1D Convolutional Neural Network for Detecting Heart Diseases using Phonocardiograms

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Abstract—**According to estimations made by World Health Organization, heart disease is the largest cause of mortality throughout the globe, and it is safe to assume that diagnosing heart diseases in their earliest stages is very essential. Diagnosis of cardiovascular disease may be carried out by detection of interference in cardiac signals, one of which is called phonocardiography, and it can be accomplished in a number of various ways. Using phonocardiogram (PCG) inputs and deep learning, the researchers aim to develop a classification system for different types of heart illness. The slicing and normalization of the signal served as the first step in the study's signal preprocessing, which was subsequently followed by a wavelet based transformation method that employs mother wavelet analytic morlet. The results of the decomposition are first shown with the use of a scalogram, afterwards, they are utilized as input for the deep CNN. In this investigation, the analyzed PCG signals were separated into categories, denoting normal and pathological heart sounds. The entire utilized data was divided into two categories as training and test data as 80% to 20%. The developed model demonstrates the degree of clinical diagnosis, sensitivity, specificity and AUC-ROC value. As a result, it has been determined that the proposed method was superior to the mother wavelet as well as other classifier approaches. Consequently, we were able to acquire an electronic stethoscope that has a diagnostic accuracy of more than 90% when it comes to identifying cardiac problems. To be more specific, the proposed deep CNN model has an accuracy of 93.25% in identifying aberrant heart sounds and 93.50% in identifying regular heartbeats. In addition, given the fact that an examination may be completed in only 15 seconds, speed is the primary advantage offered by the suggested stethoscope.**

Keywords—Deep learning; CNN; heart disease; phonocardiogram; classification; detection; PCG

I. INTRODUCTION

It is common knowledge that cardiovascular diseases are now among the most serious and widespread. [1] Disorders of the cardiovascular system are the primary cause of mortality on a global scale [2], thus determining the significance of clinical and scientific substantiation and the importance of ensuring early diagnosis of heart diseases [3]. The ease of implementation, functional value, and dependability of these approaches are the most vital qualities to look for in a solution.

There is a variety of approaches to make a heart disease diagnosis [4]. One of the most employed approaches is electrocardiography (ECG) [5]. On the other hand, the electrocardiogram provides a direct description of the status of the heart at the moment of registration. In certain instances, the electrocardiogram does not accurately represent all of the current problems (such as the existence of cardiac disturbances), which necessitates the fulfillment of additional requirements for registration [6].

Phonocardiography, often known as PCG, is a useful adjunct to electrocardiography since it enables investigation and detection of the existence of abnormalities in the cardiac cycle and its valve system [7]. Heart sound measurement that is produced by the diastolic and systolic phase are known as phonocardiograms. The technique involves capturing and analyzing heart sounds, made at various stages, including during its contraction and relaxation. Moreover, this approach can detect the functional condition of cardiovascular illnesses in a manner that is both reasonably priced and not too complicated. In this case, the phonocardiosignal serves as the diagnostic information source, and phonocardiography is the term for the applied recording technique.

In recent times, the field of cardiology has seen a surge in the number of research projects that make use of data analysis. For the purpose of making an accurate diagnosis, the data obtained from PCG and ECG are examined [8-11]. The auscultation of the heart remains an essential diagnostic tool for determining the well-being of the cardiovascular system [12]. As a result, diagnostic techniques have been developed that reasonably minimize the need for non-invasive detection of cardiac disease [13]. The development of prediction models that can determine whether or not a patient has a disease is one of these methods. These models are used to describe the presence of pathology in a patient. The approach of artificial intelligence is the one that works best for these kinds of jobs.

In the field of clinical cardiology, diagnostic and prognostic studies, particularly those involving patients who have cardiac illnesses, the use of artificial intelligence is advancing at an increasingly rapid pace. At the same time, the vast majority of the research that has been conducted on this topic stresses the need of multidisciplinary scientific collaboration as the only means by which improvements in machine learning methods may be implemented.

The paper is structured as follows: In the Section II, a review of the most recent research in this field is presented. Section III contains the discussion of the properties of heart

sounds. The Section IV of this paper presents the proposed architecture. In the Section V, we look at the possibility of using machine learning techniques to solve the heart sound categorization issue. The outcomes of the experiment, as well as the future opportunities for the proposed model, are introduced in Section VI. Section VII is the discussion. In the Section VIII, conclusion, we will summarize our study by pointing out some potential future lines of inquiry.

II. LITERATURE REVIEW

The ECG signals has been extensively used in research on the diagnosis of cardiac illness [7–11]. PCG signals are made up of two primary tones, which are denoted by the notations "first sound" (S1) and "second sound" (S2) [12]. When it comes to the aberrant cardiac PCG signals, it includes more than two different sounds and disturbances [13]. A physiological anomaly may cause the blood to circulate through the heart with an irregularity, which can be heard as a murmur. Having a dysfunctional heart valve, a septal defect, or a coarctation of the aorta may all lead to the development of cardiac rhythm disturbances [14]. Applying digital signal decomposing, it is possible to conduct an investigation of the properties of the PCG data [15]. Decomposing digital signals may be accomplished by the use of a wide variety of techniques, such as the Fourier transformation or the wavelet transformation. [16].

