Applicability of adaptive noise cancellation to fetal heart rate detection using phonocardiogram

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***Abstract*—This study proposes an innovative approach for fetal heart rate (FHR) extraction from phonocardiography (PCG) signals, crucial in high-risk pregnancies where traditional methods like cardiotocography (CTG) may be insufficient. The method utilizes adaptive noise cancellation (ANC) to mitigate interference from surrounding noise, ensuring accurate FHR monitoring. Through a multistage cascaded adaptive filter, the system dynamically adjusts stages and step sizes to effectively isolate FHR. Implementation includes an 8th order bandpass filter with specified frequencies for optimal signal extraction. Extensive testing demonstrates superior performance compared to existing techniques, offering a promising solution for continuous and long-term FHR monitoring in high-risk scenarios.**

Index Terms - Adaptive Noise Cancellation (ANC), Cardiotocography (CTG), Fetal Heart Rate (FHR), Phonocardiography (PCG)

I. Introduction

The normal FHR (Fetal Heart Rate) ranges from 110 to 160 beats/min, with variability ranging from 6 to 25 beats/min. This normal baseline with variability is a result of a healthy central and autonomic nervous system working in tandem. Because of the significant developmental changes to the nervous system, FHR should not be used until after 20 weeks of gestation, at which time the monitoring becomes more accurate.

In recent years, advancements in medical technology have significantly improved the diagnosis and treatment of various health conditions. However, the early detection of heart disease in fetuses remains a challenge, potentially leading to severe complications and adverse outcomes.Between 1950 and 1994, 42% of infant deaths reported to the World Health Organization were attributable to cardiac defects.

Heart Disease stands as one of the most prevalent and critical health challenges affecting newborns and infants worldwide. Characterized by structural abnormalities in the heart and major blood vessels, Its necessitates early diagnosis and intervention to improve patient outcomes. The integration of Artificial Intelligence (AI) has emerged as a groundbreaking approach to enhancing the accuracy and efficiency of Heart disease prediction, offering the potential to revolutionize pediatric healthcare.

Current diagnostic methods rely heavily on manual interpretation of ultrasound images and clinical data, which can introduce subjectivity and variability. This often results in missed or delayed diagnoses, impacting the health of both the fetus and the expectant mother.

In response to this critical gap in prenatal care, This research aims to harness the power of artificial intelligence (AI) to enhance the detection of heart disease in foetuses. By leveraging advanced machine learning techniques and image analysis algorithms, we seek to develop an accurate and efficient AI system that can analyze prenatal ultrasound images and other relevant medical information.

This research holds the promise of transforming the landscape of fetal medicine by providing healthcare professionals with a reliable tool for early detection and diagnosis of heart disease. By bridging the diagnostic divide with AI-driven insights, we envision improved healthcare outcomes, reduced risks, and better quality of life for both mothers and their unborn children. Through this innovative approach, we strive to contribute to the advancement of prenatal care and underscore the profound impact of technology in safeguarding the health and well-being of the most vulnerable population – our future generations.

Through this exploration, the potential benefits of AI-based heart disease prediction come to light. Timely and accurate identification of heart disease risk factors can lead to improved clinical decision-making, personalized treatment plans, and enhanced patient outcomes. This aims to shed light on how AI technologies are shaping the landscape of congenital heart disease prediction[3,5] and fostering a new era of early intervention and precision medicine in pediatric cardiology.

This research aims to address a significant healthcare challenge – the early detection of congenital heart disease in fetuses. Heart disease is a critical issue affecting newborns and infants globally, characterized by structural heart abnormalities. Current diagnostic methods, primarily reliant on manual interpretation of prenatal ultrasound images and clinical data, suffer from subjectivity and inconsistency, potentially resulting in delayed diagnoses that can have severe consequences for both the fetus and the expectant mother.

