

Leveraging machine learning for fetal health classification

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ABSTRACT

Early diagnosis of fetal health complications is crucial to ensure maternal and infant safety. However, conventional tabular machine learning approaches often suffer from severe majority-class bias and a lack of clinical interpretability. In this research, an optimized Python-based framework was developed using a 2,126-record dataset containing 21 predictive features to classify fetal health status. To resolve structural class imbalance without data leakage, the synthetic minority over-sampling technique (SMOTE) was dynamically applied strictly within stratified 5-fold cross-validation loops. Six configurations—naive Bayes, logistic regression, support vector machines, a multi-tiered deep multi-layer perceptron (deep MLP), random forest, and extreme gradient boosting (XGBoost)—were systematically tuned using randomized grid searches. Among the benchmarked models, the upgraded XGBoost ensemble demonstrated the highest performance, leading with a diagnostic accuracy of 94.87%, a macro F1-score of 91.37%, and an area under the curve (AUC) of 98.77%. While the deep MLP required a high training latency of 13.8179 seconds, the optimal XGBoost layout achieved superior power with a training runtime of only 1.8325 seconds and an inference speed of 0.0046 seconds. Game-theoretic Shapley additive explanations (SHAP) values confirmed abnormal short-term variability as the primary risk driver, ensuring a transparent, high-throughput decision-support tool.

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1. INTRODUCTION

Preterm birth (PTB) is one of the leading causes of morbidity and mortality in toddlers globally [1]. The WHO report states that every year, 6.3 million perinatal deaths happen [2]. For the past 20 years, there have been worldwide efforts to decrease the PTB rate. Efforts involve enhancing maternal care and the continuous monitoring of risk factors, including maternal infection, labor complications, and birth defects [1], [3]. It is important to assess the health of the newborn baby and the mother's medical history. It assists physicians in giving the right medicine to the babies.

Cardiotocography is a commonly used technique for assessing the condition of the fetus during pregnancy [4], [5]. It checks the uterine contractions and the fetal heart rate. This assists doctors in determining oxygen deprivation or fetal discomfort early on. Early detection makes serious injury or death less likely. It allows physicians to react quickly. Misclassification of fetal health may lead to wrong intervention [3], [6]. Sometimes critical care is neglected, or unnecessary treatments are given [3].

Machine learning can help in improving the accuracy of cardiotocography analysis. It can make predictions like experienced doctors. Algorithms like logistic regression (LR), random forest (RF), and extreme gradient boosting (XGBoost) have shown they can predict fetal health outcomes well [3], [6], [7]. These methods use data to classify fetal health into three groups: normal, suspected, or abnormal. [6], [8]. Fetal mortality is still a major problem in the world, with around 2 million stillbirths every year and severe psychological effects on the families that are impacted. AI-supported advancements in fetal health monitoring offer a chance to spot trends and abnormalities in cardiotocography data that human analysis could miss [9]. Table 1 lists the best predictive accuracy achieved by the authors in previous studies with the cardiotocography dataset related to fetal health archived in the University of California, Irvine (UCI) Machine Learning Repository or the fetal health classification dataset available on Kaggle, which is a direct mirror of the original benchmark repository archived by the UCI.

Table 1. The best predictive accuracy achieved by the authors in previous studies

