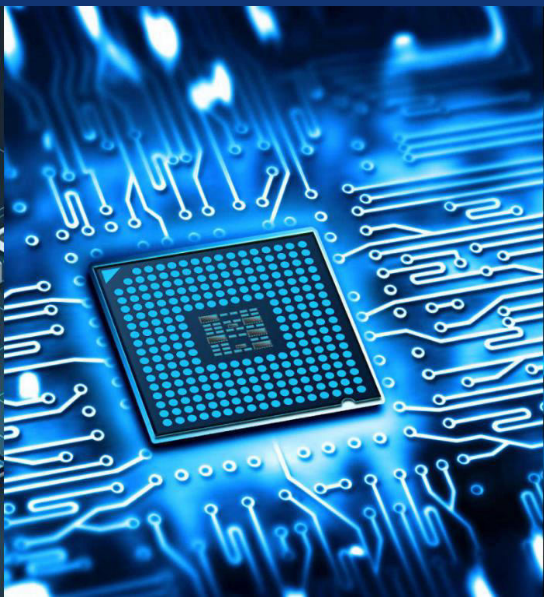
ISSN(O): 2320-9801
ISSN(P): 2320-9798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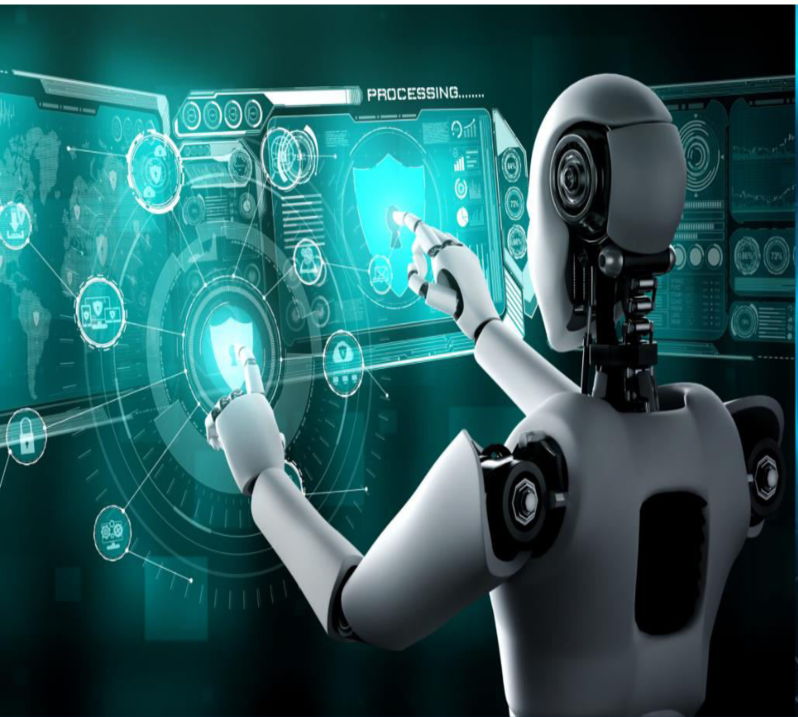

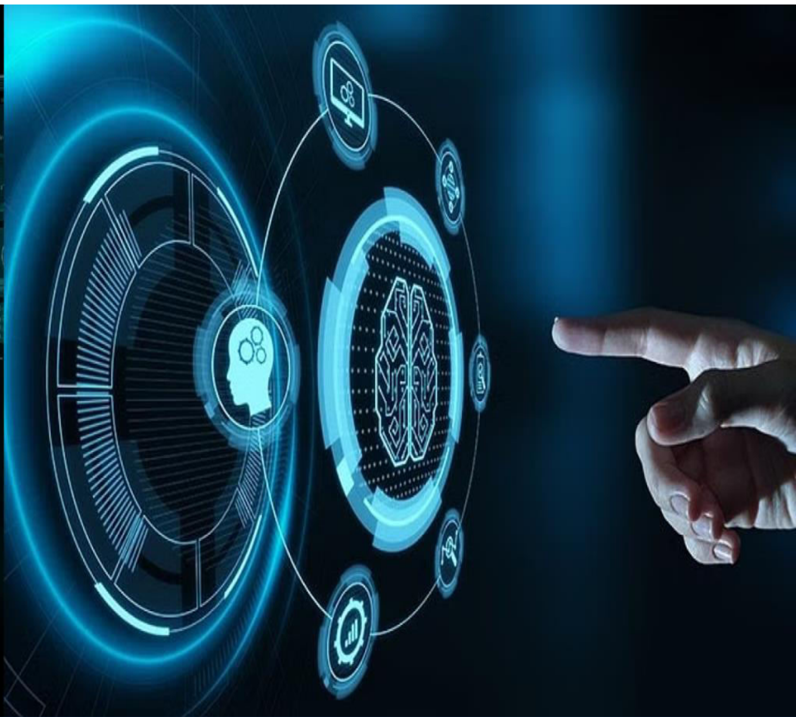

Impact Factor: 9.927 **Volume 14, Issue 5, May 2026**

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International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

