Automated Detection of Rheumatic Heart Disease via Unsegmented Heart Sound Analysis

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Abstract

Rheumatic Heart Disease (RHD) remains a significant cause of morbidity and mortality in many parts of the world, particularly in low-resource settings. Early detection and intervention are critical to mitigating its progression and reducing associated complications. This paper presents an automated approach for the detection of RHD utilizing unsegmented heart sound analysis through deep learning techniques. By leveraging Spectro-temporal representations of raw heart sound signals, our proposed method aims to capture subtle yet discriminative patterns indicative of RHD pathology. The deep learning model is trained on a dataset comprising a diverse range of heart sounds, including those from both RHD-positive and RHD-negative individuals. Through rigorous evaluation of unseen data, our approach demonstrates promising performance in accurately distinguishing between RHD and healthy heart sounds. Furthermore, the proposed methodology offers the potential for scalable and cost-effective screening in resource-limited settings, thereby facilitating early identification and management of RHD cases. This work contributes to the advancement of computer-aided diagnostic tools for cardiovascular diseases, with implications for improving healthcare outcomes and reducing the burden of RHD globally.

Key Words: Rheumatic Heart Disease, Heart Sound Analysis, Deep Learning, Automated Detection, Unsegmented Signals, Spectro-Temporal Representation, Cardiovascular Disease.

1. INTRODUCTION

Rheumatic Heart Failure (RHF), also known as congestive heart failure, is a medical condition in which the heart is unable to pump blood effectively, leading to a range of symptoms and complications. It is a long-term or Rheumatic condition, as opposed to acute heart failure, which occurs suddenly. RHF can be caused by various underlying conditions, including coronary artery disease (CAD), hypertension, heart valve disorders, cardiomyopathies, and other heart-related diseases. It can also result from non-cardiac factors such as kidney disease, and diabetes, and lifestyle factors like obesity and excessive alcohol consumption.

Management and treatment of Rheumatic heart failure typically involve lifestyle modifications, medication to improve heart function and reduce symptoms, and sometimes surgical interventions such as heart valve repair or replacement. Heart transplantation may be explored for severe cases in humans in numerous cases where the ailment affects the quality of life for the affected individuals.

Effective management of the illness requires early identification and routine RHF monitoring. New technologies are being investigated to help with the early diagnosis and treatment of RHF, which can enhance the quality of life for those who have this illness. Examples of these technologies include machine learning models and remote monitoring systems.

Rheumatic heart failure (RHF) is a Rheumatic, progressive condition underscored by the heart's inability to supply enough perfusion to target tissues and organs at the physiological filling pressures to meet their metabolic demands. RHF has reached epidemic proportions in the population, as its incidence is increasing by 2% annually. In the developed world, RHF affects 1-2% of the total population and 10% of people older than 65 years.

Currently, the diagnosis and treatment of RHF use approximately 2% of the annual healthcare budget. In absolute terms, the USA spent approximately 35 billion USD to treat RHF in 2018 alone, and the costs are expected to double in the next 10 years. Despite the progress in medical- and device-based treatment approaches in the last decades, the overall prognosis of RHF is still dismal, as the 5-year survival rate of this population is only approximately 50%.

During the normal course of RHF therapy, we witness alternating episodes of compensated phases, in which the patient feels well and does not exhibit symptoms or signs of systemic fluid overload, and decompensated phases, in which the patient is clearly experiencing symptoms and signs of systemic fluid overload, including dyspnea, peripheral edema, liver congestion, and pulmonary edema. In the later cases, patients frequently need to be admitted to the hospital in order to get intravenous treatment (diuretics, inotropes) in order to successfully achieve a negative fluid balance and return to the compensatory condition.

Early identification of heart failure aggravating would let a treating physician to promptly modify the patient's outpatient medical care, thereby preventing hospitalization. At this time, a skilled doctor can identify HF worsening through physical examination and distinctive alterations in the patient's heart failure biomarkers, which are derived from the patient's blood.