The main references emphasize the utilization of advanced machine learning techniques and image analysis algorithms to develop an AI system capable of analyzing prenatal ultrasound images. This approach aims to bridge the diagnostic gap by providing healthcare professionals with a reliable tool for early detection and diagnosis of heart disease in fetuses.

This research proposes the integration of AI technologies to revolutionize pediatric healthcare by offering precise and timely identification of heart disease risk factors. The implementation of machine learning algorithms and image analysis techniques requires a solid mathematical foundation. Understanding concepts such as pattern recognition, statistical modeling, and algorithm optimization is crucial for developing an accurate AI system for detecting congenital heart disease in fetuses[3,5].

II. Literature Review

[1] A low cost device for fetal heart rate measurement: The paper introduces a compact, low-cost device for multi-lead fetal heart rate measurement, highlighting the necessity for advanced signal processing techniques due to challenges posed by low signal magnitude compared to background noise. It also proposes the development of a measuring probe for recording and storing PCG data, along with the creation of an online database for such data.

[2] A Wireless and Wearable System for Fetal Heart Rate Monitoring: This paper discusses the development of a flexible, wearable wireless fetal ECG monitoring system capable of accurately detecting fetal heart rate, maternal heart rate, and uterine contractions. The system is designed to conform to the skin, providing comfort during wear, and offers continuous monitoring for over 6 hours. Data transmission is facilitated through Bluetooth, enabling portable measurements anywhere, ensuring effective and safe monitoring of fetal and maternal health.

[3] A Research Review on Fetal Heart Disease Detection Techniques: Aimed at enhancing early detection and prediction of Fetal Heart Disease, this study utilizes a large database of patient information and employs the random forest method.

[4] An assessment of the usefulness of image pre-processing for the classification of first trimester fetal heart ultrasound using convolutional neural networks: Investigating the impact of image pre-processing on the classification of first-trimester fetal heart ultrasound, this study aims to assess whether pre-processing affects the model's ability to distinguish between key views and irrelevant frames.

[5] Global birth prevalence of congenital heart defects 1970–2017: updated systematic review and meta-analysis of 260 studies: A series of studies have highlighted the increasing global prevalence of congenital heart defects (CHD) over the past few decades, with significant regional variations.

[6] Early evaluation of the Fetal Heart: This paper emphasizes the importance of early evaluation of the fetal heart, discussing key ultrasound findings indicative of cardiac defects, the heart-thorax relationship, and the significance of operator experience and training in identifying fetal cardiac anomalies.

[7] Learning deep architectures for the interpretation of first-trimester fetal echocardiography a study protocol for developing an automated intelligent decision support system for early fetal echocardiography: The paper outlines the development of an Intelligent Decision Support System (IS) utilizing two-dimensional video files from standard first-trimester fetal echocardiography to identify fetal cardiac anomalies, aiming to provide early and accurate prenatal diagnosis of CHD and improve treatment options.

[8] Fetal Congenital Heart Disease Echocardiogram Screening Based on DGACNN: Introducing the DGACNN network architecture, this paper achieves state-of-the-art accuracy of 85% in recognizing fetal congenital heart disease (FHD), demonstrating potential for application in other ultrasound medical image classification tasks.

[9] A new Fiber-Optic Sensor, combined with Phonocardiographic technology and an Adaptive Filtering System, allows for noninvasive, continuous monitoring of fetal heart rates with enhanced accuracy.This study presents an adaptive signal processing system capable of extracting fetal heart rate information from high-quality fetal phonocardiograms, filtered from maternal abdominal phonocardiograms, by performing fetal phonocardiogram signal peak detection.

[10] Observations on heart rate and pH in the human fetus during labor: Specific fetal heart rate deceleration patterns are linked with disturbances in acid-base balance during labor.

[11] The electronic evaluation of fetal heart rate: Modern electronic techniques offer a more accurate evaluation of fetal heart rate during both normal and abnormal labor compared to current clinical methods.

