2022 3rd International Conference for Emerging Technology (INCET)
Belgaum, India. May 27-29, 2022

2022 3rd International Conference for Emerging Technology (INCET) | 978-1-6654-9499-1/22/$31.00 ©2022 IEEE | DOI: 10.1109/INCET54531.2022.9825189

Multi-Class Classification and Prediction of Heart Sounds Using Stacked LSTM to Detect Heart Sound Abnormalities

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***Abstract*— The changes in lifestyle, food habits, and working conditions cause various diseases in human lives, cardiovascular diseases are one of those. Not only aged people, middle-aged and young people are also suffering due to this and lead to death in the early ages. So there is a significant need in detecting cardiovascular diseases in beginning itself. Through early detection and persistent treatment, the death rate in the early ages due to cardiovascular diseases can be reduced. However, it is necessary to have an efficient model to detect heart disease at an early stage even without the presence of a trained clinical expert. This paper studies the implementation of deep learning models to classify heartbeat sounds into various classes. We proposed a stacked LSTM model to classify the heartbeat sound into multiple classes based on the features obtained from the audio signals. The implementation can even predict the class of an unlabelled heartbeat sound. The model classifies the heartbeat sounds into 4 classes with accuracies 85% and 87% on training and validation sets respectively. In further the proposed model parameters can be improved to increase the classification and prediction accuracy.**

***Keywords*— Heartbeat Sounds, Stacked LSTM, Cardiovascular diseases, Deep Learning, Machine Learning.**

I. Introduction

Cardiovascular diseases are one of the primary causes of most deaths in the world. In earlier, mostly aged people were affected by these types of diseases. But now even middle-aged people are also affected by cardiovascular diseases due to changes in their lifestyle and other factors such as smoking, alcohol consumption, diabetes, etc. As prevention is better than cure, it is better to prevent the situations that lead to heart diseases. But, the measures that should be taken to prevent are relying on continuous monitoring of heartbeat sound. The heart is the primary organ that is responsible to pump blood into the arteries and veins overall the body. While pumping blood it makes two types of sounds, first heart sound (S1) called 'LUB' represents "the closure of the inflow valves which marks the beginning of the systole when blood pushed out of the heart to the lungs and body", second heart sound (S2) called as 'DUB' represents "the conclusion of outpouring valves (aortic and aspiratory), which denotes the start of diastole, the comparatively longer phase when the heart is refilled"[1][2]. These heart sounds are to be considered normal sounds. Sometimes heart may respond with other sounds such as artifact, murmur, extrahls, or extrasystole, etc., indicating the malfunctioning of the heart. "*Murmur* is a low-frequency sound produced by turbulent flow over the valves. During *systole*, high-speed flow in aorta valves can also create this sound. It can be a sign of malfunction of the valves or insufficiency in the blood flow when there is a leakage over a valve that fails to close. *Extra heart sound* is described to be a sign of advanced heart disease caused by the abnormal flow of blood in the ventricles. In addition to these sounds, some other sounds like an *artifact*, *extrasystole,* etc. can be present". Recognition of the difference between usual and unusual heart sounds is a hectic task that involves highly skilled physicians with deep expertise which can be gained through the continuous clinical training process. An automatic heart sound classifier will show promising outcomes in differentiating the usual and unusual heart sounds. Deep learning models [28] [29] can be used to of typical and strange heart sounds.

A. *M L and D L Models for Heart Sound Classification*

An artificial neural network was used to categorize the heart sounds based on the features extracted using Mel-Frequency Cepstral Coefficients from the heart sounds [3]. The learning and analysis phases of the implemented model were represented using the following figures.

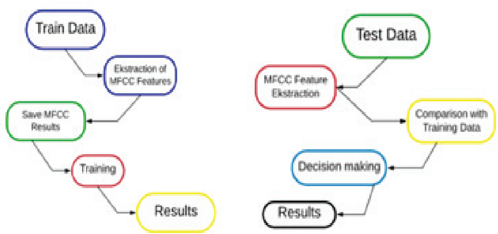

Fig. 1 Learning and Analysis Phases of Proposed ANN Method for Heart Sound Categorization [3]

