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Leveraging Real-Time Data for Stillbirth Prevention and Risk Mitigation

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Abstract: This study leverages real-time data and predictive analytics to mitigate stillbirth risks using machine learning techniques. We utilized the Cardiotocography (CTG) dataset to classify fetal health states as Normal, Suspect, or Pathologic. The preprocessing included data cleaning, correlation-based feature selection, and scaling. Eight machine learning models—Logistic Regression, Support Vector Machine (SVM), Decision Tree, Random Forest, Gradient Boosting, AdaBoost, XGBoost, and LightGBM—were trained and evaluated using standard metrics. Bayesian hyperparameter tuning was employed for performance enhancement. SHAP was used to explain feature importance. Ensemble models like LightGBM and XGBoost achieved the highest performance (F1-score ~0.992).

Keywords: Stillbirth Prevention, Machine Learning, Cardiotocography, Fetal Risk Assessment, Real-Time Monitoring, Predictive Analytics, SHAP, Hyperparameter Tuning

I. INTRODUCTION

Stillbirth—defined as the delivery of a fetus showing no signs of life at 28 weeks of gestation or later—remains a profound global health concern, claiming nearly 1.9 million lives annually (WHO, 2023). Despite technological and medical advancements, stillbirth continues to affect families disproportionately, with Sub-Saharan Africa and South Asia accounting for nearly 80% of global cases.

Various factors including maternal health issues (e.g., hypertension, diabetes), fetal complications (e.g., congenital anomalies), and external elements (e.g., access to healthcare) contribute to stillbirth. Monitoring fetal well-being is thus a critical part of obstetric care. Cardiotocography (CTG) is a non-invasive diagnostic method that tracks fetal heart rate and uterine contractions to evaluate fetal health. While CTG is widely used, manual interpretation often suffers from subjectivity. This study aims to automate CTG analysis using machine learning (ML) techniques for reliable and timely identification of fetal distress.

Our objective is to apply and evaluate multiple ML models on the CTG dataset to predict fetal states and mitigate the risk of stillbirth. We also employ SHAP to enhance model transparency and interpretability.

II. METHODOLOGY

The methodology followed a structured pipeline, combining data processing, model development, and interpretability as outlined below:

1) Dataset Acquisition & Exploration: The Cardiotocography (CTG) dataset was obtained from a publicly available source. It was explored for structure, class distribution, and statistical patterns using descriptive analytics.
2) Data Cleaning: The dataset initially contained 2130 entries. We removed 4 rows with missing values and 1 duplicate entry. Metadata columns such as FileName, Date, and SegFile were dropped.
3) Normalization: Min-Max Scaling was applied to scale feature values between 0 and 1. This ensured uniformity across all features, which is particularly important for models sensitive to feature magnitude.
4) Feature Selection: Pearson correlation analysis was used to identify and remove highly correlated features (e.g., LB) to reduce redundancy and multicollinearity in the data.
5) Model Development: Eight machine learning models were selected: Logistic Regression, SVM, Decision Tree, Random Forest, Gradient Boosting, AdaBoost, XGBoost, and LightGBM. These were chosen based on their track record in classification tasks, especially for structured healthcare data.
6) Hyperparameter Optimization: Bayesian Optimization was employed instead of grid or random search to efficiently tune hyperparameters and achieve optimal performance using fewer iterations.
7) Model Evaluation: The models were evaluated using standard metrics such as F1-score, precision, and recall. Cross-validation was used to ensure robust generalization.

8) Interpretability using SHAP: To improve clinical transparency and model trust, SHAP (SHapley Additive exPlanations) was used to analyze the contribution of each feature to predictions.

SHAP was preferred over LIME due to its consistency, theoretical foundation in game theory, and superior ability to handle tree-based ensemble models.

It provides both global interpretability (overall feature importance) and local interpretability (explanation for individual predictions), making it suitable for sensitive applications like fetal health prediction.

III. DATA DESCRIPTION

The dataset used is the Cardiotocography (CTG) dataset, containing 2,126 records and 40 features. These include fetal physiological signals, heart rate variability indicators, statistical descriptors, domain-specific evaluations, and class labels representing fetal condition. Below are detailed explanations of each feature:

A. *Fetal Signals*

- LB (Baseline Heart Rate): Average fetal heart rate measured over a 10-minute window. Indicates overall fetal cardiac activity baseline.
- AC (Accelerations): Number of short-term increases in fetal heart rate. Reflects fetal responsiveness and well-being.
- FM (Fetal Movements): Number of fetal body movements detected. Increased movement generally suggests healthy development.
- UC (Uterine Contractions): Number of uterine muscle contractions. Helps evaluate labor progression and fetal stress response.

