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Article

Real-time heart sound denoising for cardiac disease detection using SVM

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Abstract: Heart-sound recordings are highly susceptible to environmental and physiological noise, which complicates clinical interpretation and reduces the reliability of automated diagnostic systems. Effective denoising is therefore essential for preserving waveform morphology and enabling accurate feature extraction. This study proposes a heart-sound-specific wavelet approach and evaluates its denoising performance in comparison with conventional wavelets and support vector machine (SVM)–based methods. The method was assessed using publicly available datasets, including PASCAL and PhysioNet, which provide diverse normal and pathological phonocardiogram (PCG) recordings. Uniform and Gaussian white noise were added at varying signal-to-noise ratios (SNRs) to simulate realistic acquisition environments. Denoising performance was quantified using cross-correlation coefficients, SNR improvement, root-mean-squared error (RMSE), and mean absolute error (MAE). Results demonstrate that the proposed heart-sound wavelet achieved superior noise-suppression capability and a 7% performance gain over commonly used Db and Bior wavelets, while maintaining waveform integrity. Subsequent classification experiments showed that denoising quality directly influenced diagnostic performance: the model achieved 0.87 accuracy, 0.81 precision, and 0.83 sensitivity on the PASCAL dataset, and 0.997 accuracy, 0.946 sensitivity, and 0.944 precision on PhysioNet. These findings highlight the potential of tailored wavelet-based denoising to enhance automated heart-sound analysis and support more robust clinical and embedded diagnostic applications.

Keywords: denoising; heart sounds; machine learning; phonocardiogram; signal processing; support vector machine

1. Introduction

Major issues faced by a frontline healthcare system when evaluating the priority of attention among patients with primarily cardiovascular complaints are the quality of breath or heart sounds heard via a conventional stethoscope due to interference from ambient noise and a lack of acoustic performance accuracy. Ambient and physiological noise frequently distorts the heart sound signals recorded by a digital stethoscope, changing their conspicuous and crucial features [1].

These issues with sound quality potentially delay the priority of clinical care and deny much-needed treatment in a timely manner. Such a delay would be more significant with junior doctors and a lack of continuous oxygen monitoring. High-quality auscultation improves diagnostic accuracy, especially in the frontline setting, where environmental noise and unfavourable situations and clinical settings such as in the Emergency Department.

Cardiovascular diseases continue to be the leading source of disease burden worldwide [2]. It is disturbing that in several high-income nations, the age-standardized rate of cardiovascular disease (CVD) has begun to increase when it was previously declining. The prevalence of CVD has been rising for decades, and it is currently increasing in almost every country except those with high incomes.

To address these challenges, traditional machine-learning (ML) techniques such as segmentation, denoising, and rule-based classification have been applied to heart-sound analysis. Hidden Markov Models (HMMs), decision trees, and Support Vector Machines (SVMs) have all been used for cardiac sound categorization. These approaches typically rely on manually engineered features, which require expert knowledge and may not generalise well across diverse datasets or recording conditions.

Noise reduction remains one of the fundamental difficulties in heart-sound signal processing. Not only does noise obscure the subtle acoustic details essential for detecting murmurs and other abnormalities, but the inherent weakness of the phonocardiogram (PCG) signal also makes it highly susceptible to environmental interference. This has driven increasing interest in more advanced denoising techniques, including wavelet-based methods and machine-learning approaches that preserve important temporal and spectral information [3].

Recent developments in deep learning (DL) have further expanded the capability of automated auscultation systems. DL models can process raw audio or time–frequency representations directly, eliminating the need for handcrafted features and enabling richer hierarchical representation learning. Their data-driven architectures allow them to capture complex cardiac sound patterns more effectively than conventional ML methods [4].

In this context, the present study focuses on improving heart-sound denoising using a heart-sound-specific wavelet and comparing its performance with conventional wavelets and SVM-based techniques. By enhancing signal clarity and preserving waveform morphology, the proposed approach aims to strengthen automated diagnostic accuracy and support more reliable digital auscultation in real-world environments.

