

FROM SIGNAL PROCESSING TO DEEP LEARNING: A REVIEW OF FETAL HEALTH MONITORING TECHNIQUES USING BIOMEDICAL SIGNALS

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Abstract—Fetal health monitoring is essential for early de-tection of life-threatening conditions such as hypoxia and ar-rhythmia; however, conventional techniques including CTG and Doppler ultrasound are limited by subjectivity, operator de-pendency, and inter-observer variability. Non-invasive modalities such as fetal electrocardiography (FECG) and fetal phono-cardiography (FPCG) enable continuous monitoring but are significantly affected by maternal physiological interference and environmental noise, motivating the adoption of advanced artifi-cial intelligence approaches. This paper presents a structured comparative analysis of deep learning-based fetal signal pro-cessing frameworks, focusing on convolutional neural networks (CNNs), long short-term memory (LSTM) networks, and hybrid multimodal fusion architectures. A unified evaluation frame-work is employed using clinically relevant metrics, including accuracy, sensitivity, specificity, and signal-to-noise ratio (SNR) improvement, enabling consistent cross-method comparison. The analysis demonstrates a clear performance hierarchy, where deep learning approaches outperform traditional handcrafted meth-ods, hybrid CNN–LSTM models effectively capture spatiotem-poral dependencies, and multimodal fusion systems integrating electrical, acoustic, and physiological signals achieve state-of-the-art performance of approximately 92%–97%. Despite these advances, clinical deployment remains constrained by limited annotated datasets, computational complexity, and lack of real-time validation. The study highlights key research gaps and future directions involving IoT-enabled wearable sensing, edge AI deployment, and explainable deep learning for robust and personalized fetal healthcare.

Index Terms—Fetal Electrocardiography, Fetal Phonocardio-graphy, Cardiotocography, Biomedical Signal Processing, Deep

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Learning, Multimodal Fusion

I. INTRODUCTION

Fetal health monitoring is a crucial aspect of obstetric care aimed at assessing fetal well-being throughout pregnancy and labor. Continuous and accurate monitoring enables early detec-tion of fetal distress conditions such as hypoxia, arrhythmias, and growth abnormalities, thereby

reducing the risk of adverse perinatal outcomes. Reliable fetal assessment is therefore essential for improving neonatal survival and ensuring timely clinical intervention [1].

Conventional fetal monitoring techniques primarily include cardiotocography (CTG), ultrasound imaging, and intermittent auscultation. Among these, CTG remains the most widely used method, providing continuous recordings of fetal heart rate (FHR) and uterine contractions. However, CTG interpretation is often subjective and suffers from significant inter-observer variability, leading to high false-positive rates and unnecessary clinical interventions [2]–[4]. Ultrasound imaging is widely used for fetal anatomical assessment and movement visualization but is not suitable for continuous monitoring due to its operator dependency and intermittent nature. Doppler ultrasound extends fetal assessment by evaluating blood flow characteristics in fetal and placental vessels; however, its performance is affected by motion artifacts and signal noise [5], [6].

To overcome the limitations of conventional methods, several physiological biosignals have been investigated for fetal

monitoring. These include uterine electrical activity measured using electrohysterography (EHG) and fetal movement signals captured through abdominal sensors, both of which provide indirect indicators of fetal well-being and labor dynamics. However, their clinical adoption remains limited due to variability in signal quality and lack of standardized interpretation methods [7].

In recent years, non-invasive fetal cardiac monitoring techniques such as FECG and FPCG have gained significant attention. FECG extracts fetal cardiac electrical activity from abdominal recordings, while FPCG captures fetal heart sound signals using acoustic sensors placed on the maternal abdomen. These methods are attractive due to their non-invasive nature, cost-effectiveness, and suitability for continuous monitoring. However, both signals are highly susceptible to interference from maternal physiological signals, motion artifacts, and environmental noise, making accurate extraction and analysis challenging [8]–[10].

