Heart Murmur Detection using Supervised Machine Learning

Saad Hafez Moulana, Ahmad Luqman, Rawad Abdulghafor, Sharyar Wani, Adamu Abubakar
[1]Department of Computer Science, Kulliyyah of Information & Communication Technology,
International Islamic University Malaysia, Kuala Lumpur, Malaysia
s.h.alhaaj@gmail.com

Abstract— Murmurs are unusual heartbeat sounds that can be used to aid in diagnosing underlying health problems. Doctors often will manually perform heart auscultations, that is, attempt to hear these sounds using a stethoscope. This can be inaccurate as these murmurs are very subtle and can be muffled by background noises. Plus, it requires training, and the skill is easily lost if not practiced. It also requires having an appointment with a doctor, which is time consuming and sometimes inefficient. However, when successfully performed, it can provide valuable insights about the heart functionality of a patient. These murmurs can be either innocent which are safe, or abnormal. Heart murmurs are abnormal heartbeat sounds that can be shown in systole or diastole cardiac pathologies, yet manually diagnosing is inaccurate all the time. Hence by identifying murmurs we can classify them since they play a significant role in the diagnosis of a certain type of disease. Hence this project aims to present a system that enables to detect murmurs easily with efficient results and people can use it remotely without the need to visit their doctors. In this research, we proposed supervised machine learning specifically Mel Frequency Cepstral Coefficient to solve the previously mentioned problem statements, the main objectives are: To segment the systolic and diastolic phases of a heartbeat, to identify the heartbeat sounds as it is mixed with background sounds and to classify the abnormal heartbeat sounds with murmurs present from the normal ones. When trained and validated, the algorithm showed results of that train score 70.0%, test score 68.0% and validation 70.0%.

Keywords— Heart Murmurs, Heart Auscultation, Feature Extraction, Mel Frequency Cepstral Coefficient.

I. Introduction

In this research LSTM has been implemented as it has shown to provide better classification performance, in addition to lower computational cost. These may prove useful in the future when attempting to utilize this algorithm in real world applications such as wearable medical devices [1]. Heart murmur detection is an important step in the cardiac auscultation and efficient detection of murmurs is important to achieve diagnosis. An abnormal heart murmur can indicate a serious problem in the heart which can happen when a person has illnesses such as anaemia, overactive thyroid [2], or fever. By utilizing machine learning, we can greatly improve the chances of detecting a heart murmur. This technology can be useful in digital healthcare and provide a way to detect murmurs without having close contact with the patient. In this research we are taking data from Kaggle named as Heartbeat Sounds and will be implementing feature extraction using Mel Frequency Cepstral Coefficient as it is a very common and efficient technique used for signal processing. If we can achieve high accuracy and precision, and further improve on this research it would be possible to provide patients the ability to get a remote diagnosis without needing to be physically present at any health institution. We will also be aiding doctors in their assessments of patients and could help in detecting something a doctor could have otherwise missed out. Also, a lot of time can be saved for both sides, in addition to reducing the risk of being infected during a medical visit. Heart disease like many other diseases is best treated when detected early. As such, accurately recognizing symptoms during the early stages are of utmost priority. Doctors have many ways of detecting these signs with one of them being heart auscultations. This method relies on identifying the various heartbeat sounds and figuring out a well off. heart from a problematic one. Despite being a common and major tool in early detection, this technique deeply relies on individual skills of the listener, which in this case would be the doctor. Though, even with trained ears, errors still occur often leading to second and third attempts. We aim to overcome these many shortcomings by utilizing machine learning specifically, to train an algorithm with the hopes it can perform at an equal or better rate than trained professionals.

II. Significance of Project

Most people in their ordinary life have no idea if they are to face heart problems in the future and they tend to not visit the doctor for regular check-ups since it is time and money consuming for them. It is often too late by the time a diagnosis is concluded. Murmur detection is the cornerstone of diagnosis of congenital heart disease thus It is significantly important to have the ability to diagnose patients at the early stages so that doctors can deal with the diseases. Especially nowadays with Covid-19 pandemic people are more afraid to visit or go to the hospitals so they would rather have the chance to diagnose themselves while at comfort in their homes. Detecting relevant symptoms and forming a diagnosis is a skill that requires years to acquire and refine-however, AI can present these interpretations in a more constant and attractive way and an intelligent stethoscope with decision support abilities would be of great value.

