Prediction of ECG-Biomarkers for Fetal Arrhythmia Using Non-invasive Fetal ECG

Author

Razia Zaman Ela

Student Id: 170042071

Supervisor

Dr. Md. Azam Hossain

Assistant Professor, Department of CSE, IUT

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Declaration of Candidates

This is to certify that the work presented in this thesis is the outcome of the analysis and investigation carried out by the candidates under the supervision of Dr. Md. Azam Hossain Sir in the Department of Computer Science and Engineering (CSE), IUT, Dhaka, Bangladesh. It is also declared that neither of this thesis nor any part of this thesis has been submitted anywhere else for any degree or diploma. Information derived from the published and unpublished work of others has been acknowledged in the text and a list of references is given.

Razia Zaman Ela

(Signature of the Author)

Razia Zaman Ela

Student Id: 170042071

Academic Year: 2021-2022

May 2022

(Signature of the Supervisor)

Dr. Md. Azam Hossain

Assistant Professor

Department of Computer Science & Engineering (CSE)

Islamic University of Technology (IUT)

May 2022

Abstract

A noninvasive Fetal Electrocardiogram (ECG) is expected to be an unrealized predictive tool in fetal arrhythmia diagnosis and post-treatment. The generated fetal ECG data cannot be stored in real-time by existing fetal heart monitoring systems used in hospitals and is refined for use in enterprise-level health and wellness services. This study aims to quantify the ECG biomarkers and predict Fetal arrhythmia using Non-invasive fetal ECG data. We investigated the recordings of a total of 24 pregnant women using the Non-Invasive Fetal ECG Arrhythmia Database (NIFEA DB) (February 19, 2019) from physionet.org. We extracted ECG Fiducial Features and performed various statistical analyses on them to quantify ECG biomarkers. After performing statistical analysis we can conclude that changes in fetal arrhythmia ECG are associated with the properties of ECG markers. Machine-learning algorithms were investigated to predict fetal arrhythmia through Noninvasive Fetal ECG signals. The Overall accuracy of various Machine Learning Models is as followed: C5.0 is 95%, KNN is 94 %, CHAID is 90%, Neural Network is 81 %, and CART is 79 %. A non-invasive approach to predict fetal arrhythmias based on fetal ECG is expected to be used in portable fetal monitoring systems.

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Chapter 1

Introduction

1.1   Overview

Arrhythmias or irregular heartbeats can happen to babies who are still in their mother's womb. This condition is known as Fetal cardiac arrhythmias (ARRs). If an arrhythmia is left untreated, it can lead to serious problems for the baby, including congestive heart failure. The fetal heart is fully formed by the 16th week of pregnancy and beats at a rate of 110 to 160 beats per minute (bpm). Fetal arrhythmia refers to an irregular heartbeat, an abnormally slow heart rate (180 bpm), or a combination of an irregular rhythm and an irregular heartbeat. Some problems with abnormal fetal rhythms are benign, but others can lead to fetal heart failure which is dangerous for both the fetus and the mother. The sooner the problem is identified; the better-prepared doctors can be to treat the baby. Therefore, fetal arrhythmias must be closely monitored to be treated with the help of an appropriate treatment plan, for example, the use of intrauterine antiarrhythmic therapy. Several studies have promoted the development of a portable system that allows remote fetal heart rate diagnosis and monitoring. Recent studies support that fetal arrhythmias are identified in 1-3% of pregnancies [1], of which about 10% are mentioned as a possible source of morbidity.

1.2   Motivation

 In the past, sensitive cases of arrhythmias were considered mild, but prenatal heart specialists now say that any form of abnormal heartbeat needs to be identified and closely observed to avoid complications fetus with life-threatening failure. Fetal echocardiography is the principal method of fetal heart rate assessment. Continuous echocardiographic recordings are short in duration and

require a physician. Researchers promoting Non-invasive fetal electrography(NI-FECG)in this context. NI-FECG confers a number of supremacy for example inexpensive, the likelihood of local analysis, and the possibility of continuous long-term remote monitoring. For FECG signal acquisition a surface electrode is placed on a pregnant woman's abdomen and then the physician performs NI-FECG.

1.3 Problem Statement

The potentiality of NI-FECG to provide a precise estimate of fetal heart rate is supported by several recent studies. As there is an overlap in time and frequency between fetal and maternal electrocardiograms, separation of NI-FECG requires modern signal processing methods. [2] And, that's why this procedure is challenging. Several studies support that NI-FECG helps to diagnose fetal arrhythmias and, in most cases, provides supplemental information on arrhythmias than echocardiography which is recorded using ultrasound of the heart [4]. We tend to extract fiducial ECG features from the NIFECG dataset and apply machine learning techniques to detect fetal arrhythmias.

1.4 Research Contribution

The main contribution of our study is basically performing several investigations that are based on statistical analysis, bio signal processing, and robust machine learning methodologies for predicting fetal arrhythmia to support the feasibility of a portable fetal ECG monitoring system. The purpose of our study is as follows:

- To find out whether it is possible to estimate the cardiac biomarkers that indicate activity changes due to arrhythmia in the fetus.
- Whether it is feasible to Detect fetal arrhythmia using ECG Fiducial Features?

Chapter 2

Background Study

2.1 Electrocardiography

Over a century ago, electricity was invented by a Dutch physiologist named William Einthoven. The record-keeping process of electrical action that takes place during a cycle of cardiac activity is essentially an electrocardiogram (ECG). The cardiac tissue generates electrical activity in the form of small potential and it is usually picked up by the electrodes of the electrocardiogram signal. Specialized cells in the sinoatrial node (SA node) produce electrical activity. Due to the polarity reversal of the cardiac cell wall, there is a more positively charged impulse process on its external surface at rest in general. This inversion creates a negative on the outermost surface of the cell wall, which propagates like an impulse to adjacent cardiac tissue. The electrocardiogram is used to detect heart diseases such as ischemia, myocardial infarction, arrhythmia, conduction disorder, etc.
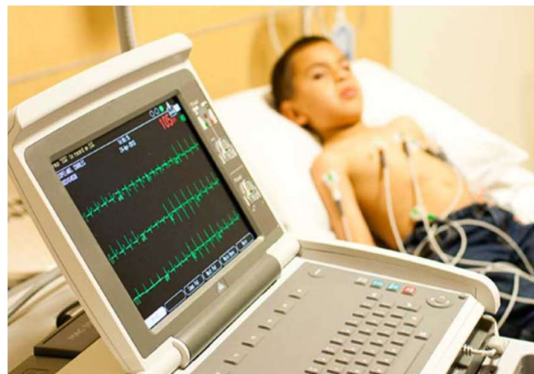

