Answer Sheet for Assessment 1
L349 - Mobile Health

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1030 words (excluding bibliography, headers, and captions)

Part 1: Audio Processing Basics [25 marks]

Task 1.2

Question 1: Discuss any differences between the two files in the time domain, giving possible reasons.

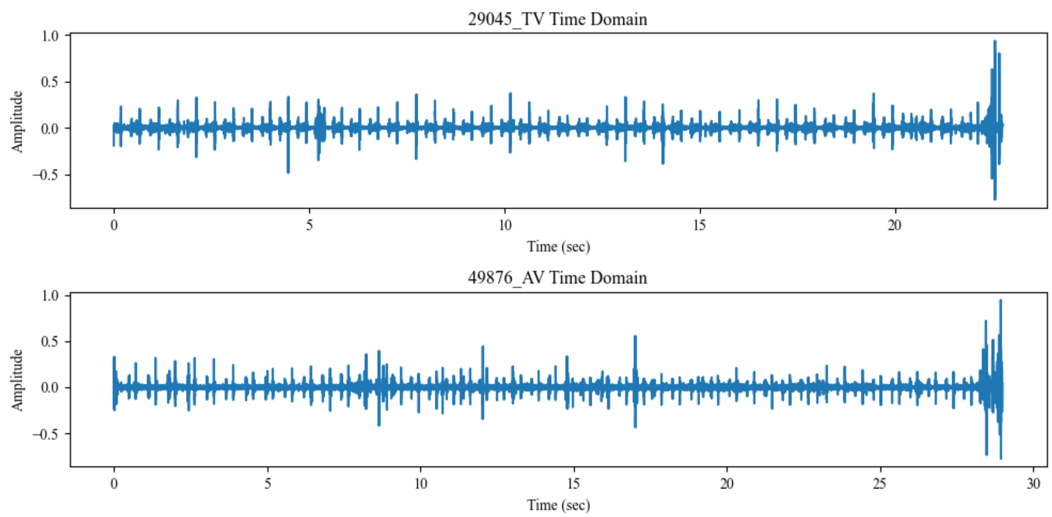

Figure 1: Time domain plot of the 29045_TV and 49876_AV audio files. Full length.

Table 1 provides an overview of the differences between the two files in the time domain.

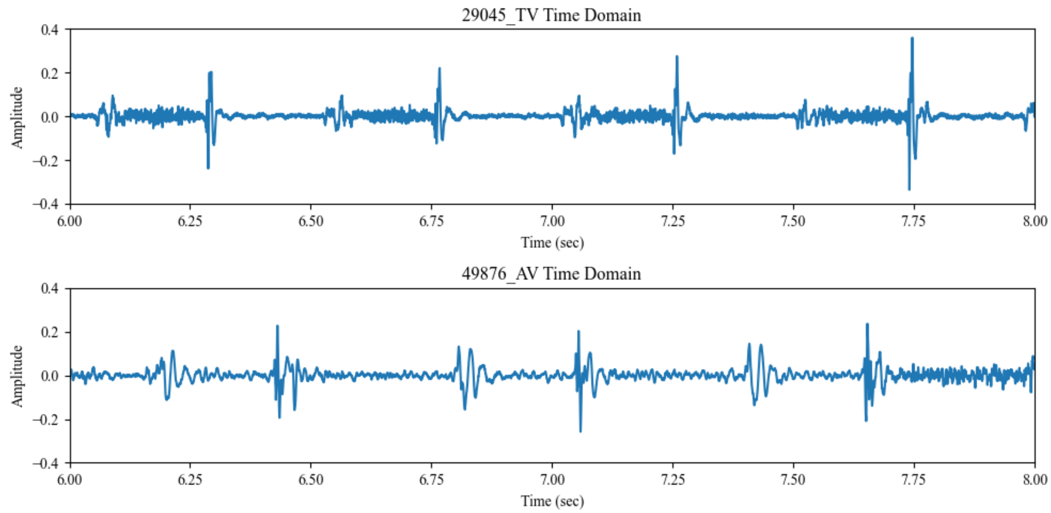

Figure 2: Time domain plot of the 29045_TV and 49876_AV audio files. Zoomed x-axis (time). Both plots show a clear heart beat. While the

Table 1: Comparison of Heartbeat Audio Signals in Time Domain

File	**Observations**	**Possible Reasons**
29045_TV Figure 1 & Figure 2	- clearly recognisable heartbeats, especially when zoomed in - constantly noticeable amplitude between S1 and S2, otherwise relatively small amplitude - heart rate: ∼120 bpm, frequency: ∼2 Hz	- clear sound recording with little noise - noticeable amplitude between S1 & S2 indicates murmur - higher heart rate potentially consequence of heart conditions that might also cause murmor
49876_AV Figure 1 & Figure 2	- heartbeats (incl. S1 & S2) can also be identified, but with greater irregularity and variation in amplitude - stronger fluctuations throughout - heart rate: ∼90 bpm, frequency: ∼1.5 Hz	- Less accurate recording with more noise

Question 2: Based on the above, can you visually differentiate between the murmur and non-murmur heart sounds? Predict which is the murmur and which is the non-murmur.

- 29045_TV looks more regular and less conspicuous at first glance
- nevertheless, possible limitations of the sound file quality (i.e. noise, recording accuracy etc.) must also be taken into account
- research shows: sound development between S1 ("lub") and S2 ("dub") is particularly relevant to identify murmur [23]
- Only **29045_TV** shows noticeable amplitude here (see Figure 2)-> could represent "blowing, whooshing, or rasping sound heard during a heartbeat", indicating a murmur [30]
- possible murmur type: pattern is similar to mitral regurgitation ("C" in graphic), but as it is strongly audible at the tricuspid valve, it might indicate a tricuspid regurgitation [9, 14]
- -> 29045_TV = murmur, 49876_AV = non-murmur,

Task 1.3

Question 1: Discuss any differences between the frequency domain representations of the murmur and non-murmur files.

