A Machine Learning Framework for Fetal Arrhythmia Detection via Single ECG Electrode

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Abstract. Fetal Arrhythmia is an abnormal heart rhythm caused by a problem in the fetus's heart's electrical system. Monitoring fetal ECG is vital to delivering useful information regarding the fetus's condition. Acute fetal arrhythmia may result in cardiac failure or death. Thus the early detection of fetal arrhythmia is important. Current approaches use several electrodes to acquire abdomen ECG from the mother, which causes discomfort. Moreover, ECG signals acquired are extremely noisy and have artifacts from breathing and muscle contraction, which hardens ECG extraction. In this study, a machine learning framework for fetal arrhythmia detection. The proposed framework uses only a single abdomen ECG. It employs multiple filtering techniques to remove noise and artifacts. It also extracts 16 significant features from multiple domains, including (time, frequency, and time-frequency features. Finally, it utilizes four machine learning classifiers to detect arrhythmia. The highest accuracy of 93.12% is achieved using Boosted decision tree classifier. The performance of the proposed method shows its competing ability compared to other methods.

Keywords: Discrete wavelet transform (DWT); Electrocardiography (ECG); Peak energy envelop (PEE); Shannon energy envelope (SEE); Machine learning

1 Introduction

Arrhythmia is an aortic condition characterized by alterations in the normal heartbeat, including rhythm. [1]. Fetal arrhythmia refers to irregular fetal heartbeats which may be too fast or too slow [2]. In terms of hazard, this aortic abnormality may impair cardiac pumping by not being coordinated by the heart muscle. Infant arrhythmias occur in only 1-2% of all pregnancies and are classified according to frequency and regularity. Almost all arrhythmias fall into one of three categories: irregular, tachycardia, or bradycardia. Normal fetal heart rates range from 120-160 bpm at 30 weeks gestation and 110-150 bpm at term [3]. Bradycardia is a heart rate of fewer than 100 beats per minute, and tachycardia is a heart rate greater than 180 beats per minute. The most often used diagnostic method to detect an arrhythmia is via cardiac electrocardiogram (ECG). Several studies have used ECG signals to detect and classify arrhythmias[4], [5], [6]. On the MITDB dataset, Rooijakkers et al. [5] suggested a method for R- peak identification of fetal ECG (f- ECG) signals utilizing a discrete-time- continuous wavelet transform with an error detection rate of 0.22 percent[6]. other hand, Apsana et al.[7] utilized an Independent Component Analysis (ICA)-based algorithm to detect fetal arrhythmia with a 93.71 percent

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accuracy, whereas Devika et al.[8] used ICA to diagnose myocardial infarction with a 96.77 percent accuracy. [9], global and temporal adaptive techniques for detecting fetal beats from abdominal ECG were used. Besides, Lo et al.[10] used a temporal frequency technique, such as the short-time Fourier transform, for feature extraction, followed by classification using a convolutional neural network (CNN) [11] [12], to identify arrhythmia with a 92.65% accuracy. Acharya et al.[13] suggested a CNN-based deep learning system for automated diagnosis of congestive heart failure using ECG data. Singh et al. [14]suggested a Short-Term Long Memory (LSTM) network with an accuracy of 88.1 percent for detecting and classifying arrhythmia. The above-mentioned deep learning architectures [10] [14] need a large amount of data and computing time to train the suggested models. As a result, a novel real-time strategy has been presented to decrease processing time. Using a single abdomen ECG electrode, this study proposed a machine learning framework for fetal arrhythmia detection. It uses multiple filtering techniques and several features extraction methods from multiple domains. It employs 4 classifiers to detect fetal arrhythmia. The following is the layout of this paper. Section 2 describes the proposed technique in detail, including the MIT-BIH dataset, data description, DWT, SEE, feature extraction, selection, and learning and classification algorithms. Section 3 presents the findings. Section 4 provides the conclusion.