Figure 1: Electrocardiography

2.2   Non-invasive Fetal ECG

NI-FECG is a non-invasive fetal ECG and at the earlier stage of pregnancy, it can theoretically be performed Fetal ECG (F-ECG) was first monitored more than a centennial ago by Cremor. NI-FECG is a widely supportive non-invasive alternative to fetal monitoring and diagnosis of different fetal-related abnormalities. For FECG signal acquisition a surface electrode is placed on a pregnant woman's abdomen and then the physician performs NI-FECG. It is assured by NI-FECG to help identify fetal arrhythmia with the aid of a consecutive analysis of the fetal heart rate (FHR) for the beat-to-beat alterations. Several recent studies support the extent of the NI-FECG to deliver a specific approximation of the fetal heart rate. The Extraction process of NI-FECG is also challenging as it involves modern signal processing methods. There is a temporal and frequency intercept between the embryonic and the maternal electrocardiograms. [13][14].

It would be relevant to acknowledge the Non-invasive Fetal ECG leads orientation and arrangement before describing various fetal ECG abnormalities.
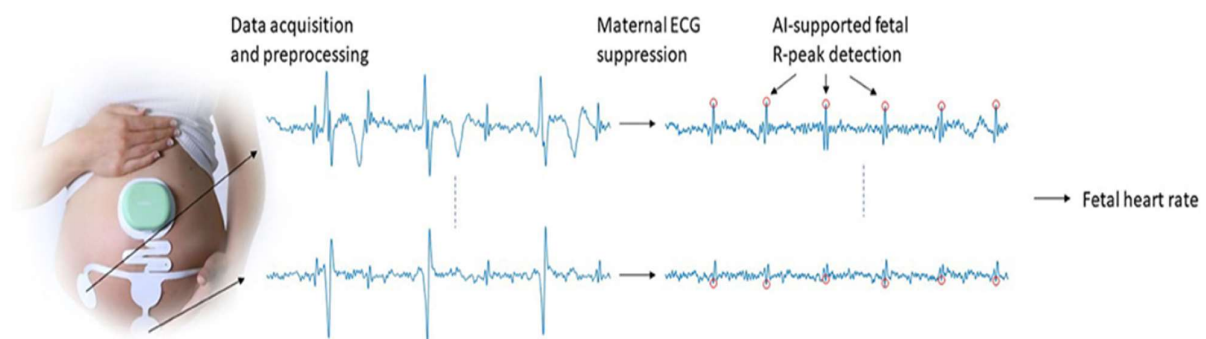

Figure 2: Noninvasive Fetal ECG

NIFECG recordings are usually collected using a device consisting of five to six abdominal electrodes placed over the mother's abdomen and two chest electrodes (earth and maternal electrocardiogram [MECG]). The electrodes are kept connected to a portable Cardio laboratory electrocardiogram monitor to record the following signals: 1 thoracic and 4 to 5 abdominal leads. Study [15] demonstrated that a systematic review was performed to highlight normal fetal ITCs using NIFECG and that all outcomes included fetal ITC (wave time). P, PR interval, QRS duration, and QT interval) were pooled at preterm (≤ 32 weeks), moderate to late (32–37 weeks), and term (37–41 weeks) births.

He concluded that NIFECG established effectiveness in the quantification of fetal ITC, mainly at advanced gestational age. In the study, it was determined that NIFECG helps identify fetal arrhythmias and also provides more evidence of arrhythmias than echocardiography.

2.3   ECG Waveform

The characteristic ECG waves are called P, QRS, and TU waves in alphabetical order. Their time intervals, amplitudes, and shapes provide important information about heart health and condition.

The P wave indicates depolarization of the heart. The QRS complex shows ventricular

depolarization. Ventricular repolarization is indicated by TU waves. Whenever the depolarizing current propagates towards the positive electrode of that lead, a positive wave of the ECG lead is recorded by the electrocardiograph. Similarly, as the current propagates away from the pole, a negative wave appears in the case.
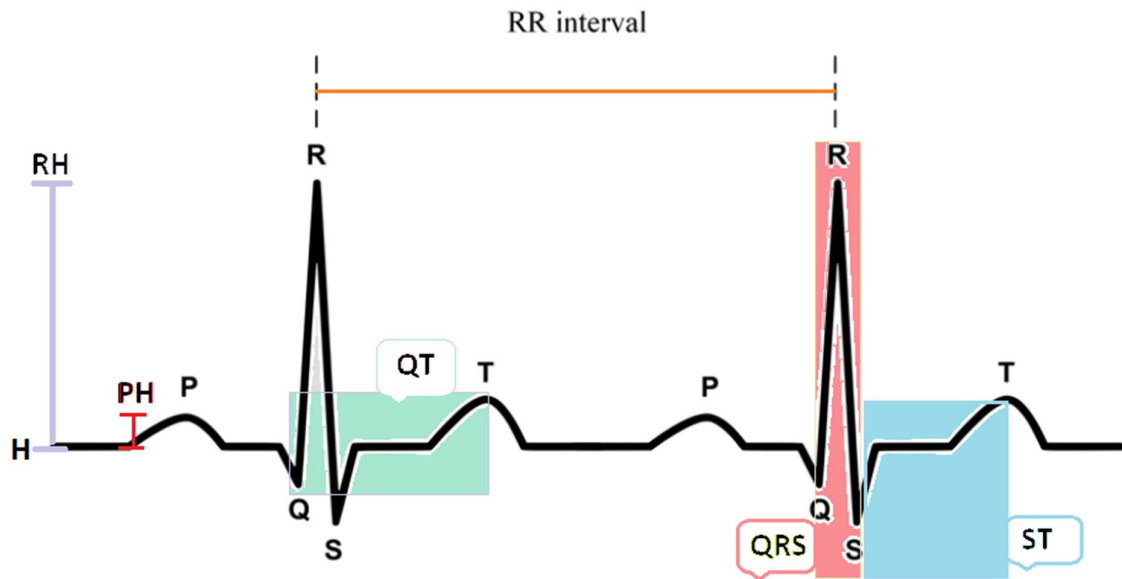
Figure 3: ECG Waveform

2.4　Fetal Arrhythmia

Fetal arrhythmia is an expression used to describe an abnormality in the fetal heart rate. These include increased heart rate recognized as tachycardia, slow heart rate proclaimed as bradycardia, and preterm birth. The conventional heart rate of the fetus is 120-160 beats per minute. About 13% [15] of all fetuses are affected by fetal arrhythmias, and about 10% of these arrhythmias are severe [16]. Fetal arrhythmias are identified by regular prenatal auscultation or fetal monitoring. Fetal tachycardia is specified as a heart rate above 180 bpm, and fetal bradycardia is a heart rate below 100 bpm. When assessing fetal arrhythmias, maternal disorders, infections, thirstiness, blood deficiency, fever, physical exercise, medication use, or hormonal abnormalities should be considered. This is because these conditions can affect the heart rate of the fetus.