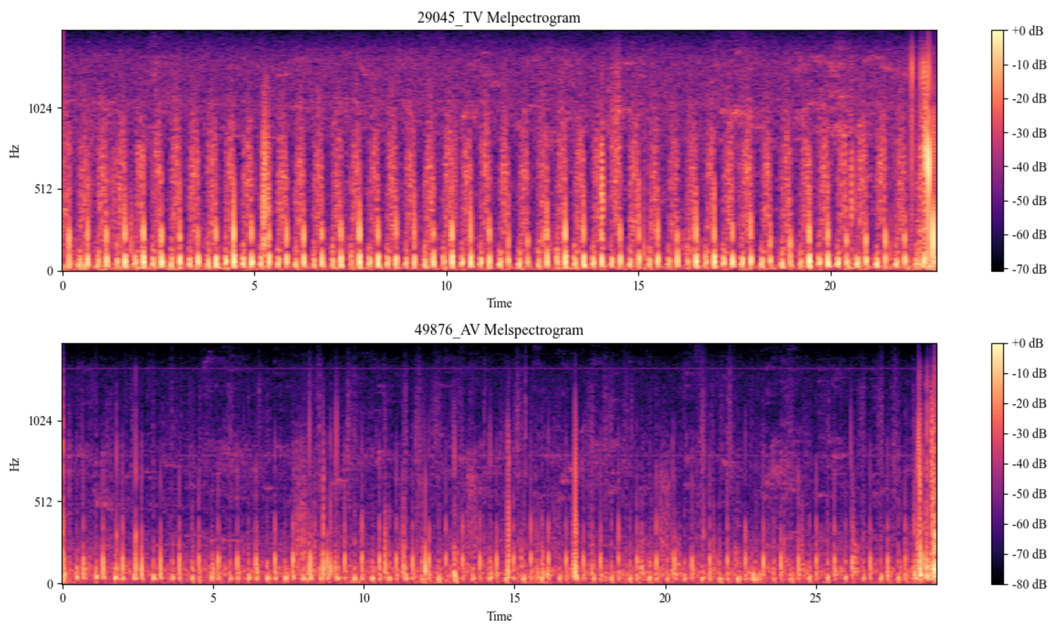

Figure 3: Melspectogram representation of 29045_TV and 49876_AV.

- 29045_TV (Murmur):
  - concentration of peaks primarily in low-frequency range, up to ∼150Hz
  - exhibits two further peaks in the distribution of frequencies around ∼250Hz and ∼650Hz
  - generally more spread-out
  - melspectogram representation, especially when zoomed (Figure 4), clearly reveals S1 and S2 with energy in high frequency –> corresponds to typical high(er) frequencies of murmurs [2]
- 49876_AV (Non-murmur):
  - almost exclusively concentration of peaks in low-frequency range, although slightly higher, up to ∼200Hz
  - exhibits some isolated high-frequency peaks, likely noise
  - melspectogram shows short "bursts" for S1 & S2, indicating normal heart beats

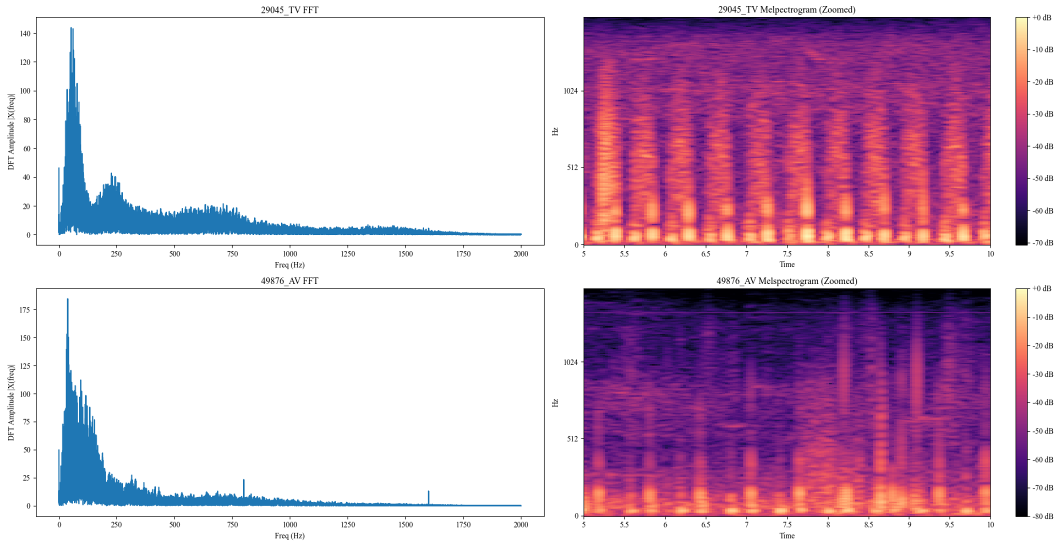

Figure 4: Enter Caption

Question 2: Are there any features that are evident in the frequency domain that you could not distinguish in the time domain?

- time domain was not able to show which frequencies make up the signal –> frequency domain allows conclusions regarding involved frequencies and the extent of their involvement
- graphs reveal that the 29045_TV signal is composed of much stronger higher frequencies than the 49876_AV signal, which, in line with scholarship [e.g. 2, 11, 25], confirms the classification of 29045_TV as murmur

Task 1.4

Question 1: Discuss and provide reasons for your choice of filter type and cutoffs.

- 1. Step: consider findings of initial visual analysis of (unfiltered) frequency domain graphs -> Figure 5 exhibits majority of peaks to a maximum of $\sim$1000Hz –> cutoff latest after 1000Hz seems reasonable
- 2. Step: confirm and identify detailed cutoffs as well as filter types by consulting relevant scientific research about the typical frequency range for heart sounds and murmurs, and settings typically used in heart sound analyses -> Table 2 informed decision to use **6th-order Butterworth bandpass filter (BBF) with cutoff frequency from 20 to 600 Hz** (should cover nearly all heart sounds and murmurs)

Question 2: Provide a discussion of the differences between the raw and filtered data, and thus on the importance of filtering in signal processing. Are there any potential disadvantages or tradeoffs of applying signal processing?

Differences between data:

- filtered signal in time domain is visually "thinner"
- isolated and clear outliers (i.e. "noise") are removed
- filtered FFT plots reveal focus on strong frequencies and regions with relatively high amplitude
- filtered time domain plots exhibit less noise around regions of interest (i.e. heartbeat sound between S1 & S2) -> indicates reason for signal processing

Importance of filtering in signal processing:

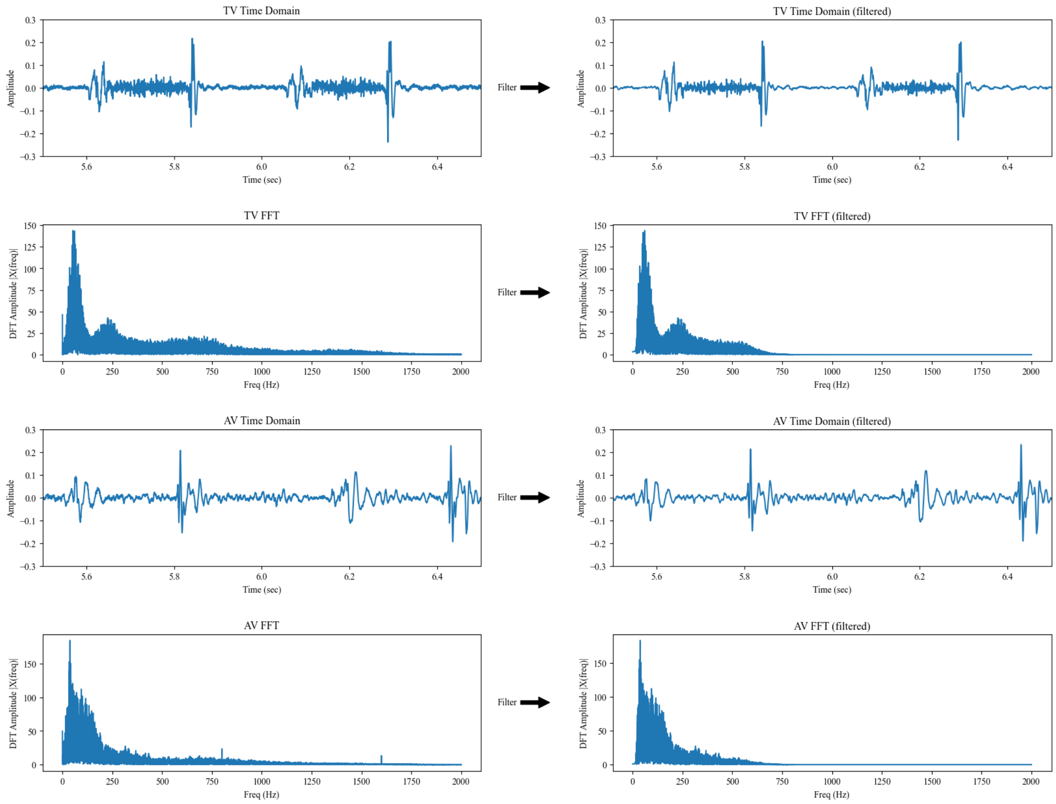

Figure 5: Enter Caption

- one of the most important, and typical first steps in analysis of (heart) sounds [28, 19]
- goal: reveal information in measurements/signal [7, 12], remove undesired/unwanted signal components (e.g. noise), increase reliability, facilitate analysis of relevant signal portion [10]

Disadvantages & Trade-offs:

- filtering is a challenging task [5]
- facilitates analysis but also brings the danger of accidentally removing relevant sound components, especially in heart sound recording where noise often lies in same frequency range [28]

Task 1.5

Question 1: Discuss whether you can differentiate between the signals or not and if not, why not.

- both files show numerous irregularities in the signal in their time domain graphs (unfiltered & filtered) -> heartbeats can be visually detected, but not as clearly analysed as in Task 1.2
- FFT diagrams and melspectograms (Figure 6 & Figure 7 suggests a murmur in AV_29045, due to stronger higher frequencies and two regions with peaks, but AV_39043 exhibits strong energy in these areas as well (yet, plots suggest AV_39043
- -> overall no clear visual classification possible