B. *Variability Measures*

- ASTV (Abnormal Short-Term Variability): Percentage of time with abnormal rapid heart rate changes. Higher values may indicate fetal distress.
- MSTV (Mean Short-Term Variability): Average beat-to-beat variability. Assesses moment-to-moment changes in fetal heart rate.
- ALTV (Abnormal Long-Term Variability): Percent of time with abnormal long-range variability. A sign of possible oxygen or nervous system issues.
- MLTV (Mean Long-Term Variability): Average long-term variation in fetal heart rate. Indicates autonomic nervous system stability.
- DL (Light Decelerations): Number of mild reductions in heart rate. Can be normal but excessive may require monitoring.
- DS (Severe Decelerations): Count of pronounced heart rate drops. Often associated with fetal hypoxia or cord issues.
- DP (Prolonged Decelerations): Frequency of extended heart rate reductions. Typically signals ongoing fetal compromise.
- DR (Deceleration Rate): Percentage of time fetal heart rate is decelerating. Indicates potential fetal stress or asphyxia.

C. *Statistical Descriptors*

- Min: Minimum fetal heart rate during the test. Sudden drops may indicate poor fetal oxygenation.
- Max: Maximum fetal heart rate. May point to fetal movement, stress, or complications.
- Mean: Average fetal heart rate. Offers a baseline view of fetal cardiac activity.
- Median: Middle value of the heart rate dataset. Robust against outliers and skew.
- Mode: Most frequently recorded heart rate. Useful in identifying dominant rhythm patterns.
- Variance: Measures spread in heart rate data. High variance may reflect abnormal variability.
- Tendency: Direction of heart rate trend (rising or falling). Indicates changing fetal condition over time.

D. *Aggregated Evaluations*

- A, B, C, D, E: Composite evaluations of fetal state based on different clinical rules. Provide varied insights on fetal health.
- AD, DE, LD: Advanced combinations of deceleration and evaluation metrics. Help refine diagnostic granularity.
- FS (Fetal State): Clinical evaluation of overall fetal health based on multiple features. Helps predict outcomes like distress.

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E. Class Label (Target)

NSP (Fetal State Class): The target label indicating fetal condition:

- 1 = Normal: Healthy fetus
- 2 = Suspect: Requires closer observation
- 3 = Pathologic: Indicates fetal distress; clinical intervention likely needed

IV. DATA PREPROCESSING

Initial Dataset: 2130 rows × 40 columns

Cleaning:

- Removed 4 rows with missing values
- Removed 1 duplicate row

Feature Reduction:

- Dropped FileName, Date, and SegFile (metadata)
- Removed LB due to high correlation with other features

Final Dataset: 2126 rows × 36 columns

Scaling: Applied Min-Max scaling

Split: 80% training and 20% testing

V. PREDICTION MODEL

We applied the following eight classification algorithms:

1) Logistic Regression – A linear classifier effective for binary/multiclass problems.
2) SVM (Support Vector Machine) – Handles nonlinear decision boundaries using kernels.
3) Decision Tree – Interpretable model based on hierarchical feature splits.
4) Random Forest – Ensemble of decision trees; reduces overfitting.
5) Gradient Boosting – Sequentially builds trees that correct errors of previous ones.
6) AdaBoost – Weights misclassified points more heavily in future iterations.
7) XGBoost – Highly optimized gradient boosting framework.
8) LightGBM – Gradient boosting model that's fast and efficient with large datasets.

These models were tuned using Bayesian optimization to enhance performance with minimal training time.

Before tuning, performance scores were as follows:

Model	Precision	Recall	F1-Score	Accuracy
Logistic Regression	0.986	0.986	0.986	0.986
SVM	0.983	0.984	0.983	0.984
Decision Tree	0.981	0.981	0.981	0.981
Random Forest	0.982	0.981	0.981	0.981
Gradient Boosting	0.982	0.981	0.981	0.981
AdaBoost	0.969	0.969	0.969	0.969
XGBoost	0.984	0.984	0.983	0.984
LightGBM	0.986	0.986	0.986	0.986