2.5   Fetal ECG Parameter: Normal vs Abnormal ranges

There are previous studies available that establish the standard ranges and values of fetal ECG parameters [8]. Chia and Taylor [6] [7] respectively conducted experiments in a group around 20 weeks of gestation and they found the following mean values shown in Table 1 in the case of a normal fetus.

Table 1: Fetal ECG parameters and the respective mean value for normal ranges

Fetal ECG Parameters	Mean Value
P wavelength	43.9 ms
PR interval	102.1/91.7 ms
QRS duration	47.2/40.7 ms
QT interval	224.0/242.3 ms
T wave duration	224.0/242.3 ms

In their study, Sato and Naoaki provided measurements of Fetal ECG parameters of 12 abnormal fetuses along with their abnormality. [9]

Chapter 3

Literature Review

Extraction of clinical attributes from the NIFECG morphology was originated by Clifford et al. [18] and Behar et al. [19]. These studies include fetuses with no reported heart disease. Whether the estimates of these physiological properties were precise enough to yield usable medical information was the conclusion of the study due to the above limitations. This study demonstrated the suitability of non-invasive FECG as a complementary technique for detecting fetal atrioventricular block and thus assisting clinical decisions [20].

 Another study conducted a systematic review to highlight normal fetal CTI using NIFECG and encompassing fetal CTI (PR interval, QRS duration, P wave duration, QT interval). The results have been shown to be premature birth. We conclude the effectiveness of NIFECG for quantifying fetal CTI in (≤32 weeks), mid-to-late preterm birth (32-37 weeks), and maturity (37-41 weeks), predominantly advanced pregnancies. In this study, NIFECG was found to help identify fetal arrhythmias. A diagnosis was made from the extracted NIFECG records to determine if NIFECG and fetal echocardiography proved the presence of an arrhythmia. Compared to the reference diagnosis of fetal echocardiography. This study [22] shows that NIFECG enables the detection of fetal arrhythmias and provides, for the first time, additional clues to arrhythmias rather than echocardiography.

Table 2 provides a relative comparison of classification performance results from machine learning models using different ECG-derived cardiac functions. In study [5], Dimitri developed an algorithm for ECG analysis and arrhythmia detection using ECG records from 47 subjects. They used the

SVM model and achieved 97% accuracy. In a study [10], they used physionet's MIT-BIH database to classify various cardiac abnormalities. Block from normal, bradycardia, tachycardia, and ECG signals. Another study [11] used the MIT-BIH database to classify normal and abnormal subjects at risk of arrhythmia based on ECG signals and achieved an accuracy of 97.5.

Table 2: Comparability of classification performance results of machine-learning models using various ECG-derived cardiac features

Study	Study Population	Purpose	ML Model & Results
Dimitra Azariadi et al. [5]	48 half-hour of two-channel of ECG recordings, obtained from 47 subjects	Develop an algorithm for ECG analysis and classification to detect arrhythmia	SVM Model ; Accuracy:97%
Debnath et al. [10]	ECG signal is collected from the MIT -BIH database. around 26 datasets are used for training purposes.	Classify different heart abnormalities e.g. normal, bradycardia, tachycardia, and a block from ECG signal.	Backpropagation Neural Network(BPNN)
Venkatesan et al.[[11]	MIT BIH database: Participants in the group of healthy and heart-related diseases between 18 and 40 with different backround	Classify normal and arrhythmic risk abnormal subjects from ECG signals.	KNN based classifier with DWT, accuracy:97.5%

Chapter 4

Datasets and Preprocessing

To understand the cardiac activity of fetal arrhythmias, we used ECG signals from the non-invasive fetal ECG arrhythmia database. This includes records from subjects with fetal arrhythmias and normal heart rates. The ECG reference feature was processed and extracted. We examined cardiac characteristics through statistical analysis and hypothesis testing to identify important and important ECG characteristics associated with fetal arrhythmias. We also used machine learning algorithms to automate the classification of fetal arrhythmia and control groups.

4.1   Demographics of the Participants

Participants in the study are pregnant women who were hospitalized after routine examinations at the Kharkiv Perinatal Center or the Ukrainian Pediatric Heart Center in Kieu. Among the participants, the median gestational age of women diagnosed with fetal arrhythmias is 36 weeks, ranging from 22 to 41 weeks. Again, the median gestational age for women diagnosed with normal fetal heart rhythm is 21 weeks, with a range of 20-36 weeks. Here, a total of 24 pregnant women were included in this analysis, two of whom were NR twins. The prevalence of fetuses with ARR was 2.3% in the dataset population. NI-FEKG was recorded after echocardiography during regular medical visits of the same participants. The time interval between echocardiography and NI-FECG was usually less than 30 minutes. NI-FEKG records were successful in all pregnant women included.