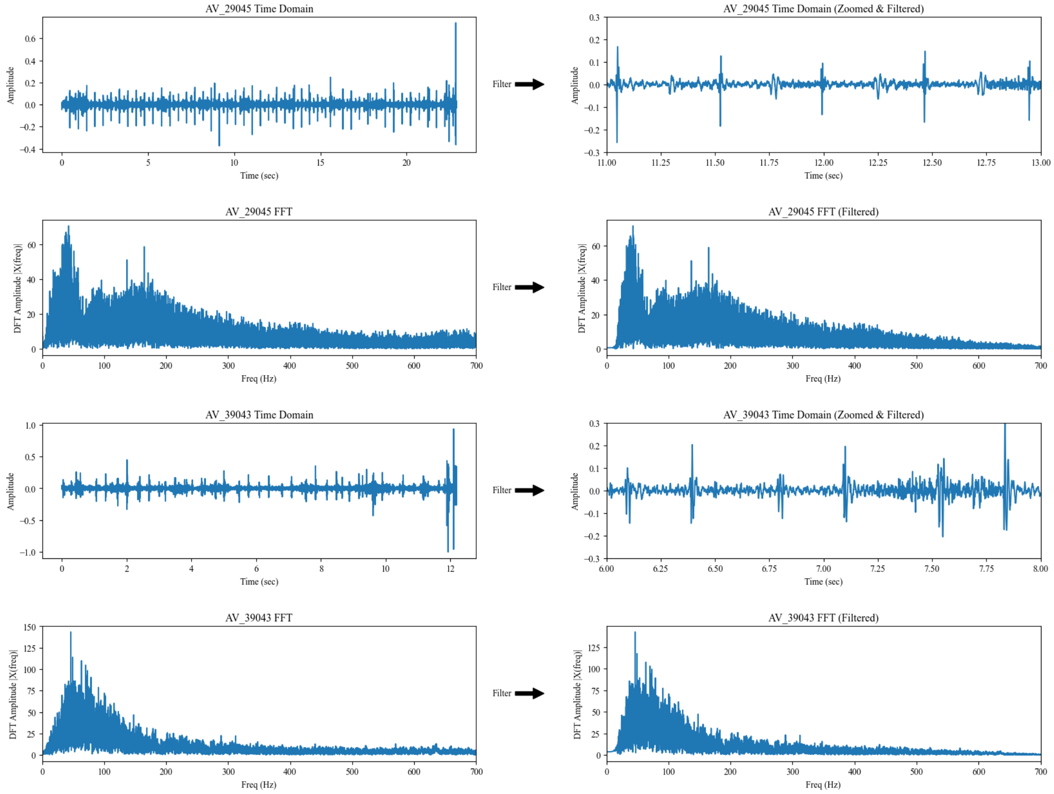

Figure 6: Enter Caption

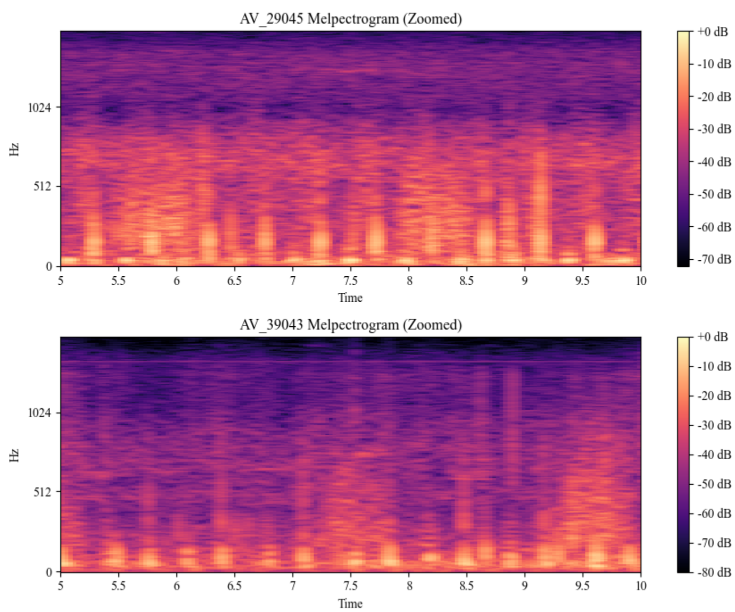

Figure 7: Enter Caption

Element of Interest	Relevant Frequencies	Filter Specified?	Source
Cardiopulmonary auscultation	50-1200 Hz	N/A	Charbonneau and Sudraud [1]
Heart sound	40-1100 Hz	BFF	El-Segaier et al. [4] Markaki et al. [13]
Heart sound	25-900 Hz	6th-order BBF	Chakir et al. [16]
Heart beat	40-500 Hz	4th-order BBF	Shekhar et al. [25]
S1 and S2	50-500 Hz	N/A	Spencer and Pennington [15]
S3 and S4	20-200 Hz	N/A	Spencer and Pennington [15]
Critical heartbeat	70-120 Hz	N/A	Bankaitis [29]
Murmurs	80-500 Hz	N/A	Tomas et al. [11]
Murmurs	200-410 Hz	N/A	Donnerstein [2]
Murmurs	< 300 Hz	N/A	Spencer and Pennington [15]
Murmurs	20-150 Hz, < 500 Hz	N/A	Rennert et al. [3]
Most murmurs	< 200 Hz	N/A	Debbal and Bereksi-Reguig [6]

Table 2: Overview of selected frequency and filter settings for analysing heartbeat and murmur sounds in scientific literature

Part 2: Dataset processing [15 marks]

Task 2.2

Question 1: What is the ratio of normal to murmur patients? And what is the ratio of normal to murmur samples? Can you think of any implications of this?

- #Normal Patients: 135, #Murmur Patients: 56, **Ratio: 2.41**
- #Normal Samples: 584, #Murmur Samples: 180, **Ratio: 3.24**
- Implications: identified ratios show that dataset is imbalanced -> strong negative impact on model performance!
  - bias: models might be biased towards predicting majority class (i.e. normal diagnoses), due to higher frequency –> poor generalisation capabilities
  - generally, but especially given class imbalance, accuracy is not a good evaluation metric
  - data resampling needed to mitigate imbalance!
  - common problem in medical and heartbeat sound datasets [8, 22]

Question 2: Prepare some graphs representing basic demographic split across classes, such as sex, age, etc. Make sure you use the correct type of graph for your data to display the information intuitively.

