Automatic Detection of Paediatric Congenital Heart Diseases from Phonocardiogram Signals

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***Abstract*—The World Health Organization (WHO) claims that 0.8% to 1.2% of newborns worldwide are affected by congenital heart diseases (CHDs). There are many methods for CHD identification, and the most prevalent is phonocardiography (PCG). It is a non-invasive method that offers crucial knowledge about the sounds (S1, S2, S3, and S4) and beats of the heart. This research study aims to train a binary categorization system using a deep neural network for CHDs by using a combination of local and public datasets. The local dataset (LD) had 583 signals (normal and abnormal PCG), while the public dataset (PD) taken from Michigan University had 23 PCG recordings. Both datasets were down-sampled to 8 kHz. The band pass filter was designed such that it ensured that any signals outside of the 20–650 Hz range were filtered out, allowing only the desired frequencies to be processed. All signals were chunked at a signal duration of 4 seconds. For data augmentation, pitch-shifting was applied and passed to a 1D convolutional neural network (CNN). The best results were achieved for case C, with an accuracy of 98.56%, precision of 98.57%, F1 score of 98.56%, specificity of 98.0%, and sensitivity of 99.0%.**

***Index Terms*—Deep neural network, congenital heart diseases, chunking, convolutional neural network, data augmentation, digital stethoscope, pitch-shifting, classification.**

I. Introduction

Congenital heart disorders are cardiac conditions that exist from birth, including pulmonic valve disease (PVD), mitral valve disease (MVD), aortic valve disease (AVD), and tricuspid valve disease (TVD). Below are the few cases of CHD with a little description:

a) Atrial Septal Defect (ASD): An ASD is a septal malformation, which is a wall that isolates the heart's left and right sides. As a result, the heart's chambers become mixed with both oxygenated and deoxygenated blood.

b) Patent Ductus Arteriosus (PDA): An aperture known as the ductus arteriosus separates the two main blood vessels that emerge from the heart. It is a portion of the developing baby's circulatory system that normally shuts soon after birth, but if it stays open, it leads to patent ductus arteriosus.

c) Tetralogy of Fallot (TOF): TOF is an amalgamation of four CHDs: pulmonary stenosis, ventricular septal defect (VSD), misplaced aorta, and right ventricular hypertrophy.

d) Ventricular Septal Defect (VSD): A VSD is a split in the wall that divides the heart's bottom chamber. If it is sufficiently wide, the amount of blood that escapes between the chambers could harm the heart and lungs permanently and raise the risk of heart attack.

Heart defects are one of the significant causes of death in children and adults. According to Michigan University research, cardiac defects in newborn babies occur in 1 out of every 100 babies worldwide [1]. In the case of cyanotic CHDs, TOF is generally the most common heart defect [2]. Many research studies highlight that babies born with heart

defects die in large numbers due to a lack of proper care and prevention [3]. Currently, medical specialists and experts use traditional diagnostic techniques to investigate cardiac defects in paediatric patients, which are expensive and require a significant amount of time for diagnosis. Here, we aim to develop an intelligent decision support system for the classification of CHDs. The aim of this research study is to enhance the current diagnostic system by bringing cutting-edge technology into use.

During our research at Rehman Medical Institute (RMI) and Lady Reading Hospital (LRH) in Peshawar, patients were coming from the local areas; however, there were significant numbers of patients coming from across the border, i.e., Afghanistan. Fig.1 shows frequency wise distribution of heart diseases in Local Data (LD). In total, 30% of patients had ventricular septal defects (VSD), with PVD patients accounting for 20%. Similarly, the other diseases also contributed a considerable amount. One aspect of that research was to show which diseases are most common in children.

