Congenital Heart Disease Detection Using Clinical Data and Auscultation Heart Sounds: a Machine Learning Approach

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Abstract

Congenital heart disease (CHD) is the most common congenital malformation and has high morbidity and mortality related to late diagnosis. Screening protocols are lacking and only 1% of murmurs are associated with CHD. The decline in auscultation skills highlights the need for better screening. This study aims to create and evaluate models for the detection of CHD using clinical data and sound features. These features were extracted using pure conventional MFCC and selected MFCC through matrix profiling and motif search. Four combinations of data were used to train decision trees (DT) and artificial neural networks (ANN), and the area under the curve (AUC) was compared. Posteriorly, models were also trained for the detection of any cardiac pathology. In both pathologies, the ANN model using clinical data and conventional MFCC showed the highest performance with AUC of 0.761 for CHD and 0.791 for any cardiac pathology. However, this is only a slight improvement when compared with the ANN models using only clinical data (0.747 and 0.789, respectively. Additionally, the inclusion of motif selected MFCC seems to worsen the model performance. Although further research is still needed, this is a potential improvement in CHD screening, particularly for primary care physicians.

Keywords

Heart Auscultation, Machine Learning, Congenital Heart Disease, Mel-frequency Cepstral Coefficients, Matrix Profile, Decision Tree, Artificial Neural Network, Computer Assisted Decision

1. Introduction

1.1. Background

Congenital heart disease (CHD) is the most common congenital defect in the world [1, 2] and is defined as an abnormal development of the structures of the heart and/or great vessels which is present at birth.

In terms of global birth incidence, recent studies estimated a birth incidence of more than 17/1000 in 2017 [3, 4], which represents an increase of 4.2% from 1990 [5, 6]. As for global prevalence, it is estimated that nearly 12 million people were living with CHD in 2017, representing

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an increase of 18.17% since 1990 [4].

Looking at the mortality of CHD, several studies mention a clear decline in mortality since 1990 up to 2017 [3, 4]. Nevertheless, CHD remains the cause of 69% of deaths in children younger than 1 year and in the top 10 causes of death in children of this age group [4]. It is also responsible for more than double the years of life lost when compared to other cardiac diseases, such as rheumatic heart disease (RHD) [4].

Focusing on the morbidity, of all heart disease, CHD is one of the most common causes of years lived with disability (YLD) in individuals under 20 years, along with RHD [4]. Morbidity caused by CHD is related to late diagnosis and can include pulmonary hypertension [7], neurodevelopmental deficits [8, 9, 10] and delayed growth [11, 12].

Due to the context portrayed above, it is ever more important to have appropriate screening and early diagnosis strategies. Currently, screening consists of prenatal ultrasounds and a pulse oximetry test at birth, in countries where a formal screening protocol exists [13]. Still, this screening detects only between 82.8 and 92% of critical CHD [14] and critical CHD only amount to about 25% of all CHD [15]. This means that approximately 75% of CHD are not detected at birth.

Even though there are other signs and symptoms associated with CHD, by far the most concerning to general physicians and parent is the presence of a murmur, and this is the main cause for referral to a pediatric cardiology appointment [16, 17]. Nonetheless, estimates show that between 50 and 72% of children will have a murmur during infancy and adolescence [16, 17, 18, 19] and that only 1% of these are associated with a CHD, pathologic murmurs [16, 18].

To aggravate the situation, doctor's cardiac auscultation skills are in decline [20], with a study reporting a sensitivity of 73% and specificity of 78% for the detection of an abnormal murmur by primary healthcare physicians [21] and even the cardiac auscultation skills of pediatric resident being suboptimal [22]. One study found that the overall accuracy of cardiac auscultation skills in pediatricians was 73%, which is low when compared to 83% overall accuracy for cardiologists [23]. This illustrates the necessity for an assisted-decision tool primary care physicians and pediatricians could use when referring children with murmurs to a pediatric cardiologist.

1.2. Prior Work

In recent years, there has been an exploration of the potential artificial intelligence brings to the analysis of heart sounds. Several studies have attempted to detect cardiac pathology from cardiac auscultation recordings [24]. In the area of pediatrics, a few studies were able to use these methods to detect specific types of CHD [25, 26, 27] or distinguish normal and abnormal heart sounds [26, 28, 29]. Those who tried to identify CHD had a limited number of participants [30]. Nonetheless, to the best of our knowledge, no study has yet explored the detection of CHD using both clinical and heart sound data.

