International Journal on Engineering, Science and Technology
Volume 4, Issue 3, 2022 ISSN: 2642-4088

Detection of Cardiovascular Abnormalities Using Artificial Intelligence and Heart Sounds

Komron Aminian
University of Texas Health Sciences Center at San Antonio, United States, https://orcid.org/0000-0002-9901-6912

James Flynn
Project Farma, United States, https://orcid.org/0000-0003-2354-9568

Anand Valavalkar
University of Texas at Austin, United States, https://orcid.org/0000-0002-6403-9188

Ashkan Aminian
University of Texas at San Antonio, United States, https://orcid.org/0000-0001-6940-5645

Mehran Aminian
St. Mary's University, United States, https://orcid.org/0000-0002-5146-1697

Farzan Aminian
Trinity University, United States, https://orcid.org/0000-0002-1050-4611

Abstract: Auscultation of the heart is one of the most crucial techniques physicians use to learn about a patient's heart. Therefore, a lot of effort has been devoted to developing more sophisticated stethoscopes to assist physicians for better diagnosis. Most of this work has been to design stethoscopes to provide clearer signals. This work is an initial effort to include an Artificial Intelligence (AI) system in the stethoscope to perform a preliminary diagnosis of multiple heart conditions. To train the neural network, heart sounds representing 42 different issues are used. Due to the limited number of training data, noise is added to the available heart sounds. This serves the dual purpose of increasing the training data and to partially account for the variation in the heart sounds collected from different patients. These heart sounds are used to extract features such as mean, median, standard deviation, signal entropy, kurtosis, skewness, etc. for neural network training. An optimal neural network architecture is developed to classify these 42 heart conditions with 98% accuracy.

Keywords: engineering, life preservation, smart systems

Introduction

As human heart pumps blood into the veins and arteries, it generates sounds which can be heard using stethoscope. The normal heart sound can be divided into two major parts called S1 and S2. The closure of mitral and tricuspid valves at the start of systole causes the S1 sound while the S2 sound is generated by the closure of the aortic and pulmonic valves at the end of systole. Certain heart abnormalities leave their distinct features in the heart sounds which may be used by cardiologists for medical diagnostics. This can range from innocent heart murmur which is harmless to severe heart issues that may need attention. Electrocardiogram (ECG) is another useful system for diagnosing heart abnormalities. Unlike auscultation, ECG is based on the electrical activity of the heart which is a much cleaner signal than the sound. With ECG equipment becoming cheaper and more readily available in doctors' offices, the use of ECG machines has become more common among physicians. The problem with ECG equipment, however, is its lack of availability in remote areas. The problem in these areas is even more exasperated by lack of access to cardiologists.

Some work has been done to address this issue. For example, a group at MathWorks ("Suhum", "2019") extracted features from heart sounds obtained from PhysioNet to detect cardiovascular issues using K-nearest neighbors. This system is capable of distinguishing between abnormal and healthy hearts with accuracy of 75% for normal and 98% for abnormal cases. Another similar idea was to develop a system based on Artificial Intelligence (AI) to detect afib arrythmias with 99% sensitivity and 97% specificity (EKO Health, 2017). Another AI based system has been developed to classify pathologic, innocent and no murmurs with 93% sensitivity, 81% specificity and

88% accuracy (Pediatric Cardiology, 2018). Convolutional neural network has also been used to classify normal and abnormal heart sounds with 91% accuracy (Bilal, M. 2021). Additionally, a group at Johns Hopkins University developed AI based stethoscope capable of diagnosing pneumonia with 87% accuracy (Elhilali, M., West j., 2019).

The focus of all the research in this area so far was to classify just normal and abnormal heart conditions or diagnose very few heart abnormalities. This led to the development of many useful devices. However, not many studies have been done to make individual diagnosis of many different heart conditions which is the aim of this work. This is particularly important for telemedicine and providing healthcare services to people living in remote areas who may not have access to physicians. Here, an AI based system is developed to classify 42 different heart conditions with high level of accuracy as described below.

