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The Implicit Threats: Detecting Fetal Arrhythmia Exploiting ECG Signals

Sudeep Kumar Shah¹, Harish Yadav², Gagandeep Singh Sandhu³, Abhishek Kumar Shah⁴, Dr. I Ambika⁵

U.G. Student, Department of CSE(DS), Jain (Deemed-To-Be) University, Bangalore, India¹⁻⁴

Associate Professor, Department of CSE(DS), Jain (Deemed-To-Be) University, Bangalore, India⁵

ABSTRACT: This paper proposes a deep learning-based method for detecting fetal arrhythmia using fetal electrocardiogram (FECG) signals. Inspired by successful arrhythmia detection in adult ECG signals, the approach involves segmenting FECG signals and classifying them as normal or arrhythmic. Training the model with categorized segments improves classification accuracy, minimizing the impact of heartbeat detection errors. The study utilizes the MIT-BIH dataset, employing diverse machine-learning algorithms to capture complex patterns in fetal ECG signals. The proposed methodology represents a significant advancement in perinatal medicine, contributing to enhanced prenatal care through the integration of advanced technology for timely fetal arrhythmia detection.

KEYWORDS : ECG, Machine learning, Fetal, Heart, Heart Rate

I. INTRODUCTION

This study emphasizes the critical importance of fetal heart rate (FHR) in assessing fetal health, particularly during the vulnerable prenatal and postpartum periods. Fetal arrhythmia, a potential cause of unexpected infant death, motivates the exploration of accurate detection techniques. Various fetal biological signals, including non-invasive fetal electrocardiogram (FECG), are employed for this purpose, with FECG being cost-effective and widely utilized. Traditional approaches rely on heartbeat detection, but accuracy issues arise due to external disturbances. The project's core involves extracting key features from FECG signals, focusing on markers like R, P, Q, S, T peaks, and interval durations. Signal preprocessing and dimensionality reduction, notably Principal Component Analysis (PCA), enhance data quality for ML models. Logistic Regression(LR), Linear Discriminant Analysis(LDA), K Nearest Neighbors, Decision Trees, Naive Bayes, and Support Vector Machines are evaluated for precision in classifying healthy and arrhythmic fetal conditions. Visualizations aid in illustrating feature distributions, correlations, and the impact of dimensionality reduction, with the overarching goal of contributing a reliable, non-invasive methodology for early fetal arrhythmia detection and improved prenatal care.

