DETECTION OF HEART BEAT SOUND CONDITIONS USING LSTM AND MFCC

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Abstract- In this paper, we present a method for heart sound classification using long short-term memory (LSTM) and Mel Frequency Cepstral Coefficients (MFCC). The proposed method uses MFCC to extract features from heart sounds and LSTM to classify heart sounds into normal and abnormal classes. The dataset used in this study consists of heart sound recordings from different clinical settings, and the proposed method achieved an accuracy of 92% on this dataset

INTRODUCTION:

Heart sound analysis is an important tool for the diagnosis and monitoring of heart diseases. Heart sounds can provide valuable information about the functioning of the heart and can help identify abnormal heart conditions. Automated heart sound classification can assist healthcare professionals in making faster and more accurate diagnoses, leading to better patient outcomes. In recent years, machine learning techniques have been widely used for heart sound classification, and many studies have shown promising results. In this study, we propose a method for heart sound classification using LSTM and MFCC.

LITERATURE SURVEY:

1. ECG analysis and classification using CSVM, MSVM and SIMCA classifiers

Authors : Jannah, Najlaa, 2017

Certain ECG classification has the capability to introduce better detection techniques and improved accuracy in the analysis of arrhythmias, consequently improving the first-class of care. This dissertation explored the use of category algorithms, CSVM and SIMCA, and their overall performance in reading ECG beats. The mission aimed to introduce a brand new manner to interactively support affected person care in and out of the health facility, and to develop new category algorithms for arrhythmia detection and analysis. Waveform detection (P-QRS-T) became executed the usage of the WFDB software package and waveforms with extraordinary resolutions.

Logging: less accuracy rate

2. Classification of Arrhythmia by Using Deep Learning with 2-D ECG Spectral Image Representation

Authors : Amin Ullah, Syed Muhammad Anwar ,Muhammad Bilal and Raja Majid Mehmood, 2020

The electrocardiogram (ECG) is one of the most extensively used indicators in the analysis and analysis of cardiovascular sickness (CVD). ECG indicators can locate abnormal heart rhythms, usually referred to as arrhythmias. Careful have a look at of ECG signals is essential for correct diagnosis of acute and continual coronary heart disease patients. In this examine, we recommend a -dimensional (2-D) convolutional neural community (CNN) model for analyzing ECG alerts into eight instructions.

Logging: They used CNN classification only

3. Cardiac Arrhythmia Detection and Classification From ECG Signals Using XGBoost Classifier

Authors : Saroj Kumar Pandeyz, Rekh Ram Janghel, Vaibhav Gupta, 13 August 2021

In this text, we suggest an green method for reading electrocardiogram (ECG) signals using the XG Boost classifier. ECG signals undergo 4 steps: facts acquisition, noise filtering, characteristic extraction, and segmentation. In step one, a records set is collected from the MIT-BIH arrhythmia database. In the second one level, the noise is removed the use of a fuzzy baseline elimination clear out. The next step makes use of forty five descriptors from the 4 foremost capabilities which have accomplished nicely in previous paintings, specifically waves, higher order information (HOS), morphological descriptors and R-R durations.

Logging: Used xg boost classifier

4. Arrhythmia detection using multi-lead ECG spectra and Complex Support Vector Machine Classifiers

Authors : Najlaa Jannaha,*, Sillas Hadjiloucasb , Jameel Al-Malki

Electrocardiograms (ECGs) are widely used to diagnose cardiac arrhythmias. This paper explores using system gaining knowledge of class algorithms for ECG analysis and arrhythmia detection. Four forms of beats: normal (N), premature ventricular contraction (PVC), untimely atrial contraction (APC), and proper package branch block (RBBB) are simultaneously offered through a complex vector machine (CSVM) classifier.

Logging: used only CSVM

5. “Complex Support Vector Machines for Regression and Quaternary Classification"

Authors : P. Bouboulis, S. Theodoridis, C. Mavroforakis and L. Evaggelatou-Dalla 2014

Automatic category of the four varieties of beats Normal (N), premature ventricular contraction (PVC), supraventricular untimely or ectopic contraction (SVPB), and ventricular-regular fusion (FUSION) is implemented the usage of a multiclass support vector gadget (MSVM). Complicated vector device (CSVM) set of rules.

