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An Explainable AI Driven Machine Learning Approach for Maternal Health Risk Analysis

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***Abstract*—Maternal health during pregnancy is a severe issue, particularly in the rural areas of developing countries like Bangladesh, where a lack of access to healthcare and inadequate infrastructure increase risks. Maternal healthcare has a great deal of difficulty due to the absence of reliable tools for forecasting health concerns. Negative results frequently result from the traditional method's inability to diagnose and manage pregnancy-related problems correctly. While there are several ways to monitor maternal health conditions, machine learning has the potential to increase diagnosis accuracy, efficiency, and speed. In this research, by using several machine learning classifiers, we built a model that can analyze the maternal health risk during pregnancy. The Maternal Health Risk dataset from the UCI machine learning repository was used in this study. SMOTE was utilized to address the class imbalance data and generated an additional 99000 data. We assess the model before and after using SMOTE. Accuracy, precision, recall, and F1-Score were utilized to evaluate the model's performance. Extreme Gradient Boosting (XGBoost) is our standout performer, with an accuracy of 84% and 95% before and after using SMOTE, respectively. Additionally, Explainable AI was used to increase the model's readability. This study demonstrates the power of machine learning, which could revolutionize maternal health care by identifying maternal health risks early.**

***Index Terms*—Machine Learning, Maternal Health Risk, Explainable AI, SMOTE, Feature Selection**

I. Introduction

The velocity of maternal death is extremely high. The phrase "Maternal Health Risk" covers potential problems or negative implications that a woman can encounter during her pregnancy, delivery, or the postpartum period. These dangers damage the fetal well-being in addition to the mother's health and life [1]. In impoverished nations with limited access to prenatal care and proper healthcare, maternal illnesses are prevalent. Maternal mortality is still an enormous issue in the world, with thousands of women losing their lives each year [2]. According to The research [3], the ratio of maternal deaths to 100,000 live births was 196 in 2016 in Bangladesh (with an uncertainty range of 159–234). 38% of maternal deaths happened on the day of delivery, and 6% occurred on one day after delivery.

Risks to the wellness of mothers may take numerous forms, including gestational diabetes, infections, pre-eclampsia (high blood pressure), and bleeding. Maternal age (especially in very young or older moms), previous chronic diseases (e.g., hypertension, diabetes), nutritional shortcomings, or poor medical treatment are among the underlying causes that frequently trigger these disorders [4]. The issue gets worse by social variables, like access to healthcare, education, and poverty, which disproportionately impact women in underserved and rural areas. Since these issues are unforeseeable, spotting them early and monitoring them periodically is crucial. Inadequate recognition of high-risk pregnancies, limited access to trained birth attendants, and tardy assistance all contribute to poor maternal health outcomes [5]. To reduce these risks, early intervention and appropriate monitoring are therefore essential. Machine learning can be used to identify maternal health risks and prevent maternal mortality.

Machine learning has the prospective to predict hazards and detect pregnancy risks early. It presents a possible approach to improving maternal wellness [6]. By examining vast datasets comprising clinical indicators, demographic data, and medical records, machine learning algorithms are capable of identifying trends and relationships that would not be visible using standard methods. These machine-learning models can help medical professionals make data-driven decisions swifter, improve care for expectant mothers, and allocate resources more wisely [7].

This research presents a model that can analyze maternal health risks during, before, and after pregnancy using several machine-learning techniques to prevent maternal mortality. Various performance matrices were used to evaluate the machine learning classifier's performance, and Explainable AI was applied to improve the readability of the machine learning model. The following are our major contributions

- Seven Machine learning classifiers such as RF, XGB, DT, SVM, LR, KNN, and Gaussian NB were used to train the proposed model.
- Feature selection techniques like Recursive Feature Elimination with Cross Validation (RFECV) and Forward Feature Selection (FFS) were used.
- The Synthetic Minority Over-sampling Technique was

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utilized to secure a balanced dataset and generated an additional 99000 data
- Explainable AI (XAI) techniques like LIME and SHAP were used to enhance the machine learning model's readability.