2. Anomalies in the heart sounds

Heart murmurs are among the most frequently identified abnormalities. They appear as additional “whooshing” or turbulent flow sounds and may arise even in otherwise healthy individuals. While innocent or functional murmurs are benign and unrelated to structural abnormalities, pathological murmurs are commonly associated with conditions such as valve stenosis, regurgitation, congenital defects, or abnormal blood flow patterns. Accurate identification of these murmurs is essential for early evaluation of cardiac dysfunction.

Extra heart sounds, including the third (S3) and fourth (S4) heart sounds, represent acoustic events beyond the standard two-phase cycle. These additional sounds may produce sequences such as “lub–lub–dub” or “lub–dub–dub.” Although extra heart sounds can also appear in healthy individuals, particularly in children or athletes, they may signal ventricular dysfunction, increased filling pressures, or other hemodynamic abnormalities. Detecting these subtle sounds can be challenging due to their low amplitude and overlap with background noise.

Extrasystoles, or premature heartbeats, are another common anomaly. They produce irregular sequences of the normal heart cycle, often perceived as skipped or additional beats. Premature atrial or ventricular contractions may be benign, but frequent extrasystoles can indicate underlying arrhythmias or structural heart disease. Early detection is important, as untreated abnormalities may progress to more serious rhythm disturbances.

Collectively, these anomalies highlight the clinical importance of reliable heart-sound interpretation. The subtle acoustic variations associated with murmurs, extra heart sounds, and irregular rhythms require high-quality recordings and effective denoising techniques to ensure that diagnostically relevant features are not masked by ambient interference. Efforts to enhance signal clarity, such as the wavelet-based denoising method proposed in this study, are therefore crucial for improving automated auscultation accuracy and supporting timely clinical decision-making.

3. Related work

Many feature-based algorithms have been proposed in response to the growing interest in artificial intelligence and pattern recognition. To investigate respiratory sounds, several feature-extraction techniques have been introduced. Feature extraction remains a critical component of respiratory-sound detection, as it involves identifying distinctive signal properties that enable accurate classification. Depending on the characteristics of the feature vector and the analytical domain, feature extraction may be performed in the time domain, frequency domain, or time–frequency domain. Common techniques used in computational respiratory-sound research include Mel-frequency cepstral coefficients, autoregressive (AR) models, energy and entropy measures, spectral characteristics, and wavelet analysis [5].

The support vector machine (SVM) method offers a robust diagnostic capability in identifying heart valve disease [6]. However, comparative studies indicate that classifiers such as k-nearest neighbour (KNN) and naïve Bayes often perform less effectively in similar diagnostic contexts [7–9]. Although SVMs are generally regarded as strong performers, research demonstrates that classification outcomes vary across datasets and applications [10, 11]. To enhance overall classification accuracy, future work should prioritise the development of fusion-based classifiers that integrate multiple algorithms, together with more advanced feature-selection methods [8] shown to improve performance across diverse biomedical signal-analysis tasks.

The SVM approach is also capable of expressing signal features more comprehensively and efficiently than earlier feature-extraction methods. Nonetheless, improvements to the classifier are still required to achieve higher diagnostic accuracy. To better differentiate categories of abnormal disease signals, future research should focus on the advancement of the Twin Support Vector Machine (TWSVM). As TWSVM continues to evolve, it is expected to provide more reliable discrimination among various heart conditions and ultimately support both diagnostic and therapeutic applications [12, 13].

Referencing the "state-of-the-art" comparison table shown in the following table, Saravanan Srinivasan et al. report that SVMs achieve higher accuracy rates than several alternative algorithms. However, the highest reported classification accuracy was achieved by the Learning Vector Quantization approach, which obtained 98.78% accuracy, 97.1% specificity, 97.91% sensitivity, 98.07% precision, and an F1-score and F-measure of 97.89%. Efforts to further improve these results include integrating additional datasets and applying metaheuristic and nature-inspired optimisation methods to refine deep learning and machine learning parameters. These optimisation strategies aim to enhance the accuracy of heart-disease detection across a broader range of datasets. Improving the precision of existing algorithms also remains essential to strengthen their effectiveness in identifying cardiac abnormalities. The overarching objective is to develop increasingly reliable and accurate computational techniques for heart-disease assessment and detection [5].