An ensemble classifier was developed based on the "Decision tree model, Support vector machines, Logistic regression, K-Nearest Neighbors" etc., to determine the quality of signals in radar-recorded heart sounds [4]. CardioXNet was proposed to classify five classes of cardiac auscultation. CardoXNet is a lightweight CRNN architecture that consists of two-phase learning 1. Representation Learning 2. Sequence Residual Learning. The Representative Learning phase is used to derive the features from raw PCG signals whereas the sequential residual learning phase is used to extract the time-based information [5]. A profound neural organization (DNN) technique is proposed for perceiving S1 and S2 heart sounds. In this strategy, heart sound signs were first changed over into a grouping of Mel-recurrence cepstral coefficients (MFCCs). The K-implies calculation was applied to bunch MFCC highlights into two gatherings to refine their portrayal and discriminative capacity [30]. The refined elements were then taken care of to a DNN classifier to perform S1 and S2 acknowledgment [6]. A convolutional neural network was proposed for heart sound grouping without division. In this technique, the heart cycles with various beginning positions are blocked from the heart's strong signs during the preparation stage. Then, at that point, the spectrograms of the captured heart cycles are scaled to a decent size and contribution to the planned CNN engineering. Consequently, the prepared CNN can produce elements of various beginning situations in the testing stage. Finally, the order task is finished by the help vector machine (SVM) [7]. A deep gated RNN was proposed by combining the convolutional and recurrent layers. the component extraction is performed by a 1-layered convolutional front end, which figures out how to extricate recurrence and waveform highlights. Subsequent intermittent layers learn modern long haul conditions concealed in the extricated time-recurrence highlights of the pulses. A feed-forward consideration instrument is utilized to total the conveyed data in the result of the last intermittent layer into a solitary choice. The result of every span is weighted by significance and a weighted normal is processed as a decent portrayal of the entire recording. This last advance can be deciphered by inserting each handled recording into a decent vector space. Utilizing this consideration weighted normal, a multi-facet perceptron characterizes each recording as ordinary/strange [8]. CNN-VGG16 model was used to extract features of PCG signals and support vector machines are used to classify the heart sound based on the features extracted from VGG16 architecture [9]. An arrangement between the first and second heart sound of scalograms created by the Morse scientific wavelet was analyzed for CNN, support vector machine (SVM), and k-closest neighbors (kNN) classifiers. Tests of the first and second heart sound were extricated from an openly accessible dataset of typical and strange heart sound accounts, and extent scalograms were determined for each example. These scalograms were utilized to prepare and test CNNs. Order utilizing highlights extricated from a completely associated layer of the organization was contrasted and straight paired example highlights. The CNN accomplished a normal characterization precision of 86% while recognizing the first and second heart sound. Highlights extricated from the CNN and grouped utilizing an SVM accomplished comparative outcomes (85.9%) [10]. Propose the utilization of intermittent neural organizations and take advantage of ongoing progressions in consideration based on figuring out how to section the PCG signal. This permits the organization to recognize the most notable parts of the sign and dismissal uninformative data [11]. The SVM is utilized for grouping signals as typical or Abnormal. The SVM used a Gaussian bit, which was naturally scaled utilizing a heuristic system [12]. Decision tree and random forest models were used to classify abnormal heart sounds [13]. Deep learning models can be used to classify and predict heart sounds based on the features studied from the training phase.

B. Stacked LSTM model

A stacked LSTM model was used to process the sequential data. This paper shows the implementation of a stacked LSTM model to classify and predict heart sounds by observing various features in heart sounds at different time steps. Stacked LSTM is one of the extensions of the conventional LSTM model. Multiple hidden LSTM layers were combined to form a stacked LSTM architecture. In stacked LSTM architecture, each hidden layer consists of multiple memory cells, which makes the model deeper. In stacked LSTM takes a 3D input, after processing produces a single value for each one input sequence of time steps.

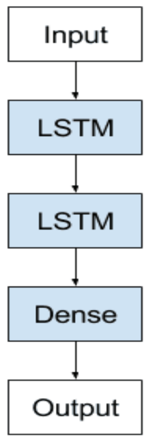

Fig. 2. Stacked Long Short-Term Memory Architecture

The remaining sections that are explained in this paper are - In the second section background work related to heart sound classification was explored. Later in the third section, the objectives, in the fourth section the stacked LSTM model implemented was explained. Finally, in section five, the experimentation and results obtained were discussed. Finally, in section 6, the conclusions and future scope of the work are elaborated.