The remaining sections of our research are represented by the headings that follows. In Section II, A comprehensive assessment of the literature is carried out, where the current methods are examined along with their inherent drawbacks. Section III explains data preparation and feature extraction in depth, and the dataset and methods used for machine learning-based maternal health risk are examined. The results of several machine learning methods are then critically assessed in Section IV. Section V summarizes the main conclusions and potential future work.

II. Related Work

A number of researchers have proposed models and methods to forecast pregnancy issues using both conventional and machine learning techniques, highlighting their importance to a mother's health. Nevertheless, this area of study is still considered insufficient and is currently the subject of ongoing investigations. Several previous studies have been reviewed and presented here to understand the current state of this subject. *B.U. Maheswari et al.* [8] used a number of machine learning methods to estimate the mother's risk level using the maternal health risk dataset. The performance of these algorithms was examined before and after using the Synthetic Minority Over-sampling Technique (SMOTE) to balance the data. The findings show that, following SMOTE enhancement, hyperparameter adjustment of the XGBoost resulted in an accuracy of 88.89% for predicting mothers' risk level. To provide gynecologists confidence in the ML model, this study additionally embeds the Explainable AI (XAI) utilizing Shapley additive explanations (SHAP) and LIME (Local Interpretable Model-agnostic Explanations). To demonstrate the interpretability of the ML model at both the global and local levels, a variety of graphs are produced using LIME, SHAP, and ELI5. *D Thakkar et al.* [9] looks into the possibility of using medical data to forecast maternal health risk using machine learning techniques. The Maternal Health Risk Dataset was selected for the study. Algorithms like Random Forest, XG Boost, Support Vector Classifier, Decision Tree, and Logistic Multiclass are evaluated using ensemble learning-based feature engineering. The results demonstrate that Random Forest can accurately identify maternal health risks, which is important for reducing negative outcomes and facilitating prompt treatments during pregnancy. Random Forest achieved an outstanding accuracy of 94.26%. *M.A Kafi et al.* [10] classified the risk factor values using a range of supervised learning techniques, including the KNN, DT, RF, Gaussian NB, and SVM Classifier. They obtained 98% accuracy for Random Forest, 91% accuracy for KNN, 97% accuracy for Decision Tree, and 94% and 93% accuracy for SVM and GaussianNB, in that order, respectively. *Assaduzzaman et al.* [7] used machine learning models such as Random Forest, CatBoost, XGBoost, Decision Tree, and Gradient Boosting To forecast threats to maternal health risk. The dataset's anomalies were dealt with enhanced data pretreatment strategies like data cleaning and feature engineering. The Random Forest model yielded the best results in terms of precision, recall, F1-score, and accuracy, all reaching 90%. *M. Fatmawati et al.* [11] Used a dataset of 1,014 records. This study focuses on categorizing maternal risk factors using DT and KNN algorithms. The effectiveness of both models was assessed using T-tests and cross-validation. At 71.50% accuracy, the KNN algorithm performed superior to the decision tree. *R. Nagavibha et al.* [12] developed an accurate system for classifying fetal health using machine learning. The collection includes comprehensive data on the symptoms and indicators of pregnancy, especially in high-risk cases or those with developing fetal health concerns. Using a combination of ensemble-based processes and several machine learning models like Light Gradient Boosting Machine (LGBM), Linear Discriminant Analysis, Quadratic Discriminant Analysis, DT, RF, KNN, SVM, and Gradient Boosting, the LGBM has been found to be an exceptional performer, achieving an accuracy of 96.9%. *E. EfeoĞlu et al.* [13] utilized decision tree methods (Random Forest, Rep Tree, Random Tree, SimpleCart) and the Adaboost algorithm, the authors of the research leverages machine learning to divide up threats to maternal health. Pregnant women's health statistics were reviewed, and risk intensity was categorized in this study. The best accuracy was 86.09% after Adaboost and Random Tree were combined. By streamlining the process to assess risk level, this method aims to lower the workload of physicians and enhance more effective maternity health M.F. Ukrit et al. [14] introduced a model thats primary goal was to detect pregnancy risk for three cases: high, medium, and low. A combination of RF, GB, and AdaBoost with DT and soft voting yields the greatest accuracy of 81.5%, according to the authors' analysis of a number of machine learning models, including LR, RF, SVM, NB, KNN, GB, AdaBoost, Ensemble RF, voting classifier, and XGBoost.

