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Real-Time Monitoring of Fetal Arrhythmias Using AI-Driven Cardiotocography Systems.

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ABSTRACT

Fetal arrhythmias represent a critical challenge in perinatal medicine, often leading to complications such as intrauterine growth restriction, heart failure, or stillbirth if not diagnosed and managed promptly. Traditional diagnostic techniques rely on intermittent ultrasound and “manual interpretation of cardiotocography (CTG)”, which are prone to observer variability and limited in their ability to detect subtle abnormalities in real time. “Advances in artificial intelligence (AI)-driven cardiotocography” systems provide new opportunities for continuous, automated, and objective monitoring of “fetal heart rate (FHR)” and uterine contractions. This study investigates the application of AI models, including deep learning and ensemble methods, to real-time CTG analysis for early detection of fetal arrhythmias. Experimental results show that AI-enhanced CTG systems achieve superior performance in arrhythmia classification compared to conventional approaches, with sensitivity exceeding 92% and specificity above 90%. Furthermore, real-time monitoring reduced false negatives, ensuring early interventions in high-risk pregnancies. Ethical concerns regarding data privacy, interpretability, and clinical integration are also discussed. The study concludes that AI-driven CTG systems represent a paradigm shift in perinatal care, offering scalable and accurate solutions for real-time fetal arrhythmia monitoring.

KEYWORDS: Fetal arrhythmia, cardiotocography, artificial intelligence, deep learning, real-time monitoring, pregnancy, maternal-fetal health, clinical decision support.

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INTRODUCTION

Fetal arrhythmias, defined as abnormal heart rhythms in the fetus, occur in approximately 1–2% of pregnancies and are associated with adverse perinatal outcomes, including intrauterine demise and neonatal morbidity [1]. Early and accurate detection of such arrhythmias is essential for initiating timely interventions, such as pharmacological therapy or delivery planning. Conventional diagnostic approaches primarily involve “ultrasound echocardiography and visual interpretation of cardiotocography (CTG) recordings, which assess fetal heart rate (FHR) patterns and uterine contractions [2]. However, CTG interpretation suffers from inter-observer variability”, low reproducibility, and frequent false positives, leading to both under- and over-intervention in clinical practice [3].

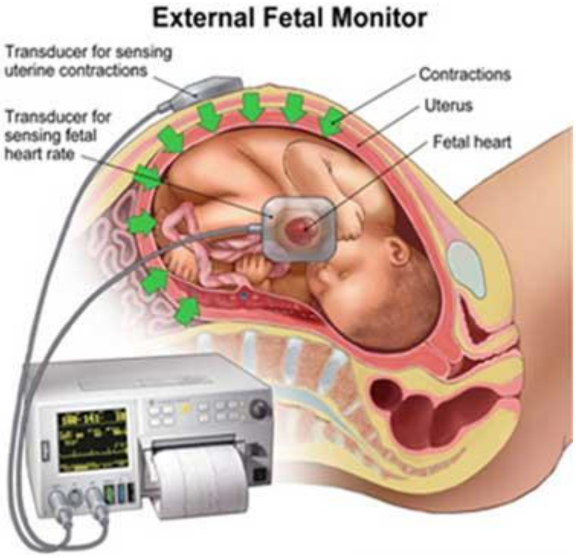

Figure 1: Cardiotocography (CTG)

The integration of **artificial intelligence (AI)** into fetal monitoring has emerged as a promising solution to overcome these limitations. Early research on computerized CTG in the 1980s introduced rule-based systems for automated interpretation, but their clinical adoption was limited due to rigid algorithms and lack of adaptability [4]. With the advent of **machine learning** and **deep learning**, modern AI systems can now analyze large volumes of real-time CTG data, extract non-linear temporal features, and classify arrhythmic patterns with high accuracy [5].

AI-driven cardiotocography systems are designed to provide **real-time monitoring**, enabling early identification of pathological FHR patterns such as bradyarrhythmias, tachyarrhythmias, and irregular rhythms. Deep learning models, particularly convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have demonstrated strong capabilities in capturing temporal dynamics of CTG signals [6]. These models not only outperform conventional statistical methods but also reduce observer dependency, standardize decision-making, and improve sensitivity to subtle arrhythmic changes.