4.2   Dataset Description

To analyze our assumptions, we used the non-invasive fetal ECG arrhythmia database (NIFEA DB) (February 19, 2019) at physionet.org, a collection of free medical research data. The dataset includes a set of fetal arrhythmia records from 12 subjects and a set of controlled normal rhythm records from 14 subjects performed using non-invasive fetal electrocardiogram (NIFECG) techniques. increase. This dataset contains 500 NIFECG records that are constantly recorded over a variety of time periods, from a minimum of 7 minutes to a maximum of 32 minutes. Each record contains 5 channels, including 5 abdominal channels and 1 maternal thoracic channel. The sampling frequency was 500Hz or 1kHz. The records are labeled ARR for fetuses with arrhythmias and NR for fetuses with normal rhythm.. For our research purpose, we have used the recording of the ECG channel.
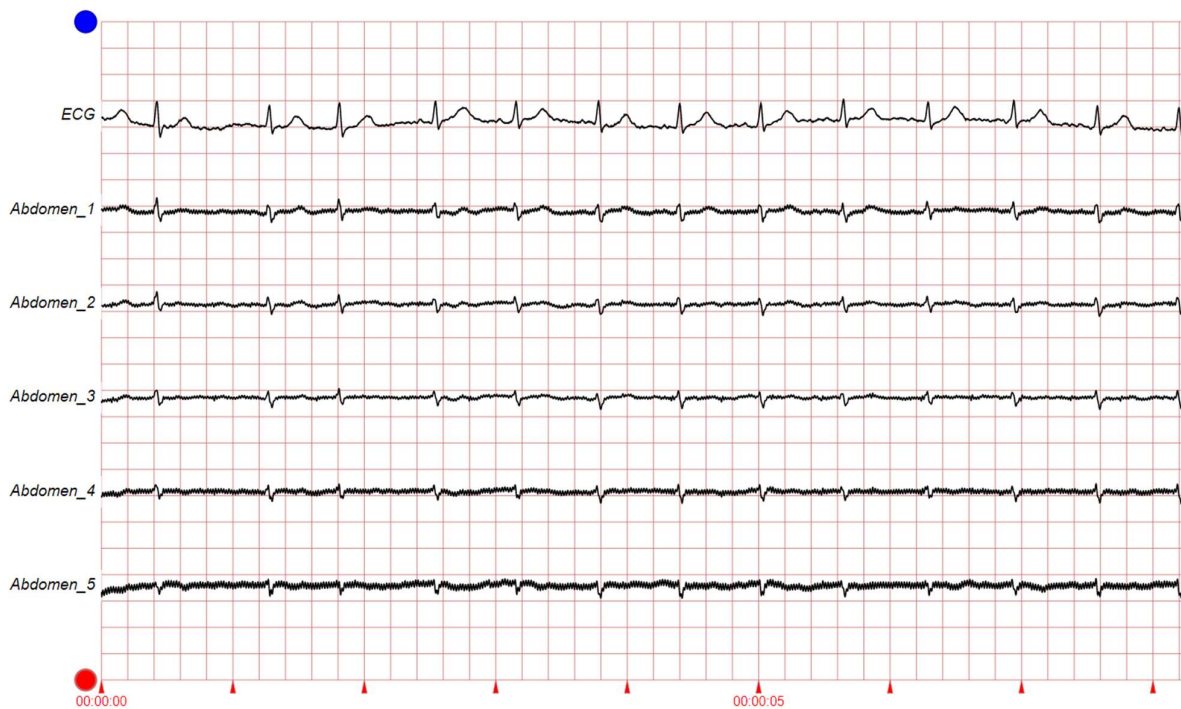
Figure 4: Normal Noninvasive Fetal ECG signal
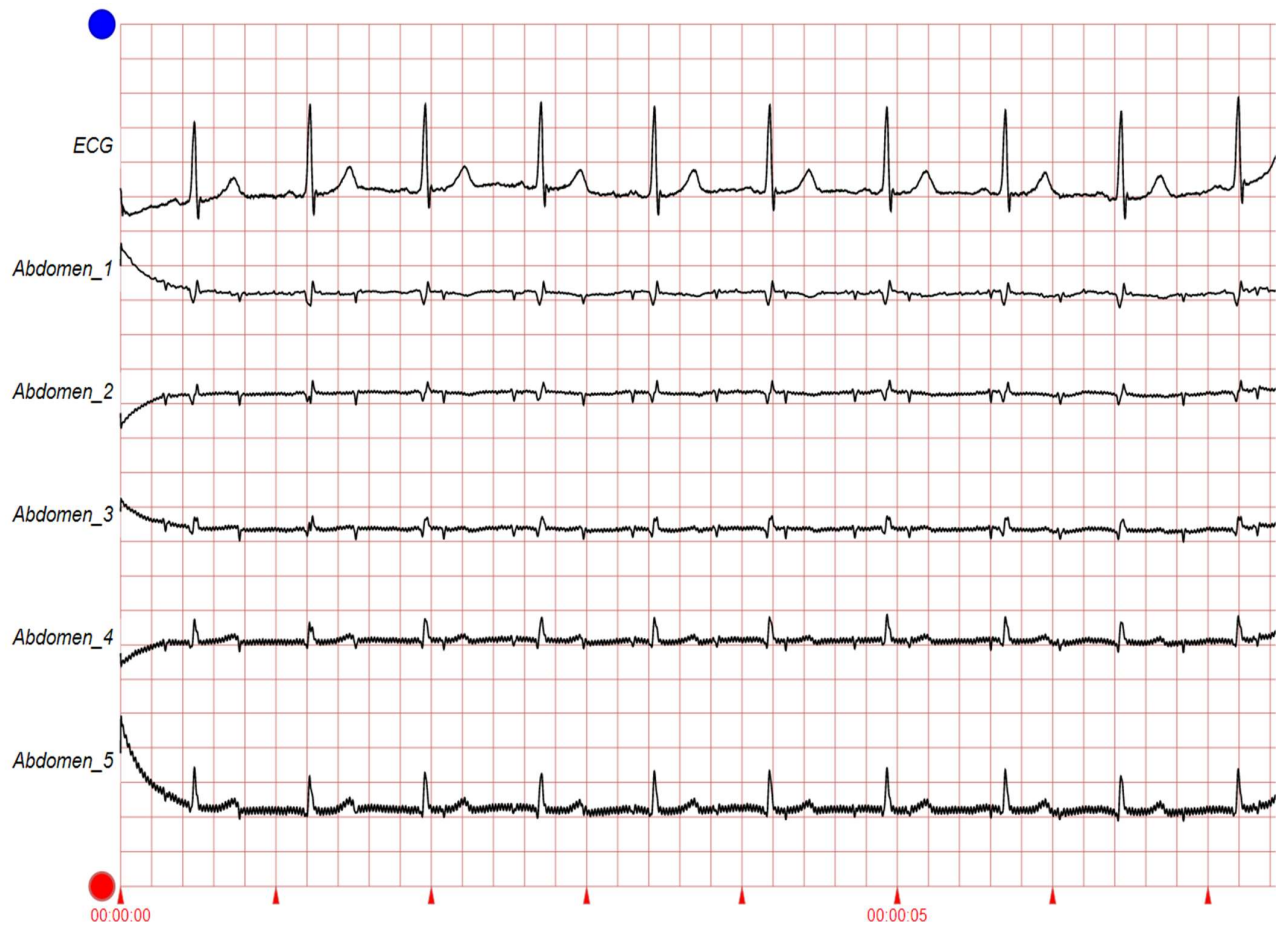
Figure 5: Noninvasive fetal ECG arrhythmias signal