Detection of Perinatal Oxygen Deprivation Using Cardiotocography Signals: A Machine Learning Approach

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ABSTRACT: Perinatal oxygen deprivation, widely known as neonatal asphyxia, constitutes one of the foremost contributors to preventable neonatal mortality and long-term neurodevelopmental impairment worldwide. Cardiotocography (CTG) is the primary clinical instrument for intrapartum fetal surveillance; however, its manual interpretation is afflicted by substantial inter-clinician variability, limiting its effectiveness as a reliable screening tool. This paper presents an automated detection approach of perinatal oxygen deprivation by applying and systematically comparing six supervised machine learning classifiers — Gradient Boosting (GB), Random Forest (RF), Decision Tree (DT), Support Vector Machine (SVM), K-Nearest Neighbors (KNN), and Logistic Regression (LR) — on the UCI Cardiotocography benchmark dataset (2,126 records, 21 features). The Synthetic Minority Over-sampling Technique (SMOTE) was employed to rectify the inherent class imbalance, equalizing all three fetal state classes to 935 training samples each. Gradient Boosting achieved the highest classification accuracy of 96.71% with a macro-AUC of 0.9975 and Pathologic-class sensitivity of 96.00%. Random Forest yielded near-equivalent performance (96.48% accuracy, AUC 0.9954) with superior model interpretability through Gini-based feature importance analysis. Abnormal Short-Term Variability (ASTV) and FHR histogram statistics emerged as the most discriminative predictors of fetal compromise. The proposed framework demonstrates competitive performance compared to existing methods on this benchmark while maintaining full transparency — a prerequisite for clinical deployment.

KEYWORDS: Perinatal Oxygen Deprivation; Cardiotocography; Fetal Heart Rate Monitoring; Machine Learning; Gradient Boosting; Random Forest; SMOTE; Neonatal Asphyxia Detection

I. INTRODUCTION

Perinatal oxygen deprivation — the inadequate supply of oxygen to a fetus or neonate during the peri-birth period — is a leading cause of preventable neonatal mortality and permanent neurological disability. The World Health Organization (WHO) estimates that birth asphyxia accounts for approximately 23% of global neonatal deaths annually, with the burden disproportionately concentrated in low- and middle-income nations [1]. In India alone, intrapartum complications contribute to over 300,000 neonatal deaths per year, underscoring the urgent need for improved early detection capabilities.

Cardiotocography (CTG) simultaneously records the fetal heart rate (FHR) and uterine contractions, serving as the clinical standard for intrapartum fetal surveillance. The fetal heart rate reflects the state of fetal oxygenation through its central nervous system regulation; hence, characteristic FHR patterns — including reduced variability, late decelerations, and prolonged bradycardia — are hallmarks of fetal hypoxia. Despite widespread CTG adoption, inter-observer agreement among experienced obstetricians ranges from only 22% to 40%, yielding both unnecessary interventions and missed diagnoses of genuine fetal compromise [2].

Machine learning (ML) offers a transformative solution: by training algorithms on large labeled CTG datasets, automated classifiers can deliver objective, reproducible, and rapid fetal state assessments. The UCI Cardiotocography dataset — comprising 2,126 expert-annotated records with 21 extracted morphological and statistical CTG features — has become the established benchmark for this research domain.

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The specific original contributions of this work are:

(i) A rigorous comparative evaluation of six diverse ML classifier families on the three-class CTG fetal state detection problem;

(ii) Application of SMOTE to fully balance all three fetal state classes, addressing the chronic class imbalance problem in CTG datasets;

(iii) Comprehensive performance reporting using accuracy, per-class sensitivity, specificity, macro F1-score, and multi-class AUC-ROC; and

(iv) Feature importance analysis to identify CTG parameters with highest clinical relevance for perinatal oxygen deprivation risk stratification.