[12] Pattern of the normal human fetal heart rate: Beginning at week 28, there is a suggestion that episodes of high heart rate variance, lasting 10 minutes, could serve as a numerical indicator of normalcy in fetal heart rate patterns.

[13] The development of fetal heart rate patterns during normal pregnancy: Baseline variability of fetal heart rate increases with gestational age during normal pregnancy.

[14] Numerical Analysis of the normal human Antenatal Fetal Heart Rate: Fetal heart rate fluctuations can be classified into mild and high cyclical episodes starting around 27 weeks of gestation.

[15] Fetal Heart Rate Monitoring Based on Adaptive Noise Cancellation and Maternal QRS Removal Window: The adaptive noise cancellation

method demonstrates superior performance in fetal heart rate detection compared to independent component analysis.

III. Motivation

This paper aims to tackle the pressing issue of heart disease in newborns and infants by leveraging cutting-edge machine learning techniques and AI systems to enhance early detection and prediction. By harnessing the power of AI, we seek to improve the accuracy and effectiveness of heart disease prediction, thereby potentially saving lives and reducing healthcare burdens. Through this research, we aim to contribute to the development of more reliable and efficient methods for diagnosing fetal heart disease, ultimately improving outcomes for infants and their families.

IV. Problem Domain

The critical domain of fetal heart rate monitoring, specifically addressing the formidable challenges associated with noise interference in phonocardiography signals [1]. It underscores the imperative for effectively denoising these signals to enable accurate analysis. The paper explores the application of adaptive noise cancellation (ANC) techniques[9] to extract fetal heart rate amidst noisy environments. Emphasizing the necessity of a robust mathematical framework, the study aims to facilitate the development of precise AI systems for the early detection of congenital heart diseases in fetuses.

V. Problem Definition

The proposed AI-powered diagnostic tool aims to specifically address conditions such as tachycardia (rapid heartbeats) and bradycardia (slow heartbeats) in fetal heart disease[3,10,13]. These abnormal heart rate patterns play a crucial role in indicating potential cardiac issues in the fetus. Tachycardia, characterized by excessively rapid heartbeats, may suggest conditions like fetal arrhythmias or cardiac abnormalities, whereas bradycardia, marked by unusually slow heartbeats, can indicate problems such as fetal distress or cardiac conduction defects.

By analyzing and identifying these abnormal heart rate patterns through advanced image analysis and machine learning techniques, the diagnostic tool plays a vital role in providing early detection and intervention for fetal heart disease[1]. This real-time assessment of heart rate patterns enables healthcare practitioners to promptly identify potential cardiac issues, initiate appropriate interventions, and optimize prenatal care strategies, ultimately improving health outcomes for both the fetus and the expectant mother.

VII. Problem Formulation or Representation or Design

The procedure involves recording heartbeat sounds and extracting crucial data through signal processing. For machine learning, the dataset is split, target variable encoded, and mode BPM and average BPM selected as features. Feature scaling ensures model stability. Evaluation includes metrics like accuracy and visualization through scatter plots. This concise approach maintains clarity and effectiveness.

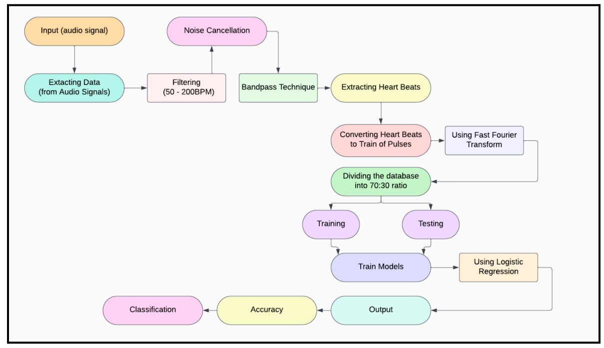

Figure I
Algorithmic Pipeline For Heartbeat Detection

The diagram outlines the process for determining the accuracy of fetal heart rate measurements from audio signals. It begins with inputting the audio signal from an ultrasound device and proceeds with data extraction, noise cancellation, and filtering to focus on fetal heartbeats (50-200 BPM). Normal heart rates (120-160 BPM) are identified, and abnormal rates are classified accordingly. The signal undergoes refinement using bandpass techniques and classification methods to isolate fetal heart rate. Accuracy is assessed either by comparison to a reference method or evaluating measurement consistency. The dataset is split for training/testing, and machine learning models, potentially using FFT and Logistic Regression, are employed to analyze the signal's frequency domain and distinguish fetal heartbeats from other sounds.