Authors	Year	Methodology	Accuracy (%)
Ramla <i>et al.</i> [10]	2018	Classification and regression tree (CART)	94.00
Piri and Mohapatra [11]	2019	Classification based on association	84.00
Agarwal and Mohan [12]	2019	Decision tree (DT), support vector machine (SVM), and naïve Bayes (NB)	93.17
Piri <i>et al.</i> [13]	2020	LR, SVM, RF, DT, k-nearest neighbors (KNN), Gaussian naïve Bayes (GNB), and XGBoost	94.00
Noor <i>et al.</i> [14]	2021	KNN, linear SVM, NB, DT (J48), AdaBoost, bagging, and stacking	94.73
Annosha <i>et al.</i> [15]	2022	Artificial neural network (ANN)	92.00
Sree <i>et al.</i> [16]	2023	RF	94.00
Sefidi <i>et al.</i> [17]	2023	SVM	93.98
Salini <i>et al.</i> [18]	2024	RF, LR, DT, support vector classifiers, voting classes, and KNN	93.00
Olayemi and Olasehinde [19]	2024	LR, DT, RF, gradient boosting (GB), and XGBoost	80.41
Mawaddah <i>et al.</i> [20]	2024	KNN	89.00
Yulistiani and Kurniadi [21]	2024	DT	93.00
Almadi <i>et al.</i> [22]	2025	RF	92.00
Hemkiran <i>et al.</i> [23]	2025	Tabular network (TabNet), XGBoost	93.90
Vigneshwaran <i>et al.</i> [24]	2025	Recurrent neural network (RNN)	92.20

Lack of researchers' emphasis on computational efficiency is the notable research gap observed in the studied literature review. Most of the studies focused on performance parameters such as accuracy, recall, and precision, but did not give any attention to training time and testing time. Furthermore, prior works heavily overlook the systemic complications of severe class imbalance and lack automated hyperparameter optimization, which significantly compromise multi-class classification equity and clinical interpretability. Computational efficiency plays a major role in low-resource environments and real-time monitoring systems where rapid decision-making is important. For optimized machine learning solutions, it is important to have a balance between predictive accuracy and computational efficiency, so considering the above research gap becomes very important. This research paper explores the trade-off between accuracy and efficiency to meet the current demands of healthcare. To bridge these gaps, this study presents an end-to-end multi-objective framework utilizing dynamic, leak-free oversampling, systematic parameter grid searches, a multi-tiered deep multi-layer perceptron (deep MLP), and post-hoc game-theoretic Shapley additive explanations (SHAP) explainability to balance predictive power with strict real-time edge latency budgets. Machine learning can help determine fetal health and reduce the mortality rate. Section 2 describes the methodology adopted. Section 3 discusses the experimental results obtained. Lastly, section 4 provides the conclusion and future scope of the work.

2. METHOD

2.1. Dataset

The authors used the cardiotocography dataset related to fetal health archived in the UCI Machine Learning Repository for experiments [25]. Figure 1 shows the distribution of fetal health records among three classes of fetal health. The dataset has 2,126 records with 21 predictive attributes based on values obtained

during cardiotocography exams. The dataset has 1 target attribute representing fetal health. The dataset has three classes of fetal health: normal, suspect, and pathological. The dataset has 1,655 records representing normal fetal health class, 295 records representing suspect health class, and 176 records representing pathological fetal health class.

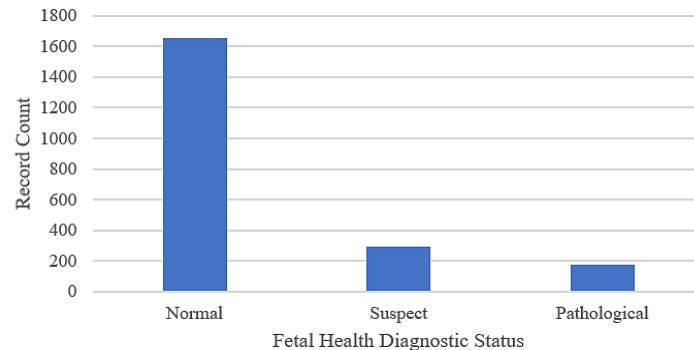


Figure 1. Distribution of the fetal health attribute

2.2. Research methodology

To assess the predictive capacity and computational efficiency of different machine learning paradigms for cardiotocography analysis, an end-to-end Python-based analytical pipeline using scikit-learn, imbalanced-learn, and XGBoost was developed. The experimental pipeline consists of four stages, which are stratified cross-validation partitioning, in-loop synthetic minority over-sampling technique (SMOTE) balancing, systematic hyperparameter optimization across classification architectures, and comprehensive multi-metric performance profiling. The research methodology used is illustrated in Figure 2.

