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Heart Sound Classification using a Hybrid of CNN and GRU Deep Learning Models

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Abstract

Auscultation is a process where a stethoscope is used to listen to the heart sound signal to analyse the heart's functionality. Due to the stethoscope's non-invasiveness, convenience, and cost-effectiveness, it is the most common primary screening tool medical fraternities use. However, the scarcity of medical experts and the subjectivity in the analysis hinders the reliability of diagnosis using auscultation. Therefore, computer-aided analysis of heart sound signals will be helpful in this scenario. This paper presents a hybrid deep learning-based method to classify the heart sound signal into five classes. The method begins with the signal pre-processing followed by decomposition using Discrete Wavelet Transform (DWT) up to five levels. The obtained DWT coefficients are used to train the hybrid model, composed of two Convolution neural network (CNN) layers following one Gated Recurrent Unit (GRU) network layer. CNN models are suitable for extracting meaningful features, while the GRU exploits the time-dependent features. This combination helps classify the heart sound signal since they exhibit complex quasi-cyclic features. An overall accuracy of 99.3% is obtained for a publicly available dataset. It shows the proposed method's efficacy for classifying heart sound signal and superiority over the existing methods. Such a method will be beneficial in reducing the burden of heart valve diseases by early detection of diseases and initiating the proper medication.

Keywords: Heart Sound Signal; Phonocardiogram; Discrete Wavelet Transform, Gated Recurrent Unit, Convolution Neural Network

1. Introduction

Cardiovascular diseases (CVDs) cause most of the mortality among non-communicable diseases around the globe [1]. This burden can be reduced by early-stage detection of CVDs and initiating proper medication. Manifestation of various CVDs, including heart valve disease and arrhythmia, occurs early in the heart sound signals, reflecting the mechanical activity of the heart valves and chambers [2]. Auscultation is the most common approach medical fraternities

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use to listen to the signal using a stethoscope and analyse them manually. However, the scarcity of medical experts and subjectivity in the diagnosis hinders its applicability to a wider population, especially in remote and rural areas. Considering the scarcity of medical experts, automatic analysis of heart sound signals is crucial.

Several research methodologies have recently focused on heart sound signal analysis and classification. The complex patterns present in these signals pose challenges, leading to the development of various innovative approaches. Table 1 summarizes some of the recent methods for analysing and classifying heart sound signals proposed in the literature and are discussed as follows.

In earlier approaches, researchers extracted the time-frequency domain features and used them to train classical machine learning models for classification. Such a method is proposed in [3] extracted the magnitude and phase of the spectrogram as a feature to detect heart valve disorders. In [4], a two-stage approach was proposed that employs tunable-quality wavelet transform features for classifying PCG signals. The first stage detects the abnormality using the tunable-quality wavelet transform (TQWT) features and support vector machine (SVM). In case of any abnormality is detected, the second stage performs the signal classification into four pathological categories using the same features and KNN method. Other features considered for this purpose are Mel-Frequency Cepstral Coefficients (MFCC) [5], Shannon energy [6], and Cochleagram features [7].

Recent approaches are focused on deep-learning based machine learning models to classify the heart sound signal and achieved remarkable results. Devi et al. [8] proposed a method that combines scalogram and deep learning techniques for classifying unsegmented PCG signals. In [9], a deep Wavenet model-based technique was presented for heart signal classification. Jain et al. [10] introduced a lightweight 1D-CNN model for categorizing heart sound signals into five groups. The method first transforms the signal in a multi-resolution domain using DWT, and then the 1D-CNN model is trained on the transformed signal. In a similar approach, Fan et al. [11] trained a CNN model on the coefficients of learnable lifting wavelet transform (Le-LWT). N. Bhagel et al. [12] and K. Ranipa et al. [13] applied CNN models for heart sound signal classification. Bhardwaj et al. [14] transformed the signal into scalogram images using continuous wavelet transform (CWT) and used these images to train a 2-D CNN model. These advanced methods and deep learning techniques have significantly improved the accuracy and efficiency of heart sound signal classification. The development of such innovative methodologies holds the promise of reducing the burden of cardiovascular diseases and improving patient outcomes.