III. LITERATURE REVIEW

In the following section, a brief background of the related work is presented. Over the years there has been some significant work by researchers in relation to heart murmurs detection. The study of [3] discusses the importance of murmur detection since in many cases heart murmurs are detected accidentally. Detecting murmurs at a young age especially for babies will lead to early diagnosis of coronary heart disease which can cause death without treatment in the right time. However, this paper emphasizes on training for cardiac auscultation to improve the ability of prediction and not replace the cardiovascular examination with echocardiography as it is still valuable. In the work of [4] Hidden Markov Model was used to recognize heart murmurs along with Mel frequency cepstral coefficient was implemented to extract features for signal classification. Heart sounds were segmented using Morlet wavelet function and identified heart sounds as S1 and S2 and were classified through multiple steps to remove peaks, calculate the first order, find positive and negative and to find the start point and ending point for S1 and S2. The results were 91% to 100 % for the HMM model. In the work of [5] The proposed methods are Hidden Markov Model to build a classification model for heart murmur recognition and Mel frequency cepstral coefficient with 13 MFCC coefficients. The research studied 1069 records of heart sounds with S1 and S2 being isolated from different sounds. MFCC is used to extract a feature matrix for each sort of heart sounds. Results of this research were 96% for correct classification rate and 98% sensitivity. The study of [6] has reported the implementation of two novel algorithms which are to segment the heart sounds and the other to detect heart murmurs based on PCG signals. For heart sound segmentation the Morlet mother wavelet was chosen according to the frequency of sounds. A k-means classifier was prepared and trained by utilizing these 250 features to classify the segments. Results in this paper were separated into two results firstly Heart Sound Segmentation sensitivity resulted as 89.2% and for positive predictive value the percentage is 98.6%. Secondly, Murmur Detection Results were 52.38% and 79.40% for sensitivity and specificity, respectively. The study of [7] has reported based on PCG signals from 86 children 24 with normal heart sounds and 62 having congenital heart disease (CHD) murmurs with a recording time of 20s per patient, PCG signals were normalized and denoised by discrete wavelet transform. PCG classification was made of 86 artificial neural networks to be trained or tested in MATLAB. This research had results of accuracy 93%, 93.5% sensitivity and 91.7% specificity. In the work of [8] PCG signals pre-processed in two stages: filtering and segmentation, PCG signals that were recorded had a frequency over 8 kHz Heart sounds S1 and S2 happen within a scope of 200 Hz and the system filters them. Wavelet transform dependent on Complex Morlet Wavelet was implemented to find peak locations with also k-means to minimize the sum of distances. They had results of accuracy as 99.14%, sensitivity 100% and specificity 98.28%. The study of [9] has proposed several steps to process signals which are obtaining heart sound signal, noise removal, examining the PCG signal at a particular frequency rate, feature extraction, training and classification. Features extracted were classified using support vector machine, centroid displacement based KNN and DNN. Overall maximum accuracy is 97.9% while implementing MFCCs and discrete wavelet transform 97.4% in the event of centroid displacement based KNN. Nicholas and Vadim have explained in [10] that Deep learning (DL) is a high dimensional data reduction technique for constructing high-dimensional predictors in input-output models. DL is a form of machine learning that uses hierarchical layers of latent features. Deep learning is data intensive and provides predictor rules for new high-dimensional input data. The fundamental problem is to find a predictor (X) of an output Y. Deep learning trains a model on data by passing learned features of data through different layers of hidden features. That is, raw data is entered at the bottom level, and the desired output is produced at the top level, the result of learning through many levels of transformed data. Deep learning is hierarchical in the sense that in every layer, the algorithm extracts feature into factors, and deeper levels factors become the next levels features. Deep learning is a technique used within machine learning which utilizes vast amounts of data and neural networks with multiple layers in order to understand patterns within a data set.