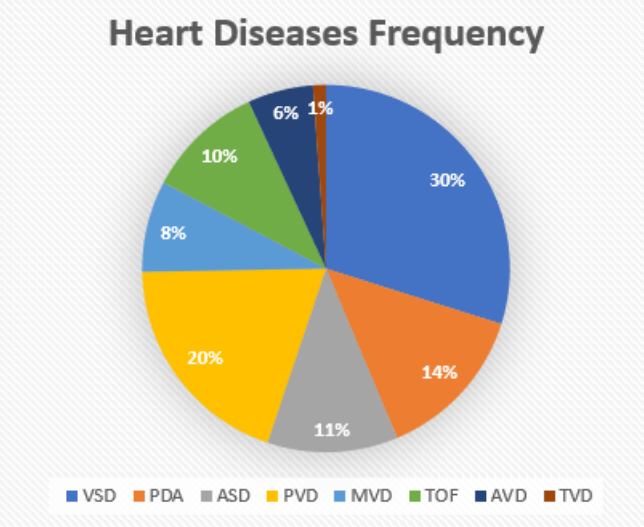

Fig. 1. shows frequency wise distribution of heart diseases in Local Data (LD)

II. LITERATURE REVIEW

In [4], Yaseen et al. focused on the classification of heart sound signals by extracting mel-frequency cepstral coefficients (MFCCs) and discrete wavelet transforms (DWTs). For the classification, they employed k-nearest neighbours (kNN), deep neural networks, and support vector machines (SVM). Ghaffari et al. (2017) used an automated PCG diagnostic system for the prognosis of the VSD in infants and adolescents extricated from MFCC and kNN. The dataset used consisted of 55 children, ranging in age from 6 months to 2 years [5]. Chen et al. performed a real-time automated analysis of healthy and unhealthy heart sound (HS) using the Physionet Challenge 2016 dataset (CinC) with 1D-CNN and a long-term memory network (LSTM) [6]. In [7], Akbari et al. evaluated trained SVM, kNN, and multilayer perceptron (MLP) on extracted features named wavelet transform (WT), MFFCs, power spectrum, and maximum for the classification of PCG signals. In [8], Roy et al. classified valvular heart disease using three different datasets and two classifiers: SVM and Random Forest (RF). Nassralla et al. concentrated on the classification of regular and irregular PCG recordings using the PhysioNet datasets by the extraction of different time and frequency features from HS. Their proposed approach incorporated pre-processing, segmentation, feature extraction, and classification (RF) with 92% [9]. Infinite impulse response filters and CNN were proposed for the cardiovascular disease (CVD) identification model. They achieved 87% accuracy for the PASCAL dataset and 97% accuracy for the PhysioNet dataset [10]. In [11], Aziz et al. used empirical mode decomposition for denoising raw PCG signals, extracted one-dimensional local ternary patterns (1D-LTP), and achieved 95.24% accuracy with an SVM classifier and 10-fold cross-validation. Zhang et al. combined two noise reduction algorithms and variational model decomposition, down sampled the dataset to 2 kHz, and classified the data using an artificial neural network (ANN) with 92.23% accuracy [12]. Ahmad et al. performed a classification of PCG signals using statistical properties and a fuzzy inference system that removes absolute boundaries and assigns a degree of association to every segment of the signal. The output is computed with 97% accuracy using envelogram computation [13]. In [14], Singh et al. classified PCG signals using linear discriminant analysis, SVM, and k-NN with a sensitivity of 95.04% and a specificity of 98.72%. Table VI presents a comprehensive comparison of overall research methods.

