



Predictive Analytics for Maternal Mortality in Bangladesh: An Interpretable ML Framework with Ensemble Methods

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Abstract

Maternal mortality in Bangladesh remains a critical public health challenge, with recent evidence indicating stagnation in mortality reduction despite expanded facility-based delivery and skilled birth attendance. Accurate identification of high-risk cases is essential to enable targeted intervention and resource allocation. This study develops an interpretable machine learning framework for maternal mortality prediction using the nationally representative Bangladesh Maternal Mortality Survey 2016 (BMMS-2016). A comprehensive data integration and feature engineering pipeline was implemented across demographic, socioeconomic, and maternal healthcare domains. Given the severe class imbalance inherent in maternal death outcomes, multiple resampling strategies—including Tomek Links undersampling, SMOTE, ADASYN, and

CTGAN—were systematically evaluated in conjunction with diverse classifiers and ensemble methods. Among all configurations, Random Forest combined with SMOTE achieved the best overall performance (ROC-AUC: 0.9635; Accuracy: 0.9016; F1-score: 0.8928), demonstrating superior precision-recall balance suitable for rare-event prediction. Tree-based ensemble models consistently outperformed baseline classifiers. Model interpretability was ensured through SHAP analysis, revealing region type, maternal age, and administrative division as the most influential predictors and highlighting substantial geographic and demographic disparities. An interactive Tableau dashboard translates predictive insights into accessible visual analytics for policy and decision support. The findings underscore the importance of explicit imbalance handling and explainable artificial intelligence frameworks in maternal health risk modeling, offering a scalable and transparent approach for data-driven maternal mortality reduction strategies.

Keywords: maternal mortality prediction, interpretable machine learning, class imbalance techniques, SMOTE, ADASYN, CTGAN, Tomek Links, ensemble learning, Random Forest, SHAP explainability, healthcare risk



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1 Introduction

A major ongoing issue in Bangladesh is the increasing difficulty in addressing maternal mortality. The number of maternal deaths during or soon after childbirth is not declining, despite the fact that there have been major increases in the number of facilities and skilled individuals present at childbirth, as well as in other efforts to reduce the rates of these maternal deaths. Furthermore, many of the deaths of mothers often occur after the women had visited various healthcare facilities multiple times without receiving definitive care, indicating that their high-risk pregnancies were not effectively identified or managed by the healthcare system. As such, there is a growing need for predictive approaches that can help to identify women who are at risk of death from pregnancy or childbirth, especially approaches that can be created based upon the type of data that can be collected regarding these women.

Maternal mortality refers to a mother's death owing to complications arising from childbirth or pregnancy, an issue that remains a forefront public health challenge around the globe which is pronounced in low- and middle-income countries. This problem is further complicated in developing countries due to limited access to antenatal care and the shortage of skilled birth attendants [1]. Maternal mortality is one of the very important health indicators of any country for its general health status, with an estimated 287,000 women losing their lives to pregnancy-related complications in 2020 globally [2]. Class imbalance is a fundamental challenge in rare-event prediction tasks such as maternal mortality, where the minority class (death) is vastly outnumbered by the majority class (survival) [3]. Addressing this imbalance through synthetic oversampling is essential to prevent classifiers from being biased toward the majority class and to ensure adequate sensitivity in detecting high-risk cases.

The significance of prenatal care is highlighted since effective maternal health care increases the probability of a successful pregnancy and a healthy baby. One of the most crucial aspects of pregnancy is the diagnosis of high-risk pregnancy, which can be extremely beneficial to expectant mothers. Early diagnosis can also lower maternal mortality and morbidity. In low- and middle-income nations, approximately 99% of maternal deaths worldwide occur, with the majority attributable to obstetric haemorrhage,

hypertensive disorders, and unsafe abortion. The ability to anticipate high-risk pregnancies in advance is extremely helpful as it can occasionally assist doctors in deciding whether to continue or terminate the pregnancy, thereby lowering maternal deaths [4].

Complications during pregnancy are influenced by biological, social, and environmental factors, with risks amplified by older maternal age, pre-existing chronic illnesses, limited healthcare access, and lifestyle habits [5]. Ensemble learning combined with feature engineering has demonstrated strong predictive performance in maternal health risk assessment, enabling the identification of key physiological and socioeconomic risk factors that contribute to adverse pregnancy outcomes [6]. Postpartum hemorrhage (PPH) represents a significant threat to maternal health, particularly in developing countries, where it remains a leading cause of maternal mortality. Unfortunately, only 60% of pregnant women at high risk for PPH are identified, leaving 40% undetected until they experience PPH. Effectively managing PPH requires prompt recognition of risk factors and responding to excessive bleeding. Diagnosing PPH is challenging due to underestimated blood loss and variable presentation of risk factors [7]. Similarly, pregnancy is a critical period for women's health, and access to pregnancy monitoring systems remains challenging due to geographical conditions, limited economic resources, and inadequate healthcare infrastructure. In areas with socioeconomic disadvantages, healthcare providers may exhibit lower interest in establishing healthcare services, thereby reducing the availability and affordability of medical facilities for the local population [8]. In Bangladesh, studies applying machine learning algorithms to nationally representative survey data have shown that only a fraction of women complete adequate antenatal care visits, with factors such as wealth status, media exposure, and education identified as critical determinants [9].

In recent years, machine learning approaches have emerged as powerful tools for predicting health outcomes, with ensemble methods demonstrating superior performance in handling complex, high-dimensional healthcare data [10, 11]. These approaches enable algorithms to reveal hidden knowledge and patterns that may not be obvious based on prior assumptions. Quad-ensemble machine learning frameworks have shown remarkable capabilities in predicting maternal health risk during pregnancy, integrating multiple

ensemble techniques to improve classification across high-risk, medium-risk, and low-risk categories with outstanding performance across all test configurations [12]. Perinatal mortality prediction is another crucial application of ensemble machine learning in maternal health, where homogeneous ensemble methods applied to demographic health survey data have achieved prediction accuracies exceeding 90%, with gradient boosting identified as the best-performing algorithm [13]. ADASYN adaptively generates synthetic samples by focusing on minority instances that are harder to learn, using a weighted distribution based on local class density, thereby reducing classifier bias in imbalanced datasets more effectively than uniform oversampling approaches [14]. Studies using ensemble methods with ADASYN oversampling have shown that voting classifiers combining Random Forest and XGBoost achieve 87.19% accuracy in predicting pregnancy risk levels, with blood sugar identified as the most significant predictor [15].

In Bangladesh, the mode of delivery is shaped by a complex interplay of sociodemographic and healthcare-related factors [16]. Studies applying machine learning to nationally representative survey data have identified place of delivery, baby weight, maternal BMI, birth interval, and wealth status as the most influential determinants of delivery mode [16]. In Bangladesh, despite decades of investments in maternal healthcare, the completion of the maternal continuum of care remains low, with only 25.3% of women completing all essential maternal health services [17]. The continuum of care, defined as receiving at least four antenatal care visits with a medically trained provider, delivery by a skilled birth attendant at a health facility, and postnatal care within 48 hours, represents a critical framework for reducing maternal mortality [17]. The most closely related prior work by Mamun et al. [18] applied Random Forest with SMOTE oversampling to the Bangladesh Maternal Mortality Survey 2016 (BMMS-2016), achieving a ROC-AUC of 0.957 and an accuracy of 0.892. However, that study did not evaluate deep generative oversampling methods such as CTGAN, nor did it provide individual-level SHAP decomposition through waterfall and beeswarm visualisations. The present study directly extends this line of research by addressing these gaps. Additionally, ensemble learning-based feature engineering studies analyzing maternal health during pregnancy have demonstrated that combining decision trees, bidirectional LSTM,

and temporal convolutional networks can effectively capture complex risk patterns, with Random Forest achieving 83% accuracy in maternal risk level classification [6].

