The Scientific Temper (2025) Vol. 16 (9): 4827-4833
E-ISSN: 2231-6396, ISSN: 0976-8653
Doi: 10.58414/SCIENTIFICTEMPER.2025.16.9.17
https://scientifictemper.com/

RESEARCH ARTICLE

# DAJO: A Robust Machine Learning–Based Framework for Preprocessing and Denoising Fetal ECG Signals

**M. Merla Agnes Mary[1*], S. Britto Ramesh Kumar[2]**

## Abstract

Accurate Fetal Heart Rate (FHR) detection and fetal electrocardiogram (fECG) analysis are vital for early identification of fetal distress. However, clinical fECG signals are often degraded by maternal ECG, baseline drift, powerline interference, and uterine contractions, reducing diagnostic reliability. To address this, the study presents a DAJO, a preprocessing framework that combines Denoising, Adaptive filtering, Joint FHR detection, and Optimized feature extraction. The workflow employs ensemble filters for noise suppression, adaptive filtering to enhance fetal-specific components, and a modified Hamilton–Tompkin's method for robust FHR estimation. CNN-based feature extraction further ensures compact yet discriminative signal representation. Experimental results demonstrate that DAJO achieves 97% accuracy, 95% precision, 92% recall, 98% specificity, and a 95% F1 score, confirming its effectiveness. This highlights the DAJO as a robust preprocessing solution that preserves physiological integrity while improving automated FHR detection.

**Keywords:** Preprocessing, Denoising, Filtering Methods, Segmentation, Feature Extraction, Fetal ECG.

## Introduction

Fetal monitoring remains a vital tool in modern obstetrics for the early detection and management of neonatal distress. Among available methods, fetal electrocardiography (fECG) provides a non-invasive assessment of the fetus's cardiac activity using abdominal leads, offering detailed morphological information such as P-waves, QRS complexes, T-waves, and beat-to-beat variability (Rahmayanti, Nabillah, Humaira Pradani, Muhammad Pahlawan, and Retno Vinarti, 2022). Unlike cardiotocography (CTG), which mainly tracks uterine contractions and FHR, fECG enables more precise evaluation of conditions like hypoxia, arrhythmias, and acid–base imbalance (Puspitasari, Riskyana Dewi Intan, M. Anwar Ma'sum, Machmud R. Alhamidi, and Wisnu Jatmiko, 2022). However, its clinical use is limited by low signal-to-noise ratio, baseline drift, maternal ECG interference, motion artifacts, and electrode displacement. Effective preprocessing and noise reduction are therefore essential before diagnostic analysis.

Machine learning has been applied to fECG preprocessing tasks such as noise suppression, maternal ECG removal, signal quality assessment, and data imputation (Rahmayanti, Nabillah, Humaira Pradani, Muhammad Pahlawan, and Retno Vinarti, 2022). Classical models like SVM, RF, KNN, and logistic regression, trained on handcrafted features, improve variance detection, while regression-based methods such as ensemble regressors and Gaussian processes reconstruct missing data more effectively than simple interpolation (Bertieaux, Julien, Mohammadhadi Shateri, Fabrice Labeau, and Thierry Dutoit, 2023).

Deep learning reduces reliance on manual feature design by integrating preprocessing into the learning process (Devi, S. Suganthi 2024). CNNs function as adaptive filters to enhance QRS detection and suppress noise, while LSTMs capture temporal dependencies, and their hybrid combinations deliver improved performance for both classification and preprocessing of fECG and CTG/FHR signals (Roscher & van der Haar, 2024). A critical step is maternal ECG removal: traditional approaches like adaptive filtering

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**How to cite this article:** Mary, M.M.A., Kumar, S.B.R. (2025). DAJO: A Robust Machine Learning–Based Framework for Preprocessing and Denoising Fetal ECG Signals. The Scientific Temper, **16**(9):4827-4833.

Doi: 10.58414/SCIENTIFICTEMPER.2025.16.9.17

**Source of support:** Nil

**Conflict of interest:** None.

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**Received:** 07/09/2025 **Accepted:** 21/09/2025 **Published:** 23/09/2025

and ICA struggle with overlapping QRS complexes, whereas CNN-based models trained on fetal-specific signals achieve higher accuracy by unifying feature extraction, filtering, and artifact removal (Fuentealba, Patricio, Alfredo Illanes, and Frank Ortmeier, 2019).

