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Automated Feature Extraction and Classification of Foetal Phonocardiogram Signals Using Time-Frequency Analysis and Machine Learning

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ABSTRACT
Automated analysis of foetal phonocardiogram (foetal PCG) signals can provide valuable insights into the health and development of the fetus during pregnancy. The system employs Continuous Wavelet Transform (CWT), Short-Time Fourier Transform (STFT), and Empirical Mode Decomposition (EMD) to extract relevant features from PCG signals. CWT provides precise time-frequency localization, STFT offers a broad spectral overview, and EMD adaptively decomposes the signal to identify subtle variations. Principal Component Analysis (PCA) reduces dimensionality, followed by ReliefF for feature selection, focusing on the most indicative features. A Support Vector Machine (SVM) classifier then automates the classification of foetal heart sounds. The system currently has a 45.75% classification loss, indicating potential for improvement, but its integrated methodology shows promise for foetal heart monitoring.

Keywords: *Foetal PCG, Short-Time Fourier Transform (STFT), Principal Component Analysis (PCA), Support Vector Machine (SVM)*

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I. Introduction

Foetal phonocardiogram (foetal PCG) signals provide valuable information about the cardiovascular health of a developing fetus. Computer technology, signal processing, and sensor technology have greatly improved automated heart sound analysis, making it vital for medical checkups. These improvements help doctors better assess heart health, leading to earlier diagnoses and better monitoring. Wearable devices and smartphone applications now allow heart sound monitoring outside of hospitals, enabling remote patient monitoring and customized treatment.

Signal processing methods minimize noise, identify important characteristics, and separate signals, isolating cardiac information to identify heart sounds such as S1-S4. specially designed algorithms measure these characteristics to find irregularities in heart sounds. This integrated approach of time-frequency analysis and machine learning has the potential to enhance the early and accurate detection of foetal abnormalities, enabling improved pregnancy management. Machine learning models, trained with lots of data, automate diagnoses by learning the connections between sound characteristics and specific heart health conditions. Recent research aims to make even more improvements, ultimately enhancing heart care.

The analysis of these acoustic signals can aid in the early diagnosis of various cardiac conditions, enabling timely interventions to improve foetal and neonatal outcomes. However, the manual interpretation of foetal PCG signals is a complex and subjective process, making automated analysis a compelling solution. [1] The nature and source of this signal are important to develop a competent tool for further analysis and processing, in order to enhance and optimize cardiac clinical diagnostic approach. [1].

In this research paper, we propose a comprehensive framework for the automated feature extraction and classification of foetal phonocardiogram signals using time-frequency analysis and machine learning techniques. Previous studies have demonstrated the potential of machine learning in discriminating healthy and pathological foetal conditions based on Cardiotocographic recordings [2]. Additionally, recent work has shown the viability of machine learning approaches for detecting bursts in the electroencephalogram of preterm infants without the need for a predefined feature set. [3]

II. Literature Review

Research has shown the potential of phonocardiography signal processing and machine learning techniques in analysing foetal heart sounds and diagnosing various cardiac conditions. A study integrated machine learning with physiology-based heart rate features extracted from a single antepartum Cardiotocographic recording to distinguish healthy and IUGR foetuses, achieving promising results. [2] Another study examined the efficacy of different machine learning techniques in predicting cardiovascular diseases, highlighting the importance of selecting appropriate models. [4] Moreover, preeclampsia, a serious pregnancy complication, is a documented cause of foetal and neonatal morbidity and mortality, underscoring the need for accurate and early detection to enable timely interventions and improve outcomes. [5] Current diagnostic approaches for foetal conditions still rely heavily on clinicians' observations and an ensemble of tools, such as laboratory parameters, biomarkers, and ultrasound findings, making limited use of advanced statistical methods like machine learning. [4] PCG compression [6] uses traditional methods, while ECG compression [7] [8] employs optimization for better tunability and efficiency, showing a divergence in biomedical signal processing. In [9] relation between foetal cardiac activities with gestational age and maternal conditions has been analysed. Meta analysis approach justifies the parameters like compression ratio and percentage root mean square difference for compression of EMG signals [10].