IV. METHODOLOGY

The first step is to identify the problem that this research is aiming to solve. By interviewing a medical consultant, it is found that heart auscultation is a common procedure which is often hard to train and harder yet to get right. Hence, this research will attempt to solve this issue by using machine learning to classify heartbeat sounds into several categories, namely 'artifact', 'murmur' and 'normal'.

V. TOOLS USED

Before going ahead with the machine learning steps it is important to choose the right digital environment to work on for this research. Free and readily available tools were used in this research, they were Python 3.0, Kaggle, Keras, and TensorFlow.

VI. MACHINE LEARNING STEPS

With the environment all set next step is to go ahead and follow the following steps of
machine learning

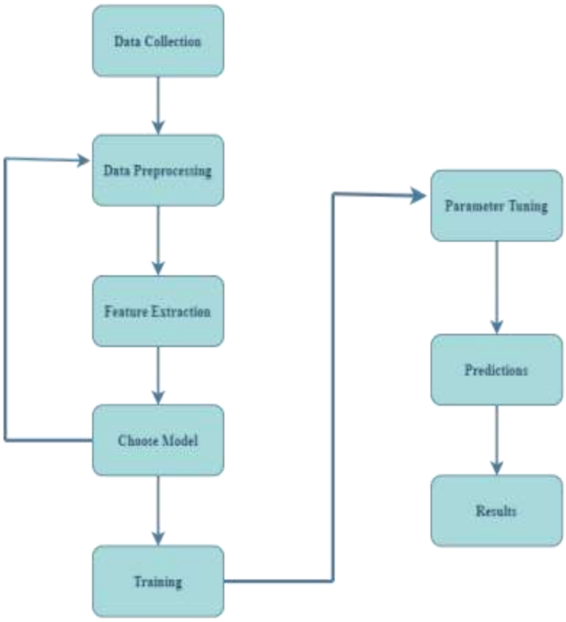


Fig. 1 Methodology - machine learning steps

VII. DATA COLLECTION

To get good results for this research a dataset with both good quality and quantity of data had to be chosen. Data was collected from an existing dataset.

Dataset

The dataset was obtained from Kaggle with a name of Heartbeat Sounds. The data was collected from two sources which are the first one from the general public via the iStethoscope Pro iPhone app and the second one is from a clinic trial in hospitals using the digital stethoscope DigiScope. The dataset consists of 832 audio sounds that differ from 1 second to 30 seconds. Dataset is divided into two parts, first one named as set_a.csv which has been recorded from the general public via an iPhone app, And the second part named as set_b.csv that was recorded using a digital stethoscope from a clinic trial in hospitals.

	dataset	fname	label	sublabel
count	832	832	585	149
unique	2	832	5	2
top	b	set_b/Bunlabelledtest_186_1306073648738_C.wav	normal	noisynormal
freq	656	1	351	120

Fig. 2 Dataset after merging set a and set b.

VIII. PRE-PROCESS DATA

After deciding on the dataset and understanding its contents we proceeded to process the data. This is an essential step to ensure good results. This included removing missing data and normalizing them. Normal heart sounds have a clear "lub dub, lub dub" pattern, with a shorter time from "lub" to "dub" when the heart rate is less than 140 beats per minute [11]

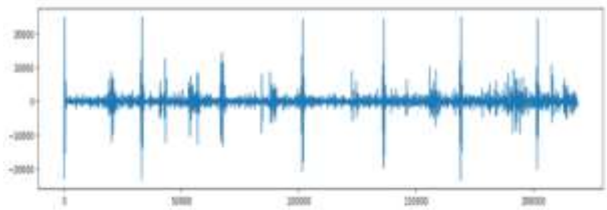


Fig. 3 wave by audio frames

IX. FEATURE EXTRACTION

Before we build the model, we firstly must decide on the features we would like to extract from the audio dataset provided. Mel Frequency Cepstral Coefficient (MFCC) is a reliable feature to be used. Thus, it is implemented in this paper.