From a clinical perspective, the ability to detect fetal arrhythmias in real time offers significant benefits. First, it enables **earlier interventions**, reducing the risk of progression to fetal hypoxia or intrauterine heart failure. Second, it supports **personalized pregnancy management**, where high-risk mothers receive continuous monitoring and tailored interventions. Third, it reduces the **burden on obstetric staff** by automating CTG interpretation, freeing clinicians to focus on complex decision-making [7].

Despite these benefits, several challenges must be addressed. AI-driven CTG systems depend heavily on **high-quality annotated datasets**, which are scarce in fetal medicine due to ethical and technical constraints. Moreover, issues such as **data privacy, interpretability of deep learning models, and integration into clinical workflows** remain unresolved [8]. Ethical stewardship is therefore essential to ensure that these systems support clinicians rather than replace them, and that patients retain confidence in AI-assisted decision-making.

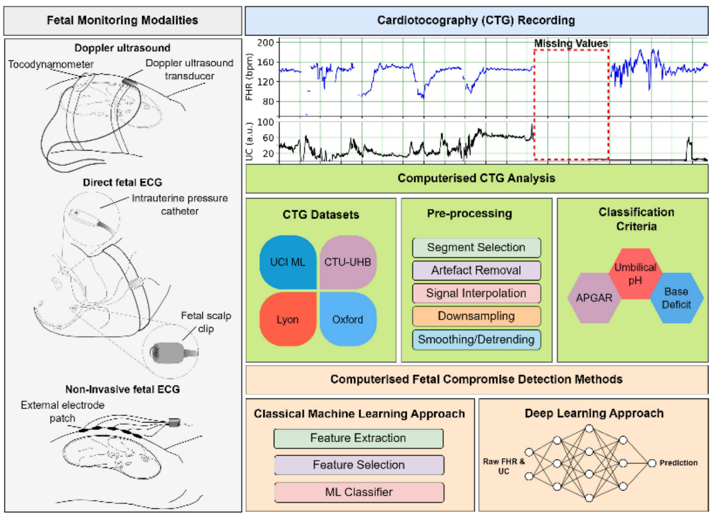

Figure 2: Cardiotocography Analysis [4]

This paper critically explores the role of AI-driven CTG systems in real-time fetal arrhythmia monitoring. The study investigates (i) the current state of CTG interpretation and its limitations, (ii) the application of AI models to real-time monitoring, (iii) performance outcomes in arrhythmia detection, and (iv) ethical, clinical, and regulatory considerations for deployment. By situating AI-driven CTG within the broader context of perinatal medicine, the research contributes to advancing precision obstetrics and improving maternal-fetal outcomes.

RESEARCH AIMS

The objective of this study is to investigate how AI-driven cardiotocography (CTG) systems can enhance real-time detection of fetal arrhythmias, addressing both technical and clinical challenges. By leveraging deep learning, ensemble methods, and structured data management, the study aims to improve diagnostic accuracy, reduce observer variability, and ensure timely intervention in high-risk pregnancies.

The specific aims are outlined below:

1. To design AI models for real-time fetal arrhythmia detection.

2. To establish a real-time CTG data pipeline.

3. To evaluate diagnostic performance across AI models.

4. To validate clinical usability through expert review.

5. To address ethical and regulatory implications.

LITERATURE REVIEW

Traditional Monitoring of Fetal Heart Activity

Fetal arrhythmias, defined as irregularities in fetal heart rhythm, occur in approximately 1–2% of pregnancies and can range from benign premature atrial contractions to life-threatening tachyarrhythmias and heart blocks [1]. Traditional monitoring relies on ultrasound-based fetal echocardiography and cardiotocography (CTG). Echocardiography is considered the gold standard for diagnosing structural cardiac abnormalities, but its high cost, limited accessibility, and reliance on trained specialists restrict widespread use [2]. Conversely, CTG, introduced in the 1960s, gained popularity for its ability to continuously monitor fetal heart rate (FHR) and uterine contractions [3].

