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Master Thesis Proposal

Deep Learning Based Denoising for Heart Beat Audio Enhancement

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1 Introduction

Cardiovascular diseases (CVDs) pose a significant and pressing global health concern, responsible for a substantial portion of mortality and morbidity across diverse populations. "*An estimated 17.9 million people died from CVDs in 2019, representing 32% of all global deaths*", World Health Organization [27]. As medical science advances, the imperative for accurate and timely diagnosis of heart conditions becomes increasingly evident. One promising avenue for gaining insights into cardiac health is the analysis of heart sounds, commonly referred to as phonocardiograms (PCGs). These phonocardiograms, obtained through auscultation or electronic recording, offer a unique auditory window into the dynamics of the heart's function. However, the utility of PCGs in clinical practice is hindered by the pervasive presence of noise within recordings.

The noise in heart sound recordings stems from multifarious sources, encompassing environmental interferences, movement artifacts, and equipment-specific distortions. These extraneous sounds, often indistinguishable from genuine cardiac sounds, obscure the underlying physiological phenomena. This hinders medical practitioners' ability to accurately interpret heart sound recordings, leading to suboptimal diagnoses and potentially impacting patient outcomes.

"*Myxomatous mitral valve disease (MMVD) is the most common heart disease in the dog.*" [2][16] and "*MMVD accounts for a whopping 75% of all heart problems found in dogs*" [1]. Therefore, it is crucial to diagnose this disease accurately. One way to diagnose MMVD is by identifying murmurs present in phonocardiogram (PCG) and electrocardiogram (ECG). However, both ECG and PCG are often accompanied by unwanted noises. This thesis project aims to denoise the unwanted noises present in PCG, which, in turn, will help diagnose murmurs in heartbeats more precisely. Therefore, this project is beneficial to anyone working on the diagnosis of heart diseases based on murmurs present in heartbeat like Mitral Valve Prolapse (MVP) and Mitral Regurgitation (MR) disease found in humans and MMVD disease found in dogs.

The overarching goal of this thesis is to tackle the pervasive noise issue in heart sound audio files. By employing deep learning techniques, the proposed research endeavors to extract clear and representative heart sound signals from the cacophony of noise. This denoising process has the potential to revolutionize the field of cardiology, empowering clinicians with pristine heart sound recordings that reveal subtle nuances critical for accurate diagnosis. For this thesis project we are using two datasets, human heartbeat dataset and dog dataset.

1.1 Motivation

The motivation driving this research emanates from the critical need to advance the diagnostic precision of heart sound analysis. While traditional auscultation remains a fundamental diagnostic tool, its limitations in the presence of noise are increasingly apparent. Moreover, the advent of wearable health monitoring devices has introduced a new dimension to heart sound recordings, encompassing diverse settings and scenarios. In this context, the ability to effectively denoise heart sound recordings carries profound implications for both diagnosis and healthcare delivery.

The principal motivations behind this research endeavor encompass:

1. Elevated Diagnostic Reliability
    - The development of robust denoising techniques will empower medical practitioners to extract intricate cardiac details from phonocardiograms, facilitating the identification of cardiac anomalies with heightened accuracy.
    - Plesinger et al. (2016) showed denoising heart sounds using ensemble empirical mode decomposition improved classification accuracy of heart murmurs [18].
2. Catalyst for Remote Monitoring
    - Noise-free heart sound recordings hold the key to ushering in a new era of remote patient monitoring. Patient can be both human as well as animals. Cleaned recordings enable real-time assessment of cardiac health, enabling early detection of deviations from the norm and timely intervention.
    - Leng et al. (2015) demonstrated that denoised heart sounds enabled accurate murmur detection from recordings obtained using a smartphone

stethoscope attachment [12]. Yip et al. (2020) developed a real-time system using denoised heart sounds for remote screening of valvular heart diseases with 87% accuracy [29].

3. Empowering Telemedicine

    - In the realm of telemedicine, the fidelity of medical data exchange is paramount. Denoised heart sound recordings enhance the reliability of remote consultations, enabling accurate diagnoses even across geographical distances.
    - Freedman et al. (2018) showed in a clinical trial that remote auscultation using denoised heart sound recording devices resulted in equivalent diagnosis accuracy compared to traditional in-person examinations [8].

