Heart Disease Prediction from heart beat audio signals using Machine Learning and Network Analysis

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Github page: https://github.com/DavideLigari01/advanced-biomedical-project

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Abstract — —TO BE DEFINED—

Keywords ——TO BE DEFINED—

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3. Dataset Description

The dataset for this project was obtained from a Kaggle repository titled *Dangerous Heartbeat Dataset (DHD)* [1], which in turn sources its data from the PASCAL Classifying Heart Sounds Challenge 2011 (CHSC2011) [2]. This dataset comprises audio recordings of heartbeats, categorized into different types of heart sounds. Specifically, the dataset consists of 5 types of recordings: Normal Heart Sounds, Murmur Sounds, Extra Heart Sounds, Extrasystole Sounds, and Artifacts. Data has been gathered from the general public via the iStethoscope Pro iPhone app and from a clinic trial in hospitals using the digital stethoscope DigiScope.

4. Heart Diseases

4.1. Normal Category

In the Normal category, there are normal, healthy heart sounds. These may contain noise in the final second of the recording as the device is removed from the body. They may contain a variety of background noises (from traffic to radios). They may also contain occasional random noise corresponding to breathing, or brushing the microphone against clothing or skin. A normal heart sound has a clear "lub dub, lub dub" pattern, with the time from "lub" to "dub" shorter than the time from "dub" to the next "lub" (when the heart rate is less than 140 beats per minute). Note the temporal description of "lub" and "dub" locations over time in the following illustration:

In medicine, we call the lub sound "S1" and the dub sound "S2". Most normal heart rates at rest will be between about 60 and 100 beats ("lub dub"s) per minute. However, note that since the data may have been collected from children or adults in calm or excited states, the heart rates in the data may vary from 40 to 140 beats or higher per minute. Dataset B also contains noisy_normal data normal data which includes a substantial amount of background noise or distortion. You may choose to use this or ignore it, however, the test set will include some equally noisy examples.

4.2. Murmur Category

Heart murmurs sound as though there is a "whooshing, roaring, rumbling, or turbulent fluid" noise in one of two temporal locations: (1) between "lub" and "dub", or (2) between "dub" and "lub". They can be a symptom of many heart disorders, some serious. There will still be a "lub" and a "dub". One of the things that confuses non-medically trained people is that murmurs happen between lub and dub or between dub and lub; not on lub and not on dub. Below, you can find an asterisk* at the locations a murmur may be.
Dataset B also contains noisy_murmur data murmur data which includes a substantial amount of background noise or distortion. You may choose to use this or ignore it, however, the test set will include some equally noisy examples.

4.3. Extra Heart Sound Category

Extra heart sounds can be identified because there is an additional sound, e.g., a "lub-lub dub" or a "lub dub-dub". An extra heart sound may not be a sign of disease. However, in some situations, it is an important sign of disease, which if detected early could help a person. The extra heart sound is important to be able to detect as

4.4. Artifact Category

In the Artifact category, there are a wide range of different sounds, including feedback squeals and echoes, speech, music, and noise. There are usually no discernible heart sounds, and thus little or no temporal periodicity at frequencies below 195 Hz. This category is the most different from the others. It is important to be able to distinguish this category from the other three categories, so that someone gathering the data can be instructed to try again.

4.5. Extrasystole Category

Extrasystole sounds may appear occasionally and can be identified because there is a heart sound that is out of rhythm involving extra or skipped heartbeats, e.g., a "lub-lub dub" or a "lub dub-dub". (This is not the same as an extra heart sound as the event is not regularly occurring.) An extrasystole may not be a sign of disease. It can happen normally in an adult and can be very common in children. However, in some situations, extrasystoles can be caused by heart diseases. If these diseases are detected earlier, then treatment is likely to be more effective. Below, note the temporal description of the extra heart sounds:

5. Goals

6. Feature Extraction

6.1. Methodology

6.2. Features Type

MFCC
Mel-Frequency Cepstral Coefficients (MFCCs) are representations of the short-term power spectrum of sound. They are derived by taking the Fourier transform of a signal, mapping the powers of the spectrum onto the mel scale, taking the logarithm, and then performing a discrete cosine transform. MFCCs are effective in capturing the timbral texture of audio and are widely used in speech and audio processing due to their ability to represent the envelope of the time power spectrum.

Chroma STFT
Chroma features represent the 12 different pitch classes of music (e.g., C, C#, D, etc.). They are particularly useful for capturing harmonic and melodic characteristics in music. By mapping audio signals onto the chroma scale, these features can identify pitches regardless of the octave, making them useful for analyzing harmonic content in heart sounds.

RMS
Root Mean Square (RMS) measures the magnitude of varying quantities, in this case, the amplitude of an audio signal. It is a straightforward way to compute the energy of the signal over a given time frame. RMS is useful in audio analysis for detecting volume changes and can help identify different types of heartbeats based on their energy levels.

ZCR
Zero-Crossing Rate (ZCR) is the rate at which a signal changes sign, indicating how often the signal crosses the zero amplitude line. It is particularly useful for detecting the noisiness and the temporal structure of the signal. In heartbeat classification, ZCR can help differentiate between normal and abnormal sounds by highlighting changes in signal periodicity.

CQT
Constant-Q Transform (CQT) is a time-frequency representation with a logarithmic frequency scale, making it suitable for musical applications. It captures more detail at lower frequencies, which is essential for analyzing the low-frequency components of heart sounds. CQT can help

identify rhythmic and harmonic patterns in the audio.

Spectral Centroid
The spectral centroid indicates the center of mass of the spectrum and is often perceived as the brightness of a sound. It is calculated as the weighted mean of the frequencies present in the signal, with their magnitudes as weights. In heart sound analysis, a higher spectral centroid can indicate sharper, more pronounced sounds, while a lower centroid suggests smoother sounds.

Spectral Bandwidth
Spectral bandwidth measures the width of the spectrum around the centroid, providing an indication of the range of frequencies present. It is calculated as the square root of the variance of the spectrum. This feature helps in understanding the spread of the frequency components in the heart sounds, which can be indicative of different heart conditions.

Spectral Roll-off Spectral roll-off is the frequency below which a certain percentage of the total spectral energy lies. It is typically set at 85% and helps distinguish between harmonic and non-harmonic content. In heartbeat classification, spectral roll-off can be used to differentiate between sounds with a concentrated energy distribution and those with more dispersed energy.

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