II. BACKGROUND WORK

[14] proposed an automatic and efficient method to extract the MFCC features from heart sounds, and a supervised classification method was implemented to classify the normal and abnormal heart sounds for the detection of heart disease. [15] polyphase antialiasing filter was used to down-sampled the PCG signal to 1kHz, in the second stage segmentation of heart sounds were done then the meta-classifier models are used to classify the heart sounds into normal and abnormal. [16] “J48, Naive Bayes, KNN, SVM, Random Forest, Bagging, and Boosting machine learning algorithms” were implemented to classify the heart sounds to identify the heart failure detection. [3] Artificial Neural Network (ANN) is used to extract MFCC features from the heart sounds dataset and for classifying the normal and abnormal cases. [5] proposed CardioXNet, which incorporates the features of recurrent neural networks. [17] an artificial neural network was used to classify the Normal and Extra systolic heart sounds in PASCAL Heart Sounds (HS) database. [13] decision tree algorithm was used to classify the normal and abnormal heart sounds. [18] in this paper, the authors developed a new algorithm based on the autoregressive model to classify the normal and abnormal heart sound recordings. As the first step, wavelet analysis

was used to remove noises from the audio files. Next, the sound files were decomposed by the wavelet method to reconstruct the bands with different frequencies. Later the normalized Shannon energy was calculated, finally using power spectrum analysis of autoregressive model used for classification. [19] proposed a cardiac diagnostic model using CNN. In this paper, the authors first applied Windowed-sinc Hamming filter algorithm to remove signals regarded as noise. Then the audio recordings were segmented, CNN is trained to extract features from the segmented audio files. [20] proposed "Markov-switching autoregressive (MSAR)" process to segment the heart sounds. The MSAR model to a "switching linear dynamic system (SLDS)" that together model both the switching AR dynamics of underlying heart sound signals and the noise effects. Introduced a new process through union of "switching Kalman filter" and the duration-dependent "Viterbi algorithm", which incorporates the duration of heart sound states to improve state decoding. [21] A multi-modal classifier based on the techniques support vector machines and extreme learning machines was proposed to classify the heart sound recordings. In this method two feature sets were generated, one from the segmentation results by using peak finding method and the other from the audio signal analysis. The concluding heart sound grouping outcome ("normal / abnormal") is determined by ensemble the two classifiers with polling. [22] A CAD-based model by applying CNN algorithm was developed for automatic detection of abnormal heart sounds. [12] Explained the details provided in the "PhysioNet/Computing in Cardiology 2016 Challenge". An execution of an advanced segmentation procedure has been provided by the Challenge coordinators, leaving the primary focus on the classification task. In this paper the authors concentrated on classification task by considering various features. A simple time varying spectral feature for heart sound classification was introduced, this model classifies the heart sounds based on a single feature. This feature was tested on both binary and multi class classification models [23]. The authors implemented 4 phases to classify the usual and unusual patterns of heart sounds in normal people and heart disease patients. The four phases are 1. Decomposition of heart sound signal into sub bands. 2. Decomposing the sub bands into intrinsic modes using a variational mode decomposition method. 3. Deriving the features. 4. Applying classification frameworks to classify normal and abnormal patterns [24]. The authors proposed a heart sound classification algorithm to classify the heart sounds into either normal or murmur, compared the results with the challenge finalists and concluded that their model having improved classification accuracy compared to the those [25]. The authors worked on both binary as well as multi class classification using convolutional neural network [1]. Implemented a binary classification algorithm to classify healthy and unhealthy heart sounds in two stages. In the first stage segmentation was done and in the second stage the features were extracted and applied classification methods [26]. Introduced residual modules in heart sound classification. It works in two steps, in the first step it generates spectrograms from audio signals and in the second step residual network trained to classify the audio signals [27].

III. OBJECTIVES

The key goals of this paper are

- Analysing different heart sounds to understand which type of heart sound might indicate heart disease.
- Reviewing the state-of-the-art simulations used in heart disease prediction and heart sound classification.
- Developing a deep neural network to predict the heart disease based on heart sound.
- Analysing the performance of developed network in terms of accuracy and loss.

IV. HEART SOUND CLASSIFICATION AND PREDICTION

Heart beat sound classification and prediction was done by using stacked LSTM network, which is an extension to original LSTM which consists of a single hidden LSTM layer followed by a standard feedforward output layer, whereas stacked LSTM has multiple hidden layers. The stacked LSTM model helps in achieving greater model complexity.