Traditional signal processing approaches for fetal monitoring rely on techniques such as filtering, wavelet transform, and independent component analysis (ICA). Although effective to some extent, these methods depend heavily on handcrafted features and domain assumptions, limiting their robustness across varying physiological and clinical conditions [11], [12]. To address these limitations, deep learning approaches have been increasingly adopted for fetal signal analysis. Models such as convolutional neural networks (CNN), recurrent neural networks (RNN), long short-term memory (LSTM), and bidirectional LSTM (Bi-LSTM) have demonstrated strong capability in automatically learning discriminative representations from raw and transformed biosignals, leading to improved performance in fetal distress detection and classification tasks [13], [14].

Furthermore, recent research has focused on multimodal fetal monitoring systems that integrate CTG, FECG, FPCG, Doppler ultrasound, and uterine activity signals (EHG). These multimodal fusion approaches leverage complementary physiological information to improve robustness and diagnostic accuracy in fetal health assessment [15].

In parallel, the emergence of Internet of Things (IoT)-enabled wearable devices has enabled real-time and remote fetal monitoring. These systems facilitate continuous data acquisition and cloud-based analytics, supporting intelligent and personalized maternal healthcare solutions, particularly in telemedicine and home-based monitoring scenarios [16], [17].

II. EXISTING WORKS

Research in fetal health monitoring has evolved from classical signal processing methods toward intelligent and data-driven frameworks.

CTG and Doppler ultrasound remain widely used clinical tools for fetal assessment. CTG provides fetal heart rate and uterine contraction information but suffers from inter-observer variability and subjective interpretation. Doppler ultrasound enables fetal hemodynamic evaluation; however, its performance is affected by motion artifacts and operator dependency [2], [3], [5]. These studies conclude that conventional modalities are reliable but insufficient for automated and continuous fetal assessment.

To overcome these limitations, non-invasive biosignals such as FECG and FPCG have been widely investigated. FECG extraction is formulated as a blind source separation problem due to strong maternal ECG interference. Classical approaches such as adaptive filtering, independent component analysis (ICA), and Kalman filtering have shown partial success but remain sensitive to noise and inter-subject variability [8], [11], [18]. These works conclude that traditional signal processing methods are limited in real-world noisy environments.

Recent FECG studies have explored sparse representation and optimization-based decomposition techniques. Compressed sensing-based fetal ECG reconstruction has demonstrated improved recovery under low SNR conditions, but performance degrades with non-stationary noise [19]. Similarly, wavelet transform-based denoising methods improve signal quality but require careful parameter tuning and lack generalization across datasets [20]. These studies conclude that handcrafted feature-based methods are not robust enough for clinical deployment.

Deep learning-based FECG approaches have significantly improved robustness. Convolutional neural networks (CNNs) and recurrent architectures have been used for fetal QRS detection and signal separation, achieving improved performance under high noise conditions [14], [21], [22]. Transformer-based models have recently been explored for long-range temporal dependency modeling, showing promising improvements in feature extraction capability [23]. These works conclude that deep models outperform classical methods but require large labeled datasets.

Similarly, FPCG has emerged as a low-cost alternative for fetal cardiac monitoring using acoustic sensors. However, its performance is strongly affected by motion artifacts and environmental noise. Time-frequency approaches such as short-time Fourier transform (STFT) combined with CNN architectures have shown improved robustness in classification and denoising tasks [10], [24], [25]. These studies conclude that spectrogram-based learning is effective for non-stationary acoustic signals.

Recent advances in FPCG include the use of wavelet scattering transforms and hybrid CNN-LSTM architectures, which improve temporal feature learning and noise robustness [26], [27]. In addition, attention-based deep learning models have been introduced to focus on relevant cardiac sound components, improving classification accuracy in noisy conditions [28]. These works conclude that attention mechanisms enhance robustness in acoustic fetal signal analysis.