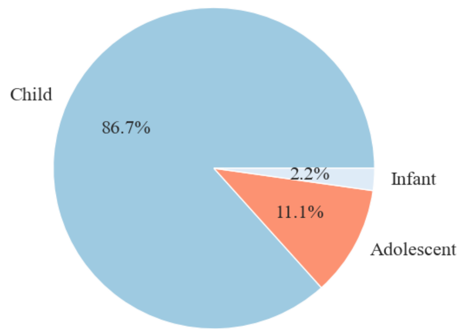

Figure 8: Age Distribution of Patients

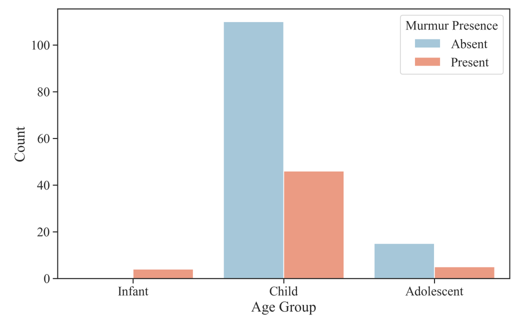

Figure 9: Age Distribution of Patients with and without Murmur

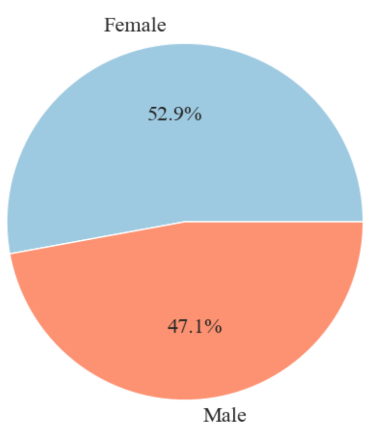

Figure 10: Sex Distribution of Patients

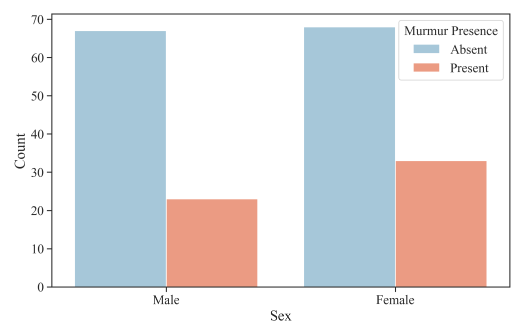

Figure 11: Sex Distribution of Patients with and without Murmur

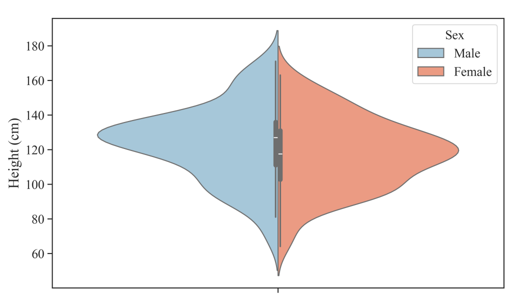

Figure 12: Height Distribution by Sex

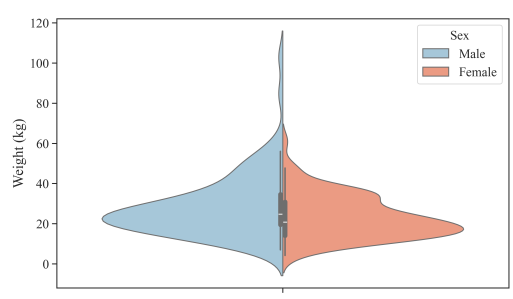

Figure 13: Weight Distribution by Sex

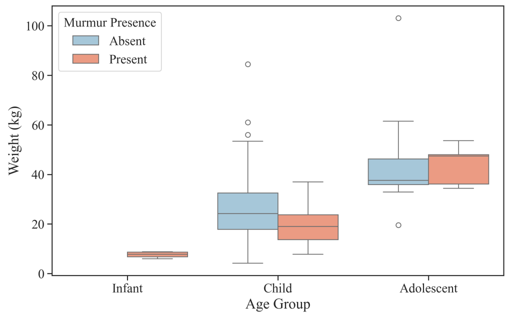

Figure 14: Weight Across Age Groups

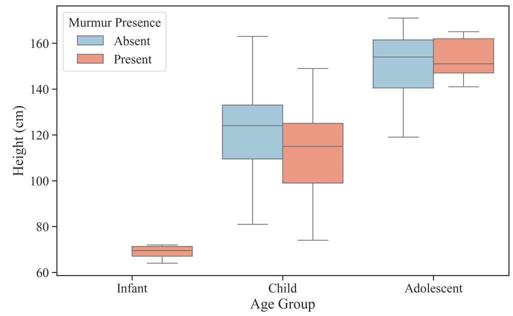

Figure 15: Height Across Age Groups

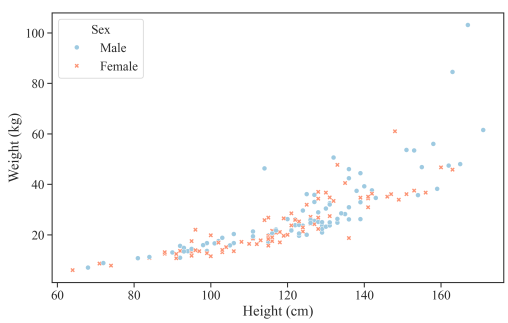

Figure 16: Height vs. Weight

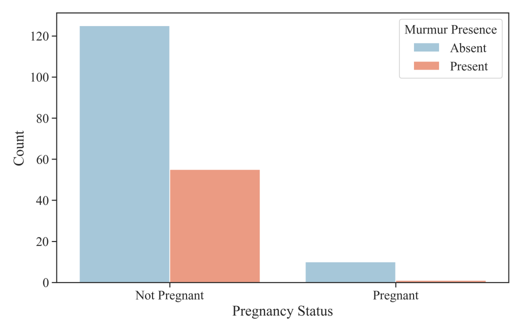

Figure 17: Pregnancy Status Distribution

Question 3: What significance does the demographic split carry in datasets used for ML?

- significant relevance for identifying potential biases in models and datasets -> if imbalanced, model might only perform well on majority class [17]
- diverse dataset is necessary for model to generalise well across gender, age, different populations etc., otherwise: bad performance for underrepresented groups! [20] –> important regulatory and ethical implications: healthcare is sensitive domain and models should not discriminate against selected groups! [24]
- demographic information can be used to inform personalised treatment plans, drug development etc.

Task 2.4

Question 1: What is the effect of tackling the imbalance on the resulting classification performance? Give results to compare different methods of tackling imbalance.

- Challenges and risks to consider according to Leevy et al. [17]:
  - upsampling: risk of overfitting as minority class samples are replicated
  - downsampling: potential loss of useful information as majority class is reduced
- comparison of the classification results using upsampling (see Table 7) vs. downsampling (see Table 5) reveals that both resampling method allow for a balanced dataset leading to improved results
- upsampling seems to result in marginally better performance in general, especially

Part 3: Feature extraction [30 marks]

Task 3.1

Question 1: Which features did you choose and why? Use literature and/or performance assessments to inform your decisions.

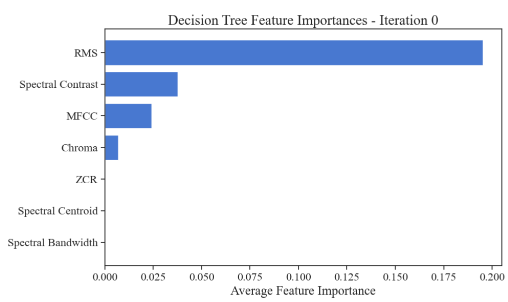

Figure 18: Decision Tree Mean Feature Importances

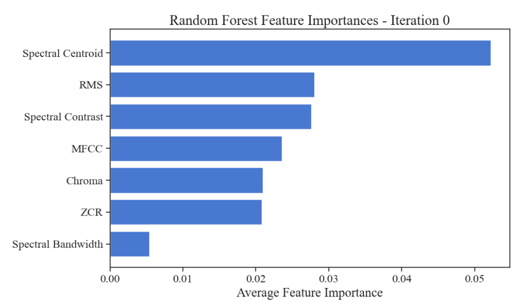

Figure 19: Random Forests Mean Feature Importances

Question 2: What parameters have you chosen for the features that you extracted (e.g. hop length, window size, etc.) and why?

Approach:

1. choose most promising features
2. grid search on parameters
3. for each combination, calculate the mean difference between the distributions of the feature calculated for the murmur vs. normal class
4. pick the parameter(s) yielding the biggest difference
5. set this parameter for other features

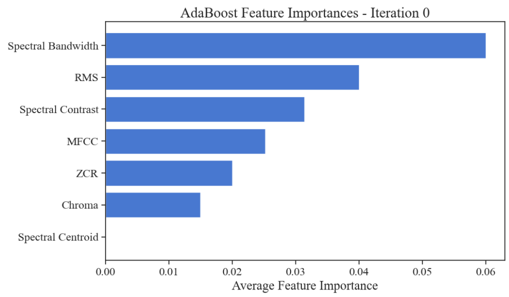

Figure 20: Ada Mean Aggregated Feature Importances

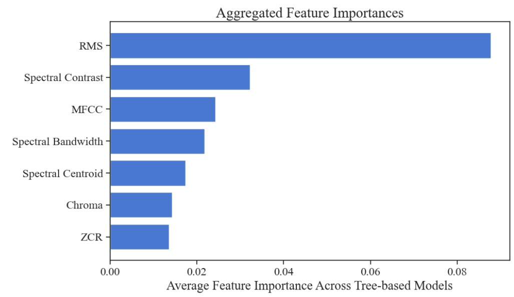

Figure 21: Mean Aggregated Feature Importances

Table 3: Selection of Librosa [33] Features for Heart Sound Classification

Feature	Name	Function	Reason
MFCC	Mel frequency cepstrum coefficients	Captures timbral aspects	Widely used in heart sounds analysis [21]
Chroma	Chroma Features	Captures harmonic content	Useful for identifying harmonic patterns within heart sounds which might indicate health status or pathologies.
ZCR	Zero Crossing Rate	Measures frequency of sign changes	indicative of turbulence or irregularities in heart sounds, widely used [16]
RMS	Root Mean Square Energy	Measures signal energy	Reflects the energy of heart sounds, helpful in detecting the presence and intensity of heartbeats.
Spectral Centroid	Spectral Centroid	Indicates "center of mass" of the spectrum	Provides a measure of the brightness of a sound, useful for characterizing heart sound texture.
Spectral Contrast	Spectral Contrast	Measures contrast in spectral peaks and valleys	Can distinguish between different phonological aspects of heart sounds, aiding in the identification of abnormal sounds.
Spectral Bandwidth	Spectral Bandwidth	Measures width of the spectrum	Can indicate the spread of energy across frequencies, useful for detecting anomalies in heart sounds.