4.3   Feature Extraction

We used the AcqKnowledge software to extract the ECG reference function from the record. After the analysis, 26206 records were collected, including 13945 records from arrhythmic fetuses and 12261 records from normal rhythmic fetuses. After analyzing the record, I found some missing values. Replaced the missing values with the average of the same characteristics of the same fetal group.
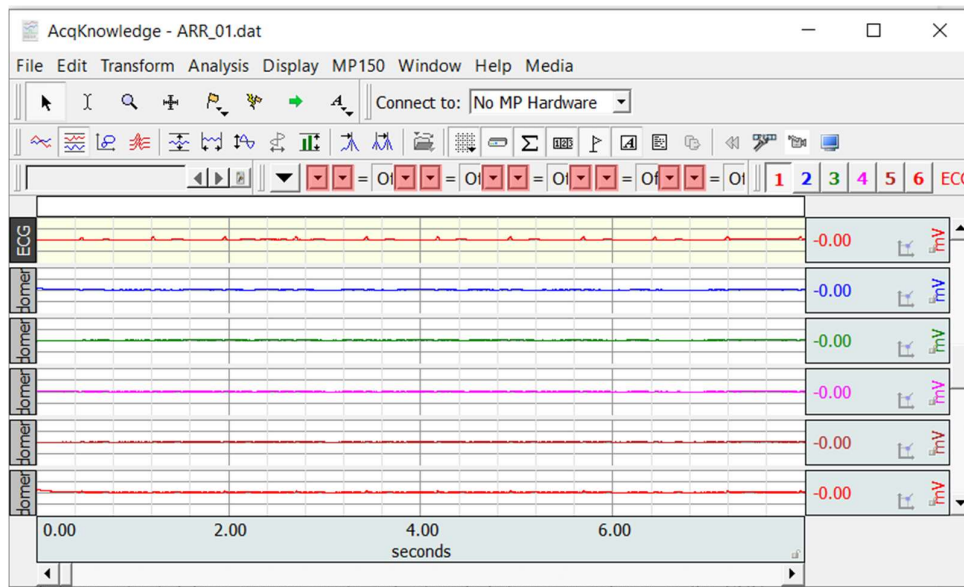
Figure 6: Acqknowledge Software

4.4 ECG Fiducial Features

Reference features were extracted from the ECG waveforms of non-invasive fetuses. Extract various reference features from each ECG record, including cycle-by-cycle time and voltage measurements of Q- and S-wave events and QRS events extracted from various points and intervals between the waveforms of the ECG signal cycle. bottom. The following is a description of the various ECG reference characteristics.

RR Interval: The time between consecutive R peaks of the ECG waveform, measured in seconds. Heart rate is measured using the RR interval, which is expressed in heart rate per minute (BPM).

R height (R-H): R-wave amplitude of the ECG cycle. The unit is mV.

PH height (P-H): Height of one cycle P-wave peak measured at mV.

QRS: The period from the start of the Q wave to the end of the S wave. This includes the R wave.

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QT: The time from the start of the Q wave to the end of the T wave is measured in seconds. ST: The time from the beginning of the wave to the end of the T wave is measured in seconds.

QTC: Modified QT interval period adjusted for the RR interval. The PRQ interval is the period between the start of the P and Q waves and is measured in seconds.

	B	C	D	E	F	G	H	I	J	K	L	M	N
1	Subject	Type	Cycle	Time	RR-I	HR	R-H	P-H	QRS	PRQ	QT	QTC	ST
2	ARR1	ARR	1	0.472	0.744	80.64516	0.8645	-0.08324	0.096	0.121	0.37731	0.46042	0.29909
3	ARR1	ARR	2	1.216	0.742	80.86253	1.09623	-0.05199	0.091	0.222	0.369	0.42838	0.294
4	ARR1	ARR	3	1.958	0.745	80.53691	1.11375	0.05699	0.095	0.125	0.38	0.44026	0.3
5	ARR1	ARR	4	2.703	0.731	82.07934	1.12698	-0.07951	0.083	0.126	0.367	0.42925	0.298
6	ARR1	ARR	5	3.434	0.742	80.86253	1.08875	-0.02323	0.092	0.148	0.375	0.43534	0.298
7	ARR1	ARR	6	4.176	0.754	79.5756	1.11074	-0.04248	0.087	0.132	0.376	0.43301	0.304
8	ARR1	ARR	7	4.93	0.763	78.63696	1.08251	-0.04451	0.102	0.14	0.398	0.45564	0.31
9	ARR1	ARR	8	5.693	0.745	80.53691	1.03574	-0.09951	0.092	0.132	0.4	0.46343	0.324
10	ARR1	ARR	9	6.438	0.755	79.4702	1.0195	-0.005	0.081	0.131	0.379	0.43618	0.313
11	ARR1	ARR	10	7.193	0.757	79.26024	1.23827	0.12876	0.098	0.142	0.384	0.44135	0.301
12	ARR1	ARR	11	7.95	0.751	79.89348	1.22251	-0.01323	0.084	0.109	0.376	0.43388	0.307
13	ARR1	ARR	12	8.701	0.746	80.42895	1.10499	0.02	0.112	0.153	0.4	0.46312	0.304
14	ARR1	ARR	13	9.447	0.736	81.52174	1.05375	0.04823	0.081	0.131	0.369	0.43012	0.304
15	ARR1	ARR	14	10.183	0.732	81.96721	1.20075	0.05041	0.084	0.16151	0.374	0.43714	0.305
16	ARR1	ARR	15	10.915	0.735	81.63265	1.10623	-0.07748	0.115	0.132	0.403	0.47007	0.303
17	ARR1	ARR	16	11.65	0.756	79.36508	1.06999	-0.03748	0.086	0.137	0.369	0.42439	0.299
18	ARR1	ARR	17	12.406	0.749	80.10681	1.01251	-0.06248	0.086	0.132	0.368	0.42521	0.297
19	ARR1	ARR	18	13.155	0.758	79.15567	1.00627	0.00376	0.092	0.125	0.379	0.43532	0.303
20	ARR1	ARR	19	13.913	0.752	79.78723	1.12875	-0.04075	0.109	0.122	0.411	0.47395	0.317
21	ARR1	ARR	20	14.665	0.754	79.5756	1.04052	-0.07248	0.087	0.138	0.376	0.43301	0.305
22	ARR1	ARR	21	15.419	0.747	80.32129	1.0045	-0.00376	0.084	0.123	0.372	0.43041	0.304