Contribution of the paper: The paper's main contribution is a novel hybrid CNN and GRU network model for the heart sound signal classification. This combination helps extract complex quasi-cyclic features from the heart sound signal, which results in an effective signal classification. Moreover, the proposed method exploits the multi-resolution characteristics of the signal by decomposing the signal into five levels using DWT. Decomposing the signal into five levels exhibits a better separation of the S1, S2, and the sound components related to pathological murmurs. Separation of these components improves the model's efficacy in classifying the signals. The obtained coefficients are arranged in a 1D array and used as input to the model. The experiments are conducted on a publicly available dataset with five classes.

Organisation of the paper: The paper presents a comprehensive understanding of the proposed method and its evaluation. Section 2 delves into the details of the proposed method, where each step is thoroughly described. The pre-processing phase presents essential techniques like downsampling, filtering, resizing, and normalization. Following this, the decomposition process is elaborated using DWT. The classification steps involving the application of the proposed hybrid model are carefully explained. Moving on to Section 3, we showcase the obtained results of our experiments. We present the performance of individual components, including CNN, GRU, and the hybrid model, in classifying heart sound signals. Moreover, valuable insights are provided about the hybrid model's superiority compared to individual models and existing methods from the literature. Finally, Section 4 offers a concise and comprehensive conclusion of the study.

2. Proposed Method

As shown in Fig. 1, the proposed method performs in three steps. The first step is pre-processing the signal, decomposition using DWT, and classification of the signal using the proposed hybrid deep learning model in five categories.

Table 1. Literature review for the classification of PCG signal.

Sl. no	Author name & year	Dataset	Methodology used	Accuracy
1	Khan et al. [15] (2018)	Yaseen Khan Dataset	MFCC, DWT and SVM.	97.90%
2	Ghosh et al. [3] (2019)		Random forest (RF) classifier	98.55%
3	Bhagel et al. [16] (2020)		Augmentation, normalization, and filtering	98.6%
4	Ranipa et al. [17] (2021)		MFCC and CNN	98.5%
5	Shuvo et al. [18] (2021)		CardioXNet	98.2%
6	Jain et. al. [10] (2023)		1D CNN and DWT	98.6%
7	Kay and Agarwal [19] (2017)	Physionet Challenge 2016	Propagation neural networks	90%
8	S Das et al. [20] (2019)		Cochleagram ANN	95%
9	Chen et. al. [21] (2019)		Deep Convolutional Neural Networks (DCNNs)	92.47%
10	Arora et al. [22] (2019)		Xgboost, RNN	92.9%
11	Chowdhury et al. [6] (2020)		MFCC, DNN	97.2%
12	E Nehary et al. [23] (2021)		FFT Mel-spectral coefficients and CNN	97.18%
13	S Tiwari et al. [24] (2021)		Deep learning and ConvNet	96%

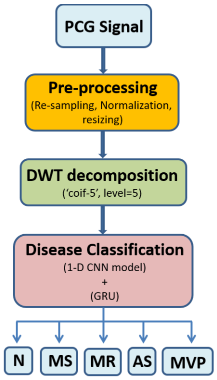

Fig. 1. Block diagram of the proposed method.

2.1. Pre-processing

The study uses a publicly available dataset containing 1000 signals with an 8kHz sampling frequency. The signal is pre-processed as follows to ensure uniformity and enable effective analysis. First, recognizing that the relevant frequency range for normal and abnormal heart sounds is below 500 Hz, downsampling is performed to convert the sampling frequency from 8 kHz to 1 kHz. This downsampling allowed us to focus on the critical frequency components while reducing computational load. Next, a high-pass Butterworth filter was used to suppress the frequency contents below 20 Hz to remove any respiration-related components present in the signals. This step helped isolate the heart sound-specific information from potential interference. Since the dataset's signals typically covered three cardiac cycles but varied in length due to differing heart rates, we made them uniform by padding them with zeros. However, this padding was later removed during resizing, which ensured that all signals became equal in length. To eliminate any variations in amplitude range across different signals caused by inter-class differences, z-score normalization is employed. This normalization technique standardized the amplitude values, enabling fair comparisons and eliminating bias due to signal magnitude. These pre-processing steps standardized the heart sound signals and made them suitable for subsequent analysis and classification.

