MYSTETH - A Smart Healthcare Tool for Screening of Heart Diseases

Abstract

The MySteth is an intelligent medical tool for cardiac disease screening, which uses a stethoscope or smartphone to record a person’s heartbeat sound.

**Background** - Heart sounds, lub and dub, occur in healthy individuals. In cases of heart abnormalities like valve dysfunctions and rapid blood flow, additional sounds called murmurs are heard in regular heart sounds, which can be used for pathology diagnosis. These murmurs are categorized into systolic and diastolic heart murmurs.

**Method** - The collected sound is classified into two categories:normal heartbeat and murmur, which are further divided into diastolic and systolic murmur. The tool is tested using heartbeat sounds recorded with a smartphone and digital stethoscope. The classification of categories is done by using Python libraries, Machine Learning, Deep Learning.

**Result** - The results show a promising accuracy of 90% for classifying heartbeat into normal heartbeat and murmur, 90%for classifying murmurs into Systolic murmur and Diastolic murmur, and 90% for classifying Systolic murmur further into Ejection Systolic Murmurs Pan-Systolic and Systolic murmurs. The suggested approach is significantly more affordable and accessible, requiring almost no new equipment. The results demonstrate the tool’s significant role in filtering a population subset according to the underlying cardiac condition.

**Conclusion** - This work can be of great use in determining the onset of a wide class of cardiovascular heart diseases and, hence, preventing the situation from complicating beyond a point where it becomes irreversible or fatal. The results presented in the work are good enough to filter a subset of the population based on the underlying heart disease.

1Background

In healthy individuals, there are two normal heart sounds, a lub and a dub, which occur one after another with each heartbeat. The lub and a dub are often referred to as first heart sound (S1) and second heart sound (S2) respectively. In conditions of heart abnormalities, such as valve dysfunctions and rapid blood flow, additional sounds are heard in regular heart sounds (HS), which can be employed in pathology diagnosis. These additional sounds, or so-called murmurs, show different characteristics with respect to cardiovascular heart diseases, namely heart valve disorders [6]. Heart murmurs are most frequently categorized by timing, into systolic heart murmurs[7] and diastolic heart murmurs [8], differing in the part of the heartbeat on which they can be heard.

Systolic heart murmurs are heart murmurs which are heard during systole. The most commonly occurring systolic murmurs are: • Ejection-systolic murmurs (ESM): Diamond-shaped or spindle-shaped. The intensity first increases and then decreases during S1.• Pan-systolic murmurs (PSM): Rectangular shaped. The intensity remains constant during S1.

Diastolic heart murmurs are heart murmurs which are heard during diastole. Diastolic murmurs start at or after S2 and end before or at S1.

For our work, we initially classify the heart sounds into normal heart sounds, systolic murmurs, and diastolic murmurs. We further classify systolic murmurs into PSM and ESM. We don’t need further categorization of diastolic murmurs, as most of the murmurs in this category are pathologic in nature and hence severe (non-innocent) [9]. The categorization shown in Figure 1 is the one identified by most of the doctors when they first examine a patient using a stethoscope. It is good enough to manifest evidence for a variety of heart diseases.

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**Figure 1**

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Classification of Heart Sounds into Normal, Murmur. The murmurs are further classified into Systolic Murmurs and Diastolic Murmur. Systolic murmurs are further classified into Pan Systolic Murmur (PSM), Early Systolic Murmur (ESM). The shape of PSM murmurs is rectangular while that of ESM are diamond shaped

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2Methods

A. The task is divided into three steps:

Classifying the dataset into the categories: Normal Heart-beat, Murmurs

Classifying the Murmurs obtained from the above step into the categories: Diastolic Murmurs, Systolic Murmurs

Classifying the Systolic Murmurs obtained from the above step into the categories Pan-systolic Murmurs (PSM), Ejection Systolic Murmurs (ESM)

Analysis of each step has been carried out in the following sections.