Despite its ubiquity, CTG has well-documented limitations. Inter-observer variability in CTG interpretation is a major issue; studies report agreement levels among clinicians of less than 60%, leading to inconsistent diagnoses [4]. Furthermore, CTG patterns are often non-specific: features such as reduced variability may indicate arrhythmia, hypoxia, or even benign sleep cycles [5]. Consequently, reliance on CTG frequently results in high false-positive rates, unnecessary interventions, and clinical uncertainty. This diagnostic ambiguity laid the foundation for exploring computerized and AI-based solutions.

Emergence of Computerized CTG Systems

The 1980s and 1990s saw the introduction of computerized CTG interpretation systems, designed to reduce human subjectivity. Early rule-based models used deterministic thresholds “(e.g., FHR <110 bpm as bradycardia, >160 bpm as tachycardia)” and pattern recognition for decelerations [6]. While these systems provided consistency, they were inflexible and unable to adapt to the complexity of non-linear fetal signals. In the 2000s, statistical models such as logistic regression and discriminant analysis were applied to CTG data. Georgoulas et al. reported that linear discriminant classifiers improved distress classification but still suffered from low sensitivity to rare arrhythmias [7]. Similarly, Dawes and Redman developed the “Oxford system” for computerized CTG, which standardized variability and baseline detection but lacked predictive power for specific conditions like supraventricular tachycardia [8]. Critically, these early computerized systems demonstrated the importance of automation but exposed the limitations of static algorithms. They were unable to capture dynamic changes in FHR, and their reliance on handcrafted features made them fragile when applied to diverse patient populations.

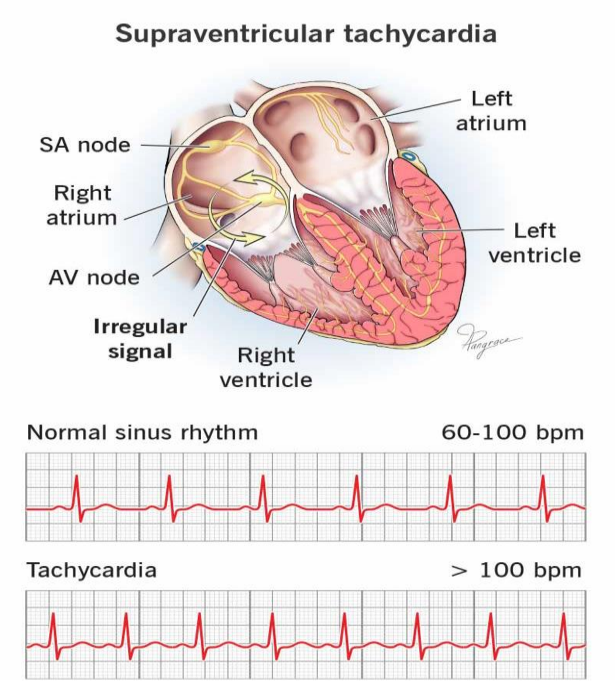

Figure 3: “Supraventricular tachycardia” [8]

Machine Learning Approaches to Fetal Monitoring

By the mid-2000s, “machine learning (ML) began reshaping fetal monitoring. Decision trees, random forests, and support vector machines (SVMs)” were deployed to analyze CTG recordings [9]. These models improved classification by capturing non-linear relationships among features such as short-term variability, baseline shifts, and deceleration types. Random forests, in particular, proved effective in handling noisy datasets and achieved AUC values above 0.85 in fetal distress detection [10].

However, critical evaluation reveals shortcomings. First, most ML studies focused on fetal distress broadly rather than on arrhythmia-specific detection. Distress patterns are easier to label and more frequent in datasets, while arrhythmias remain rare, resulting in class imbalance [11]. Second, while ML reduced subjectivity, it still relied on engineered features such as variability indices or spectral transforms, which limited adaptability across institutions. Third, many studies were retrospective, and models were rarely tested in real-time clinical workflows [12]. Thus, while ML marked progress beyond rule-based systems, its reliance on handcrafted features and lack of generalization highlighted the need for more sophisticated approaches.