2.2. DWT decomposition

DWT is a discrete version of the continuous wavelet transform, where the scaling and translation parameters' values are discrete and differ with a power of two. For the cost-effective implementation of the DWT, Mallat proposed a subband coding method called the Mallat tree [25], as shown in Fig. 2. In this technique, a multiresolution analysis is performed on the signal to decompose it into different levels of detail. The process begins by applying high and low-pass filters and then decimating the obtained filtered signals using both filters by a factor of two to compress the signal while preserving the essential information effectively. The next step involves subjecting the approximation coefficients to the same filtering and downsampling process. The analysis filters can be applied to the approximation coefficients to generate the next-level coefficients. This decomposition process can be repeated multiple times, creating a hierarchy of approximation coefficients at different levels of resolution. Each level provides a progressively lower frequency representation of the original signal, capturing different levels of detail. This hierarchical decomposition is what constitutes the multiresolution signal analysis. By decomposing the signal into various levels of approximation and detail coefficients, this technique allows for a comprehensive and detailed analysis of the original signal at different frequency scales.

This work uses 'coif-5' (coiflet wavelet with five vanishing moments) as the mother wavelet to decompose the signal upto five levels. Decomposing a signal using DWT divides the frequency range of the signal into two halves, and hence detailed levels (1 to 5) will cover the frequency range 250-500 Hz, 125-250 Hz, 63-125 Hz, 32-63 Hz, and 16-32 Hz, for a signal with 1 kHz sampling frequency. Such a decomposition separates the fundamental heart sounds (typical range 20-120 Hz) with murmur sounds (150-400 Hz), which helps in effective signal classification. The approximation level signal composed of less than 16 Hz frequency generally contains the noise and is discarded. The obtained coefficients are used to form a 1D array, which is used as a sample of the model.

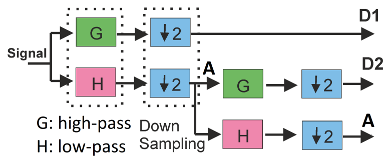

Fig. 2. Mallat tree for decomposition of the signal.

2.3. *Disease classification*

For the classification, a novel hybrid deep-learning model based on CNN and GRU networks has been proposed, as shown in Fig. 3. CNN network helps to identify the relevant patterns from the signal. At the same time, the GRU exploit the long-range time dependencies of patterns effectively and requires fewer parameters than more complex models like LSTMs (Long Short-Term Memory). Table 2 depicts the details of each layer used in the model. In

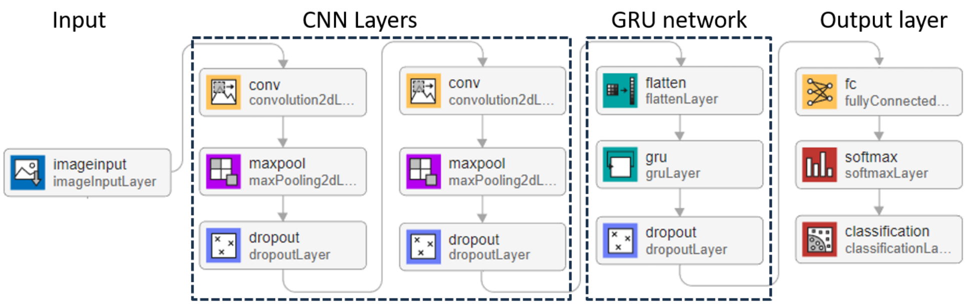

Fig. 3. Architecture of the proposed hybrid deep learning model.

the CNN network, there are two pairs of convolution, max-polling and dropout layers. The flattened output of CNN network is applied to the GRU network with 64 hidden units. In the end, a fully-connected layer with five neurons is present since there are five classes to classify. The softmax layer converts the output produced by the fully-connected layer to a probability associated with each class.

2.4. *CNN network*

The CNN network, which originated with the design of the LeNet by Y LeCun et al. [26], is primarily designed for visual data like images and videos. It has been widely used for various applications, including classification, object detection, segmentation, and more. CNN network automatically and adaptively processes the input and extracts valuable information to distinguish between multiple classes. CNN learns the kernel functions through backpropagation using different layers, such as convolution, pooling, and fully connected layers.

Table 2. Description of each layer used in the proposed hybrid model.