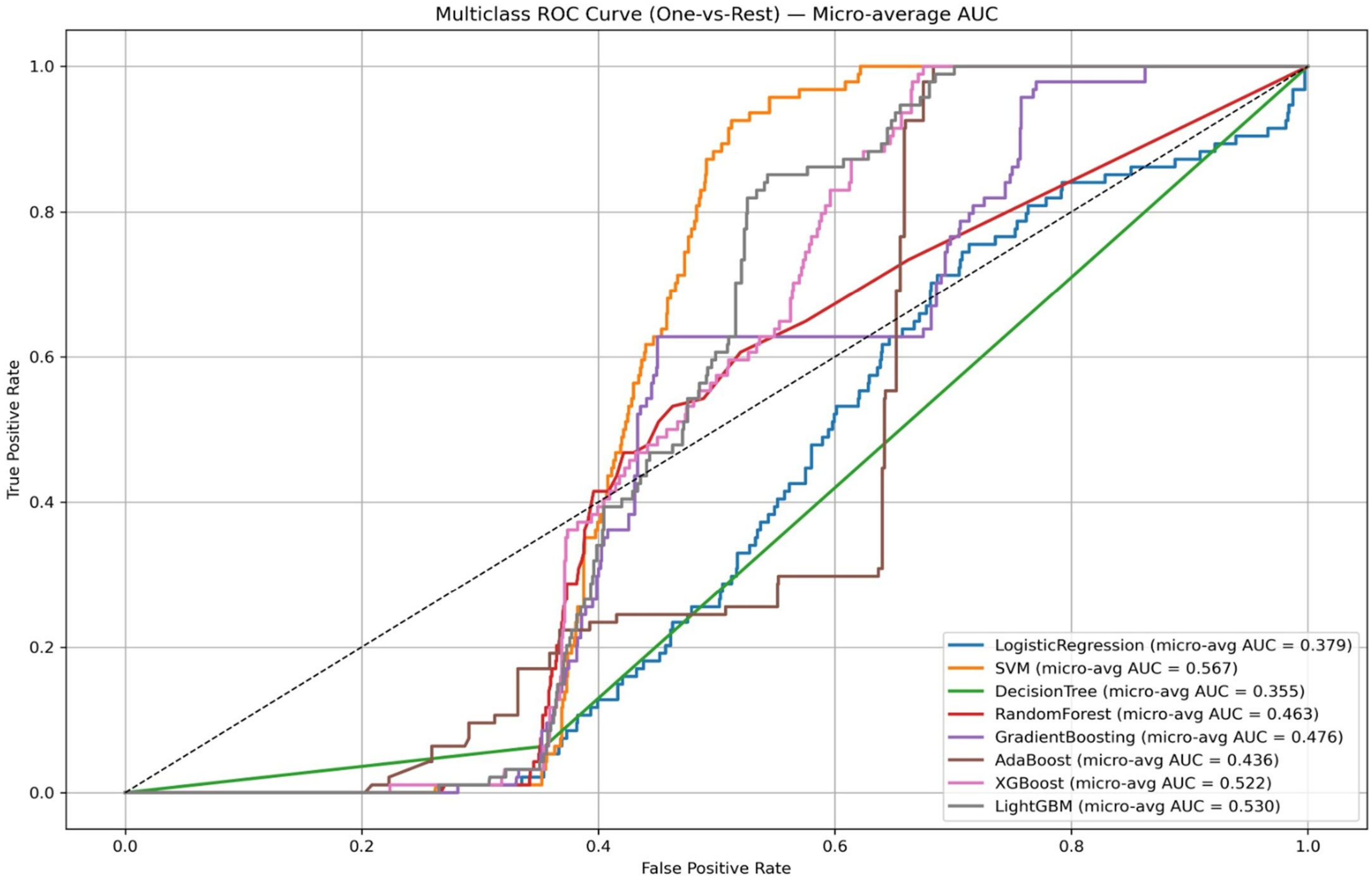

Figure 1. A comparison of the ROC curves of various machine learning methodologies.

VI. RESULT AND DISCUSSION

A. Performance Metrics after Hyperparameter Tuning

Hyperparameter tuning significantly improved the performance of all models, especially ensemble techniques. The best cross-validation F1-scores and corresponding hyperparameters are summarized below:

Model	Best CV F1	Best Parameters
Logistic Regression	0.988257	{'C': 0.01078, 'penalty': 'l2', 'solver': 'lbfgs'}
SVM	0.990595	{'C': 6.5554, 'gamma': 0.01364, 'kernel': 'rbf'}
Decision Tree	0.983069	{'max_depth': 30, 'min_samples_leaf': 2, 'min_samples_split': 3}
Random Forest	0.990516	{'n_estimators': 500, 'max_depth': 9, 'max_features': 'sqrt'}
Gradient Boosting	0.992315	{'n_estimators': 470, 'learning_rate': 0.04975, 'max_depth': 8}
AdaBoost	0.986949	{'n_estimators': 461, 'learning_rate': 0.62474}
XGBoost	0.992317	{'n_estimators': 135, 'learning_rate': 0.39442, 'max_depth': 5, 'subsample': 0.90025, 'colsample_bytree': 0.86701}
LightGBM	0.992317	{'n_estimators': 470, 'learning_rate': 0.17234, 'num_leaves': 61, 'subsample': 0.83507, 'colsample_bytree': 0.70505}

B. Discussion

Boosting models like XGBoost and LightGBM achieved the highest F1-scores (~0.992), proving their capability in learning from high-dimensional data. SHAP analysis revealed that features such as SUSP, LD, ASTV, and MSTV played critical roles in predicting fetal states. These insights aligned with clinical interpretations, validating the reliability of our models.

