact between mother and infant, early initiation of breastfeeding, and continuous care, has been demonstrated to reduce neonatal mortality by up to 40 % and significantly improve thermal regulation, feeding patterns, and maternal-infant bonding [2]. Despite overwhelming evidence supporting its benefits, implementation rates of KMC vary considerably across different populations and healthcare systems. In Sierra Leone, neonatal mortality remains high, and understanding the determinants of KMC adoption is particularly urgent. This study leverages data from the 2019 Sierra Leone Demographic and Health Survey (DHS), providing a unique opportunity to examine KMC practices in a nationally representative sample.

The variation in KMC uptake has prompted researchers to investigate the socio-demographic, clinical, and systemic factors that predict its practice [3]. Traditional statistical approaches have identified several important predictors, including maternal education, socioeconomic status, healthcare accessibility, and delivery circumstances [4]. However, these conventional methods often struggle to capture the complex, non-linear relationships and interactions between multiple variables that may collectively influence health behaviours. The emergence of machine learning techniques offers promising opportunities to better understand and predict KMC practice by uncovering hidden patterns in large, multidimensional datasets and providing more accurate predictive models for targeted interventions [5].

Feature selection represents a critical component in developing robust machine learning models, particularly in healthcare applications where datasets often contain numerous variables with varying degrees of relevance [6]. The challenge lies not only in identifying which features are most predictive but also in understanding how different selection methodologies may influence model performance and interpretability. Traditional wrapper methods like Recursive Feature Elimination provide model-specific feature rankings [7], whilst meta-heuristic approaches such as Ant Colony Optimization offer global search capabilities that may identify optimal feature combinations missed by greedy algorithms [8]. The comparative effectiveness of these approaches in predicting health behaviours remains an active area of investigation.

Ensemble learning methods have gained considerable attention in medical prediction tasks due to their ability to combine the strengths of multiple algorithms whilst mitigating individual model weaknesses [9]. Random Forest and Extreme Gradient Boosting (XGBoost) have demonstrated particular success in healthcare applications, offering robust performance across diverse datasets and providing interpretable feature importance measures crucial for clinical decision-making [10]. However, the comparative performance of these ensemble methods against traditional classification algorithms in predicting KMC practice has not been thoroughly investigated, particularly when combined with different feature selection strategies.

While previous studies have explored individual and health system determinants of KMC, few have applied advanced machine learning methods to large-scale, population-based datasets in sub-Saharan Africa. Moreover, there is limited comparative evidence on the effectiveness of different feature selection and classification approaches for predicting KMC uptake. The current study addresses this knowledge gap by implementing a comprehensive machine learning framework to predict KMC practice using a large, nationally representative dataset. The primary aim is to compare the effectiveness of three distinct feature selection techniques Adaptive Ant Colony Optimization, Recursive Feature Elimination, and Backward Feature Selection in identifying optimal predictors for KMC adoption. The specific objectives include: (1) evaluating the predictive performance of seven machine learning algorithms across different feature subsets; (2) determining the most effective combination of feature selection method and classification algorithm; (3) assessing the value of ensemble approaches compared to individual classifiers; and (4) identifying consensus features that consistently predict KMC practice across multiple selection methodologies. This comprehensive approach offers novel insights into the application of advanced machine learning techniques for maternal and child health prediction, providing evidence-based guidance for developing targeted interventions to improve KMC uptake.

2. Methods

2.1. Study design and rationale

This study adopted a supervised machine learning approach to investigate predictors of Kangaroo Mother Care (KMC) practice. The research process involved data cleaning, preprocessing, feature selection, model development, hyperparameter tuning, cross-validation, ensemble learning, and final model evaluation. This structured pipeline was designed to ensure a robust and reproducible analysis, with each stage contributing to the identification of the most effective predictive model for KMC uptake. Fig. 1 provides a visual overview of the key steps followed in the study.

2.2. Dataset description

This study utilizes data from the 2019 Sierra Leone demographic and health survey, a nationally representative, cross-sectional survey of women aged 15–49 years. The DHS employed a two-stage stratified cluster sampling design. All women who reported a live birth in the two years preceding the survey and for whom KMC practice data were available were included. The dataset used in this study comprises 7,377 individual records derived from a nationally representative maternal and child health survey. It includes over 23 variables spanning socio-demographic characteristics, maternal health indicators, delivery conditions, and media exposure. The target variable is binary, representing whether Kangaroo Mother Care (KMC) was practiced (1) or not (0). The dataset is structured to facilitate classification tasks and is suitable for the application of supervised machine learning models.