Layer	Learnable Properties	Number of Learnable
Convolution-1 32 filters 1x33, stride [1,1], padding same	Weight 1x33x1x32 Bias 1x1x32	1088
Maxpooling-1 max pooling [2x2], stride [1,1], padding same	-	0
Dropout-1 (50%)	-	0
Convolution-2 16 filters 1x13, stride [1,1], padding same	Weight 1x13x32x16 Bias 1x1x16	6672
Maxpooling-2 max pooling 2x2, stride [1,1], padding same	-	0
Dropout-2 (50%)	-	0
Flatten		0
GRU (64 units)	Input (192x47) RecurrenWeight (192x64) Bias 192x1	9050304
Dropout-3 (50%)	-	0
FullyConnected (5 classes)	Weights 5x64 Bias 5x1	325
Softmax	-	0
classification	-	0

In the proposed model, two layers of CNN have been used, as shown in Fig. 3. Each layer consists of a convolution, max-pooling, and dropout layer. The input size for the first layer is 2942, the number of DWT coefficients for each sample. The extracted features are first flattened and then applied as input to the GRU network.

2.5. GRU network

Long Short-Term Memory (LSTM) networks generally encounter the vanishing gradient problem. Cho et al. [27] proposed the Gated Recurrent Unit (GRU) as a solution. The GRU has demonstrated its effectiveness in capturing long-term dependencies. Fig. 4 shows a single unit of a GRU network. It consists of several gates, including the reset and update gates. These gates have a specific role in updating the network's hidden state at each time step during sequential data processing. The reset gate adaptively identifies which information from the past should be retained and which should be discarded, thus overcoming the vanishing gradient problem. At the same time, the update gate adds new information to the hidden state. By incorporating these additional gates, the GRU architecture effectively manages information flow, making it more robust and computationally efficient than traditional LSTM networks. The GRU's output is then calculated based on the updated hidden state. What sets GRUs apart is their ability to retain information from distant past steps without subjecting it to excessive temporal processing, as well as their capability to discard irrelevant information for accurate predictions.

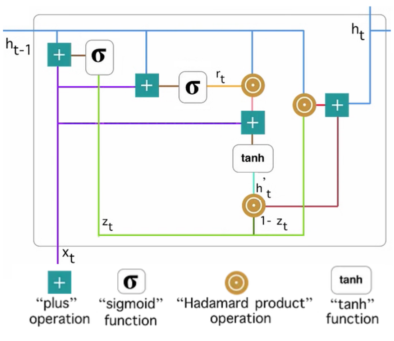

Fig. 4. One unit of GRU network [27]

3. Results and Discussion

The experiments are conducted on the Yaseen Khan dataset [5]. This dataset consists of a total of 1000 audio samples of five classes: 200 samples for each class, including Aortic Stenosis (AS), Mitral Valve Prolapse (MVP), Mitral Regurgitation (MR), Mitral Stenosis (MS), and Normal (N). Each pathological category contains 200 samples, resulting in a balanced dataset. Fig. 5 illustrates these different categories. Each audio sample has the following specifications: format (.wav), Bit Rate (128 kbps), quantization bits (16 bits per sample), and Duration (Approximately three seconds). The Matlab software (MathWorks Inc.) was used to conduct the experiments. Matlab offers a versatile and powerful environment for signal processing, data analysis, and machine learning tasks, making it well-suited for investigating heart sound signals in this study.

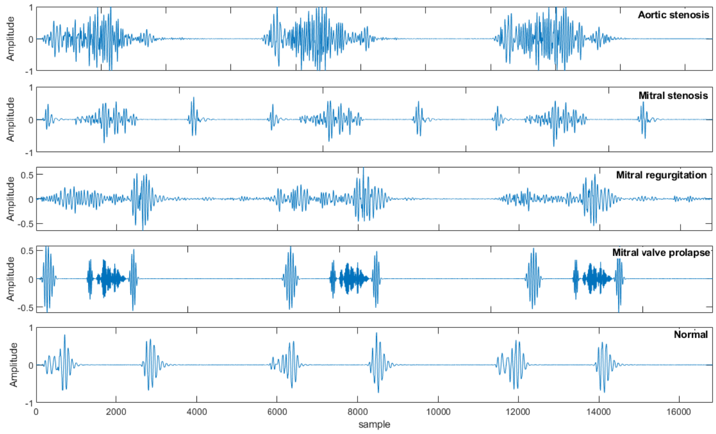

Fig. 5. Heart sound signal: Aortic stenosis, Mitral Stenosis, Mitral Regurgitation, Mitral Valve Prolapse, and Normal

