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Embedded platform based heart murmur classification using deep learning approach

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***Abstract*---**Ubiquitous Perturbations in cardiac auscultation properties, cardiovascular diseases (CVDs) are widely recognized. In the auscultation procedure, the appearance of pathological cardiac murmurs is linked to heart disorders. A noble automated detection system using 1-D Convolutional Neural Network (CNN) for the detection of pathological heart murmurs is proposed in this study, which removes the difficult task of extracting and selecting features. It directly acts on the phonocardiogram (PCG) signals. The fundamental purpose of this research is to develop a classification model for consistent recognition of cardiac murmurs when the data-set is imbalanced. In view of this, the proposed study for the imbalanced data-set incorporates the Adaptive Synthetic (ADASYN) approach to generate synthetic data for the minority class. The outcome analysis illustrates the positive result in the identification of heart murmurs on both balanced and imbalanced data-sets. Therefore, the developed deep learning model will learn better from the minority class and classify heart murmurs accurately.

***Keywords*---**adaptive synthetic, sampling approach, convolutional neural network, heart murmurs, imbalanced dataset.

Introduction

According to the World Health Organization (WHO), cardiovascular diseases (CVDs) are the leading cause of death worldwide. CVDs take the lives of 17.9 million people every year which is 31% of all global deaths [1]. Though several programs have been launched by the WHO across the globe, in order to promote

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the preventive measures and regulations of CVDs in essential medical services. CVDs however, still involves a grave worry in the resource-limited regions of the planet. Due to the shortage of medical expertise, insufficient access to testing facilities, and poor supply chain resources, delivering basic health services for people in developing and poor countries is a difficult issue [2]. The stethoscope is the most significant device used for heart auscultation and this is the commonly used procedure for diagnosing cardiovascular anomalies since 1816 [3] [4]. But understanding the cardiac activity by hearing to the heart sounds emanating from the auscultation using a stethoscope requires the skill and experience of a person. It is very difficult to distinguish the low-frequency heart tone components such as third heart tones, S3, and murmurs by human ears with the aid of the auscultation technique. Signal processing methods like spectrogram analysis [5] are quite effective in identifying low-frequency heart sounds. The low frequency and low intensity of the sound of the nonlinear and non-stationary PCG signals make auscultation a difficult work [6] [7]. The American Heart Association has conceded that a significant number of doctors can't perform heart auscultation adequately and precisely [8]. Such a horrible situation, the detachment of the cardiologist in various pieces of the globe, and to avoid inconsequential therapeutic administrations costs shows the steady advancement of improved heart auscultation method which can be satisfied with the use of signal processing methods [9] [10]. The first and second heart sounds, S1 and S2, are the most prominent sounds of the heart cycle. The murmurs that are heard as whooshing are triggered by the high-speed stream of blood. Cardiac complications are shown by the occurrence of murmurs in heart cycles. The murmurs that arise somewhere in the range of S1 and S2 is the systolic murmur while that shows up during the S2 and S1 is named as diastolic murmur. Timing distinguishes the systolic and diastolic murmur, such as early mid or late systolic or diastolic murmur [11] [12].

The most important venture for any robotized heart sounds investigation is the identification and division of first and second heart sound [13] [14]. The state of art on heart murmur analysis reveals that relevant features are extracted from PCG signals for identification of pathological heart murmurs [15]. Commonly used pathological murmur detection characteristics include spectral energy [16], wavelet coefficient energy [17], cepstral feature [18], and autoregressive spectral components [19]. For the murmur classification, these identified features have been fed to classifiers such as SVM and artificial neural network (ANN) [18] [20]. Jusak et. al [21] shows that murmur extraction from pathological heart sound signals decomposed using Complete Ensemble Empirical Mode Decomposition (CEEMD) algorithm with Pearson distance metric achieves better results than EEMD. The classification of pathological heart murmurs using the ANN and the ensemble ANN are reported in [22] [23]. [24] and [25] suggest a faster method focused on statistical parameters extraction and S-transform to identify heart murmurs. The empirical wavelet-based decomposition of murmur recognition has been stated in [26]. Abnormal heartbeat patterns have been detected by exploiting techniques such as slicing and FFT to PCG signals and classifying with state-of-the-art Cloud-based CNN models [27]. A segmentation free method to classify heart murmurs from PCG signal has been reported in [28] which uses simple statistical feature (SF) with ESVM classifier. The achieved classification accuracy of this reported method is 82.6% on 56 samples. The power spectrum estimation, wavelet transform (WT) and Mel frequency Cepstrum coefficients (MFCC) have been used as features using classifiers: support vector machine (SVM), k-nearest neighbour (k-NN), multilayer perceptron (MLP) and maximum likelihood (ML) for classification of heart murmurs from normal PCG signals [29]. A technique that uses feature extraction methods using LPC (Linear Predictive Coding) and classification using k-NN (k-Nearest Neighbour) to identify heart murmurs has been studied in [30]. An automatic framework for detection of heart murmurs has been proposed that uses MFCCs features for both the balanced and imbalanced data sets [31].