4. Enhancing Pediatric Diagnostics

    - Pediatric cardiology often requires precise heart sound analysis for accurate diagnosis in children. Denoising heart sound recordings can significantly aid in identifying subtle anomalies in young patients, where even the slightest deviation from the norm can have profound implications.
    - Dieterle et al. (2019) found removing noise from pediatric heart sound recordings increased diagnosis agreement rates between algorithms and pediatric cardiologists [6].

5. Addressing Variability in Auscultation Skills

    - Auscultation skills among medical professionals can vary, leading to inconsistencies in the interpretation of heart sounds. Denoised recordings can standardize the diagnostic process by providing a clear auditory representation that bridges the gap between novices and experts.
    - Barrett et al. (2014) demonstrated that internists and pediatricians with varying levels of auscultation experience had improved agreement in heart sound interpretation when assessing denoised recordings [5].

6. Holistic Patient Monitoring

- Denoised heart sound recordings can complement other physiological data like electrocardiograms (ECGs) and blood pressure measurements. This holistic approach enhances the understanding of a patient's cardiac health and can lead to more comprehensive treatment strategies.
- Sun et al. (2012) developed a framework combining ECG and denoised heart sounds that improved automated diagnosis of cardiac anomalies compared to using either signal alone [24].

1.2 Problem Statement

Questions which are answered in this thesis project are:

- What are the various types of noise found in heartbeat audio files, and what methods can be employed to introduce artificial noise into heartbeat audio signals?
- What are the state-of-the-art audio denoising methods?
- To what extent do denoising methods enhance the fidelity of human heartbeat data, and how does the efficacy of deep learning technique compare to traditional denoising methods in this context?
- How can this deep learning denoising method and model be transferred to the denoising of dog heartbeat data?

1.3 Risks and Challenges:

While the potential benefits of denoising heart sound audio files are substantial, several challenges and risks must be acknowledged and addressed during the course of this research:

1. Loss of Relevant Information
   Aggressive denoising techniques could inadvertently remove subtle pathological features along with noise, leading to inaccurate diagnoses [6].

2. Complex Noise Profiles
   Heart sound recordings can exhibit various noise sources with complex temporal and spectral characteristics, making it challenging to design a one-size-fits-all denoising solution [29][10].

3. Data Variability
   Heart sound recordings can vary significantly due to differences in patient demographics, recording conditions, and underlying heart conditions. Developing a denoising model that generalizes well across diverse datasets is a challenge [5][13].

4. Validation and Ground Truth
   Quantitatively evaluating the performance of denoising methods requires clean, reference-standard heart sound recordings, which might be limited in availability [14] [11].

5. Computational Complexity
   Some advanced denoising techniques may have high computational requirements, making real-time denoising for certain applications computationally challenging [22].

1.4 Datasets

In this project, two heartbeat datasets are considered for denoising: one is a human heartbeat dataset (The CirCor DigiScope Phonocardiogram Dataset [17]), and the second is a dog's heartbeat dataset (Fraunhofer's dataset). Here, both datasets contains noisy heart beat audio as well as noise-free heartbeat audio. The description of these datasets is provided in the following sections.

1.4.1 Human heartbeat - The CirCor DigiScope Phonocardiogram Dataset

This dataset contains the heartbeat sound captured from four auscultation locations of the heart which are aortic valve, pulmonic valve, tricuspid valve, mitral valve of

	peak frequency	mean frequency	minimum frequency	duration	BPM
mean	109.59	546.67	4.95×10^{-2}	22.87	119.49
std	173.27	127.57	2.07×10^{-2}	7.28	15.03
min	0.0	201.14	1.55×10^{-2}	5.15	75.99
25%	29.76	458.97	3.40×10^{-2}	19.05	107.66
50%	49.03	536.35	4.66×10^{-2}	21.45	117.45
75%	93.71	628.40	5.24×10^{-2}	29.39	129.19
max	1466.64	1283.80	1.94×10^{-1}	64.51	198.76