3.1. Results using proposed model

A random partitioning of the dataset is performed to divide it into two sets: training (70%) and test (30%). The model's training process spans 100 epochs using SGDM optimization with a 0.01 learning rate and employing a batch size of 128 instances. Fig. 6 describes the training and validation phase of the model and the obtained accuracy and loss curve during these phases. Training of the module consumes 39 seconds on a single GPU (8GB RAM) system. The figure is indicating that the model gets trained satisfactorily around 100 iterations. However, training was performed till the 400 iterations to check if the model was getting overfitted. Since the validation loss decreased continuously, no overfitting was observed. It is possible due to the incorporation of the dropout layers helping the model to be better regularized.

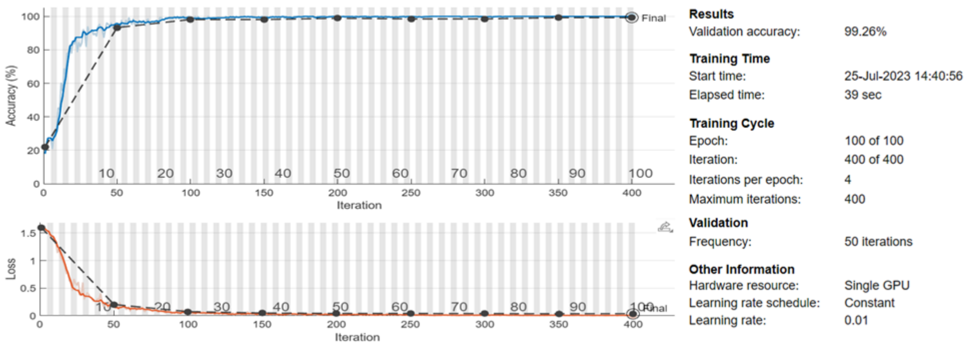

Fig. 6. Accuracy and loss curve during the training and validation of the model

The experiments are performed with the proposed hybrid model, as well as for the CNN model and GRU model individually. The confusion matrix obtained using these models is provided in Fig. 7. CNN model achieved 96.6% accuracy, the GRU model achieved 51.7% accuracy, and the hybrid model achieved 99.3% accuracy. It shows that the hybridization of CNN and GRU networks produces better results than the individual models. It is expected because the hybrid of CNN and GRU networks helps extract relevant patterns and exploit their time dependency. The CNN model alone produces satisfactory results. However, the GRU model's performance degrades drastically. These results indicate that the hybridization of the different models.