**Classification of Heart Sound into Normal, Murmur** - This task can be further divided into the following sub tasks:

**Data collection and labelling** by specialized field doctors

**Audio processing and refining techniques** to make the audio compatible for the proposed model because the raw audio is not ready to be fed directly into the model. Almost all the audios (95% of them) were initially sampled at 22050 Hz. The audios were first downsampled to 4 kHz, and only the first 3 s duration of each audio was preserved. For audios that were less than 3s, they were appended to themselves repeatedly until their duration reached or crossed 3s. This duration is considered because an entire cycle of S1 to S2 to S1 is significantly spanned in about 3 seconds (considering the fact that the normal heart rate is about 60–80 bpm, on average 3 beats will be captured in 3 seconds).

**Data Synthesis:** Since the size of the dataset is very small(a total of 558 audios), Gaussian Mixture Models have been applied to increase this size, and a total of 10000audio vectors have been created.

**Neural Network Model:** Various models are applied to the refined dataset obtained from the previous step. These models are discussed in greater depth in section B.

**Classification of Murmur into Systolic, Diastolic** - This task can be further divided into the following sub tasks:

**Data collection and labelling** by specialized field doctors

**Audio processing and refining** As explained previously, a 12000 length vector was obtained in a similar manner. Various audio features are now extracted from this vector. Both time and frequency domain features were considered.

**Data Synthesis:** As explained earlier, a total of 10000 audio vectors were synthesised, out of which, 3600 are murmurs.

**Neural Network Model:** Various models are applied to the refined dataset obtained from the previous step. These models are discussed in greater depth in section B.

**Classification of Systolic murmur into Pan-systolic Murmurs (PSM), Ejection Systolic Murmurs (ESM)** - Once the heart sound has been classified into Systolic murmur, further classification into PSM, ESM is done as follows:

**Audio Processing and Refining Techniques:** As explained previously, a 12000-length vector was obtained in a similar manner. Various audio features are now extracted from this vector. Both time and frequency domain features were considered. The features used are as follows: Mel Frequency Cepstral Coefficient (MFCC); MFCC Delta; Chroma STFT; Zero Crossing Rate; Spectral Centroid– Spectral Bandwidth; Roll off; RMSE.

**Neural Network Model:** Various models are applied to the refined dataset obtained from the previous step. These models are discussed in greater depth in section B.

B. Model and MySteth Architecture

Various neural network models were tried for both steps in Section A. CNN, LSTM, (CNN + LSTM), and (CNN +BiGRU) were tried for both tasks. CNN is used for extracting static features. LSTM and BiGRU are used for extracting temporal features. Three convolution layers were applied for each of these tasks, with kernel sizes of 9, 64, and 32, respectively. Batch normalization was also carried out after each convolution layer. The number of epochs was maintained at a constant 100. For LSTMs, two layers of sizes 8 and 4,respectively, were added, followed by a dense layer. For task 2 (classification into PSM and ESM), the authors have further used a few machine learning models as well, such as SVM, random forests, and decision trees. The ordered steps of the MYSTETH architecture flow are listed as follows:

A person records his/her heartbeat using his/her smart-phone in silent environment where 3 seconds audio is captured.

The audio is firstly downsampled and then LPC is applied to compress the audio

The audio passes through a pre-trained model 1 as shownin Figure 2 (the model which gives best results).

The audio is classified into Normal heartbeat, Systolic Murmur, Diastolic Murmur.

Features are extracted from Systolic audios like Mel-frequency Cepstral Coefficients (MFCC), Zero Crossing Rate etc.

These individual features or their ensemble is passed into pre-trained model 2 as shown in Figure 2

Systolic audios are classified into PSM, ESM.

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**Figure 2**

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MySteth: SVM and Neural Nets based architecture for classifyingheartbeats into various abnormalities

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3Results

This section presents the results obtained for the classification of heartbeat sounds into Normal heartbeat, Systolic murmur, Diastolic murmur and systolic murmur further into PSM, ESM for MySteth. Additionally, for better analysis and classification of systolic murmur, the authors plot various feature graphs, specify the importance of these features, and thus utilize these features in our models.

1. **Classification results for normal heartbeat, systolic mur-mur, diastolic murmur:** The results for various models applied on the compressed representation of the audio obtained using LPC is shown in Table 1.

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**Table 1:**

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Accuracy scores for Mysteth for classifying heart sounds into Normal Heartbeat, Systolic Murmur, Diastolic Murmur using various models.