2.3. Data preprocessing

A structured preprocessing pipeline was applied to prepare the dataset for machine learning tasks. This involved initial data cleaning to remove duplicates and handle missing values. Outlier detection was performed on continuous variables using standardized z-scores, with a threshold of $|z| > 3$. This cut-off corresponds to values more than three standard deviations from the mean, a widely accepted statistical rule that flags extreme observations while retaining valid variability in the data. Categorical variables were encoded based on their measurement level: nominal variables were one-hot encoded, while ordinal variables were encoded according to their natural order to preserve interpretability and enhance model performance. All numerical features were normalised using Min-Max scaling to ensure consistency across feature ranges. The dataset was then partitioned into training (80 %) and testing (20 %) sets using stratified sampling to preserve class distribution. To address class imbalance in the target variable, the Synthetic Minority Over-sampling Technique (SMOTE) was applied to the training set.

2.4. Feature selection techniques

To improve model performance, identify optimal features, reduce computational time and enhance interpretability, three distinct feature selection techniques were applied. Each method was chosen based on its methodological strengths in identifying relevant predictors from high-dimensional data:

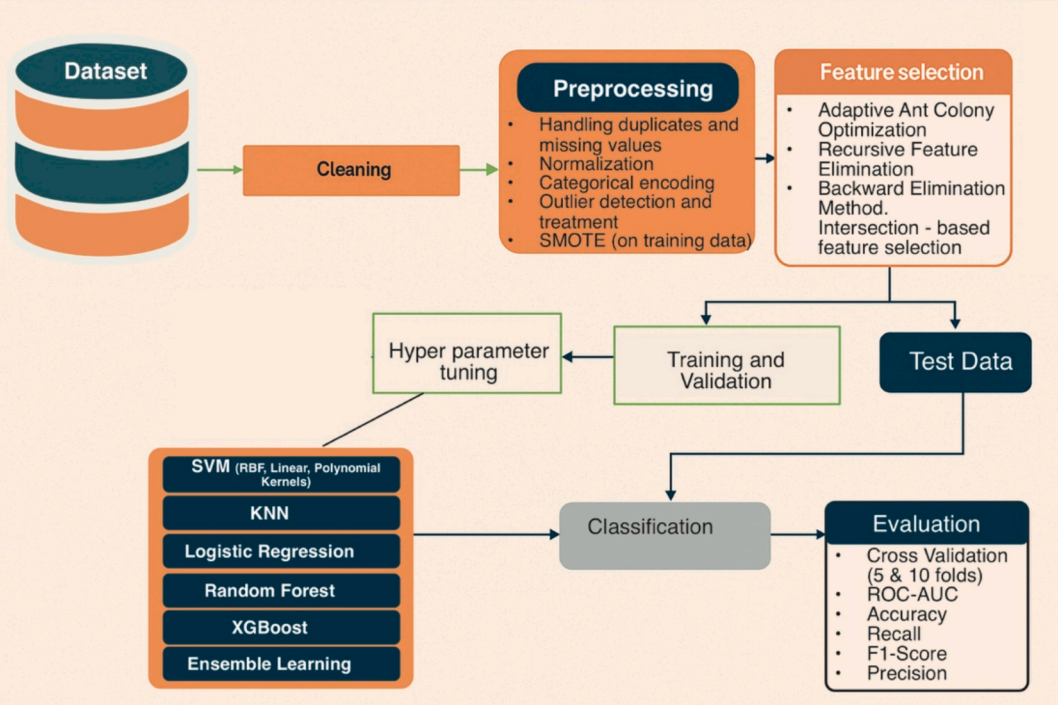

Fig. 1. Machine learning pipeline for classification of KMC practice.