Figure 1 illustrates a six-stage preprocessing workflow, beginning with Data Profiling and progressing through Data Cleaning, Data Reduction, Data Transformation, Data Enrichment, and finally Data Validation. Recent advances show that intelligent, adaptive methods based on machine learning (ML) and Deep Learning (DL) are increasingly replacing conventional preprocessing strategies in fECG analysis. ML techniques support noise detection, data imputation, and signal quality evaluation, whereas DL approaches provide end-to-end solutions for tasks such as time–frequency augmentation, denoising, and maternal ECG cancellation.

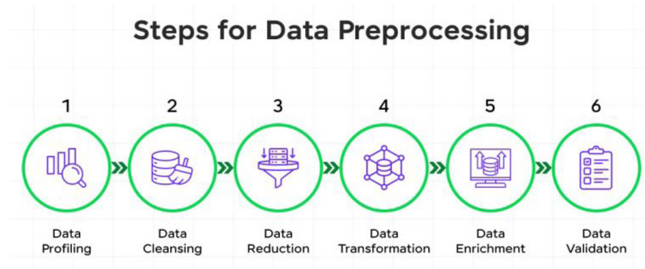


**Figure 1:** Steps for Data Preprocessing

### *Literature Review*

Recent studies on fetal health classification have explored various preprocessing strategies and machine learning frameworks. Rahmayanti, Nabillah, Humaira Pradani, Muhammad Pahlawan, and Retno Vinarti (2022) compared several models on the UCI dataset, applying outlier removal, multicollinearity handling, and unsampling. The tree-based ensemble of LightGBM, Random Forest, and XGBoost consistently outperformed with deep learning models such as ANN and LSTM, although generalizability was limited due to the lack of external validation. Building on this, (Puspitasari, Riskyana Dewi Intan, M. Anwar Ma'sum, Machmud R. Alhamidi, and Wisnu Jatmiko, 2022) used GANs to address class imbalance in FHR signals, incorporating normalization and beat error reduction, with deep CNN-based models like ResNet and EfficientNet.

Hybrid approaches have also gained momentum. Bertieaux, Julien, Mohammadhadi Shateri, Fabrice Labeau, and Thierry Dutoit (2023) explored both supervised classifiers and unsupervised anomaly detectors, demonstrating that a modified GANomaly model provided superior robustness against class imbalance. Similarly, (Devi and S. Suganthi, 2024) introduced an ensemble-based framework combining advanced preprocessing with kernel-PSO feature selection. This framework consistently outperformed conventional ensembles and single classifiers, especially on high-dimensional data. Roscher, Anton Johan, and Dustin van der Haar (2024) applied 1D CNNs to both CTU-UHB and UCI datasets, using preprocessing steps such as interpolation, smoothing, and morphological feature extraction. However, the lack of advanced imbalance handling raised concerns about overfitting.

Fuentealba, Patricio, Alfredo Illanes, and Frank Ortmeier (2019) focused on CTU-UHB signals, using CEEMDAN decomposition and TV-AR analysis to derive modal–spectral features. When combined with statistical and morphological descriptors, these features improved classification with traditional models like SVM and LDA. Salini, Yalamanchili, Sachi Nandan Mohanty, Janjhyam Venkata Naga Ramesh, Ming Yang, and Mukkoti Maruthi Venkata Chalapathi (2024) applied standard preprocessing and resampling-based class balancing. However, their work was limited to the UCI dataset and relied on pre-extracted features rather than raw signal engineering.

Signal-driven approaches have seen significant advancements in recent years. Alqahtani, Rawad A., Gaseb N. Alotibi, and Turky N. Alotaiby (2025) proposed hypoxia detection using normalized fECG signals and CSP-based feature extraction. They validated this approach against both objective and expert annotations. Hardalaç, Fırat, Haad Akmal, Kubilay Ayturan, U. Rajendra Acharya, and Ru-San Tan (2024) optimized Random Forest classification through recursive feature elimination and Bayesian tuning. This achieved near-perfect identification of pathological cases, using SHAP-based interpretability. Xiao, Yahui, Yaosheng Lu, Mujun Liu, Rongdan Zeng, and Jieyun Bai (2022) introduced a deep fusion framework (DFFN). This combined CNN-BiLSTM network with handcrafted features outperforms either approach alone on the JNU-CTG dataset. Addressing temporal complexity (Rao, Lin, Jia Lu, Hai-Rong Wu, Shu Zhao, Bang-Chun Lu, and Hong Li, 2024) proposed a multi-scale LSTM method. These trained models on FHR signals at different sampling rates, combining predictions via weighted voting to improve classification under variable conditions.