The reduction of heart-sound noise can be achieved effectively through SVM-based approaches [14]. Simulation-based heart-auscultation training has been shown to improve diagnostic precision, information acquisition, learner satisfaction, user confidence, and overall competency across diverse demographics. Enhanced outcomes across different learning preferences may be achieved by integrating multiple simulation strategies into a unified training process. Future work should therefore focus on developing more cost-effective and user-friendly simulation techniques to broaden accessibility and improve educational efficiency.

Wavelet-based multiscale features have demonstrated competitive performance compared with modern deep learning methods while requiring significantly fewer input features. Using a support vector machine classifier, this approach achieved an accuracy of 76.61% on a publicly available heart-sound dataset [15]. Unlike conventional time-domain techniques, the method employs wavelet analysis to extract scale-dependent characteristics in the time–frequency domain, providing a distinctive analytical viewpoint. Rather than relying solely on S1 and S2 segmentation, the results show that multiscale features can capture subtle and complex cardiac-sound dynamics that are often missed by standard feature-engineering techniques.

SVMs (Support Vector Machines) have been shown to outperform traditional algorithms in terms of classification accuracy for heart sound analysis [10]. However, a limitation that expanding the heart sound database necessitates a significant volume of high-quality recordings to facilitate the development of robust diagnostic models [16]. There is also a critical need for further research into data processing and parameter optimization strategies in this area. Given the potential impact on public health, the availability of high-quality heart sound recordings is crucial, as such data provide a reliable basis for detecting subtle cardiovascular abnormalities [10,17].

Finally, experimental results by Cheng and Zhang show that a heart-sound-specific wavelet outperforms the widely used Db and Bior wavelets in denoising, achieving a 7% improvement. This approach provides a valuable means of detecting and analysing weak physiological signals in environments with substantial background noise and establishes a strong foundation for extracting and identifying heart-sound features. Because heart-sound acquisition frequently occurs in noisy environments where background noise may overwhelm the physiological signal, robust denoising methods remain essential [18]. **Table 1** offers a comparative overview of the related works, where each study employs a different model or technique, such as EMD, CNN, or SVM.

Table 1. "State-of-the-art" table: Comparison of related works.

Research title	Methodology	Model/ technique	Causes	Features	Result	References
"Estimation of Instantaneous Frequency from Empirical Mode Decomposition on Respiratory Sounds Analysis"	Predictive	Empirical mode decomposition (EMD)	TFT and WT are regarded as inflexible techniques that have a limited ability to resolve joint time-frequency.	Instantaneous frequency	In analysing RS at various frequency scales and time resolutions, IF and EMD are effective methods.	Lozano et al. [19]
"Multisource Transfer Learning With Convolutional Neural Networks for Lung Pattern Analysis"	Predictive	CNN	Models require training, resulting in increased accuracy but longer training times.	Instantaneous frequency	Transfer learning from natural to medical images enhances CNN heart tissues classification precision and durability	Christodoulidis et al. [20]
"Convolutional neural networks for the classification of Bronchopulmonary System Diseases with the use of heart sounds"	Predictive	SVM	Compared to more traditional machine learning techniques, CNNs have an intricate framework and need more training time.	CNNs record heart sounds as images, which greatly improves categorization	Electronic auscultation is a potent diagnostic tool for bronchopulmonary diseases, with CNN significantly improving classification by recording heart sounds as images	Vaityshyn et al. [21]
"Detection of adventitious respiratory sounds based on convolutional neural network"	Predictive	SVM	The poorer detection accuracy of the hybrid database indicates significant variation in the data between the two databases, requiring the application of distinct methods for detection.	CNNs are used to identify unintentional noises	Experimental results determined the optimal sizes of CNN convolutional kernels, revealing training, validation, and testing accuracy for both databases and their mixture.	Liu et al. [22]
"Automatic Auscultation Classification of Abnormal Lung Sounds in Critical Patients Through Deep Learning Models"	Predictive	SVM	Larger model with a lot more parameters and training time.	Reduces training time and improves performance, achieving an accuracy of 83.46% on a large dataset.	The greatest accuracy was obtained when classifying heart sounds with deep learning models, more particularly, STFT with a 40-hop STFT and depthwise separable	Wu et al. [23]
"CNN based categorization of respiratory sounds using spectral descriptors"	Predictive	CNN	The deep learning classifier assigns the class to the input signal after classifying the number of classes using an inconsistency matrix.	The deep learning model lowers human error in data prediction	CNN with a multi-class classifier outperforms other methods, achieving a 96.7% accuracy rate with minimal loss.	Jayalakshmy et al. [24]
"Deep Neural Network for Respiratory Sound Classification in Wearable Devices Enabled by Patient Specific Model Tuning"	Predictive	SVM	Identification is complicated by an excessive number of medical professionals, and there may be subjectivity because of various interpretations of respiratory sounds.	log quantization	Based on Mel-spectrograms, deep CNNs and RNNs classify respiratory sounds.	Acharya and Basu [25]