Unfortunately, the clinical worsening of an RHF patient likely means that we are already dealing with a fully developed RHF episode that will most likely require a hospital admission. Additionally, in some patients, characteristic changes in heart sounds can accompany heart failure worsening and can be heard using Phonocardiogram.In healthy subjects, 2 heart sounds are typically heard (called S1 and S2).

S1 is caused by the closure of the mitral valve and ventricular wall in the early systole, and S2 is caused by the closure of the aortic and pulmonary valves at the beginning of the diastole. Here, the time between S1 and S2 is referred to as the cardiac cycle's contraction phase, or systole, while the interval between S2 and S1 is referred to as its relaxation phase, or diastole. Extra cardiac sounds (such S3 and S4) that are never regarded as normal can be produced by certain cardiac diseases.

A third sound (S3) that usually occurs 0.1–0.2 seconds following the second sound (S2) can frequently be heard in the event of RHF (during the decompensation phase). It has recently been shown that some physiological markers, including the presence of extra heartbeats or elevated blood pressure in the pulmonary circulation, begin to manifest several weeks prior to the RHF patient experiencing a decompensation episode that is clinically noticeable.

This is also an important therapeutic window where outpatient-based treatment interventions can reverse RHF deterioration and return the patient to a compensated state without the need for hospital admission. Many studies conducted in the last few years have suggested using PCG signals captured with a digital stethoscope to automatically diagnose various cardiac problems using Machine Learning (ML) techniques. However, there aren't many techniques that specifically target RHF detection.

A typical machine learning (ML) pipeline for identifying various heart conditions looks like this: first, the signals are segmented by identifying the "typical" heart sounds (S1 and S2); next, the signals are denoised; next, specific frequency-domain and time-domain features are extracted; and finally, a feature-based ML model is learned (e.g., using ML algorithms, such as Random Forest or Support Vector Machine - SVM) that can distinguish between healthy and unhealthy sounds.

The majority of the features in use today are derived from knowledge of audio and signal processing and medicine. A comprehensive assessment of the patient is used by clinicians to identify RHF patients instead of relying solely on cardiac sounds because a PCG recording that appears unhealthy to one expert may sound healthy to another (i.e., lengthy medical history, blood pressure, laboratory testing, etc.)

One explanation for this confusion is because, in the most recent PhysioNet cardiology challenge, experts classified as "unknown" 9.7% of the recordings, while the remaining recordings were classified as either healthy or unwell. End-to-end learning, or machine learning models that learn straight from the raw data without the requirement for features, may be able to outperform traditional feature-based machine learning, according to recent developments in Deep Learning (DL).

2.PROPOSED METHOD

It consists of the following two main components: a classic ML component (represented with colored squares on the right side of the figure) and an end-to-end DL component (represented with non-colored squares). The input to the classic ML pipeline is the same as the input to the end-to-end DL pipeline, but the classic ML pipeline contains a feature extraction process to extract features from the raw data and to format the data into a classic ML format.

The end-to-end DL operates directly with the raw data and doesn't require feature extraction. Furthermore, signals from the temporal and frequency domains are supported by both pipelines. A recording-based machine learning model then combines the outputs of the two halves to provide the final prediction, which indicates whether a recording is from a patient or a healthy subject. The ensuing subsections provide an explanation of the method's specifics.