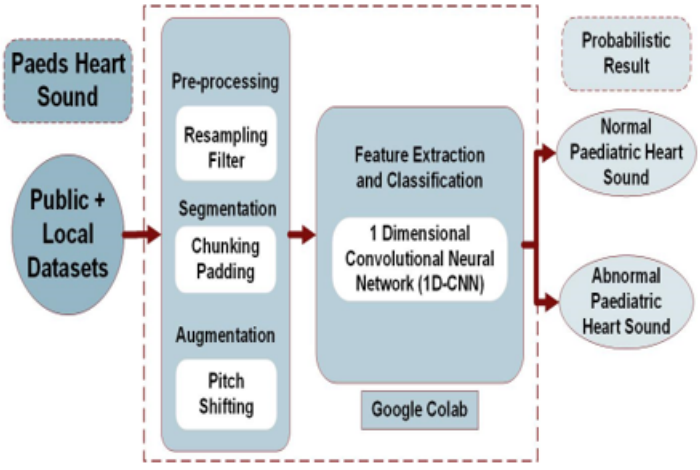

Fig. 2. Block diagram of the proposed methodology

III. RESEARCH METHODOLOGY

A. Summary of the intended research

Fig. 2 displays the suggested approach for classifying paediatric CHDs from PCG signals. The HS signals are acquired from local and publicly available datasets. Their sampling frequencies were different; that's why they were downsampled

to 8 kHz. Medical experts confirmed that the best time for detecting abnormalities in cardiac signals ranges from 3 to 6 seconds. [15] have used signal durations of 3 seconds, [16] have used signals of 4 seconds' duration, and similarly, [17] have used signals of 6 seconds' duration. The dataset in this proposed study was divided into four second chunks based on the availability of the data. That's why the PCG signals were divided into 4-second chunks, and all those signals that were not multiples of 4 were padded with the help of sample padding. It is done to understand the dataset and improve the model's performance in real-time. After preprocessing and segmentation, these padded HS signals are given as input to the 1D-CNN classifier to classify normal and abnormal HS with an accuracy of 98.56%. This research study presents the following innovative features:

- It is primarily concerned with paediatric CHDs and has created a system for classifying HS in children as normal or abnormal.
- During data collection from hospitals, the demographic distribution of CHDs was thoroughly analysed, which highlights the impact of this proposed study in Pakistan. It is expected that the results of this research study can provide valuable insights into the prevalence of CHDs in Pakistan and can also help in formulating new policies for screening and early detection of CHDs.
- In this proposed methodology, 1D CNN was trained on a combination of local and public data (with a majority of local data). It employed a 1D CNN model for early detection of congenital heart defects (CHDs) in children.
- It presents the challenges and issues of using local data for deep neural network training in terms of data annotation, dataset collection, model generalization, and hyperparameter tuning.

B. Dataset

For the proposed methodology, two datasets are used, whose details are given below.

a) Local Dataset (LD): LD was gathered from local hospitals, including the Rehman Medical Institute (RMI) and Lady Reading Hospital (LRH) in Peshawar, and included 168 abnormal paediatric HS signals related to various CHDs and 415 normal paediatric HS signals. The recording period for each signal lasts between 10 and 12 seconds, with some traces of environmental and lung sounds. The tool that were used in this proposed study included electronic stethoscope (uSteth), google colab, Audacity and MATLAB softwares.

b) Public Dataset (LD): PD dataset: This data was collected by professionals from the University of Michigan Medical School [18]. It was collected through an electronic stethoscope at a sampling rate of 1 kHz from four different locations known as the apex area aupine, the apex area left decubitus, the aortic area sitting, and the pulmonic area sitting. This dataset includes 21 high-quality abnormal and 2 normal HS signals, and the recording duration is between one minute and one minute and fifteen seconds. Raw form of time domain plots of both dataset are shown in Fig. 3