1.3. Goal of This Study

This study aims to produce machine learning models for the detection of CHD using clinical data and auscultation sound features. We hypothesized that by adding heart sound features to

the existing clinical data, we would be able to improve the ability of the model to discriminate individuals with and without CHD. The ideal being that this tool would be useful for screening of CHD.

2. Methods

2.1. Data Collection and Preprocessing

This is a retrospective study, which reuses the data obtained from two volunteer mass screening programs, thus forming a convenience series. These programs were conducted in Eastern Brazil between July and August 2014, and June and July 2015, and included all participants presenting voluntarily within this period. Eligibility criteria for screening was patients younger than 21 years of age.

When preprocessing the data, individuals identified as fetus, as having had previous cardiac surgery and as not having an echocardiogram were removed. Errors identified in variable codification were corrected. Variables were computed from information in other variables and percentiles according to age were calculated for some variables.

Additionally, the body mass index (BMI) percentile was used to stratify children younger than 19 years, inclusively, as underweight (BMI percentile ≤ 5), normal (BMI percentile <5 and >85), overweight (BMI percentile ≥ 85) and obese (BMI percentile ≥ 95). For children older than 19 years, underweight was defined as a BMI <18.5, overweight was defined as a BMI ≥ 25 and obese was defined as a BMI percentile ≥ 30. Clinical indication variables were recoded into logical variables. Variables including information on diagnosis or orientation and irrelevant information were removed, as well as redundant variables. Finally, variables with more than 50% missing data were also removed.

Echocardiogram diagnosis was used as reference standard to create the outcome variable, presence or absence of CHD. Due to the exclusion criteria, the were no cases with missing data on the reference standard result. Echocardiogram diagnosis was chosen as reference standard because it is the gold standard for detection of CHD. Additionally, another outcome variable was created using information from the echocardiogram diagnosis and the cardiology diagnosis to represent presence or absence of any cardiac pathology.

2.1.1. Variables Computed

$$OxygenSaturationDifference = RightArmSaturation - LegSaturation$$

$$MeanArterialPressure = (2 * DiastolicPressure + SystolicPressure)/3$$

$$BodyMassIndex = Weightkg/(Heightcm^2) * 10000$$

2.1.2. Percentiles Calculated

Body Mass Index, Height, Weight, Arm Circumference, Abdominal Circumference, Systolic Blood Pressure, Diastolic Blood Pressure, Mean Arterial Pressure, Heart Rate

2.2. Preprocessing of Heart Sounds and Extraction of Features

The heart sound recordings were obtained during the mass screening programs and included recordings from four anatomical locations (aortic, pulmonary, mitral and tricuspid). Along with these were files indicating the beginning and end times for the four main components of a heart sound (S1, systole, S2, and diastole).

2.2.1. Mel-Frequency Cepstral Coefficients

MFCC is a well-known and used feature for speech recognition systems [31]. These features were extracted for each heartbeat. However, because there we had incomplete heartbeat segments in the file annotations and there was a wide range of recording durations, we created functions to count the number of complete heartbeats present and measure their duration. Standardly, MFCCs are calculated for a window of 0.025s with 0.010s hops from the start of each window, with an overlap between frames. From our analysis, the 25th percentile for the number of heartbeats in each recording was 10, so we decided to extract this number of heartbeats, where possible, and impute missing values for the missing heartbeat segments in the shorter recordings. Additionally, the heartbeats measured on average 0.60s, which with standard parameters would give us 60 frames. Taking this into account and given the fact that we had to correct for the variation in heartbeat duration, we used formula 4 to calculate the hop time for each heartbeat to get 60 frames from each and multiplied that value by 2,5 to obtain the window time maintaining the original standard ratio. A total of 12 MFCCs were extracted for each frame.

$$hoptime = heartbeatduration/frames$$

2.2.2. Matrix Profile and Motif Finding

In a parallel process, the whole recording was converted into MFCC frames, and these were used to obtain the matrix profile with a window size of 60 frames, for the same reason as before. With this we attempted to identify and extract 3 motifs from each recording, which are 60 frame segments of all 12 MFCCs. Where motifs could not be extracted, data was imputed as missing.