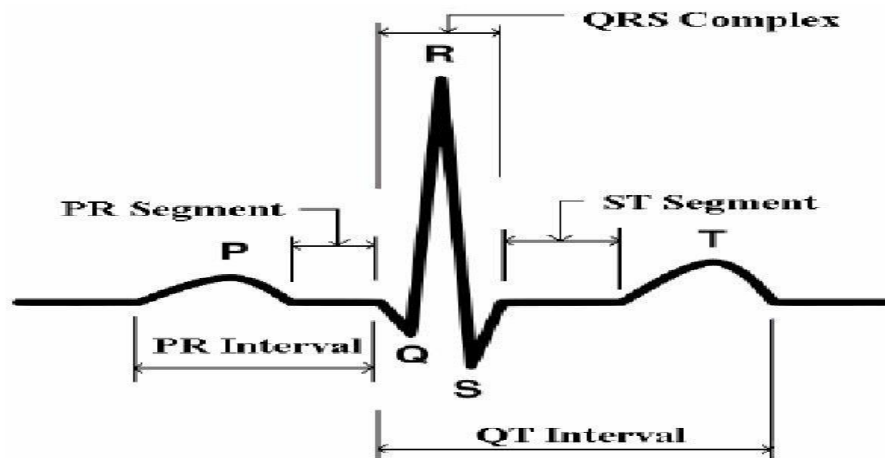


Fig.1: ECG

II. II. RELATED WORK

Pavel and colleagues[1] developed a systematic approach for identifying fetal arrhythmia by creating an algorithm to extract features from the fetal ECG signal. They identified eight key features which were then analyzed using a Kernel Support Vector Machine (SVM) classifier, employing a Gaussian Kernel for the detection of fetal arrhythmia. To assess the effectiveness of their model, they applied leave one out (LOO) cross-validation, which yielded a detection accuracy of 83.33 percent, with a specificity of 91.67 percent and a sensitivity of 75 percent. Their study demonstrates the feasibility of a novel, non-invasive, and cost-effective method for diagnosing fetal arrhythmia. Alfaras et al.[2] introduced a rapid and fully automatic ECG arrhythmia classification system leveraging a brain-inspired machine learning model called Echo State Networks. This system simplifies feature processing by needing only one ECG lead and follows an inter-patient training and validation method. It suits online classification, aligning with the latest developments in health-monitoring wearables and wireless devices. By employing ensemble methods, the system can train at high speeds through parallel processing. The classifier's performance was tested on two ECG databases, the MIT-BIH AR and the AHA, where it achieved high sensitivity and positive predictive values, demonstrating its competitiveness with or superiority to other automatic ECG classifiers, especially in handling ventricular ectopic beats. Apsana et al.[3] developed an innovative early detection algorithm for fetal arrhythmia using ECG analysis. They applied the Independent Component Analysis (ICA) for preprocessing and extracting fetal ECG signals and a peak detection algorithm with state-machine logic for feature extraction. The Naive Bayesian classifier was then used for classification. Their model, validated with data from the Physionet database, showed a promising accuracy of 93.71 percent, suggesting its potential for early fetal arrhythmia detection. Ganguly et al.[4] proposed creating an automated system for arrhythmia detection from fetal ECG data of female patients, utilizing 1D convolution for both filtering and feature extraction. While the current classifier showed a high accuracy rate of 96 percent, further improvements could be achieved by adding more layers to the neural network, albeit at a higher computational cost. This approach not only lowers computational demands but also fine-tunes the feature extraction process, making it suitable for embedded system applications. Kaviya et al.[5] tackled the problem of noise in ECG signals, such as muscle movement (electromyogram noise) and external interferences, including baseline wandering and powerline interference. They introduced a sophisticated ECG denoising method combining Adaptive Threshold Filter (ATF), Extended Kalman Filter (EKF), and Dynamic Time Wrapping (DTW) algorithm. This multifaceted approach efficiently removes noise through a four-step process, tested on signals from the MIT BIH arrhythmia database, demonstrating its effectiveness in enhancing ECG signal clarity. Mohebbian et al.[6] focused on the challenges of extracting non-invasive fetal electrocardiogram (FECG) signals from maternal ECG (MECG) signals, considering the low amplitude of FECG, R wave overlaps, and noise contamination. They criticized traditional decomposition methods for their complexity and introduced a novel approach using an architecture that combines an attention layer, sine activation function, and cycle generative adversarial neural network. This method, evaluated in terms of FECG extraction quality and fetal QRS detection, showcases a promising direction for efficiently mapping MECG to FECG despite the inherent challenges.

III. METHODOLOGY

The proposed methodology for fetal arrhythmia detection involves a comprehensive approach, beginning with the acquisition of fetal ECG data from reliable sources or databases. Subsequently, preprocessing techniques are applied to ensure data quality, including resampling, noise reduction, baseline correction, and normalization. Feature extraction becomes pivotal, identifying key components such as R-peaks, P-peaks, QRS complexes, QT intervals, and various heart rate-related metrics. Feature selection techniques are then employed to narrow down the most relevant features, often using statistical analyses or domain-specific knowledge to reduce computational complexity. The extracted data is then converted into a csv file and a model is trained based on ResNet for the detection of arrhythmia. The methodology aims to contribute a reliable and non-invasive methodology for fetal arrhythmia detection, potentially revolutionizing prenatal care by facilitating early detection and subsequent medical intervention.

A. Data Acquisition: We made advantage of the PhysioNet website's non-invasive fetal ECG arrhythmia database. A single maternal chest channel and four or five abdominal channels were utilized to record the non-invasive fetal electrocardiograms. There were 14 healthy Electrocardiogram records and 12 irregular rhythms in the list of records. 500 Hz or 1 kHz sampling rates were used for the signals.

B. Signal Processing: Loading ECG Data: Using wfdb to load the ECG data from the provided database. Resampling: Resampling the ECG signals to a standardized frequency of 300 Hz to ensure uniformity across different recordings. This is vital as various recordings might have different sampling rates, which could lead to inconsistency in analyses. Normalization Function: Employing min-max normalization (normalize function) to scale the ECG signals. This process scales the amplitude values between 0 and 1, ensuring that all signals are in a standardized range.

C. Feature Extraction: The properties of an ECG signal are largely determined by its time interval, amplitude, and segment length. The T wave, P wave, and QRS complex, known as fiducial points, are the main components of the cardiac cycle. The majority of data from a single heartbeat is contained within these segments. Accurately identifying the boundaries and pinpointing the peaks of these fiducial points is crucial for extracting the ECG signal's characteristics. ECG Signal Processing: The NeuroKit2 library is employed for detailed signal processing. Signal Cleaning: This step removes noise and artifacts from the ECG signals, resulting in a cleaned signal. R Peaks Detection: Detection of R peaks within the ECG signal using the nk.ecgpeaksfunction. Heart Rate Calculation: The heart rate is computed from the detected R peaks. ECG Delineation: Detection of different ECG waves-P, Q, S, and T peaks. Peak Indices Retrieval: Extraction of peak indices for P, Q, S, and T waves from the delineated features. Time-domain Feature Calculation: Extraction of timedomain features such as minimum, maximum, mean, and standard deviation of the cleaned signal. Feature List Creation: Compilation of extracted features into a list for further analysis and processing. Heartbeat Detection: The location of heartbeats is identified using the positions annotated in the databases. In the MIT-BIH AR database, annotations are marked at the peak of the QRS complex's largest local extrema. This study does not delve into beat detection, as there are already existing reports of highly precise automated methods for detecting beats. RR Calculation: The RR interval refers to the duration between consecutive heartbeats. Specifically, for a given heartbeat labeled as i , the RR interval, $RR(i)$, is the time difference between heartbeat i and the one before it, heartbeat $(i-1)$.