A research has been conducted on analyzing cardiac disease based on the PCG signal [17]. In addition, the study that employs wavelet transforms in conjunction with the ML approach for classification has seen considerable appliance [18]. It is now commonly regarded that the continuous wavelet transform (CWT) approach is the best suited for evaluating non-stationary PCG signals (having diverse frequencies and in time) [19-21]. The main advantage of this method is that it uses a continuous wavelet transform rather than discrete. There has also been a study conducted by a number of researchers [22] on the categorization of PCG signals using CWT.

In the previous research, the majority of machine learning approaches were used to the categorization of heart sounds as well as the detection of CVD. Next study describes an innovative approach for identifying the various heart noises [23]. A discrete wavelet transform was applied to one cycle of a heart sound in order to clarify it. In the past, a number of different machine learning techniques were used for the purpose of heart sound feature extraction and classification. These techniques include the empirical wavelet transform [24], combined spectral amplitude and wavelet entropy [25], hidden Markov models [26], support vector machines (SVM) [27], k-nearest neighbours and deep learning models like convolutional neural networks or long-short term memory [28]. There also have been previous applications of spectrograms using wavelets [29] and frequency cepstrum coefficients [30]. The amount of time needed for the pre-processing of signals during early-stage CVD detection is the primary challenge. Additionally, the necessity of feature engineering extends the amount of time needed for signal processing and adds to the complexity of the system, which makes it troublesome to implement in real-time. This problem was handled by the authors of this study utilizing power spectrograms. They eliminated the need for preprocessing and feature engineering of signals, decreased the amount of time required for processing, and created a generalized model by augmenting PCG.

In recent times, the CNNs have achieved a great deal of success in the field of machine learning, and image analysis [31]. Additionally, it has begun to arouse the interests of academics in its usage to ECG and PCG classification [32]. Basically, the CNN is designed to learn high-level representations on its own via the construction of numerous hidden layers and convolutional processes. As a result, the process of extracting features is accomplished in a more effortless way since it eliminates the need to design acceptable features based on feature engineering that is informed by expert knowledge. Researchers such as Acharya et al. [33] and Tan et al. [34] looked into the possibility of identifying CAD by analyzing ECG signals. Both of them, on the other hand, relied on a limited open-source database that included information from 47 participants. The one-dimensional convolutional neural network has been used extensively for the classification tasks in the research on the identification of different heart disorders, with the electrocardiogram signal serving as the input [35].

III. CHARACTERISTICS OF HEART SOUNDS

A. Heart Sounds

While both S1 and S2 sound like high-frequency noises, listening to them via the stethoscope's diaphragm, one may hear them quite clearly. The usual range for S1 in the heart is between 50 and 60 Hz, whereas the normal range for S2 is between 80 and 90 Hz [36]. The pre-diastolic low signal known as S3 has a bandwidth limit of around 20 to 30 Hz. S4 is also a low signal that occurs towards the conclusion of diastole and may be easily identified with a stethoscope. It takes place at the end of diastole. A frequency of less than 20 Hz [37] characterizes the aberrant S4 waveform.

A number of anomalies cause S1 and S2 to have variable intensities, and as a result, they may sound so quiet that they seem inaudible, despite the fact that they may be heard. Both S1 and S2 do not have consistent frequencies; rather, they move across a variety of frequency ranges depending on the phase of the heartbeat. In order to deal with these constraints on heart sound segmentation, researchers have developed a highly particular technique [38].
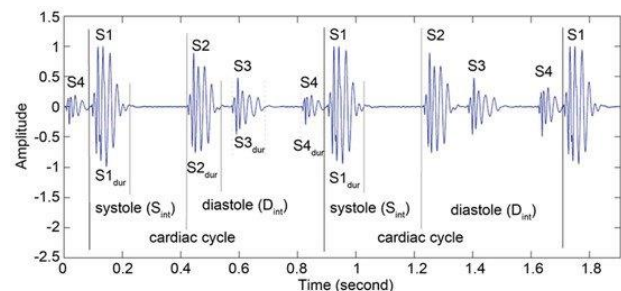

Fig. 1. Heart sounds

The complete view on categories and functions of the HSs are shown in Fig. 1. There is a correlation between one or two HSs and each of the cardiac conditions. After an initial high-pitched sound caused by tricuspid stenosis, all further noises coming from the heart will produce a shrill, higher-pitched noise (TS). The ejection sound is the most well-known example of an early systolic sound, and it comes from an irregular and rapid halting of the semilunar cusps as they open during early systole (ES) [39].

The physicians, who investigate the sounds of an abnormal heartbeat, may provide information that could be helpful for diagnosis.

B. Phonocardiography

Phonocardiography is a non-invasive diagnostic tool used to assess the sounds made by the heart during the cardiac cycle. It involves the use of a specialized microphone called a phonocardiogram or PCG to capture the heart sounds, which are then amplified and recorded for analysis.