a. **Adaptive Ant Colony Optimization (ACO):** A bio-inspired metaheuristic that simulates the foraging behaviour of ants was used to explore the feature space efficiently and identify combinations of variables that contribute significantly to classification performance. Adaptive ACO was selected due to its powerful metaheuristic capabilities, which are particularly well-suited for complex, high-dimensional problems [11]. Unlike simpler greedy methods, ACO's nature-inspired, probabilistic search allows exploration of a broad spectrum of feature combinations by simulating the collective intelligence of ant colonies, enhancing its ability to discover globally optimal or near-optimal feature subsets.
b. **Recursive Feature Elimination (RFE):** A wrapper-based method that iteratively removes the least important features based on model weights, typically using a base estimator like Random Forest to evaluate feature relevance [6]. RFE was chosen because it offers a robust, model-driven approach that directly ties feature relevance to the performance of a specific machine learning model. RFE operates by iteratively training a base estimator on a diminishing set of features, ranking their importance at each step. The algorithm was configured to select a final subset of 10 features, a pre-specified number chosen to balance model interpretability and predictive performance.
c. **Backward Elimination:** A statistical approach that begins with all features and sequentially removes those with the least significance based on p-values, typically within a logistic regression framework [12]. Backward Feature Selection was included as it represents a classic, greedy wrapper-based method that provides a distinct contrast to RFE's recursive nature and ACO's global metaheuristic search.

The final set of features included variables that were selected by at least two of the three feature selection methods (ACO, RFE, and Backward Elimination). This consensus-based approach was used to enhance feature stability and reduce the influence of method-specific biases.

2.5. Model development

To predict KMC practice, seven supervised machine learning algorithms were implemented. The selected models represent a balanced mix of linear, nonlinear, distance-based, and ensemble approaches, enabling a robust evaluation of classification performance under varied assumptions:

a. **Logistic Regression (LR):** Employed as a baseline model due to its simplicity, interpretability, and established use in healthcare research for binary outcomes.
b. **Support Vector Machine (SVM):** Implemented with three kernel functions (linear, polynomial, and radial basis function) to capture varying degrees of complexity in decision boundaries.
c. **K-Nearest Neighbours (KNN):** A non-parametric, instance-based algorithm chosen for its ability to detect local data structures without imposing distributional assumptions.
d. **Random Forest (RF):** An ensemble technique building multiple decision trees using bootstrapped datasets and randomly selected features at each split, selected for its robustness and ability to handle noisy and imbalanced data.
e. **Extreme Gradient Boosting (XGBoost):** A highly efficient implementation of gradient boosting algorithms incorporating regularisation techniques to improve model generalisation and prevent overfitting.
f. **Stacking Ensemble:** integrates multiple base learners (Random Forest, XGBoost, and Logistic Regression). Logistic Regression was used as the *meta*-learner because of its simplicity, low overfitting risk, and ability to effectively combine outputs from heterogeneous base models. Out-of-fold predictions from the base learners were used as inputs to train the *meta*-learner.
g. **Voting Ensemble:** A soft voting ensemble averaging the predicted class probabilities from the base learners.

All models were trained using the scikit-learn and XGBoost libraries in Python on a SMOTE-resampled dataset to address class imbalance.

2.6. Hyperparameter optimization

To enhance the predictive performance and generalisability of the developed models, hyperparameter tuning was conducted using a grid search strategy embedded within 5-fold cross-validation. This approach systematically explored a defined range of parameter values for each algorithm, with selection criteria based on the highest average ROC-AUC score across validation folds. The tuning process was performed using the GridSearchCV module from the scikit-learn library, ensuring reproducibility and consistency.

The final hyperparameter configurations selected for the top-performing models were:

- **Random Forest:** n_estimators = 200, max_depth = 20, min_samples_split = 5, min_samples_leaf = 2
- **XGBoost:** n_estimators = 250, max_depth = 12, learning_rate = 0.1, subsample = 0.8, colsample_bytree = 0.9
- **SVM (RBF Kernel):** C = 10, gamma = 0.01, kernel = 'rbf'

2.7. Performance evaluation methods and metrics

Cross-validation was used to ensure model robustness and prevent overfitting. During hyperparameter tuning, 5-fold cross-validation was applied within GridSearchCV to evaluate parameter combinations. After tuning, both 5-fold and 10-fold cross-validation were used on training data to assess model stability and estimate generalisation performance.

To assess the performance of the developed classification models, a comprehensive set of standard evaluation metrics was employed:

- **Accuracy:** Overall proportion of correctly classified instances
- **Precision:** Proportion of true positive predictions among all positive predictions
- **Recall (Sensitivity):** Proportion of actual positives correctly identified
- **F1-Score:** Harmonic mean of precision and recall
- **ROC-AUC:** Area Under the Receiver Operating Characteristic Curve
- **Confusion Matrix:** Detailed breakdown of classification outcomes

These metrics were calculated on the hold-out test set after model training and cross-validation to ensure unbiased evaluation of generalisation performance.