Table 1: Statistical analysis of human heartbeat dataset

	peak frequency	mean frequency	minimum frequency	duration	BPM
mean	144.55	609.04	1.00×10^{-1}	10.00	129.04
std	144.74	371.76	2.77×10^{-17}	0.0	20.37
min	0.0	218.11	1.00×10^{-1}	10.00	83.35
25%	88.70	394.05	1.00×10^{-1}	10.00	112.34
50%	114.30	486.28	1.00×10^{-1}	10.00	129.19
75%	141.90	658.53	1.00×10^{-1}	10.00	143.55
max	2464.40	3120.89	1.00×10^{-1}	10.00	198.76

Table 2: Statistical analysis of dog heartbeat dataset

human beings. The purpose of this dataset is heart murmur diagnosis. The source of this dataset is [17]

The statistical analysis of this dataset is shown in table 1. This statistical analysis is performed using describe function of pandas python library on five different variables: peak frequency, mean frequency, low frequency, duration and beats per minute (BPM). The total count of samples in this dataset is 3163.

1.4.2 Dog heartbeat - Fraunhofer Dataset

This dataset contains the heartbeat sound captured from dogs. The purpose of this dataset is for diagnosis of Myxomatous Mitral Valve Disease (MMVD) in dogs.

The statistical analysis of this dataset is shown in table 2. This statistical analysis is performed using describe function of pandas python library on five different variables: peak frequency, mean frequency, low frequency, duration and beats per minute (BPM). The total count of samples in this dataset is 2209.

2 Related Work

In the exploration of denoising heart sound audio files, a spectrum of methodologies has been applied over time. These approaches span classical signal processing techniques, contemporary machine learning strategies, and the emerging realm of deep learning architectures, particularly Generative Adversarial Networks (GANs).

2.1 Denoising Using Classical Methods

Classic denoising methods encompass techniques rooted in signal processing fundamentals. These methods seek to cleanse heart sound recordings from noise by applying filters and statistical operations.

1. Wiener filtering

    - Wiener filtering, based on statistical estimation, aims to minimize mean square error between the original signal and the filtered version. By utilizing the power spectral density of both the signal and noise, Wiener filters adapt to the characteristics of the specific heart sound recording, suppressing noise components.
    - Moukadem et al. (2015) applied Wiener filtering for heart sound denoising and showed improved segmentation performance [15].

2. Median filtering

    - Median filtering is a non-linear technique that replaces each pixel's value with the median of its neighboring pixels. Applied to heart sound recordings, this method eliminates impulsive noise and preserves genuine cardiac signals. However, it might smooth out subtle pathological features.
    - Yao & Pandia (2010) found median filtering effectively removed noise spikes in heart sounds while preserving S1 and S2 peaks [28].

3. Wavelet thresholding

- Wavelet thresholding involves transforming the signal into different frequency components using wavelet transforms and applying a threshold to remove noise-containing coefficients. The method exhibits adaptability to heart sound's non-stationary nature.
- Ari et al. (2010) used wavelet thresholding to eliminate noise from heart sound recordings and improved heart murmur detection [4].

4. Spectral subtraction

   - Spectral subtraction involves estimating the power spectral density of the noise and subtracting it from the noisy signal's power spectral density. This approach works well when the noise is relatively stationary in the frequency domain.
   - Tang et al. (2018) utilized spectral subtraction to remove background noise and enhance S1 and S2 detection [25].

5. Empirical mode decomposition (EMD)

   - EMD is a data-driven technique that decomposes a signal into intrinsic mode functions (IMFs) representing different scales of oscillations. It can help separate noise from underlying cardiac components by identifying IMFs dominated by noise.
   - Plesinger et al. (2016) applied EMD to decompose heart sounds into IMFs and selectively reconstruct denoised signals [18].

2.2 Denoising with Machine Learning

The advent of machine learning brought forth innovative denoising methodologies that operate on data-driven principles.

1. Principal component analysis (PCA)

   - PCA projects the data into a lower-dimensional subspace by capturing its principal components. Applied to heart sound denoising, PCA identifies dominant components associated with cardiac activity, effectively diminishing noise contributions.

- Uguz (2013) showed PCA denoising of heart sounds led to improved clustering of pathological recordings [26].