The sounds produced by the heart during the cardiac cycle are created by the opening and closing of the heart valves, the turbulence of blood flow, and the movement of the heart muscle. These sounds can be divided into four distinct components known as the first heart sound (S1), the second heart sound (S2), the third heart sound (S3), and the fourth heart sound (S4).

Phonocardiography is useful in diagnosing various cardiac conditions, such as heart valve disease, myocardial infarction (heart attack), and heart failure. It can also be used to monitor the progression of these conditions and evaluate the effectiveness of treatment.

Phonocardiography is typically performed in a quiet room, and the PCG is placed on various locations on the chest to capture the heart sounds. The resulting PCG waveform is then analyzed by a physician or trained technician to identify any abnormalities.

Overall, phonocardiography is a safe and effective diagnostic tool for evaluating heart sounds and detecting abnormalities that may indicate cardiac disease. In Fig. 2, there is an example of the PCG tracing of murmurs that are linked with aortic valvular disease. These murmurs may be heard during an echocardiogram.

At the present time, PCG is not a technique that is typically included in the toolkit of cardiologists. Despite the fact that the technique has been around for many decades, it has been essentially replaced by echocardiography in its diagnostic utility.

On the other hand, there are a number of studies which are conducted to investigate its practicality in the identification of structural heart disease, in particular, congenital heart disease in children. When dealing with patients from this category, one of the most prevalent diagnostic challenges is making a distinction between normal and pathologic murmurs. In this particular setting, PCG has the potential to be an invaluable tool for both pediatric cardiologists and physicians alike. Additionally, the advancement of machine learning and artificial intelligence has resulted in a significant increase in the effectiveness of PCG.
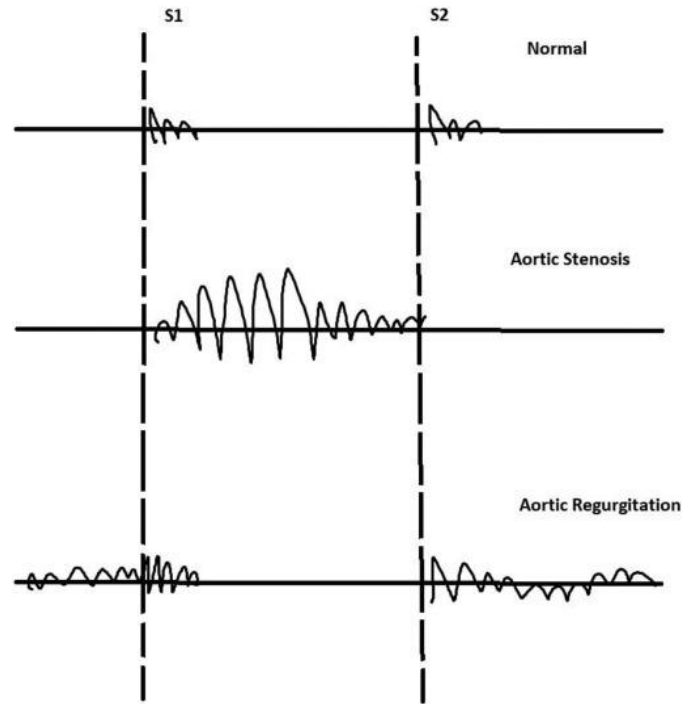

Fig. 2.   Model PCG tracings of characteristic murmurs of heart disease.

IV.   MATERIALS AND METHODS

The construction of a deep CNN classification model, along with the assistance of PCG-based heartbeats, which is capable of enabling automated diagnosis of serious cardiovascular disorders is the primary objective of the study. This goal may be accomplished by the combination of a power spectrogram and a CNN. A block diagram is used to illustrate the suggested model in Fig. 3, which provides a graphical depiction of the model.