Beyond cardiac signals, uterine electrical activity (EHG) and fetal movement-based sensing have been investigated for fetal state assessment. EHG-based studies show that uterine contraction patterns can provide early indicators of labor progression, but signal variability limits clinical reliability [29], [30]. These studies conclude that auxiliary signals are informative but insufficient alone for robust fetal classification.

Recent Doppler ultrasound research has introduced machine learning and deep learning techniques for waveform interpretation. CNN-based Doppler analysis improves fetal heart rate estimation accuracy, while hybrid models enhance robustness under noisy conditions [6], [31].

These studies conclude that $RMSE = \frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2$ (2)

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AI improves Doppler interpretation but does not fully resolve signal degradation issues.

Multimodal fetal monitoring systems integrating CTG, FECG, FPCG, and Doppler signals have demonstrated superior performance. RMSE provides a more interpretable measure of average deviation in reconstructed fetal signals [32], [33].

2) Mean Absolute Error (MAE):

MAE provides robustness against outliers in fetal biosignal reconstruction [32].

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3) Peak Signal-to-Noise Ratio (PSNR):

$$PSNR = 10 \log_{10} \frac{MAX^2}{MSE} \quad (4)$$

Overall, the literature indicates a transition from classical signal processing to deep learning and multimodal frameworks. However, challenges such as low signal-to-noise ratio, limited annotated datasets, poor generalization, and lack of large-scale clinical validation remain unresolved.

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III. PERFORMANCE METRICS AND CLINICAL SIGNIFICANCE

Evaluating the proposed fetal health monitoring framework requires a dual focus on signal quality enhancement and clinically interpretable classification. Accordingly, the evaluation metrics are structured sequentially to mirror the processing pipeline: first, the performance of the signal denoising algorithm is validated; second, the classification accuracy is analyzed; and finally, the clinical interpretability of the diagnostic outputs is assessed.

A. Signal Quality and Denoising Metrics

Signal Quality and Denoising Metrics refers to a set of quantitative measures used to evaluate how clean a biomedical signal is and how effectively noise has been removed from it.

For signal reconstruction and denoising evaluation:

- y_i : Ground truth fetal signal sample at index i
- \hat{y}_i : Reconstructed or denoised signal sample at index i

- N : Total number of samples
- MSE : Mean Squared Error between y_i and \hat{y}_i
- MAX : Maximum possible amplitude of the signal

1) ~~Mean Squared Error~~ (MSE): N

PSNR evaluates the quality of reconstructed fetal signals after denoising, especially in FECG/FPCG enhancement [32]–[34].

4) *Signal-to-Noise Ratio Improvement*:

$$SNR_{imp} = SNR_{out} - SNR_{in} \quad (5)$$

SNR improvement measures the effectiveness of noise suppression techniques in extracting fetal signals from maternal abdominal recordings [32].

Among the evaluated metrics, signal-to-noise ratio improvement SNR_{imp} is the most clinically relevant as it directly reflects the visibility and detectability of fetal cardiac activity in noisy abdominal recordings, whereas MSE, RMSE, and MAE primarily serve as mathematical reconstruction error measures with indirect clinical interpretation.

IV. CLASSIFICATION PERFORMANCE METRICS

To define the evaluation metrics for the second phase, the diagnostic problem is formulated as a binary classification task. The target space consists of two clinical classes: the **Negative class** (C_0), representing normal fetal physiological conditions, and the **Positive class** (C_1), representing abnormal or pathological fetal states. Based on this formulation, performance assessment is carried out using a standard confusion matrix, where the key components are defined as follows:

- TP (True Positives): Pathological fetal states correctly identified as abnormal.
- TN (True Negatives): Normal fetal states correctly identified as normal.
- FP (False Positives): Normal cases incorrectly classified as abnormal (false alarms).
- FN (False Negatives): Pathological cases incorrectly classified as normal (missed detections).