The major contributions of this paper are highlighted below:

- A novel architecture of 1-D CNN model has been developed to classify cardiac murmurs. The developed deep learning model is simple yet efficient to recognize heart murmurs accurately. The low computational complexity of the 1-D CNN architecture makes it quite efficient for real-time classification.
- The Adaptive Synthetic (ADASYN) sampling method has been applied to deal with imbalance data set. By generating synthetic data using the adaptive knowledge of the data distribution of original dataset, helps the classifier to train and classify the minority class accurately.
- The noise analysis of the developed 1-D CNN model has been done to confirm the robustness of the trained deep learning model to classify heart murmurs in noisy scenarios.

The rest of this paper is arranged as follows: In the sense of the proposed process, Section II describes the methods and techniques. The framework description is defined in section III. The experimental approach accompanied by findings and discussion of the proposed technique is found in Section IV. Section V contains the conclusion of this study.

Tools and Techniques

The theoretical principles for signal processing techniques and deep learning algorithms incorporated in the proposed analysis are built in this section.

1-D CNN

The time series classification (TSC) task involves sequence of one-dimensional data points (measurements) which has a natural temporal ordering. The performance of deep learning models to solve TSC problems is quite satisfactory [32]. Multilayer deep learning networks are used to model the nonlinear spatial-temporal pattern [33]. In recent empirical study shows that deep CNNs are able to achieve results that are significantly accurate than current state-of-the-art algorithms for TSC problems 1d-CNN models are quite accurate and efficient in classifying time-series bio-medical data [34]. Inspired by the recent success of 1d-CNN in TSC, a 1d-CNN model is developed for murmur classification as well.

Adaptive Synthetic Sampling (ADASYN)

The data set used for murmur classification is mostly imbalanced as the murmur samples are very rare in comparison with healthy samples. As normal class dominates the data set, the deep learning models, build on this data set, perform terribly in identifying murmur samples. To solve this kind of imbalance data set problem, ADASYN can be used. Based on the original data distribution, ADASYN will use an adaptive approach to generate synthetic data samples for the murmur class to reduce the bias introduced by the imbalanced data distribution. In this way, ADASYN will help to learn the classifier from difficult to learn examples. The dynamic adjustments of weights and adaptive learning of the data distribution are the key features of this ADASYN algorithm to perform such brilliantly in case of imbalanced data set. The complete calculation of ADASYN algorithm is shown in [35].

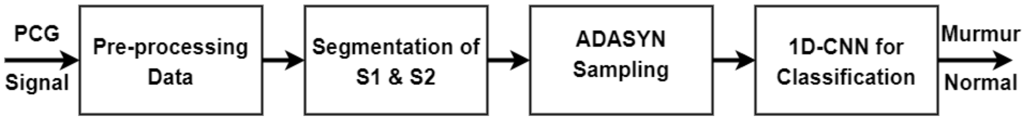


Fig 1. Flow diagram of the methodology

Fig. 1 shows the flow diagram of the entire process to recognize heart murmurs using 1-D CNN considering imbalance data-set. The sound impulses of the heart are inclined to be degraded by the noise history. Preprocessing is needed along these lines, which involves decimation and use of a low pass filter (LPF) with appropriate cut-off frequency, 800 Hz. Using Shanon's energy [36], the segmentation of S1 and S2 has been done from the pre-processed signals which is followed by the extraction of heart cycles. The extracted heart cycles are directly fed to 1-D CNN for characterization of heart murmurs. On account of the imbalanced arrangement of the samples of murmur class and normal class, the ADASYN inspecting approach of learning is applied prior to the input of the 1-D CNN to reduce the bias of normal class in the input data-set.