C. Model Interpretability using SHAP

SHAP values were used to explain model decisions. Important features included:

- SUSP: Indicator of suspicious patterns
- ASTV, MSTV: Variability measures
- LD: Light decelerations

These aligned with clinical insights, supporting the reliability of model decisions.

VII. CONCLUSION

This project effectively combined real-time cardiotocography (CTG) signals with machine learning methods to predict fetal health conditions associated with stillbirth. Among the models tested, ensemble boosting algorithms demonstrated superior performance. Incorporating SHAP values provided valuable insights into model decisions, which helps build confidence among healthcare professionals. Future work will focus on implementing these models in clinical practice and enhancing them by incorporating additional features to improve accuracy, fairness, and reliability.

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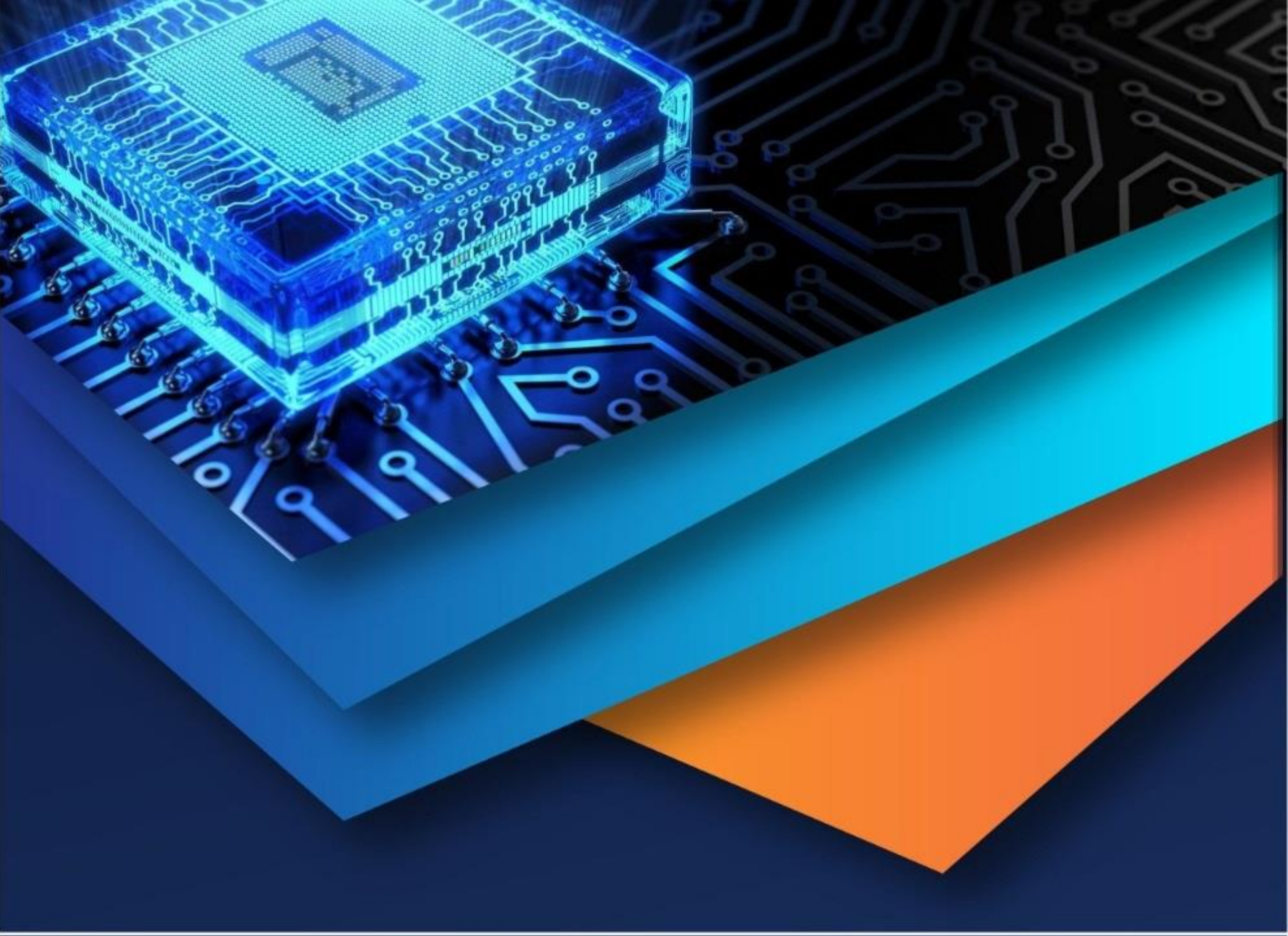

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