3. Results

3.1. Features obtained from feature selection techniques

Table 1 presents the outcomes of applying three distinct feature selection techniques to identify the most influential factors for predicting KMC practice. The Adaptive Ant Colony Optimization (ACO) method identified 23 features, whilst Recursive Feature Elimination (RFE) and Backward Feature Selection each identified 10 features.

3.2. Comparative performance of feature selection techniques

3.2.1. Model performance using RFE-selected features

Table 2 presents the detailed performance metrics of various machine learning models when trained exclusively on features identified by the Recursive Feature Elimination (RFE) technique.

Random Forest and XGBoost both achieved balanced metrics (0.69 across accuracy, precision, recall, and F1-score) with solid AUCs (0.760 and 0.762 respectively). Logistic Regression and SVM (Linear Kernel) demonstrated highly competitive AUCs of 0.777 and 0.776, indicating strong discriminative power from linear models.

3.2.2. Model performance using backward-selected features

Table 3 presents the results obtained with the Backward feature

Table 1
Feature selected for the employed feature selection techniques.

S/N	RFE selected features	Backward selection features	ACO selected features
1	Birth order number	Delivery by caesarean section	Sex of child
2	Age in 5-year groups	Type of birth	Birth order number
3	Highest educational level	Respondent currently working	Birth weight in kilograms (3 decimals)
4	Current marital status	Number of antenatal visits during pregnancy	Delivery by caesarean section
5	Place of delivery	Place of delivery	Type of birth
6	Frequency of listening to radio	Covered by health insurance	Age in 5-year groups
7	Wealth index combined	Region	Highest educational level
8	Women's individual sample weight (6 decimals)	Women's individual sample weight (6 decimals)	Current marital status
9	Primary sampling unit	Primary sampling unit	Respondent currently working
10	Sample strata for sample errors	Sample strata for sample errors	Number of antenatal visits during pregnancy
11			Place of delivery
12			Covered by health insurance
13			Frequency of reading newspaper or magazine
14			Frequency of listening to radio
15			Frequency of watching television
16			Wealth index combined
17			Region
18			Type of place of residence
19			Community literacy level
20			Community socioeconomic status
21			Women's individual sample weight (6 decimals)
22			Primary sampling unit
23			Sample strata for sample errors

Table 2
Model performance using RFE-selected features.

Model	Accuracy	Precision	Recall	F1-Score	AUC
Logistic Regression	0.67	0.69	0.67	0.63	0.777
Random Forest	0.69	0.69	0.69	0.69	0.760
K-Nearest Neighbors	0.59	0.60	0.59	0.59	0.618
SVM (RBF Kernel)	0.65	0.64	0.65	0.64	0.701
SVM (Linear Kernel)	0.68	0.69	0.68	0.63	0.776
SVM (Polynomial Kernel)	0.65	0.64	0.65	0.64	0.704
XGBoost	0.69	0.69	0.69	0.69	0.762

Table 3
Model performance using backward-selected features.

Model	Accuracy	Precision	Recall	F1-Score	AUC
Logistic Regression	0.68	0.68	0.68	0.65	0.763
Random Forest	0.71	0.71	0.71	0.71	0.772
K-Nearest Neighbors	0.69	0.69	0.69	0.69	0.738
SVM (RBF Kernel)	0.68	0.68	0.68	0.65	0.757
SVM (Linear Kernel)	0.68	0.68	0.68	0.65	0.762
SVM (Polynomial Kernel)	0.68	0.69	0.68	0.65	0.761
XGBoost	0.71	0.72	0.71	0.71	0.774

selection technique.

Random Forest and XGBoost emerged as top performers, both achieving accuracy of 0.71. XGBoost demonstrated slightly higher precision (0.72) and excellent AUC of 0.774.

3.2.3. Model performance using ACO-selected features

Table 4 presents the performance results using features selected by Adaptive ACO.

Both Random Forest and XGBoost demonstrated strong performance, each achieving accuracy of 0.71 with AUC values of 0.768 and 0.770 respectively.