Design Approach

Training Data

In this study, a set of 42 heart sound signals are used for training. These signals represent normal and 41 different conditions that may be associated with cardiovascular system. Since the number of data is not nearly enough for training, featureless white gaussian noise is added to these heart sounds to generate enough training data. Moreover, adding noise may also help to roughly account for variations in cardiovascular sounds obtained from different patients. To this end, noise from a signal-to-noise ratio (SNR) of 33 to 80 in intervals of 0.1 is added to the sound signals to generate enough training data. At an SNR of 33, the noise is dominant, but the heart sound could still be perceived. To generate labels, three physicians are consulted to classify the sounds into their appropriate diagnosis as shown in Table 1. It is obvious from this table that different heart signals may lead to the same diagnosis. For example, the signals with indices 1-5 represent healthy hearts even though the sounds are distinctly different. In this study, each of 42 heart sounds are considered to be distinct leading to the same number of labels for training. This makes the training of the neural network more difficult, but results to a more flexible classifier.

Table 1. Heart Diagnosis Categories with their Corresponding Track Number

Heart sound data index	Categories
1, 2, 3, 4, 5	Normal Heart Sound
6	Atrial Septal Defect
7, 8, 24, 28, 30, 38	Pulmonic Stenosis
9, 18	Congestive Heart Failure
10	Hypertensive Heart Disease
11	Constrictive Pericarditis
12	Bicuspid Pulmonary Valve
13	Bicuspid Aortic Valve
14, 25, 40	Mitral Stenosis
15, 42	Mitral Valve Prolapse
16	Mitral Valve Prolapse and Aortic Stenosis
17	Still’s (Innocent) Murmur
19	Pulmonic Stenosis and Pulmonary Hypertension
20	Aortic Stenosis and Aortic Regurgitation
21, 26, 29, 41	Mitral Regurgitation
22, 23, 33	Aortic Stenosis
27	Surgically Repaired Aortic Valve
31	Aortic Regurgitation
32	Mitral Valve Prolapse with Mitral Regurgitation
34	Carotid Bruit
35	Mitral or Tricuspid Prolapse
36	Pulmonic Regurgitation
37, 39	Right Bundle Branch Block

Training of neural network could become much easier if effective features extracted from the raw data are used as input. This is due to the number of these features being much smaller than the raw data leading to reduced size of the neural network architecture. Numerous mathematical techniques such as Wavelet Transform, Fourier Transform and others may be used to find these features. After extensive research (Suhm, 2019), the features listed in Table 2 were chosen for this study. The rationale behind this choice was the fact that a group at Mathworks used the same features to successfully diagnose normal and abnormal heart sounds with 98% accuracy. A brief explanation of each of these features is also given in this table.

Table 2. Features extracted from the Heart Sounds

Feature Number	Feature Name	Description
1	Mean	The mean of a set of data is found by adding up all the values then dividing that by the number of values present
2	Median	The median of a data set is the middle value of all the values
3	Standard Deviation	The standard deviation is how much a data set deviates from the mean
4	Mean Absolute Deviation	The mean absolute deviation is the average difference between all the data values in a set from the mean
5	25th percentile (Q1)	The 25th percentile of a data set is the median value of all the values less than the median
6	75th percentile (Q3)	The 75th percentile is the median value of all the values greater than the median
7	Inter quartile range (IQR)	The interquartile range of a data set is the difference between Q3 and Q. IQR is used to find any outliers in a data set.
8	Skewness	The skewness is how much the imbalance there is from the mean of a data set
9	Kurtosis	Kurtosis is how sharp the peak of a curve is compared to normal distribution. If the peak is higher than normal, this is leptokurtic. If the peak is lower than normal, this is platykurtic
10	Signal Entropy	Signal entropy is the amount of information the signal carries given by $H = -\sum p(x)\log(p(x))$
11	Spectral Entropy	Spectral entropy is the measure of the spectral power distribution and is related to signal entropy
12	Dominant Frequency Value	Frequency with the largest amplitude on the spectrum
13	Dominant Frequency Magnitude	Locates the maximum value before the cutoff frequency.
14	Dominant Frequency Ratio	Ratio of the energy of the maximum to the total energy.
15-27	Mel Frequency cepstral coefficients (MFCC 1-13)	Coefficients that make up the Mel Frequency Cepstrum (MFC). The MFC depicts the short-term power spectrum of a sound. Based on the Mel Scale, which is used to make high frequency sounds be in the range of human hearing.

