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

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

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***Abstract*—The traditional cardiotocography (CTG) test Although known as a noninvasive method for fetal heart rate (FHR) monitoring, may not be useful in risky pregnancies where continuous and long-term monitoring is needed, ultrasound waves can be harmful for the fetus. Phonocardiography may be successfully applied for long-term fetal measurement. It is recorded by means of a sensor placed on the mother's abdominal.In PCG signal recordings, a significant challenge arises from the interference of surrounding noisy signals, which corrupts the data. Corrupted signals are unsuitable for analysis and advanced processing. Thus, it is imperative to eliminate interference from these signals before employing them for further analysis and processing.The aim of this inquiry was to introduce a methodology grounded in adaptive noise cancellation or ANC for extracting the heart rate of fetuses. The proposed filtering system involves passing a noisy signal through a multistage cascaded adaptive filter, with automatic adjustments made to the number of stages and the step size for each stage. This system is designed to implement an 8th order bandpass filter with specified low cut and high cut frequencies, utilizing the 'band' filter type. The output is in the form of SOS coefficients, which can be used to implement the filter. After exhaustive research it was observed that the performance of the proposed system is comparatively better.**

Index Terms*—Fetal Heart Rate (FHR), Phonocardiography (PCG), Cardiotocography (CTG), Adaptive Noise Cancellation (ANC), Second-Order Sections (SOS) Coefficients.

I. Introduction

The range for the Fetal Heart Rate (FHR) spans from 110 to 160 beats per minute, while its variability falls between 6 to 25 beats per minute. This regular baseline, coupled with its variability, stems from the harmonious functioning of a robust central and autonomic nervous system. Due to substantial developmental shifts in the nervous system, it is not advisable to rely on FHR measurements until after the 20th week of gestation, at which juncture monitoring becomes more precise and dependable.

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. Heart disease is one such condition that requires timely identification for effective medical intervention.

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 fusion of Artificial Intelligence or 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 or AI to enhance the detection of heart disease in fetuses. 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. Through this innovative approach, early intervention and personalized treatment plans can be tailored to individual patients, fostering improved healthcare outcomes.
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

Ref	Approach Used	Technology Used	Result obtained	Comparison Done
[1]	Proposes a compact, affordable device for multi-lead fetal heart rate (fHR).Integrates a specialized probe for PCG data recording, machine learning techniques.	The paper uses The manuscript employs a compact apparatus for multi-lead fetal heart rate (fHR) measurement, leveraging LabVIEW for signal processing. Additionally, it utilizes the electret microphone model PUM-5250L-R for its sensitivity, and incorporates signal amplifiers to mitigate noise interference	The results show that the average estimated fetal heart rate (fHR) aligns with the reference range (120-150 bpm) obtained from a CTG device.	Compares diagnostic techniques for fetal heart rate emphasizing the challenges and of fetal Phonocardiography compared to other methods. It highlights the scarcity of real data for testing purposes.
[2]	Introduces a wearable fetal ECG monitoring system with wireless connectivity and real-time data display for clinical diagnosis.	Includes the development of wireless wearable fetal ECG monitoring system, laminated packaging technology, and wireless transmission of data through Bluetooth.	The wireless ECG system accurately detects fetal and maternal heart rates ensuring safety and effectiveness for over 6 hours .	Compares the developed wireless FECG monitoring system with a Philips fetal monitor, showing good consistency and effectiveness in detecting maternal and fetal heart rates in 100 participants.
[3]	Meta-heuristic techniques for feature selection, a thorough literature review to understand detection models, and the use of random forest as the finest method for FHD detection.	Various techniques including meta-heuristics, deep learning, RNN, AI, Enhanced Deep Learning Assisted CNN, Server-based Remote Diagnostic, FAUNA, Extreme Learning Machine, NVG-RAM, and signal processing.	The random forest method achieved the highest precision of 97.6285% in detecting Fetal Heart Disease (FHD). Limitations were noted regarding sample quantity and dataset.	Compares techniques, highlighting Random Forest's 97.2% accuracy and its superiority in Fetal Heart Disease (FHD) analysis, with a precision of 97.6285%.