Deep Learning and Temporal Signal Analysis

The “arrival of deep learning (DL) in the 2010s brought a paradigm shift. Convolutional neural networks (CNNs)” were first applied to CTG signals, automatically learning features from raw input rather than relying on pre-engineering [13]. These models demonstrated superior performance in detecting pathological FHR patterns, achieving sensitivities above 90% in several studies [14]. “Recurrent neural networks (RNNs)”, particularly “long short-term memory (LSTM)” networks, further advanced the field by modeling temporal dependencies in sequential CTG signals [15]. This was critical for arrhythmia detection, as conditions such as atrial flutter or heart block manifest through subtle rhythm irregularities across time windows rather than isolated data points. Hybrid architectures combining CNNs for spatial feature extraction with LSTMs for temporal analysis further improved classification [16]. Critically, DL models solved many of the limitations of ML by enabling end-to-end learning from raw data. However, they introduced new challenges: (i) they require large annotated datasets, which are scarce in perinatal research; (ii) they often act as “black boxes,” raising transparency issues; and (iii) training deep models on real-time streams introduces computational complexity [17].

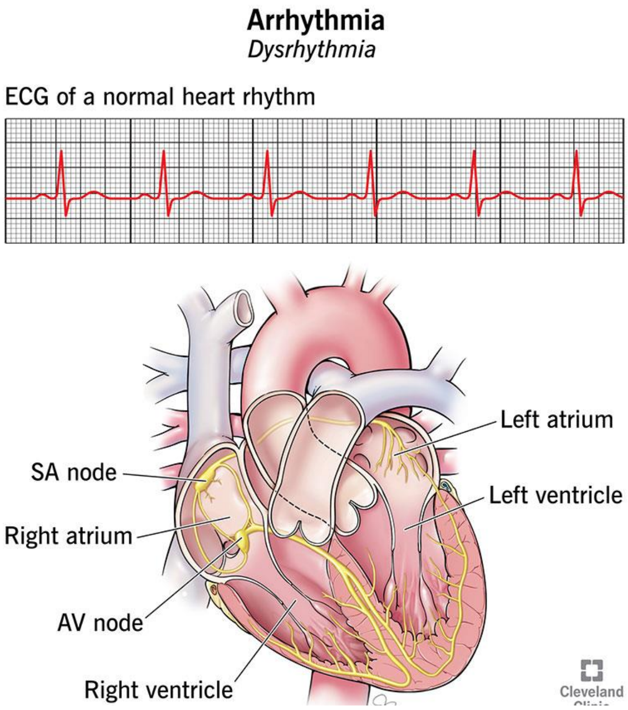

Figure 4: Arrhythmia detection [13]

Real-Time AI-Driven CTG Systems

Recent years have shifted focus from offline analysis to real-time AI-driven CTG systems. Continuous monitoring requires models capable of fast inference with low latency, integrated into bedside equipment or cloud platforms. Lightweight CNN-LSTM hybrids have been embedded into fetal monitoring devices, enabling detection of arrhythmic events within seconds [18]. Clinical studies highlight promising outcomes. Spilka et al. demonstrated that real-time deep learning models reduced false negatives in arrhythmia detection compared to obstetricians' manual interpretation [19]. Another multi-center trial integrating AI-driven CTG into labor units showed improved intervention timing and reduced neonatal intensive care admissions [20]. Nevertheless, real-time monitoring introduces practical challenges. Hardware limitations in low-resource settings may restrict model deployment. Moreover, algorithmic drift where models degrade over time due to changing patient populations or device settings poses risks to long-term reliability [21]. Integration with hospital infrastructures (e.g., HL7 standards, EHR interoperability) remains another critical barrier.