Table 2 summarizes prior studies on fetal CTG analysis, highlighting preprocessing strategies such as normalization, interpolation, outlier removal, feature reduction, and data augmentation. While these approaches often improved classification performance, several limitations persisted. Common challenges included insufficient handling of class imbalance, dependence on pH-based labels, reliance on single datasets, and limited external validation, all of which restricted generalizability. To overcome these gaps, the proposed DAJO framework introduces a comprehensive preprocessing pipeline that integrates denoising, adaptive data augmentation, joint feature extraction, and outlier-aware normalization.

**Table 1:** The main terminologies mentioned in this paper (include abbreviations)

| *ML* | *Machine Learning* | *KNN* | *KNN - K-Nearest Neighbors* |
|---|---|---|---|
| DL | Deep Learning | POC | POC - Proof of Concept |
| GAN | Generative Adversarial Network | PR | Precision |
| LSTM | Long Short-Term Memory | AUC | Area Under the Curve |
| SVM | Support Vector Machine | PSO | Particle Swarm Optimization |
| UCI | University of California | ANDOVA | Analysis of Variance |
| DFFN | Deep Feature Fusion Network | DFFN | Deep Feature Fusion Network |
| ANN | Artificial Neural Networks | CNN | Convolutional Neural Network |
| Bi-LSTM | Bidirectional Long Short-Term Memory | QI | Quick Index |
| GBM | Gradient Boosting Machine | CTU | Czech Technical University |
| UHB | University Hospital in Brno | SHAP | SHapley Additive exPlanations |
| LMS | Least Means Square | RLS | Recursive Least Squares |
| PCA | Principal Component Analysis | ICA | Independent Component Analysis |
| FHR | Fetal Heart Rate | CTG | Cardiotocography |

The remainder of this paper is structured as follows: Section 2 reviews related work, while Section 3 describes the dataset and methodology. Section 4 presents the experimental results along with discussion, and Section 5 concludes the study.

## Material and Methods

The proposed DAJO technique for extracting the fECG and estimating the FHR consists of four main stages: (1) Data Acquisition and Preprocessing, (2) Adaptive Filtering, (3) fECG Enhancement, and (4) Fetal QRS Detection and FHR Estimation.

### *Dataset*

The proposed method employs a validated dataset from the Czech Technical University (CTU) in Prague and the University Hospital in Brno (UHB), comprising 552 cardiotocography (CTG) recordings. These recordings were carefully selected from a set of 9,164 collected between 2010 and 2012 at UHB. Each CTG recording begins no more than 90 minutes before delivery and lasts up to 90 minutes, capturing the critical final stages of labor. Figure 2 describes the FHR and UA of the dataset (Spilka, Jiří, George Georgoulas, Petros Karvelis, Vangelis P. Oikonomou, Václav Chudáček, Chrysostomos Stylios, Lenka Lhotská, and Petr Janků, 2013) & (Mendis, Lochana, Marimuthu Palaniswami, Emerson Keenan, and Fiona Brownfoot, 2024).

### *Proposed Methodology*

The overall workflow is illustrated in Algorithm 1, which provides the detailed workflow pseudocode for the proposed work.

### *Data Acquisition*

The experiments were conducted using the CTU-UHB Intrapartum Fetal ECG Database**.** The dataset's well-known class imbalance before augmentation. The Normal class accounted for 81% of the samples, while the Suspicious and Pathological classifications only accounted for 12% and 7% of the samples, respectively (Mendis, Lochana, Marimuthu Palaniswami, Emerson Keenan, and Fiona Brownfoot, 2024). The dataset was balanced across the three classes using Ensemble GAN, with 447 Normal, 430 Suspicious, and 410 Pathological samples, ensuring sufficient diversity for training. This balancing reduced class bias, leading to