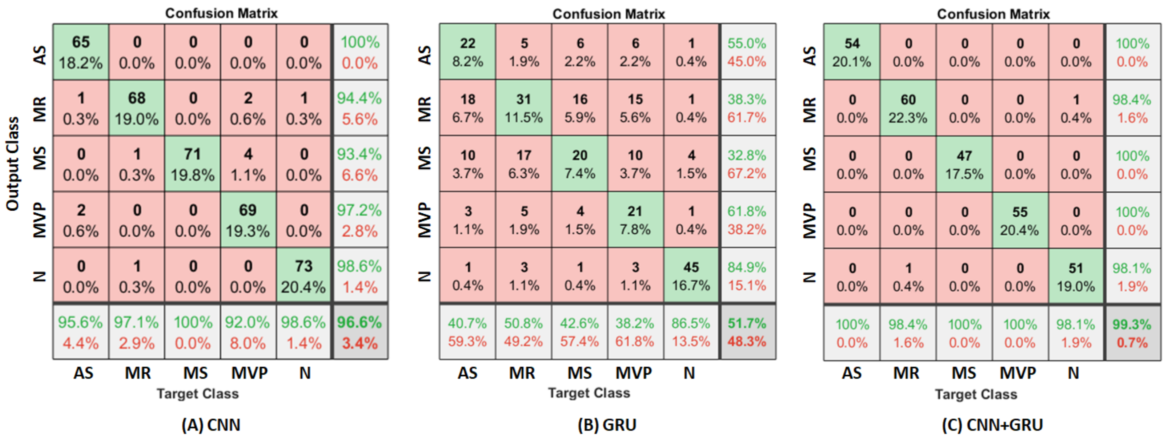

Fig. 7. Confusion matrix obtained for the hybrid model

Table 3 depicts the performance parameters obtained for the CNN, GRU and hybrid models. The results obtained using the hybrid model are superior for all five categories compared to the CNN and GRU models. The hybrid model achieved 100% F1-score for the classes AS, MS, and MVP, while 98.36% for MR and 98.08% for N. These results demonstrate the efficacy of the proposed hybrid model classifying all five heart sound signal categories. Such a system will be helpful for automatically analysing the heart sound signal.

Table 3. Obtained performance parameters using CNN+GRU model

Model	Class	sensitivity (%)	specificity (%)	precision (%)	recall (%)	F1-score (%)
CNN	AS	100	98.98	95.59	100	97.74
	MR	94.44	99.30	97.14	94.44	95.77
	MS	93.42	100	100	93.42	96.60
	MVP	97.18	97.91	92	97.18	94.52
	N	98.65	99.65	98.65	98.65	98.65
GRU	AS	55	86.03	40.74	55	46.81
	MR	0.3827	84.04	50.82	38.27	43.66
	MS	32.79	87.02	42.55	32.79	37.04
	MVP	61.76	85.53	38.18	61.76	47.19
	N	84.91	96.76	86.54	84.91	85.71
CNN+GRU	AS	100	100	100	100	100
	MR	98.36	99.52	98.36	98.36	98.36
	MS	100	100	100	100	100
	MVP	100	100	100	100	100
	N	98.08	99.54	98.08	98.08	98.08

3.2. Comparison with existing methods

Table 4 comprehensively compares the proposed model's performance with the latest methods presented in the literature, all using the same dataset. The hybrid deep-learning model produces an impressive 99.3% accuracy, which is superior to the compared methods. While some existing methods also show prominent results, the superior accuracy of the proposed model highlights its effectiveness in classifying heart sound signals. The proposed model's ability to achieve such high accuracy indicates its potential for providing reliable and precise diagnoses of heart valve disorders and other cardiac conditions. Its accuracy may reduce misdiagnoses and improve patient care, benefiting individuals with heart valve diseases and other cardiac disorders.

Table 4. Comparison with existing methods

Author (Year)	Feature extraction	Classification method	Accuracy
Khan et al. (2018)[15]	MFCC and DWT	SVM, KNN, and DNN	97.9%
Ghosh et al. (2019) [3]	wavelet synchrosqueezing transform	Random forest (RF) classifier	98.5%
Bhagel et al.(2020)[16]	Data augmentation	CNN	98.6%
Ranipa et al.(2021)[17]	MFCC, Mel Spectrum, and Spectrum contrast	CNN	98.5%
Shuvo et al.(2021)[18]	CNN based features	Bi-LSTM sequence residual learning	98.2%
Jain et. al. (2023) [10]	DWT	CNN	98.6%
Proposed hybrid model	DWT	CNN and GRU	**99.3%**

4. Conclusion

This paper proposed an innovative hybrid model combining two powerful deep learning approaches, CNN and GRU, to classify heart sound signals. The experimental results strongly support the effectiveness of the method. Two key factors are observed for these prominent results. First, using DWT to decompose the signal provides distinct and informative features that effectively differentiate heart sound categories. Secondly, the hybrid nature of the deep-learning model contributes significantly to the achieved results. As discussed, the CNN aims to extract meaningful patterns in the input, while the GRU uses time-dependent information to produce the output at present. This combination empowers the model to extract quasi-cyclostationary features which are exhibited in a typical heart sound signal. Such a system will be a boon for patients, especially the elderly and those in rural areas, to diagnose CVD early without visiting a medical expert. They will need to visit the medical expert only in case of abnormality is detected, thus reducing unnecessary visits. In future, the proposed model can be fine-tuned to effective classification even in environments contaminated by everyday noises, demonstrating its practicality beyond clinical settings.

Acknowledgements

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