Noise cancellation of fetal heartbeats is a crucial component of prenatal care and fetal monitoring within medical practice [15]. Fetal heartbeats serve as vital indicators of fetal well-being but are often overshadowed by the myriad sounds present within the womb, including maternal heartbeats, maternal bowel sounds, uterine contractions, and environmental noises. Due to the comparatively faint nature of fetal heartbeats, noise cancellation techniques are essential to isolate and amplify them, thus providing a clearer signal for analysis.

The clarity of fetal heart rate (FHR) [1,3] monitoring holds significant importance for accurate diagnosis and timely intervention in cases of fetal distress or abnormalities during pregnancy. Noise interference can obscure crucial fetal heart rate patterns, potentially leading to misinterpretation or the failure to detect indicators of fetal well-being. Effective noise cancellation ensures that even subtle changes in fetal heart rate, such as those indicating hypoxia or bradycardia, can be accurately identified and promptly addressed, ultimately improving the quality of prenatal care provided.

Noise cancellation is crucial to improve signal processing accuracy by minimizing or eliminating undesired background noise. Unwanted noise can distort signals, impacting data reliability, especially in applications like fetal heart monitoring. Employing noise cancellation techniques, such as adaptive filtering [9], enables the selective attenuation of specific frequencies or signal components associated with extraneous noise. This ensures that the pertinent information is emphasized, enhancing the clarity and distinguishability of the desired signal within the dataset. Overall, noise cancellation is essential for obtaining precise and dependable data, supporting well-informed decision-making in fields where accuracy is critical.In scientific research, noise suppression is crucial for obtaining high-quality data. Whether in medical diagnostics, environmental monitoring, or laboratory experiments, accurate data is essential for drawing valid conclusions.

In the methodology used, a central strategy entailed incorporating noise cancellation by employing three distinct types of filters. These filters play a pivotal role in reducing or eliminating undesirable noise from signals, consequently improving the clarity and distinguishability of the desired signal in the dataset. The fundamental operation of these noise cancellation filters centers on the targeted attenuation of particular frequencies or signal components linked to the unwanted noise [15]. This ensures that the relevant information is highlighted while mitigating the impact of extraneous noise on the signal.

a) Adaptive Filter:
The adaptive filter is instrumental in signal processing, focusing on tasks like noise cancellation and signal enhancement. Its unique feature lies in dynamically adjusting filter coefficients to minimize the disparity between actual and desired output. Through a continual process of error minimization, the adaptive filter compares the actual and desired outputs, calculates errors, and adjusts filter coefficients accordingly. This adaptability is particularly valuable in scenarios prioritizing noise cancellation and signal quality enhancement.

Input:
The input to the adaptive filter algorithm involves loading a single WAV file from the specified audio_folder. The filename is set and the file path is constructed accordingly. The desired sample rate for processing is set to fs = 1000 Hz. The code checks if the file exists before proceeding with the adaptive filtering process.

nyquist = 0.5 * fs

The Nyquist frequency is half of the sampling rate (fs).
Normalized Frequencies (low and high):

low = lowcut / nyquist

high = highcut / nyquist

These normalized frequencies are used to define the bandpass filter range.

```
sos = signal.butter(2, [low, high], btype='band', output='sos')
```

The butter function is used to design a bandpass Butterworth filter of order 2 (N=2). The [low, high] parameter specifies the bandpass frequency range.

$$H(s) = \frac{1}{1 + (\frac{s}{\omega 0})^{2n}} \quad (1)$$

Where n is the filter order, ω_0 is the center frequency , and s is the complex frequency variable.