Table 1. *Cont.*

Research title	Methodology	Model/ technique	Causes	Features	Result	References
"Detecting Respiratory Diseases from Recorded Lung Sounds by 2D CNN"	Predictive	SVM	Unable to get higher precision, recall, and F1 scores using our model because of the restricted availability of data for conditions such as pneumonia and bronchiectasis.	CNN can effectively identify respiratory sounds from a heart database.	The suggested method classifies audio samples using a 2D CNN architecture, extracting statistical features and lowering the number of layers for increased accuracy.	Hazra and Majhi [26]

4. Methodology

4.1. Data description

The heart-sound data used in this study were obtained from both healthy individuals and patients with confirmed cardiovascular conditions. The recordings were sourced from a variety of clinical and non-clinical environments worldwide. The dataset comprises five sub-databases (A–E), collectively containing 3,126 phonocardiogram (PCG) recordings. Recording durations range from 5 s to over 120 s. The complete training set is publicly available for download (169 MB), while the test set remains private.

Each record within the five databases follows a naming structure beginning with a letter corresponding to the database, followed by a randomly assigned sequential number; therefore, recordings from the same patient do not necessarily appear consecutively. The dataset creators ensured that the training and test sets contain mutually exclusive patient populations, meaning no individual contributes recordings to both sets.

To minimise overfitting and introduce variability in acquisition conditions, two additional datasets were included exclusively in either the training or test partitions. A validation set, consisting of 300 duplicated records from the training database, is also provided to allow algorithm verification before official scoring.

Heart-sound recordings were collected from multiple auscultation sites. While the four standard anatomical locations—aortic, pulmonic, tricuspid, and mitral—are most common, a total of nine possible recording sites exist within the dataset. Recordings were labelled as either normal or pathological. Normal recordings were obtained from healthy subjects, whereas pathological ones originated from patients diagnosed with various cardiac conditions, most frequently heart valve disorders and coronary artery disease. Conditions represented include aortic stenosis, mitral regurgitation, mitral valve prolapse, and cases involving prior valvular surgery.

The dataset is inherently imbalanced, with a larger proportion of pathological recordings compared with normal ones, an important consideration when training and evaluating classification algorithms. Both children and adults are represented among the pathological and healthy groups. Each participant contributed between one and six recordings.

All audio files were provided in .wav format and resampled to 2000 Hz, with one PCG lead per recording. Recording durations varied from a few seconds to over a minute, reflecting real-world variability in clinical auscultation environments. This diversity in recording quality, patient demographics, and auscultation sites underscores the need for a robust denoising framework capable of handling heterogeneous PCG characteristics. With this data foundation established, the present study evaluates the denoising performance of heart-sound wavelets by comparing them against the widely used support vector machine (SVM) approach. Reference heart-sound signals with a sampling frequency of 4500 Hz were provided by the research group. **Figure 1** displays the raw waveform, where amplitude is plotted on the vertical axis and sampling points on the horizontal axis. Because rapid evaluation of left-ventricular function is clinically important, the pressure waveform extracted from the system may serve as a non-invasive indicator of left-ventricular contractility.