D. Peak Detection: The model employs NeuroKit2, a Python package for biosignal analysis, to detect peaks in the fetal ECG signals. 1. R-Peaks Detection: The R-peaks represent the highest point in the QRS complex, signifying ventricular depolarization. NeuroKit2's function identifies these R-peaks in the ECG signal. 2. P, Q, S, and T Peaks: The delineation function is utilized to locate other peaks in the ECG signal. This function precisely delineates the fiducial points in the ECG waveform, including P, Q, S, and T peaks, using algorithms for detecting these specific features. The process involves signal processing techniques such as filtering, differentiation, and thresholding to identify peaks accurately: - Filtering: The ECG signal might contain noise and artifacts. Signal preprocessing, like filtering, is performed to enhance the quality of the ECG signal, making it easier to detect peaks accurately. - Differentiation: Derivative-based methods are applied to detect steep changes in the signal, which often correspond to peaks. - Thresholding: Peaks are found by establishing limitations that decide when a signal reaches a particular amplitude, signifying the existence of a peak. In order to precisely recognize the various peaks in the embryonic electrocardiogram (ECG) waves, NeuroKit2 offers effective algorithms that combine these methods, providing a reliable approach for peak detection in biosignal processing.

E. Arrhythmia Classification: The code employs a methodology to detect fetal arrhythmia using a combination of signal processing, feature extraction, and machine learning classification. Time Domain Features: The code computes various time domain features such as heart rate, minimum, maximum, mean, and standard deviation of the ECG signal, along with durations of PR, ST, QRS, QT, and RR intervals. Deep Learning Classification: Feature Matrix Creation: The extracted features are organized into a feature matrix, where each row represents a specific recording, and columns represent the extracted features. The extracted matrix is used to train a model using ResNet. Classification Outcome: The trained models are utilized to predict the presence of arrhythmia in fetal ECG signals based on the extracted features.

F. Evaluation: Once the model is trained, it is evaluated using separate validation and testing datasets to assess its performance and generalization capabilities. Various metrics, including accuracy, precision, recall, and F1-score, are commonly employed to evaluate the model's effectiveness in detecting phishing websites. The evaluation phase helps determine the model's reliability and suitability for real-world deployment.