A. *Proposed Methodology:*

The heart beat sounds dataset was gathered from "Kaggle data science community", pre-processing of data was done by combining the respective classes in two datasets set_a and set_b. The dataset was divided into training and validation sets, the unlabelled samples were considered under test set. Proposed stacked LSTM model was implemented on both training and validation sets to classify the heart sounds into class labels class 0- artifact, class 1- murmur, class 2- normal and class 3- extrahls. The proposed model was implemented on test set by selecting randomly one unlabelled sample from test set to predict its class label.

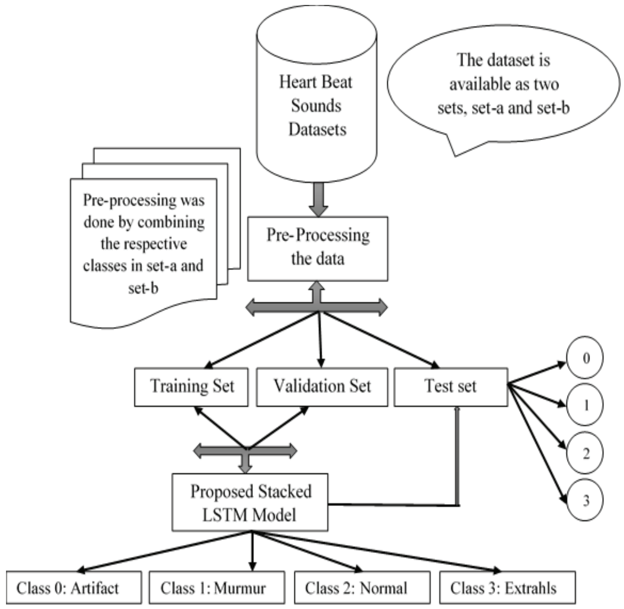

Fig. 3. Proposed Method Flow Diagram

V. EXPERIMENTATION

This section explains the experimental work done in the research to classify healthy and unhealthy heart sounds.

A. *Experimental Setup:*

The proposed model was implemented with python 3, in anaconda jupyter notebook. The basic libraries Librosa, pandas, matplotlib, keras, and tensorflow were used for experimentation. Experiments were conducted on Dell Inspiron 5000 series system, with windows 10 Operating System, in the python simulation environment. The experiments were carried out in single GPU based laptop with Intel(R) Core (TM) i7-5740U CPU @ 2.20GHz processor and 8GB RAM. For storage purposes, we used 1 TB Seagate Hard disk drive. The succeeding figure illustrates the build LSTM model for classification of heart sounds.

```
build LSTM RNN Model
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
lstm_1 (LSTM)                (None, 40, 64)            16896
_________________________________________________________________
lstm_2 (LSTM)                (None, 32)                12416
_________________________________________________________________
dense_1 (Dense)              (None, 4)                 132
=================================================================
Total params: 29,444
Trainable params: 29,444
Non-trainable params: 0
_________________________________________________________________
```

Fig. 4. Build Model

B. *Dataset Description*

Heartbeat sounds audio data was taken from the "Kaggle data science community". This dataset was originally for "a machine learning challenge to classify heartbeat sounds. The data was gathered from two sources: (A) from the general public via the iStethoscope Pro iPhone app, and (B) from a clinical trial in hospitals using the digital stethoscope DigiScope". The dataset consists of two folders set_a and set_b. The audio files from both sets were concatenated into a single group based on their class labels. We considered the maximum clip duration of 12 sec. The following code shows the different class labels in the dataset.

```
nb_classes=train_ab.label.unique()
print("number of training examples",train_ab.shape[0],"number of classes",l
print(nb_classes)
```

```
number of training examples 832 number of classes 6
['artifact' 'extrahls' 'murmur' 'normal' nan 'extrastole']
```

Fig. 5. Different Class Labels in the Dataset

The following figure shows the number of audio samples for each category. The minimum number of samples per category is 19 and the maximum number of samples per category is 351.

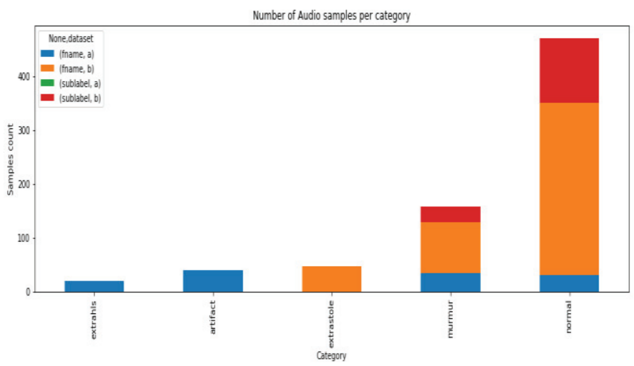

Fig. 6. Number of Audio Samples for Category

The following figure shows the sample audio files corresponding to different class labels.