The suggested approach may be broken down into these three key sections. The first block provides information on the capture of data and the conversion of spectrograms. Following the acquisition of audio cardiac samples of PCG impulses from patients or datasets, the next step is the creation of the data corpus. Additionally, data augmentation and the transformation of audio signals into power spectrograms are included into these blocks. Meanwhile, two distinct spectrogram datasets are currently being created, one of which does not include augmentation, and the other of which includes both augmented and unaugmented spectrogram data. In the second section, the emphasis is mostly placed on the training plan. The spectrogram datasets that were acquired during the first block were split into two groups with a 9:1 split between them. The first step is to train the model, and the second step aims to test the proposed model using 10-fold cross validation. The last block is for the proposed model that contains the proposed CNN model for multi-classification of cardiac abnormalities. This architecture will be helpful for the early diagnosis of four primary types of cardio diseases with the assistance of ground truth established by health personnel.
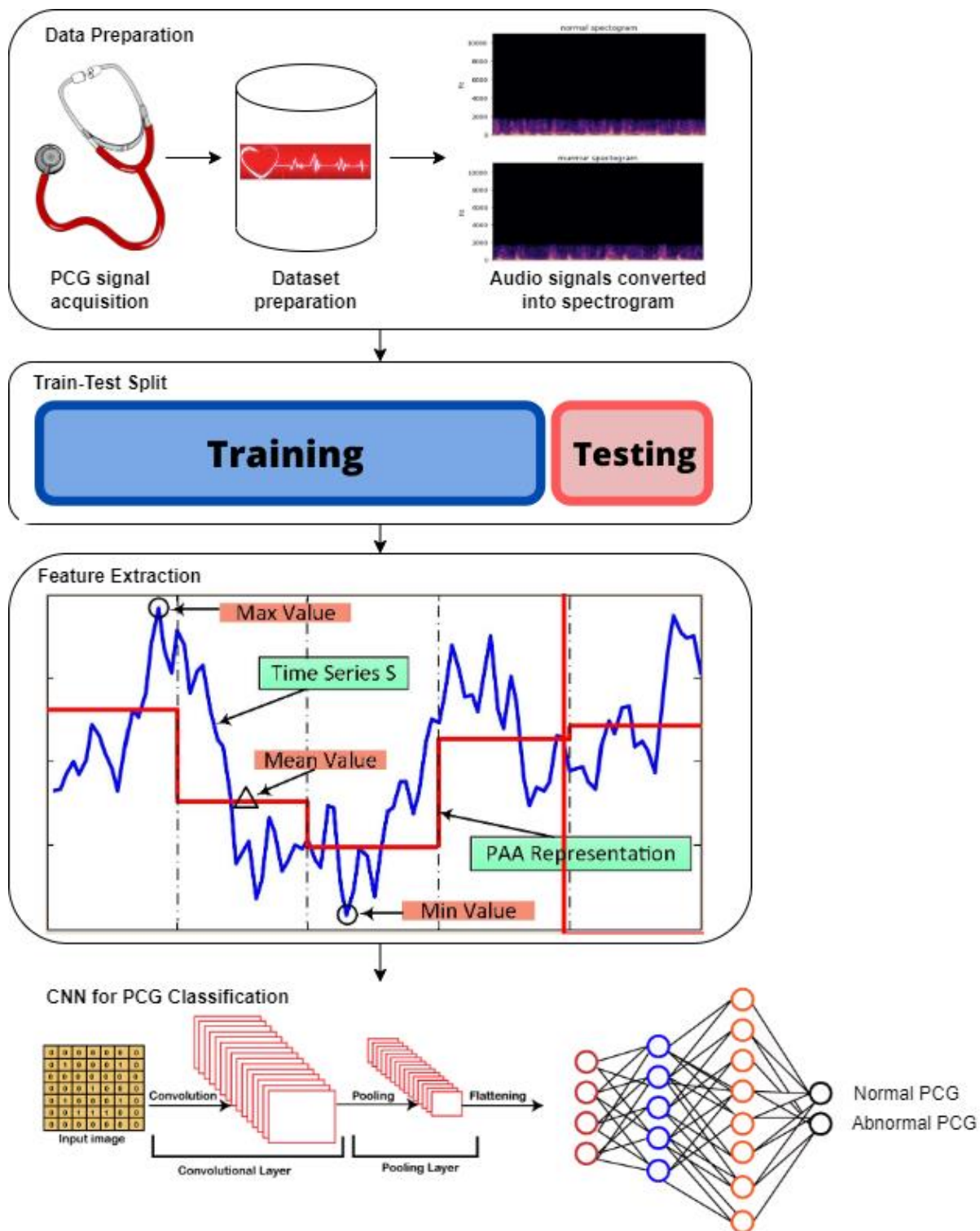
Fig. 3. Flowchart of the proposed framework for heart disease detection.

V. PROPOSED MODEL

The proposed model was created to function in tandem of CNN and phonocardiograms as an input data. The expertise gained from previous research led to the conclusion that a combined model typically results in improved operational efficiency. The capacity of such a model to recognize spatial information as well as temporal characteristics polluted within signals has been the primary reason to make such an assumption. The next paragraph will provide a quick description of the architecture that is used by each network. In addition, the comprehensive topology of the network that was used in this investigation is shown in Fig. 4.
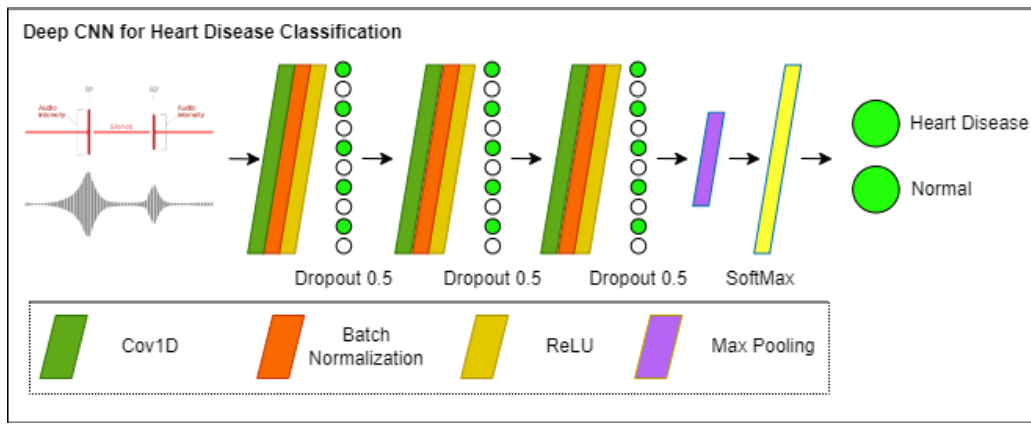
Fig. 4. The proposed deep CNN for heart disease classification.