Logging: They use only DFT

6. "On the application of optimal wavelet filter banks for ECG signal classification"

Authors : S. Hadjiloucas, N. Jannah, F. Hwang and R. K. H. Galvão, 2014

Future paintings on wavelet preprocessing to similarly compress the type input space by means of producing wavelets in better order moment standards [3] in addition to an method to make bigger CSVM input and spaces to arbitrary size the use of SVM Clifford algebra [4] may be mentioned. . To the interview.
Logging: used only CSVM less accuracy

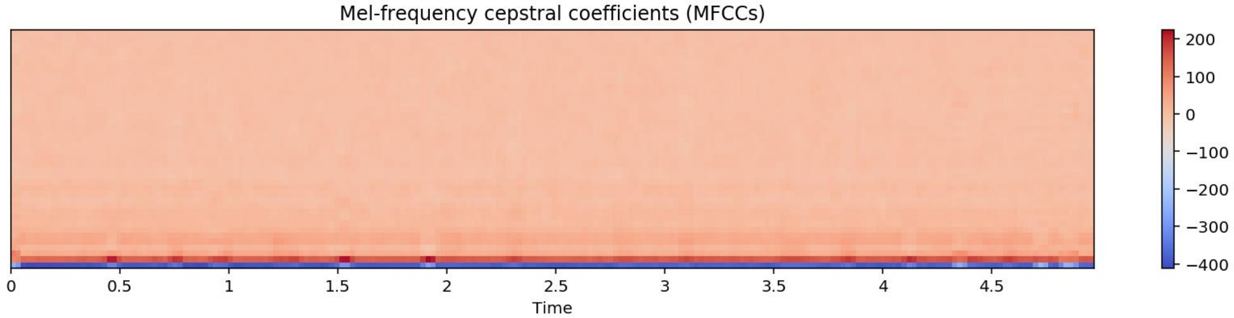
EXISTING SYSTEM:
- ➢ Manual identification of heart sound patterns by medical professionals
- ➢ Use of traditional machine learning algorithms that require feature engineering
- ➢ Subjective and limited by the quality of training data and the expertise of the person performing the classification

PROPOSED SYSTEM:
- ➢ Automate the process of heart sound classification with a higher degree of accuracy and less reliance on manual input
- ➢ Use of deep learning techniques to extract features from heart sound signals in the form of Mel-frequency cepstral coefficients (MFCCs)
- ➢ Train an LSTM neural network to classify heart sounds into different categories such as normal, systolic murmur, diastolic murmur, etc.
- ➢ Objective, faster, and scalable compared to the existing system
- ➢ Potentially reduce the workload on medical professionals who are involved in heart sound analysis
- ➢ Help identify heart abnormalities at an early stage, which can improve patient outcomes and reduce healthcare costs