III. Proposed Methodology

This research focuses on Maternal health risk analysis based on the Maternal Health Risk dataset from the University of California at Irvine's machine learning repository. The Proposed architecture for building this model is shown in Fig. 1. The methodology involves data pre-processing, training model, and overall architecture fo the proposed model.

A. Dataset Description

We gathered the Maternal Health Risk dataset from The UCI Machine Learning Repository [15]. There are 1,014 instances total, gathered from various rural Bangladeshi hospitals, local clinics, and maternal health care centers. The dataset has no missing values, and all features are represented as numerical data. Further six key maternal characteristics related to health are present in the dataset:

- Age

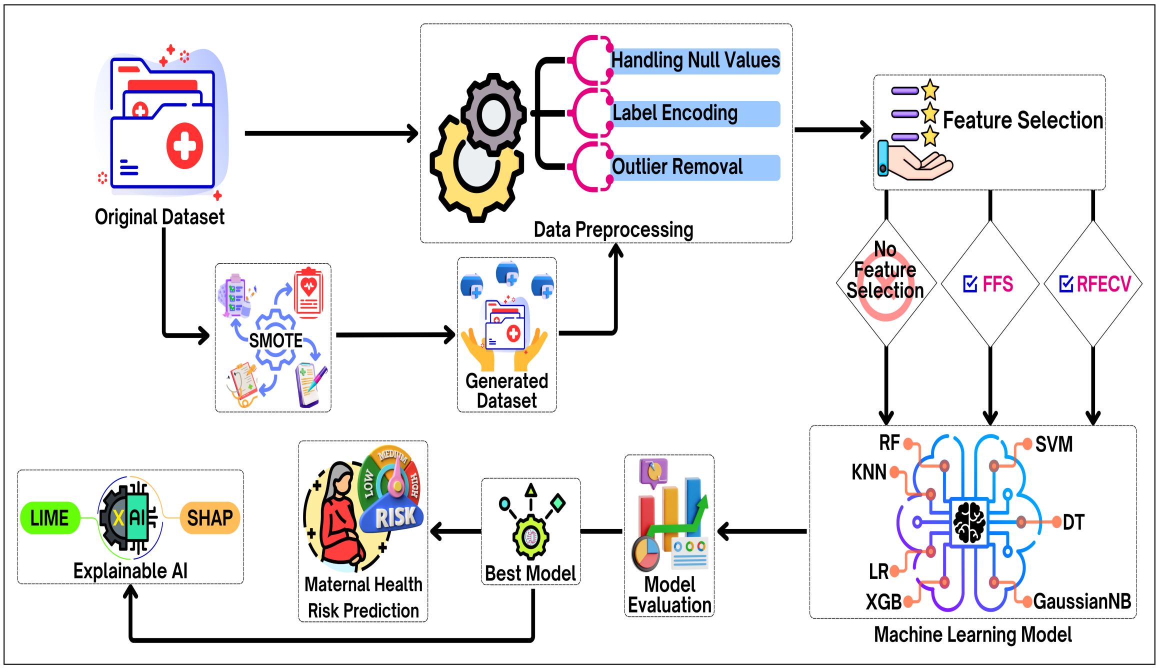


Fig. 1. Proposed Architecture for Maternal Health Risk Analysis

- Blood Pressure Systolic (SystolicBP)
- Blood Pressure Diastolic (BP-Diastolic)
- Blood Sugar (BS)
- Internal Temperature (InnerTemp)
- HeartRate

Another target variable feature, 'RiskLevel,' is a categorical variable that falls into three classes: Low Risk, Mid Risk, and High Risk. These classes represent different levels of risk to maternal health. Table 1 provides some samples from the dataset.