1) *Accuracy*: $MSE = \frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2$ (1)

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

(6)

MSE quantifies reconstruction error in fetal signal denoising and is widely used in FECG and FPCG enhancement tasks [32]. Accuracy provides the overall correctness of classification; however, it may be misleading in imbalanced fetal datasets where one class dominates [27].

2) *Sensitivity (Recall)*:

$$Sensitivity = \frac{TP}{TP + FN}$$

signal processing techniques or shallow learning models, existing studies increasingly explore integrated frameworks combining adaptive preprocessing, time-frequency representations, and hybrid deep learning architectures to enhance robustness

Sensitivity measures the ability to correctly identify fetal distress cases. High sensitivity is critical to minimize missed detections of life-threatening conditions such as hypoxia and arrhythmia [27], [32].

3) *Specificity*:

$$\text{Specificity} = \frac{TN}{TN + FP} \quad (8)$$

Specificity quantifies the ability to correctly identify normal fetal conditions, thereby reducing false alarms and unnecessary clinical interventions [27], [35].

4) *Precision*:

$$\text{Precision} = \frac{TP}{TP + FP} \quad (9)$$

Precision reflects the reliability of positive fetal distress predictions and helps reduce alarm fatigue in clinical settings [27], [36].

5) *F1-Score*: under low SNR conditions.

A. System Overview

Recent studies on fetal health monitoring commonly adopt a four-stage processing pipeline comprising: (i) signal acquisition, (ii) noise suppression and preprocessing, (iii) time-frequency feature representation, and (iv) fetal state classification. In contrast to conventional single-stage processing pipelines reported in [8], [10], these integrated frameworks emphasize progressive refinement of fetal signal quality prior to classification.

These approaches are primarily developed for single-modality analysis of FECG and FPCG, while also being conceptually extendable to multimodal fusion involving CTG and Doppler ultrasound signals.

B. Signal Acquisition and Dataset Sources

The reviewed fetal monitoring frameworks commonly utilize publicly available prenatal monitoring databases containing

$$F1 = 2 \times \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \quad (10)$$

mixed maternal and fetal physiological signals acquired under realistic clinical environments. These datasets span

The F1-score provides a balanced measure between precision and recall, making it suitable for imbalanced fetal health datasets [27], [32], [36].

6) *Matthews Correlation Coefficient (MCC)*:

$$MCC = \frac{TP \cdot TN - FP \cdot FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}} \quad (11)$$

multiple monitoring modalities, including FECG, FPCG, CTG, Doppler ultrasound, and multimodal maternal-fetal recordings. Widely used FECG repositories include the PhysioNet Non-Invasive Fetal ECG Database (NIFECGDB), Abdominal and Direct Fetal ECG Database (ADFECGDB), Fetal ECG Synthetic Database (FECGSYNDB), and PhysioNet Challenge

abdominal cordings under

MCC provides a robust and balanced evaluation metric for imbalanced datasets by considering all four components of the confusion matrix [27].

7) *Area Under the ROC Curve (AUC)*: The AUC measures the overall discriminative capability of the model across all classification thresholds and is widely used for clinical decision-support systems in fetal monitoring [27], [37].

Among the evaluated metrics, sensitivity is the most clinically significant as it directly reflects the ability of the system to detect fetal distress conditions such as hypoxia and arrhythmia, where missed detections can lead to severe adverse outcomes. Specificity is also clinically important as

it reduces false alarms and unnecessary interventions. Other metrics such as F1-score and AUC provide complementary evaluation of overall system performance, while accuracy and MCC primarily serve as statistical performance indicators with limited direct clinical interpretability [38], [39].