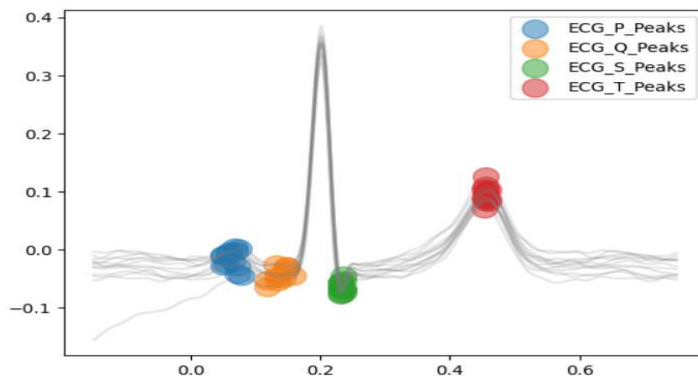


Fig.2: Different Peaks in ECG Signal

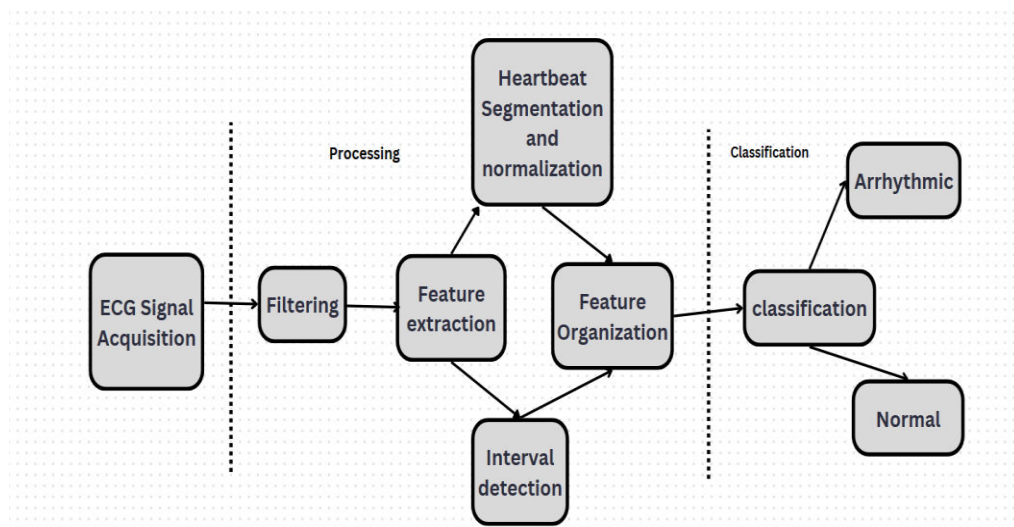


Fig.3: Sequence Diagram

IV. EXPERIMENTAL RESULTS

In the quest to advance fetal arrhythmia detection, our comparative analysis illustrates a diverse array of models, each emblematic of unique analytical methodologies. The deep learning architecture, ResNet, emerges as the paramount model, yielding an impressive accuracy of 83 percent. This marks a significant stride over the traditional algorithms—Logistic Regression, Linear Discriminant Analysis (LDA), and KNearest Neighbors (KNN)—which each report an accuracy of 67 percent, and the Decision Tree (DT) model, which trails at 50 percent. This comparison underscores the sophistication of ResNet’s multi-layered approach, adept at discerning intricate data patterns through its depth and residual connections. Such complexity enables a more nuanced understanding of the dataset, signifying its aptitude for medical diagnostic applications where accuracy is paramount. Conversely, the consistent accuracy shared by Logistic Regression, LDA, and KNN intimates their collective efficacy in modeling linearly separable data. Despite this, they do not possess the architectural complexity requisite for capturing the multi-dimensional nuances of fetal ECG data. The Decision Tree’s diminished accuracy posits a potential for overfitting, and a lack of requisite complexity needed to encapsulate the salient features of the dataset, limiting its utility in this context. In synthesis, the findings advocate for the integration of advanced deep learning frameworks like ResNet in the realm of medical diagnostics, leveraging their superior capacity to decode the latent intricacies within clinical data for enhanced predictive accuracy. The research heralds a promising avenue for fetal health monitoring, with ResNet leading the vanguard in predictive accuracy and clinical utility.

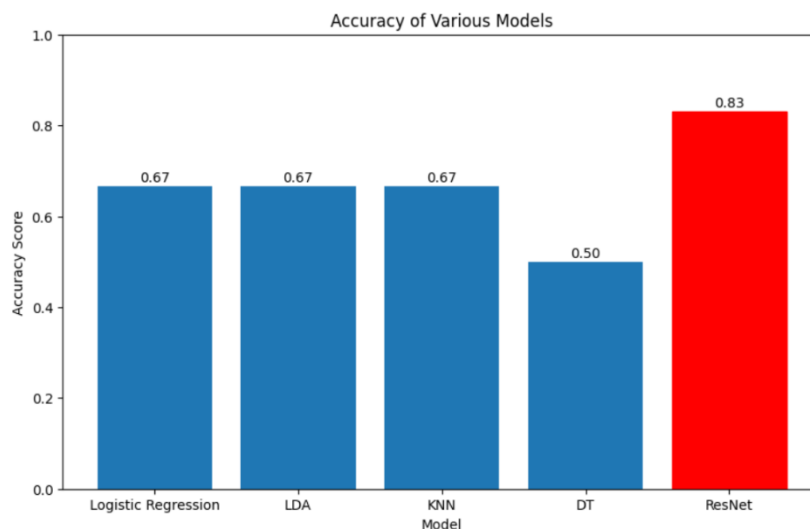


Fig.4: Accuracy of Different Models

V. CONCLUSION

This implementation showcases the potential of noninvasive fetal arrhythmia detection using fetal ECG signals, employing Python libraries like NeuroKit, Matplotlib, and WFDB for signal manipulation, visualization, and feature extraction. By precisely detecting ECG peaks and calculating essential waveform parameters with NeuroKit2, the program enables accurate identification of arrhythmic patterns. Leveraging Scikit-learn's machine learning algorithms, including Logistic Regression and SVM, the implementation effectively distinguishes healthy and arrhythmic fetal conditions. Moreover, through data pre-processing, normalization techniques, and visualization tools provided by Matplotlib, the program ensures signal uniformity, reliability, and comprehensive insights for diagnostics and research. Future enhancements could involve refining signal processing methods, integrating deep learning for feature extraction, incorporating ensemble learning techniques for classification, optimizing for realtime monitoring, and embracing multi-modal approaches to improve the identification of fetal arrhythmia and promote a more comprehensive understanding of fetal well-being.

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