Figure 6: ECG Fiducial Feature Extraction

Chapter 5

Research Methodology

5.1   Statistical Analysis

In this study, descriptive statistics were used to compare demographics of participants. ECG registration characteristics are displayed as a bar graph with error bars. The bar chart data represents the mean of each data and the 95% confidence interval (CI) for each. Statistical analysis was performed using SPSS 24 software (IBM, Armonk, NY, USA).

5.2   ECG Biomarkers for Fetal Arrhythmia

ECG waveforms are different in fetal patients with arrhythmias compared to normal fetal patients. Figure 7 shows a bar graph containing reference fetal arrhythmias and error bars for the 95% confidence interval (C.I.) of normal fetal ECG function.

As shown in Figure 7, RRI, HR, PH, RH, QRS, PRQ, QT, and QTc intervals are important predictive ECG functions for fetal arrhythmias. We investigated whether changes in fetal arrhythmia ECG were associated with ECG marker characteristics and whether they could be detected by single-read ECG recording. Table 3 established that the RR interval was -0.02 seconds shorter in the arrhythmia group compared to the arrhythmia group (95% CI, -0.021 to -0.016 seconds, p * = 0.000). The average heart rate was 3.77 bpm higher in the arrhythmia group than in the control group (95% CI, 3.37-4.18 bpm, p * = 0.000). Mean relative humidity was 0.42 mV lower in the arrhythmia group than in the control group (95% CI, 0.439 to 0.391 mV, p * = 0.000). The mean pH was 0.06 mV higher in the arrhythmia group than in the control group (95% CI, 0.0540.069

mV, p * = 0.000). The mean QRS of the arrhythmia group was 0.01 seconds longer than the mean QRS of the control group (95% CI, 0.015 to 0.016 seconds, p * = 0.000). The mean PRQ in the arrhythmia group was 0.02 seconds higher than the mean QRS in the control group (95% CI, 0.017 to 0.019 seconds, p * = 0.000). The mean QT of the arrhythmia dataset was (95% CI, 0.007 to 0.011 sec, p * = 0.000), which was 0.01 seconds longer than the mean QT of the control group. The mean QTc of arrhythmic patients was 0.02 seconds longer than the mean QT of control patients (95% CI, 0.015 to 0.017 seconds, p * = 0.000). The mean ST in the arrhythmia group was -0.002 seconds shorter than the mean ST in the control group (95% CI, -0.003 to -0.001 seconds, p = 0.003). All ECG reference features were significantly different, but the ST intervals showed inconsistencies.

Table 3. Outcomes of statistical analysis of the ECG fiducial features of fetal arrhythmia and normal rhythm (control). *(p < 0.001) specifies a significant difference.

| ECG Features | Control (C) | | Arrhythmia (A) | | Mean Difference (A-C) | 95% CI | | t-test |
	Mean	Standard Dev.	Mean	Standard Dev.		Upper	Lower	p-value
R-R Interval (RR-I), S	0.69	0.09	0.67	0.12	-0.02	-0.021	-0.016	0.000*
Heart rate (HR), BPM	88.71	13.57	92.48	18.90	3.77	3.37	4.18	0.000*
R Height (R-H), mV	0.92	0.52	0.50	1.27	-0.42	-0.439	-0.391	0.000*
P Height (P-H), mV	-0.01	0.08	0.05	0.42	0.06	0.054	0.069	0.000*
QRS, S	0.09	0.02	0.10	0.05	0.01	0.015	0.016	0.000*
PRQ, S	0.14	0.04	0.16	0.04	0.02	0.017	0.019	0.000*
QT, S	0.37	0.05	0.38	0.07	0.01	0.007	0.011	0.000*
QTc, S	0.44	0.05	0.46	0.07	0.02	0.015	0.017	0.000*
ST, S	0.30	0.04	0.30	0.06	-0.002	-0.003	-0.001	0.003

5.3   Machine Learning Analysis

Our goal is to investigate machine-learning algorithms to automatically predict fetal arrhythmia using ECG signals. Machine Learning analysis is performed using three steps: feature selection, cross-validated model training, and model testing (or validation). In the case of the feature selection process, we used the F-stat tics to assess the feature relevance of Fetal ECG fiducial Features. We selected ECG features with a p-value larger than 0.95 for further classification investigation. The error matrix, also known as the error matrix, clearly describes prediction outcomes for all target classes. Other performance parameters are calculated using confusion matrices such as accuracy, sensitivity, and accuracy. Accuracy was defined as the ratio of correct predictions to total observations and was considered the most intuitive performance metric to identify the best model. Estimate the performance evaluation matrix using the following standard formula:

$$\text{Sensitivity} = \frac{TP}{TP + FN}$$

$$\text{Specificity} = \frac{TN}{TN + FP}$$

$$\text{Precision} = \frac{TP}{TP + FP}$$

$$\text{Negative predictive value (NPV)} = \frac{TN}{TN + FN}$$

$$\text{Accuracy} = \frac{TN + TP}{TN + TP + FN + FP}$$

Where TP stands for the true positive, TN means the true negative, FP stands for the false positive, and FN means the false negative.
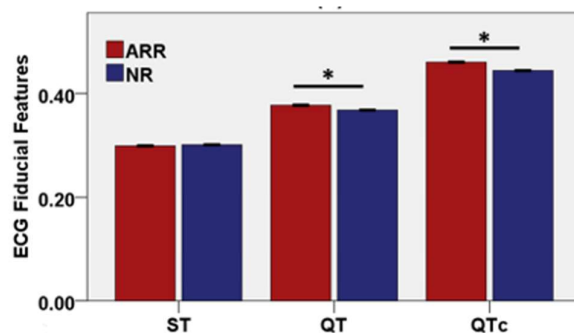
Chapter 6