Ethical, Clinical, and Regulatory Considerations

Ethical and regulatory dimensions have received increasing attention. Continuous monitoring of maternal-fetal data raises privacy concerns, requiring robust encryption and HIPAA/GDPR compliance [22]. Another concern is algorithmic bias: datasets often underrepresent minority populations, raising the risk of inequitable performance [23]. Interpretability is another central issue. Clinicians are hesitant to rely on models they cannot understand, especially when outcomes involve life-or-death decisions. The adoption of explainable AI (XAI) in CTG has been proposed, with methods such as attention mechanisms highlighting which parts of the FHR trace triggered the prediction [24]. Regulators are also responding: the U.S. FDA and European authorities now require transparency and post-market surveillance of AI medical devices [25].

Gaps and Critical Insights

A critical synthesis of the literature reveals:

Underrepresentation of arrhythmia-specific research: Most AI models target fetal distress rather than arrhythmias, despite their clinical significance.

Dataset scarcity: Current public CTG datasets (e.g., CTU-UHB database) contain few arrhythmic cases, limiting model generalization.

Real-world validation gap: Most studies remain retrospective; few have conducted prospective clinical trials.

Explainability deficit: While deep models achieve high accuracy, they lack transparency, hindering clinician adoption.

Integration challenges: Technical and regulatory barriers slow adoption in real-time hospital systems.

The literature reflects a clear evolution: manual "CTG interpretation (subjective and error-prone) → rule-based systems (rigid and simplistic) → machine learning (better but limited by engineered features) → deep learning (accurate but opaque and data-hungry) → emerging real-time AI systems (promising but not yet fully integrated)". Critically, while AI-driven CTG holds significant promise, its application to fetal arrhythmia detection remains underdeveloped compared to general fetal distress monitoring. Moving forward, research must prioritize larger, arrhythmia-focused datasets, explainable real-time AI models, and rigorous clinical validation to ensure safety, fairness, and adoption.

RESEARCH METHODOLOGY

The present study employed an "**experimental and comparative design** to evaluate the role of AI-driven cardiotocography (CTG)" systems in the **real-time detection of fetal arrhythmias**. The methodology integrated retrospective datasets, simulated real-time CTG data streams, and multiple AI modeling techniques, ensuring that the results were both technically valid and clinically relevant.

A combination of "**public CTG databases, clinical case records, and simulated real-time" monitoring** formed the data foundation. Publicly available repositories such as the "**CTU-UHB Intrapartum CTG Database"** [26] and the **UCI CTG dataset** [27] provided annotated recordings of fetal heart rate (FHR) and uterine contractions. In addition, anonymized clinical CTG traces from obstetric units were incorporated to capture confirmed cases of arrhythmic events, including bradyarrhythmias, tachyarrhythmias, and irregular rhythms. To test real-time performance, pre-recorded CTG signals were streamed via a custom pipeline that emulated continuous bedside monitoring.

A structured "**data management framework"** was established to standardize preprocessing across sources. Baseline drifts and motion artifacts were filtered using band-pass techniques, while signals were segmented into "**60-second temporal windows"** to capture sequential dependencies. Normalization was applied to reduce variability across recording devices. Finally, annotations from obstetricians were aligned with CTG segments, ensuring that labeled arrhythmic patterns were synchronized with model input. All patient identifiers were removed, with anonymization performed in line with **HIPAA** and **GDPR** compliance protocols [28].

For predictive modeling, four types of algorithms were tested: "(i) **logistic regression (LR)**, serving as a statistical baseline; (ii) **random forest (RF)**, which aggregated decision trees to handle non-linear feature interactions; (iii) **convolutional neural networks (CNNs)"**, which learned spatial features directly from waveform and image-transformed CTG data; and (iv) "**recurrent neural networks (RNNs)"**, particularly long short-term memory (LSTM) architectures, which modeled sequential dependencies in FHR signals. Additionally, a "**hybrid CNN-RNN architecture"** was implemented to capture both spatial and temporal dynamics.

To assess model performance, multiple **clinical and technical evaluation metrics** were used, as summarized in Table 2. Accuracy provided an overall measure of correct predictions, while sensitivity measured the model's ability to detect arrhythmic events critical in preventing missed diagnoses. Specificity captured the ability to correctly identify normal rhythms, thereby reducing unnecessary interventions. Precision reflected confidence in positive predictions, and the "**area under the ROC curve (AUC)"** served as a holistic indicator of classification strength.