Furthermore, the integration of explainable AI methods such as SHAP (SHapley Additive exPlanations), LIME (Local Interpretable Model-agnostic Explanations), and Grad-CAM has proven effective for healthcare decision-making by providing transparent insights into model predictions [1, 4]. Explainable Boosting Machines (EBMs) have emerged as particularly valuable tools in obstetric research, achieving accuracy comparable to black-box models like XGBoost and deep neural networks while maintaining full interpretability through shape functions that reveal the relationship between individual features and outcomes [19]. XAI increases trust and transparency in clinical settings, enabling healthcare providers to understand and validate model recommendations before incorporating them into patient care [20]. SHAP (SHapley Additive exPlanations) provides a unified framework for interpreting model predictions by assigning each feature an importance value based on Shapley values from cooperative game theory, offering both local and global interpretability [21]. Advanced ensemble frameworks integrating multiple machine learning models have been applied to real-world maternal health datasets collected from maternity hospitals and clinics, demonstrating the potential for scalable, data-driven maternal risk stratification in clinical settings [12]. The application of interpretable machine learning to predict severe maternal morbidity, shoulder dystocia, and preterm preeclampsia has revealed surprising insights into risk factors, challenging traditional clinical beliefs about the main contributors to pregnancy complications [19].

The primary contributions of this study, relative to existing work including Mamun et al. [18], are as follows:

- **Systematic evaluation of CTGAN-based oversampling:** This study is the first to benchmark a deep generative model (CTGAN) against SMOTE and ADASYN on the BMMS-2016 dataset, demonstrating its inferiority despite substantially higher computational cost.
- **Comprehensive four-strategy resampling comparison:** Tomek Links undersampling, SMOTE, ADASYN, and CTGAN are evaluated under a unified experimental protocol across

nine classifiers, providing a more complete characterisation of imbalance-handling strategies than prior work.

- **Individual-level SHAP interpretability:** Beyond global feature importance, this study provides instance-level SHAP decomposition via waterfall plots and population-level heterogeneity analysis via beeswarm plots, supporting clinical decision-making at the individual case level.
- **Interactive Tableau dashboard:** Predictive insights are translated into an accessible visual analytics interface integrating geographic, socioeconomic, and healthcare access dimensions for policy and decision support.

2 Related Work

Between 2001 and 2010, Bangladesh witnessed a significant reduction in maternal mortality rates, but there has been no statistically significant improvement between 2010 and 2016 [22, 23]. Factors include obstetric haemorrhage and hypertensive disorders, which account for almost half of maternal deaths within 24–48 hours of delivery [24]. Despite major increases in facility-based deliveries and skilled birth attendance, maternal mortality outcomes have not improved proportionally, highlighting critical gaps in risk identification [18]. Studies have shown that women with higher education, urban residence, and higher wealth index demonstrate significantly greater completion rates of maternal continuum of care [17]. Research applying ensemble learning to maternal health data has further demonstrated that age, educational level, and socioeconomic indicators are among the most influential predictors of adverse maternal outcomes, emphasizing the need for targeted, data-driven interventions [6].

Ensemble machine learning methods perform better at predicting maternal mortality compared to traditional statistical approaches, with Random Forest and XGBoost demonstrating superior performance in handling complex, non-linear relationships in healthcare data [25, 26]. The most directly comparable prior study, Mamun et al. [18], applied Random Forest with SMOTE oversampling to the BMMS-2016 dataset and reported a ROC-AUC of 0.957 and accuracy of 0.892, while undersampling techniques consistently degraded minority-class detection. Importantly, however, that work did not incorporate CTGAN-based oversampling, did not provide individual-level SHAP decomposition, and did not develop an

interactive visual analytics dashboard. The present study addresses each of these limitations within the same data context, yielding a more complete and interpretable predictive framework. Studies applying ensemble learning with feature engineering to maternal health datasets have shown that stacked and hybrid model architectures consistently outperform individual classifiers, demonstrating the advantage of combining multiple learning algorithms for complex maternal health prediction tasks [6].

Recent studies have demonstrated robust ML performance in predicting skilled birth attendance across 27 Sub-Saharan African countries, with Random Forest achieving an AUC-ROC of 92% and identifying critical determinants such as facility delivery, maternal education, wealth index, and urban residence [1]. Predicting perinatal mortality using ensemble machine learning on demographic health survey data found that gradient boosting achieved 90.24% accuracy, with feature importance analysis identifying community-based health insurance, maternal education, region and place of residence, age, and wealth status as the most determinant risk factors [13]. Advanced ensemble machine learning frameworks developed for maternal health risk prediction, such as the Quad-Ensemble ML framework (QEML-MHRC), have demonstrated that integrating multiple ensemble techniques substantially improves classification performance and enables detailed differentiation among high, medium, and low maternal risk categories [12]. Studies applying ensemble techniques to maternal health risk classification during pregnancy have shown that ensemble-based methods including boosted trees consistently outperform individual classifiers, achieving strong performance across high-risk, medium-risk, and low-risk categories [15].

Explainable AI studies using XGBoost and SHAP achieved high accuracy in maternal health risk prediction, with body mass index and preexisting diabetes emerging as the most significant risk determinants [5]. Analysis of maternal health data using explainable machine learning models revealed that topography, health infrastructure, insurance coverage, and other factors significantly influence policymaking, with SHAP and Explainable Boosting Machines (EBM) providing valuable insights into higher and lower maternal mortality regions [27]. The SHAP framework unifies six existing feature attribution methods and identifies a unique solution with desirable theoretical properties including local

accuracy, missingness, and consistency, making it particularly suitable for explaining complex ensemble model predictions in clinical contexts [21]. Synthetic oversampling via nearest-neighbour interpolation has been shown to substantially improve minority-class recall without the information loss associated with undersampling, forming the methodological basis for the SMOTE family of techniques widely applied in imbalanced healthcare classification [3]. The application of Explainable Boosting Machines (EBMs) to predict severe maternal morbidity (SMM), shoulder dystocia, and preterm preeclampsia has demonstrated that interpretable models can match the accuracy of black-box methods while revealing surprising insights, such as the importance of time from membrane rupture to delivery and maternal height in shoulder dystocia risk, challenging traditional beliefs about the main contributors to pregnancy complications [19].

Handling imbalanced data has been shown to substantially improve adverse pregnancy outcome prediction. Studies using DHS survey data with SMOTE-based class balancing demonstrated that supervised machine learning algorithms including Random Forest and XGBoost can effectively predict adverse pregnancy outcomes such as miscarriage and stillbirth, with SMOTE improving minority-class detection in highly imbalanced obstetric datasets [10]. The ADASYN adaptive synthetic sampling approach improves imbalanced learning in two complementary ways: by reducing the bias introduced by class imbalance and by adaptively shifting the classification decision boundary toward difficult-to-learn minority examples, with simulation analyses demonstrating consistent effectiveness across five evaluation metrics [14]. The systematic comparison of oversampling techniques demonstrated that SMOTE and ADASYN consistently outperformed undersampling and generative approaches like CTGAN [18]. In Bangladesh, applying machine learning algorithms to BDHS 2022 data for predicting antenatal care visit status found that the Ranger model achieved the highest predictive performance, with Boruta-based feature selection identifying wealth index, education, maternal age, and urban residence as the most influential predictors [9].

Ensemble voting and stacking approaches further enhanced prediction performance across multiple health domains. Comparative analytics of classifiers on resampled datasets for pregnancy outcome prediction revealed that Random Forest combined with SMOTE outperformed other classifier-resampling

pairs, producing individual class accuracy ≥ 0.89 and AUC ≥ 0.96 [11]. CTGAN addresses the unique challenges of tabular data synthesis through mode-specific normalization for continuous columns and a conditional generator with training-by-sampling for discrete columns, outperforming Bayesian network baselines on most real-world datasets in benchmark evaluations [28]. Stacked ensemble meta-models combining XGBoost and Random Forest as base classifiers with Gradient Boosting as the meta-classifier achieved accuracies of 86% for maternal health dataset, 82% for diabetes dataset, and 92% for hypertension dataset, demonstrating reliable performance in predicting health risks in pregnant women [8].