TABLE I
MATERNAL HEALTH RISK DATASET FROM UCI REPOSITORY

Risk Level	Training	Testing	Total Sample
High Risk	216	56	272
Mid Risk	268	68	336
Low Risk	324	82	406

B. Data Preprocessing

A number of preprocessing techniques were employed to prepare the dataset. These techniques include label encoding, which transforms categorical variables into numerical format. Following the application of the label encoder, high, mid, and low risk levels are denoted by the numbers 0, 1, and 2, respectively. We also addressed null values, but no null values were found in the dataset used in this study. Furthermore, we perform outlier detection and removal to eliminate anomalies that could distort the model's learning process. After applying these data preprocessing techniques, we used Data balancing and Feature selection techniques.

1) Data Balance Technique: We generated synthetic samples using the Synthetic Minority Over-sampling Technique (SMOTE) to address the class imbalance in our dataset. SMOTE generates new, varied data points by interpolating between minority class samples and their closest neighbors. By lowering bias towards the majority class, SMOTE improved model performance in our scenario by expanding the dataset from 1,000 to 100,000 samples, leveling the class distribution.

2) Feature Selection Technique: Two feature selection techniques were employed in this research, Forward Feature Selection (FFS) and Recursive Feature Elimination with Cross-Validation (RFECV). RFECV employs cross-validation to iteratively eliminate the least significant features based on their effect on model performance to achieve generalizability. Comparatively, FFS starts with no features and gradually adds those that enhance model performance. These methods pick the most pertinent features for high-dimensional data to minimize dimensionality, avoid overfitting, and maximize model efficiency.

3) Splitting the Dataset: The dataset used in this study was divided into testing and training sets to evaluate the proposed model's performance. We allocated 20% of the data for testing and 80% for training.

C. Model Training

we applied several machine learning classifiers both before and after applying SMOTE to address the class imbalance. We used SMOTE to artificially balance the dataset, and then we retrained the same classifiers using the 100,000 sample new dataset. As a result, we evaluate how class balancing impacted the model's performance. Also, we examined the variations in model performance by comparing the outcomes from the two stages. This allowed us to demonstrate how SMOTE successfully improved model predictions by reducing bias towards the majority class. The classifiers we used to create this model are as follows.

- Random Forest: A method for ensemble learning that builds many decision trees to improve accuracy and reduce overfitting.
- Extreme Gradient Boosting: It is a progressive implementation of Gradient boosting, whereby each new model improves speed and performance by fixing the mistakes of its predecessors.
- Support Vector Machine: A technique for supervised learning that determines the best hyperplane to divide data points into different classes.
- Logistic Regression: A linear model based on logistic functions that determines the probability of a binary outcome.
- K Nearest Neighbor: A straightforward, instance-based method that groups data items according to the closest neighbor's majority vote.
- Decision Tree: A model that divides the data into decision-making branches according to feature values, like a tree.
- Gaussian Naive Bayes: A probabilistic classifier based on the assumption of independent and normally distributed features, applying the Bayes theorem.

D. Explainable AI

We utilized Explainable AI (XAI)techniques like LIME and SHAP to enhance the machine learning model's readability. LIME offered local explanations for specific predictions by varying input features and observing how they affected the output. SHAP provided a global understanding of feature relevance by calculating each feature's contribution to the model's predictions. These techniques enabled us to understand the ways in which specific attributes affected the model's decisions, which also ensured that the decision-making process was clear and understandable to subject-matter specialists.

IV. Result and Discussion

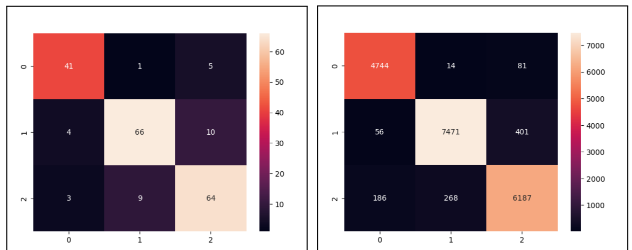
A number of performance analysis measures, such as accuracy, precision, recall, and F1-score, were used to assess the performance of the proposed maternal health risks analysis model. We conducted experiments using several machine learning classifiers to determine the most effective technique for analyzing maternal health risk. The results of the experiments are thoroughly analyzed in this section.