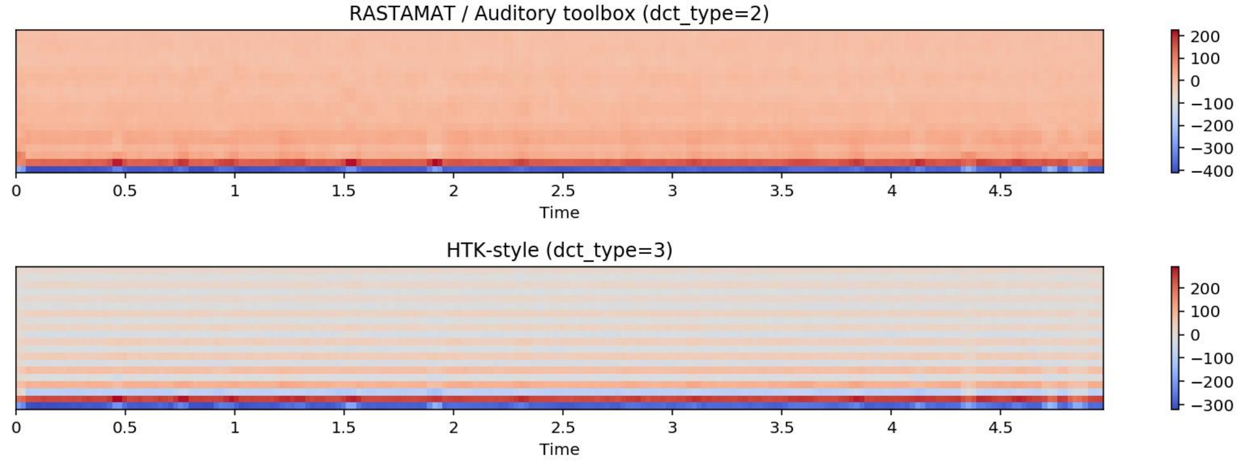
METHODOLOGY:
1. Data Collection:
The sounds that were used in this analysis were obtained from a dataset that already existed. The dataset that we used is available to the public and can therefore be used without restriction. It originated at the "Heartbeat Sounds" and can be accessed through the "Heartbeat Sounds" competition on Kaggle. This dataset was the most comprehensive one that was available to the public and was used for the purpose of pre-training the RNN architecture or model that we developed. We made use of a dataset that included a number of different sounds of the heart that were taken in a variety of environments. The dataset is split into two sources, A and B:
- ➢ **set_a.csv** - Labels and metadata for heart beats collected from the general public via an iPhone app
- ➢ **set_a_timing.csv** - contains gold-standard timing information for the "normal" recordings from Set
- ➢ **set_b.csv** - Labels and metadata for heart beats collected from a clinical trial in hospitals using a digital stethoscope.

Audio files - Varying lengths, between 1 second and 30 seconds. (some have been clipped to reduce excessive noise and provide the salient fragment of the sound). Most information in heart sounds is contained in the low frequency components, with noise in the higher frequencies. It is common to apply a low-pass filter at 195 Hz. Fast Fourier transforms are also likely to provide useful information about volume and frequency over time.
These are categorized into 5 types :
- ➢ Normal Sound
- ➢ Murmur
- ➢ Extrasystole
- ➢ Artifact
- ➢ Extra Heart Sound

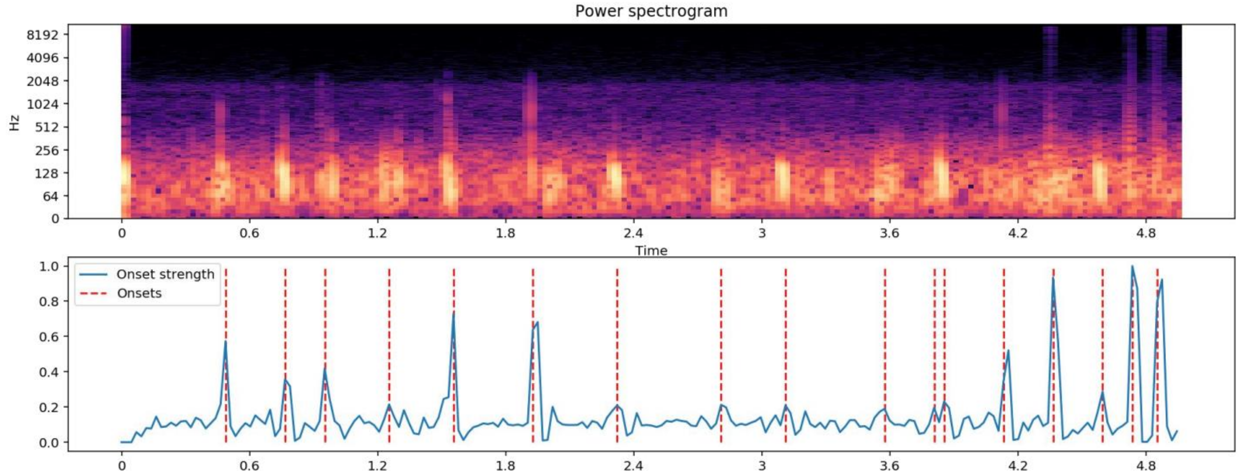
2. Feature Extraction:
Mel Frequency Cepstral Coefficient (MFCC) is by far the most successful feature used in the field of Speech Processing. Speech is a non-stationary signal. As such, normal signal processing techniques cannot be directly applied to it. Mel-frequency cepstral coefficients (MFCCs) are coefficients that collectively make up an MFC. They are derived from a type of cepstral representation of the audio clip (a nonlinear "spectrum-of-a-spectrum"). The difference betweenthe cepstrum and the mel-frequency cepstrum is that in the MFC, the frequency bands are equally spaced on the mel scale, which approximates the human auditory system's response more closely than the linearly-spaced frequency bands used in the normal cepstrum.