Chosen parameters:

- hop_length=128
- n_fft (i.e. window size)=1024, based on findings in Task 1.3
- n_mfcc=19, informed by Yaseen et al.[18]
- n_chroma=12, default parameter according to librosa documentation [**noauthor_librosafeaturechroma_stft_nodate**]

Task 3.4

Question 1: Describe the full preprocessing pipeline that you used.

1. Resample data using upsampling or downsampling techniques to address class imbalance (see Task 2.4)

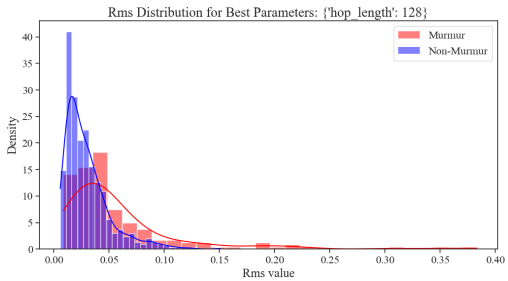

Figure 22: RMS distribution for **hop_length=128** (tested parameter values: 128, 256, 1024, 2048)

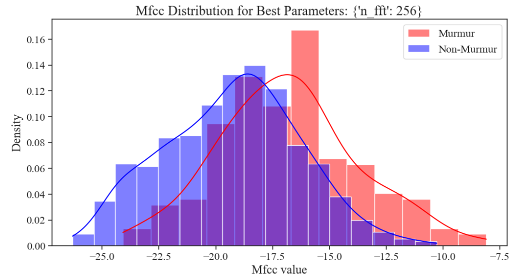

Figure 23: MFCC distribution for **n_fft=256** (tested parameter values: 128, 256, 512, 1024, 2048)

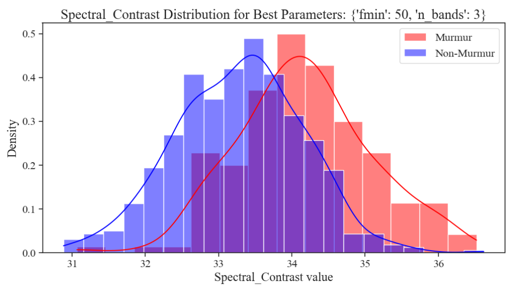

Figure 24: Spectral contrast distribution for **fmin=50, n_bands=3** (tested parameter values: fmin: [10, 20, 50], n_bands: [3, 4, 5, 6])

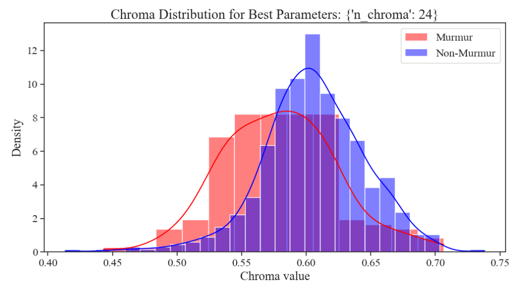

Figure 25: Chroma STFT distribution for **n_chroma=24** (tested parameter values: [12, 16, 20, 24],)

2. Filter data using the same BBF as described in Task 1.4 to remove noise
3. Extract relevant features from the audio data (see above)
4. Standardise features through $z = (x - u)/s$, with u being the mean and s the standard deviation [32]
5. Reduce data dimension through Principal Component Analysis (PCA), proven to improve performance in cardiac analysis [26, 27]

Question 2: Which features or combination of features yield the best performance and why?

Question 3: Which classifier is yielding the best overall performance?

Question 4: What effect do individual preprocessing steps have on the final result?

- comparison of Table 8 (no resampling) with Table 7 & Table 5 demonstrates significance of tackling class imbalance -> high accuracy in Table 8 stems from high specificity -> model mainly predicts majority class

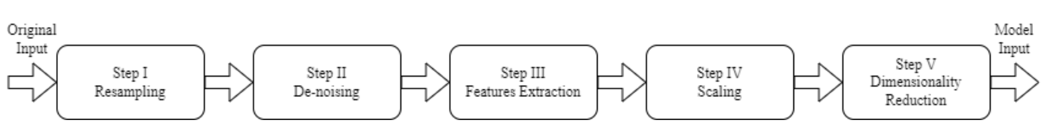

Figure 26: Full Preprocessing Pipeline, design informed by Chen et al. [21] and Zeinali and Niaki [26]

Table 4: Performance Metrics of Best Classifiers per Iteration, Based on **Acc**, **Upsampled**

No.	Input Features	Best Classifier	**Acc**	MAcc	Se	Sp
0	mfcc (n_mfcc=13)	Gaussian Process	0.698	0.578	0.348	0.808
1	mfcc (n_mfcc=19)	Gaussian Process	0.734	0.483	0.000	**0.966**
2	chroma	Decision Tree	0.661	0.517	0.239	0.795
3	mfcc, chroma	Decision Tree	0.661	0.614	**0.522**	0.705
4	chroma, spectral_centroid	Linear SVM	0.589	0.536	0.435	0.637
5	mfcc, rms, zero_crossing_rate	QDA	**0.776**	0.592	0.239	0.945
6	spectral_centroid, spectral_contrast	Random Forest	0.703	0.641	**0.522**	0.760
7	mfcc, chroma, zero_crossing_rate, spectral_contrast	Gaussian Process	0.703	0.581	0.348	0.815
8	mfcc, chroma, spectral_centroid, spectral_bandwidth	Gaussian Process	0.714	0.588	0.348	0.829
9	mfcc, chroma, zero_crossing_rate, spectral_centroid, spectral_contrast, rms	Decision Tree	0.760	**0.679**	**0.522**	0.836

Table 5: Performance Metrics of Best Classifiers per Iteration, Based on **MAcc**, **Downsampled**