3.3. Performance evaluation of common features

Table 5 shows the cross-validation results using features common to all three feature selection techniques.

Random Forest and XGBoost significantly outperformed other models with AUC values approaching 0.77, demonstrating superior discriminatory power.

3.4. Test set evaluation results

Table 6 summarises the final test set performance of all models using consensus features.

Random Forest and XGBoost achieved the highest performance with accuracy of 0.72, F1-scores of 0.78, and ROC-AUC values approaching 0.77. The ensemble methods performed competitively but did not significantly outperform the best individual models.

4. Discussion

The findings of this study demonstrate the effectiveness of machine learning approaches in predicting Kangaroo Mother Care practice, with ensemble methods consistently outperforming traditional classification algorithms. Beyond the technical achievements, this research provides important insights into the determinants of KMC uptake that can inform targeted interventions and policy development in Sierra Leone and similar low-resource settings.

4.1. Technical performance and machine learning insights

The superior performance of Random Forest and XGBoost across all feature selection techniques highlights their ability to capture complex, non-linear relationships inherent in healthcare behaviour data [13]. These results align with previous studies in medical prediction tasks, where ensemble methods have demonstrated robust performance. Specifically, Random Forest achieved 86 % accuracy, while LightGBM outperformed with 88–90 % accuracy in maternal health risk prediction [14,15]. The consistent ROC-AUC values approaching 0.77 achieved by our top models demonstrate comparable or superior performance to other maternal health prediction studies [16,17], supporting the growing evidence that ensemble methods excel in healthcare applications due to their capacity to combine multiple weak learners and reduce variance through bootstrapping and boosting mechanisms [18].

Our results corroborate findings from recent healthcare machine learning research, where Random Forest models boosted by AdaBoost algorithms have demonstrated superior performance in health prediction tasks [19,20], and Random Forest has been recognised as an ensemble learning method that combines multiple decision trees to improve predictive accuracy and control overfitting through the principle of "wisdom of the crowd" [21]. The consistent performance of XGBoost in our study aligns with its recognition as a scalable, distributed gradient-boosted decision tree machine learning library that has gained significant favour in helping individuals and teams win virtually every Kaggle structured data competition, particularly in healthcare applications where XGBoost has been successfully implemented for COVID-19 severity prediction and health monitoring in intelligent environments [22–25].

The comparative analysis of feature selection techniques reveals that Backward Feature Elimination and Adaptive Ant Colony Optimization generally yielded superior results compared to Recursive Feature Elimination. This finding is consistent with the broader literature on feature selection methodologies [26,27]. Backward elimination works in the opposite direction to forward selection: instead of starting with no features and greedily adding features, it starts with all the features and greedily removes features from the set, which may explain its effectiveness in capturing comprehensive feature interactions initially [28]. Our ACO implementation's superior performance aligns with research demonstrating that ACO algorithms inspired by ant's social behaviour in their search for shortest paths to food sources can achieve better performance than both greedy and genetic algorithm-based feature selection methods [8]. The metaheuristic approach's global search capabilities, as evidenced in our study, support findings that bio-inspired techniques including ACO can effectively handle complex feature selection problems in healthcare applications [29].

The slightly lower performance of RFE in our study contrasts with some literature suggesting its effectiveness, though this may be context-dependent [30]. RFE is a wrapper-type feature selection algorithm that begins by building a model on the entire set of predictors and computing importance scores for each predictor, then recursively removing the least important ones [30]. While RFE is recognised as an efficient approach for eliminating features from training datasets and is effective at selecting relevant features for predicting target variables, our results suggest that in the context of KMC prediction, comprehensive search strategies outperform iterative model-based elimination approaches.

The identification of consensus features across multiple selection

Table 4
Model performance using ACO-selected features.

Model	Accuracy	Precision	Recall	F1-Score	AUC
Logistic Regression	0.66	0.65	0.66	0.64	0.722
Random Forest	0.71	0.70	0.71	0.70	0.768
K-Nearest Neighbors	0.58	0.59	0.58	0.58	0.615
SVM (RBF Kernel)	0.66	0.65	0.66	0.65	0.712
SVM (Linear Kernel)	0.68	0.68	0.68	0.65	0.764
SVM (Polynomial Kernel)	0.66	0.65	0.66	0.65	0.721
XGBoost	0.71	0.70	0.71	0.70	0.770

Table 5
Cross-validation mean ROC-AUC scores.