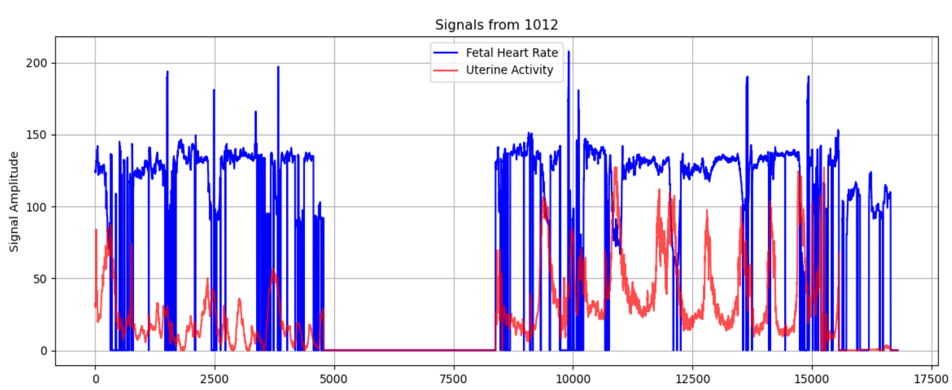


**Figure 2:** FHR and Uterine Activity Signals

**Table 2:** Comparison of related studies

| *Author (Year)* | *Dataset* | *Classes* | *Preprocessing Techniques* | *Limitations* |
|---|---|---|---|---|
| Hardalac et. al. (2024) | CTU-UHB | 3 (Normal, Suspect, Pathological) | Z-score normalization<br>Empty row/col removal<br>RFE feature elimination | Lack of generalizability |
| Xiao *et al*. (2022) | CTU-UHB, JNU-CTG (private) | Binary (Normal vs. Pathological) | Linear interpolation<br>signal denoising<br>downsampling<br>window slicing augmentation | Ignored uterine contractions and oversimplified labels (pH only) |
| Rao *et al*. (2024) | CTU-UHB | Binary | Segmentation (1-min)<br>linear random interpolation<br>window slicing augmentation | Single-label (pH), no maternal features included |
| Rahmayanti *et al*. (2022) | UCI Fetal Health (2126 records) | 3 (Normal, Suspect, Pathological) | Outlier removal (3σ)<br>VIF for multicollinearity<br>Upsampling<br>scaling | No external validation; limited feature engineering |
| Puspitasari *et al*. (2022) | CTU-UHB (552 records) | 3 (Normal, Suspect, Pathological) | Beat error removal<br>Normalization<br>outlier filtering | High complexity, moderate sensitivity, dataset-limited |
| Bertieaux *et al*. (2023) | CTU-UHB | Binary (Normal vs. Pathological) | Filtering<br>Interpolation<br>median smoothing | Threshold-based labels; no external dataset; only term deliveries |
| Devi *et al*. (2024) | CTU-UHB | 3 (Normal, Suspect, Pathological) | Variance-aware outlier filtering<br>quartile-based methods<br>Max-Min probabilistic imputation<br>feature standardization | No clear hyperparameter details; generalizability untested |
| Röscher & van der Haar (2024) | CTU-UHB, UCI Fetal Health | 3 (Normal, Suspect, Pathological) | Outlier removal<br>Interpolation<br>Smoothing<br>morphological feature extraction<br>normalization | No imbalance handling beyond stratification; risk of overfitting |
| Fuentealba *et al*. (2019) | CTU-UHB subset | Binary (Normal vs. Acidotic) | CEEMDAN decomposition<br>TV-AR spectral analysis,<br>conventional features | Binary only; dataset-specific; no multiclass extension |
| Salini *et al*. (2024) | UCI Fetal Health | 3 (Normal, Suspect, Pathological) | Missing data handling<br>resampling standardization<br>feature selection | Only UCI dataset; no CTU-UHB; no signal-based features |
| Alqahtani *et al*. (2025) | CTU-UHB (552 signals) | Binary | Normalization,<br>Z-score scaling,<br>removal of implausible values<br>instantaneous frequency analysis<br>CSP features | No external validation; possible overfitting; dataset-specific |

improved model robustness, and achieved a balanced accuracy of 96%, which was then used as the basis for subsequent preprocessing.