Machine learning approaches applied to BDHS 2022 data for predicting cesarean section delivery among Bangladeshi women found that Random Forest achieved the highest performance (accuracy: 81.79%; AUC: 0.871), with SHAP analysis identifying place of delivery, baby weight, maternal BMI, and birth interval as the most influential predictors, underscoring the value of interpretable ML in understanding delivery-related maternal health decisions in Bangladesh [16]. In Bangladesh specifically, machine learning-based prediction of maternal continuum of care completion using BDHS 2022 data found that Random Forest performed best with 82% accuracy and an AUC of 0.889, with SHAP analysis identifying wealth index, husband's and respondent's education, media exposure, and women's decision-making autonomy as the most influential predictors [17]. A systematic literature review on machine learning approaches for predicting postpartum hemorrhage identified logistic regression, extreme gradient boosting, random forest, and decision tree as the most frequently utilized methods, emphasizing the importance of algorithm selection, dataset characteristics, and model validation [7].

The application of Explainable AI in maternal health has gained significant attention for improving model transparency and clinical trust. Researchers have utilized SHAP, LIME, and Grad-CAM to provide comprehensive insights into the most important features affecting maternal outcomes, with SHAP analysis revealing that mothers of older age are more likely to experience caesarean sections or have children with Down syndrome [20]. Studies have shown that machine learning models can effectively predict risk levels based on pregnancy risk factors, with Gradient Boosting achieving 90.64% accuracy,

and Explainable AI techniques providing transparent explanations for predictions [4]. The integration of diverse clinical data sources with multi-model ensemble architectures, combined with systematic hyperparameter tuning and cross-validation, represents a promising direction for comprehensive and robust maternal health risk prediction [12]. While Mamun et al. [18] noted the value of interactive dashboards for visualising maternal mortality risk factors, the present study operationalises this concept through a fully implemented Tableau dashboard integrating choropleth maps, treemap and heatmap visualisations, and national-level key performance indicators, providing a concrete and deployable decision-support tool for policymakers. The use of interpretable machine learning models like Explainable Boosting Machines (EBMs) in obstetric research demonstrates that glass-box models can achieve accuracy comparable to black-box methods while providing valuable insights into the shape functions of individual risk factors, revealing clinically meaningful relationships such as the near-linear association between baby weight and shoulder dystocia risk for weights between 3250g and 4250g [19].

3 Methodology

3.1 Overview of the Proposed Framework

Figure 1 presents the overall conceptual workflow of the study. The framework integrates nationally representative survey data from the Bangladesh Maternal Mortality Survey 2016 (BMMS-2016), applies systematic preprocessing and feature engineering, addresses class imbalance using resampling techniques, and develops predictive models to estimate maternal mortality risk. The final output is designed to support real-world policy decision-making through interpretable and geographically contextualized risk insights.

3.2 Dataset Description

This study utilizes data from the Bangladesh Maternal Mortality Survey 2016 (BMMS-2016), a nationally representative survey aimed at estimating maternal mortality levels and assessing reproductive health indicators across Bangladesh. Three primary datasets were selected for this analysis due to their direct relevance to maternal health outcomes:

- **Household Data (BMMS16_HH.csv):** Contains household characteristics, housing conditions, asset ownership, and geographic information

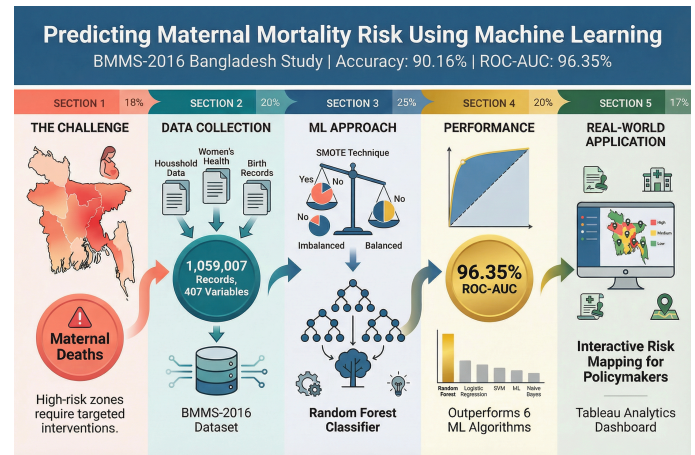


Figure 1. Overall conceptual workflow of the proposed maternal mortality prediction framework.

(878 variables; 298,284 households). This dataset provides socioeconomic and environmental context.

- **Individual Women Data (BMMS16_IQ.csv):** Includes reproductive history, antenatal care (ANC), delivery information, postnatal care, and pregnancy outcomes for women aged 13–49 (696 variables; 315,723 women). This serves as the core maternal health dataset.
- **Birth Records (BMMS16_BR.csv):** Provides detailed information on birth events, including child survival status, sex, and age (45 variables; 756,053 births), enabling linkage between maternal and child health outcomes.

Although BMMS-2016 includes additional components such as Community and Verbal Autopsy datasets, the analysis focuses on these three files as they contain the most directly relevant determinants for maternal mortality risk modeling.

3.3 Methodological Architecture

The analytical pipeline, illustrated in Figure 2, comprises four key stages: data integration, preprocessing, feature engineering, and predictive modeling.

3.3.1 Data Integration

The three primary BMMS-2016 datasets (Household, Individual Women, and Birth Records) were merged using outer joins on shared identifiers (cluster_number, household_number, division, region_type), yielding a consolidated dataset of 1,059,007 records with 407 variables.

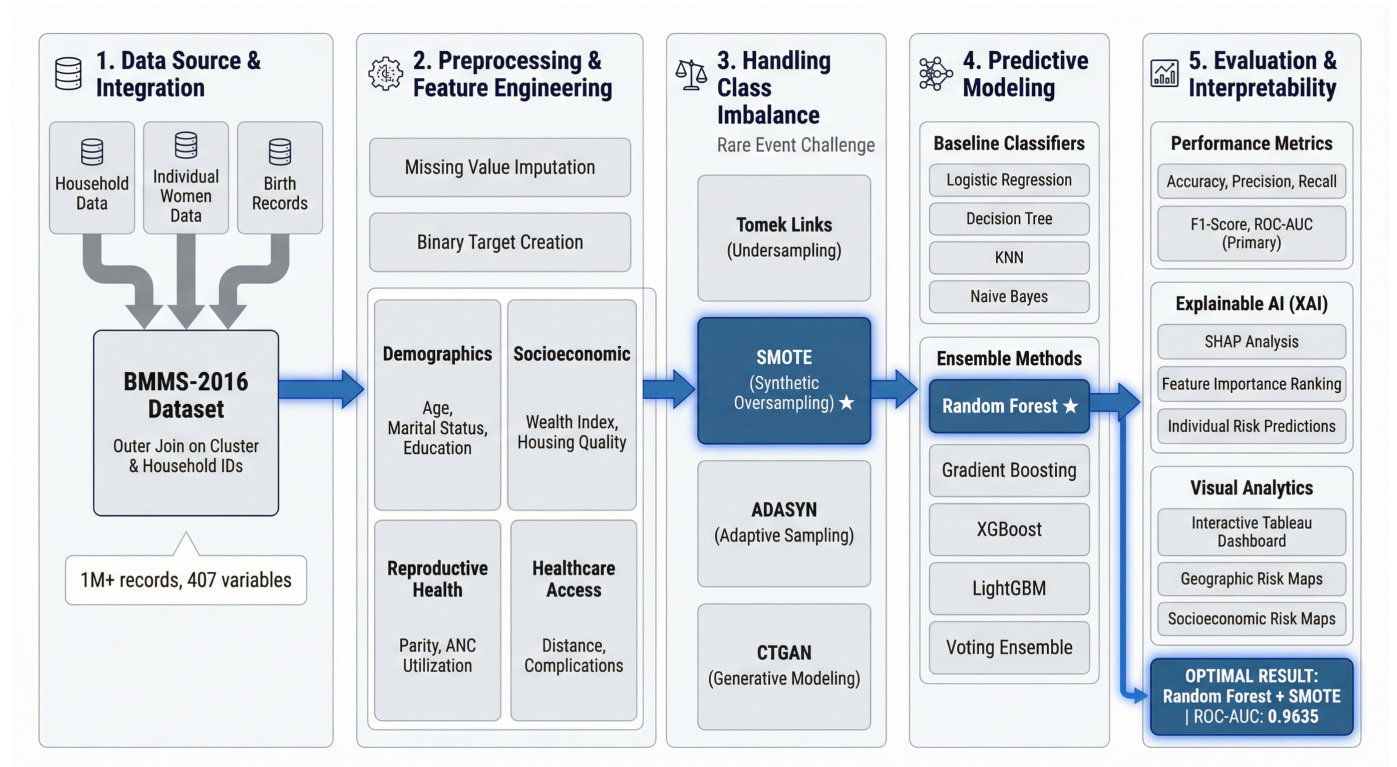


Figure 2. Methodological architecture of the analytical pipeline showing data integration, preprocessing, feature engineering, and predictive modeling stages.