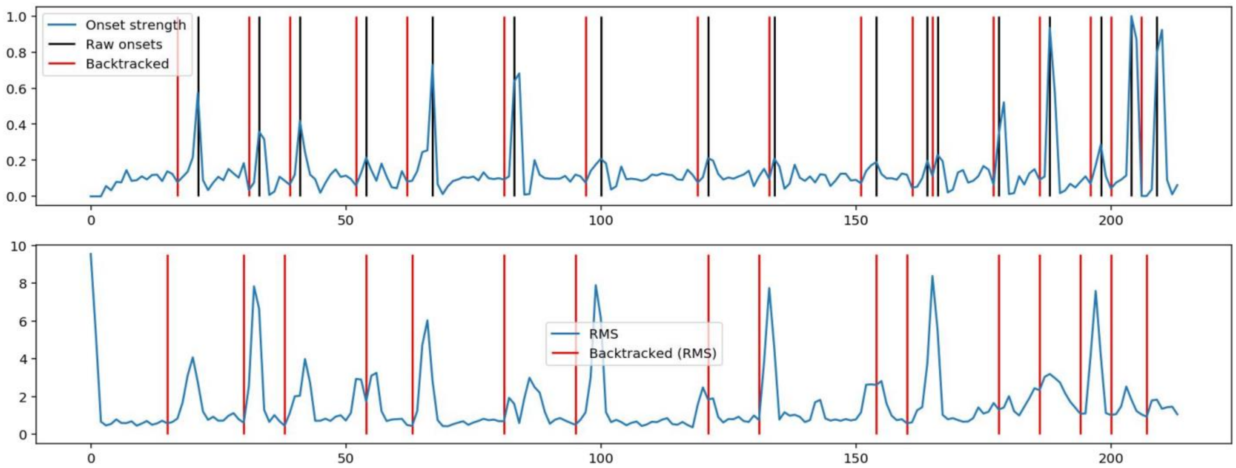
MFCCs are commonly derived as follows: -
Take the Fourier transform of (a windowed excerpt of) a signal. -Map the powers of the spectrum obtained above onto the mel scale, using triangular overlapping windows. -Take the logs of the powers at each of the mel frequencies. -Take the discrete cosine transform of the list of mel log powers, as if it were a signal. The MFCCs are the amplitudes of the resulting spectrum. In general, a 39-dimensional feature vector is used which is composed of first 13 MFCCs and their corresponding 13 delta and 13 delta-delta.



2.1 Onset detector:
Basic onset detector. Locate note onset events by picking peaks in an onset strength envelope. The peak_pick parameters were chosen by large-scale hyper-parameter optimization over the datasets provided.