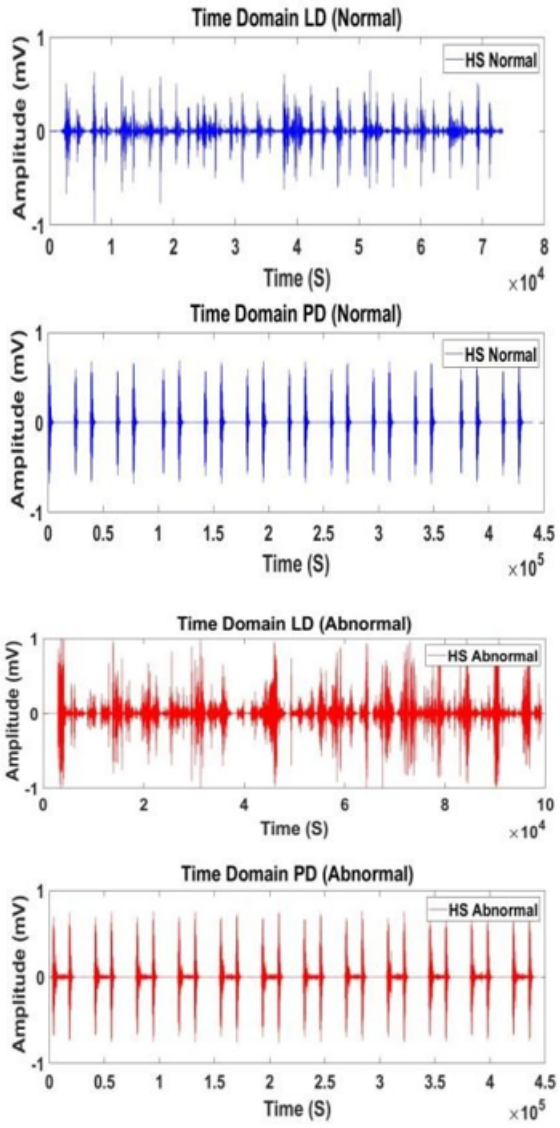

Fig. 3. Dataset plots in Raw form: Local normal, Public normal, Local abnormal and Public abnormal

c) Dataset Distribution: For multiple reasons, the local dataset collected contained a small number of HS signals. That's why, to overcome this problem and increase the amount of data, we combined local and public datasets. The total dataset after combination consisted of 189 abnormal HS signals with a duration ranging from 8 seconds to 1 minute and 15 seconds and 417 normal HS signals with a 12-second After this, all signals were divided into 4-second chunks. After this step, the dataset had 2074 samples with a signal length of 4 seconds. Table I shows the distribution of both datasets.

C. Pre-processing

The locally collected dataset contained heart sounds, but some recordings had babies crying, people talking in hospitals, stethoscopes rubbing during recording, and other environmen-

TABLE I. DATASET DISTRIBUTION

Dataset	Statistics			
	Normal HS	Abnormal HS	Sampling rate	Recording Sensor
Local data	415	168	8 kHz	uSteth
Public data	2	21	44.1 kHz	Electronic Stethoscope

tal noises. To get good accuracy, specificity, and sensitivity, we used filtering and preprocessing techniques as listed below.

a) Resampling: The sampling frequency used for LD collection was 8 kHz, while PD was sampled at 44.1 kHz. If the dataset is not balanced in terms of quality and time duration, then there is a possibility of the deep learning model producing poor and occasionally unacceptable results. That's why, to achieve adequate uniformity, these PCGs HS signals from PD were resampled at 8 kHz.

b) Filtering: Heart murmurs fall in the frequency range of 20 to 650 Hz [16], so we designed a filter whose specifications are displayed in Table II.

TABLE II. FILTER SPECIFICATIONS

Required Band (Hz)	Pass Band frequency (Hz)	Stop Band frequency (Hz)	Roll-off (dB per octave)
20-650	20	650	48

D. Segmentation (Chunking and Padding)

The dataset was chunked at 4 seconds per sample because the data used for the proposed research was insufficient to maintain the importance of AI results on the medical side. The method known as padding was used because there were hundreds of audio samples that weren't multiples of 4. It added a portion of the signal to get an approximate 4 second duration. The data significantly increased after completing this process.

E. Data Augmentation (DA)

DA techniques like pitch-shifting, time-stretching, and time-compression generate synthetic data that could marginally improve results in the case of dataset deficiency. Here, pitch shifting was applied to achieve the required goal.

a) Pitch-shifting (PS): PS alters the high-frequency portion of an audio signal. HS contains spikes with high amplitude and frequency, specifically S1 and S2. PS won't change the original signal; instead, it will slightly alter the signal of the marginally improved frequency components. Mathematically, PS is represented as,

$$(S)pitch - shift = S * (f/\beta), where \beta = 2^k/12 \quad (1)$$

where f is the frequency of the tone and β is the PS factor of k semitones. If $k > 0$, it is upshifting; otherwise, it is downshifting. Spectrograms of local normal (LN), local abnormal (LA), public normal (PN), and public abnormal (PA) after PS are depicted in Figs. 4 and 5, respectively.