Model	5-Fold AUC	10-Fold AUC
Logistic Regression	0.6511	0.6473
SVM (Linear Kernel)	0.6358	0.6469
SVM (RBF Kernel)	0.7044	0.7070
SVM (Polynomial Kernel)	0.7018	0.7039
K-Nearest Neighbors	0.6848	0.6814
Random Forest	0.7753	0.7717
XGBoost	0.7741	0.7728

Table 6
Test set evaluation results.

Model	Accuracy	Precision	Recall	F1-Score	ROC-AUC
SVM (Linear Kernel)	0.68	0.67	0.89	0.77	0.61
SVM (Polynomial)	0.66	0.69	0.79	0.74	0.69
K-Nearest Neighbors	0.61	0.70	0.60	0.65	0.66
Logistic Regression	0.68	0.68	0.88	0.77	0.6285
SVM (RBF Kernel)	0.67	0.71	0.76	0.73	0.6949
Random Forest	0.72	0.75	0.80	0.78	0.7689
XGBoost	0.72	0.75	0.81	0.78	0.7685
Stacking Ensemble	0.71	0.75	0.78	0.76	0.77
Voting Ensemble	0.71	0.75	0.79	0.77	0.7694

techniques provides valuable insights into the most robust predictors of KMC practice. Features consistently selected include birth order, maternal education level, delivery circumstances, and socioeconomic indicators, which align with existing literature on factors influencing maternal health behaviours [1,31,32]. Previous research has identified several barriers to KMC implementation including nurses' perspectives and emotions, healthcare institution barriers, and parental experiences, whilst multi-country analyses have explored health system bottlenecks affecting KMC scale-up, identifying the need for adequate manpower, clear guidelines, and sufficient supplies [33,34]. Our machine learning approach complements these qualitative findings by quantifying the relative importance of these factors in predicting KMC practice.

The performance metrics achieved by the top models (ROC-AUC values approaching 0.77) indicate good discriminatory capability, which is particularly relevant for healthcare applications where accurate risk stratification is crucial. This performance level is consistent with other successful maternal health prediction models, highlighting the potential for ML techniques to predict optimal childbirth outcomes and detect various complications during childbirth [16,17,35,36]. Our balanced performance across precision and recall aligns with recommendations from studies emphasising that ML models in maternal and fetal health must exhibit good predictive performance in both internal and external validation to be considered suitable for clinical implementation [37].

4.2. Key predictors of KMC practice and their implications

The consensus features identified across multiple selection techniques reveal critical determinants of KMC adoption. Birth order emerged as a consistent predictor, suggesting that multiparous women may have different levels of KMC uptake compared to primiparous mothers. This aligns with research from Ethiopia showing that birth order significantly predicts effective KMC practice, with multiparous mothers potentially having greater confidence and experience in newborn care practices [31]. However, the relationship is complex: whilst experience may facilitate KMC adoption, first-time mothers who receive adequate support and education may be more receptive to new practices.

Maternal education level consistently appeared across feature selection methods, reinforcing extensive evidence that education is a fundamental determinant of health behaviours. Previous studies have demonstrated that maternal education influences KMC adoption through multiple pathways: improved health literacy, better communication with healthcare providers, and greater autonomy in decision-making [1,4]. In the Sierra Leone context, where literacy rates vary considerably across regions, this finding underscores the need for tailored health education approaches that accommodate different literacy levels.

The prominence of delivery circumstances, including delivery location, caesarean section, and type of birth, as predictive features reflects the critical role of healthcare system contact in KMC initiation. Research has consistently shown that institutional delivery provides crucial opportunities for KMC introduction and support [32]. However, studies from multiple countries have identified significant barriers within health facilities, including inadequate space, insufficient staffing, and lack of clear guidelines [33,34]. Our findings suggest that strengthening facility-based KMC programmes, particularly for women delivering by caesarean section who may face additional challenges in implementing KMC, should be a priority intervention area.

Socioeconomic indicators, particularly wealth index and health insurance coverage, emerged as important predictors. This finding resonates with global evidence that socioeconomic disparities significantly affect maternal and child health service utilisation [1]. Whilst KMC is promoted as a low-cost intervention, our results suggest that broader socioeconomic factors, potentially reflecting access to healthcare facilities, ability to attend antenatal care, and overall health-seeking behaviours influence uptake. This challenges the assumption that KMC implementation is purely a matter of knowledge transfer and highlights the importance of addressing systemic barriers related to poverty and healthcare access.