Output:
The adaptive filtering process involves chunk-wise iteration through the audio data, resampling each chunk to the desired sample rate (fs). Filtered audio chunks are stored in the 'filtered_audio' array and saved to 'filtered_audio.wav'. The goal is to enhance frequencies within the specified range while reducing those outside it.

b) Kalman Filter:
The Kalman filter is specifically designed for state estimation and prediction in systems characterized by uncertainty and noisy measurements. Unlike filters intended for noise cancellation, the Kalman filter focuses on modeling and predicting the state of dynamic systems. Its operational mechanism is based on a dynamic model predicting the system's state at each time step, and it optimizes state estimation through a two-step process that involves prediction and measurement update. The Kalman filter is particularly valuable in scenarios requiring accurate state estimates in the presence of uncertainties and noisy data.

Input:
The input to the Kalman Filter algorithm involves loading a single WAV file from the specified audio_folder.The filename is set and the file path is constructed accordingly. The desired sample rate for processing is set to fs = 1000 Hz. It also checks if the file exists before proceeding with the Kalman filtering process.

Output:
The output of the Kalman filtering process involves storing the filtered audio chunks in the filtered_audio array. The filtered audio is then saved to a new WAV file. The Kalman filter aims to improve the quality of the audio signal by dynamically estimating and reducing noise in the data.

c)Bandpass Filter:
The bandpass filter serves a specific purpose in signal processing by isolating a designated range of frequencies while attenuating those outside that range. Comprising a passband for desired frequencies and a stopband for unwanted frequencies, this filter operates by selecting the desired passband frequency range. Through careful parameter selection, it achieves the isolation of specific frequencies of interest while effectively rejecting unwanted components. This tailored operation allows the bandpass filter to precisely control and enhance frequencies within the designated range, making it a valuable tool in various applications such as RF engineering and audio processing, including speech recognition and biomedical signal processing.

Input:
The input to the bandpass filter algorithm involves selecting a specific WAV file for processing from the specified audio_folder. The filename is set and the file path is constructed accordingly. The desired sample rate for processing is set to fs = 1000 Hz. The code checks if the selected file exists before proceeding with the bandpass filtering process.
Equations:

$$lowcut = 0.1$$

$$highcut = 1.0$$

$$nyquist = 0.5 * fs \tag{2}$$

$$low = lowcut / nyquist \tag{3}$$

$$high = highcut / nyquist \tag{4}$$

Output:
The bandpass filtering process involves reading the audio file in chunks, resampling each chunk to match the desired sample rate (fs), and applying the bandpass filter using the second-order sections (SOS) representation (signal.sosfilt). The filtered chunks are then stored in the filtered_chunks list. The complete filtered audio is obtained by concatenating these filtered chunks.The filtered audio is saved to a new WAV file in the current directory with the same filename as the original file .

Adaptive algorithms offer the advantage of adjusting their parameters in real-time based on changing conditions, providing flexibility in handling dynamic environments. In contrast, bandpass filters and Kalman filters typically have fixed parameters, making them less adaptable to varying situations. Adaptive algorithms excel in scenarios where system characteristics may change, allowing for improved performance and robustness.