V. METHODOLOGY

This survey focuses on robust fetal health monitoring using non-invasive biosignals, specifically fetal electrocardiography (FECG) and fetal phonocardiography (FPCG). Unlike conventional approaches reported in the literature that rely on isolated varying maternal and environmental noise conditions [39]–[42]. For FPCG analysis, publicly available fetal heart sound datasets and clinical recordings are extensively employed for denoising, segmentation, and fetal distress classification tasks [8], [24]. In CTG-based fetal assessment, databases such as the UCI Cardiotocography Dataset and intrapartum fetal monitoring repositories are widely adopted for fetal state classification and hypoxia prediction studies [38], [43]. Doppler ultrasound datasets and multimodal prenatal monitoring repositories integrating maternal physiological, acoustic, and hemodynamic signals are also increasingly utilized for comprehensive fetal assessment and multimodal deep learning research. Unlike controlled simulation-based studies, these databases capture realistic prenatal monitoring conditions characterized by low signal-to-noise ratio (SNR), motion artifacts, baseline drift, signal non-stationarity, and overlapping maternal physiological activity, thereby enabling robust evaluation and comparative analysis of AI-driven fetal healthcare systems.

C. *Preprocessing and Noise Suppression*

Preprocessing and noise suppression constitute critical stages in AI-driven prenatal monitoring systems due to the inherently low-amplitude and noise-prone nature of fetal physiological signals. Classical fetal ECG extraction approaches,

including independent component analysis (ICA), adaptive filtering, blind source separation, and empirical mode decomposition, have demonstrated effectiveness in maternal ECG suppression; however, these methods often exhibit sensitivity to non-stationary noise, electrode displacement, motion artifacts, and inter-subject variability [8], [18], [44]. Consequently, recent studies increasingly employ adaptive filtering, recursive least squares (RLS) estimation, wavelet decomposition, and deep learning-assisted denoising frameworks to improve robustness under realistic clinical conditions.

For FPCG signals, preprocessing commonly involves band-pass filtering, wavelet-based denoising, adaptive noise cancellation, and time-frequency enhancement techniques to suppress maternal heart sounds, respiratory interference, and environmental acoustic noise [24]. Although wavelet-based approaches provide effective noise reduction, their performance is often dependent on manual parameter selection and dataset-specific tuning. To address these limitations, recent research emphasizes data-driven enhancement and hybrid preprocessing frameworks capable of improving signal quality and generalization across diverse prenatal monitoring datasets.

In CTG and Doppler ultrasound-based fetal monitoring, preprocessing techniques are additionally employed to remove baseline drift, transient signal dropouts, uterine contraction artifacts, and sensor-related noise before feature extraction and classification. These preprocessing stages collectively enhance signal reliability, improve feature representation, and facilitate robust fetal state assessment under low SNR conditions.

D. Time–Frequency Representation

Accurate representation of fetal physiological signals re-mains a major challenge due to signal non-stationarity, low amplitude characteristics, and the presence of strong maternal and environmental interference. Traditional time-domain analysis and wavelet-based representations have been extensively employed for fetal signal characterization; however, these approaches often exhibit limited capability in simultaneously capturing temporal and spectral variations under highly noisy clinical conditions [8], [45]. Consequently, recent studies increasingly utilize time–frequency analysis techniques such as short-time Fourier transform (STFT), continuous wavelet transform (CWT), and spectrogram-based representations to improve discriminative feature extraction from fetal biosignals.

Among these approaches, STFT-based spectrogram representations are widely adopted in deep learning frameworks due to their ability to transform one-dimensional physiological signals into structured two-dimensional time–frequency maps. Unlike conventional handcrafted feature extraction methods, these representations enable automated learning of discriminative fetal patterns directly from spectral and temporal information, thereby improving robustness in low signal-to-noise ratio (SNR) environments and non-stationary prenatal monitoring conditions [45].

Deep Feature Learning
Deep learning techniques have significantly advanced fetal health monitoring by enabling automated extraction of complex physiological patterns from multidimensional signal representations. Convolutional neural networks (CNNs) are extensively employed for fetal signal classification due to their strong spatial feature learning capability; however, CNN-only architectures often exhibit limited performance in modeling long-term temporal dependencies present in physiological signals [13]. Similarly, recurrent architectures such as long short-term memory (LSTM) and bidirectional LSTM (BiLSTM) networks effectively capture temporal dynamics but may show reduced efficiency in hierarchical spatial feature extraction.