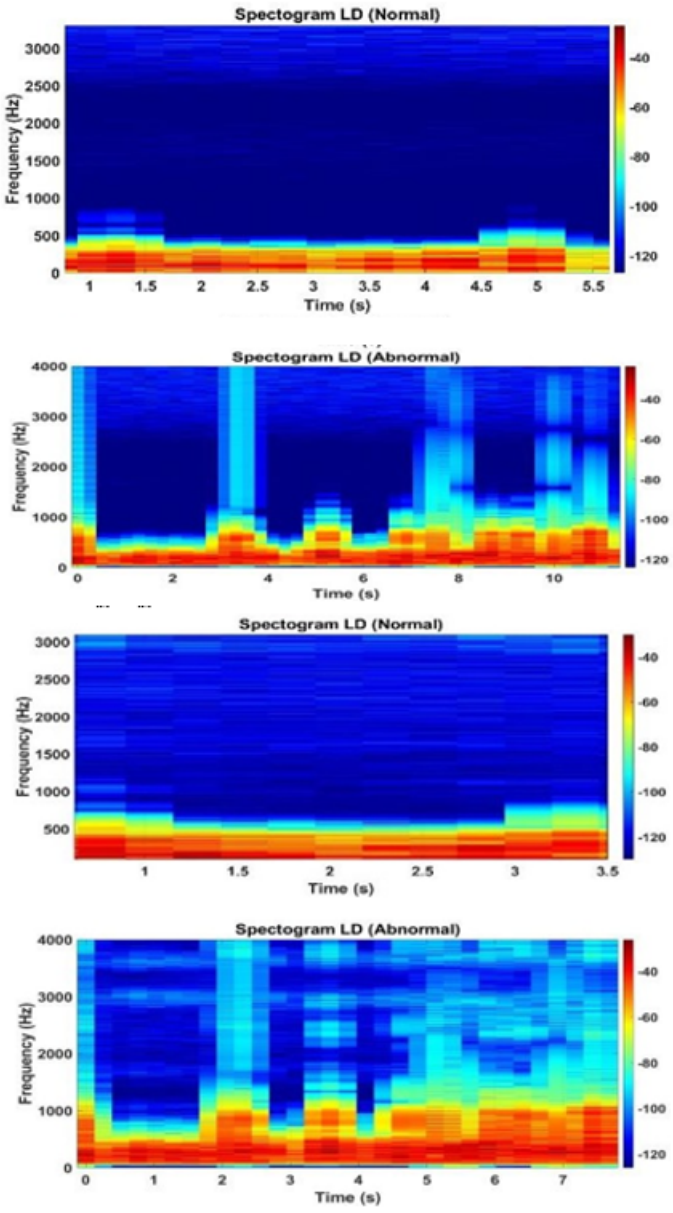

Fig. 4. Local dataset PCG signal plots (a) Unpitched LN and LA (b) Pitched LN and LA.

F. Classification

Convolutional neural networks are also known as feed-forward artificial neural networks because they employ sub-sampling and convolution techniques. 1D-CNN attained a contemporary level of performance in several applications, including the identification and timely treatment of personal biomedical data and anomaly detection.In this study, 1D CNN