Advances in preeclampsia prediction have also been explored using machine learning approaches. These studies emphasize the growing role of Artificial Intelligence (AI) and Machine learning (ML) in enhancing cardiovascular diagnostics, especially in maternal-foetal medicine.

III. Methodology

A dataset of 212 foetal PCG recordings, acquired non-invasively via a high-sensitivity microphone on the maternal abdomen, was used [11]. These recordings captured unique foetal cardiac activity. The signals underwent preprocessing at 4000 Hz to reduce noise, correct baseline drift, and remove artifacts. Thirteen features were extracted, categorized as statistical, spectral, and time-frequency. PCA reduced dimensionality, selecting the first 4 principal components to preserve key information. ReliefF further refined feature selection, prioritizing features with high predictive power. Foetal PCG signals were then classified as healthy or pathological using SVM. Classification performance was evaluated using 5-fold validation.

Performance Matrices

The performance of the proposed system is evaluated using the following metrics:

a. Mean: It is the measure of central tendency of a distribution. Mathematically it is defined as the sum of all the values divided by the total number of values.

The mean of a dataset X={x1, x2,...,xn} is given by:

$$\mu = \frac{1}{n}\sum_{i=1}^{n} x_i$$

where:

- μ is the mean,
- n is the number of samples,
- x_i is each individual value.

b. Variance: It is the square root of the average of the squares of the differences from the mean and mathematically it is defined as:

$$\sigma^2 = \frac{1}{n}\sum_{i=1}^{n}(x_i - \mu)^2$$

where:

- σ^2 is the variance,
- μ is the mean,
- x_i are the data points.

c. Skewness: Skewness describes the asymmetry of the probability distribution of a random variable about its mean. Mathematically it is defined as:

$$\gamma = \frac{\frac{1}{n}\sum_{i=1}^{n}(x_i - \mu)^3}{(\frac{1}{n}\sum_{i=1}^{n}(x_i - \mu)^2)^{\frac{3}{2}}}$$

where:

- γ is the skewness,
- μ is the mean,
- x_i are the data points.

Positive skewness indicates a distribution with an asymmetric tail extending towards more positive values.

d. Kurtosis: Kurtosis is a measure of the "tailedness" of the probability distribution of a random variable. Mathematically it is defined as :

$$k = \frac{\frac{1}{n}\sum_{i=1}^{n}(x_i - \mu)^4}{(\frac{1}{n}\sum_{i=1}^{n}(x_i - \mu)^2)^2}$$

where:

- k is the Kurtosis,
- μ is the mean,
- x_i are the data points.

e. Zero Crossing Rate: This measures the rate of sign-changes along a signal, from positive to negative or vice versa. Mathematically it is defined as:

Zero Crossing Rate = No. of zero crossings / Total samples count

f. Spectral Centroid : This gives the barycentre of the spectrogram, providing a measure of the spectral 'brightness' or 'centroid' of the signal. Mathematically it is defined as:

$$\text{Spectral Centriod } = \frac{\sum_{i=1}^{n} f_i S(f_i)}{\sum_{i=1}^{n} S(f_i)}$$

where:

- f_i is the frequency,
- $S(f_i)$ is the magnitude of the spectrum at f_i ,
- n is the total number of frequency bins.

g. Spectral Spread: This gives a measure of the spectral 'width' or 'spread' of the signal. Mathematically it is defined as:

$$\text{Spectral Spread} = \sqrt{\frac{\sum_{i=1}^{n}(f_i - Spectral\ Centriod)^2\, S(f_i)}{\sum_{i=1}^{n} S(f_i)}}$$

where:

- f_i is the frequency,
- $S(f_i)$ is the magnitude of the spectrum at f_i ,

h. Spectral Flux: This measures the spectral change or 'flux' between consecutive frames of the spectrogram. Mathematically it is defined as:

$$Spectral\ Flux = \sum_{i=1}^{n}(S_i(t) - S_i(t-1))^2$$

where:

- $S_i(t)$ is the spectral magnitude at frequency bin k and time frame t,
- $S_i(t-1)$ is the spectral magnitude at the previous time frame.

i. Spectral Entropy: This measures the 'irregularity' or 'complexity' of the spectrogram. Mathematically it is defined as:

$$H = -\sum_{i=1}^{n} P_i \log_2 P_i$$

Where, P_i is the normalized power spectrum.