A. Result Analysis

Table II compares the performance of several machine learning classifiers before and after using the Synthetic Minority Over-sampling Technique (SMOTE) with various feature selection techniques. Extreme Gradient Boosting (XGB) with no feature selection achieved the maximum accuracy of 84% and 95% before and after using SMOTE. XGBoost with RFECV also performed well, but it takes more time to train the model than no feature selection, that's why we selected XGBoost with no feature selection as our best model to analyze the maternal health risk. Other models such as RF, SVM, DT, LR, and KNN also performed well but did not perform as well as Extreme Gradient Boosting (XGBoost).

B. Confusion Matrix Representation

Fig. 2 represents the confusion matrix for XGBoost with no feature selection before and after using SMOTE. Fig (a) demonstrated that the model successfully identified 41 high-risk, 66 mid-risk, and 64 low-risk cases before using SMOTE. This indicates that the model performs well in identifying risk levels, but some misclassifications are presented. On the other hand, Fig. (b) shows the model correctly identified 4744 occurrences for high risk, 7471 instances for mid-risk, and 6187 for low risk. These findings show how well the model can detect maternal health risks for each class after using SMOTE.

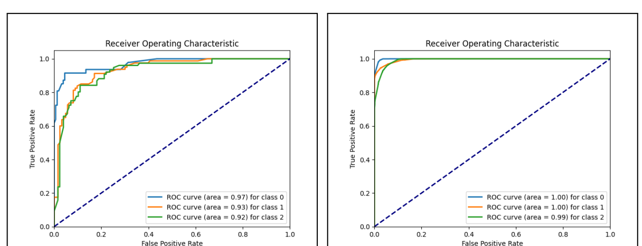


(a) Before SMOTE (b) After SMOTE

Fig. 2. Confusion Matrix for XGBoost with No Feature Selection

C. ROC Curve Representation

Fig. 3 represents the performance of Extreme Gradient Boosting before and after using SMOTE with no feature selection for the three risk classes high, mid, and low, as shown by the ROC curve. Fig. (a) shows high-risk achieved an AUC of 0.97, whereas mid and low-risk achieved an AUC of 0.94. FIg. (b) shows good classification ability based on the area under the curve (AUC) values, low risk had an AUC of 0.99, while high and mid risk both had AUCs of 1.00. These high AUC values demonstrate the model can differentiate between maternal risk categories, particularly high and mid-risk.