2.2.3. Principal Components Analysis

PCA is a technique used to obtain the combination of original variables that account for a certain amount of the total variation [32]. We used this technique to reduce the amount of data created during the sound feature extraction. For each of three sets of data, conventional MFCC, motif MFCC, and a combination of both, we identified the variables which represented 80% of the total variance.

2.3. Decision Trees and Artificial Neural Networks

Decision trees (DT) emerged as the most used approach for data mining because of their characteristics. In our case, the natural incorporation of a mixture of numerical and categorical variables and the production of interpretable results were the most important characteristics

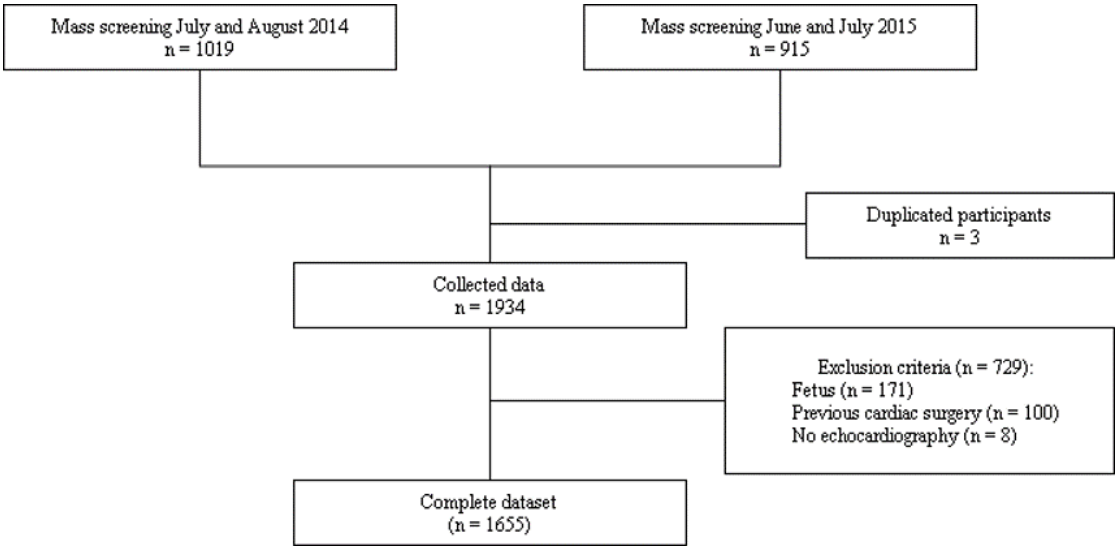

Figure 1: Flowchart of participants

[33]. Artificial neural network (ANN) is the most common method of machine learning used for the classification of cardiac sounds [24]. We trained both types of models using four versions of the dataset: clinical data alone, with conventional MFCC, with motif MFCC and with both types of features. Training was performed using bootstrapping as a resampling method with only one resample. The evaluation of the models produced was achieved through ROC curve analysis of the bootstrapping resample.

2.4. Statistical Software

We used R 4.0.5 software in every stage of this study. The packages were used for the calculation of percentiles (package childsds [34]), the descriptive and comparative analyses (packages gmodels [35] and lattice [36]), the sound file import and MFCC extraction (package readr [37], tuneR [38], stringr [39] and foreach [40]), the matrix profile calculation and motif detection (package tsmp [41]), the model training and validation (packages caret [42]), and the ROC curve analysis (package pROC [43]).

3. Results

3.1. Participants

The first mass screening yielded 1019 participants and the second yielded 915. Due to three individuals participating in both screenings, the final collected data only comprised 1934 participants. By applying the exclusion criteria for this study, the final dataset analyzed had 1655 participants. This is graphically represented in the flowchart on Fig. 1.