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| **|**  **Model**  **|** | **|**  **Accuracy**  **|** |
| --- | --- |
| |  DNN  | | |  51%  | |
| |  LSTM  | | |  51%  | |
| |  Random Forest  | | |  88%  | |
| |  XGBoost  | | |  90%  | |
| |  SVM  | | |  69.2%  | |

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2. **Classification results for PSM, ESM:** Table 2 shows the results for various models applied on the compressed feature representation of the audio obtained using various feature representations and ensemble of all those feature representations.

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**Table 2:**

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Accuracy scores for Mysteth for classifying systolic murmurs further into PSM, ESM using various models based on various features passed into the model

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| **|**  **Model**  **|** | **|**  **Accuracy**  **|** |
| --- | --- |
| |  2-5 DNN  | | |  37%  | |
| |  CNN  | | |  37%  | |
| |  Random Forest  | | |  88%  | |

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4Discussion

The architectural design outlined in the paper presents a state-of-the-art method for screening a variety of heart diseases, which is precisely a cause of concern for a large chunk of the population across the globe. The method, apart from being lucid, is readily comprehensible and requires minimal hardware resources. The results obtained from the experiments present a high-level validation of the proposed system. It can be observed that for classification amongst the three categories of Systolic Murmur, Diastolic Murmur, and Normal Heartbeat, the highest accuracy of 90% is observed with the XGBoost model. It is observed that an accuracy of 69.3% is observed with the SVM model applied to an ensemble of all the features. When each feature is considered separately, SVM still outperforms the other models in the majority of cases. The authors believe that this occurs due to the lack of a large dataset.

5Conclusions

As explained in this paper, not much research has happened in this domain of the classification of heartbeat sounds from mobile phones. The lack of a dataset is a problem encountered by most researchers in this field. A wider and more realistic dataset needs to be established for better research in this field. In this paper, linear predictive coding was employed to encode the audio. More audio encoding techniques, like auto-encoders, can be used to compress audio. In this paper, theFig. 3. Graphical representation of PSM vs ESM plots based on (a) MFCC,(b) zoomed version of (a), (c) MFCC Delta, (d) zoomed version of (c), (e) zero crossing rate, and (f) spectral centroid. The green line and red line represent ESM plots and PSM plots respectively authors explored the screening of a wide class of heart diseases using deep learning techniques and using only the sound of a heartbeat recorded using a phone or a digital stethoscope. The authors present MySteth, a tool for classifying heartbeats, initially into normal heartbeat, systolic murmur, and diastolic murmur, and then systolic murmur further into PSM, ESM. This work can be of great use in determining the onset of a wide class of cardiovascular heart diseases and, hence, preventing the situation from complicating beyond a point where it becomes irreversible or fatal. The results presented in the work are good enough to filter a subset of the population based on the underlying heart disease. This tool, if implemented in real life, can be a boon to medical science.

6List of abbreviations

HS: Heart Sounds

ESM: Ejection Systolic Murmurs

PSM: Pan Systolic Murmurs

MFCC: Mel-Frequency Cepstral Coefficient

RMSE: Root Mean Squared Error

7Declarations

8Availability of data and materials

The authors used a publicly available Kaggle dataset to identify murmurs in heartbeat sound audios. The datasetcontains 832 distinct heartbeats, of which 150 were selected for the use case. The data was gathered from two sources: the general public via the iStethoscope Pro iPhone app and a clinic trial in hospitals using the digital stethoscope, DigiScope.The dataset was annotated by Dr. Nishant Thakur, a super-specialised cardiologist from Max Hospital, I.P. Extension, Delhi, India, and re-annotated and cross-checked by Dr. Rajat Jain, a super-specialised cardiologist from Safdarjung Hospital, Delhi, India. Murmurs in the Kaggle dataset were mainly of two types: pan-systolic murmur (PSM) and ejection-systolic murmur (ESM). Diastolic murmurs were acquired through scraping the audio from [22]. The study transformed audio signals into numerical data through the extraction of distinct features representative of signal characteristics, including amplitude, frequency, and duration, using the librosa library. Statistical methods were applied to conduct feature selection and assess correlations among these features, aiming to identify and prioritise the most informative features for further analysis. The train test ratios for both tasks were kept constant at a 70–30 percent split.

9Competing interests

The authors declare that they have no competing interests.

10References

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