(a) Befor SMOTE (b) After SMOTE

Fig. 3. ROC Curve for XGBoost with No Feature Selection

TABLE II
COMPARISON TABLE OF ALL CLASSIFIERS BEFORE AND AFTER USING SMOTE

Model	Feature Selection Techniques (FS)	Accuracy		Precision		Recall		F1-Score	
		Before SMOTE	After SMOTE	Before SMOTE	After SMOTE	Before SMOTE	After SMOTE	Before SMOTE	After SMOTE
RF	NO FS	0.81	0.94	0.82	0.93	0.81	0.94	0.82	0.93
	FFS	0.78	0.92	0.79	0.92	0.78	0.93	0.79	0.93
	RFECV	0.80	0.94	0.80	0.94	0.81	0.94	0.80	0.94
XGB	**NO FS**	**0.84**	**0.95**	**0.84**	**0.95**	**0.85**	**0.95**	**0.85**	**0.95**
	FFS	0.84	0.92	0.84	0.92	0.84	0.93	0.84	0.93
	RFECV	0.84	0.95	0.84	0.95	0.84	0.95	0.84	0.95
DT	NO FS	0.80	0.93	0.81	0.94	0.81	0.93	0.81	0.92
	FFS	0.81	0.92	0.82	0.92	0.82	0.93	0.82	0.93
	RFECV	0.79	0.94	0.79	0.94	0.80	0.93	0.80	0.93
SVM	NO FS	0.62	0.81	0.64	0.83	0.63	0.82	0.59	0.82
	FFS	0.63	0.83	0.64	0.83	0.64	0.82	0.60	0.84
	RFECV	0.80	0.94	0.81	0.94	0.81	0.94	0.78	0.94
LR	NO FS	0.64	0.63	0.64	0.62	0.65	0.62	0.61	0.62
	FFS	0.60	0.64	0.61	0.65	0.60	0.62	0.58	0.63
	RFECV	0.64	0.63	0.64	0.62	0.65	0.62	0.61	0.62
KNN	NO FS	0.61	0.94	0.62	0.94	0.6	0.93	0.61	0.94
	FFS	0.65	0.92	0.66	0.92	0.66	0.92	0.66	0.92
	RFECV	0.66	0.72	0.65	0.71	0.65	0.70	0.66	0.69
GaussianNB	NO FS	0.56	0.61	0.60	0.62	0.56	0.59	0.53	0.58
	FFS	0.56	0.59	0.59	0.60	0.56	0.57	0.52	0.56
	RFECV	0.60	0.89	0.63	0.87	0.60	0.89	0.56	0.87

D. LIME Representation

Fig. 4 indicates a 100% prediction probability for low risk. The blood sugar (BS) level, which is 7.13, is the most crucial factor in identifying low-risk and significantly impacts the model's forecast. As seen by its considerable influence on the low-risk categorization, BS is the predominant component, with the remaining contributing factors being.

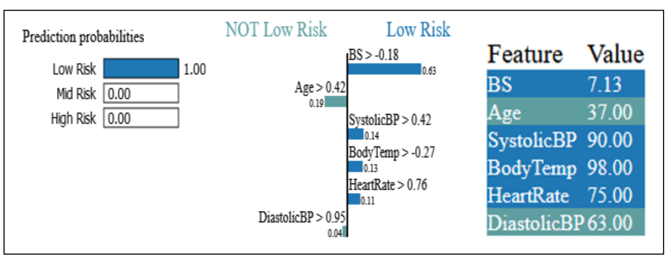


Fig. 4. LIME Representation for Low Risk for XGB After SMOTE

Fig. 5 illustrates that the model predicts a 100% probability of mid-risk. This prediction is mainly influenced by the patient's age (16), with other factors like blood sugar and systolic blood pressure also contributing. However, age is the most significant factor in determining the mid-risk classification.

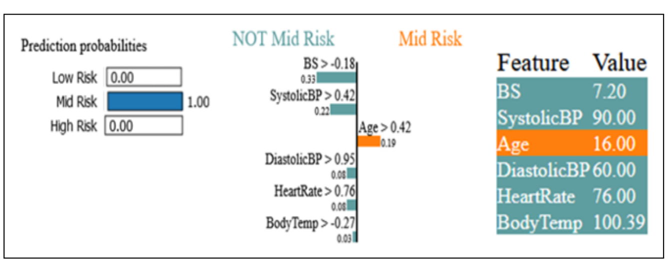


Fig. 5. LIME Representation for Mid Risk for XGB After SMOTE

Fig. 6 shows that the model predicts a 100% probability of high risk. Diastolic blood pressure (95), systolic blood pressure (120), and blood sugar (6.84) are the primary factors that determine the high-risk classification and have a significant influence on this prediction.

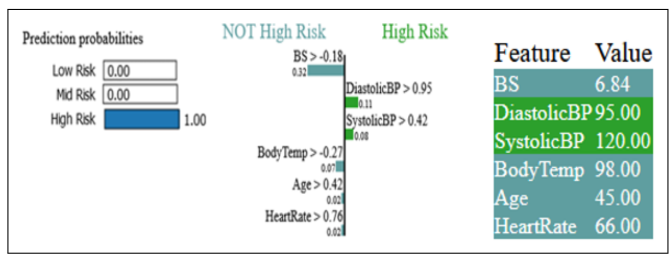


Fig. 6. LIME Representation for High Risk for XGB After SMOTE

E. SHAP Representation

Fig. 7 shows the summary plot of SHAP, indicating that diastolic blood pressure is the factor that has the most significant influence on the maternal health risk model, followed by heart rate and age. Less significantly, body temperature, blood sugar, and systolic blood pressure also have a role. The plot highlights how age and heart rate are critical factors in determining risks to maternal health during pregnancy.