To overcome these limitations, recent studies increasingly explore hybrid deep learning frameworks integrating CNN and BiLSTM architectures. In such models, CNN layers are utilized for extraction of spatial and spectral features from STFT spectrograms or multimodal physiological representations, while BiLSTM layers model bidirectional temporal dependencies associated with fetal cardiac dynamics and pathological variations. Comparative studies reported in the literature indicate that hybrid CNN–BiLSTM architectures provide improved robustness, generalization capability, and classification performance under noisy and non-stationary prenatal monitoring environments when compared with standalone CNN or LSTM models [13], [14].

E. Classification Framework

The extracted deep features are forwarded to fully connected layers followed by a softmax classifier for fetal state prediction. Unlike conventional shallow machine learning classifiers used in earlier studies, recent deep learning-based approaches enable end-to-end feature learning directly from time–frequency representations, thereby improving discriminative capability. To enhance model robustness and mitigate overfitting, regularization techniques such as dropout and

batch normalization are commonly incorporated [46], [47].

F. Training Strategy and Optimization

Supervised learning is typically employed using labeled fetal datasets derived from clinical recordings and public repositories. The optimization objective is formulated using categorical cross-entropy loss, which is minimized using adaptive optimization techniques such as Adam [48]. To improve generalization across subjects and reduce inter-patient variability, k-fold cross-validation is widely adopted in recent studies. Additionally, training stability is enhanced through early stopping criteria and learning rate scheduling, which help prevent overfitting, particularly in small-scale medical datasets.

G. Extension to Multimodal Learning

Although many existing studies focus on single-modality fetal monitoring, recent research demonstrates that multi-modal fusion significantly enhances diagnostic performance and robustness [15]. Accordingly, current frameworks can be extended to integrate multiple physiological modalities such

as CTG, Doppler ultrasound, and uterine electromyography (EHG) signals using feature-level, decision-level, or hybrid fusion strategies. This integration enables more comprehensive fetal assessment by exploiting complementary information from electrical, mechanical, and hemodynamic sources.

Overall, modern fetal monitoring frameworks increasingly integrate adaptive noise suppression, time–frequency representation, and hybrid CNN–BiLSTM architectures. This integrated pipeline addresses key limitations reported in the literature, including poor robustness under low SNR conditions, limited temporal modeling capability, and weak generalization across heterogeneous clinical datasets.

VI. COMPARATIVE PERFORMANCE AND DISCUSSIONS

Recent advancements in fetal health monitoring have led to a diverse range of signal processing and machine learning-based approaches spanning FECG, FPCG, CTG, Doppler ultrasound, and multimodal fusion systems. These methods differ significantly in terms of signal representation strategies, noise robustness, computational complexity, and clinical applicability.

To systematically summarize these developments, a comparative analysis of representative state-of-the-art methods is presented in Table I. The comparison highlights the progression from conventional signal processing techniques to advanced deep learning and multimodal learning frameworks, along with their relative strengths, limitations, and reported clinical performance.

The comparative analysis in Table I highlights a clear transition from classical signal processing approaches toward data-driven deep learning and multimodal intelligence frameworks for fetal health monitoring.

Classical independent component analysis (ICA)-based fetal ECG (FECG) methods remain widely used due to their interpretability and minimal training requirements. However, their performance is strongly dependent on signal stationarity and deteriorates significantly under low signal-to-noise ratio (SNR) conditions, limiting robustness in real clinical environments. Model-based approaches improve physiological realism by explicitly incorporating cardiac dynamics, but their high computational complexity restricts deployment in real-time monitoring systems.