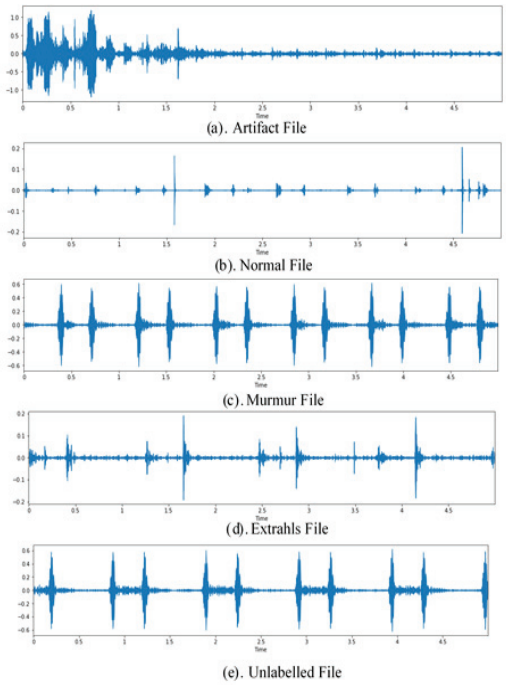

Fig. 7. Audio Files Corresponding to Each Category (a). Artifact file (b). Normal file (c). Murmur file (d). Extrahls file (e). Unlabelled file

we grouped the Extrahls and Extrastole audio files into the same category to make the dataset balanced. The following figure shows the sample audio files corresponding to each category.

C. *Results and Discussions*

The heartbeat sounds dataset was used for training, validation, and testing phases. 80% percent of data were considered for the training phase, 20% of data was considered for the validation phase. The unlabelled audio files were used for the testing phase. The below code shows the accuracy scores of the training, testing, and validation phases.

```
score=model.evaluate(x_train,y_train,verbose=0)
print("model train data score",round(score[1]*100),"%")

score=model.evaluate(x_test,y_test,verbose=0)
print("model test data score",round(score[1]*100),"%")

score=model.evaluate(x_val,y_val,verbose=0)
print("model validation data score",round(score[1]*100),"%")
```

```
model train data score 85 %
model test data score 85 %
model validation data score 87 %
```

Fig. 8. Accuracy Scores of Training, Testing, and Validation Phases

The accuracy scores obtained by the implementation of stacked LSTM model on training, testing and validation data are 85%, 85% and 87% respectively. The following figure shows the confusion matrix generated, shows the four class labels of heart sounds.

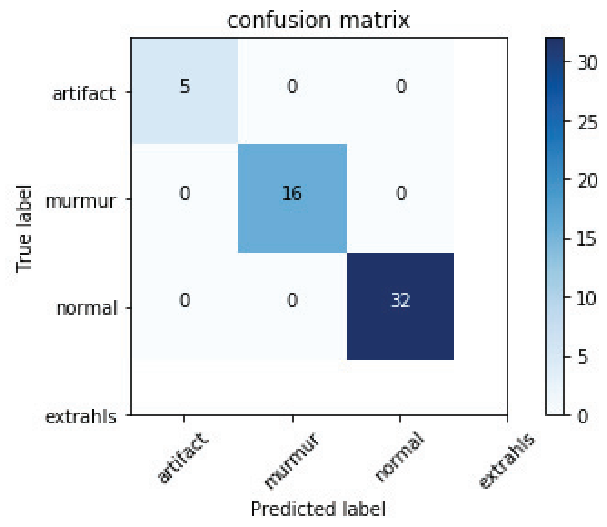

Fig. 9. Confusion Matrix Generated

The model was implemented with different epochs such as 10, 15, 20 and 30, the following figures shows the accuracy and loss measures with different epoch values.