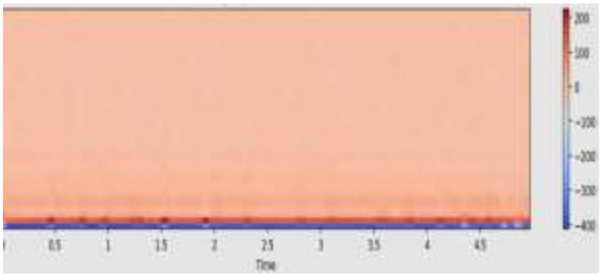


Fig. 4 Mel-frequency cepstral coefficients (MFCCs)

Sound Features:

- Onset detector: picking peaks in order to note onset events, parameters of peak pick were selected by large-scale hyper-parameter optimization.

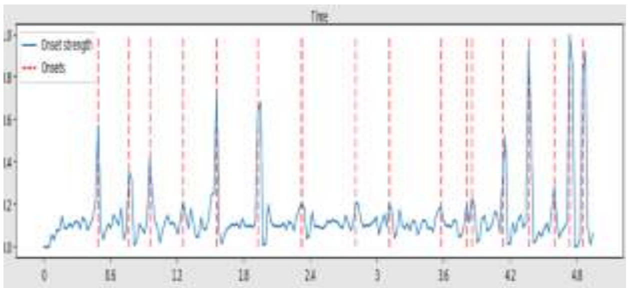


Fig. 5 Onset

- Onsets backtrack: to determine slice points for segmentation.

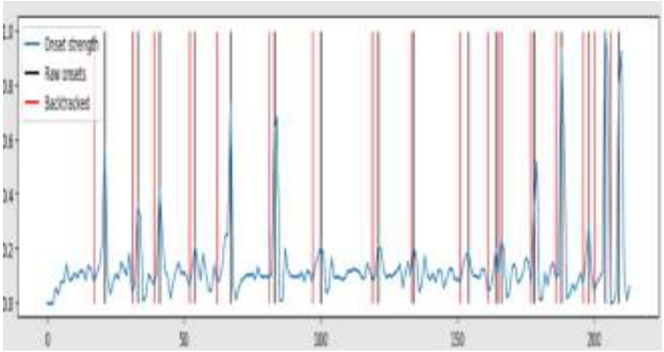


Fig. 6 Onsets backtrack

- Onset strength: is determined by mean_f max (0, S [f, t] - ref_S [f, t - lag])

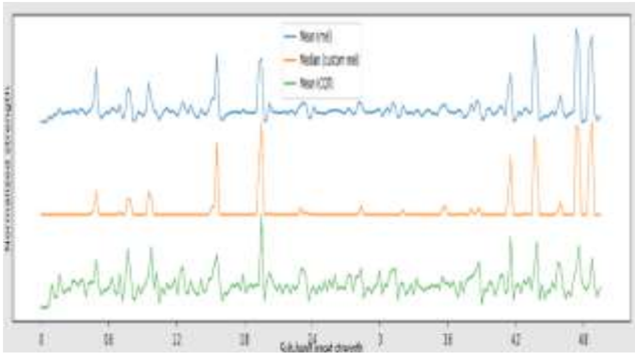
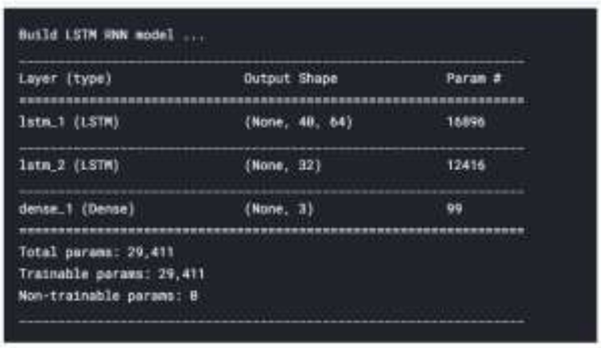


Fig. 7 Onset Strength

X. CHOOSE MODEL.

We then had to decide on a model to use, and we chose long short-term memory (LSTM). It uses gated units in its hidden layer which help decide what information should be passed to the next unit.



```
Build LSTM RNN model ...
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
lstm_1 (LSTM)                (None, 40, 64)            16896
_________________________________________________________________
lstm_2 (LSTM)                (None, 32)                12416
_________________________________________________________________
dense_1 (Dense)              (None, 3)                 99
=================================================================
Total params: 29,411
Trainable params: 29,411
Non-trainable params: 0
_________________________________________________________________
```