[4]	Investigates image processing effects on identifying fetal heart key frames with CNN, algorithm for cropping and evaluating pre-trained architectures on datasets.	ResNet18 and ResNet50 CNN architectures, utilizing 1 cycle policy, fast ai, PyTorch libraries, and Google Colab with Tesla T4 GPU. Inference time per frame is around 0.2 seconds.	Impact of pre-processing on model performance in medical imaging, highlighting a small decrease in accuracy for cropped variants compared to original images.	Compares ResNet18 and ResNet50 on different datasets, assessing pre-processing effects on labeling error rates and validation/test outcomes.
[5]	The authors used a systematic approach to review and select studies based on CHD prevalence in specific populations, classified CHD into phenotypic categories, and assessed lesion severity based on a modified classification.	Echocardiography	The comparison was made between the findings of the present study and a previous meta-analysis by van der Linde et al. in 2010, showing an increase in the number of studies and births included in the current study for a more comprehensive analysis.	The birth prevalence of congenital heart disease (CHD) globally increased over the years, reaching a peak in the period 2010-17, mainly due to improved postnatal detection of mild CHD lesions. There is a notable disparity in CHD prevalence among different geographical regions, with Africa reporting the lowest prevalence and Asia reporting the highest.
[6]	An extended cardiac assessment is conducted using transvaginal and transabdominal ultrasound techniques between the 11th and 13th weeks plus 6 days of gestation.	Four-dimensional (STIC) volumes are utilized for the comprehensive analysis of fetal cardiac structures.	Identifying congenital heart defects during the 11th to 13th weeks plus 6 days of gestation is achieved through the utilization of STIC volumes, facilitating the successful detection of cardiac anomalies.	Fetal heart assessment methods and factors, including ultrasound efficacy in detecting congenital heart defects.
[7]	Develops an AI-based Decision Support System for analyzing ultrasound data to accurately detect key	It involves processing key planes identified by sonographers, grouping frames into classes, testing deep-learning algorithms, and	Develops an IS to aid early sonographers in accurately detecting first-trimester cardiac key-planes and improving CHD diagnosis.	The paper compares model performance on videos from inexperienced vs. expert sonographers, validating frames by physicians and verifying differences in results.

	cardiac planes in the first trimester.	validating findings at the frame level.		
[8]	DGACNN enhances FHD recognition accuracy for early screenings, achieving state-of-the-art results and facilitating small data analysis through video transfer learning.	Generative Adversarial Network (GAN), specifically WGAN-GP, and Convolutional Neural Network (CNN)	DGACNN achieved an 85% FHD recognition rate, surpassing expert cardiologists, with state-of-the-art accuracy.	The paper conducted a comparison between the performance of the proposed DGACNN network and expert cardiologists in recognizing Fetal Heart Defects (FHD). The DGACNN network achieved a recognition rate of 84% in the test, showcasing its effectiveness in this domain.
[9].	Extraction of fetal PCG signals from maternal PCG signals using an adaptive filter and a fiber-optic sensor with algorithms for ongoing heart rate observation.	A new fiber-optic sensor based on phonocardiography system utilizing two Mach-Zehnder interferometric sensors for heart rate of fetuses monitoring that is non-invasive and ongoing.	Presents a system for continuous non-invasive monitoring of the fetal heart rate using sensors utilizing fiber optics and adaptive signal processing algorithms, evaluated with synthetic data.	The paper compares different fetal monitoring methods, highlighting the advantages and disadvantages of each approach, while also discussing the performance of the algorithms for LMS and NLMS in terms of various metrics.
[10]	Continuous monitoring of fetal heart rate correlating fetal heart rate patterns with fetal pH values.	Not mentioned	Distinct FHR deceleration patterns are linked with disruptions in acid-base balance. tachycardia associated with pH values above 7.25.	FHR patterns vs. fetal pH values, specific FHR patterns and disturbances in acid-base balance.
[11]	Evaluation and proposal of modern electronic techniques for monitoring fetal distress during labor.	Modern electronic techniques for monitoring fetal heart rate during labor	Not mentioned	FHR during contractions in normal breech presentations and vertex presentations, comparison of FHR patterns in primigravidas.
[12]	Enhanced technique for matching baselines to fetal heart rate	Doppler ultrasonography to capture heart rate data.	Temporal patterns of fluctuations, quickenings,	FHR patterns from normal pregnancy versus mildly hypertensive