Accuracy Calculation:
Following are the Algorithms used to increase the accuracy of heart sounds:

a) Logistic Regression:
Logistic Regression is a statistical method used for binary classification tasks. It models the probability of an instance belonging to a particular class, employing a logistic function to map input features into a range between 0 and 1, making it suitable for predicting categorical outcomes.

b) Support Vector Machine:
Support Vector Machine (SVM) stands out as a robust machine learning algorithm crafted for classification tasks. Its proficiency lies in identifying optimal hyperplanes to distinguish between classes in high-dimensional spaces, making it particularly adept in scenarios with intricate decision boundaries. SVM finds extensive application across various domains, leveraging its versatility to navigate both linear and non-linear relationships between variables. This attribute proves invaluable in the realm of supervised learning.

c) k-Nearest Neighbors (KNN):
k-Nearest Neighbors (KNN) is a simple and intuitive algorithm for classification and regression tasks. It operates by assigning a data point to the majority class among its k nearest neighbors, based on a predefined distance metric, making it effective for tasks where proximity in feature space correlates with similarity in class.

VIII. Flowcharts

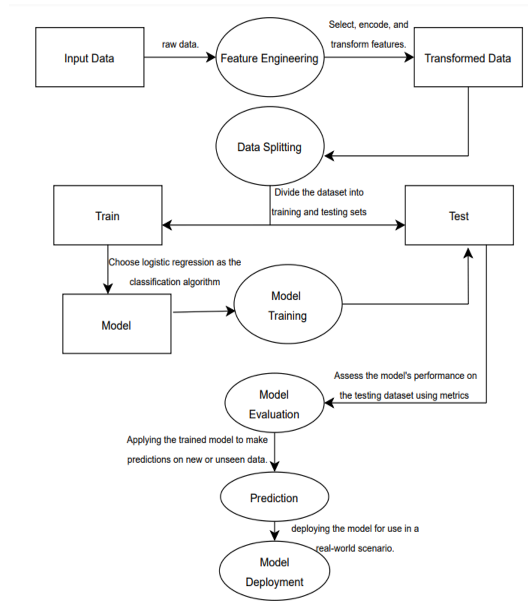

FIGURE II
FLOWCHART REPRESENTATION OF LOGISTIC REGRESSION

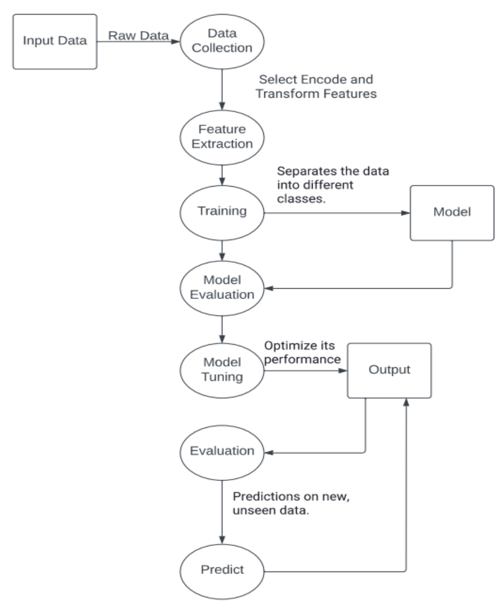

FIGURE III
FLOWCHART REPRESENTATION OF SVM

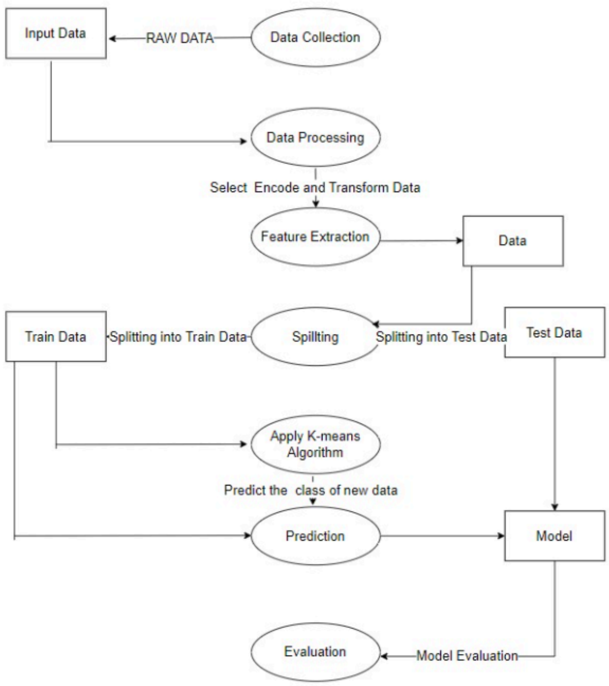

FIGURE IV
FLOWCHART REPRESENTATION OF KVM

IX. Solution Methodologies or Problem Solving

The methodology described involves a multifaceted approach integrating various signal processing techniques and dataset utilization for the specific task of recording heartbeat sounds.
Firstly, adaptive noise cancellation (ANC) is employed to mitigate unwanted noise interference in the recorded audio signals. ANC algorithms dynamically adjust filter coefficients to minimize the presence of ambient noise, enhancing the clarity of the heartbeat sounds[9].