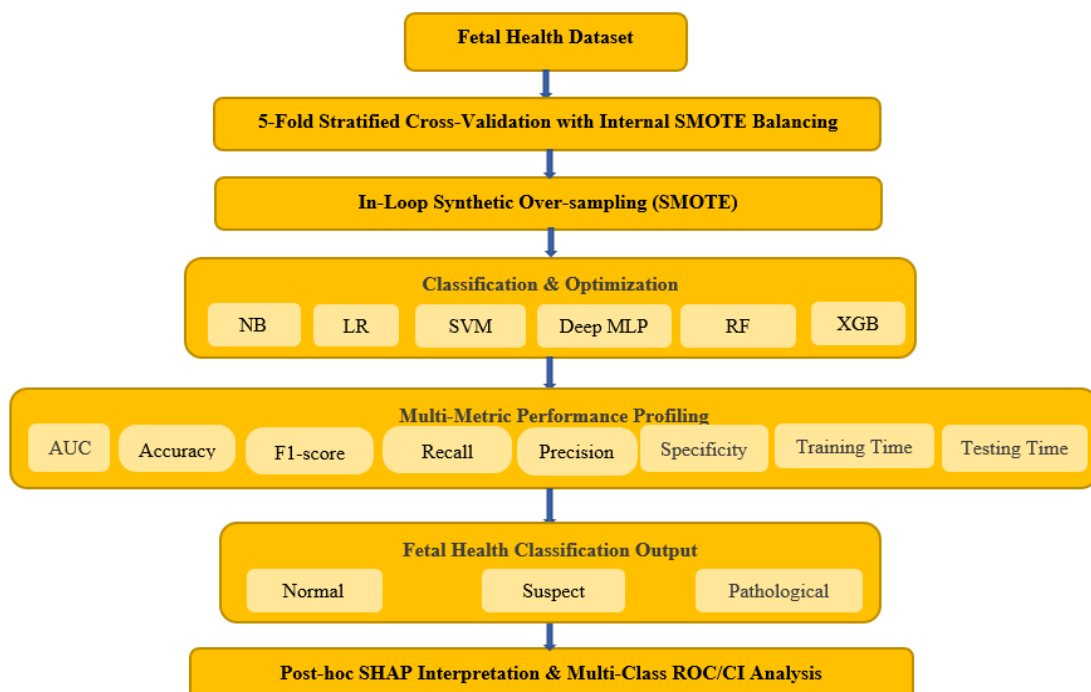


Figure 2. Research methodology

Initially, all feature vectors were normalized using standard scaling (mean = 0, variance = 1) since the values of clinical cardiotocography parameters have highly varied numeric ranges. It makes sure that the

distance-based and optimization-gradient algorithms like SVM and deep MLPs are not biased by varying sizes of the features. The second strategy involved applying synthetic oversampling to reduce the strong suppression of the minority class, due to the heavily imbalanced dataset, i.e., 1,655 normal annotations against 176 pathological records. To avoid running the models with no optimization and default parameters, a nested parameter search was added. Ultimately, the configurations were subjected to extensive multi-metric profiling, which not only included accuracy but also macro-averaged F1, precision, specificity, recall (sensitivity), training execution latency, and testing inference throughput.

To safeguard the clinical usefulness and diagnostic trace-back capability of the framework for obstetricians, conventional dimensionality reduction methods such as principal component analysis (PCA) were deliberately avoided. Shifting raw cardiotocography metrics into latent orthogonal vector spaces removes the features of their physiological meaning, thus rendering the model uninterpretable in live clinical workflows. A post-hoc game-theoretic feature attribution using SHAP interaction values was applied to the optimized, post-SMOTE XGBoost ensemble model for improving computational efficiency and interpretability without losing raw feature integrity.