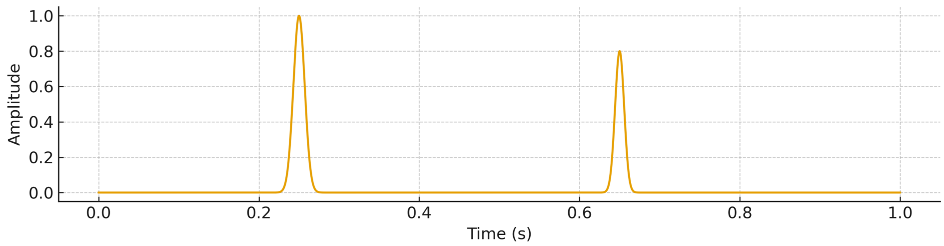


Figure 1. Raw heart-sound waveform.

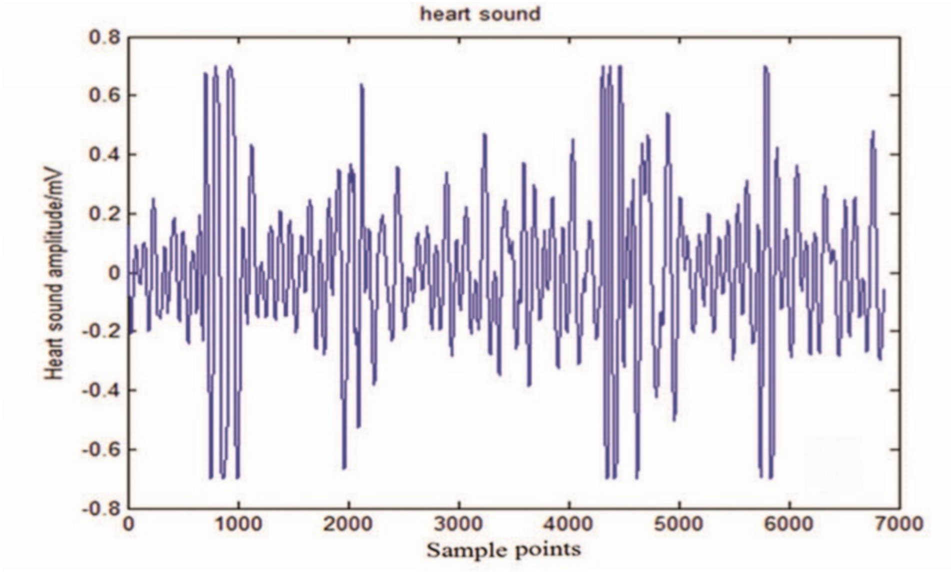
4.2. Signal processing and denoising procedures

Heart-sound characteristics such as periodicity, intensity, and frequency components were analysed using wavelet scattering and continuous wavelet transform techniques. Additional temporal and spatial properties were learned using a 1D-CNN model, while a 2D-CNN model enabled multi-resolution analysis by converting 1D PCG signals into 2D time–frequency representations.