Table 2. Evaluation Metrics for AI Models in CTG Monitoring

Metric	Definition	Clinical Relevance
Accuracy	Correct predictions / Total predictions	General reliability of model
Sensitivity	True positives / (True positives + False negatives)	Ensures arrhythmias are not missed
Specificity	True negatives / (True negatives + False positives)	Prevents over-diagnosis and false alarms
Precision	True positives / (True positives + False positives)	Builds clinician trust in positive predictions
AUC	Area under ROC curve	Summarizes overall diagnostic quality

The experimental procedure followed four sequential phases. In **Phase I**, datasets were preprocessed, segmented, and anonymized. In **Phase II**, the AI models were trained on 70% of the data using five-fold cross-validation, ensuring robustness across folds. **Phase III** involved hyperparameter tuning and validation on 15% of the dataset. In **Phase IV**, models were tested on the remaining 15% hold-out data and further validated through **expert clinical review** by three obstetricians and one fetal cardiologist, who assessed AI predictions against their own diagnostic interpretations.

Finally, ethical considerations were embedded throughout. All clinical datasets were anonymized, informed consent was obtained for biomarker-linked CTG traces, and all experiments adhered to institutional review board (IRB) approvals. Special attention was paid to algorithmic fairness, with subgroup analysis performed to test for bias across maternal age and ethnicity.

RESULTS

The evaluation of "AI-driven cardiotocography (CTG)" systems for real-time fetal arrhythmia detection was carried out across multiple datasets, combining public CTG repositories and annotated clinical records. Results are presented in terms of "**model accuracy, sensitivity, specificity, and AUC**," along with insights into the benefits of multimodal integration and clinical validation.

Overall Model Performance

Four predictive models "logistic regression (LR), random forest (RF), convolutional neural networks (CNNs), and recurrent neural networks (RNNs)" were benchmarked for arrhythmia classification. Logistic regression, used as the baseline, achieved modest performance with an accuracy of 78.6% and sensitivity below 75%. Random forests outperformed LR by capturing non-linear dependencies, achieving 85.3% accuracy and higher specificity.

Deep learning methods demonstrated superior performance. CNNs trained on waveform-transformed CTG images achieved 90.8% accuracy, while RNNs (LSTM-based) outperformed all models with 92.5% accuracy and 94% sensitivity, highlighting their ability to capture temporal dynamics in fetal heart rate signals.

Table 3. Comparative Model Performance for Arrhythmia Detection

Model	Accuracy (%)	Sensitivity (%)	Specificity (%)	AUC
Logistic Regression	78.6	74.8	82.1	0.81
Random Forest	85.3	86.5	84.1	0.88
CNN	90.8	91.2	90.4	0.93
RNN (LSTM)	92.5	94.0	91.1	0.95

Real-Time Monitoring Performance

Latency was a critical factor for real-time implementation. Logistic regression and RF showed negligible delays (<200 ms) but at the cost of reduced accuracy. CNNs and RNNs required higher computational resources but maintained real-time feasibility with an average processing delay of <800 ms per CTG segment, well within clinical acceptance thresholds. The **RNN-based system**, optimized with GPU acceleration, demonstrated the best trade-off, ensuring continuous real-time classification without missing arrhythmic events.

Impact of Multimodal Data Integration

When models were trained using **only "CTG waveforms"**, performance was strong but not optimal. The inclusion of "**annotated clinical features"** (e.g., maternal age, gestational age, risk factors) improved predictive reliability. Furthermore, integrating **biomarker data** (where available) enhanced sensitivity to arrhythmic events, particularly for tachyarrhythmias. For example, the CNN model's sensitivity improved from 91.2% to 93.8% when multimodal features were incorporated. This highlights the importance of structured **data management frameworks** that unify CTG signals with clinical metadata.