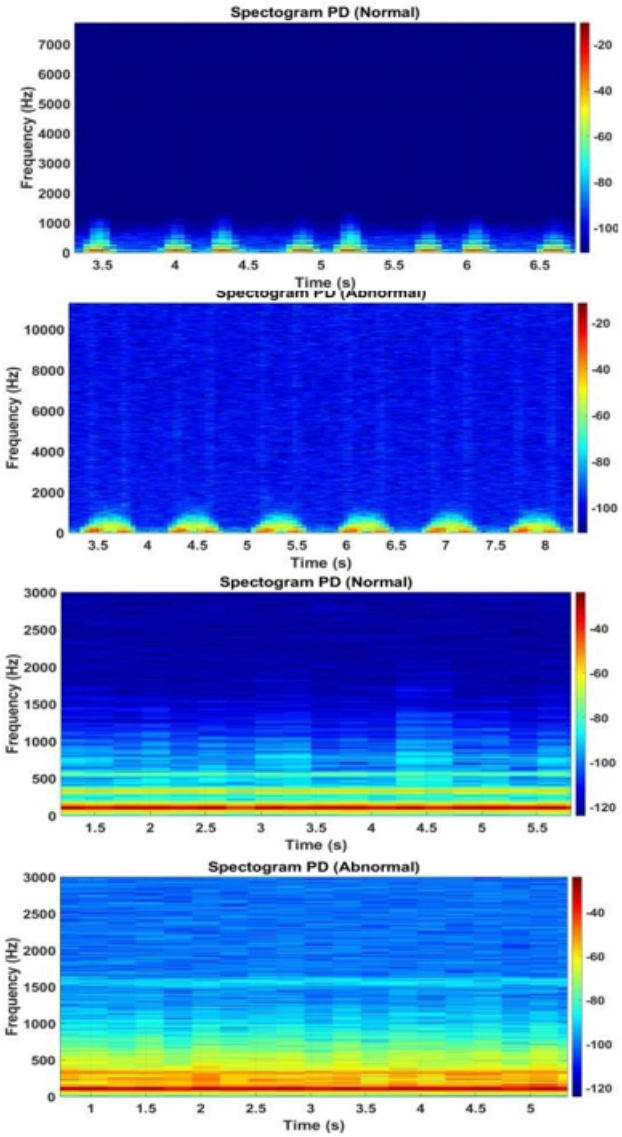

Fig. 5. Public dataset PCG signal plots (a) Unpitched PN and PA (b) Pitched PN and PA.

is used for classification, which itself extracts features from time series data. So here the LD and PD are passed through preprocessing, segmentation, and data augmentation, and then given as input to 1D-CNN for classification of the normal and abnormal HS signal. Architecture of generalized 1D-CNN is shown in Fig. 6.

IV. RESULTS AND DICUSSION

The research methodology discussed above evaluated on three different cases which are discussed below. The hyper-parameters for 1D-CNN for all cases had a batch size of 4, 100 epochs, multiple learning rates (0.1, 0.001, 0.0001) and a data split of 85% training dataset, 10% Validation and 5% real-time local test dataset.

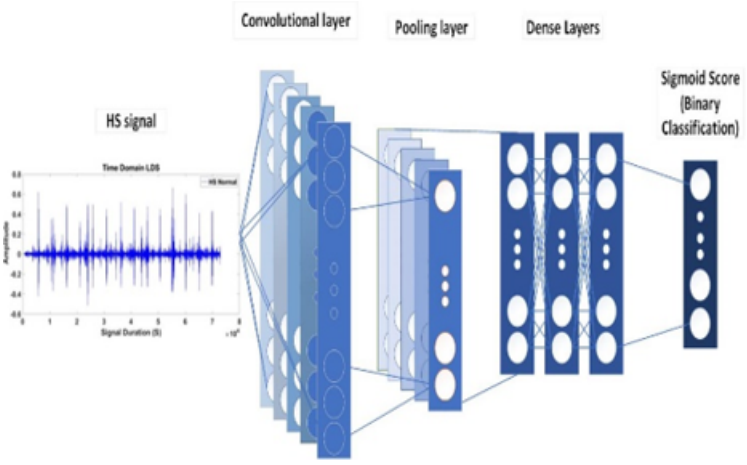

Fig. 6. shows the architecture of generalized 1D-CNN

A. CASE A

In this case, 1D-CNN model was trained on data that was neither preprocessed, segmented, nor filtered, which resulted in 894 abnormal HS and 959 normal HS of multiple signal lengths. The outcomes are displayed in Table III. Both datasets, LD and PD, contain murmurs, which are very low-frequency HS. This study's primary objective is to identify the low- frequency abnormal HS with high sensitivity, accuracy, precision, and F1 scores. Case A achieved 93% sensitivity. The model was confused during training as depicted in the Fig 7, and it does not give a good result. Moreover, the curves shows the training dataset which lacked synchronization and showed significant random variance. Therefore, after a thorough evaluation, we decided to use techniques that could improve the results, like data filtering, chunking, and data augmentation. Training and validation accuracy with loss are shown in Fig. 7.