The number of antenatal visits featured prominently in the selected predictors, supporting evidence that antenatal care provides crucial touchpoints for KMC education and preparation [31,32]. Women with more frequent antenatal contacts have greater exposure to health information and stronger relationships with healthcare providers, potentially facilitating KMC adoption. This finding suggests that integrating KMC education throughout the antenatal care continuum, rather than limiting it to immediate postnatal period, could improve uptake.

Media exposure variables, frequency of reading newspapers, listening to radio, and watching television were identified by ACO, highlighting the potential role of health communication strategies in promoting KMC. In Sierra Leone, where radio remains a primary source of health information in many communities, these findings support the development of mass media campaigns targeting KMC awareness and adoption. This aligns with broader evidence on the effectiveness of community-level interventions and health communication in maternal and child health.

Regional and community-level factors, including community literacy level and socioeconomic status, suggest that KMC adoption is influenced not only by individual characteristics but also by the broader social and healthcare environment. This finding is consistent with ecological models of health behaviour that emphasise the importance of multi-level interventions addressing individual, interpersonal, community, and health system factors [3,34]. Programmes that work solely at the individual level may be insufficient if community norms and health system structures do not support KMC practice.

4.3. Comparison with global evidence and context-specific considerations

Our findings align with and extend previous research on KMC determinants across diverse settings. Studies from multiple countries have identified similar predictors, including maternal education, facility delivery, and socioeconomic status [1,31,32]. However, the relative importance of these factors may vary by context. For instance, whilst our study found health insurance coverage to be predictive, this may reflect Sierra Leone's specific healthcare financing landscape and differs from settings with universal health coverage.

The predictive power of birth weight, delivery type, and birth order in our study parallels findings from other African contexts. Research in Amhara, Ethiopia, identified similar predictors whilst also highlighting the importance of counselling during antenatal care and postnatal follow-up [31]. The multi-country EN-BIRTH study demonstrated that measurement validity for KMC varies considerably, with coverage ranging from 3 % to 38 % across study sites, emphasising the importance of accurate measurement alongside implementation efforts [32].

Importantly, our machine learning approach complements existing qualitative and quantitative research by providing a data-driven method for identifying and ranking predictors. Whilst qualitative studies have illuminated the complex barriers to KMC implementation from providers' and parents' perspectives [3,33], our quantitative models offer a complementary approach for risk stratification and targeted intervention design.

4.4. Practical implications for KMC programme implementation

The practical implications of our findings extend beyond model performance metrics. Recent applications of machine learning in maternal health programs have demonstrated that predictive models can provide "real-time" predictions for new enrollees and enable early provision of extra support for individuals at risk, which directly aligns with our study's objectives for KMC practice prediction [38,39]. Our predictive models could be integrated into existing health information

systems to identify women at risk of low KMC uptake during pregnancy or immediately after delivery, enabling healthcare providers to offer targeted counselling and support.

Specifically, the identified predictors suggest several actionable intervention strategies:

1. Education-focused interventions: Given the strong predictive value of maternal education, developing literacy-appropriate KMC education materials and utilising visual aids and demonstrations could improve uptake among women with lower educational attainment
2. Facility-based interventions: The importance of delivery circumstances suggests that strengthening KMC initiation protocols in health facilities, particularly in operating theatres for caesarean deliveries, could significantly improve practice. Training healthcare providers on supporting KMC in diverse delivery contexts is essential
3. Antenatal care integration: The predictive value of antenatal visits indicates that incorporating KMC education and preparation throughout antenatal care, rather than only postnatally, could enhance readiness and confidence
4. Community-level approaches: The influence of community literacy and socioeconomic factors suggests that community-based interventions, including peer support groups and community health worker programmes, could address social and environmental barriers to KMC
5. Equity-focused strategies: The prominence of socioeconomic indicators highlights the need for interventions that address financial and access barriers, potentially including transportation support, extended postnatal care, and social protection measures for vulnerable families

The ensemble learning approaches, whilst competitive, did not substantially outperform the best individual models in this specific application. This finding suggests that Random Forest and XGBoost, being inherently ensemble methods themselves, may already capture much of the benefit that additional ensemble techniques might provide. This observation is consistent with research on ensemble methods for medical prediction, where weighted feature selection algorithms based on Random Forest combined with XGBoost classifiers have achieved superior prediction accuracy compared to individual algorithms [40,41]. The strong performance of linear models, particularly Logistic Regression and linear SVM, when combined with effective feature selection techniques, highlights the importance of feature engineering in predictive modelling [42].