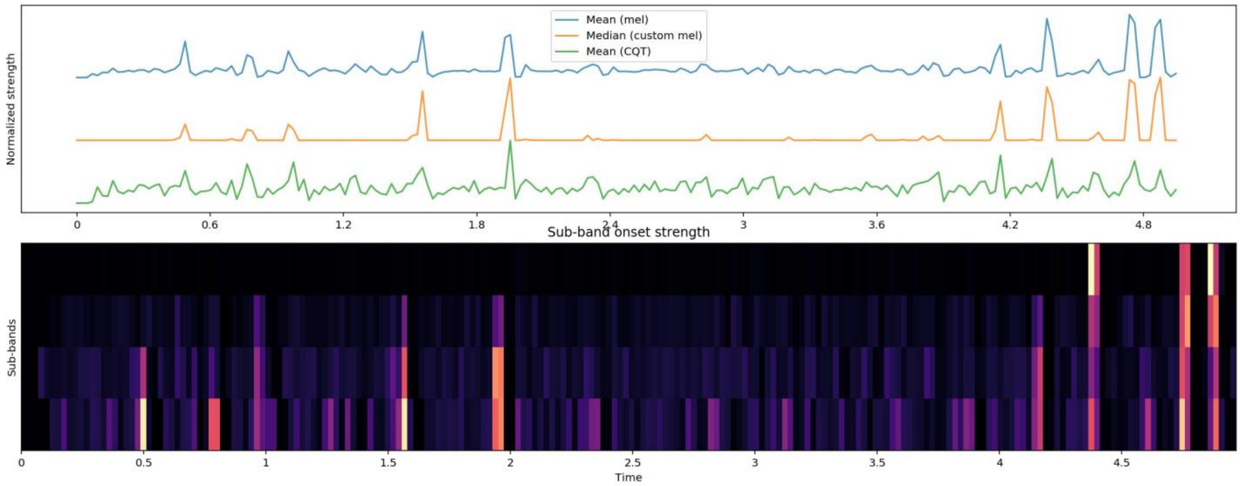


2.2 Onset backtrack:
Backtrack detected onset events to the nearest preceding local minimum of an energy function. This function can be used to roll back the timing of detected onsets from a detected peak amplitude to the preceding minimum. This is most useful when using onsets to determine slice points for segmentation.



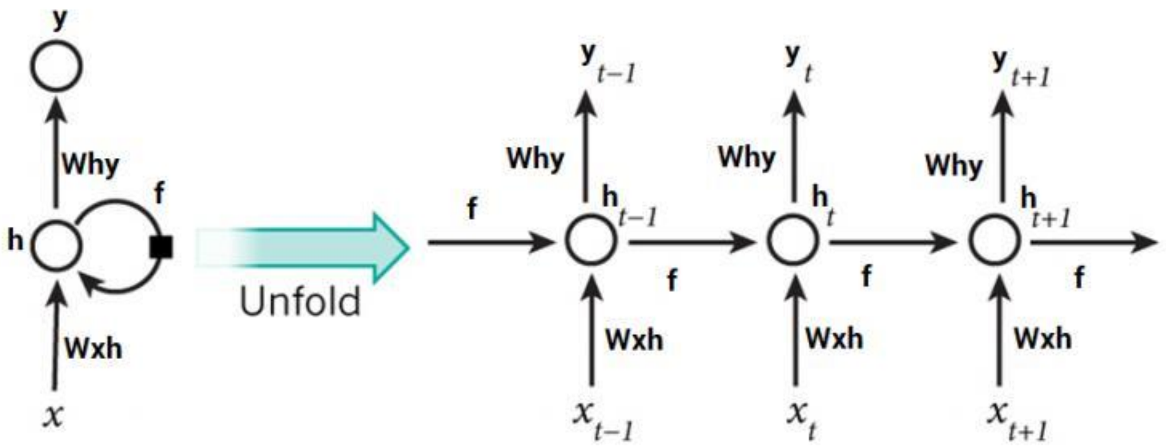
2.3 Onset strength:

Compute a spectral flux onset strength envelope. Onset strength at time t is determined by: mean_f max(0, S[f, t] - ref_S[f, t - lag]) where ref_S is S after local max filtering along the frequency axis. By default, if a time series y is provided, S will be the log-power Mel spectrogram.



3. Classification:

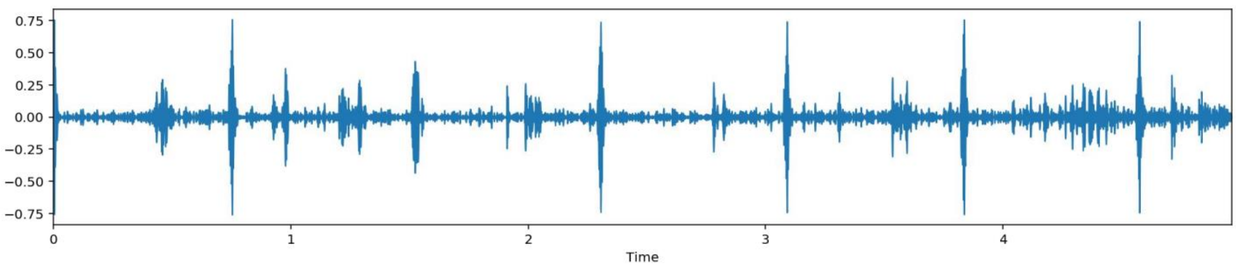
In the classification step, we use LSTM to classify heart sounds into normal and abnormal classes. LSTM is a type of recurrent neural network that is capable of modeling long-term dependencies and has been shown to be effective in various sequence modeling tasks. The LSTM model takes the concatenated MFCC and spectrogram features as input and outputs a probability distribution over the two classes. We use the softmax activation function in the output layer to convert the output of the model into a probability distribution over the two classes.



