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Short Review Paper

Risk Prediction of Fetal Heart Rate from Cardiotocography Using Artificial Intelligence and Machine Learning

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Abstract

Cardiotocography (CTG), which records the fetal heart rate (FHR) and uterine contractions (UC), is the cornerstone of fetal monitoring during pregnancy and labor. However, its manual interpretation is highly subjective, leading to significant inter and intra-observer variability and high false-positive rates for fetal distress. This review paper synthesizes recent advancements in applying Artificial Intelligence (AI) and Machine Learning (ML) techniques to CTG data to develop objective, accurate, and automated systems for predicting fetal risk. We explore the spectrum of ML algorithms employed, features extracted from CTG signals, performance metrics, and persistent challenges including data scarcity and class imbalance. AI/ML integration holds immense promise for improving clinical decision-making and neonatal outcomes.

Keywords: Risk Prediction, Fetal Heart Rate, Cardiotocography, Artificial Intelligence, Machine Learning.

Introduction

Cardiotocography and Fetal Risk: CTG is a non-invasive monitoring tool used to assess fetal well-being, primarily by detecting fetal hypoxia[1,2].

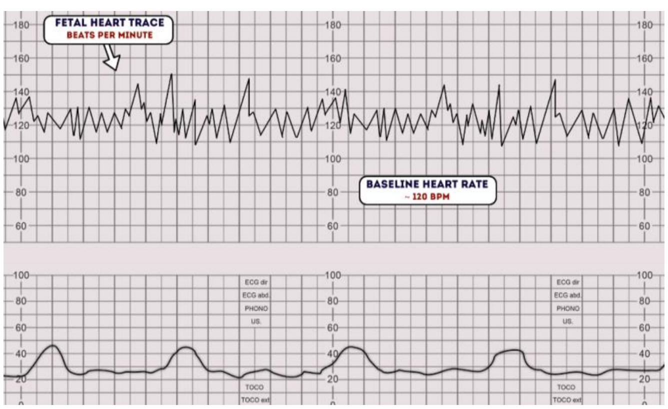

Figure-1: CTG trace showing fetal heart rate (FHR) and uterine contractions (UC).

It generates a graphical recording of two parameters: the FHR measured by ultrasound and the UC measured by a tocodynamometer. Clinical interpretation relies on key parameters including baseline FHR, variability, accelerations, decelerations, and long-term trends[3].

Despite its widespread use in intrapartum monitoring, manual interpretation of cardiotocography (CTG) remains highly subjective and prone to variability. Although standardized clinical guidelines such as those proposed by the International Federation of Gynecology and Obstetrics (FIGO) and the National Institute of Child Health and Human Development (NICHD) are routinely applied, substantial inter- and intra-observer disagreement persists, with studies reporting only moderate levels of consistency among clinicians[4]. This subjectivity contributes to a high false-positive rate, often resulting in unnecessary operative interventions, including emergency cesarean sections and assisted vaginal deliveries, which expose both mother and fetus to avoidable risks[5]. These limitations highlight a critical need for objective and automated CTG analysis approaches that can reduce observer dependency, improve diagnostic accuracy, and support clinical decision-making in labor management.

Application of Artificial Intelligence and Machine Learning

AI and ML techniques offer a data-driven alternative to bypass human subjectivity by learning patterns directly from CTG data[6]. The objective is to predict adverse outcomes such as fetal acidosis (pH < 7.05), abnormal Apgar scores, or NICU admissions.

Machine Learning Approaches: Classical machine learning models for cardiotocography (CTG) analysis predominantly depend on manually engineered features derived from fetal heart rate and uterine contraction signals. Among these methods, Support Vector Machines (SVMs) have been extensively employed for binary classification tasks, particularly in distinguishing normal from pathological CTG patterns, owing to their robustness in handling high-dimensional feature spaces[7]. Random Forest (RF) classifiers have also been widely adopted, as they offer improved interpretability through ensemble-based decision structures and have demonstrated classification accuracies typically ranging between 90% and 93%[8]. More recently, boosting-based algorithms such as Extreme Gradient Boosting (XGBoost) have shown superior predictive performance, achieving accuracy levels between 92% and 96% in the detection of fetal acidosis, thereby highlighting their effectiveness in handling complex non-linear relationships within CTG data[9].

In contrast, deep learning (DL) approaches aim to minimise dependence on handcrafted feature extraction by learning hierarchical representations directly from raw CTG signals or their visual representations. Convolutional Neural Networks (CNNs) have been particularly effective in automatically capturing spatial and temporal patterns from CTG images or signal-based inputs, enabling improved feature learning without explicit domain-driven engineering[10]. Additionally, Recurrent Neural Networks (RNNs), including Long Short-Term Memory (LSTM) architectures, have been applied to model the temporal dynamics inherent in fetal heart rate recordings, allowing these models to effectively capture long-term dependencies and trends critical for accurate fetal monitoring and outcome prediction[11].