2 Materials and methods

2.1 Discrete wavelet transform (DWT)

DWT analyzes data in the time-frequency domain by using orthogonal basis functions. commonly used in medical applications. For 1-D signals, the DWT convolves the input signal with low and high pass filters. Afterward, a downsampling procedure is done. Two clusters of coefficients are generated after this process involving details and approximation coefficients. The coefficients are further analyzed using low and high pass filters for multi-level DWT analysis.

2.2 Data description

The NIFEA DB (non-invasive fetal ECG Arrhythmic Database) comprises recordings of 12 fetal arrhythmias ECGs and 14 regular rhythmical ECGs. This data was acquired from pregnant women during routine medical visits. The fetal median gestational age for ECG signals with arrhythmia is 36 weeks (22–41 weeks). For normal ECGs, the fetal average gestational age is 21 weeks (20–36 weeks).

2.3 Proposed model

The proposed method consists of four steps, including preprocessing of raw data, segmentation, feature extraction, and finally, classification. In the first step, several filters are used to remove noise and artifacts. Next, ECG signals are segmented using a fixed window size. Afterward, 11 features were extracted from each segment in time, frequency, and time-frequency domains then added 5 different features to increase the accuracy. Finally, four machine learning classifiers are used to detect fetal arrhythmia.

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Figure 1 represents the block diagram of the proposed method of arrhythmia identification.

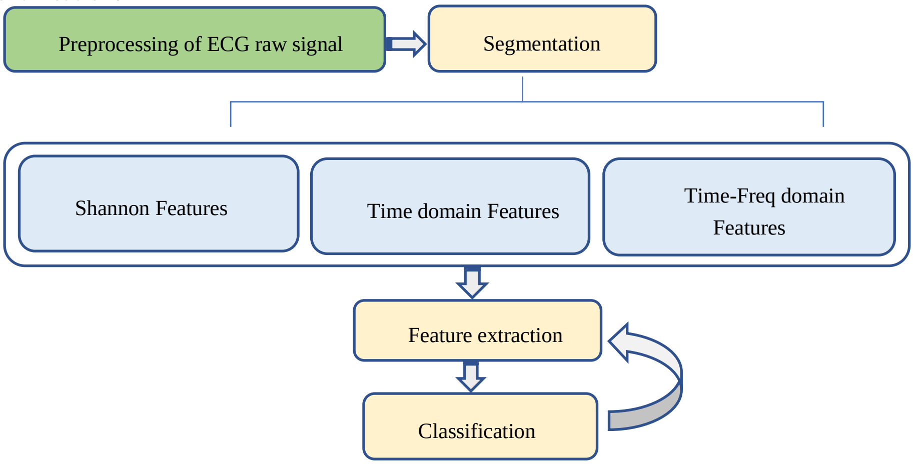

Fig. 1. Flowchart of the proposed method for classifying normal and arrhythmic ECG signals.

2.3.1 Preprocessing of the raw signal

Initially, a notch filter is used to eliminate the 50 Hz powerline interference. Afterward, a 2nd order low pass Butterworth filter at 0.5Hz cut-off frequency is used to remove artifacts. Finally, a 4th order Butterworth bandpass filter is utilized to filter R-peaks.

2.3.2 Segmentation

Segmentation is the process of dividing a signal into many parts that have similar statistical properties, such as amplitude and frequency. The statistical characteristics of ECG signals change over time, which makes them non-stationary. Segmenting an ECG signal necessitates the identification of the numerous waves contained in it, such as the P wave, ORS complex, and S waves. These are called fiducial points. Many QRS detection techniques are based on the differentiation procedure. Therefore, the first and second derivatives are used in this study. The R-peak locations were obtained from the dataset to obtain these heartbeat segments. The average heartbeat consists of around 355 samples, almost including the R-peak and samples around it. An asymmetrical fixed window equivalent to 400 ms is used in this study as such window size contains the fiducial points per heartbeat. The authors identify the R peak on a scale of one and the P and T waves on scales of three and four, respectively, using a Db1 wavelet. Finally, the db4 waveform is used to detect QRS complexes [15].