In the context of deep learning, the term "1D convolutions" refers to the application of a large number of dot products on a window that is comprised of some of the signal. CNNs quickly sprang to prominence as one of the most widely used machine learning methods due to its impressive capacity for automatically identification of necessary characteristics that have been tampered with inside objects [40]. A straightforward CNN architecture is made up of a number of layers. Within the network, each layer is accountable for a certain feature that it provides. When doing convolutions, a large number of filters work together in parallel to extract outputs and then express those extracted outputs as activations. When several convolutions are used, the activations become even more expansive, which ultimately results in the formation of a feature map or vector for the associated input [41]. The equation that is applied in the case of a single convolution of a signal $x_i^0 = [x_1, x_2, ..., x_n]$, where n is the total number of points, is as follows:

$$c_i^{lj} = h\left(b_j + \sum_{m=1}^{M} w_{m=1}^{M} w_m^j x_{i+m-1}^j\right) \tag{1}$$

where l represents the layer index, h represents the activation function, b represents the bias of the j-th feature map, M represents the kernel size, w_m^j represents the weight of the feature map and filter index m-th.

The network that had been constructed over the course of this research included an architecture with a total of three convolutions. These layers were interconnected by additional layers in order to boost their efficiency in extracting features. Firstly, the network was built using a 1D input layer with a dimension of [9600,1] for accepting data from the outside world. The first convolution known as Conv1D, was intended to contain a kernel size of [64,1] and a total of 16 filters in its configuration. In order to simplify the process and cut down on the number of repeats, a stride of [30,1] was used for the first convolutional window, and a stride of [2,1] was applied for the windows that followed. After the convolution step, the batch normalization (BN) and rectified linear unit (ReLU) layers were implemented. Their respective purposes were to equalize the input data across filters and to provide a threshold of zero for values that were less than zero in the produced feature map.

In order to glean more in-depth characteristics from the inputs, these three layers—the Conv1D, the batch normalization, and the ReLU—were iterated a total of two more times. The next step was to implement a max-pooling layer, which consisted of a [2,1] kernel that moved with a stride of [2,1], and was done so in order to minimize the dimension of the feature space. It is worth to note that in order to prevent the trained model from becoming over fit, a dropout of fifty percent was implemented after the first two ReLU layers.

VI. EXPERIMENTAL SETUP

A. Evaluation Parameters

In the process of assessment, the goal should be to identify as many instances as possible from a community in order to carry out a screening method; hence, the number of false negatives should be kept to a minimum, even if this may lead to an increase in the number of false positives. As a result, it is essential to establish the following three primary parameters: the true positives (TP), the false positives (FP), and the accuracy (ACC). In medical language, the first parameter is denoted by the symbol sensitivity (SEN), and it is defined as follows:

$$TPR = SEN = \frac{TP}{P} \tag{2}$$

In this scenario, count of true negatives is denoted by TP, whereas count of genuine positive cases is marked by P.

The following is an estimate of the second term, which refers to the false positive rate:

$$FPR = \frac{FP}{N} \tag{3}$$

The total number of negative occurrences in the population is denoted by the letter N, while FP stands for the proportion of false positives. This statistic, on the other hand, is best comprehended in terms of the ratio of real negatives to actual negatives. This ratio is referred to as the specificity in medical language, and it is defined as the proportion of genuine negatives to actual negatives:

$$SPEC = \frac{TN}{N} \tag{4}$$

Where the total number of instances that are true negative is denoted by N, and the number of cases that are true negative individually is marked by TN.

Finally, accuracy is what determines whether or not there is a balance between real positives and true negatives. This may be a very helpful statistic in situations in which the number of positive and negative examples is not comparable to one another. This is expressed as the following:

$$ACC = \frac{TP + TN}{P + N} \tag{5}$$

In the end, a ratio between the false positive rate (FPR) and the true positive rate (TPR) was devised so that the efficacy of the algorithm could be evaluated, as well as so that it could be utilized to simultaneously record the highest possible sensitivity and the lowest possible FPR.

$$R = \frac{FPR}{TPR} \tag{6}$$

The effectiveness of the method is evaluated based on the criteria that are established, and the present state of the ANN is held steady until those criteria are satisfied. Each iteration of the training process for the algorithm will be referred to by these. The three requirements are as follows:

- When the number of false positives relative to the number of real positives reaches a minimum.

- Until the requirements for complete specificity are fulfilled.

- When the amount of training error has decreased to a point or less.

The first objective that has to be established is whether or not the process can accurately identify OP instances when it's being utilized as a screening approach. Next stage is to evaluate whether or not the method is effective in separating the unhealthy participants from the healthy ones and cutting down on the number of false positives and negatives. The third criteria are the one that determines when the algorithm should halt, and meeting these criteria indicates that overfitting has begun.