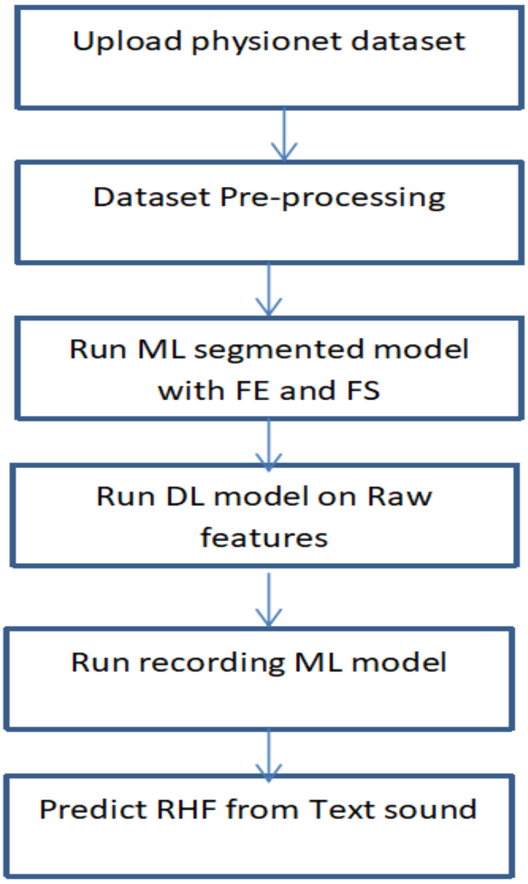

Fig-1: Proposed model

2.1 DATASET STUDY

The PhysioNet Challenge database consists of six datasets (A through F, recorded by six research groups - participants of the competition) containing a total of 3,153 heart sound recordings, lasting from 5 seconds to just over 2 minutes. The recordings were obtained in either a clinical or a nonclinical environment, from both healthy subjects and pathological patients, and at different locations on the body.

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Though they might occur in any of nine places, the four common locations were the aortic, pulmonic, tricuspid, and mitral areas. Children and adults are included in the samples of pathological patients as well as healthy subjects. One to six recordings may have been contributed by each subject or patient. That being said, the dataset does not specify which recording is owned by whom. Every recording was converted to "wav" format and resampled to 2,000 Hz.

There is only one PCG lead per recording. Many of the recordings are distorted by different noise sources, including talking, breathing, stethoscope motion, and intestinal sounds, because they were frequently made in uncontrolled settings. In addition, some recordings were difficult or even impossible to classify as normal or abnormal. The summary of the recordings in the Challenge database can be found in Fig.2. In addition, each of the six teams recording the training sets also produced a testing set, which was used for the evaluations of the contributed algorithms. We did not have access to the testing sets; therefore, we did not include them in our analysis.

We recorded 110 healthy people (meaning that they had no medical condition) and 51 people diagnosed with RHF. For 22 RHF patients, recordings were obtained both during the decompensation episode (when hospitalized) and during the compensated phase (when discharged). The recordings were always obtained at Erb's point, and each recording was up to 30 s long (stethoscope's limit). For some healthy people, more than one recording was obtained to increase the amount of data in the study (recordings of patients were obtained in clinical settings, which limited the available time).

			Proportion (%)		
Data	#Subjects	#Recordings	Abnorm.	Normal	Unsure
A	121	409	67.5	28.4	4.2
B	106	490	14.9	60.2	24.9
C	31	31	64.5	22.6	12.9
D	38	55	47.3	47.3	5.5
E	356	2054	7.1	86.7	6.2
F	112	114	27.2	68.4	4.4
ALL	764	3153	18.1	73.0	9.7