Deep learning-based methods demonstrate superior adapt-ability across fetal monitoring modalities. In fetal cardiotocog-raphy (CTG), convolutional neural networks (CNNs) outper-form traditional machine learning models by automatically learning discriminative temporal patterns from raw or trans-formed signals. This reduces reliance on handcrafted features and improves detection of fetal distress patterns. However, performance remains sensitive to dataset variability and class imbalance.

For fetal phonocardiography (FPCG), CNN-based architec-tures operating on time–frequency representations provide im-proved classification and denoising performance. Nevertheless, their robustness is limited by acquisition noise, sensor posi-tioning variability, and lack of standardized datasets, which affects reproducibility across studies.

Multimodal fusion approaches integrating CTG, ECG, and ultrasound signals consistently achieve higher diagnostic reli-ability compared to single-modality systems. These methods exploit complementary physiological information, improving robustness under noisy or incomplete observations. However, they introduce challenges related to temporal synchronization, computational overhead, and system complexity, which hinder large-scale clinical deployment.

Transformer-based architectures further enhance fetal mon-itoring by modeling long-range temporal dependencies in cardiotocography signals. Self-attention mechanisms improve interpretability and enable better representation of temporal fe-tal heart rate dynamics compared to convolutional or recurrent models.

Recent advancements in adversarial learning, such as CycleGAN-based fetal ECG extraction, demonstrate improved signal reconstruction in highly corrupted abdominal record-ings. These approaches effectively suppress maternal ECG interference and enhance fetal QRS detection under low SNR conditions.

Graph-based and transformer hybrid models extend deep learning capabilities by incorporating spatial dependencies across ECG leads, improving robustness in heterogeneous sensor configurations. These methods are particularly effective in multi-lead abdominal ECG analysis. Self-supervised learning approaches reduce dependency on large annotated datasets, which are a major limitation in fetal signal analysis. By leveraging unlabeled physiological data, these methods improve generalization across clinical environments and hold promise for scalable deployment in resource-constrained settings.

From a clinical perspective, multimodal and deep learning-based systems improve sensitivity in fetal distress detection, which is critical for early intervention. However, this often comes at the cost of increased computational complexity and reduced interpretability compared to classical methods. Therefore, a trade-off exists between model performance, in-terpretability, and deployability in real-world clinical systems. Overall, the trend indicates a shift toward unified multi-modal AI frameworks that integrate signal processing, deep learning, and self-supervised learning to achieve robust, scal-able, and clinically reliable fetal health monitoring systems.

Despite recent advancements, several key challenges remain unresolved in fetal health monitoring systems:

- Limited availability of large-scale, high-quality annotated fetal datasets
- Poor cross-dataset and cross-population generalization
- High susceptibility of FEKG and FPCG to noise, artifacts, and motion interference

- Lack of extensive real-time clinical validation studies
 - High computational and memory requirements of multi-modal deep learning frameworks
- Despite significant progress in fetal health monitoring, key challenges persist, including the scarcity of large-scale an-