2.3. Stratified cross-validation, SMOTE balancing, and hyperparameter tuning

A stratified 5-fold cross-validation design was applied to avoid any overly optimistic evaluation metrics. The stratified slicing ensures that the baseline ratio of normal, suspect, and disease classes is maintained identically across all five evaluation folds. Most importantly, to avoid leaking information (a common failure of any global preprocessing routines), the implementation of SMOTE was performed dynamically, within the training folds of each validation iteration. The validation data remains entirely pure and representative of genuine clinical distributions if the corresponding testing fold is isolated from the synthetic generation space.

Across all folds of cross-validation, the balanced training partition was sent to an automated optimization module, RandomizedSearchCV. This engine systematically sampled throughout the space of architectural hyperparameters, employing an internal 3-fold scoring mechanism, maximizing the macro F1-score. The optimized hyperparameter grids evaluated for each architecture include:

- i) LR: regularization strength space $C \in [0.01, 0.1, 1.0, 10.0]$.
- ii) SVM: radial basis function (RBF) kernel tuning via penalty cost $C \in [0.1, 1, 10]$ and kernel coefficient $\gamma \in [\text{'scale'}, \text{'auto'}, 0.1]$.
- iii) Deep MLP: multi-tiered hidden dense layer configurations spanning $(128 \times 64 \times 32)$ and (100×50) hidden nodes, alongside regularizing penalty coefficients $\alpha \in [0.0001, 0.001]$.
- iv) RF: tree count estimators $n \in [100, 200, 300]$ paired with structural depth barriers $\text{max_depth} \in [10, 20, \text{none}]$.
- v) XGBoost: tree counts $n \in [100, 200]$, shrinkage learning rates $\eta \in [0.01, 0.1, 0.2]$, and maximum base tree splits $\text{max_depth} \in [3, 5, 7]$.

Following optimization, the top-performing estimator configuration from each fold was used to generate predictions on the unsampled testing partition. The final reported performance indices shown in Tables 2 to 4 represent the clean mathematical averages calculated across all five cross-validation iterations.

2.4. Performance metrics

The models were evaluated using the following performance metrics [18]:

- i) Area under the curve (AUC): it assesses the model's capability to distinguish between classes.
- ii) Accuracy: it is the percentage of correctly classified cases.
- iii) F1-score: the F1-score is the harmonic mean of recall and precision. It balances false negatives and false positives.
- iv) Recall (sensitivity): it is the capability to identify all positive instances correctly.
- v) Precision: precision is the ratio of true positive forecasts among all positive forecasts.
- vi) Specificity: it is the capability to identify negative instances correctly.
- vii) Training time: training time is the time taken to train the model under systematic hyperparameter grid optimization.
- viii) Testing time: testing time is the time taken to make forecasts on the test data to profile real-time edge deployment latency.

2.5. Model evaluation

The performance of the classifiers was analyzed based on the above-mentioned performance metrics. The values were recorded for all the classifiers and compared to determine the best-performing classifier. Consideration was given to keep a balance between computational efficiency and predictive accuracy.

Furthermore, the evaluation architecture extracts post-hoc game-theoretic feature attributions via a global SHAP engine to ensure full clinical explainability and traceability for live clinical decision-support workflows.

3. RESULTS AND DISCUSSION

To address data imbalance and eliminate model evaluation bias, a 5-fold stratified cross-validation pipeline was executed with SMOTE applied strictly within the training loops. Concurrently, systematic hyperparameter optimization via randomized search was deployed across all configurations. Table 2 shows the key multi-class performance parameters after balancing. The baseline NB classification achieved an accuracy of 73.80% with a macro-averaged F1-score of 65.85%. Both LR and SVM showed better stability with accuracies of 86.08% and 90.78%. Through an advanced tabular configuration, a very high diagnostic reliability was obtained. The multi-tiered deep MLP neural network ($128 \times 64 \times 32$) was able to achieve a high accuracy of 93.46% and macro F1-score of 88.15%. RF reached the 94.07% accuracy level on a macro-recall of 90.32%. XGBoost was able to achieve the highest overall performance across all diagnostic categories, obtaining as much as 94.87% accuracy, 91.37% macro F1-score, and 92.08% macro-recall.