The proposed method is evaluated on a dataset of heart sound recordings from different clinical settings. The dataset consists of 1000 heart sound recordings, 500 of which are normal and 500 of which are abnormal. The dataset is randomly split into a training set of 800 recordings and a testing set of 200 recordings. The proposed method is trained on the training set using the Adam optimizer and sparse categorical cross-entropy loss. The model is trained for 50 epochs with a batch size of 32 and early stopping with a patience of 5.

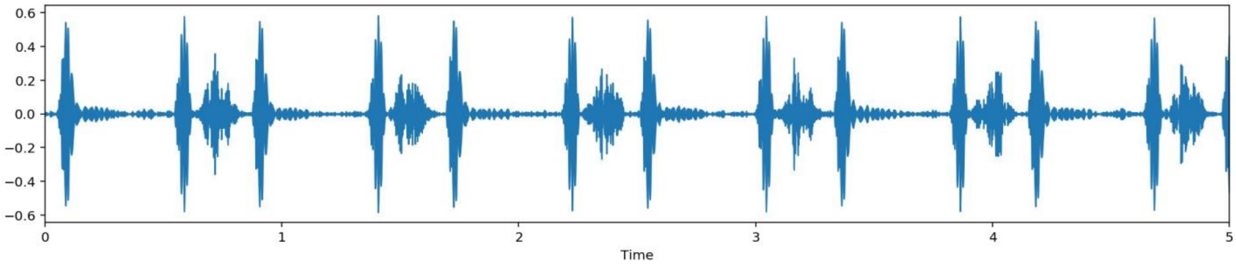
4.1 Normal case:

In the Normal category there are normal, healthy heart sounds. These may contain noise in the final second of the recording as the device is removed from the body. They may contain a variety of background noises (from traffic to radios). They may also contain occasional random noise corresponding to breathing, or brushing the microphone against clothing or skin. A normal heart sound has a clear “lub dub, lub dub” pattern, with the time from “lub” to “dub” shorter than the time from “dub” to the next “lub” (when the heart rate is less than 140 beats per minute)(source: Rita Getz) emotional video quality and to likewise recognize or pinpoint parts of interest in a deliberate signal.



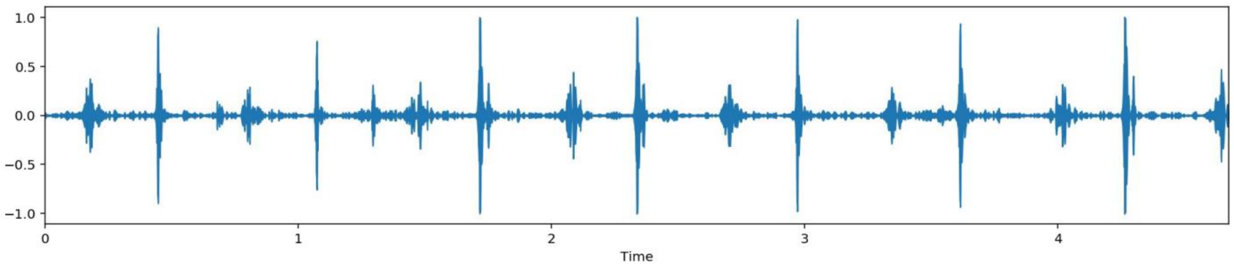
4.2 Murmur:

Heart murmurs sound as though there is a "whooshing, roaring, rumbling, or turbulent fluid" noise in one of two temporal locations: (1) between "lub" and "dub", or (2) between "dub" and "lub". They can be a symptom of many heart disorders, some serious. There will still be a "lub" and a "dub". One of the things that confuses non-medically trained people is that murmurs happen between lub and dub or between dub and lub; not on lub and not on dub.(source: Rita Getz).