No.	Input Features	Best Classifier	Acc	**MAcc**	Se	Sp
0	mfcc (n_mfcc=13)	Nearest Neighbors	0.615	0.568	0.478	0.658
1	mfcc (n_mfcc=19)	Linear SVM	0.552	0.571	0.609	0.534
2	chroma	Random Forest	0.500	0.560	**0.674**	0.445
3	mfcc, chroma	Gaussian Process	0.641	0.622	0.587	0.658
4	chroma, spectral_centroid	Linear SVM	0.615	0.583	0.522	0.644
5	mfcc, rms, zero_crossing_rate	RBF SVM	0.667	0.624	0.543	0.705
6	spectral_centroid, spectral_contrast	Gaussian Process	0.661	**0.666**	**0.674**	0.658
7	mfcc, chroma, zero_crossing_rate, spectral_contrast	Linear SVM	**0.682**	0.642	0.565	**0.719**
8	mfcc, chroma, spectral_centroid, spectral_bandwidth	RBF SVM	0.630	0.638	0.652	0.623
9	mfcc, chroma, zero_crossing_rate, spectral_centroid, spectral_contrast, rms	AdaBoost	0.677	0.661	0.630	0.692

Table 6: Performance Metrics of Best Classifiers per Iteration, Based on **MAcc**, **Upsampled**

No.	Input Features	Best Classifier	Acc	**MAcc**	Se	Sp
0	mfcc (n_mfcc=13)	Nearest Neighbors	0.667	0.610	0.500	0.719
1	mfcc (n_mfcc=19)	Linear SVM	0.557	0.575	0.609	0.541
2	chroma	Neural Net	0.552	0.542	0.522	0.562
3	mfcc, chroma	Decision Tree	0.661	0.614	0.522	0.705
4	chroma, spectral_centroid	Naive Bayes	0.573	0.570	0.565	0.575
5	mfcc, rms, zero_crossing_rate	Neural Net	0.677	0.639	0.565	0.712
6	spectral_centroid, spectral_contrast	Naive Bayes	0.667	0.677	**0.696**	0.658
7	mfcc, chroma, zero_crossing_rate, spectral_contrast	AdaBoost	0.693	0.634	0.522	0.747
8	mfcc, chroma, spectral_centroid, spectral_bandwidth	Random Forest	0.698	0.630	0.500	0.760
9	mfcc, chroma, zero_crossing_rate, spectral_centroid, spectral_contrast, rms	AdaBoost	**0.760**	**0.686**	0.543	**0.829**

Table 7: Performance Metrics of Best Classifier Candidates, Based on **MAcc**, **Upsampled**

No.	Input Features	Best Classifier	Acc	**MAcc**	Se	Sp
6	spectral_centroid, spectral_contrast	**Naive Bayes**	0.667	0.677	**0.696**	0.658
9	mfcc, chroma, zero_crossing_rate, spectral_centroid, spectral_contrast, rms	**AdaBoost**	**0.760**	**0.686**	0.543	**0.829**

Table 8: Performance Metrics of Best Classifiers per Iteration (based on Acc), **without resampling**

No.	Input Features	Best Classifier	Acc	MAcc	Se	Sp
0	mfcc (n_mfcc=13)	RBF SVM	0.771	0.544	0.109	0.979
1	mfcc (n_mfcc=19)	RBF SVM	0.781	0.551	0.109	0.993
2	chroma	Linear SVM	0.760	0.500	0.000	1.000
3	mfcc, chroma	Decision Tree	0.776	0.570	0.174	0.966
4	chroma, spectral_centroid	Linear SVM	0.760	0.500	0.000	1.000
5	mfcc, rms, zero_crossing_rate	QDA	0.792	0.588	0.196	0.979
6	spectral_centroid, spectral_contrast	Decision Tree	0.771	0.552	0.130	0.973
7	mfcc, chroma, zero_crossing_rate, spectral_contrast	Gaussian Process	0.781	0.596	0.239	0.952
8	mfcc, chroma, spectral_centroid, spectral_bandwidth	RBF SVM	0.781	0.566	0.152	0.979
9	mfcc, chroma, zero_crossing_rate, spectral_centroid, spectral_contrast, rms	QDA	0.797	0.591	0.196	0.986

Part 4: Your Own Data [10 marks]

Note: two recordings were analysed to mitigate potential recording differences/errors

Task 4.1

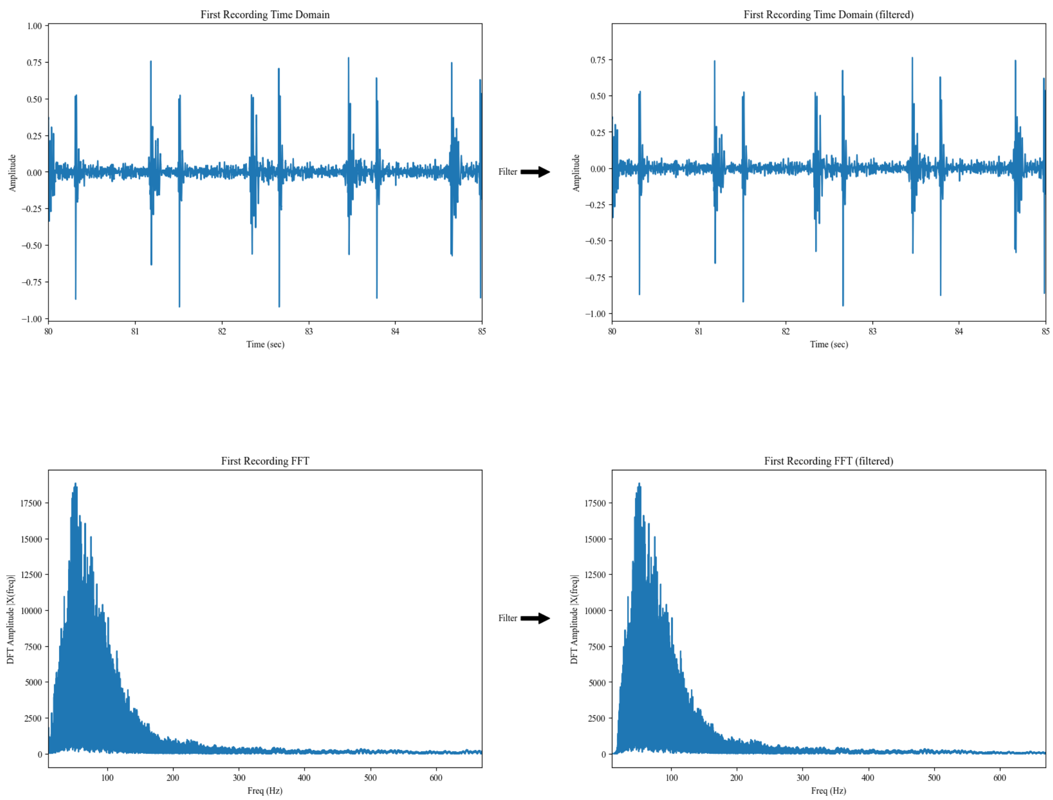

Figure 27: First Recording of Own Heart Sound Data (time domain and frequency domain)

Question 1: What differences are there between the frequency spectrums of your recording and the files we provided? Discuss why there might be differences.