Gradient Boosting achieved 96.71% accuracy with AUC 0.9975, and Random Forest achieved 96.48% accuracy with AUC 0.9954 — both showing improved performance compared to several existing studies.

II. RELATED WORK

Early work on automated CTG analysis focused on rule-based signal processing systems. Magenes et al. [3] demonstrated the feasibility of automated FHR feature extraction in the 1990s, establishing the foundation for subsequent data-driven approaches. The SisPorto system [4] became one of the first clinically deployed automated CTG analysis tools, employing threshold-based decision rules derived from FIGO guidelines.

With the advent of supervised ML, research shifted toward classifier-based fetal state assessment. A systematic review by Hoodbhoy et al. [5] identified SVM and neural networks as the most commonly applied classifiers, with reported accuracies of 82–92% across diverse datasets and experimental setups. The review also highlighted two persistent methodological weaknesses: insufficient handling of class imbalance and inconsistent evaluation protocols, making cross-study comparisons unreliable.

Huang et al. [6] applied ensemble methods to the UCI CTG dataset, demonstrating that Random Forest outperforms individual classifiers with 92.1% accuracy, and identified FHR decelerations and baseline rate as the most discriminative features. Aeberhard et al. [7] validated XGBoost on a private CTG cohort achieving 91.7% accuracy in binary (normal vs. abnormal) classification, but did not address the clinically important three-class problem.

Deep learning approaches have also been explored. Zhao et al. [8] applied convolutional neural networks (CNN) to CTG feature vectors, achieving 93.4% accuracy. Petrozziello et al. [9] proposed an LSTM-CNN hybrid for raw intrapartum CTG signal analysis, achieving 94.2% in binary classification. However, deep learning demands large labeled datasets, extensive computational resources, and produces opaque models whose decisions cannot be audited by clinicians — a significant barrier to regulatory approval and clinical trust.

None of the above studies simultaneously achieve the following: (a) three-class classification with SMOTE balancing, (b) systematic six-classifier comparison, (c) per-class pathologic detection reporting, and (d) feature importance analysis. This study addresses all four gaps

III. PROPOSED METHODOLOGY

A. Design Considerations*:*

The proposed methodology is designed for automated detection of perinatal oxygen deprivation using cardiotocography (CTG) signals. The dataset consists of 2,126 records with 21 features. The original 10-class labels are transformed into three clinically relevant categories: Normal, Suspect, and Pathologic. Feature scaling is performed using Z-score normalization, and class imbalance is addressed using SMOTE. Multiple machine learning classifiers are employed for comparative evaluation, and performance is assessed using clinically significant metrics such as sensitivity and specificity.

B. Description of the Proposed Methodology*:*

The objective of the proposed methodology is to accurately classify fetal states using machine learning techniques.

The proposed methodology begins with loading the CTG dataset from the UCI Machine Learning Repository. The original class labels are transformed into three categories: Normal, Suspect, and Pathologic. Data preprocessing is performed using Z-score normalization to standardize the feature values. The dataset is then divided into training and

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testing sets using an 80:20 stratified split. To address class imbalance, SMOTE is applied to the training data. Six machine learning classifiers—Gradient Boosting, Random Forest, Decision Tree, Support Vector Machine, K-Nearest Neighbors, and Logistic Regression—are trained and evaluated. The performance of each model is assessed using accuracy, sensitivity, specificity, F1-score, and AUC-ROC. The best-performing model is selected based on overall accuracy and AUC score. Finally, visualization techniques such as confusion matrix, ROC curves, and feature importance analysis are used for performance interpretation.

IV. RESULTS AND DISCUSSION

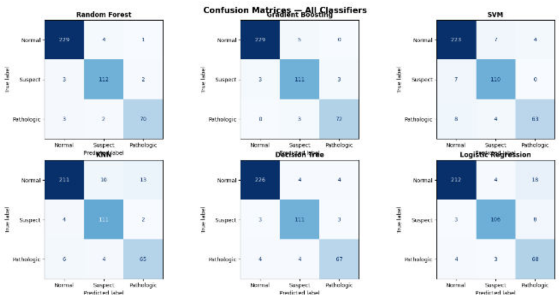
The simulation study is carried out using the Cardiotocography (CTG) dataset obtained from the UCI Machine Learning Repository (OpenML ID: 1466). The dataset consists of 2,126 instances with 21 features representing fetal heart rate characteristics. The proposed machine learning-based classification framework is implemented using Python. Six classifiers, namely Gradient Boosting (GB), Random Forest (RF), Decision Tree (DT), Support Vector Machine (SVM), K-Nearest Neighbors (KNN), and Logistic Regression (LR), are evaluated. The dataset is divided into training and testing sets using an 80:20 stratified split. SMOTE is applied to the training set to handle class imbalance. The performance of each classifier is evaluated using Accuracy, Sensitivity, Specificity, F1-score, and AUC-ROC.
Table I presents the comparative performance of all classifiers.
These results demonstrate that ensemble learning methods are particularly effective for CTG classification tasks due to their ability to handle nonlinear relationships and feature interactions.