Table 1
Socio-demographic and clinical characteristics of participants

		With CHD (n=459)	Without CHD (n=1196)	Overall (n=1655)	*p* value	Missing
		n(%)	n(%)	n(%)		n(%)
Gender (female)		225(49.0)	550(46.0)	775(46.8)	.293	0(0)
Age Group					<.001	14(0.85)
	Neonate (0-1 month)	8(1.8)	5(0.4)	13(0.8)		
	Infant (1-24 month)	119(26.1)	235(19.8)	354(21.6)		
	Child (2-12 years)	276(60.5)	848(71.6)	1124(68.5)		
	Adolescent (12-16 years)	50(11.0)	89(7.5)	139(8.5)		
	Young Adult (16-21 years)	3(0.7)	8(0.7)	11(0.7)		
Ethnicity					.004	0(0)
	Asian	0(0)	1(0.1)	1(0.1)		
	Black	8(1.7)	9(0.8)	17(1.0)		
	Mixed Race	337(73.4)	964(80.6)	1301(78.6)		
	White	114(24.8)	222(18.6)	336(20.3)		
BMI for age					<.001	96(5.80)
	Underweight	57(13.2)	65(5.8)	122(7.8)		
	Normal	242(55.9)	631(56.0)	873(56.0)		
	Overweight	50(11.5)	149(13.2)	199(12.8)		
	Obese	84(19.4)	281(25.0)	365(23.4)		
Murmur					<.001	51(3.08)
	Present	345(78.8)	340(29.2)	(685(42.7)		
	Absent	93(21.1)	826(70.8)	919(57.3)		

In terms of the target pathology, we included 1196 (72.3%) healthy individual and 459 (27.7%) individuals with CHD. The socio-demographic and clinical characteristics of the participants are reported on Table 1. The differences in distribution of these variables within the primary outcome groups are also included in the table. For gender, there are no significative differences in terms of the presence of CHD. There were statistically significative difference in age group proportions, with CHD being more common in neonates, infants and adolescents than in the child and young adult groups. In terms of ethnicity, it is relevant to note the lesser proportion of mixed race individuals having CHD, when compared to other ethnicities.

Looking at clinical characteristics, there is a significant difference in the proportion of individual with CHD according to BMI, with this group presenting a higher proportion of underweight patients than the group without CHD. Additionally, in the group with CHD there were individuals with a murmur as there were more individuals without a murmur in the group without the disease.

Regarding the distribution of the severity of the disease, from those with CHD 409 (89.1%)

Table 2
AUC values for cardiac pathology models

	Clinical data	Clinical data + Conventional MFCC + Motif MFCC	Clinical data + Conventional MFCC	Clinical data + Motif MFCC
DT	0.733	0.676	0.733	0.712
ANN	0.789	0.784	**0.791**	0.740

Table 3
AUC values for CHD models

	Clinical data	Clinical data + Conventional MFCC + Motif MFCC	Clinical data + Conventional MFCC	Clinical data + Motif MFCC
DT	0.747	0.713	0.720	0.714
ANN	0.747	0.757	**0.761**	0.721

had simple CHD, while only 50 (10.9%) had complex CHD. As for cardiac pathologies in general, there were a total of 628 (37.9%) individuals with a cardiac diagnosis. From those, 459 (73.1%) had CHD and 169 (26.9%) did not have the disease. Looking at the types of murmurs present in the population, in terms of timimg, there were 10 (1.5%) continuous murmurs, 4 (0.6%) diastolic murmurs, 670 (97.8%) systolic murmurs and 1 with missing classification.

Concerning the recordings used in this study, the median of recording duration was 10s, ranging between 2s and 65s. The median of heartbeats per recording was 16, with a range of 3 to 94 heartbeats, and each heartbeat lasted on average 0.60s, with a minimum of 0.30s and a maximum of 1.27s.

3.2. Test Results

When detecting cardiac pathology, the clinical data models showed AUC of 0.733 for DT and 0.789 for ANN. When all sound features were included, the AUC fell for both (0.676 and 0.784, respectively). The best model for this classification was the ANN trained with clinical data and conventional MFCC (Fig. 2), with its equivalent DT showing an AUC of 0.733. When training only with motif MFCC the AUC where 0.712 for DT and 0.740 for ANN.