Results and Discussion

The table 1 below presents a summary of the extracted features from the 212 recordings. Form this table we can inferred that features like kurtosis, spectral flux, and spectral entropy exhibit large variations that means these features may be more crucial for classification as compared to mean and skewness.

Table 1: Statistical overview of Statistical and Spectral features

Sr. No.	**Features**	**Min**	**Median**	**Max**
1	Mean	-0.00028	-8.7686e-08	0.00019
2	Variance	0.00067	0.00707	0.0272
3	Skewness	-0.34	0.0206	0.57
4	Kurtosis	7.05	15.2	137.35
5	Zero Crossings	8423	78556	1.93e+05
6	Spectral Centroid	7578	47475	1.63e+05
7	Spectral Spread	13905	54390	1.73e+05
8	Spectral Entropy	13.76	16.13	18.39
9	Spectral Flux	7.11e+07	6.53e+08	1.96e+10

Figure 1 shows the correlation matrix among the selected features. This figure highlights strong relationships between some features, suggesting the importance of dimensionality reduction. Spectral features (Spectral Centroid, Spectral Spread, Spectral Entropy, Spectral Flux) are highly correlated with each other but are very less correlated with statical features (Mean, Variance, Skewness, Kurtosis, Zero-Crossing).

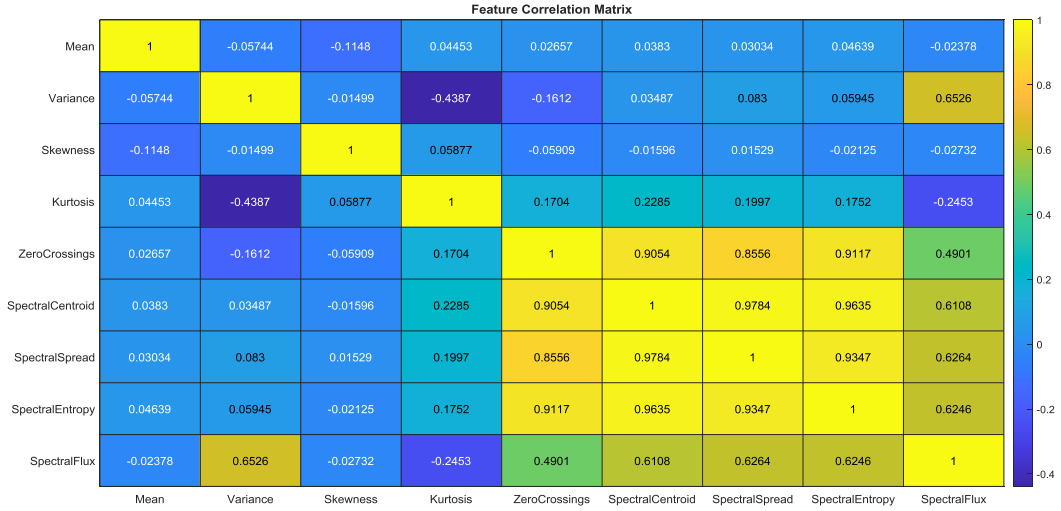

Figure 1: Correlation Matrix for extracted Features

Figure 2 shows the PCA plot. The first 4 principal components capture around 80% of the total variance in the data. It suggests that this reduced feature space can effectively represent the original high-dimensional dataset.