### *Signal Preprocessing (Denoising)*

The raw abdominal signals are first pre-processed to remove noise and artifacts outside the frequency band of interest while preserving the morphological features of the ECG. A zero-phase 4th-order Butterworth bandpass filter with cut-off frequencies of 0.5 Hz and 45 Hz is applied to eliminate baseline wander and high-frequency noise. The transfer function $H(s)$ of a lowpass Butterworth filter of order is given by:

$$|H(j\omega)|^2 = \frac{1}{1+\left(\frac{\omega}{\omega_c}\right)^{2n}} \tag{1}$$

*Notch filter*

A 2nd-order IIR notch filter is applied to suppress the powerline interference at 50 Hz (or 60 Hz, depending on the region). The filter's transfer function with a notch frequency:

$$H_{notch}(z) = \frac{1 - 2cos\left(2\Pi f_{0|} f_s\right) z^{-1} + z^{-2}}{1 - 2rcos\left(2\Pi f_{0|} f_s\right) z^{-1} + r^2 z^{-2}} \tag{2}$$

*Median Filtering*

To remove sharp, impulsive noise and artifacts a non-linear median filter of order is applied. The filter replaces each sample with the median value of the neighboring samples.

$$x_{med}[n] = median\{x[n-k], \ldots, x[n], \ldots, x[n+k]\} \quad (3)$$

Algorithm 1. DAJO Preprocessing Workflow for fECG and FHR Detection

- Inputs: $D\_real, D\_synth$
- Merge datasets: $D = align\_and\_resample(D\_real \cup D\_synth)$
  - For each recording $x(t)$ in :
  - Remove DC/baseline wander: apply high-pass Butterworth $\rightarrow x\_hp(t)$
  - Notch filter to remove powerline interference $\rightarrow x\_notch(t)$
  - Median filter to remove impulse spikes $\rightarrow x\_med(t)$
  - Maternal ECG (MECG) cancellation: maternal lead $\rightarrow x\_adapt(t)$
  - obtain $x\_wav(t)$ to preserve morphology
  - Apply bandpass smoothing $x\_clean(t)$
  - Feature extraction: feed $x\_clean(t)$ to CNN feature extractor $\rightarrow$ feature vector
  - R-peak detection (Hamilton–Tompkins) on fetal channel(s) to get RR intervals, P, QRS, ST candidates $\rightarrow$ segments
  - Segment-level analysis: $s \in S$
- Dimensionality reduction / de-mixing: perform PCA, then ICA on the feature matrix F $\rightarrow F_{reduced}$
- Output: $D\_preprocessed = \{x_{clean}, f, S, F_{reduced}\}$

*Adaptive Filtering*

An adaptive noise cancellation (ANC) framework using the Least Mean Squares (LMS) algorithm operates by continuously adjusting the coefficients of an adaptive filter to minimize the power of the error signal. The primary input $y[n]$ to an adaptive filter is one of the preprocessed signals. A reference input $u[n]$ is created from another channel, which is highly correlated.

$$\begin{aligned} y[n] &= w^T[n]u[n] \\ e[n] &= d[n] - y[n] \\ w[n+1] &= w[n] + \mu e[n]u[n] \end{aligned} \quad (4)'$$

The error signal $e[n]$ which is the output of the ANC system, is the cleaned fECG signal.

***Beat Segmentation (Hamilton-Tompkins Algorithm)***

The locations of the detected fetal R-peaks are used for FHR calculation.

$$Beat_i^{norm} \frac{Beat_i - \mu}{\sigma} \quad (5)$$

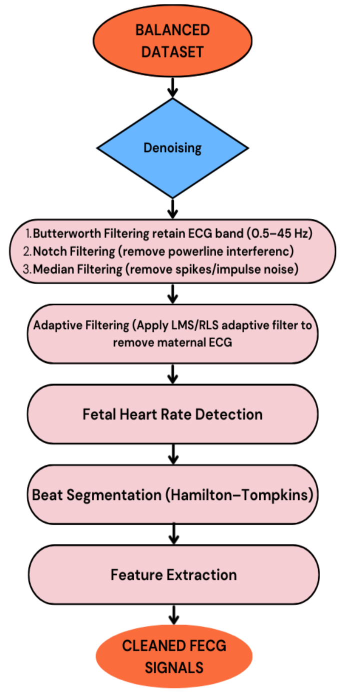


**Figure 3:** Proposed methodology flow diagram

***Feature Extraction***

The Instantaneous FHR in beats per minute (BPM) is calculated from the intervals between successive detected fetal R-peaks (RR intervals):

$$FHR_{inst}[k] = \frac{60}{t_{fpeak}[k] - t_{fpeak}[k-1]} \quad (6)$$

Finally, the FHR time series is post-processed (e.g., using median filtering) to remove physiologically implausible outliers caused by false or missed detections, resulting in a smooth, cleaned FECG-derived FHR trend for clinical interpretation.