2.3.3 Feature extraction

This study extracts features from time and time-frequency domains. This section will explain the feature extraction methods used and how features are calculated. In the time domain, five features are calculated, including heart rate variability (HRV) [16], mean

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R-R interval, root means square of R-R interval, average heart rate, and the standard deviation of R-R interval. A 4 dB 1-D DWT is applied to each segment for the time-frequency domain, and the four detail coefficients are collected in one vector. Afterward, five features are calculated from this vector, including root mean square (RMS), mean, standard deviation, skewness, and kurtosis. Furthermore, some features based on Shannon theory are computed involving Shannon energy envelope (SEE), peak energy envelope (PEE), and final R-peak. Figure 2 shows the SEE. Figure 3 shows the PEE, and 4 shows the final R peak.

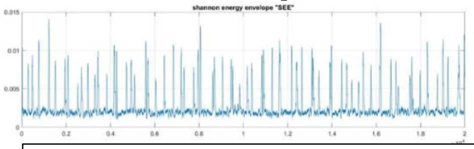

Fig. 2. The Shannon energy envelop (SEE).

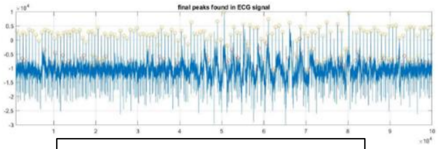

Fig. 3. The final R peaks

2.3.4 Classification

In the classification step, four machine learning classifiers are used involving a decision tree with 100 n-estimators, two minimum samples split, one minimum sample leaf, and seven levels of the decision tree that acts to boost the algorithm because it can be implemented with if conditions not like SVM kernel function. Boosted DT, k-nearest neighbor (k-NN), and ensemble subspace K-NN. For the k-NN, the number k is 1, and the Euclidean distance metric is used. For DT, the Gini-index splitting matrix is utilized. 5-fold cross-validation is employed in this study to decrease the estimated variance for classifiers. The data set was divided into five subsets. Each time, the test set is drawn from one of the five subsets, while the training set is drawn from the other four. Each fold's test data was utilized four times as train data and once as test data.

2.4. Performance metrics

Several tests have been conducted to validate the suggested strategy. These metrics include sensitivity (SEN), specificity (SPF), accuracy (ACC), positive predictive value (PPV), negative predictive value (NPV), Matthews Correlation Coefficients (MCC), and the F1 score. Where TP is the true positive, TN is the true negative, and FP and FN are the false positive and negative, respectively.

$$\mathrm{SEN}=\frac{\mathrm{TP}}{\mathrm{TP+FN}}\times 100(\%). \quad (1) \qquad \mathrm{SPF}=\frac{\mathrm{TN}}{\mathrm{TN+FP}}\times 100(\%). \quad (2)$$

$$\mathrm{ACC}=\frac{\mathrm{TP+TN}}{\mathrm{TP+FN+TN+FP}}\times 100(\%). \quad (3) \qquad \mathrm{PPV}=\frac{\mathrm{TP}}{\mathrm{TP+FP}}\times 100(\%). \quad (4)$$

$$\mathrm{NPV}=\frac{\mathrm{TN}}{\mathrm{TN+FN}}\times 100(\%). \quad (5) \qquad \text{F1-score}=2\,\frac{PPV\times SEN}{PPV+SEN} = \frac{2\times TP}{2\times TP+FN+FP}\times 100(\%). \quad (6)$$

$$\mathrm{MCC}=\frac{\mathrm{TP\times TN-FN\times FP}}{\sqrt{\mathrm{(TP+FN)(TP+FP)(TN+FN)(TN+FP)}}}\times 100(\%). \quad (7)$$