Result and Discussion
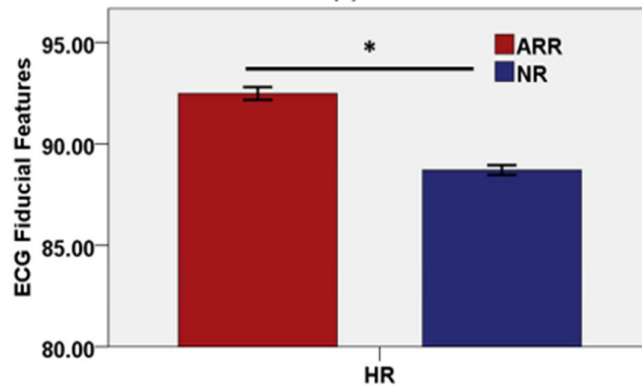
6.1 Statistical Result

To investigate our assumption, we have used the value of Mean and Standard Deviation of Each ECG Fiducial feature to establish a comparative analysis between the signals of the Fetal Arrhythmic Group and Normal fetus Group.
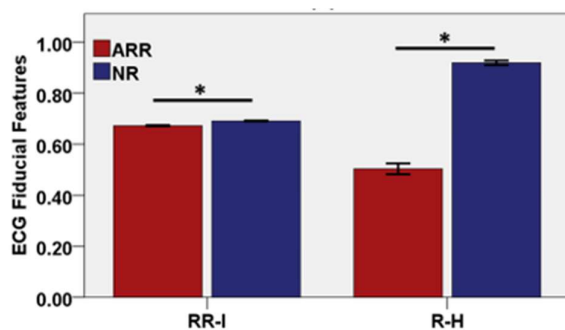
(a)

(b)

(c)

Figure 7: Statistical results of ECG fiducial features of arrhythmia fetus (ARR) and normal rhythm fetus (NR). Bar describes the relative difference between baseline and error bar as the 95% CI. (a) R-R Interval (RR-I) and R-height (R-H) of ECG fiducial pattern of arrhythmia fetus (ARR) and normal rhythm fetus (NR). (b) ST, QT, and QTc interval of ECG fiducial pattern of arrhythmia fetus (ARR) and normal rhythm fetus (NR). (c) Heart rate (HR) of arrhythmia fetus (ARR) and normal rhythm fetus (NR). $*(p < 0.001)$ indicates a significant difference

6.2   Classification of Fetal Arrhythmia and Normal Rhythm

A machine-learning algorithm was used for the binary classification of arrhythmia rhythm and, normal rhythm. Tables 4 and 5 show the performance matrix of the five machine learning models (C5.0, ANN, CHAID, neural network, and CART model) as a result of the predicted performance of arrhythmia. The ROC performance curves of the machine learning model are shown in Figures 7 (a) and 7 (b), and ECG function training and test datasets were used to classify arrhythmias and, normal rhythms. The C5.0 model classified the training dataset with the highest AUC (99%) and

accuracy (ACC: 95%). RH and PRQ have emerged as the most important arrhythmia classifiers using the C5.0 model. This model classified the test dataset by AUC (96%) and accuracy (ACC: 91%). The C5.0 model showed the highest sensitivity, highest specificity, and highest accuracy in the classification of arrhythmic and normal rhythms. The ANN model categorized training datasets by AUC (99%) and accuracy (ACC: 94%). This model categorized the test dataset by AUC (95%) and accuracy (ACC: 89%). The CHAID model classified training datasets by AUC (96%) and accuracy (ACC: 90%). PRQ, QRS, and RH have emerged as the most important arrhythmia classifiers using the CHAID model. This model classified the test dataset by AUC (96%) and accuracy (ACC: 89%). The neural network model classified the training dataset by AUC (89%) and accuracy (ACC: 81%). QTc and PH have emerged as the most important arrhythmia classifiers using this model. The neural network model classified the test dataset by AUC (90%) and accuracy (ACC: 82%). The CART model classified the training dataset by AUC (87%) and accuracy (ACC: 79%). RH and PRQ have emerged as the most important arrhythmia classifiers using this model. The neural network model classified the test dataset by AUC (87%) and accuracy (ACC: 79%).

Table 4. Classification Performance variables of C5.0, KNN, CHAID, Neural Network, CART Model using training dataset for classification of ECG features of fetal arrhythmia and control normal.

ML Model (Training)	Accuracy	Sensitivity	Specificity	Precision	Negative Predictive Value	AUC	Gini
C5.0	0.95	0.95	0.96	0.96	0.94	0.99	0.97
KNN	0.94	0.94	0.94	0.95	0.94	0.99	0.98
CHAID	0.90	0.91	0.89	0.91	0.90	0.96	0.92
Neural Network	0.81	0.77	0.86	0.87	0.77	0.89	0.79
CART	0.79	0.69	0.90	0.89	0.72	0.87	0.74

Table 5. Classification performance variables of C5.0, KNN, CHAID, Neural Network, CART Model using a testing dataset for classification of ECG features of fetal arrhythmia and control normal.

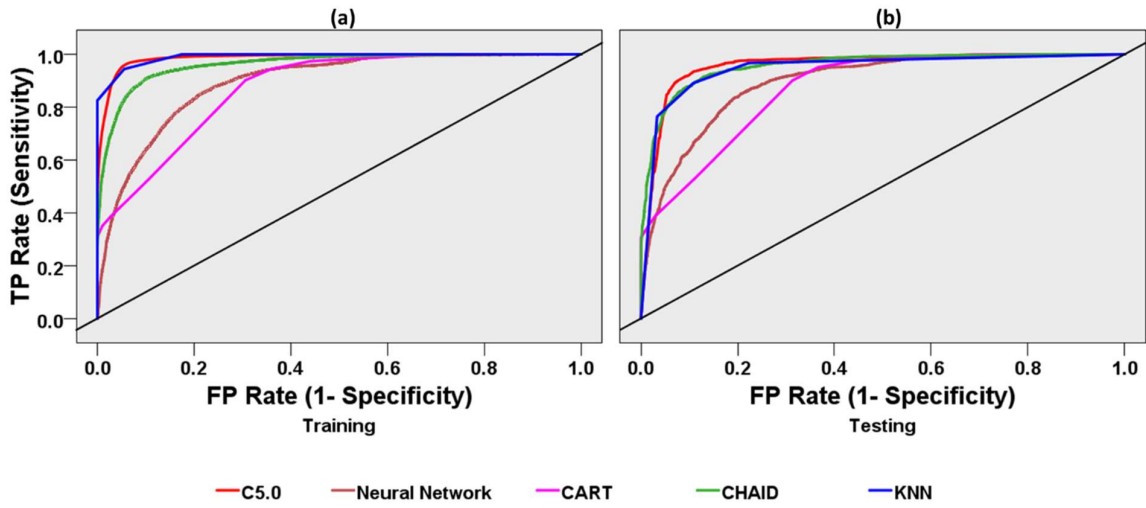| ML Model (Testing)	Accuracy	Sensitivity	Specificity	Precision	Negative Predictive Value	AUC	Gini
C5.0	0.91	0.90	0.92	0.93	0.89	0.96	0.91
KNN	0.89	0.89	0.89	0.90	0.88	0.95	0.89
CHAID	0.89	0.89	0.88	0.90	0.88	0.96	0.91
Neural Network	0.82	0.77	0.87	0.87	0.77	0.90	0.79
CART	0.79	0.69	0.90	0.89	0.72	0.87	0.74