Input Features and Pre-processing: In classical machine learning approaches for cardiotocography (CTG) analysis, models are typically built using hand-crafted clinical features derived from expert domain knowledge. These features commonly include baseline fetal heart rate (FHR), short-term and long-term variability, the presence of accelerations and decelerations, and uterine contraction (UC) frequency. Such parameters are extracted in accordance with established clinical interpretation standards, including the guidelines proposed by the International Federation of Gynecology and Obstetrics (FIGO) and the National Institute of Child Health and Human Development (NICHD), ensuring clinical relevance and interpretability of the predictive models[3].

In contrast, deep learning (DL) models operate directly on raw time-series data, enabling them to automatically learn discriminative representations from unprocessed FHR and UC signal sequences. By bypassing manual feature engineering, DL approaches can capture complex temporal and nonlinear patterns inherent in CTG recordings that may not be easily identifiable through traditional handcrafted features[10].

A major challenge in CTG-based fetal outcome prediction is the significant class imbalance present in most datasets, as pathological outcomes occur far less frequently than normal cases. To address this issue, several data balancing strategies have been employed. These include Synthetic Minority Oversampling Technique (SMOTE) to artificially increase the number of minority class samples, random under sampling to reduce the dominance of the majority class, and cost-sensitive learning approaches in which higher misclassification penalties are assigned to minority class errors. Such techniques aim to improve model sensitivity toward pathological cases while maintaining overall classification robustness[12].

Performance Evaluation and Clinical Promise

Performance Metrics: Models are assessed using classification metrics including: Recent studies show ML models achieving AUC values greater than 0.90 for predicting fetal acidosis[9], significantly outperforming manual analysis.

Table-1: Performance metrics for evaluating machine learning models in fetal risk prediction.

Metric	Description	Importance
Sensitivity	TP / (TP + FN)	Prevents missed fetal distress diagnoses
Specificity	TN / (TN + FP)	Reduces false alarms and unnecessary interventions[13]
AUC-ROC	Class separability measure	Threshold-independent performance indicator[9]

Clinical Benefits: AI- and ML-based cardiotocography (CTG) systems offer several clinically significant benefits compared with conventional visual interpretation. These systems provide objective and reproducible analysis that is independent of clinician experience, thereby reducing inter- and intra-observer variability. By enabling early detection of fetal risk, AI/ML approaches support timely clinical decision-making and intervention. Furthermore, automated CTG interpretation can improve workflow efficiency, particularly in low-resource and high-burden clinical environments where access to specialist expertise is limited[6].

Despite notable advances, the widespread clinical implementation of AI-driven cardiotocography (CTG) systems remains constrained by several unresolved challenges[14].

Technical and Data Challenges: One of the primary limitations is the absence of standardized and diverse CTG datasets, which restricts meaningful cross-study comparisons and benchmarking of algorithms. In addition, many models demonstrate limited generalizability when applied to heterogeneous patient populations, reducing their reliability in real-world clinical settings[15]. The quality of CTG recordings also poses a significant challenge, as signal noise, artefacts, and missing data can adversely affect model performance and robustness[1].

Clinical Integration Challenges: For successful clinical adoption, model interpretability is essential. Clinicians require transparent and explainable outputs to develop trust in AI-based decision-support systems. Explainable artificial intelligence (XAI) techniques can assist by identifying key features that contribute to high-risk predictions, thereby supporting clinical reasoning and accountability[16]. Furthermore, integrating multimodal data—such as maternal clinical characteristics, ultrasound findings, and labour progression—has the potential to enhance predictive accuracy and clinical relevance of CTG-based models[17].

Future Research Priorities: Future research should focus on the development of personalized fetal risk assessment models that account for individual maternal and fetal characteristics. The adoption of federated learning frameworks is also recommended to enable collaborative model training across multiple institutions while preserving data privacy and security[18]. Additionally, integrating AI-powered CTG systems with telemedicine platforms could extend access to advanced fetal monitoring in rural and underserved healthcare settings.

Conclusion

AI and ML have demonstrated significant potential in improving the accuracy, consistency, and clinical usefulness of CTG interpretation. Although challenges remain regarding data quality, model generalizability, and clinician trust, emerging technologies such as XAI and federated learning are paving the way for widespread clinical integration. The future of fetal monitoring lies in intelligent, automated, and equitable CTG systems that enhance maternal–fetal outcomes.

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