Fig-2: Overview of PhysioNet Challenge Dataset

2.2 METHODOLOGY

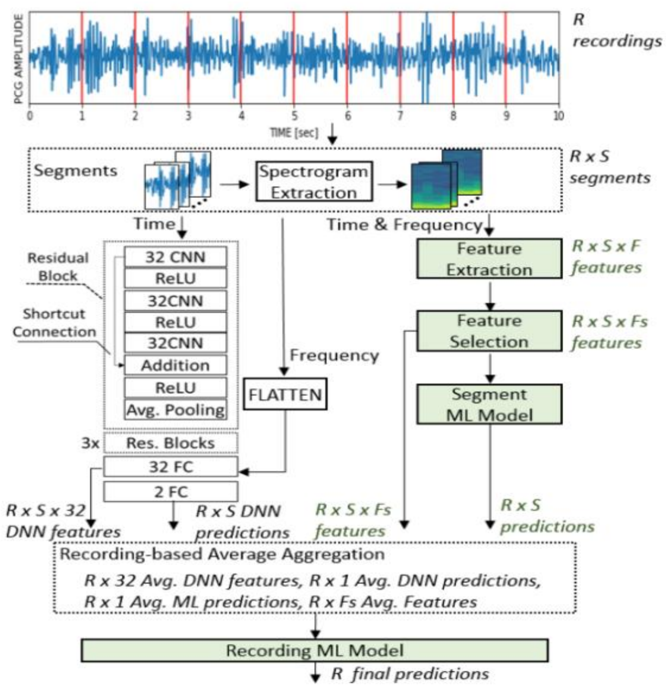

Fig-3: System Architecture

Each segment is represented by segment-based features, which describe only the segment itself, and recording-based features, which describe the whole recording. The shortest segment size used in our experiments was one second so that each segment contained at least one complete heartbeat (with common heart rates above 60 beats per minute).

Our goal is to obtain both short-term and long-term information by extracting features from the segments as well as the entire recordings. The long-term information explains the entire recording, whereas the short-term information from the segment-based features mostly defines the Heartbeats. Since we receive F-features for each R-recording and S-segment, the feature extraction component's output is labeled as "R x S x F features" in Fig.2.

A feature selection step is necessary to prevent overfitting because there are many times more potential features (1941 x 2) for each segment than there are recordings in the majority of the experimental datasets. Generally speaking, there are three types of feature selection methods: ranking methods (also called filter methods), wrapper methods, and combinations of the two.

Using the mutual information values between the features and the class values, we prioritized the features. Only the top-ranked m features—where m is the number of training samples—were used. 10% of the randomly chosen examples from the training data were used to rank the features. In Figure 2, the feature selection component's output is identified as "R x S x Fs features." A segment-based classifier was trained subsequent to the feature selection process.

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The segment-based classifier uses the segments as input instances, represented via the selected features from the previous step, and outputs the estimated class probabilities for each segment (segment-class probabilities) of each recording. The output probabilities are marked as “R x S predictions” in Fig. 3. The segment-class probabilities are later used as the input to the recording-based classifier. The segment-based classifier was trained using the Random Forest (RF) algorithm. We chose the RF algorithm because it is robust to noise in the input features. The recording-based classifier is described in the Combining Classic ML and end-to-end DL section.

2.3 OVERVIEW OF TECHNOLOGIES

Libraries used:

Pandas -

Pandas is a Python computer language library for data analysis and manipulation. It offers a specific operation and data format for handling time series and numerical tables. It differs significantly from the release3-clause of the BSD license. It is a well-liked open-source of opinion that is utilized in machine learning and data analysis.

NumPy -

The NumPy Python library for multi-dimensional, big-scale matrices adds a huge number of high-level mathematical functions. It is possible to modify NumPy by utilizing a Python library. Along with line, algebra, and the Fourier transform operations, it also contains several matrices-related functions.

Matplotlib -

It is a multi-platform, array-based data visualization framework built to interact with the whole SciPy stack. MATLAB is proposed as an open-source alternative. Matplotlib is a Python extension and a cross-platform toolkit for graphical plotting and visualization.

Scikit-learn -

The most stable and practical machine-learning library for Python is sci-kit-learn. Regression, dimensionality reduction, classification, and clustering are just a few of the helpful tools it provides through the Python interface for statistical modeling and machine learning. It is an essential part of the Python machine-learning toolbox used by JP Morgan. It is frequently used in various machine learning applications, including classification and predictive analysis.