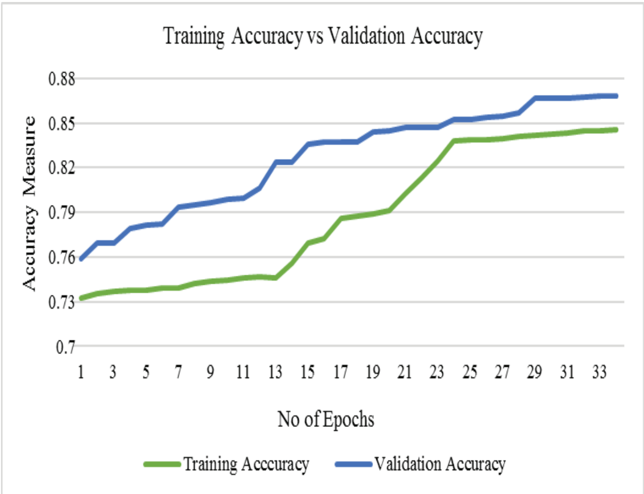

Fig. 10. Training Accuracy Vs Validation Accuracy

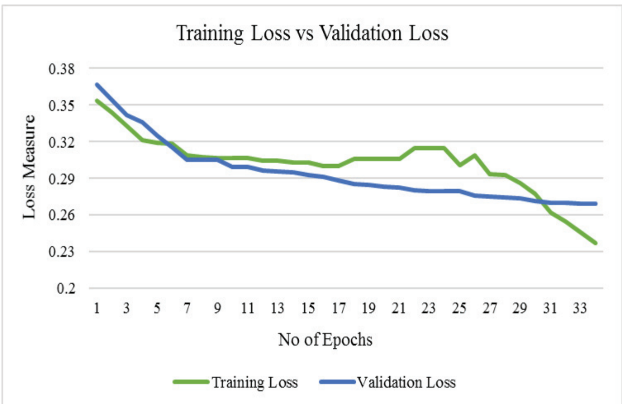

Fig. 11. Training Loss Vs Validation Loss

D. Prediction

All the labelled audio files were considered for training and unlabelled audio clips were used for prediction. Unlabelled samples from the test set were randomly selected for prediction and their class labels were predicted using the trained stacked LSTM models. The following figure shows the prediction of an unlabelled audio file from test, and it is predicted as normal.

```
prediction test return: 2 - normal
```

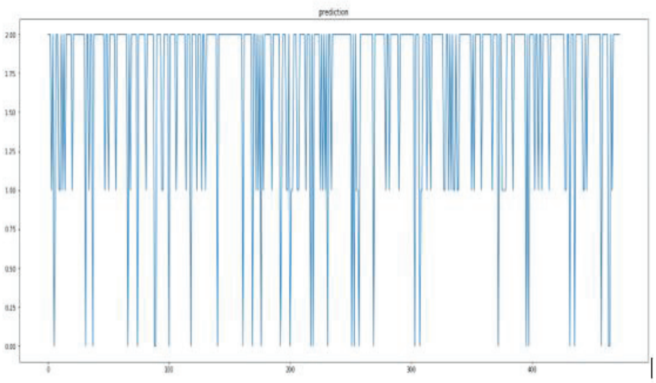

Fig. 12. Prediction of the Class Label of an Unlabelled File

VI. Conclusions and Future Scope

The heart sounds LUB (S1) and DUB (S2) are considered normal heartbeat. But sometimes the heart responds with other sounds indicating a malfunctioning of the heart. Recognition of the difference between normal and abnormal heart sounds is a hectic task that involves highly skilled physicians with deep expertise which can be gained through the continuous clinical training process. An automatic heart sound classifier will show promising outcomes in differentiating the normal and abnormal heart sounds. Deep learning models can be used to of typical and strange heart sounds. This paper studies state of the art in "machine learning and deep learning" models used for heart sound classification were discussed. In this paper, a stacked LSTM model was implemented to classify and predict heart sounds. Stacked LSTM is one of the extensions of the conventional LSTM model. Multiple hidden LSTM layers were combined to form a stacked LSTM architecture. In stacked LSTM architecture, each hidden layer consists of multiple memory cells, which makes the model deeper. In stacked LSTM takes a 3D input, after processing produces a single value for each one input sequence of time steps. The heartbeat sounds audio data was taken from the "Kaggle data science community", pre-processing of data was done by combining the respective classes in two datasets set_a and set_b. The dataset was divided into "training and validation sets", the unlabelled samples were considered under the test set. The proposed stacked LSTM model was implemented on both training and validation sets to classify the heart sounds into class labels class 0- artifact, class 1- a murmur, class 2- normal, and class 3- extrahls. The proposed model was implemented on the test set by selecting randomly one unlabelled sample from the test set to predict its class label. The results show that the proposed stacked LSTM model works with an efficiency of 85% on "training data" and 87% on "validation data". In further the model can be enhanced to improve the accuracy of classification.

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