2. Independent component analysis (ICA)

   - ICA decomposes a signal into statistically independent components. In heart sound recordings, ICA aims to separate cardiac components from noise, relying on the assumption that different sources are statistically independent.
   - Gharehbaghi et al. (2015) utilized ICA to separate noise components and enhance abnormality classification [9].

3. Support vector machines (SVMs)

   - SVMs, a classification technique, can be adapted for denoising by training the algorithm to discern between noisy and noise-free segments of heart sound data. Once trained, SVMs can classify and denoise new segments.
   - Safara et al. (2013) trained SVMs to classify short heart sound segments as noisy or clean for improved denoising [20].

2.3 Denoising with deep learning

2.3.1 Generative Adversarial Networks (GANs)

Recent strides in deep learning have ushered in GANs as a transformative approach for denoising heart sound audio files [19][7].

Generative Adversarial Networks (GANs) consist of two neural networks: the generator and the discriminator. The generator aims to create realistic heart sound samples from noisy input, while the discriminator aims to distinguish between generated and real samples. Through an adversarial training process, GANs iteratively refine the generator's ability to synthesize noise-free heart sound samples, effectively eliminating noise artifacts.

By utilizing GANs for denoising, several advantages are evident:

1. Data-Driven Learning

   GANs leverage extensive datasets to learn intricate representations and relationships inherent in heart sound recordings, enhancing the extraction of relevant cardiac information.

2. Adaptability
   GANs adapt to different noise profiles and variations in heart sound recordings, making them versatile tools for a range of clinical scenarios.

3. Preservation of Subtle Features
   GANs, through their generative nature, have shown potential to preserve delicate pathological features while mitigating noise, which is crucial for accurate diagnoses.

4. Reduced Manual Feature Engineering
   GANs minimize the need for manual feature engineering, as they autonomously learn the most relevant features from data.

5. Real-Time Application
   GANs can be trained to perform denoising in real-time, facilitating immediate clinical deployment and remote patient monitoring.

2.3.2 LSTM U-Net (LU-Net)

This architecture is proposed in the paper "An End-to-End Deep Learning Framework for Real-Time Denoising of Heart Sounds for Cardiac Disease Detection in Unseen Noise" [3] for denoising heart beat audio files. This model is made up of encoder-decoder structure with skip connections. Bidirectional LSTM modules are used in the skip connections to capture temporal relationships present in quasi-periodic heartbeat sounds.

The pipeline of this method is shown in the figure 1. As can be seen after preprocessing the datasets, part of pure audio is mixed with different signal-to-noise (SNR) values to obtain noisy dataset then both pure and noisy dataset is used to train the model. During training, different noisy datasets are passed through the trained model to obtain noise-free data and measure the performance of the model. In this thesis project, this method is considered for experimentation along with Empirical mode decomposition (EMD). Dog dataset will denoised with both