Keras -

Google's Keras is a cutting-edge deep learning API for creating neural networks. It is created in Python and is designed to simplify the development of neural networks. Additionally, it enables the use of various neural networks for computation. Deep learning models are developed and tested using the free and open-source Python software known as Keras.

h5py -

The h5py Python module offers an interface for the binary HDF5 data format. Thanks to p5py, the top can quickly halt the vast amount of numerical data and alter it using the NumPy library. It employs common syntax for Python, NumPy, and dictionary arrays.

2.4 RESULTS

Rheumatic Heart Disease (RHD) is an autoimmune response to a bacterial attack that deteriorates the normal functioning of the heart valves. The damage to the valves affects the normal blood flow inside the heart chambers which can be recorded and listened to via a stethoscope as a phonocardiogram. However, the manual method of auscultation is difficult, time-consuming and subjective. In this study, a convolutional neural network-based deep learning algorithm is used to perform automatic auscultation and it classifies the heart sound as normal and Rheumatic.When categorizing unsegmented data, it is not necessary to extract the first, second, systolic, and diastolic heart sounds. The CNN network's design is composed of several levels. Max pooling is used after batch normalization and convolutional layers to down sample the feature maps. Finally, a final max pooling layer is added, which pools the input feature map globally over time, along with a completely linked layer. The network has five convolutional layers.Using a Mel Spectro-temporal representation, the current work demonstrates the application of a deep convolutional neural network. For this current study, an RHD heart sounds data set. In propose paper, we are using the heart sound dataset from the PHYSIONET website and this dataset contains heart signals data, the heart signals get trained with Classic ML algorithms, and then heart recording voice data will get trained with a deep learning algorithm.

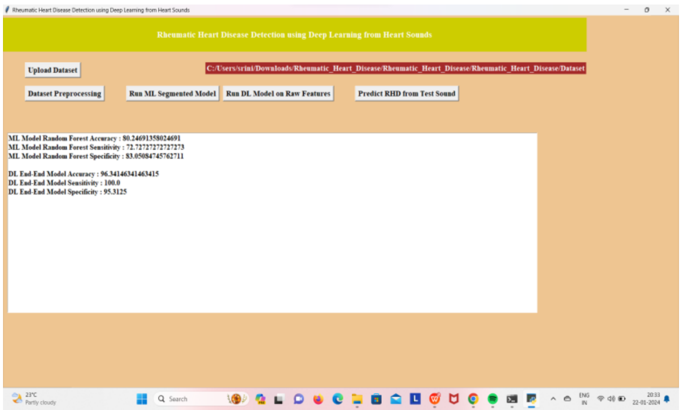

Fig-4: Predicting the accuracy

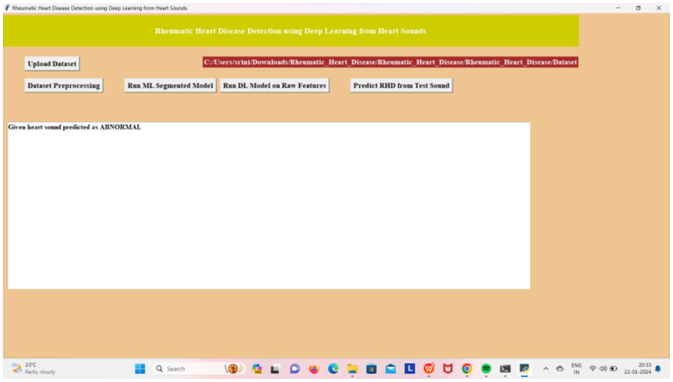

Fig-5: Predicting the RHD from Test Sound

3.CONCLUSIONS

It has been demonstrated that deep convolutional networks which are designed for image recognition can be successfully trained to classify heart sound spectral images. Our trained model obtained the best overall accuracy sensitivity and 98.2% specificity in detecting RHD. This can help to develop timely, affordable, and reliable access to cost-effective technologies for the detection and prevention of rheumatic heart disease.

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