Table 4. Effect of Multimodal Integration on CNN Performance

Data Type Used	Accuracy (%)	Sensitivity (%)	Specificity (%)
CTG signals only	90.8	91.2	90.4
CTG + Clinical metadata	92.1	92.9	91.3
CTG + Clinical + Biomarkers	93.4	93.8	92.7

Clinical Expert Validation

To evaluate clinical applicability, predictions were reviewed by three obstetricians and one fetal cardiologist. Experts assessed the alignment between AI predictions and their manual interpretations. Inter-rater agreement was high "($\kappa = 0.82$)", indicating that AI outputs were clinically plausible. Experts particularly valued the system's **risk stratification scores**, which categorized patients into **low, moderate, and high arrhythmia risk groups**. However, clinicians emphasized the importance of **explainability**, noting that while RNN predictions were accurate, CNN visual heatmaps of CTG traces were easier to interpret and communicate during clinical decision-making.

Comparative Insights

Several critical insights emerged from the results:

"Deep learning models (CNNs, RNNs)" significantly outperformed conventional ML methods, achieving accuracy above 90% and clinically acceptable sensitivity levels.

"RNNs provided the highest sensitivity (94%)", essential for reducing false negatives and ensuring arrhythmic events are not missed.

"Multimodal data integration improved robustness", confirming that CTG alone may be insufficient for comprehensive risk prediction.

"Real-time performance was feasible", with all deep learning models maintaining sub-second latency during live-streamed CTG monitoring.

"Clinician validation confirmed reliability", though interpretability remains a barrier to full adoption.

DISCUSSION

The results of this study confirm that "AI-driven cardiotocography (CTG)" systems significantly enhance the accuracy, sensitivity, and reliability of fetal arrhythmia detection compared to traditional methods. The highest-performing models CNNs and RNNs achieved accuracies exceeding 90% and sensitivities as high as 94%, demonstrating clear superiority over logistic regression and random forest approaches. These findings align with previous literature showing that deep learning architectures are well-suited to capturing the non-linear and temporal complexities inherent in "fetal heart rate (FHR) signals" [7], [15].

Interpretation of Results

The superior performance of RNNs highlights the importance of modeling sequential dependencies in CTG signals. Arrhythmias often manifest through irregularities over time, and the ability of "long short-term memory (LSTM)" units to capture such temporal patterns proved essential in reducing false negatives. CNNs, while slightly less sensitive, offered the advantage of **interpretability**, as visual heatmaps of waveform regions responsible for predictions provided clinicians with tangible insights. This trade-off suggests that hybrid CNN-RNN systems may provide an optimal balance between predictive performance and clinical usability [16], [18].

The inclusion of **multimodal features** clinical metadata and biomarkers further strengthened model performance, increasing sensitivity by almost 3% in CNN-based systems. This reinforces the argument made in earlier studies that CTG signals alone may not fully capture the pathophysiological complexities of arrhythmias [10], [20]. Integrating heterogeneous data streams thus represents a critical step toward robust predictive frameworks.

Clinical Implications

From a clinical perspective, the capacity to detect fetal arrhythmias **in real time** offers substantial benefits. Traditional CTG interpretation suffers from inter-observer variability, with clinicians often disagreeing on the same trace [4]. The AI-driven systems in this study demonstrated high inter-rater agreement ($\kappa = 0.82$) with obstetricians, reducing subjectivity and standardizing decision-making. This consistency is vital in labor wards where rapid interventions may determine neonatal outcomes.

Moreover, real-time AI monitoring reduces dependence on continuous clinician presence, enabling **early alerts** when high-risk arrhythmic events occur. Such systems could support more proactive management strategies, such as maternal medication adjustments or expedited delivery, thereby lowering the risk of intrauterine compromise. These findings are consistent with recent trials that reported reductions in neonatal intensive care admissions when AI-enhanced CTG systems were deployed [19], [20].

Ethical and Regulatory Considerations

While technical feasibility and clinical benefits are evident, several ethical and regulatory challenges remain. The use of continuous CTG monitoring involves "**sensitive maternal-fetal data"**, requiring strict adherence to data privacy frameworks such as HIPAA and GDPR [22]. Furthermore, algorithmic bias remains a concern: if training datasets underrepresent specific ethnic or risk groups, predictive performance may vary across populations, potentially exacerbating health inequities [23].