Differences:

- own recordings are visibly less noisy and exhibit a significantly stronger concentration of lower frequencies -> majority of the signal consists of frequencies < 200 Hz -> contrast to provided files, especially recordings of patients with a murmur
- visible differences in overall amplitude (own recording exhibits generally stronger amplitude)

Reasons:

- different physiology of the recorded individual
- different recording setup (i.e. different locations)
- different recording device (i.e. private iPhone vs. digital stethoscope used in PhysioNet Challenge [31])
- different environment leading to different noise

1030 words (excluding bibliography, headers, and captions)

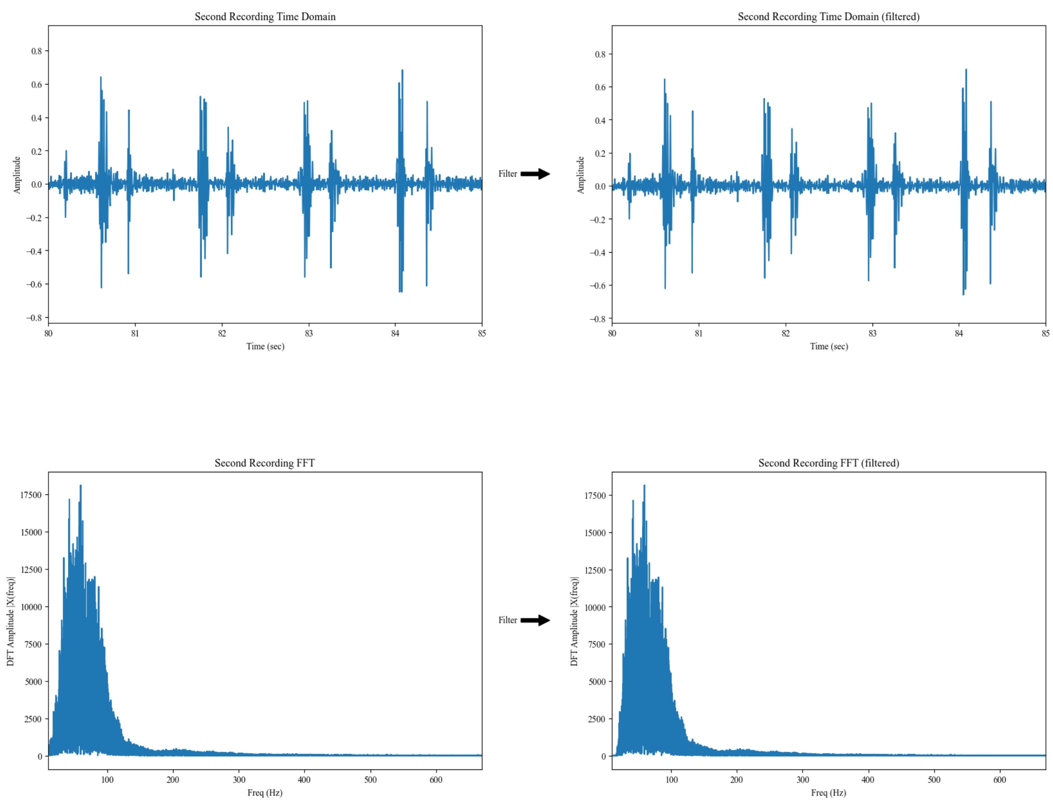

Figure 28: Second recording of own heart sound data (time domain and frequency domain)

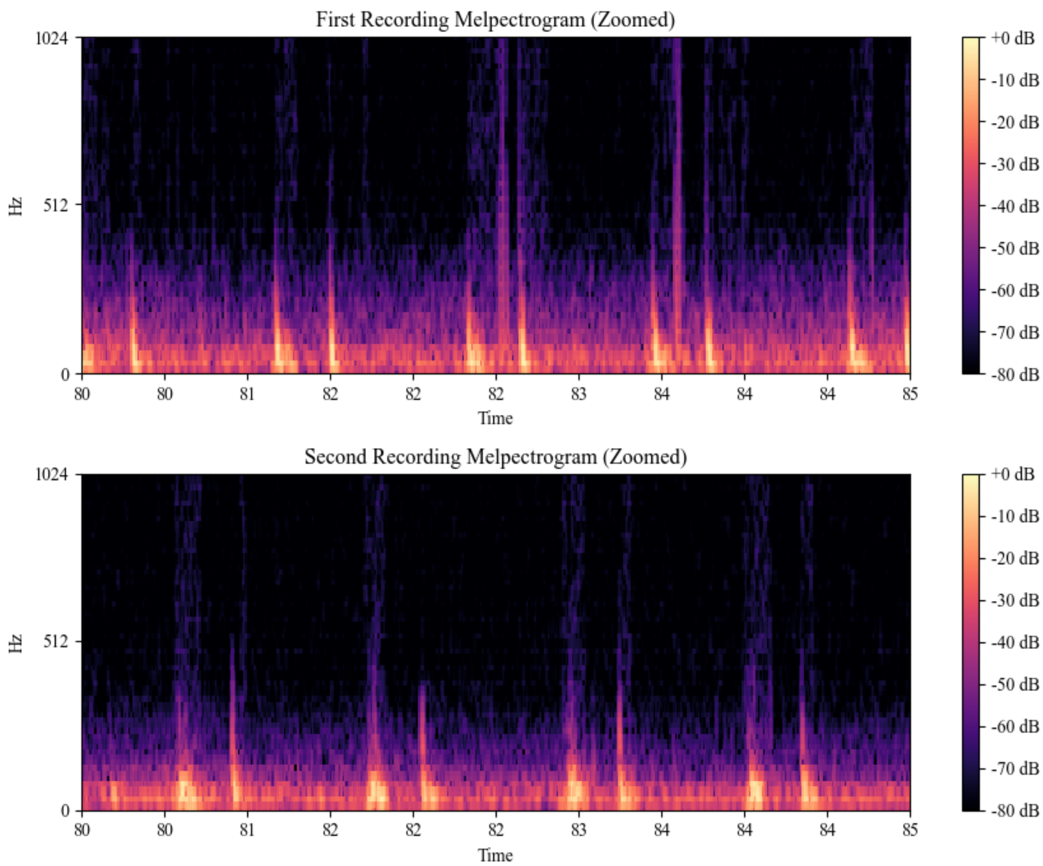

Figure 29: Melspectograms of heart sound recordings

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