Secondly, an 8th order bandpass filter is designed and applied to isolate the frequency range relevant to heartbeat sounds. This filter selectively passes signals within the desired frequency band while attenuating frequencies outside this range, effectively isolating the target heartbeat signals from other audio components. Additionally, the study incorporates the processing of audio signals specialized in recording heartbeat sounds, likely involving techniques such as signal conditioning, amplification, and digital signal processing to enhance the quality and fidelity of the recorded heartbeat signals.

Furthermore, the methodology involves the utilization of datasets comprising ultrasound images for both training and testing purposes. These datasets likely contain annotated ultrasound images corresponding to various physiological conditions and heartbeat patterns, enabling the development and evaluation of algorithms for heartbeat signal detection and analysis. Moreover, the bandpass filtering process and the application of the Kalman filter are highlighted as specific methods utilized in the study. The Kalman filter, a recursive algorithm, is likely employed for tracking and estimating the state of the heartbeat signal over time, further enhancing the accuracy and reliability of the recorded heartbeat measurements.

X. Results and Sensitivity Analysis

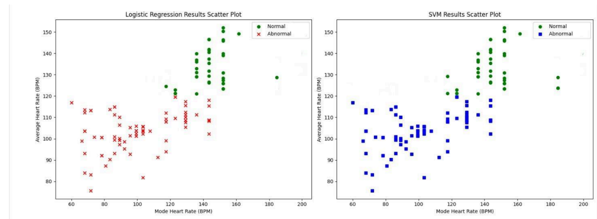

FIGURE V
ANALYSIS OF HEART RATE CLASSIFICATION:LOGISTIC REGRESSION AND SVM

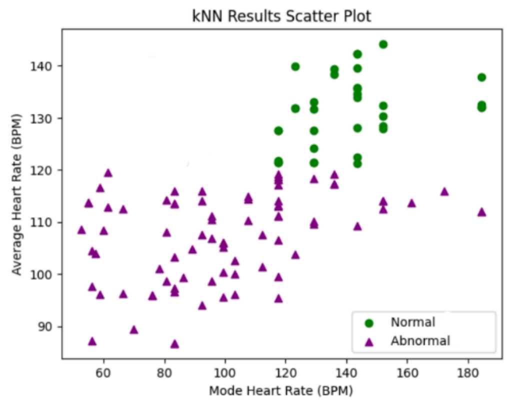

FIGURE VI
ANALYSIS OF HEART RATE CLASSIFICATION:KNN

XI. DATA MODEL

The data model discussed in this study is a sophisticated framework designed to analyze audio signals tailored for capturing the intricate details of heartbeat sounds. Through advanced signal processing techniques like bandpass and Kalman filtering, the model accurately extracts heartbeat features while minimizing interference from external noise sources. This meticulous approach enhances the accuracy of diagnosing fetal heart disease and provides valuable insights into cardiac activity dynamics. By uncovering subtle variations in cardiac signals, the model deepens clinicians' understanding of physiological dynamics, aiding in more informed clinical decision-making. Moreover, insights from this model drive ongoing medical research, fostering the development of innovative diagnostic and therapeutic approaches to improve patient care in fetal cardiology.