For CHD, both the DT and ANN models of the clinical data showed AUC of 0.747. The DT and ANN models of clinical data with both types of sound features showed AUC of 0.713 and 0.757, respectively. Nonetheless, the best model for the detection of CHD was also the ANN trained using clinical data and conventional MFCC, with an AUC of 0.761 (Fig. 3). The equivalent DT presented an AUC of 0.720. The models trained with clinical data and motif MFCC performed poorly with AUC of 0.714 for the DT model and 0.721 for the ANN model. Values of AUC for both cardiac pathology and CHD models are summarised on Table 2 and Table 3, respectively.

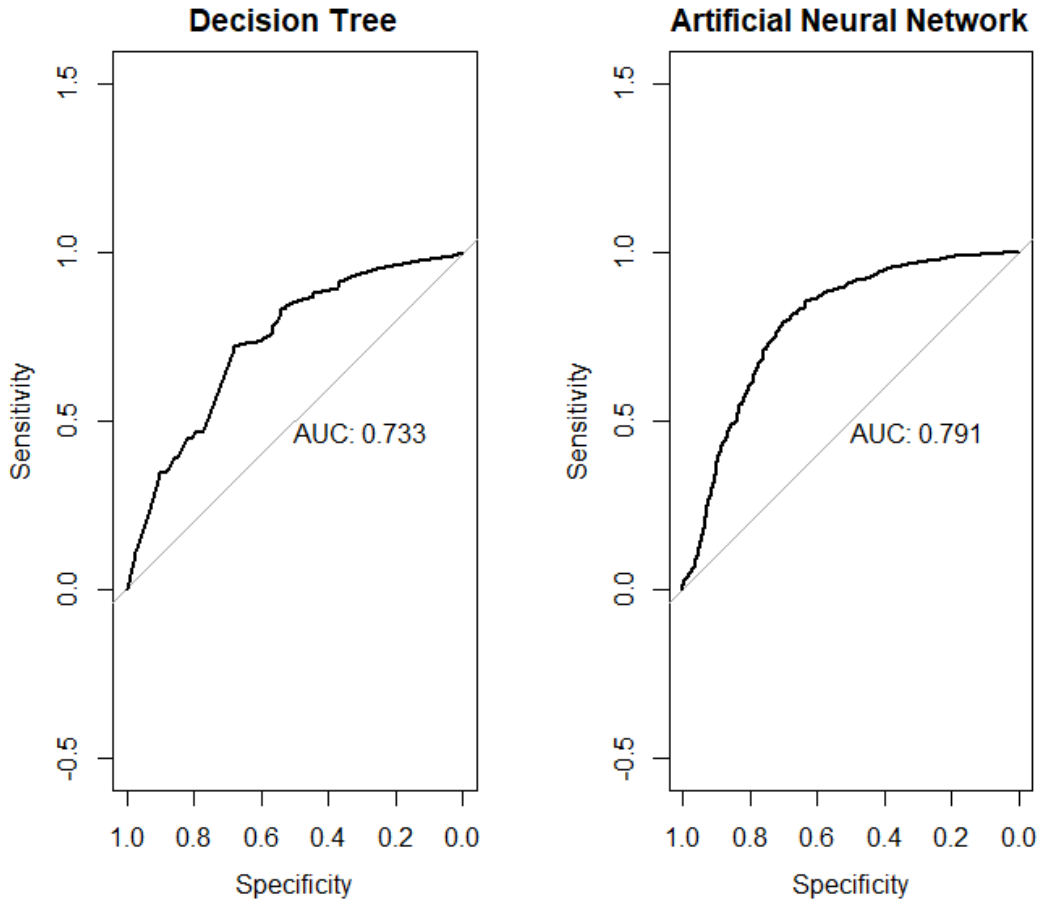

Figure 2: ROC curves of cardiac pathology models using clinical data and conventional MFCC

4. Discussion

4.1. Principal Results

The results show a slight improvement in the performance of the models, particularly when using solely conventional MFCC. This is in line with their use in previous studies in this area [24, 25, 26, 27, 28, 29, 30], even though we would expect a more evident improvement on the models.

Moreover, motif MFCC seem to clearly worsen the performance of the models, this could be due the algorithm used being optimized for 3 MFCCs per frame. The selection of the cepstrum which better characterize cardiac sound could improve the quality of the features extracted through this method.