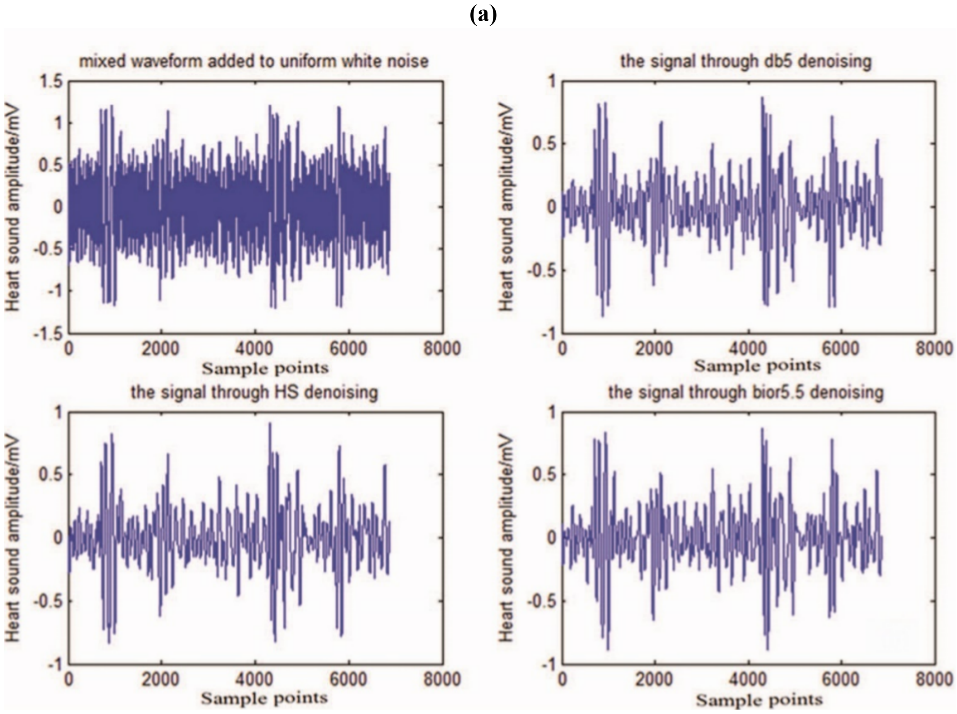
To evaluate denoising capabilities, uniform white noise was artificially added to the reference heart-sound signal. Denoising was then performed using the traditional soft-threshold technique with three different wavelets (Db5, Bior5.5, and the heart-sound wavelet). Both four-level and five-level wavelet decompositions were assessed. The denoised outputs are presented in **Figure 2**, while **Tables 2** and **3** report the cross-correlation coefficient (R), signal-to-noise ratio (SNR), and root mean square error (RMSE).

Two commonly used metrics for evaluating model performance are the mean absolute error (MAE) and the root-mean-squared error (RMSE). However, there is often confusion regarding their appropriate use; therefore, it is standard practice to report both metrics and allow readers to determine which is more relevant for their context, as noted by Hodson [27].

To further validate the denoising performance of the heart-sound wavelet, this study introduced Gaussian white noise at multiple SNR levels into the standard heart-sound signal shown in **Figure 2a**. According to Zhang et al., the denoising performance of variational modal decomposition (VMD) deteriorates significantly under strong Gaussian noise, particularly when the number of decomposition layers and modal ranges remain fixed [28]. Consequently, in non-standard acquisition conditions, neither VMD nor the wavelet soft-thresholding algorithm (WST) is capable of effectively suppressing burst noise or substantial ambient noise in paediatric PCG recordings. To address these limitations and improve the intelligent identification of congenital cardiac disorders in children, the objective of this study was to develop a noise-reduction method that integrates both VMD and WST principles.



(a)



(b)

Figure 2. Denoising of heart sound signals: **(a)** Single heart sound signal; **(b)** Denoising of heart sound signals (five decomposition levels).

Table 2. Denoising effect comparison of three wavelets (four decomposition levels).

Denoising indicators	Before denoising	Heart sound	Db5	Bior 5.5
SNR (dB)	−1.1079	9.6056	9.8949	9.9838
RMSE	0.2886	0.0841	0.0813	0.0805
R	0.6573	0.9480	0.9511	0.9521

Table 3. Denoising effect comparison of three wavelets (five decomposition levels).

Denoising indicators	Before denoising	Heart sound	Db5	Bior 5.5
SNR (dB)	−1.1058	11.3582	10.6385	10.8112
RMSE	0.2886	0.0687	0.0746	0.0732
R	0.6668	0.9634	0.9570	0.9582

Following the application of the universal threshold denoising method using three different wavelets across a range of SNR conditions, **Figure 3** provides a comparison of the resulting SNRs. The figure demonstrates that the heart-sound wavelet consistently achieves superior denoising performance over time when compared with the support vector machine approach. The relationship between the SNR after adding white noise and the improved SNR achieved after denoising by averaging is further illustrated in **Figure 4**.