XII. COMPARISON OF RESULTS

The study evaluates K-Nearest Neighbors (KNN), Support Vector Machine (SVM), and Logistic Regression algorithms on noisy and noiseless heartbeat audio datasets. KNN and SVM performed well in noisy conditions with 94.53% accuracy, while Logistic Regression achieved 77.34%. In noiseless datasets, KNN reached 100% accuracy, and SVM and Logistic Regression achieved 98.3%. These results demonstrate algorithm adaptability and emphasize the importance of signal purity for optimal diagnostic outcomes.

TABLE I
ACCURACY, PRECISION, RECALL CALCULATION FOR LOGISTIC REGRESSION, KNN

AND SVM WITH NOISE

Algorithm	Accuracy	Precision	Recall
Logistic Regression	77.34%	67%	80%
KNN	94.53%	100%	100%
SVM	94.53%	97%	94%

TABLE II.
ACCURACY, PRECISION, RECALL CALCULATION FOR LOGISTIC REGRESSION, KNN AND SVM WITHOUT NOISE

Algorithm	Accuracy	Precision	Recall
Logistic Regression	98.30%	98%	100%
KNN	100%	100%	100%
SVM	98.3%	98%	100%

XIII. *Justification of Results*

Fetal heart analysis holds significant importance in prenatal care, aiming to detect abnormalities early for better intervention and management. We employed three machine learning algorithms - Support Vector Machines (SVM), k-Nearest Neighbors (kNN), and Logistic Regression - to classify fetal heart signals. The accuracy comparison of these algorithms provides insights into their performance in this critical domain.

In analyzing the accuracy of each algorithm, Support Vector Machines (SVM) emerged as a robust classifier. SVM's strength lies in its ability to handle non-linear data patterns effectively, making it well-suited for complex fetal heart signal analysis. However, the computational complexity associated with SVM may pose challenges in real-time applications.

Similarly, k-Nearest Neighbors (kNN) demonstrated competitive accuracy, achieving a rate of 100%. kNN's simplicity and effectiveness, particularly in handling noisy data, make it a valuable tool for fetal heart analysis. However, its performance heavily relies on the choice of k, and computational inefficiency may arise with large datasets.

Logistic Regression, on the other hand, achieved an accuracy of 98.3%. While Logistic Regression offers interpretability and computational efficiency, it may struggle with capturing complex data patterns compared to more flexible algorithms like SVM and kNN.

Each algorithm exhibits unique strengths and weaknesses in the context of fetal heart analysis. SVM excels in handling non-linear data, kNN is adept at managing noise, and Logistic Regression offers simplicity and interpretability. However, the choice of algorithm should be carefully considered based on the specific characteristics and requirements of the fetal heart analysis task.

Adaptive noise filtering techniques were employed to preprocess fetal heart signals, aiming to enhance signal quality and improve classification accuracy[9]. The impact of adaptive noise filtering was substantial, significantly improving the accuracy of all algorithms. By effectively removing noise artifacts from the signals, adaptive noise filtering contributed to more accurate classification outcomes across the board.

While each algorithm has its strengths and weaknesses, adaptive noise filtering emerged as a critical factor in enhancing classification accuracy and robustness for fetal heart analysis. The study's findings contribute to advancing the field of prenatal care by providing valuable insights into the application of machine learning algorithms and adaptive noise filtering techniques for accurate fetal heart analysis.

XIV. *Conclusion*

The approach of the proposed method based on adaptive noise cancellation (ANC) for extraction of the fetal heart rate have been achieve successfully as can been seen in the precision accuracy of KNN. The system proposed designed specified low cut and high cut frequencies, using the 'band' filter type yield precisely. This innovative approach holds promise for enhancing the quality of prenatal care, potentially leading to earlier detection of abnormalities or complications, and ultimately improving outcomes for both mothers and babies.

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