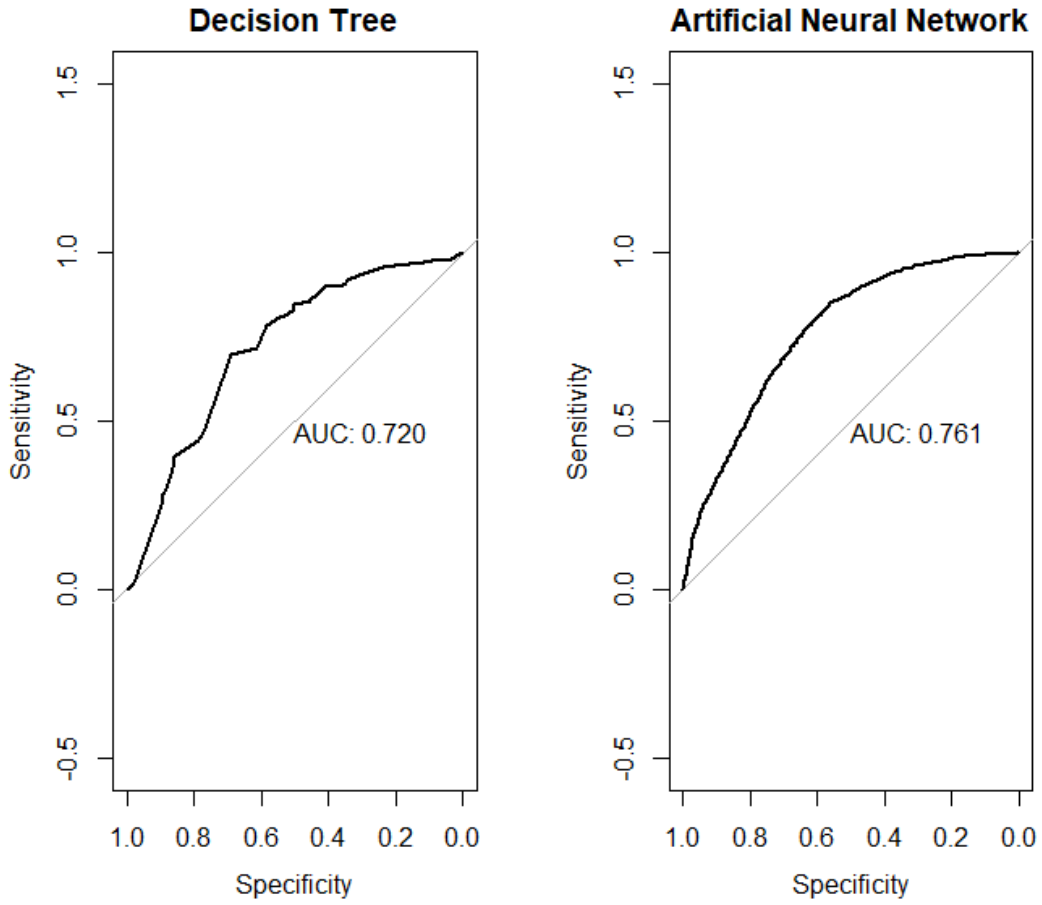

Figure 3: ROC curves of CHD models using clinical data and conventional MFCC

4.2. Limitations

There are several limitations to this study. Firstly, the use of a second-hand dataset makes it difficult to preprocess the data in a more efficient way. Additionally, we had little information on the manner in which the screening was conducted, and, because of this, there are doubt on who performed the echocardiograms and the cardiac auscultation. This is turn raises the question of the observer's experience. Also, due to the nature of voluntary screenings, there is probably a selection bias which overestimates the presence of pathology within the population.

Regarding the sound feature extraction, by using MFCC we have limited our analysis of sound in the frequency domain. Because some pathologies may influence the duration of the heartbeat components and the loudness of the sound, time and amplitude features could potentially be added in future works as a way to solve this limitation.

In terms of the models training, these results are limited in the fact that only one bootstrapping resample was performed. These experiments should be repeat with more resamples to obtain a

better estimate of the performance of the models.

4.3. Conclusions

There is much room for improvement and experimentation in this field. Further research is needed on the extraction and selection of features, preferably avoiding the need for segmentation of heart sound. It is also important to create a tool that is computationally efficient and that can be used in more basic processing devices. This has the potential to become a useful tool in the screening of CHD.

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