3.3.2 Variable Selection and Harmonization

Relevant variables were selected using BMMS-2016 codebooks and domain knowledge. Cryptic survey codes were renamed for interpretability (e.g., `qhclust` → `cluster_number`), while redundant variables were excluded to reduce dimensionality.

3.3.3 Missing Value Handling

Missing values were addressed through variable-specific imputation: mean/median for numerical variables, mode imputation for categorical variables, and domain-driven handling for structurally missing data.

3.3.4 Target Variable Construction

The binary target variable *maternal_death* was constructed by:

1. Identifying female deaths among women aged 13–49.
2. Classifying pregnancy-related timing (during pregnancy/childbirth, within 6 weeks postpartum, or 6 weeks to 12 months postpartum).
3. Assigning 1 for pregnancy-related deaths and 0 for non-pregnancy-related deaths.

3.4 Feature Engineering

Feature engineering was conducted across four domains to capture established determinants of maternal mortality, transforming raw survey responses into predictive variables:

- **Demographic Features:** Age categorization, marital status, education level, and household composition indicators.
- **Socioeconomic Indicators:** Asset-based wealth index, housing quality (floor, wall, roof materials), and access to electricity, water, and sanitation.
- **Reproductive and Maternal Health Features:** Parity, fertility history, antenatal care (ANC) utilization, delivery characteristics, and postnatal care indicators.
- **Healthcare Access and Complications:** Distance to health facilities, financial preparedness for emergency obstetric care, and self-reported complications during pregnancy, delivery, and postpartum.

3.5 Handling Class Imbalance

Maternal mortality represents a rare event, resulting in significant class imbalance. To address this challenge:

- **SMOTE (Synthetic Minority Oversampling Technique)** was applied to generate synthetic samples of the minority class through interpolation between existing instances.
- Alternative sampling strategies, including Tomek Links and ADASYN, were evaluated for comparison.
- Stratified train-test splitting (80% training, 20% testing) preserved the original class distribution in both subsets.

SMOTE demonstrated superior performance when combined with ensemble methods and was selected as the optimal balancing technique.

3.6 Model Development

A systematic model development approach was employed:

- **Baseline Classifiers:** Logistic Regression, Decision Tree, K-Nearest Neighbors (KNN), and Naive Bayes served as performance benchmarks.
- **Ensemble Methods:** Random Forest, Gradient Boosting, XGBoost, LightGBM, and Voting Ensemble were implemented to capture complex nonlinear relationships.
- **Hyperparameter Optimization:** Cross-validation with grid search was used to identify optimal model configurations and prevent overfitting.

Random Forest combined with SMOTE outperformed all other configurations.

3.7 Model Evaluation and Interpretability

Model performance was rigorously assessed using multiple metrics:

- Accuracy, precision, recall, F1-score, and ROC-AUC were calculated to evaluate classification performance from multiple perspectives.

The optimal model (Random Forest with SMOTE) achieved:

- Accuracy: 0.9016
- F1-score: 0.8928
- ROC-AUC: 0.9635

To enhance interpretability and policy relevance:

- **Feature Importance Analysis:** Global ranking of predictor variables identified key risk factors.
- **SHAP Analysis:** Provided both local (instance-level) and global interpretability by quantifying each feature’s marginal contribution.
- **Visual Analytics:** Risk predictions were structured for integration with geographic information systems and interactive dashboards to support evidence-based policymaking.

The proposed framework integrates robust data engineering, class balancing, ensemble learning, and explainable AI to deliver a comprehensive, policy-relevant approach to maternal mortality risk prediction.

4 Data Characteristics and Initial Findings

Exploratory analysis was conducted to understand dataset structure, examine key variable distributions, and explore relationships between maternal mortality and potential risk factors.

4.1 Maternal Mortality Outcome Distribution

Figure 3 illustrates the pronounced class imbalance, with maternal death representing a rare event relative to survival. This finding necessitated specialized sampling techniques and evaluation metrics focused on minority class detection.

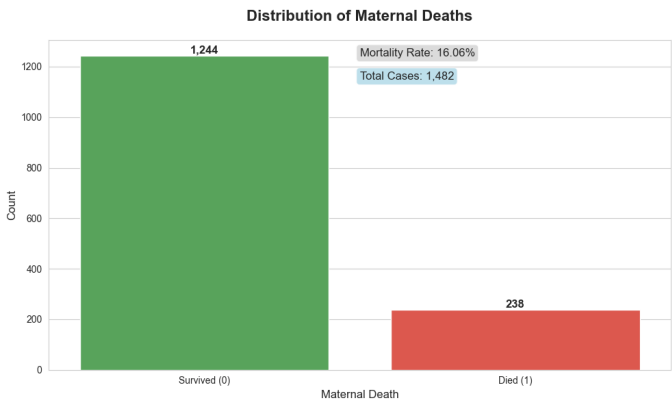


Figure 3. Distribution of maternal mortality outcomes highlighting the class imbalance between survival and maternal death cases.

4.2 Correlation Analysis of Numeric Variables

The correlation heatmap (Figure 4) reveals several key relationships:

- Maternal death indicators demonstrate expected positive intercorrelations.

- Age and parity exhibit moderate positive correlation, reflecting established fertility patterns.
- Healthcare utilization metrics (ANC visits, skilled birth attendance) form distinct correlation clusters.
- Delivery interventions (cesarean section, facility delivery) display specific association patterns with maternal outcomes.

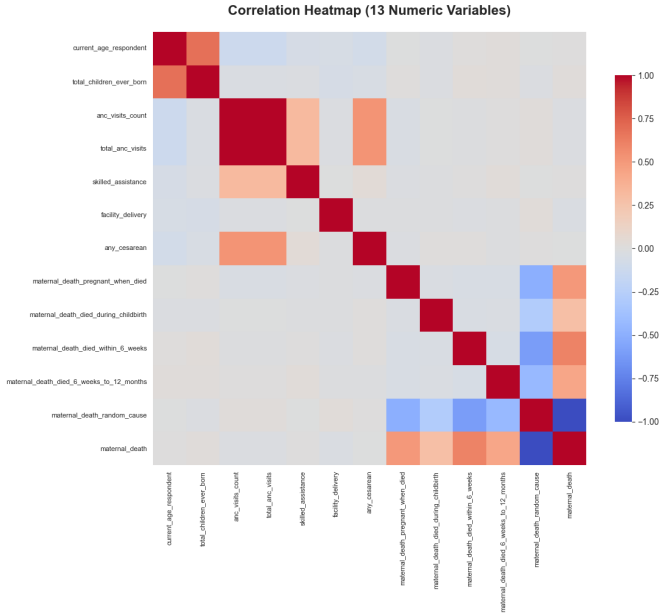


Figure 4. Correlation heatmap of numeric variables showing interrelationships among maternal characteristics, healthcare utilization, and delivery outcomes.

These initial findings informed subsequent feature selection and modeling decisions, highlighting potential risk indicators and protective factors for maternal mortality.