TABLE III. Results For Case A

Classification Metric	Validation data	Test data
Accuracy (%)	92.66	94.03
Precision (%)	92.65	94.14
F1 Score (%)	92.65	94.05
Specificity (%)	90.0	95.0
Sensitivity (%)	94.0	93.0

B. CASE B

In case B, all the data was filtered with a filter having cutoff frequencies of 60-650 Hz using Audacity software. After pre-processing, filtration, and segmentation (chunks of 4 seconds), the dataset was expanded to 1639 normal HS and 1632 abnormal HS.The improved results are depicted in

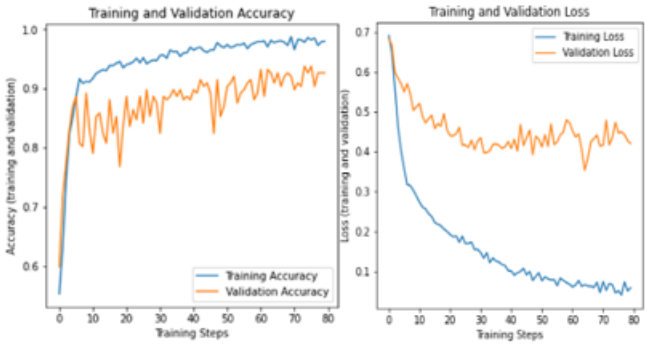

Fig. 7. Training and validation accuracy, Training and validation loss

table IV. Test dataset sensitivity significantly improved to 95%. However, there was still random variance in the curves of Fig. 8 which left room for further improvements. Fig. 8 shows training and validation accuracy with loss.

TABLE IV. RESULTS FOR CASE B.

Classification Metric	Validation data	Test data
Accuracy (%)	96.16	97.25
Precision (%)	96.23	97.35
F1 Score (%)	95.17	97.25
Specificity (%)	96.0	99.0
Sensitivity (%)	94.0	95.0

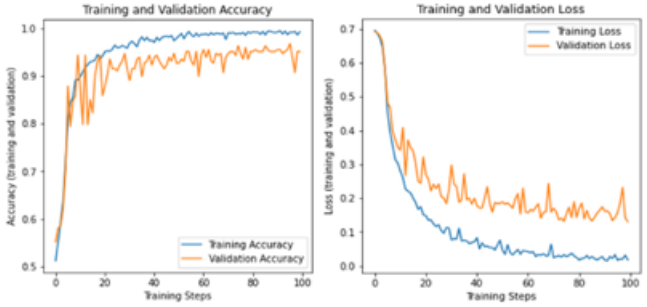

Fig. 8. Training and validation accuracy, Training and validation loss

C. CASE C

For case C, the dataset passed through preprocessing, filtration, segmentation, and data augmentation techniques. The segmented dataset was expanded by the pitch-shifting technique, which increased the normal HS to 3230 and the abnormal HS to 2302. The enhanced results are shown in table V. It can be seen that the sensitivity achieved of the trained model sharply raised to 98.0%, which is the highest on combined LD and PD in comparison with [4], [5], and [7] in Table VI. Fig. 9 shows training and validation accuracy with loss.

TABLE V. RESULTS OF CASE C.