	recordings in humans,use of Doppler ultrasound to assess normality in pregnancies.		and slowing down in fetal heart-rate traces.	pregnancy,focusing on episodic variations, accelerations, decelerations.
[13]	Longitudinal observational study analyzing characteristics of fetal heart rate, focusing on differences between gestational age.	Not mentioned	Significant decrease in baseline heart rate as gestation advanced, changes in heart rate variability, short episodes of bradycardia and tachycardia.	FHR during quiet and active intervals, comparison between different gestational ages, frequency and magnitude of accelerations and decelerations, changes in baseline variability with gestation.
[14]	Application of numerical method for separating frequency components of fetal heart rate.	Utilizing ultrasound records alongside numerical methodologies for the segregation of frequency components pertaining to heart rate of fetuses.	The investigation of heart rate of fetuses parameters and their prevalence across various gestational stages, along with the duration and variability of low variation episodes.	Fetal heart rate variables at different gestational ages, variations in heart rate before and after the completion of 35 weeks of gestation, the duration and variability of low variation episodes are examined, while after 36 weeks of gestation, their length and variation are further scrutinized.
[15]	The methodology employed encompasses a three-stage process for detecting fetal heart rate from abdominal ECG recordings, comprising preprocessing, adaptive noise cancellation (ANC) for fetal ECG extraction, and a window for removing maternal QRS complexes.	Adaptive noise cancellation (ANC) and independent component analysis (ICA)	The ANC based method achieved an average sensitivity of 85.8% and an average positive predictivity of 67.6%, outperforming the ICA based method in detecting the fetal heart rate.	The comparison is between the new method employing adaptive noise cancellation (ANC) and an alternative three-stage technique leveraging independent component analysis (ICA) for fetal ECG extraction.

[1] 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]This paper delves into the creation of a versatile, wearable wireless fetal ECG monitoring system designed to precisely detect 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] 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] Examining the influence of image pre-processing on the classification of first-trimester fetal heart ultrasound, this study endeavors to evaluate whether pre-processing influences the model's capacity to differentiate between critical perspectives and extraneous frames.

[5] 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] 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]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]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]The study introduces an adaptive signal processing framework proficient in extracting fetal heart rate data from top-tier fetal phonocardiograms. These are discerned from maternal abdominal phonocardiograms through the execution of fetal phonocardiogram signal peak detection.

[10]Specific fetal heart rate deceleration patterns are linked with disturbances in acid-base balance during labor.

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

[12]Periods of significant heart rate fluctuation that last ten minutes starting around 28 weeks are suggested as a potential numerical index of normality in fetal heart rate patterns.

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

[14]Cyclic episodes of little and significant variance in heart rate of fetuses can be identified from 27 weeks onwards.

[15]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 support the creation of more dependable and efficient methods for diagnosing fetal heart disease, ultimately improving outcomes for infants and their families.

V. 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 or ANC techniques[9] to extract heart rate in fetuses 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 begins with the use of an audio signal specialized in recording the sounds of a heartbeat. This audio signal undergoes careful processing to extract essential data linked to the heartbeat. Through the application of signal processing techniques, algorithms for filtering are employed during the extraction phase.

Machine Learning Model Implementation:

a. Split the dataset for model training, into a training set (70%) and a testing set (30%) and evaluation.
b. Encode the target variable (heart rate classification) into binary form (0 for "Normal" and 1 for "Abnormal").
c. Use mode BPM and average BPM as input features for the logistic regression model.
d. Apply feature scaling or normalization to ensure that input features (mode BPM and average BPM) have similar scales and do not unduly influence the model.

Model Evaluation:

a. Assess model performance measured by F1-score, recall, accuracy, and precision.
b. Visualize classification results with scatter plots to interpret the model's effectiveness in distinguishing heart rate categories.