## Results and Discussion

The proposed DAJO preprocessing framework was evaluated on a balanced CTU-UHB fECG dataset comprising both real and augmented signals. The pipeline integrates ensemble denoising, adaptive filtering, fetal QRS detection for FHR estimation, and CNN-based feature extraction with PCA/ICA for feature reduction. Experimental results show that DAJO achieves 97.0% accuracy, with a Precision of 95%, a Recall of 92%, a Specificity of 98%, and an F1-score of 95%. These outcomes confirm its effectiveness in detecting FHR while preserving clinically relevant features such as QRS width, ST deviation, and RR interval variability. Compared to conventional preprocessing methods, DAJO demonstrates superior robustness against noise sources including maternal ECG interference, baseline drift, and powerline artifacts. Figure 4 illustrates the performance comparison with existing models.

**Table 3:** Comparison table of existing methods with the proposed method

| *Author* | *Accuracy (%)* | *Specificity (%)* | *Recall (%)* | *Precision (%)* | *F1 Score (%)* |
|---|---|---|---|---|---|
| Rao.et.al (2024) | 86 | 85 | 89 | 86 | 85 |
| Hardale et.al (2024) | 96 | - | 96 | 92 | 94 |
| Roscher et.al (2024) | 93 | 85 | 82 | 95 | 88 |
| Deng et.al. (2023) | 95 | 91 | 90 | 99 | 94 |
| DAJO (proposed Method) | 97 | 99 | 92 | 95 | 95 |

The high specificity (98.8%) suggests that DAJO is particularly effective in identifying normal fetal patterns with minimal false alarms, while the recall (92%) indicates good sensitivity in detecting abnormal cases, though there remains room for improvement in capturing all pathological signals.

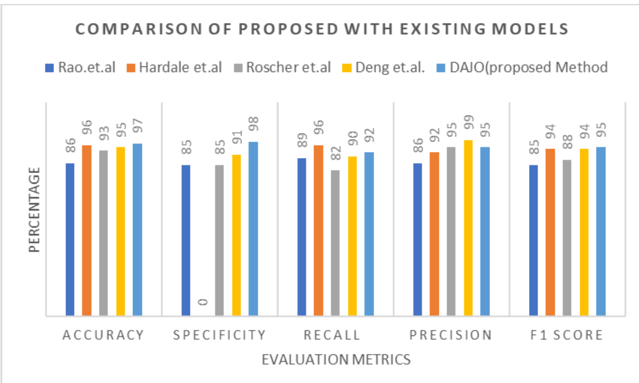


**Figure 4:** Comparison of the existing model with the proposed model

### *Limitations and Future Enhancement*

Despite these promising results, certain limitations must be acknowledged. The evaluation relied on a dataset that may not fully capture the variability of broader clinical populations, which could restrict generalizability. In addition, the dependence on CNN-based feature extraction requires diverse and representative training data to ensure robust generalization. Future improvements will focus on strengthening robustness and clinical applicability. Efforts will include designing lightweight filters and faster neural architectures for real-time deployment in portable or wearable monitoring devices.

## Conclusion

The proposed DAJO framework integrates adaptive filtering, denoising, FHR detection, and feature optimization into a unified preprocessing pipeline for fECG signals. By effectively removing baseline drift, powerline interference, and maternal ECG, it enhances fetal QRS clarity and improves FHR reliability. CNN-based feature learning with dimensionality reduction ensures preservation of both temporal and morphological information during beat segmentation and extraction. The findings show excellent performance with 97% accuracy, 95% precision, 92% recall, 98% specificity, and 95% F1 score, demonstrating robustness across both real and synthetic data. Overall, DAJO provides a structured and efficient preprocessing solution that supports accurate FHR estimation and offers a strong foundation for advanced diagnostic and classification models in fetal monitoring

## Acknowledgement

I would like to acknowledge and express my sincere gratitude to the Head of the Department for guidance, resources, and timely feedback, and to the Principal of the Institution for providing the facilities and institutional support necessary to write and complete the paper.

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