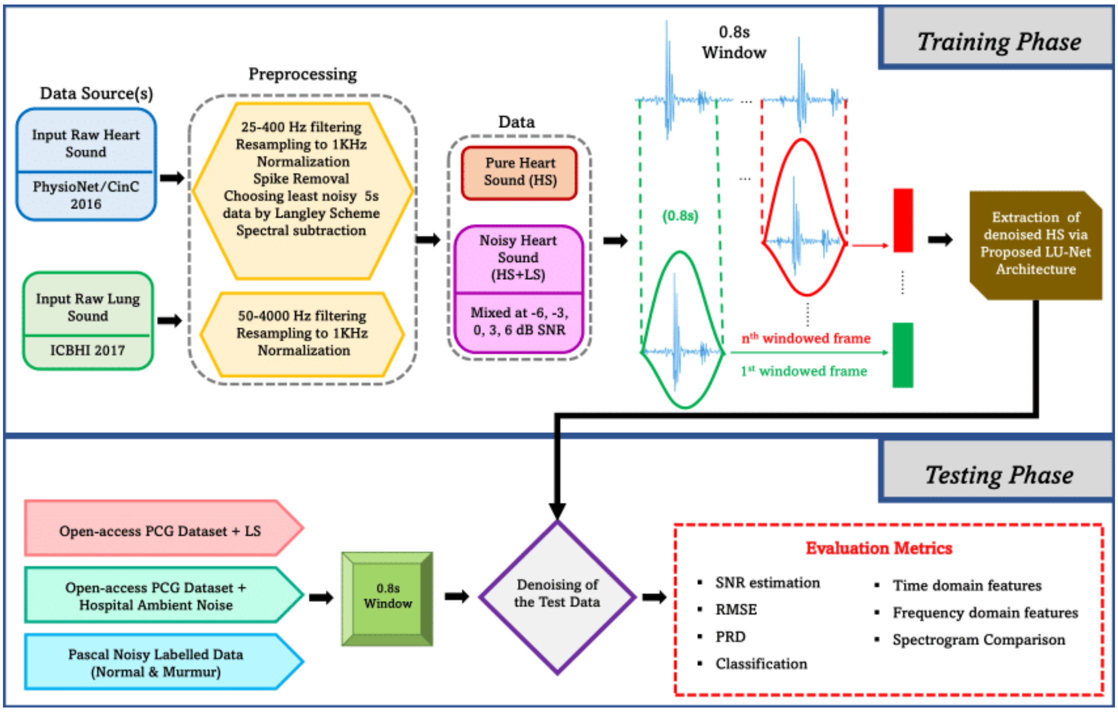

Figure 1: Pipeline of LU-Net denoising method

LU-Net and EMD technique and comparison of their performance will be preformed. The advantages of this architecture is:

1. Effective noise suppression
2. Retains critical morphology
3. Exploits domain knowledge

3 Project Plan

3.1 Work Packages

The project will include the following packages:

WP1 Literature search

This work package aims to perform literature search on denoising of audio data.

T1.1 Literature review

In this task, collection of literature related to denoising of audio data is done.

T1.2 Comprehend related work

In this task after going through the literature, an understanding of the denoising on audio data is achieved and how denoising is used for heartbeat dataset is studied.

WP2 Dataset analysis assessment

This work package aims to analyse the dataset.

T2.1 Dataset analysis

In this task, the dataset is analysed to find information about the data. Statistical analysis is performed on the dataset to get deep understanding of the data.

T2.2 Dataset assessment

In this task, the amount of clear quality data required for training the denoising model is assessed and separated.

WP3 Audio data augmentation

This work packages involve the creation of noise dataset to train and evaluate the denoising method.

T3.1 Noise data creation

In this task, different kinds of noise is added to the clear quality data to create artificial noise data.

WP4 Experimentation

This work package involves conduction of experiments.

T4.1 Train / create denoising model for different methods

In this task, human heartbeat dataset along with artificial noise data is used to train/create the different denoising methods.

T4.2 Tuning of denoising model

In this task, denoising methods is tuned.

T4.3 Transfer of denoising model

In this task, the tuned denoising model transferred to dog heartbeat to obtain clear heartbeat data

WP5 Evaluation

This work package involves evaluation of results obtained from WP4.

T5.1 Evaluation of experiments

In this task, the results of the experiments conducted are evaluated.

T5.2 Comparison of results

In this task, result of denoising on human heartbeat dataset and denoising on dog heartbeat dataset is compared and analysed.

WP6 Project report

This work package involves writing the project report. It will be done concurrently with all previous work packages.

T6.1 Documentation of literature review and data analysis

In this task, a detailed analysis of the denoising is done and the same will be documented in the project report along with analysis of the dataset.

T6.2 Documentation of execution and results

In this task, the execution of methods and the results obtained is documented. Results of comparative evaluation is also documented in this task.

T6.3 Conclusion

In this task, conclusion of the project is documented.

T6.4 Determine improvements and future works

In this task, improvements and future works of this thesis study is documented.

T6.5 Final report

In this task, final report is generated after proofreading.

3.2 Milestones

In order to perform this thesis project in an organized manner, the project is divided into the following milestones.