5 Modeling and Evaluation

This section presents the supervised machine-learning framework developed to predict maternal mortality using demographic, healthcare-access, and socio-economic indicators. Due to the severe class imbalance in the outcome variable, both undersampling and oversampling strategies were incorporated into the modelling pipeline. Multiple classifiers were trained and evaluated under each strategy to assess robustness and clinical suitability. Let the dataset be defined as in Equation 1:

$$D = \{(x_i, y_i)\}_{i=1}^N, \quad y_i \in \{0, 1\} \quad (1)$$

where $y_i = 1$ denotes maternal mortality (minority class) and $y_i = 0$ denotes survival (majority class).

The class partitions are therefore defined in Equation 2:

$$\begin{aligned} D_{\min} &= \{(x_i, y_i) \in D : y_i = 1\}, \\ D_{\text{maj}} &= \{(x_i, y_i) \in D : y_i = 0\} \end{aligned} \quad (2)$$

5.1 Handling Class Imbalance

Maternal mortality is a rare but critical outcome, leading to strong class imbalance that can bias standard classifiers toward the majority class. To mitigate this effect, both undersampling and oversampling techniques were employed.

5.1.1 Undersampling Techniques

Tomek Links Undersampling: Tomek Links identify borderline samples belonging to opposite classes that are mutual nearest neighbours. Removing the majority-class instance from each pair improves class separability. Let $x_i \in D_{\text{maj}}$ and $x_j \in D_{\min}$. A pair (x_i, x_j) forms a Tomek Link if the conditions in Equation 3 are satisfied:

$$y_i \neq y_j, \quad (3)$$

$$d(x_i, x_j) = \min_{x_k \in D, k \neq i} d(x_i, x_k), \quad (4)$$

$$d(x_i, x_j) = \min_{x_k \in D, k \neq j} d(x_j, x_k), \quad (5)$$

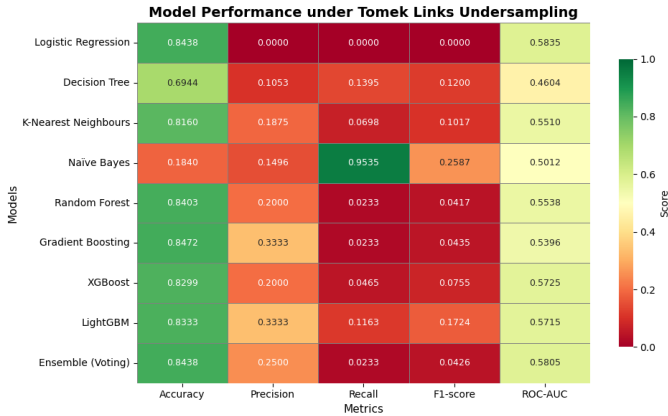
where d denotes a distance metric (Euclidean distance in this study). In other words, the two samples are each other's nearest neighbours while belonging to opposite classes. Removing the majority-class member increases the margin between classes and reduces overlap. The Tomek Links undersampling algorithm is presented in Algorithm 1.

The performance of various classifiers trained on the dataset after applying Tomek Links undersampling is summarized in Table 1.

Table 1. Model Performance under Tomek Links Undersampling.

Model	Acc	Prec	Rec	F1	AUC
Logistic Regression	0.8438	0.0000	0.0000	0.0000	0.5835
Decision Tree	0.6944	0.1053	0.1395	0.1200	0.4604
KNN	0.8160	0.1875	0.0698	0.1017	0.5510
Naive Bayes	0.1840	0.1496	0.9535	0.2587	0.5012
Random Forest	0.8403	0.2000	0.0233	0.0417	0.5538
Gradient Boosting	0.8472	0.3333	0.0233	0.0435	0.5396
XGBoost	0.8299	0.2000	0.0465	0.0755	0.5725
LightGBM	0.8333	0.3333	0.1163	0.1724	0.5715
Ensemble (Voting)	0.8438	0.2500	0.0233	0.0426	0.5805

Figure 5 provides a heatmap visualization of the model performance metrics under Tomek Links undersampling.

Algorithm 1: Handling Class Imbalance using Tomek Links Undersampling**Data:** Dataset D **Result:** Refined dataset D' Separate dataset into majority class D_{maj} and minority class D_{min} ;Initialize refined majority set $D'_{maj} = D_{maj}$;**for** each sample $x_i \in D_{min}$ **do** Identify nearest neighbour x_j in D_{maj} ; Identify nearest neighbour x_k of x_j in D_{min} ; **if** $x_k = x_i$ **then** Remove x_j from D'_{maj} ; **end****end**Construct refined dataset $D' = D_{min} \cup D'_{maj}$;**return** D' ;**Algorithm 2:** Handling Class Imbalance using SMOTE**Data:** Dataset D **Result:** Balanced dataset D' Separate dataset into majority class D_{maj} and minority class D_{min} ;Initialize synthetic set $D_{syn} = \emptyset$;**for** each sample $x_i \in D_{min}$ **do** Find k nearest minority neighbours; **for** each required synthetic instance **do** Select neighbour x_{nn} ; Draw $\lambda \in [0, 1]$; Generate $x_{new} = x_i + \lambda(x_{nn} - x_i)$; Add $(x_{new}, 1)$ to D_{syn} ; **end****end**Construct balanced dataset $D' = D \cup D_{syn}$;**return** D' ;**Figure 5.** Heatmap visualization of model performance metrics under Tomek Links undersampling.**5.1.2 Oversampling Techniques**

SMOTE Oversampling: SMOTE generates synthetic minority samples by interpolating between nearest neighbours in feature space. For a minority instance x_i and one of its k nearest neighbours x_{nn} , a synthetic sample is produced as shown in Equation 6:

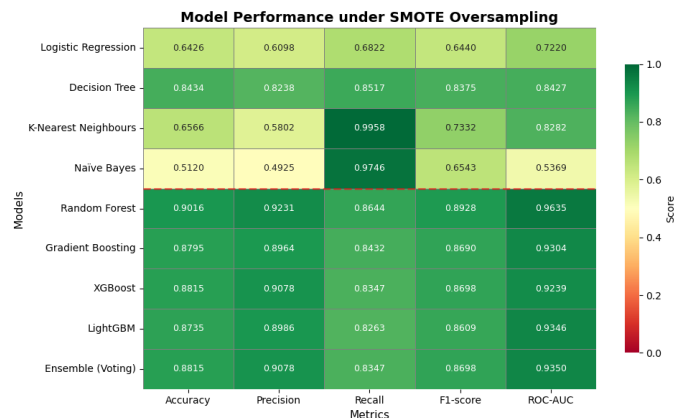
$$x_{new} = x_i + \lambda(x_{nn} - x_i), \quad \lambda \sim U(0, 1). \quad (6)$$

This linear interpolation expands the minority decision region while reducing the risk of overfitting associated with simple duplication. The SMOTE oversampling algorithm is detailed in Algorithm 2.

Table 2 presents the performance metrics achieved by different classifiers after applying SMOTE oversampling.

Table 2. Model Performance under SMOTE Oversampling.

Model	Acc	Prec	Rec	F1	AUC
Logistic Regression	0.6426	0.6098	0.6822	0.6440	0.7220
Decision Tree	0.8434	0.8238	0.8517	0.8375	0.8427
KNN	0.6566	0.5802	0.9958	0.7332	0.8282
Naive Bayes	0.5120	0.4925	0.9746	0.6543	0.5369
Random Forest	0.9016	0.9231	0.8644	0.8928	0.9635
Gradient Boosting	0.8795	0.8964	0.8432	0.8690	0.9304
XGBoost	0.8815	0.9078	0.8347	0.8698	0.9239
LightGBM	0.8735	0.8986	0.8263	0.8609	0.9346
Ensemble (Voting)	0.8815	0.9078	0.8347	0.8698	0.9350

Figure 6 displays a heatmap visualization of model performance under SMOTE oversampling.**Figure 6.** Heatmap visualization of model performance metrics under SMOTE oversampling.

CTGAN-Based Oversampling: CTGAN is a deep generative model tailored for tabular data and learns

complex feature dependencies through adversarial optimisation, as formulated in Equation 7:

$$\min_G \max_D E_{x \sim P_{\text{data}}} [\log D(x|c)] + E_{z \sim P_z} [\log (1 - D(G(z|c)))]. \quad (7)$$

where G generates candidate samples while D attempts to discriminate between real and synthetic observations. The CTGAN-based oversampling procedure is outlined in Algorithm 3.