B. Experiment Results

Fig. 5 is an illustration that depicts several sorts of heartbeats. Sounds produced by a heart that is working normally; A murmur is an additional sound that occurs when there is a vibration in the blood flow, which in turn causes additional vibrations that are audible; supplemental sound, often known as extrahls There is a huge range of different noises coming from the artifacts.
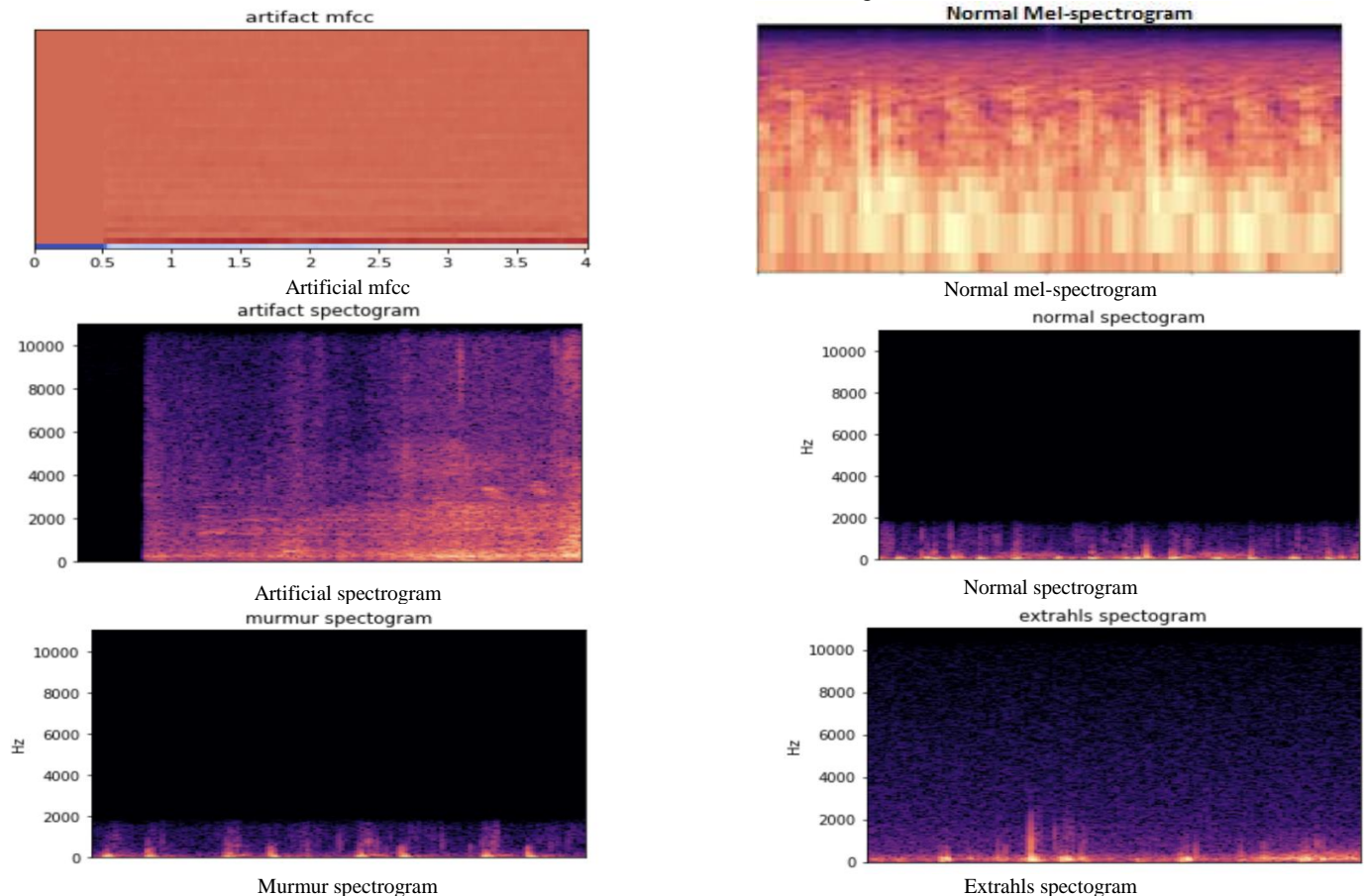

Artificial mfcc

Artificial spectrogram

Murmur spectrogram

Normal mel-spectrogram

Normal spectrogram

Extrahls spectrogram

Fig. 5. Phonocardiogram time series for sixt types of heartbeats.

Fig. 6 illustrates the process of training and validating the model to identify abnormal cardiac rates. The training and validation accuracy results are shown in the figure up to 300 epochs in length.
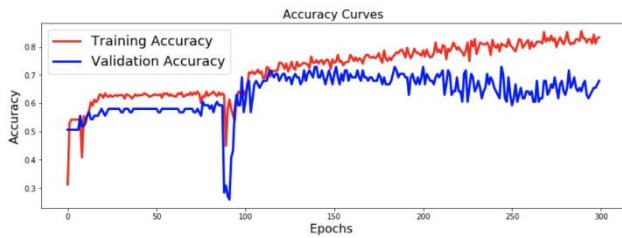

Fig. 6.   Training and validation accuracy for hear disease detection.