M1 Complete literature search by the end of first month

M2 Complete dataset analysis and assessment by the end of second month

M3 Complete audio data augmentation by the end of third month

M4 Complete experimentation by the end of fifth month

M5 Complete the evaluation of experimentation results by the end of fifth month

M6 Report submission by the end of sixth month

3.3 Project Schedule

Gantt-chart describing the project timeline is shown in Figure 2

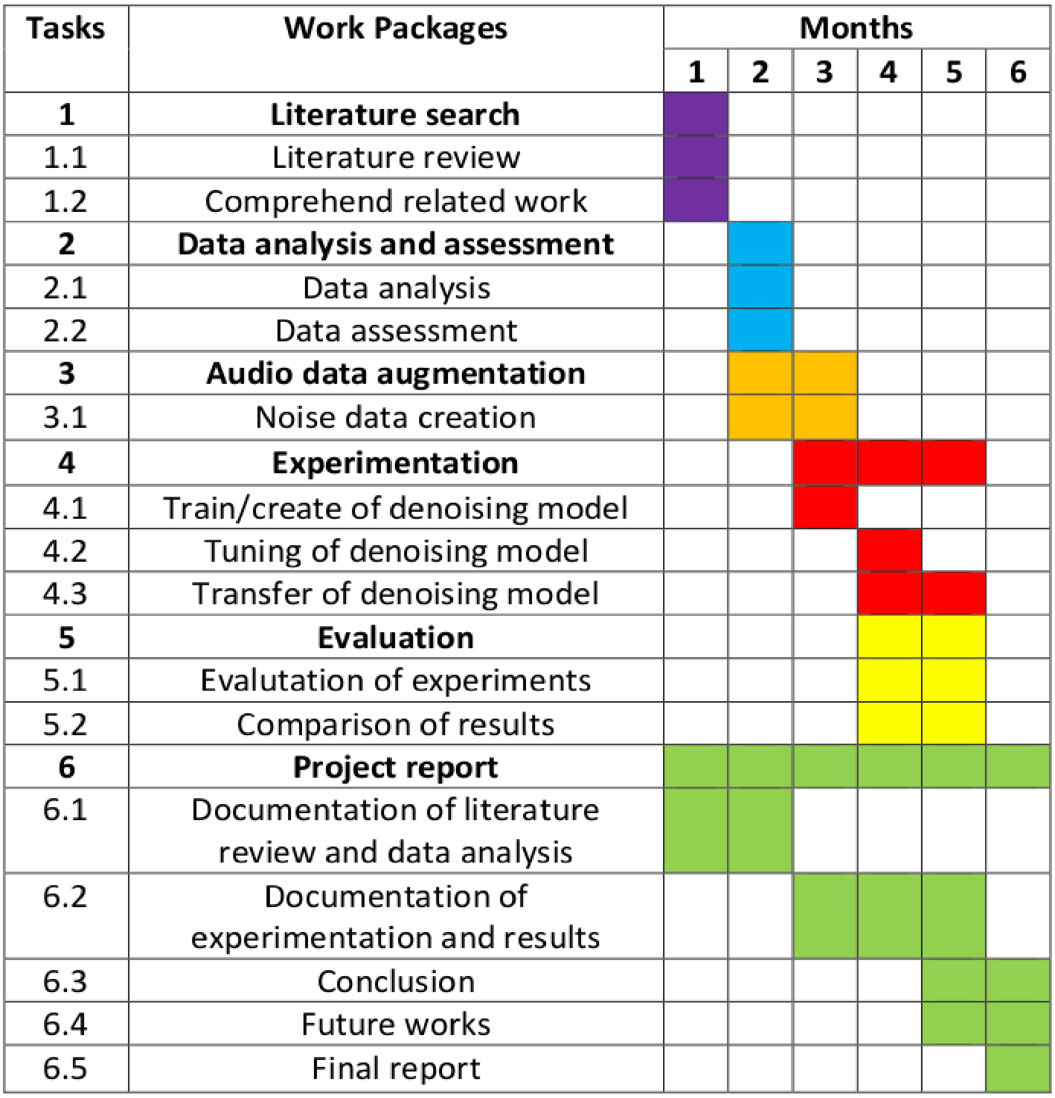

Figure 2: Timeline of the project

3.4 Deliverables

Minimum Viable

- Literature search
- Data analysis
- Data assessment

- Audio data augmentation
- Training of denoising model on human heartbeat dataset
- Final report

Expected

- Transfer of denoising model to dog heartbeat dataset
- Comparison of results

Maximum

- Denosing of dog heartbeat audio files using Empirical mode decomposition (EMD) classical method
- Classification of dog heartbeat murmur dataset before and after denoising

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