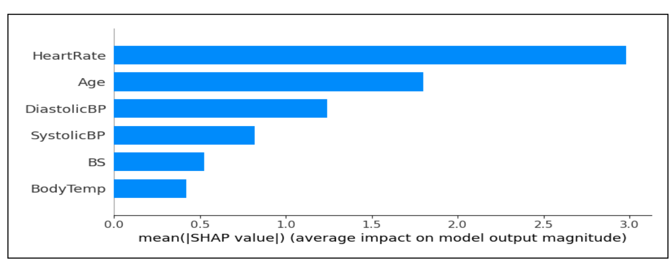


Fig. 7. Summary Plot of SHAP for XGB After SMOTE

Fig. 8 illustrates the SHAP of XGB with no feature selection after SMOTE. The model was heavily influenced by heart rate and age, with higher values substantially raising the estimated risk. Both diastolic and systolic blood pressure plays key role, while the effects of body temperature and blood sugar on predictions are more variable. The figure highlights how many aspects influence the model's risk rating, with age and heart rate being the most critical variables.

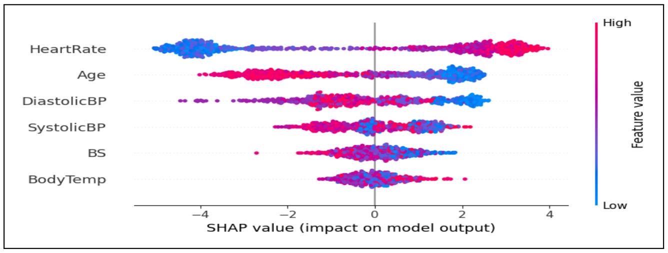


Fig. 8. SHAP Representation for XGB After SMOTE

F. Comparison with Existing Work

In this part of our research, we compared our proposed method with existing research papers that used the same dataset from the UCI Machine Learning repository. Table III shows that our method outperforms all existing works with an accuracy of 95% with XGBoost after applying SMOTE. This demonstrates that the model is effective and reliable in analyzing maternal health risks during pregnancy.

TABLE III
COMPARISON WITH EXISTING WORK

Ref. No.	Model/Architecture	Highest Accuracy
[8]	RF, DT, KNN, SVM, LR, NB, GB, AdaBoost CatBoost, and XGBoost	88.89% with XGBoost
[9]	RF, XG Boost, SVC, and DT	94.26% with RF
[11]	DT, KNN	71.50% with KNN
[13]	DT, RF, and Adaboost	86.09% with Adaboost
[14]	LR, RF, SVM, NB, KNN, GB, and AdaBoost, XG Boost, and Soft Voting	81.5% with Soft Voting
Proposed Model	RF, DT, LR, KNN, SVM, XGBoost, and Gaussian NB	**95% with XGBoost**

V. CONCLUSION & FUTURE WORK

Maternal health risk analysis and identification during pregnancy is essential to lower the likelihood of health issues developing throughout pregnancy, delivery, and the postpartum phase. This study effectively demonstrates how machine learning models may be used to forecast risks to maternal health. For this research, we conducted a benchmark analysis using the publicly available dataset from the UCI Machine Learning Repository. Seven Machine learning classifiers were used in this study to identify maternal health risks early. Extreme Gradient Boosting with no feature selection achieved 84% and 95% accuracy before and after using SMOTE, respectively. The integration of Explainable AI techniques has further enhanced transparency by highlighting the most influential factors in each prediction. This paper expands the range of diagnostic possibilities for Maternal Health Risk and provides a baseline for future research. In the future, we aim to add more data to improve the performance of the model, and more robust algorithms, such as transfer learning and deep learning, may be applied further.

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