Algorithm 3: Handling Class Imbalance using CTGAN-Based Oversampling

Data: Minority samples $D_{\min}$

Result: Balanced dataset D'

Extract minority-class samples $D_{\min}$;

Initialize generator G and discriminator D ;

for $epoch = 1$ to E **do**

 Sample noise vector z and conditional vector c ;

 Generate synthetic samples via G ;

 Update discriminator and generator;

end

Construct balanced dataset D' ;

return D' ;

The classification results following CTGAN oversampling are shown in Table 3.

Table 3. Model Performance under CTGAN Oversampling.

Model	Acc	Prec	Rec	F1	AUC
Logistic Regression	0.7411	0.8136	0.5246	0.6379	0.7737
Decision Tree	0.7815	0.7630	0.7213	0.7416	0.7818
KNN	0.6817	0.7816	0.3716	0.5037	0.6886
Naive Bayes	0.4703	0.4495	0.9727	0.6149	0.5329
Random Forest	0.8290	0.9111	0.6721	0.7736	0.8469
Gradient Boosting	0.8409	0.9677	0.6557	0.7818	0.8554
XGBoost	0.8100	0.8456	0.6885	0.7590	0.8484
LightGBM	0.8076	0.8355	0.6940	0.7582	0.8619
Ensemble (Voting)	0.8290	0.9051	0.6776	0.7750	0.8588

Figure 7 presents a heatmap visualization of model performance under CTGAN oversampling.

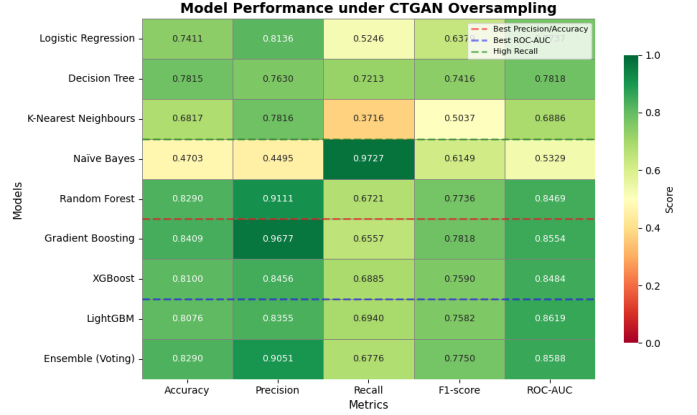


Figure 7. Heatmap visualization of model performance metrics under CTGAN oversampling.

ADASYN Oversampling: ADASYN adaptively generates synthetic samples based on local learning difficulty, as defined in Equations 8 and 9:

$$r_i = \frac{\Delta_i}{k} \quad (8)$$

$$g_i = \frac{r_i}{\sum r_i} \times G \quad (9)$$

where Δ_i denotes the number of majority neighbours and G is the total synthetic requirement. Thus, regions with higher class overlap receive more artificial data. The ADASYN oversampling algorithm is presented in Algorithm 4.

Algorithm 4: Handling Class Imbalance using ADASYN

Data: Dataset D

Result: Balanced dataset D'

Separate dataset into D_{maj} and D_{min} ;

for each $x_i \in D_{min}$ **do**

 Compute difficulty ratio r_i ;

 Generate g_i synthetic samples;

end

Construct balanced dataset D' ;

return D' ;

Table 4 displays the performance metrics for models trained with ADASYN oversampling.

Table 4. Model Performance under ADASYN Oversampling.

Model	Acc	Prec	Rec	F1	AUC
Logistic Regression	0.5955	0.5620	0.6332	0.5955	0.6390
Decision Tree	0.8501	0.8482	0.8297	0.8389	0.8480
KNN	0.6509	0.5743	0.9956	0.7284	0.8183
Naive Bayes	0.4949	0.4816	0.9738	0.6445	0.5313
Random Forest	0.8932	0.9234	0.8428	0.8813	0.9598
Gradient Boosting	0.8480	0.9016	0.7598	0.8246	0.9062
XGBoost	0.8604	0.8889	0.8035	0.8440	0.9119
LightGBM	0.8624	0.8785	0.8210	0.8488	0.9248
Ensemble (Voting)	0.8604	0.8927	0.7991	0.8433	0.9193

Figure 8 provides a heatmap visualization of model performance under ADASYN oversampling.

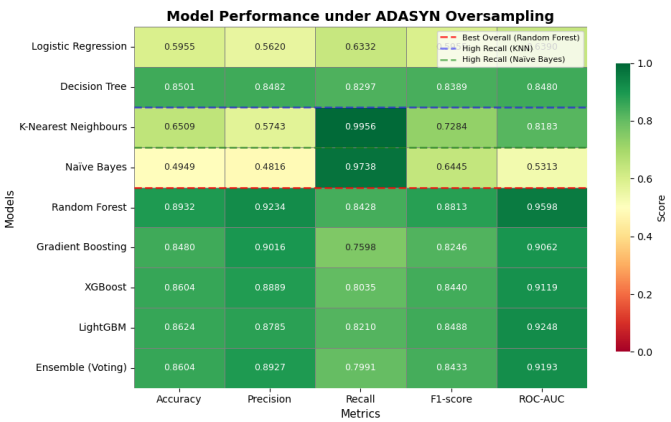


Figure 8. Heatmap visualization of model performance metrics under ADASYN oversampling.

Based on the comprehensive evaluation across all sampling techniques and classifiers presented in Tables 1 through 4 and visualized in Figures 5 through 8, the following recommendations emerge:

- Primary configuration: Random Forest with SMOTE oversampling—optimal precision-recall balance for clinical deployment.
- Secondary options: LightGBM or Voting Ensemble with SMOTE for computational efficiency or robustness.
- Technique to avoid: Tomek Links undersampling—severe information loss degrades minority class detection.
- Specialized use: Naïve Bayes with oversampling for high-recall screening applications.

The experimental framework establishes SMOTE oversampling with ensemble methods, particularly Random Forest, as the most effective approach for maternal mortality prediction in Bangladesh.

5.2 Summary of Findings

The highest results were achieved with the SMOTE technique and ensemble models. As shown in Table 2, the Random Forest model achieved the highest results, with a ROC-AUC of 0.9635, an accuracy of 0.9016, a precision of 0.9231, a recall of 0.8644, and an F1-score of 0.8928. It also demonstrated a strong precision–recall balance suitable for rare-event prediction. ADASYN produced satisfactory results, with the Random Forest model achieving a ROC-AUC of 0.9598 as shown in Table 4. The performance of the CTGAN technique was considerably weaker despite its higher computational cost. Its best results yielded a maximum ROC-AUC of only 0.8619, as detailed in Table 3. The Tomek Links technique consistently underperformed and severely degraded the models’ performances in detecting minority classes, as evidenced in Table 1. Ensemble methods yielded better performance than simpler classifier models. Random Forest was the top-performing model, followed by LightGBM, XGBoost, Gradient Boosting, and the Voting Ensemble model. These yielded ROC-AUC values above 0.92 when combined with the SMOTE technique, as shown in Table 2. The KNN and Naive Bayes models achieved very high recall but suffered from low precision scores.

6 Model Interpretability using SHAP

SHAP analysis was applied to enhance transparency and explainability of the predictive models, addressing the “black box” nature of machine learning in healthcare applications. This approach quantifies feature contributions to both global model behavior and individual predictions, supporting clinical and policy decision-making.

Global feature importance was assessed using SHAP summary analysis, ranking predictors by their overall impact on model predictions. Figure 9 presents this global feature importance analysis.

Key observations: Region type (rural vs. urban) emerged as the most influential predictor, followed by maternal age and administrative division, highlighting demographic and geographic disparities.

Individual predictions were decomposed using SHAP waterfall plots to reveal how specific feature values influence risk estimates for particular cases. An example of such decomposition is shown in Figure 10.