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3 Results

The section discusses the results of the proposed machine learning framework for fetal arrhythmia detection. Table I shows the performance metrics attained using the four machine learning classifiers. As can be noticed from Table I, the highest accuracy is achieved using the boosted DT classifier. The boosted DT classifier achieved an accuracy of 93.12%, a sensitivity of 99.14%, specificity of 82.72%, PPV of 90.77%, NPV of 98.25%, and MCC of 81.35%, and F1-score of 94.77%. The confusion matrix of the boosted DT is shown in Figure 5. The DT classifier obtained a slightly lower accuracy of 92.13% than the boosted DT. A sensitivity of 94.5%, specificity of 88.07%, PPV of 93.14% NPV of 90.33%, MCC of 93.02%, and F1-score of 93.82% are obtained using DT classifier. The receiving operating characteristic (ROC) curve and the area under ROC (AUC) are displayed in figures 3 and 4.

Table 1. Classifiers Evaluation (%) of the proposed method

Classifier	SEN	SPF	ACC	PPV	NPV	MCC	F1
Boosted DT	99.14	82.72	93.12	90.77	98.25	81.35	94.77
Ensemble-Subspace KNN	90.54	85.82	88.80	91.63	84.11	76.04	91.08

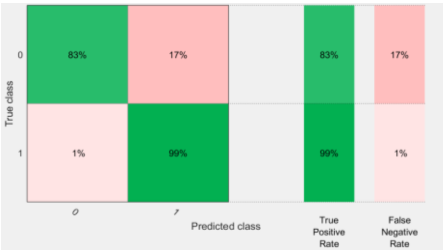

Fig. 4. Confusion matrix (Boosted DT).

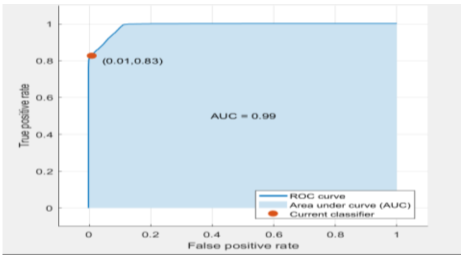

Fig. 5. ROC curve (Ensemble boosted trees).

The proposed method's results are compared with other related studies and shown in Table II to further validate the proposed framework's performance. The proposed method provides an average classification accuracy of 93.12% based on five-fold cross-validation. This accuracy is obtained with only one ECG channel, which is not the case in the other studies. The outstanding performance of the proposed framework verifies its competing ability compared to other related studies.

Table 2. (Compared different related studies with the same dataset and others)

Study Ref.	Method	channel	Accuracy
[17]	2-stages filtering with SVM & gaussian kernel method	Single ECG channel	83.3%
[18]	Filtering, ECG Suppression, and R-peak detection	Abdomen channels	94.1%
[19]	ICA-RLS-EMD method for extracting the neonatal ECG from the abdomen	Six Abdomen channels	92.7%

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[20]	two-stage improved non-linear adaptive filter for ECG extraction	Six Abdomen channels	94.5%
[21]	LMS and PHS indexes compared	Single ECG channel	87.7%
[22]	Deep learning layers with rate 0.001 input learning layer	ECG and one Abdomen channel	95.76%
Our work	Proposed method	Single ECG channel	93.12%

Abbreviations: (ICA) independent component analysis, (RLS) recursive least squares, (EMD) empirical mood decomposition, (SVM) support vector machine, (LMS) local maxima similarity, (PHS) pulse harmonic strength.

4 Conclusion

In this study, the detection performance after numerous stages of the proposed framework is quite promising, improving the accuracy from 91% to 93.12% using real-time decision trees and ensemble classifiers. The results show that a single ECG channel can detect fetal arrhythmia, thus helping clinicians detect fetal arrhythmia rapidly and more accurately than manual detection. In future work, the dataset size may be increased, and deep learning, along with many other improvements such as the feature selection approach, may be used to provide more promising results. A variety of other optimization techniques can also be used to improve the evaluation results.

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