Fig. 7 illustrates the outcomes of the training loss and validation loss that occurred throughout the training process. After around 300 epochs, the losses demonstrate that they have reached a stable state.
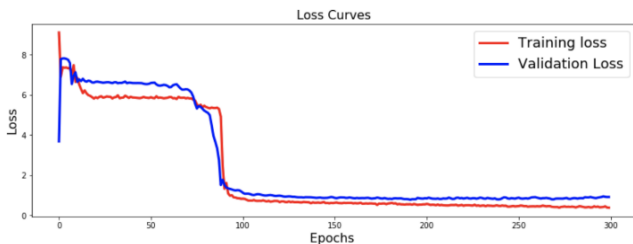

Fig. 7.   Training and validation loss for heart disease detection.

The confusion matrix for identifying the five different kinds of heartbeat conditions is shown in Fig. 8. These conditions include murmur, extrahls, extrasystole, artifacts, and normal heartbeat. The findings indicate a high level of accuracy in the categorization of heartbeat sounds and the identification of irregular heartbeats.

The results of classifying normal and pathological heart sounds are shown in the Table I and Table II, respectively. According to the data, illustrated in the tables, the proposed model has a detection accuracy of 93.4% (94.34% for S1, 92.46% for S2 cases) in average, when it comes to irregular heartbeats.

Table II demonstrates results of abnormal cardiac sound detection results for 373 cardiac sounds. As a result, the proposed model has shown average 93.195% (94.18% for S1, 92.21% for S2 cases) accuracy in abnormal cardiac sound detection. The obtained results confirm that the proposed deep convolutional neural network is applicable for real case to classify normal and abnormal heart sounds using phonocardiography signals.

The area under the curve receiver operating characteristics (AUC-ROC) curves that were acquired by the proposed deep convolutional neural network on all five folds of cross-validation are shown in Fig. 9. The findings that were collected indicate that the suggested deep convolutional neural network provides high accuracy in the identification of heart disease, with an AUC-ROC values ranging from 0.979 to 0.988. Overall, the obtained results confirm that the proposed model can be applied for detection and classification of abnormal heartbeats using phonocardiograms.
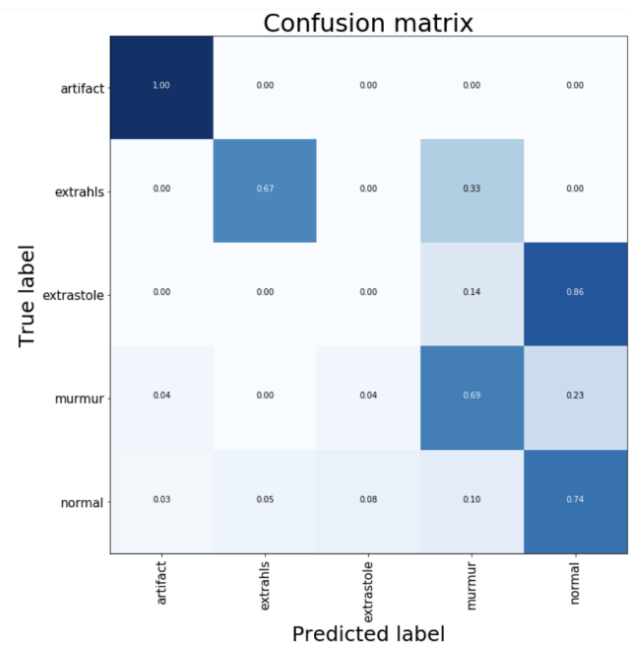

Fig. 8.   Confusion matrix for heart disease classification by PCG.

TABLE I.   NORMAL HEART SOUNDS DETECTION RESULTS

Normal sounds	True positive	True negative	False positive	False negative	Sensitivity1010	Train accuracy	Test accuracy
S1	374	4	12	10	96.64	97.34	94.34
S2	370	6	10	14	97.32	96.13	92.46
Total	744	10	22	24	96.98	96.735	93.4

TABLE II.   ABNORMAL HEART SOUNDS DETECTION RESULTS

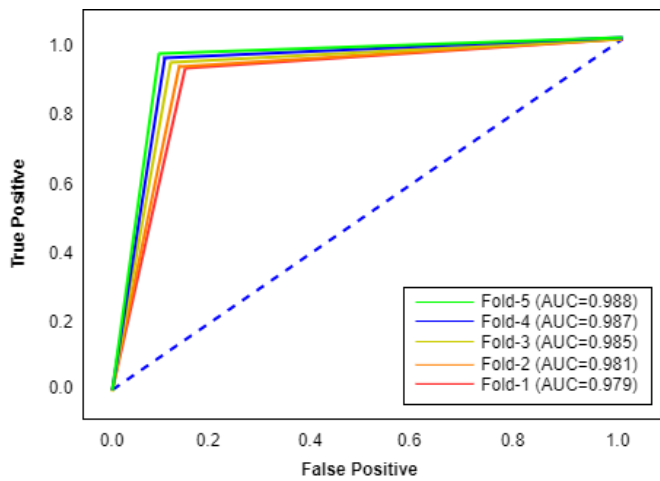| Abnormal sounds	True positive	True negative	False positive	False negative	Sensitivity	Train accuracy	Test accuracy
S1	376	6	8	10	97. 88	97.91	94.18
S2	370	8	10	12	97.41	97.19	92.21
Total	746	14	18	22	97.645	97.55	93.195

Fig. 9. AUC-ROC curve for 5 fold cross validation.