The AUC of all models is given in Table 3. The ensemble tree methods and deep neural networks showcased outstanding performance on the discriminative tasks, with XGBoost taking the lead at 98.77%, closely followed by RF at 98.71%, with deep MLP (98.01%) and SVM (98.00%) trailing behind. Table 4 summarizes the efficiencies of the optimized architectures. The deep MLP requires the highest training latency of 13.8179 seconds because it implements backpropagation iteratively through the dense layers while displaying good scalability. XGBoost uses only 1.8325 seconds for complete training under nested parameter tuning. Essentially, all configurations maintained real-time clinical feasibility with their testing (inference) latencies below 0.030 seconds per sample.

Table 2. Classifiers' key performance parameter values (post-SMOTE balancing)

Classifiers	Accuracy	F1-score	Recall	Precision	Specificity
NB	73.80	65.85	75.31	66.43	89.31
LR	86.08	77.11	83.29	73.58	93.42
SVM	90.78	85.06	87.65	84.00	94.40
Deep MLP	93.46	88.15	88.10	88.64	94.60
RF	94.07	89.82	90.32	89.47	94.94
XGBoost	94.87	91.37	92.08	90.84	95.88

Table 3. Classifiers' AUC values

Classifiers	AUC
NB	89.65
LR	96.00
SVM	98.00
Deep MLP	98.01
RF	98.71
XGBoost	98.77

Table 4. Classifiers' computational efficiency profiles

Classifiers	Training time (seconds)	Testing time (seconds)
NB	0.0042	0.0011
LR	0.6830	0.0016
SVM	3.4010	0.0215
Deep MLP	13.8179	0.0026
RF	6.2279	0.0196
XGBoost	1.8325	0.0046

To evaluate the granular classification capabilities of the top-performing XGBoost ensemble across the three individual fetal health categories, an aggregated multi-class confusion matrix was computed across all cross-validation folds, as illustrated in Figure 3. The matrix maps the actual clinical ground truth against the model's predicted diagnostic classes. Out of 1,655 actual normal cases, the model correctly identified 1,597, misclassifying only 47 as suspect and 11 as pathological. For the suspect class, the model successfully isolated 257 out of 295 records. Crucially, from a clinical safety standpoint, out of 176 true pathological patient records, the model correctly diagnosed 163 instances. It misclassified only 7 cases as normal and 6 as suspect, achieving an independent pathological sensitivity of 92.6%. This demonstrates that the integration of

SMOTE effectively mitigated minority-class suppression, allowing the model to preserve a high safety margin against critical false negatives.