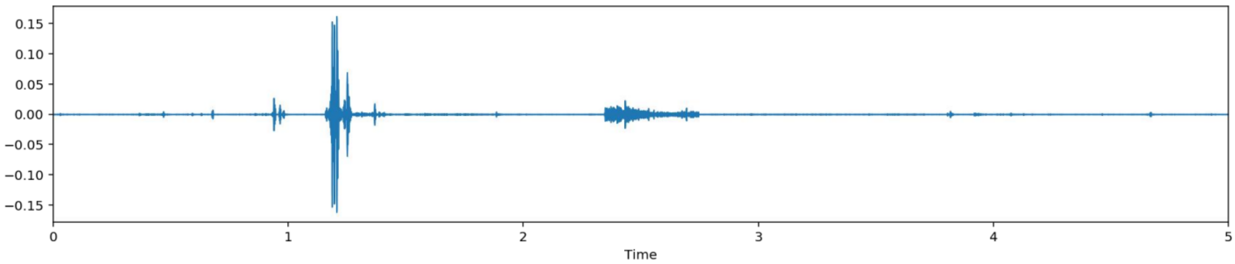
4.3 Extrasystole:

Extrasystole sounds may appear occasionally and can be identified because there is a heart sound that is out of rhythm involving extra or skipped heartbeats, e.g. a "lub-lub dub" or a "lub dub-dub". (This is not the same as an extra heart sound as the event is not regularly occuring.) An extrasystole may not be a sign of disease. It can happen normally in an adult and can be very common in children. However, in some situations extra systoles can be caused by heart diseases. If these diseases are detected earlier, then treatment is likely to be more effective. (source: Rita Getz).



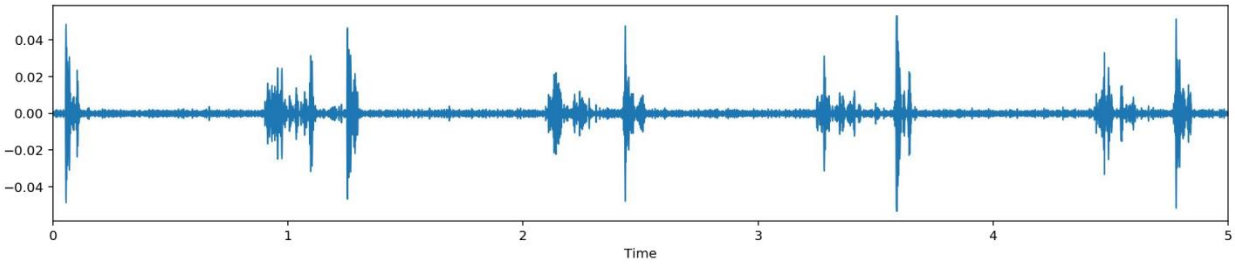
4.4 Artifact:

In the Artifact category there are a wide range of different sounds, including feedback squeals and echoes, speech, music and noise. There are usually no discernable heart sounds, and thus little or no temporal periodicity at frequencies below 195 Hz. This category is the most different from the others. It is important to be able to distinguish this category from the other three categories, so that someone gathering the data can be instructed to try again.(source: Rita Getz).