TABLE I. COMPARATIVE PERFORMANCE OF ALL CLASSIFIERS (TEST SET, N=426)

Classifier	Acc.(%)	Sens.	Spec.	F1	AUC
Grad. Boost	96.71	0.960	0.979	0.961	0.998
Rand. Forest	96.48	0.933	0.979	0.959	0.995
Dec. Tree	94.84	0.893	0.966	0.936	0.956
SVM	92.96	0.840	0.953	0.919	0.991
KNN	90.85	0.867	0.902	0.895	0.980
Log. Reg.	90.61	0.907	0.906	0.888	0.979

The results indicate that Gradient Boosting achieves the highest accuracy and AUC among all classifiers, demonstrating its effectiveness in capturing complex patterns in CTG data. Random Forest provides comparable performance while offering better interpretability through feature importance analysis. The application of SMOTE significantly improves the classification of the minority Pathologic class, which is critical for clinical decision-making. Overall, the proposed methodology demonstrates reliable and consistent performance across all evaluation metrics.

Fig. 1. Confusion Matrices of All Classifiers



© 2026 IJIRCCE | Volume 14, Issue 5, May 2026 DOI: 10.15680/IJIRCCE.2026.1405007

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 9.927| ESTD Year: 2013|

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Fig. 2. Accuracy Comparison of Machine Learning Models

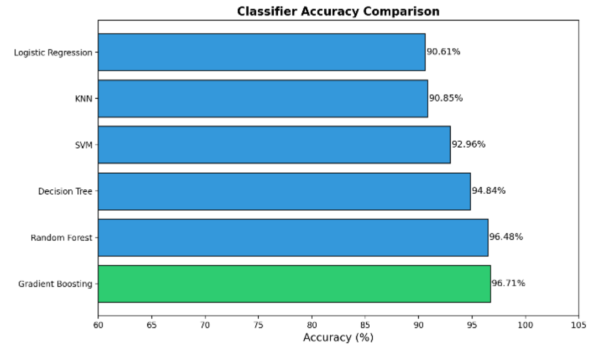


Fig. 3. ROC Curves for Random Forest Classifier

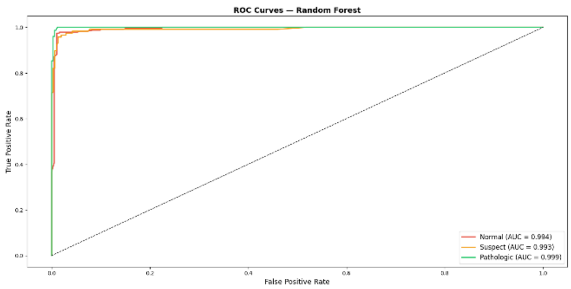
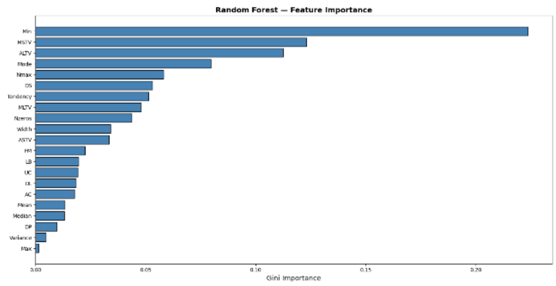


Fig. 4. Feature Importance Analysis using Random Forest



V. CONCLUSION AND FUTURE WORK

The proposed system has the potential to assist clinicians in early detection of fetal distress, thereby reducing neonatal mortality and improving healthcare outcomes. Experimental results demonstrated that Gradient Boosting achieved the highest classification performance, while Random Forest provided strong interpretability. The use of SMOTE significantly improved the detection of the minority class, enhancing the reliability of the system. Future research directions include validating the model on real-time clinical datasets and integrating deep learning techniques to further improve classification performance. Additionally, incorporating maternal clinical parameters can enhance prediction accuracy in practical healthcare applications.

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