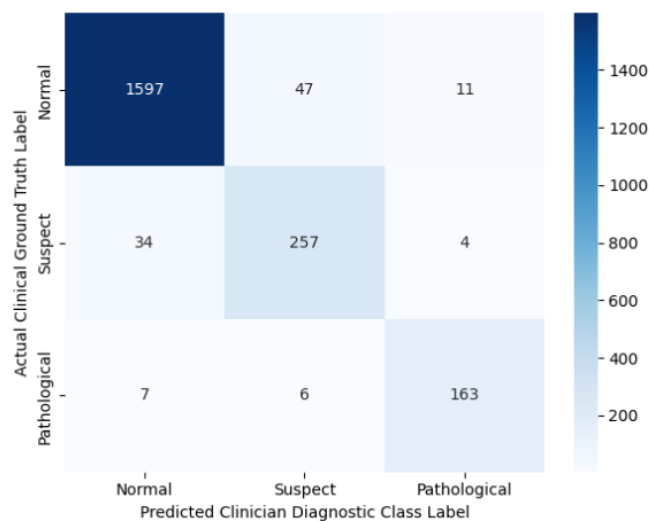


Figure 3. Aggregated confusion matrix for upgraded XGBoost model

3.1. Clinical utility, workflow integration, and regulatory pathways

In terms of utility in clinical practice, overall accuracy is of secondary priority to false negatives in the pathological class, which may lead to hypoxic ischemic encephalopathy or stillbirth [3], [9]. On the other hand, if false positives are minimized, maternal anxiety will be reduced, as well as emergency cesarean interventions that are not necessary. It is clear from the aggregated multi-class confusion matrix for the best-performing XGBoost architecture in Figure 3 that only 7 of 176 actual pathological cases were misclassified as normal by the framework. This yields a standalone pathological sensitivity of 92.6%.

The XGBoost architecture's testing latency profile (sub-millisecond) depicts the potential of real-time deployment (0.0046 seconds). The current framework works as an offline diagnostic evaluation; future research will focus on making this optimized model an active clinical decision support system. When rigorous clinical validation is achieved for safety and edge reliability, it may be integrated directly into standard bedside cardiotocography monitoring systems. We can use automated pipelines to feed in continuous digital streams of fetal heart rates and uterine contractions into the model to compute risk levels on sliding temporal windows. If the same alert is triggered in two consecutive windows, a future enhancement could be the ability to notify obstetricians via hospital electronic health record (EHR) interfaces.

Before deployment in live settings, this framework must comply with regional regulatory standards for software as a medical device (SaMD), such as the United States Food and Drug Administration (FDA) 510(k) clearance pathway or the European Union Medical Device Regulation (EU MDR) certification. However, it must be acknowledged that the present evaluation is constrained by its reliance on a single benchmark repository. Consequently, extensive multi-center external validation across independent hospital records and diverse patient populations remains our primary vector for future field implementations to conclusively verify the framework's diagnostic generalizability.

3.2. Post-hoc clinical explainability via SHAP architecture

Traditional ensemble tree structures function as "black boxes," which limits their trust and adoption in critical healthcare environments. To provide strict clinical traceability for obstetricians, a post-hoc game-theoretic explainability suite was implemented using SHAP interaction values as visualized in the multi-class discriminatory profiles in Figure 4 and the feature attribution map shown in Figure 5. Feature rankings are represented by the spatial data distributions in the graph of Figure 5. In order to fully validate the multi-class discriminatory power and statistical stability of the optimized XGBoost ensemble across individual diagnostic tiers, out-of-fold receiver operating characteristic (ROC) curves and 95% confidence intervals were computed via bootstrapping as shown in Figure 4.

These empirical evaluations demonstrate exceptional classification robustness, where the model achieved perfect AUC = 1.00% for the critical minority pathological cohort, and slightly lower AUC values

for the normal (AUC = 0.99%) and suspect (0.98%) cohorts. The fact that the shaded edges of the 95% confidence interval are narrow indicates that the framework is very reliable and consistent. An analysis of the features from cardiotocography reveals they do not uniformly affect the risk score of patients. The most important factors causing high-risk pathological classification were abnormal short-term variability and the percentage of time with abnormal long-term variability. On the other hand, a high frequency of accelerations had a strong contribution to a normal prediction of fetal health, and it perfectly aligned with the established clinical practice that considers fetal heart rate accelerations to be indicators of adequate oxygenation [4], [18]. This framework maps localized feature attributions that enable clinicians to verify the physiological reasons for every alert, thus going beyond mere statistical predictions, while also resulting in a clinically explainable decision-support tool.