Figure 7. ROC Performance curve of five machine-learning models (C5.0, KNN, CHAID, Neural Network, CART Models) to classify the fetal arrhythmia and control normal.

Figure 8. Receiver on Investment (ROI) Performance curve of five machine-learning models 22(C5.0, KNN, CHAID, Neural Network, CART Models) to classify the fetal arrhythmia and control normal.
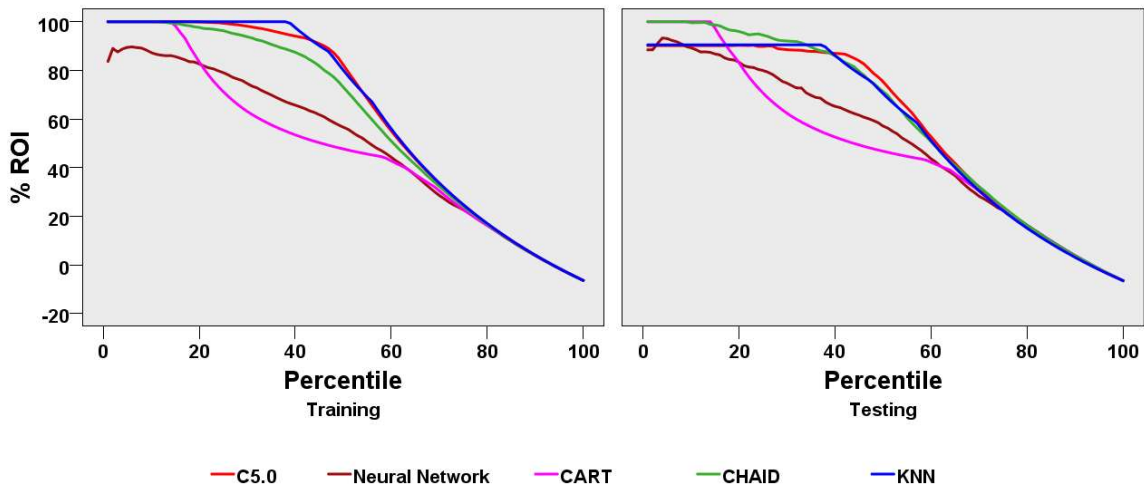
6.3   Discussion

With the advent of AI, which uses traditional advanced algorithms for many real-world tasks, many improvements have been made possible. Consider the example of logistic regression. Undoubtedly, estimating statistics and coefficients requires strong assumptions such as co-linearity between variables and independent observations. In this case, statistical inference can slow down the performance of the model. Artificial Intelligence algorithms overcome or reduce these assumptions by improving prediction and classification. Therefore, cardiology as well as can benefit from AI and machine learning in combination with other real-time surveillance systems[23].

Our goal is to investigate the feasibility of a portable ECG-based monitoring system and evaluate cardiac biomarkers that indicate changes in activity due to fetal arrhythmias. Arrhythmias share some health risk factors and the underlying heart condition. In this study, we reviewed various methods of ECG analysis to demonstrate the automatic detection of ECG landmarks. However, not all studies have experimented with the same leads and databases. Some studies support utilizing single-lead ECG in this context [25], On the other hand, 12-lead ECG is mainly used in clinical practice and is not practical for real-time observation using portable ECG devices. Studies have shown that representing ECG data from other reads in a single read may require highly accurate and time-dependent sequential data interpolation techniques.

To acknowledge the contributions of this research, we introduce a comparative summary table (Table 3) listing the contributions compared to other related work using the NIFECG dataset to perform various analyzes of fetal ECG.

Table 6: Comparability of classification performance results of machine-learning

models using various ECG-derived cardiac features

Study	Purpose	ML Model & Results
Lee JS et al. [24]	To evaluate the performance of fetal QRS complex identification	Model: CNN precision: 75.33% recall: 80.54% accuracy:91.33
Zhong W et al. [23]	Detection of fetal QRS complexes	Model: CNN precision: 92.89 % recall: 90.27 % accuracy:93.27 %
Sharma et al. [22]	Detects fetal cardiac arrhythmia from noninvasive fetal ECG signal using deep learning neural network	Model: CNN precision: 96.17 % recall: 96.21 % accuracy:96.31 %
This study	Detects fetal cardiac arrhythmia from the ECG Fiducial Features of noninvasive fetal ECG signal	Model: C5.0 Accuracy: 95%, Model: KNN Accuracy: 94 %, Model: CHAID Accuracy: 90%, Model: Neural Network Accuracy: 81 %, Model: CART Accuracy: 79 %

Chapter 7

Conclusion

Predicting fetal arrhythmias is recognized as a technology that enables a fetal cardiac monitoring system with wearable machine learning. ECG biomarkers for fetal arrhythmias were quantified by non-invasive fetal ECG signals. ECG reference features were processed and extracted from non-invasive fetal ECG. We examined several cardiac characteristics by utilizing various statistical analyses and hypothesis testing to identify dominant ECG characteristics associated with fetal arrhythmias. Machine learning algorithms are utilized to automate the classification of fetal arrhythmia groups and control groups. In the future, our work can be used to develop a portable fetal ECG diagnostic device suitable for the 24-hour continuous monitoring of fetal arithmetic patients.

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