Key observations: Individual risk predictions result from the cumulative effect of multiple moderate-sized

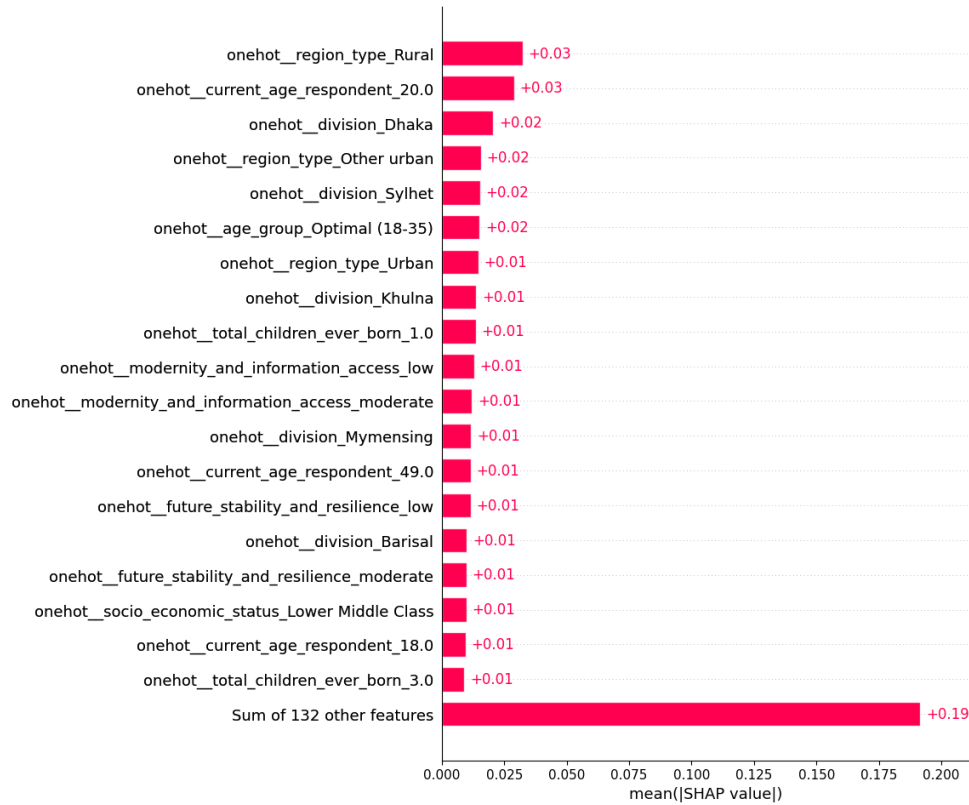


Figure 9. Global feature importance analysis using SHAP values, ranking predictors by their overall impact on model predictions.

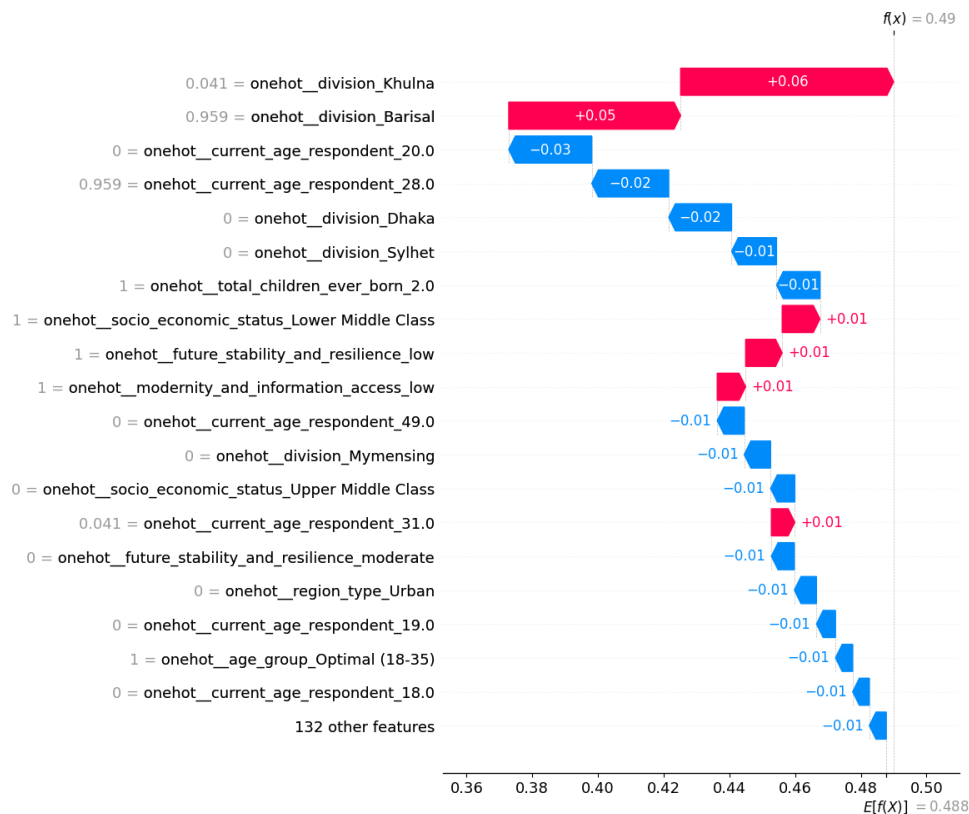


Figure 10. Example of individual SHAP decomposition using a waterfall plot, showing how specific feature values contribute to the predicted maternal mortality risk for a particular case.

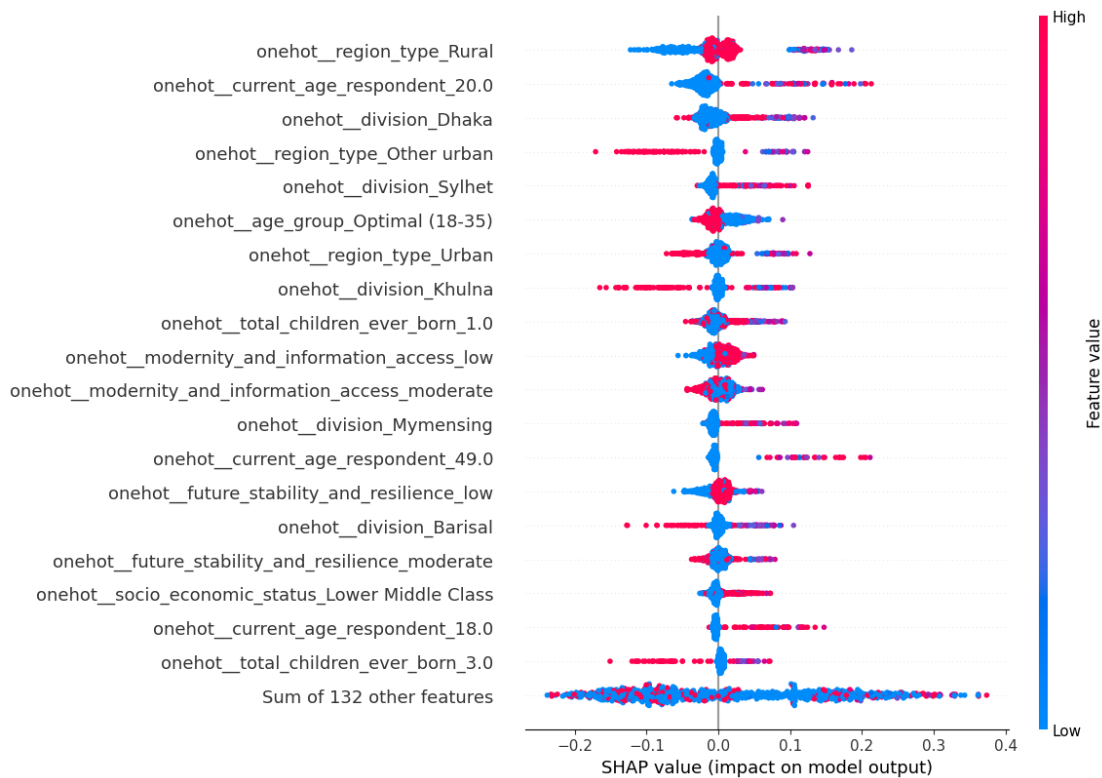


Figure 11. SHAP beeswarm plot showing the heterogeneity of feature effects across the population, highlighting both risk-increasing and protective contributions to individual maternal mortality predictions.

feature contributions, with balanced consideration of both risk-increasing and protective factors.