Table I: Layerwise Trainable Parameters in 1-D CNN

Layer	Output Shape	Parameters
Conv	(None,80000,128)	1152
Dense	(None,20)	2580
Dense	(None,1)	21
Total number of trainable parameters		3625

Experimental Methodology

Data Acquisition

The PCG signals were obtained from the Michigan Heart Sound and Murmur Library [37] including an aggregate of 258 cardiovascular cycles from both normal and abnormal murmurs. The sampling frequency of the signals received was 44.1 kHz.

Experiment

1) Preprocessing

The PCG signals are decimated and passed into an LPF with a cut-off frequency of 800 Hz in preprocessing stage as the heart murmurs often have frequencies lower than 800 Hz [15]. The segmentation of S1 and S2 is performed centred on Shannon's energy technique [37]. Fig. 2: An architecture of the proposed 1-D CNN.

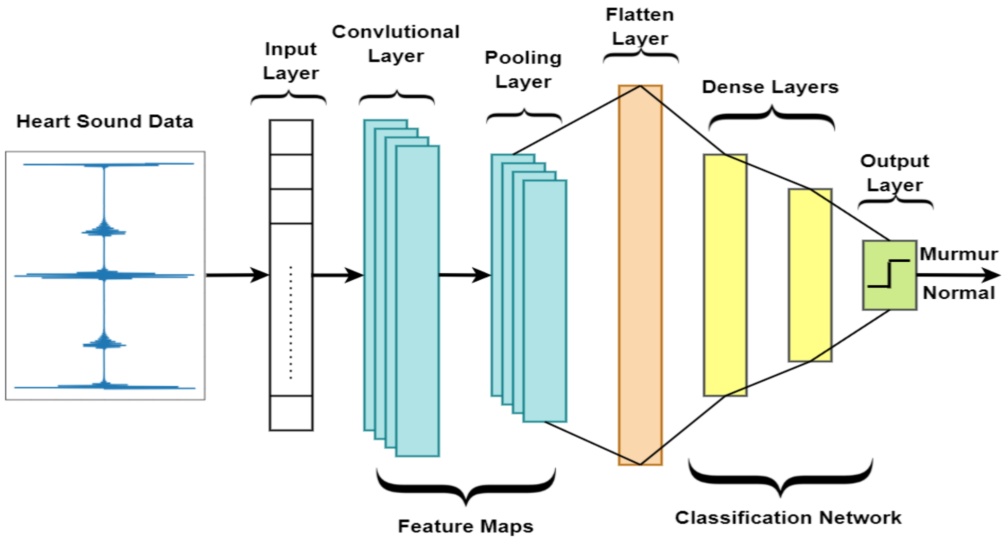


Fig. 2: An architecture of the proposed 1-D CNN

2) Classification

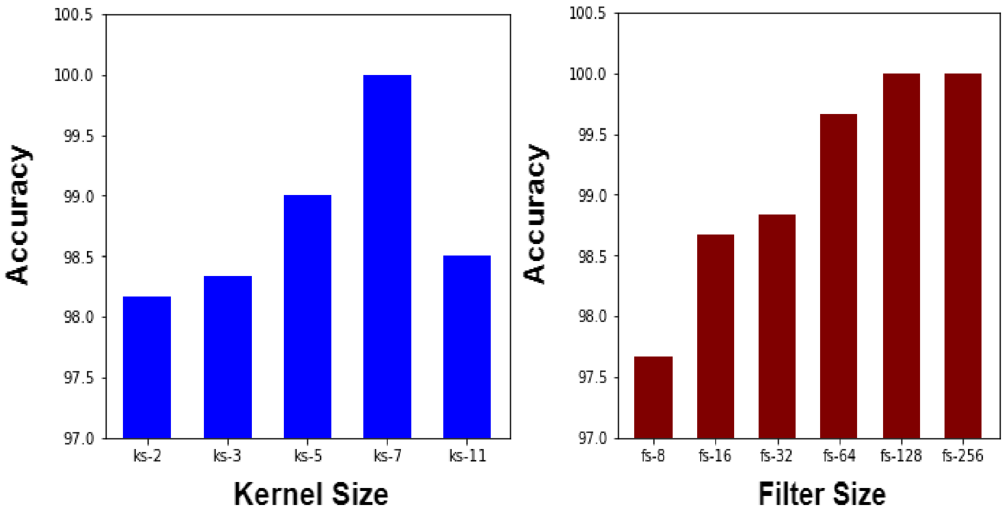
The layout of the proposed 1-D CNN model for classification of murmurs is planned to be easy and powerful in achieving precision while reducing the difficulty of computation. The input layer is a one-dimensional array of 80,000 data points. To extract the feature from time-series data, a convolutional layer of 128 filters of kernel size 7 is placed, followed by a pooling layer to reduce the dimension of the feature space. The output of the Max-Pool layer is then flattened and further classified through the consecutive dense layers. The full configuration of the proposed architecture for CNN is shown in Fig. 2. With the grid search strategy, the hyperparameters of the proposed CNN architecture have been optimised. For each