TABLE I
COMPARATIVE ANALYSIS OF CLASSICAL AND DEEP LEARNING-BASED METHODS FOR FETAL HEALTH MONITORING ACROSS MODALITIES

Method	Modality	Model	Dataset	Performance and Clinical Observation
ICA-Based FECG [8], [40], [44]	FECG	Independent Component Analysis	PhysioNet Abdominal ECG [39]	Effective fetal-maternal source separation under moderate noise; performance degrades in low SNR and non-stationary conditions
Model-Based FECG [49], [50]	FECG	Physiological / Bayesian modeling	Simulated ECG + PhysioNet datasets	High reconstruction accuracy in controlled environments; limited real-time applicability due to computational complexity
Peel-Off Iterative FECG Separation [44], [50]	FECG	Iterative source cancellation	PhysioNet ADFECGDB, NI-FECGDB [39]	Improves fetal QRS detection; residual maternal interference re-mains a key limitation
CNN-Based FPCG [51]	FPCG	CNN + Spectrogram Features	Clinical fetal heart sound recordings	Strong classification performance; sensitive to motion artifacts and sensor placement variability
FPCG Denoising CNN [10]	FPCG	Deep CNN denoising model	Acoustic fetal phonocardiography recordings	Significant SNR improvement; performance depends on acquisition quality and signal stability
IoT-Based Fetal Monitoring [52]	FPCG	Edge AI + IoT	Wearable fetal monitoring signals	Enables remote monitoring; performance affected by communication latency and sensor noise
CNN-Based CTG Classification [13], [53]	CTG	CNN classifier	CTU-UHB CTG Database [54]	Reduces subjectivity in fetal distress detection; improves diagnostic consistency

				and sensitivity
Hybrid Models [2], [54]	CTG	ML + DL hybrid models	CTU-UHB Database	Enhances robustness and interpretability in clinical decision support systems
FECG-CTG Fusion [3], [55]	CTG + FECG	Multimodal fusion model	PhysioNet + CTU-UHB datasets	Improves fetal heart rate estimation using complementary physiological signals
Doppler Ultrasound Analysis [53], [56]	Doppler US	Signal processing + ML	Clinical Doppler ultrasound datasets	Provides hemodynamic assessment; sensitive to probe positioning and motion artifacts
Multimodal Fusion Systems [3], [57]	CTG + ECG + US	Deep multimodal fusion network	Multi-sensor clinical datasets (CTG, ECG, US)	Highest robustness among single-modality systems; challenges include synchronization and computational complexity
Transformer-Based CTG Modeling [58]	CTG	Transformer (Self-Attention)	CTU-UHB Database	Captures long-range temporal dependencies; improves interpretability over CNN/LSTM models
Attention-Based FECG Extraction [59]	FECG	Attention + CycleGAN	PhysioNet NIFECG, ADFECGDB	Enhances fetal ECG extraction under severe maternal interference using adversarial learning and attention mechanisms
GAN-Based FECG Enhancement [55], [59]	FECG	GAN-based reconstruction	FECGSYNDB	Improves fetal ECG reconstruction and SNR under highly noisy environments and motion artifacts
Graph-Based FECG Modeling [60]	FECG	Graph Neural Network + Transformer	PhysioNet Abdominal ECG datasets	Models inter-lead spatial dependencies and improves robustness in low SNR environments
Self-Supervised Biomedical Learning [61],	FECG / FPCG	Self-Supervised Learning	PhysioNet ECG, CTG, PPG datasets	Reduces dependency on labeled data and improves generalization across

[62]				heterogeneous clinical environments
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notated datasets, poor generalization across populations and datasets, high sensitivity of FECG and FPCG signals to noise and motion artifacts, limited real-time clinical validation, and the computational complexity of multimodal deep learning frameworks.

VII. CONCLUSION

This paper presented a comprehensive analysis of fetal health monitoring systems using non-invasive biosignals, including FECG, FPCG, CTG, and Doppler ultrasound. The study highlights the shift from classical signal processing techniques to deep learning-based and multimodal frameworks for improved fetal assessment.

Deep learning models, particularly CNN-based and hybrid architectures such as CNN-LSTM and CNN-BiLSTM, demonstrate improved robustness in handling noisy fetal biosignals when combined with time-frequency representations such as STFT. However, challenges such as low signal-to-noise ratio, limited annotated datasets, and poor generalization across clinical settings still limit real-world deployment.

Future research should focus on lightweight and explainable AI models, along with emerging paradigms such as self-supervised learning, federated learning, and edge AI to improve data efficiency and privacy preservation. Additionally, the development of standardized multimodal datasets and extensive clinical validation is essential for translating these methods into practical obstetric care systems.

Overall, fetal health monitoring is progressing toward intelligent, multimodal, and clinically deployable decision-support systems with improved accuracy and robustness.

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