Fig. 8 LSTM Model

XI. TRAINING

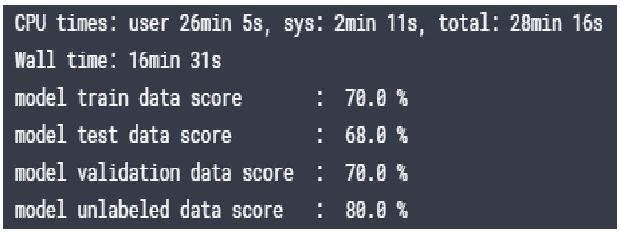
Since we have 832 audio sounds, we will classify them into 6 classes, next step is to get audio data without padding the highest quality audio so we can extract normalized mfcc features from data using kaiser_fast technique for faster extraction, encoding of categories is limited to 3 types: 'artifact', 'murmur' and 'normal'.

```
training started..... please wait.

Epoch 00001: loss improved from inf to 1.04287, saving model to ./best_model_trained.hdf5

Epoch 00002: loss improved from 1.04287 to 0.84975, saving model to ./best_model_trained.hdf5

Epoch 00003: loss improved from 0.84975 to 0.77986, saving model to ./best_model_trained.hdf5
```

Fig. 9 Model Training

XII. EVALUATE MODEL.

We evaluate the model by splitting the dataset into training set, test set and validation set. by shuffling the data many times, we then proceed to divide the entire dataset 60% to be trained, 20% as a test set, and lastly 20% for validation. based on the results of accuracy, precision, and recall we can tell if the model is good.



```
CPU times: user 26min 5s, sys: 2min 11s, total: 28min 16s
Wall time: 16min 31s
model train data score       :  70.0 %
model test data score        :  68.0 %
model validation data score  :  70.0 %
model unlabeled data score   :  80.0 %
```

Fig. 10 Model Evaluation

XIII. PARAMETER TUNING

After evaluating our model, we then tried further improving our model by tuning the parameters. This is done to increase accuracy as it is essential for diagnosis. In this case those parameters would include learning rate, number of nodes and layers.

XIV. PREDICTION/TEST

This is the last step in the machine learning process which is to show the results and percentages that were achieved in this research. The higher the percentage of accuracy and Precision means that the model succeeded.

XV. RESULTS

The study was conducted on 832 audio sounds that were gathered through iStethoscope Pro iPhone app and digital stethoscope DigiScope in a public hospital. sound features have been extracted from the audios using Mel Frequency Cepstral Coefficient (MFCC). In this research long short-term memory (LSTM) was implement as model to train the data and sounds were categorized into three types 'artifact', 'murmur' and 'normal'. The result of this research shows that the model has train score 70.0%, test score 68.0% and validation 70.0%.