The heterogeneity of feature effects across the population was visualized using a SHAP beeswarm plot, as shown in Figure 11.

Key observations: Feature effects exhibit significant variation across individuals, reflecting clinical heterogeneity, with the model capturing context-dependent relationships where some factors show both positive and negative effects.

7 Tableau Dashboard Design

An interactive Tableau dashboard was developed to complement the machine learning analysis, enabling visual exploration of maternal mortality risk factors in Bangladesh. The dashboard integrates geographic, socioeconomic, and healthcare access data to support data-driven decision-making.

The dashboard presents maternal health indicators through multiple coordinated visualizations, as illustrated in Figure 12.

The dashboard includes: Geographic Risk Distribution via choropleth map showing regional mortality variations; Socioeconomic Disparities through

treemap and heatmap visualizations revealing elevated mortality among rural, lower-socioeconomic populations; and Key Performance Indicators providing national overviews of healthcare access and outcomes. The dashboard transforms complex maternal health data into accessible visual insights, supporting evidence-based interventions and targeted resource allocation. Interactive capabilities enable stakeholders to explore specific risk patterns and regional disparities.

8 Discussion

This study demonstrates the critical impact of sampling strategies on maternal mortality prediction. As shown in Tables 2 and 1, Random Forest with oversampling achieved superior performance (ROC-AUC: 0.9635), while undersampling limited overall discrimination despite enhancing minority-class sensitivity. Tree-based ensemble models consistently outperformed simpler classifiers, confirming their suitability for capturing complex maternal health interactions. The integration of SHAP interpretability, as visualized in Figures 9 through 11, addressed model transparency concerns, while the interactive Tableau dashboard shown in Figure 12 enabled spatial and socioeconomic risk exploration. The findings

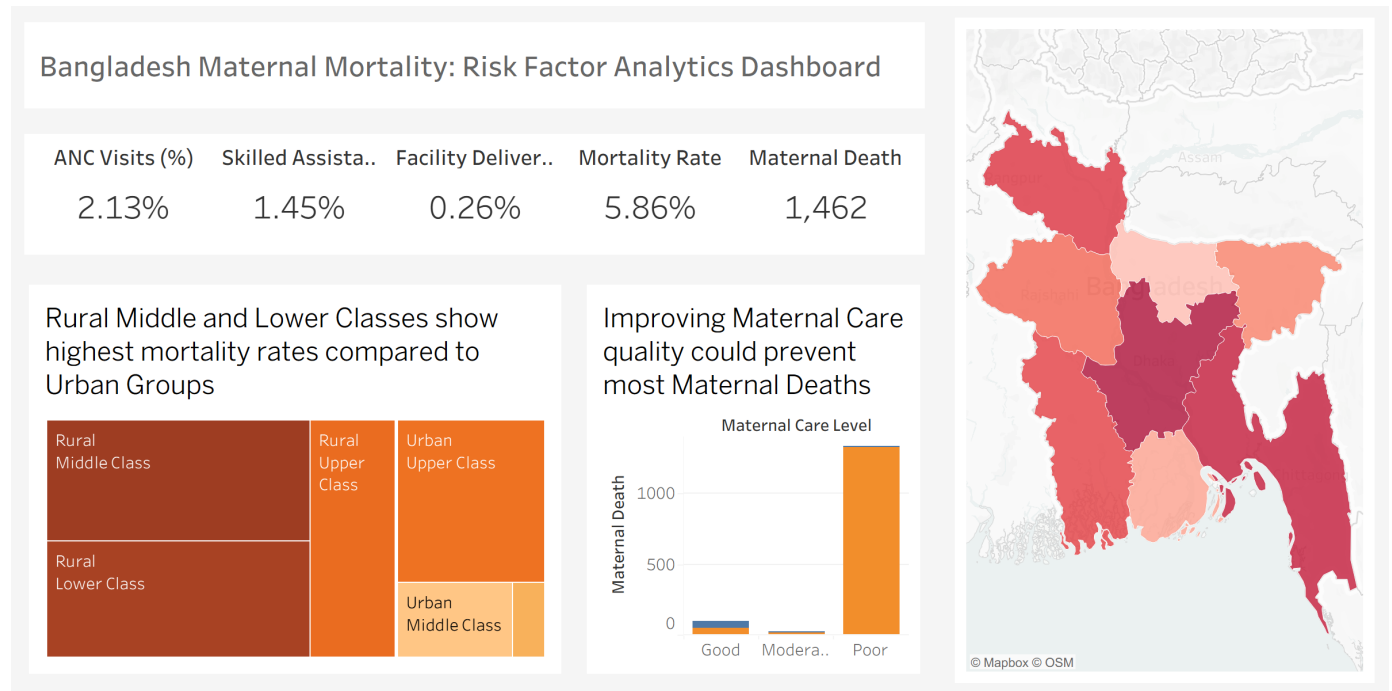


Figure 12. Interactive Tableau dashboard showcasing maternal health indicators, including geographic, socioeconomic, and healthcare access data for risk exploration.

emphasize the necessity of explicit class imbalance handling and interpretable frameworks for rare health outcomes, supporting evidence-based maternal health decision-making.

9 Conclusion

The analysis presented in this research paper reveals the exceptional capabilities of ensemble methods in handling maternal mortality data. The contributions of this research to the field of maternal mortality prediction and machine learning models include a comprehensive validation of sampling strategies for maternal mortality prediction, the establishment of the superiority of ensemble methods over other machine learning approaches, the identification of critical factors contributing to maternal mortality through the rigorous comparison of machine learning models, and a reproducible framework for maternal mortality prediction.

In conclusion, this research has identified the best-performing machine learning model for predicting maternal mortality in Bangladesh. This model is the Random Forest model with SMOTE oversampling, which yielded exceptional performance metrics (ROC-AUC: 0.9635; F1-Score: 0.8928; Precision: 0.9231; Recall: 0.8644), as detailed in Table 2. The findings of this research will facilitate future research in this domain, especially the integration of these models into clinical applications.

Relative to the most closely related prior study on the same dataset [18], the present work makes three distinct incremental methodological contributions without claiming superior predictive performance: (1) the first systematic benchmarking of CTGAN-based oversampling on BMMS-2016, establishing its computational cost-performance trade-off relative to SMOTE and ADASYN; (2) extended SHAP interpretability encompassing individual-level waterfall decompositions and population-level beeswarm analysis, enabling clinically actionable instance-level explanations; and (3) a fully implemented interactive Tableau dashboard translating model outputs into policy-accessible visual analytics. It should be noted that Mamun et al. [18] reported a marginally higher ROC-AUC of 0.957 compared to 0.9635 achieved here; the contributions of the present study lie in methodological breadth, interpretability depth, and decision-support tooling rather than in raw predictive performance alone. These contributions collectively advance the state of interpretable maternal mortality prediction in the Bangladesh context.

Data Availability Statement

The primary dataset, Bangladesh Maternal Mortality Survey 2016 (BMMS-2016), is publicly available via UNC Dataverse (<https://bit.ly/4jxbo3O>). All analysis

code and processed data are available in the project's GitHub repository (<https://bit.ly/4sJVEPI>).

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Conflicts of Interest

The authors declare no conflicts of interest.

AI Use Statement

The authors declare that Deepseek-V3 was used solely for data analysis and language editing in the preparation of this manuscript. All scientific interpretations, results, and conclusions were determined by the authors.

Ethical Approval and Consent to Participate

This secondary analysis uses anonymized, publicly available data from the Bangladesh Maternal Mortality Survey 2016 (BMMS-2016). The original survey received ethical approval from relevant Bangladeshi authorities. No additional ethical approval was required for this secondary analysis.

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