Classification Metric	Validation data	Test data
Accuracy (%)	97.15	98.56
Precision (%)	97.15	98.57
F1 Score (%)	97.15	98.56
Specificity (%)	98.0	98.0
Sensitivity (%)	95.0	99.0

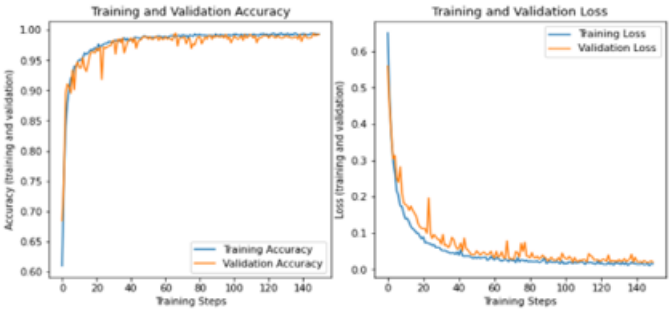

Fig. 9. Training and validation accuracy, Training and validation loss

V. STUDY LIMITATIONS

Due to limitations in the dataset and study duration, this research was restricted to a small group of CHDs, which led to a couple of weaknesses: first, the study is only valid for binary classification (normal and abnormal), multiclass classification is warranted in the future. Second, murmurs are low frequency noise, therefore presence of low-frequency ambient noise may result in incorrect results. We can't completely cancel out environmental noise. However, future advancements in sensor and filter technology may control this issue.

VI. CONCLUSION

The future of artificial intelligence in healthcare management seems bright, particularly for the accurate diagnosis of various ailments such as CHDs. In recent years, many academic and medical researchers have worked in this sector and have frequently produced significant discoveries. This article used signal processing and deep learning techniques to categorize HS into pediatric normal and abnormal HS. Previous studies focused on adult-based HS diagnosis, but in the current study, we proposed a paeds based local dataset to help cardiac experts identify CHDs in infants.

The current study proposes a 1D-CNN-based intelligent model that can classify a paediatric HS as normal or abnormal in real-time. The public data contained 21 abnormal HS with an average signal duration of 1 minute, while the local data contained 143 signals with an average signal duration of 12

TABLE VI. COMPARISON OF RELATED RESEARCH METHODOLOGIES

Reference	Dataset	Pre-processing / Features	Classifiers	Accuracy(%)
[4]	Self-collected data	MFCC, DWT, MFCC+DWT	SVM	97.9
			DNN	92.1
			k-NN	97.4
[5]	Self-collected data	MFFC	k-NN	93.2
[6]	CinC	-	1D-CNN, LSTM, and Conv1D +LSTM	-
[7]	Self-collected data	Power spectrum estimation, WT, and MFCC	SVM and k-NN	92.5
[8]	Heart Sound Dataset (1000 samples) PASCAL Challenge Dataset B. CinC	Root Mean Square, Signal Energy and Power, Zero-Crossing Rate, Total Harmonic distortion, Skewness, and Kurtosis	SVM	99
			KNN	76
			RF	99
			Naïve Baye	96
			ANN	65
[9]	CinC	Time features and frequency features (MFCCs, wavelet entropy, and the power spectrum)	RF	92
[10]	PASCAL and CinC	Mel-Frequency spectrum images	CNN	-
[11]	Self-collected data	Fusion of 1D-LTPs and MFCCs	SVM	95.24
[12]	Self-collected data	Time and frequency	VMD and WST	-
[13]	E-general medical dataset (300 samples)	Time domain	Fuzzy inference	-
[14]	CinC	Time domain	KNN	97.82

seconds, containing various CHDs. The proposed methodology outperformed the models trained on adult and paediatric HS available publicly in terms of accuracy and sensitivity. We evaluated three different sets of datasets, and case C achieved the highest accuracy of 98.56%, 98.57% precision, 98% specificity, and 99% sensitivity on the real-time unseen test dataset.

The medical community could choose from several digital stethoscopes (DS) available on the market, but none of them can analyze HS and identify diseases. Detailed examination and analysis of HS using artificial intelligence algorithms could serve as the foundation for a device that will aid cardiologists in making better judgements and improve the screening of abnormalities in the population. The future development of such an intelligent DS could be done by integrating a proposed algorithm into any digital stethoscope.

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