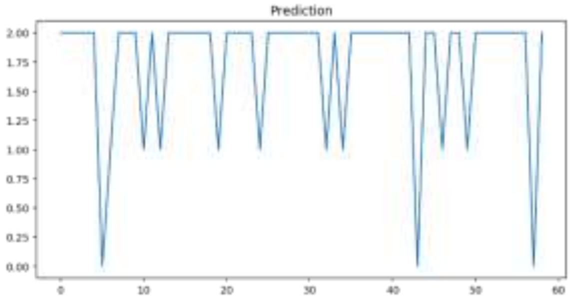


Fig. 11 Prediction

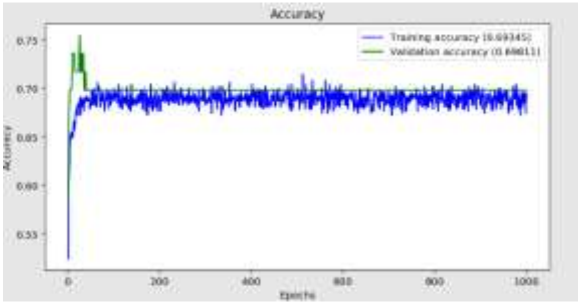


Fig. 12 Accuracy

XVI. CONCLUSIONS

Modern techniques are replacing cardiac auscultation in the last 30 years [12]. Yet it not an easy task for normal people to perform heart auscultations as requires years of practice, a system that allows people to diagnose themselves in the comfort of their home was in mind as we are living in pandemic days. A machine learning approach was taken in this research to be able to analyze heart sounds and detect murmurs in the early stages by applying the machine learning steps. Mel Frequency Cepstral Coefficient (MFCC) was implemented in this research to extract the required sound features so that they will be trained in the model that has been chosen which is long short-term memory (LSTM). After modeling and exploring the data, we can conclude the Results of this research that the model achieved train score 70.0%, test score 68.0% and validation 70.0%. Model selection, feature selection and model evaluation were all conducted and lead to reasonable performances by the algorithm. This research has high potential and will be beneficial in the medical domain and could help a lot of people. We aim to improve our model results by doing more optimization.

ACKNOWLEDGMENT

The authors would like to thank the Malaysia International Islamic University.

REFERENCES

[1] S. Saadatnejad, Oveisi, M., & Hashemi, M. (2019). LSTM-based ECG classification for continuous monitoring on personal wearable devices. IEEE journal of biomedical and health informatics, 24(2), 515-523.

[2] Mayo (2019), https://www.mayoclinic.org/diseases-conditions/heart-murmurs/symptoms-causes/syc-20373171

[3] Kang, G., & Zhang, H. (2019). Significance of cardiac murmurs in detection of congenital heart disease. Cardiology In the young, 29 (10),1317–1318. https://doi.org/10.1017/S1047951119002038

[4] Zhong, Lisha & Wan, Jiangzhong & Huang, Zh iwei & Cao, Gaofei & Xiao, Bo. (2013). Heart Murmur Recognition Based on Hidden Markov Model. Journal of Signal and Information Processing. 04. 140-144. 10.4236/jsip.2013.42020.

[5] Kotb, M. A., Nabih, H., El Zahraa, F., El Falaki, M., Shaker, C. W., Refaey, M. A., & Rjoob, K. W. (2016). Improving the recognition of heart murmur. Int. J. Adv. Comput. Sci. Appl, 7(7), 283-287.

[6] Pedrosa, Joao & Castro, Ana & Vinhoza, Tiago. (2014). Automatic heart sound segmentation and murmur detection in pediatric phonocardiograms. 2014 36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBC 2014. 2014. 2294-7. 10.1109/EMBC.2014.6944078.

[7] Wang, Jiaming & You, Tao & Yi, Kang & Gong, Yaqin & Xie, Qilian & Qu, Fei & Wang, Bangzhou & He, Zhaoming. (2020). Intelligent Diagnosis of Heart Murmurs in Children with Congenital Heart Disease. Journal of Healthcare Engineering. 2020. 1-9. 10.1155/2020/9640821.

[8] Amiri, Amir M. & Armano, Giuliano. (2013). Early Diagnosis of Heart Disease Using Classification and Regression Trees. Proceedings of the International Joint Conference on Neural Networks. 10.1109/IJCNN.2013.6707080.

[9] Yaseen, & Son, Gui-Young & Kwon, Soonil. (2018). Classification of Heart Sound Signal Using Multiple Features. Applied Sciences. 8. 2344. 10.3390/app8122344.

[10] Nicholas G. Polson and Vadim O. Sokolov. Deep learning. page 1, 2018.

[11] Peter Bentley, Glenn Nordehn, Miguel Coimbra, Shie Mannor and Rita Getz for PCG dataset from "The PASCAL Classifying Heart Sounds Challenge 2011.

[12] Martínez-Alajarín, J., López-Candel, J., & Ruiz-Merino, R. (2007, June). Classification and diagnosis of heart sounds and murmurs using artificial neural networks. In International Work-Conference on the Interplay Between Natural and Artificial Computation (pp. 303-312). Springer, Berlin, Heidelberg.