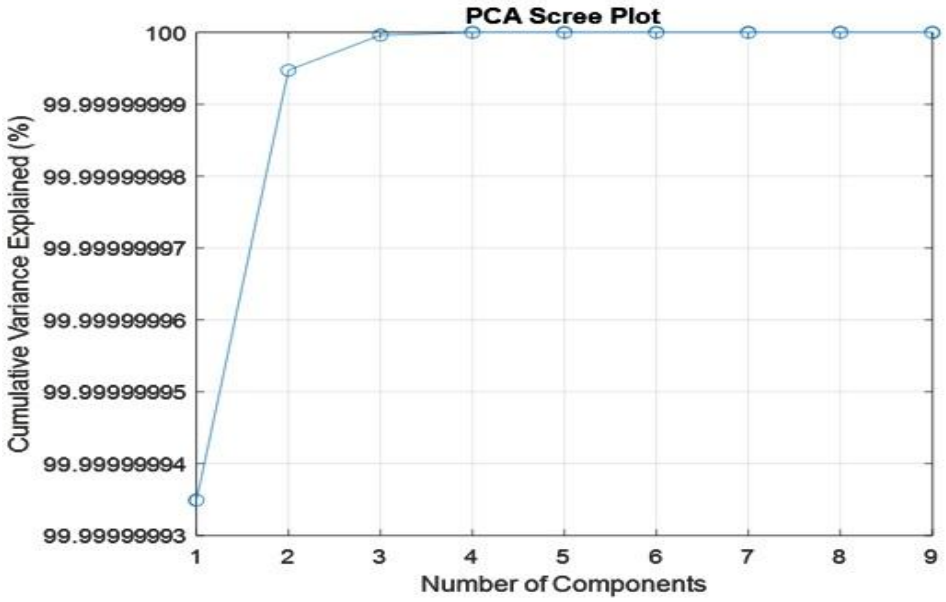

Figure 2: PCA plot between Number of components vs Cumulative variance

Figure 3 shows Relief Feature Score. The higher the score, the more important a feature is for classifying foetal PCG signals as healthy or pathological. Spectral Spread and Spectral Entropy has high predictive power, indicating their importance in distinguishing between healthy and pathological foetal conditions based on the foetal PCG signals.

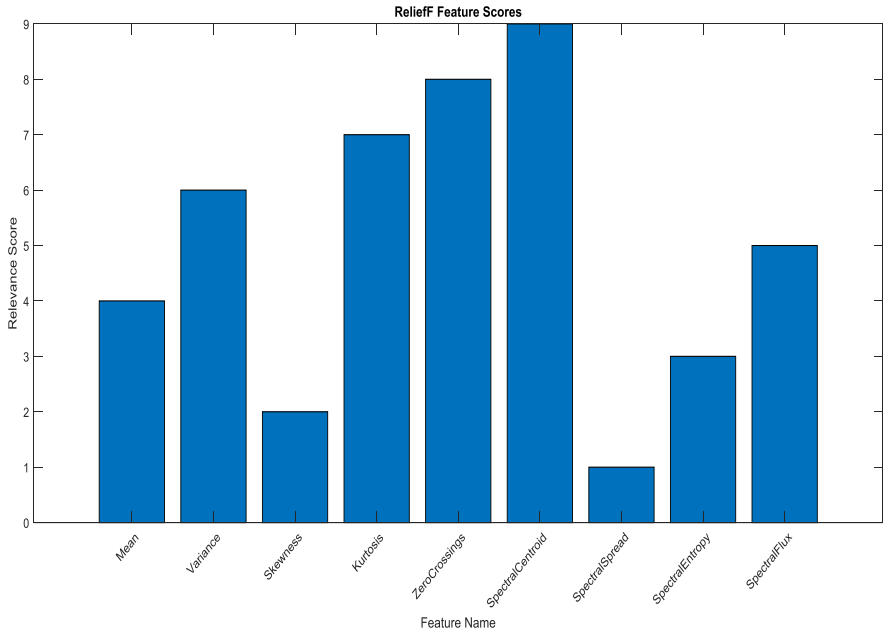

Figure 3: Relief Feature Scores

IV. Conclusion

This study presents a comprehensive framework for the automated analysis of foetal phonocardiogram signals. The proposed approach employs advanced signal processing and machine learning techniques to extract key temporal, spectral, and time-frequency features and classify foetal cardiac health. The results highlight the potential of this system to serve as a non-invasive, robust tool for early detection of foetal abnormalities, supporting clinical decision-making and improving maternal-foetal outcomes. Despite a 45.75% loss, the system shows promise for foetal heart monitoring.

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