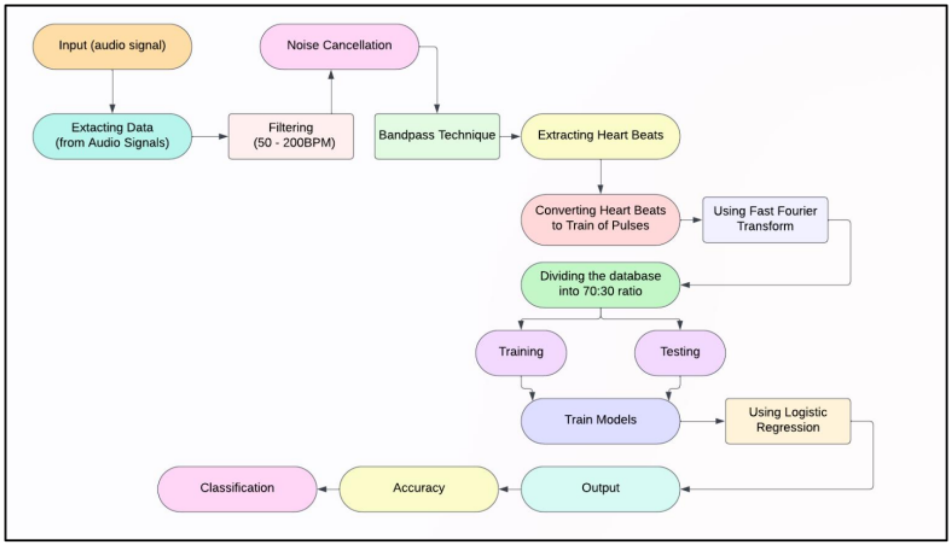

Figure 1. Modular Diagram

The diagram illustrates the process of determining the accuracy of fetal heart rate measurements extracted from audio signals. The process begins with the input of an audio signal, typically acquired through an ultrasound device. Subsequent steps include extracting relevant data, canceling noise, and filtering the signal to focus on the frequency range of fetal heartbeats (50-200 BPM). During the analysis, heartbeats between 120 to 160 beats per minute are considered normal, while heart rates outside this range are classified as abnormal. The signal is then refined using a bandpass technique and classification methods to isolate the fetal heart rate. The accuracy of the extracted data is assessed, either by comparison to a reference method or by evaluating the consistency and reliability of the measurements. The heartbeats are converted into a series of discrete pulses, and the dataset is separated into sets for testing and training.A machine learning model is trained using the training dataset and then tested on the remaining 30% to evaluate its performance. Fast Fourier Transform (FFT) and Logistic Regression techniques might be employed during this process to convert the signal into the frequency domain and distinguish between fetal heartbeats and other sounds or noise in the audio signal.

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. The results conclusively demonstrated that the adaptive filter outperformed the other two filters, establishing its superiority in the given context.

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.

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

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:

$$\text{lowcut} = 0.1$$

$$\text{highcut} = 1.0$$

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

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

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

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:
One statistical technique is logistic regression employed in binary classification tasks. It simulates the likelihood of an occurrence belonging to a particular class, employing a logistic function for feature mapping in input into a range from 0 to 1 ,making it suitable for predicting categorical outcomes.

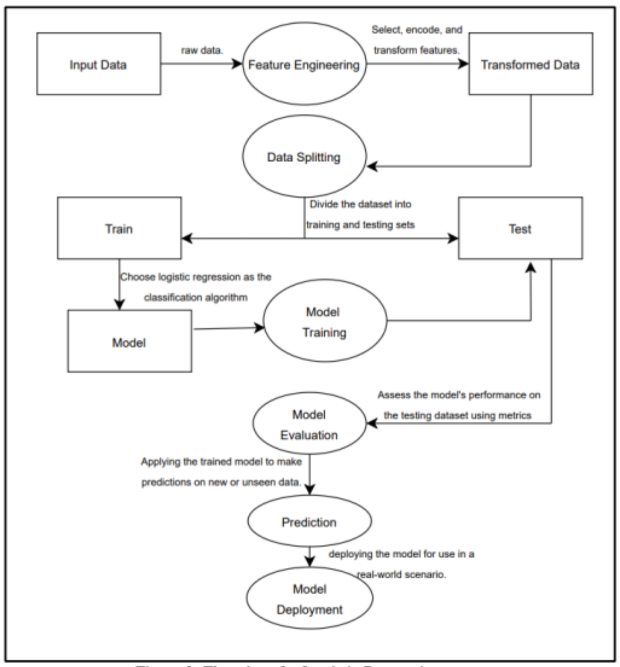

Figure 2. Flowchart for Logistic Regression

b) Support Vector Machine:

SVM, or support vector machine is a powerful machine learning algorithm specifically designed for classification jobs.. 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.