Results and Conclusion

As mentioned before, white gaussian noise was added to the original signal to generate enough data for training. This led to generating 96811 data from which 67769, 14521 and 14521 were used for training, validation and testing, respectively. Two different neural network architectures were used in this study.

The details of these architectures are shown Tables 3 and 4.

Table 3. Architecture of the First Neural Network

Layer 1	Layer 2	Layer 3	Layer 4	Layer 5	Layer 6	Classification Accuracy
45 neurons ReLu*	Dropout	35 neurons ReLu	Dropout	25 neurons ReLu	Dropout	97.43%

Note that the input and output layers are not included in these tables since their specifications are dictated by 27 input features (see Table 2) and 42 output classes (see Table 1), respectively. As shown here, both neural networks achieved a classification accuracy of around 97%.

Table 4. Architecture of the Second Neural Network

Layer 1	Layer 2	Layer 3	Classification Accuracy
50 neurons ReLu*	40 neurons ReLu	30 neurons ReLu	97.65%

The training progress and other information for these networks are shown in Figures 1 and 2.

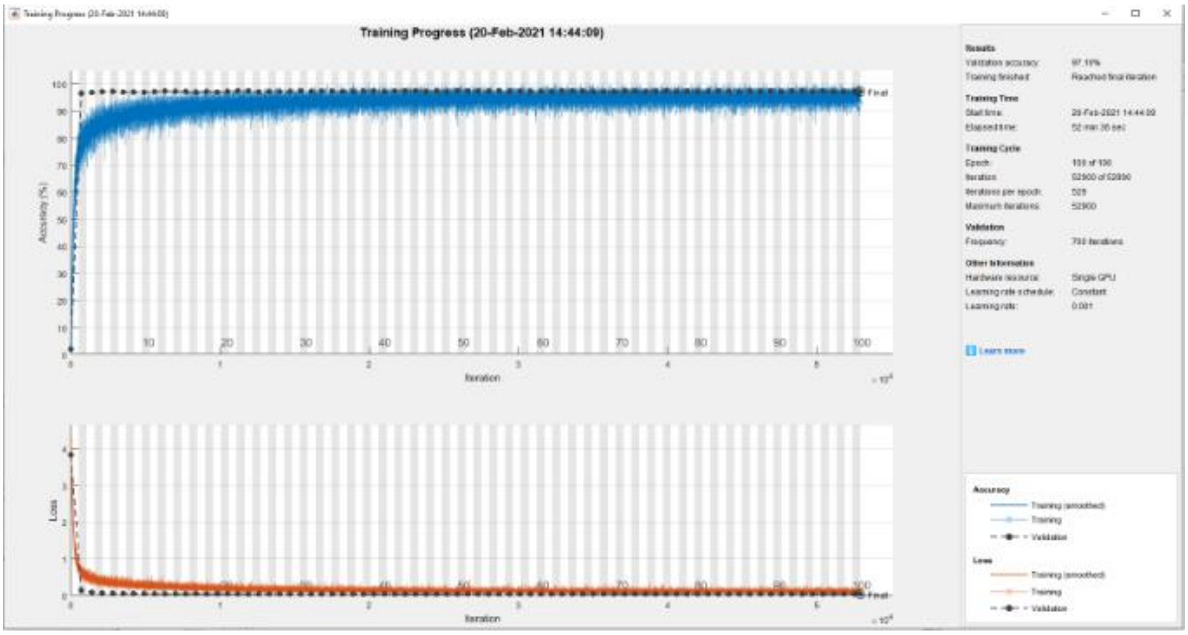

Figure 1. Training Progress for 45, 35, 25 with Two Dropout Layers (100 Epoch)

The future goal of this project is to make a stethoscope that utilizes AI to make a diagnose of heart defects. However, to effectively make a smart stethoscope, much more data is needed. This requires many hours of specialized medical staff to collect the data from many patients. The controlled environment and assumptions used in this work are not the most accurate representation of a real medical environment. The spontaneity and unpredictability of the practice of medicine is hard to replicate. While the fully functional smart stethoscope may be years away, but once developed it can vastly improve access to proper health care especially in remote areas.