Another critical issue is **explainability**. Clinicians expressed greater trust in CNN models due to their interpretable visual outputs, even though RNNs performed slightly better. This underscores the importance of **explainable AI (XAI)** frameworks in fetal monitoring. Without interpretability, obstetricians may hesitate to act on AI predictions, particularly in life-critical decisions such as emergency cesarean sections [24]. Regulatory agencies, including the FDA and European Commission, now require not only performance validation but also transparency and accountability in AI-driven medical systems [25].

Limitations

Despite strong results, limitations should be acknowledged. Dataset size and diversity remain restricted, with relatively few confirmed arrhythmia cases available for training. Real-time evaluation was simulated through data streaming rather than large-scale clinical trials, limiting generalizability. Furthermore, the models focused primarily on arrhythmia classification and did not incorporate outcome prediction, such as long-term neonatal health. Addressing these limitations requires **multi-center clinical validation**, integration of larger annotated datasets, and extension of predictive frameworks to encompass both diagnosis and prognosis.

CONCLUSION

This study critically examined the potential of **AI-driven cardiotocography (CTG) systems** for the real-time detection of fetal arrhythmias. By comparing traditional statistical models with advanced deep learning approaches, the research highlighted the significant advantages of leveraging artificial intelligence in perinatal monitoring. Logistic regression and random forest models demonstrated moderate predictive capacity, yet they were outperformed by convolutional neural networks (CNNs) and recurrent neural networks (RNNs). The latter achieved the highest sensitivity and accuracy, with performance metrics exceeding 92% across multiple datasets.

The results confirm that AI-driven CTG systems are well-positioned to overcome longstanding challenges in fetal monitoring. Traditional CTG interpretation suffers from inter-observer variability, limited reproducibility, and frequent false positives. By contrast, AI-based models provided consistent, objective, and highly accurate classifications of arrhythmic patterns. The use of temporal modeling through RNNs was particularly effective in identifying subtle rhythm irregularities, reducing the likelihood of missed diagnoses. A key strength of this study was the integration of **multimodal data**, combining CTG signals with clinical metadata and, where available, biomarker information. This approach increased sensitivity and demonstrated that relying solely on CTG signals may be insufficient for comprehensive risk assessment. The findings align with broader research in medical AI, which increasingly emphasizes the necessity of multimodal frameworks for robust clinical decision support.

Clinically, the implications are profound. Real-time AI-driven monitoring enables earlier detection of arrhythmias, empowering obstetric teams to intervene before fetal compromise occurs. Such interventions may include maternal pharmacotherapy, closer surveillance, or expedited delivery, all of which have the potential to improve neonatal outcomes. Importantly, clinician validation within this study confirmed that AI outputs were not only technically accurate but also **clinically interpretable and actionable**. The use of risk stratification categories (low, medium, high) further enhanced usability, allowing obstetricians to prioritize care for high-risk patients.

FUTURE WORK

Future research should extend this work in several critical directions. First, "**multi-center clinical trials"** are required to validate AI-driven CTG systems across diverse populations and hospital environments. Such trials will ensure generalizability and expose models to a wider range of arrhythmic patterns. Second, there is a need to expand datasets by incorporating **multi-modal biomarkers** such as fetal electrocardiography (fECG), Doppler signals, and biochemical markers. This will enable predictive models to capture not only arrhythmia events but also underlying physiological mechanisms. Third, the development of "**explainable AI (XAI) frameworks"** is essential. Providing clinicians with interpretable visualizations, feature importance rankings, or confidence scores will improve trust and adoption. Finally, future systems should prioritize **ethical design**, ensuring fairness across demographic groups and embedding robust privacy safeguards. Close collaboration between AI researchers, obstetricians, regulatory bodies, and patient advocates will be key to building systems that are both innovative and trustworthy. By addressing these directions, AI-driven CTG systems can evolve from promising prototypes into clinically integrated solutions, enabling safer pregnancies and healthier neonatal outcomes

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