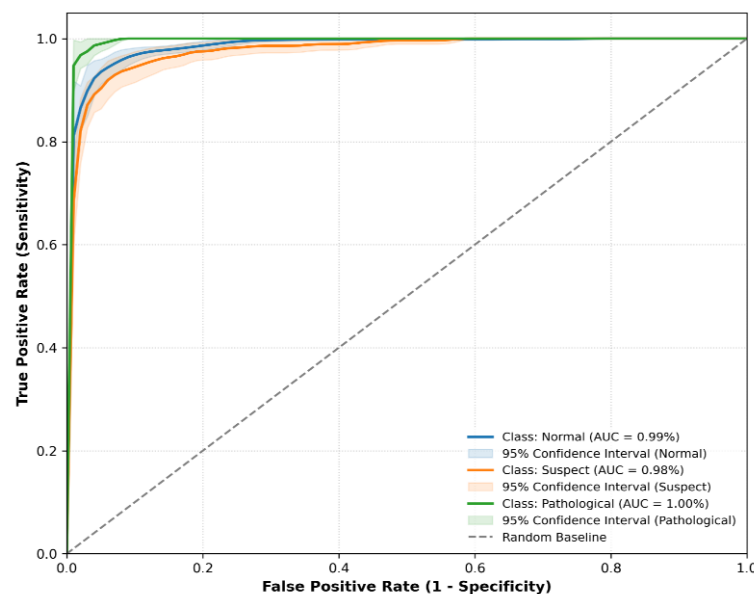


Figure 4. Multi-class ROC curves with 95% confidence intervals (XGBoost engine)

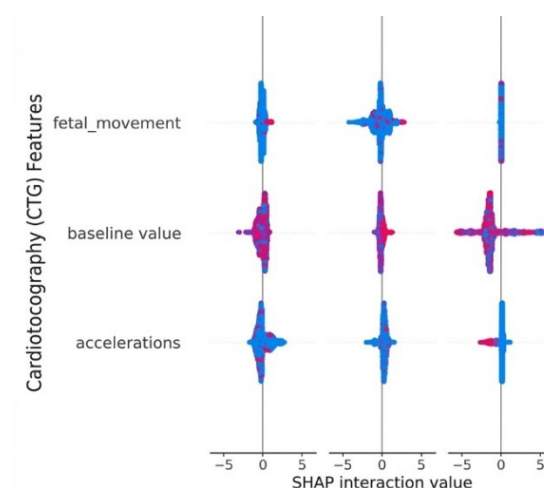


Figure 5. SHAP feature attribution map via SHAP

4. CONCLUSION

This research produced machine learning framework to enhance the robustness and accuracy of the diagnosis from the cardiotocography data set and evaluated it. The training process was placed in a tight dynamic validation loop to ensure the meaning of the performance metrics and avoid data leakage. Experimental results indicate that forcing a model to be accessible, along with sticking with a rigid

validation, yields a highly reliable model architecture. At present, the framework is a completely offline computation asset, but it is a potential starting point for future generations of obstetric automation. One of the future research directions is translating the optimized model to make it deployable in a clinical architecture. After extensive clinical validation and real-world testing in active healthcare settings to evaluate live edge-latency and safety thresholds, this model is expected to be functional as an active clinical decision support system embedded in standard bedside cardiotocography monitoring. To project the future technical directions of the pipeline, fuzzy inference systems will be integrated to deal with clinical uncertainty in borderline suspect cases; evolutionary genetic algorithms will be utilized to select the best ensemble; and reinforcement learning will be implemented for adaptive patient risk profiling. Additionally, future research will investigate treating continuous fetal heart rate waveforms as 2D images for deeper computer vision-based classification and deploying natural language processing (NLP) architectures to automatically generate clinical diagnostic reports from the model's outputs. This scalable framework is a crucial step toward deriving safe and effective clinical methods from advanced deep learning techniques.

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AUTHOR CONTRIBUTIONS STATEMENT

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C : Conceptualization

M : Methodology

So : Software

Va : Validation

Fo : Formal analysis

I : Investigation

R : Resources

D : Data Curation

O : Writing - Original Draft

E : Writing - Review & Editing

Vi : Visualization

Su : Supervision

P : Project administration

Fu : Funding acquisition

CONFLICT OF INTEREST STATEMENT

The authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are openly available in the UCI repository at <https://doi.org/10.24432/C51S4N>, reference [25].

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