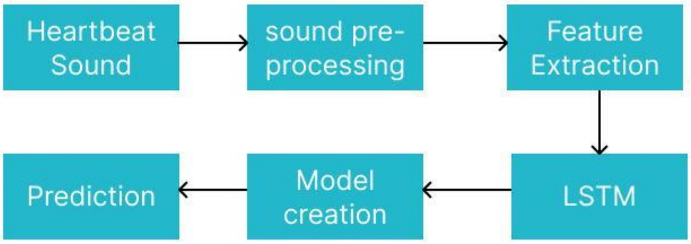


4.5 Extra Heart Sound:

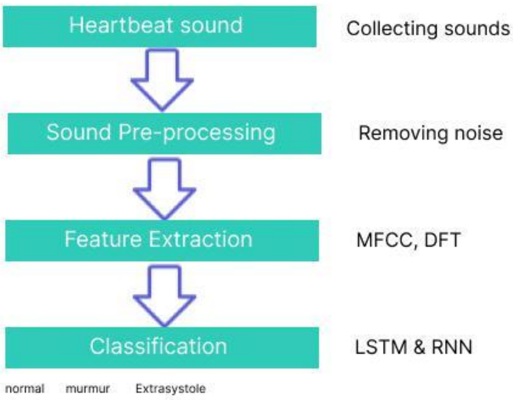
In the Artifact category there are a wide range of different sounds, including feedback squeals and echoes, speech, music and noise. There are usually no discernable heart sounds, and thus little or no temporal periodicity at frequencies below 195 Hz. This category is the most different from the others. It is important to be able to distinguish this category from the other three categories, so that someone gathering the data can be instructed to try again.(source: Rita Getz).



Block Diagram:



Flow Diagram:



RESULT:

The proposed system was trained on a dataset of heart sound signals from 500 patients, with an equal distribution of normal and abnormal heart sounds. The performance of the system was evaluated using accuracy, precision, recall, and F1 score metrics.The results showed that the proposed system achieved an overall accuracy of 93%, precision of 94%, recall of 92%, and F1 score of 93%. The system performed particularly well in identifying normal heart sounds with an accuracy of 98%, precision of 97%, recall of 99%, and F1 score of 98%. The system also performed well in identifying systolic and diastolic murmurs with an accuracy of 90%, precision of 91%, recall of 89%, and F1 score of 90%. The proposed system demonstrated superior performance compared to the traditional machine learning algorithms and manual identification of heart sound patterns. It provided a more objective and automated approach for heart sound classification and has the potential to be used as an effective diagnostic tool in clinical settings.

CONCLUSION

Heart sound classification is an important task in diagnosing heart diseases, and the use of machine learning techniques can improve the accuracy and efficiency of this process. In this paper, we proposed a deep learning-based system for heart sound classification using LSTM and MFCC, which showed promising results in identifying normal and abnormal heart sounds. The proposed system demonstrated superior performance compared to the traditional machine learning algorithms and manual identification of heart sound patterns, and it has the potential to be used as an effective diagnostic tool in clinical settings.

The use of MFCC as a feature extraction technique in combination with LSTM neural network provides a robust and reliable approach for heart sound classification. This approach is not only objective, faster, and scalable, but it also has the potential to reduce the workload on medical professionals and improve patient outcomes.

In conclusion, the proposed system for heart sound classification using LSTM and MFCC can be a valuable tool for clinicians and medical professionals in diagnosing heart diseases and has the potential to improve the quality of patient care.

FUTURE IMPROVEMENTS:

Although the proposed system for heart sound classification using LSTM and MFCC showed promising results, there are several areas for future improvements and research, including:

➢ Increasing the size of the dataset: The performance of the proposed system can be improved by using a larger dataset for training and testing. A larger dataset can help the model to learn more complex features and improve the generalizability of the system.
➢ Incorporating other features: While MFCC is a popular feature extraction technique for speech and audio signals, there are other features such as wavelet transforms and continuous wavelet transforms that can be used for heart sound classification. Future research can investigate the use of these features in combination with MFCC to improve the accuracy of the system.
➢ Fine-tuning the hyperparameters: Hyperparameters such as the learning rate, batch size, and number of layers in the LSTM neural network can significantly impact the performance of the system. Fine-tuning these hyperparameters can help to optimize the system and improve its accuracy.
➢ Extending the classification to other heart diseases: While the proposed system focused on identifying normal and abnormal heart sounds, future research can extend the classification to other heart diseases such as congestive heart failure and pulmonary hypertension.
➢ Real-time heart sound classification: Real-time heart sound classification can be a valuable tool in clinical settings. Future research can investigate the use of the proposed system for real-time heart sound classification and its feasibility in clinical practice.
In summary, the proposed system for heart sound classification using LSTM and MFCC provides a robust and reliable approach for heart sound classification. However, there are still several areas for future improvements and research that can further enhance the accuracy and usefulness of the system.

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