relevant combination, a grid of hyperparameter values is set up. Fig. 3a and 3b show the variation of the performance of the model according to the variation of kernel size and number of filters. The accuracy is maximum with the kernel size as 7 and number of filters as 128. In the same way, learning rate is confirmed as 0.01. The model has been trained on 100 epochs and batch size of 10. The training and testing loss versus epoch curve is shown in fig. 4. It is also useful to decide the number of parameters of a CNN model in order to measure the complexity. Table I shows the total number of trainable parameters of the proposed 1-D CNN model for murmur classification.

The accuracy (AC) of the classifier is calculated using the standard definition in terms of TP: True Positive, TN: True Negative, FP: False Positive and FN: False Negative as:

$$Accuracy(AC) = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

$$Sensistivity(SN) = \frac{TP}{TP + FN} \tag{2}$$

$$Specificity(SP) = \frac{TN}{TN + FP} \tag{3}$$



(a) (b)

Fig. 3: Bar plot of (a) Accuracy versus Kernel Size and (b) Accuracy versus Number of Filters.

The AC, SN and SP denote accuracy, sensitivity and specificity respectively.

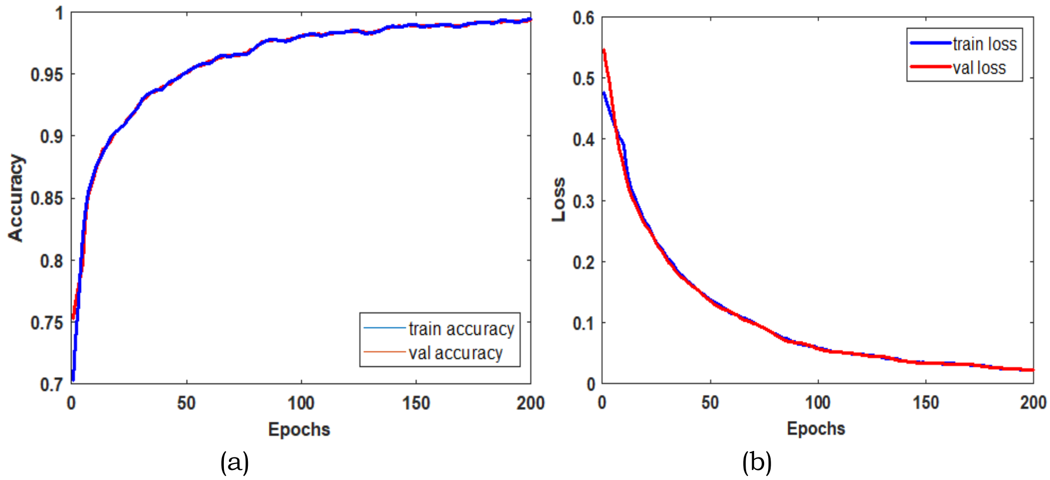


Fig. 4: (a) Accuracy Vs Epoch (b) Loss Vs Epoch of the Proposed 1-D CNN Model

Results and Discussion

The simplest deep neural network is multi-layer perceptron (MLP). For murmur classification, a simple perceptron model has been developed for comparing the performance with the proposed 1d-CNN model. The model has a single hidden layer with 32 artificial neurons. As MLP is a fully connected network, in the first layer the trainable parameters are:

$$80000 \, X \, 32 + 32 = 2,560,032$$

and for the output layer: $32 \, X1 + 1 = 33$. Total trainable parameters are 2; 560; 065, which is quite high and it will increase the model complexity.

Table II: Comparison of Different Classification Methods For Balanced Dataset. (Murmurs, N1 = 120, and Normal, N2 = 120).

Classification Methods	Only Real Data		
	Accuracy (%)	Sensitivity (%)	Specificity (%)
MLP	94.32	91.25	97.14
CNN	100.00	100.00	100.00

The performance of the simple perceptron model with the proposed 1d-CNN architecture is compared in table II. From table II, it is quite evident that proposed 1D-CNN model is highly accurate for perfectly balanced dataset. But in practical scenario, dataset of murmur won't be that perfectly balanced. So, imbalance in the data-set has been created intentionally to check the performance of the proposed classifier. We implemented 1-D CNN for murmur detection for the given dataset by making it imbalanced at different ratios like 1:10, 2:10, 3:10, 4:10, and 5:10. Here 1:10 ratio means, we have considered one murmur sample for 10 normal samples. table III shows the performance of the CNN model for imbalanced dataset. From table III, it is quite evident that when unbalancing ratio is 1:10 it affects the performance maximum.

Table III: performance of 1d-cnn on imbalanced dataset. Here metric parameters are expressed in percentage. Ac: accuracy, sp: specificity, and sn: sensivity

Classifier	Matric (%)	Imbalance dataset				
		(1:10)	(1:20)	(1:30)	(1:40)	(1:50)
CNN	AC	90.62	91.25	92.29	94.32	96.29
	SN	94.75	95.26	96.53	96.87	97.51
	SP	55.23	60.34	66.67	75.56	90.70

The main challenge when dealing with an imbalanced dataset is that one class dominates another class, resulting in a poorly equipped model when it is unable to effectively distinguish the minority class. Synthetic data has been developed using the ADASYN technique to enhance the efficiency of the proposed CNN model and the result is shown in table IV. After training the best model has been stored and to check the robustness of the model noise analysis has been done. Gaussian noise has been added with zero mean and the standard deviation is varied from 0.01 to 0.5 range. The noise has been added to the test data. From table V, the result clearly suggests that the performance of the trained 1-D CNN model starts degrading after the standard deviation of the noise is around 0.07.

Table IV: performance of cnn for adasyn output of imbalance dataset of ratio 1:10

ssification Methods	Dataset using ADASYN		
	Accuracy(%)	Sensitivity(%)	Specificity(%)
CNN	99.98	99.95	99.87

Table V: performance of the trained 1d-cnn model on noisy dataset

Classifier	Metric	Variation of noise in standard deviation					
		0.01	0.02	0.05	0.07	0.1	0.5
CNN	AC(%)	100.00	95.83	89.97	66.67	55.22	47.76
	SN(%)	100.00	99.03	95.78	92.45	88.89	76.96
	SP(%)	100.00	96..32	84.63	64.56	34.36	14.57

Conclusion

A novel approach to cardiac murmur identification based on 1-D CNN has been established in this study. For the balanced dataset, the proposed 1-D CNN classifier achieved an average classification accuracy of 100%. Furthermore, the proposed method provides an answer for the identification of heart murmurs when the dataset is imbalanced using the ADASYN sampling approach, as the classifier's performance worsens once the dataset is imbalanced. This heart murmur classification research focuses on achieving high precision when the dataset is imbalanced by removing the need for extraction and selection of features. The results obtained in this analysis provide a sound base for potential studies in various types of murmur recognition for bigger imbalanced datasets.

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