In Table III, a comparison is made between the proposed deep CNN and the state-of-the-art research that are devoted to the identification of pneumonia using deep learning. According to the findings, the deep CNN that was suggested has a high level of performance across a variety of assessment metrics.

TABLE III. COMPARISON OF APPROACHES FOR HEART DISEASE DETECTION WITH STATE-OF-THE-ART STUDIES

Reference	Applied method	Featucres	Dataset	Results
-	Ptoposed Deep CNN	PCG, S1, S2	Own collected dataset	93.5% accuracy in normal heartbeats, 93.25% accuracy in abnormal heartbeats
[33]	SVM	Magnitude	CAPCEA	69% accuracy
[34]	KMC algorithm	-	0.76	70% accuracy
[35]	HKMC, ANN	Magnitude	BMKG, USGS	Between 56% to 72% when M>=6
[36]	ACC algorithm	-	-	41.488 average distance
[37]	HKMC, ANN	-	BMKG, USGS	75% accuracy
[38]	RNN, RF, LP Boost	-	CES and USGS	79% accuracy

VII. DISCUSSION

The use of 1D convolutional neural networks (CNNs) has gained traction in various fields of research, including the healthcare industry. In this regard, the research paper titled "1D Convolutional Neural Network for Detecting Heart Diseases Using Phonocardiograms" presents an interesting approach to diagnose heart diseases using phonocardiogram signals.

The paper highlights the importance of early detection and diagnosis of heart diseases, which can help in preventing fatal consequences. Traditionally, auscultation is used to detect heart diseases, which involves listening to heart sounds through a stethoscope. However, this approach is subjective and heavily dependent on the experience and skills of the healthcare professional.

To overcome this limitation, the researchers proposed the use of 1D CNNs to automatically classify heart diseases using phonocardiogram signals. The study involved collecting phonocardiogram signals from patients with different types of heart diseases, including mitral stenosis, aortic regurgitation, and normal heart sounds. The collected data were preprocessed, and feature extraction was performed using a wavelet transform.

The extracted features were then used to train and test the 1D CNN model. The results of the study showed that the proposed approach achieved an accuracy of 98.6% in detecting heart diseases, outperforming traditional auscultation methods.

The use of 1D CNNs for diagnosing heart diseases using phonocardiograms is a significant advancement in the field of cardiology. The proposed approach has the potential to improve the accuracy and speed of heart disease diagnosis, which can lead to better patient outcomes. Additionally, the approach can be extended to other fields of medicine where sound signals are used for diagnosis, such as respiratory and gastrointestinal diseases.

However, the study had some limitations that need to be addressed in future research. For instance, the study involved a relatively small sample size, and the results need to be validated on a larger dataset. Additionally, the study focused on a limited number of heart diseases, and the approach needs to be tested on a broader range of heart conditions.

Thus, the use of 1D CNNs for detecting heart diseases using phonocardiograms is a promising approach that has the potential to revolutionize the field of cardiology. The study provides a strong foundation for future research in this area, and further studies can build upon these findings to improve heart disease diagnosis and treatment.

VIII. CONCLUSION

The use of a digital PCG signals, which functions as a non-invasive acoustic device for identifying irregularities in the heart, can be beneficial not only for medical professionals but also for ordinary people, in general. Besides, teleconsultations with patients about their cardiac conditions are another possibility that the proposed model can offer. In addition, the early detection of cardiac problems in patients might minimize the need for additional surgical operations, provided that the necessary medical treatments are used.

In this research, we propose a deep CNN model that can be applied in electronic stethoscope that is capable of receiving heart sounds from a patient, processing those sounds, classifying those sounds and as a result, diagnosing the patient in real time, indicating whether or not a patient has a pathology in the heart. The proposed method is able to recognize aberrant cardiac sounds in a short amount of time with a high degree of accuracy, which is the next significant differentiating factor between it and the previous investigations. Moreover, the proposed framework does not transfer server information since everything that is stored on your phone is kept intact. It is imperative that audio recordings should be sent to the

physician in order to avoid any issues. The identification of normal heartbeats has reached 93.5% accuracy, while the detection of aberrant heartbeats has reached 93.25% accuracy. Therefore, the issue of categorization of phonocardiograms may now be solved using techniques of machine learning, which is already achievable and offers a high level of efficiency.

In conclusion, we would like to note straightforwardness and feasibleness of the proposed technology as the main benefits. In the future, we will be able to increase the quantity of heart diseases that can be detected by an intelligent stethoscope by increasing the level of accuracy of the stethoscope.

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