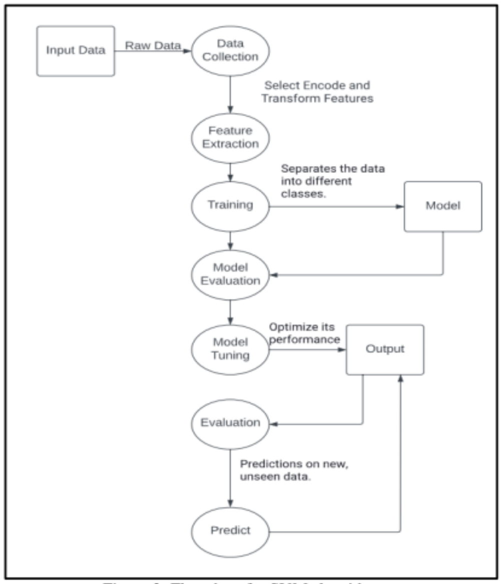

Figure 3. Flowchart for SVM algorithm

c) k-Nearest Neighbors (KNN):

The k-Nearest Neighbors or KNN technique is a straightforward and easily understandable method for both regression and classification applications.. 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.

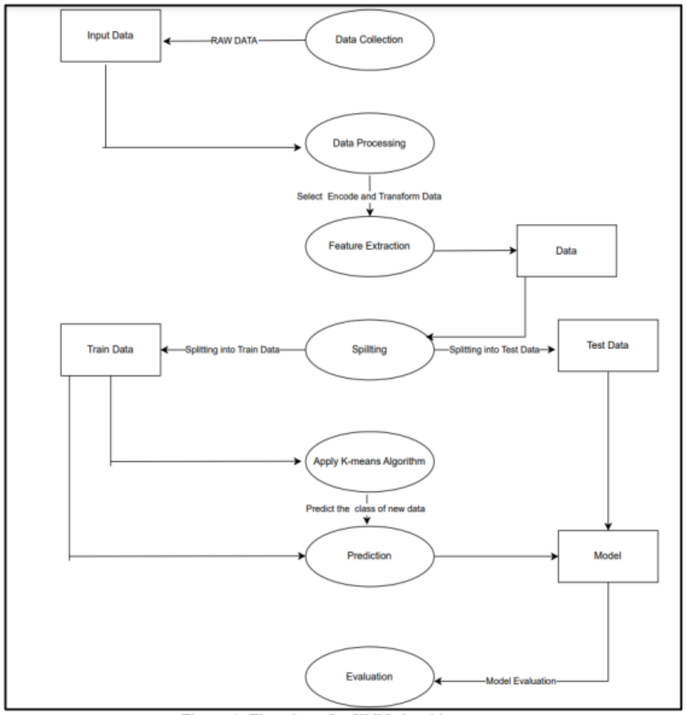

Figure 4. Flowchart for KNN algorithm

VIII. 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.

IX. Results and Sensitivity Analysis

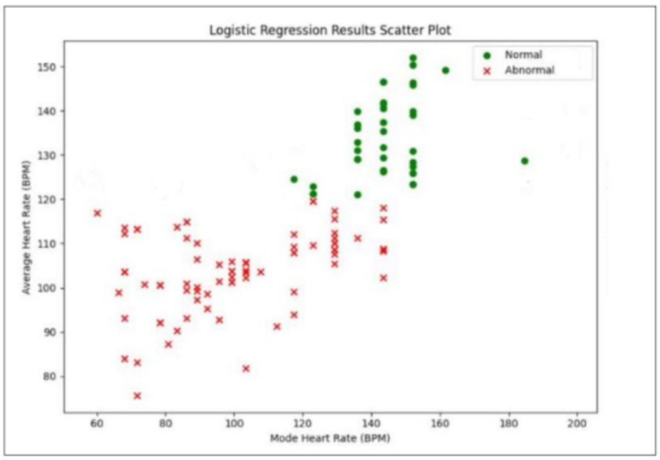

Figure 5. Scatter Plot for Logistic Regression

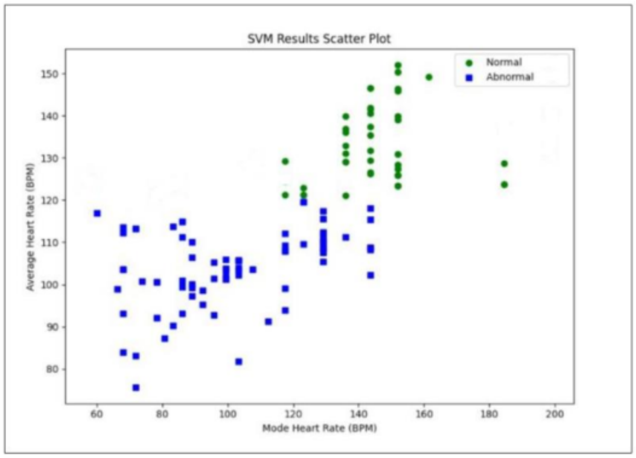

Figure 6. Scatter Plot for SVM algorithm

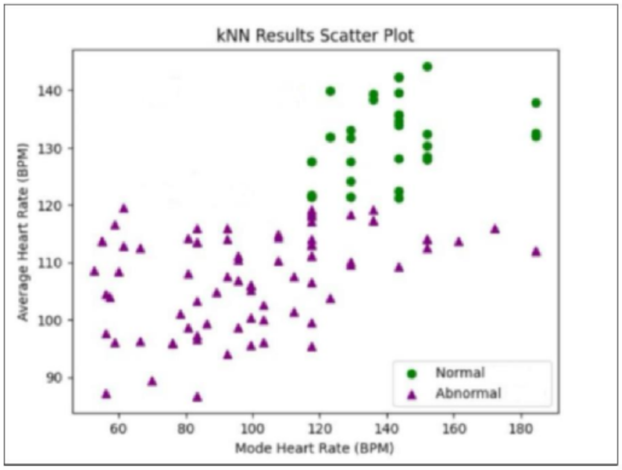

Figure 7. Scatter Plot for KNN algorithm

X. 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.

XI. COMPARISON OF RESULTS

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This section extensively evaluates the performance of three classification algorithms -K-Nearest Neighbors, or KNN, Support Vector Machine, or SVM, and Logistic Regression - on both noisy and noiseless audio datasets capturing heartbeat sounds. The study meticulously examines the adaptability of these algorithms to varying audio conditions, emphasizing their ability to effectively classify heartbeat signals amidst background noise. Furthermore, the section highlights noteworthy improvements in classification accuracy when the algorithms operate on noiseless datasets, underscoring the pivotal role of signal purity in optimizing diagnostic outcomes. Through this comparative analysis, [Author] provides valuable insights into the robustness and efficacy of different classification approaches in the context of heartbeat signal processing.