Overall, our results support the finding that machine learning techniques in healthcare can assist medical practitioners in enhancing maternal and fetal health outcomes through early and precise prediction leading to prompt interventions, particularly in resource-constrained settings where model interpretability and computational efficiency are important considerations [14,37,43]. The clinical relevance of our findings is underscored by the broader context of KMC implementation challenges. The International Confederation of Midwives has emphasised that KMC is relevant and important across all economic contexts, requiring healthcare provision where mothers, infants and families form an inseparable centre around which maternal-newborn service delivery is organized [44]. Our predictive models could support this vision by enabling healthcare providers to identify mothers who may require additional support in KMC implementation, thereby improving overall programme effectiveness and neonatal outcomes.

5. Limitations of the study

Several limitations should be acknowledged in interpreting the results of this study. Firstly, the cross-sectional nature of the data limits the ability to establish causal relationships between predictors and KMC practice, as temporal sequences cannot be determined from the available dataset. The study relies on self-reported KMC practice, which may be subject to recall bias and social desirability bias, potentially affecting the accuracy of the target variable.

The dataset, whilst nationally representative, may not fully capture regional variations in healthcare practices, cultural factors, or policy implementations that could influence KMC adoption. The binary classification of KMC practice (practiced/not practiced) may oversimplify the reality of partial or intermittent KMC implementation, potentially limiting the nuanced understanding of practice patterns.

The feature selection techniques employed, whilst comprehensive, may have different sensitivities to correlated features and could potentially exclude relevant predictors that work synergistically. The hyperparameter optimization was limited to grid search methods, and more advanced optimization techniques such as Bayesian optimization might yield improved results.

The generalizability of the models to different populations, healthcare systems, or temporal contexts remains to be validated. The study did not account for potential changes in healthcare policies, training programs, or cultural attitudes towards KMC that might have occurred during the data collection period.

Finally, the evaluation metrics, whilst comprehensive, focus primarily on predictive accuracy rather than clinical utility or cost-effectiveness, which are important considerations for real-world implementation of predictive models in healthcare settings.

6. Conclusion

This study demonstrates the successful application of machine learning techniques for predicting Kangaroo Mother Care practice, with ensemble methods, particularly Random Forest and XGBoost, achieving superior predictive performance. The comparative analysis of feature selection techniques reveals that Backward Feature Elimination and Adaptive Ant Colony Optimization are more effective than Recursive Feature Elimination in identifying discriminative features for this healthcare prediction task.

The consensus feature approach provides robust identification of key predictors, offering valuable insights for developing targeted interventions to improve KMC uptake. The achieved performance metrics (ROC-AUC $\approx$ 0.77) indicate good discriminatory capability suitable for clinical decision support systems.

These findings contribute to the growing body of evidence supporting the use of advanced machine learning techniques in maternal and child health research. The identified predictors and model frameworks can inform the development of screening tools and targeted intervention strategies to improve KMC adoption rates, ultimately contributing to better neonatal outcomes.

Future research should focus on external validation of these models across different populations and healthcare contexts, investigation of model interpretability through advanced explainable AI techniques, and assessment of the clinical utility and cost-effectiveness of implementing such predictive models in real-world healthcare settings.

CRediT authorship contribution statement

Augustus Osborne: Writing – review & editing, Writing – original draft, Methodology, Investigation, Data curation, Conceptualization. **Afeez A. Soladoye:** Writing – review & editing, Writing – original draft, Validation, Software, Methodology, Investigation, Formal analysis. **Kobloobase O. Usani:** Writing – review & editing, Writing – original draft, Software, Methodology, Investigation. **Ayomide Israel Adekoya:** Writing – review & editing, Writing – original draft, Methodology, Investigation. **Ojima Z. Wada:** Writing – review & editing, Writing – original draft, Methodology, Investigation. **David B. Olawade:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Project Management, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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