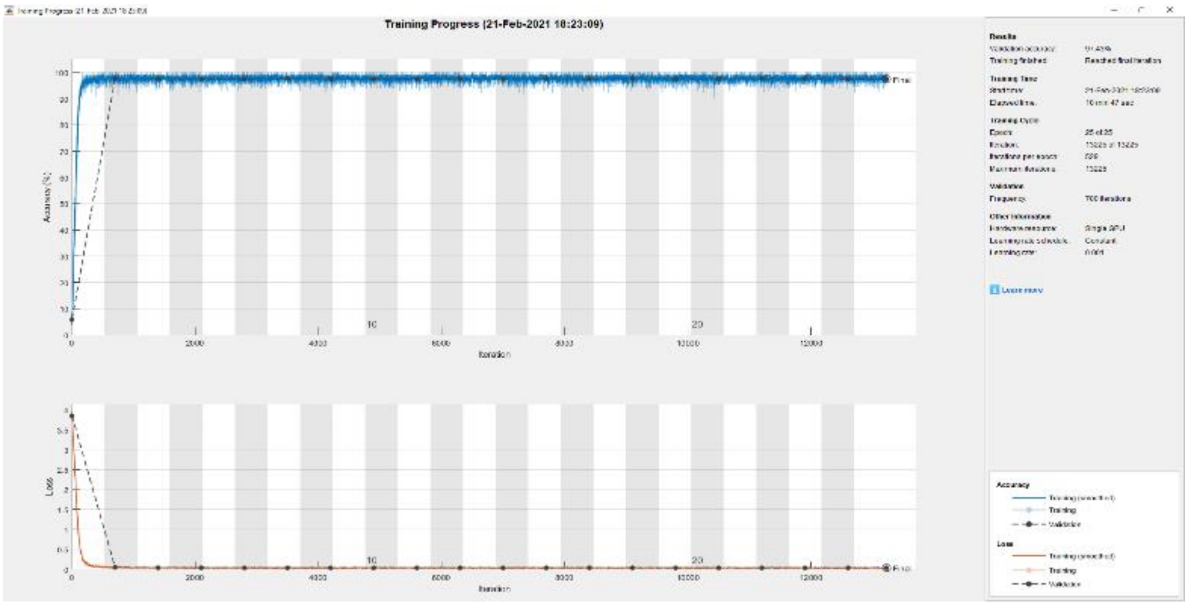

Figure 2. Training Progress for 50, 40, 30 without Dropout Layers

References

Suhm, B. (2022). *Heart Sound Classifier* (https://www.mathworks.com/matlabcentral/fileexchange/65286-heart-sound-classifier).

Elhilali, M., West j., (2019, January 31). *A Smart Stethoscope Puts AI in Medics' Ears.* IEEE Spectrum, https://spectrum.ieee.org/a-smart-stethoscope-puts-ai-in-medics-ears.

Easy Auscultation, Lessons, Quizzes, Guides, Heart and Lung Sounds. www.easyauscultation.com/aortic-stenosis.

EKO Health, (2017). *FDA Clears Eko's Digital Stethoscope AI for Spotting Cases of Afib, Heart Murmur,* assets.website-files.com/5d43b941a4923b9c4685f98d/5e2fc70cca409a6dadabe2de_Eko_AI_Press Release.pdf.

Pediatric Cardiology, (2018). *Artificial Intelligence-Assisted Auscultation of Heart Murmurs: Validation by Virtual Clinical Trials.*

Bilal, M., (2021). ***Heart sounds classification using convolutional neural network with 1D-local binary pattern and 1D-local ternary pattern features.*** Elsevier, Applied Acoustics.

National Heart Lung and Blood Institute, U.S. Department of Health and Human Services. *Heart Murmur*, www.nhlbi.nih.gov/health-topics/heart-murmur.

Mayo Clinic, Mayo Foundation for Medical Education and Research (2018, 5 April), *Heart Murmurs*, www.mayoclinic.org/diseases-conditions/heart-murmurs/symptoms-causes/syc-20373171.

LearntheHeart.com. *Heart Sounds Topic Review: Heart Sounds Topic Review*, www.healio.com/cardiology/learn-the-heart/cardiology-review/topic-reviews/heart-sounds.