In the comparative analysis, we assessed the accuracy of three classification algorithms—Logistic regression, support vector machines, or SVMs, and k-nearest neighbors, or KNN—applied to both noisy and noiseless audio datasets capturing heartbeat sounds. For the challenging task of discerning heartbeats from noisy audio signals, KNN and SVM showcased robust performance, achieving a high accuracy of 94.53%, while Logistic Regression demonstrated commendable results at 77.34%. In contrast, when dealing with noiseless heartbeats, the algorithms displayed even more impressive accuracy levels. KNN achieved a perfect accuracy of 100%, while both SVM and Logistic Regression reached an accuracy of 98.3%. This comprehensive evaluation underscores the algorithms' adaptability to varying audio conditions and highlights the significant improvements in accuracy when working with pristine, noise-free signals. Such findings contribute to the understanding of these algorithms' efficacy in real-world scenarios and emphasize the potential for accurate heartbeat analysis across diverse applications

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

With Noise:

TABLE I. ACCURACY, PRECISION, RECALL CALCULATION FOR LOGISTIC REGRESSION, KNN AND SVM WITH NOISE

Without Noise:

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

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

XII. JUSTIFICATION OF RESULTS

Fetal heart analysis holds significant importance in prenatal care, aiming to detect abnormalities early for better intervention and management. We employedthree machine learning algorithms: logistic regression, k-nearest neighbors, or kNN, and support vector machines, or SVM - 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 or 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 or 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.

XIII. *Conclusion*

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The approach of the proposed method based on the extraction of the fetal heart rate using adaptive noise cancellation (ANC) 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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