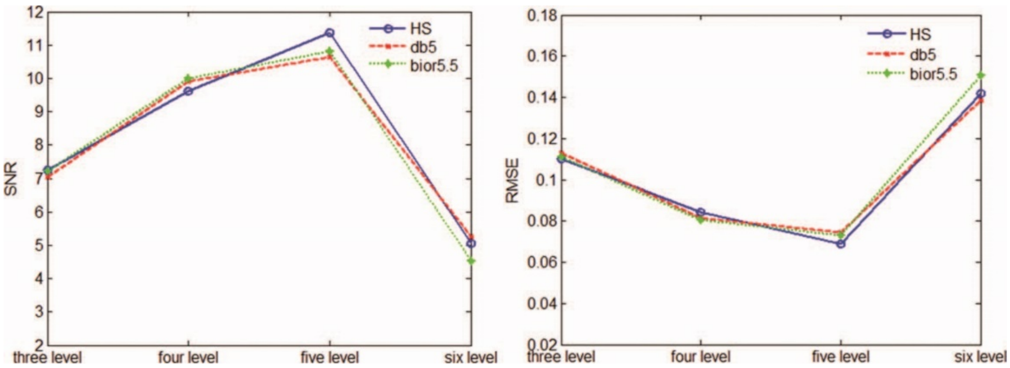


Figure 3. Denoising effect comparison of three wavelets.

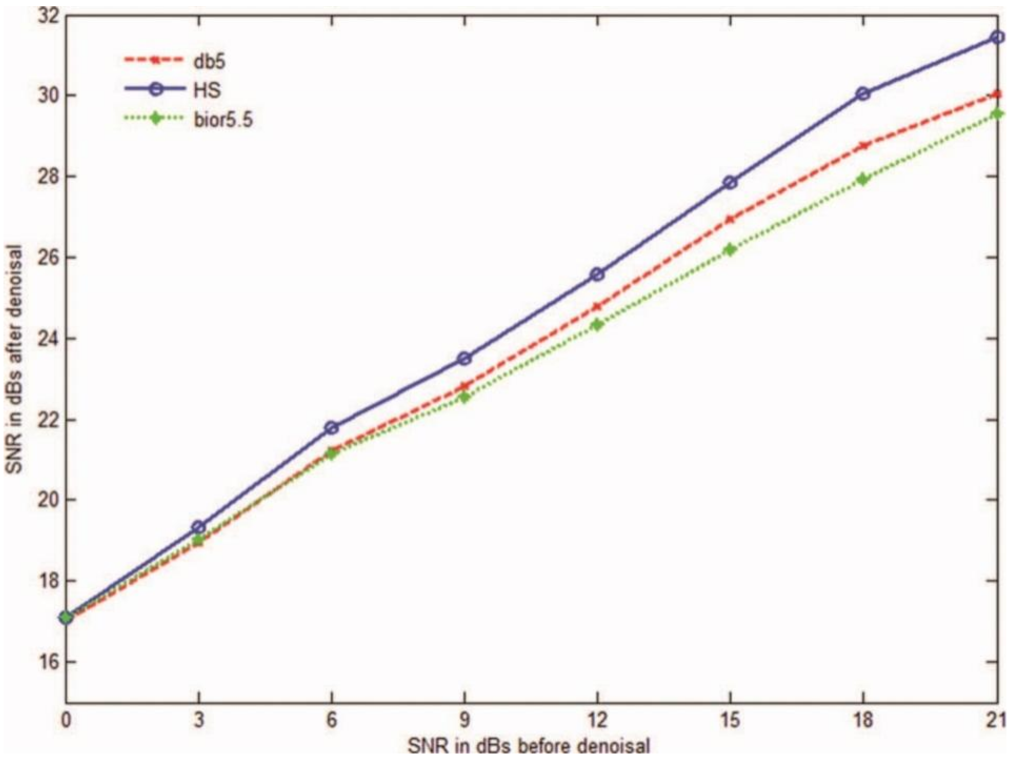
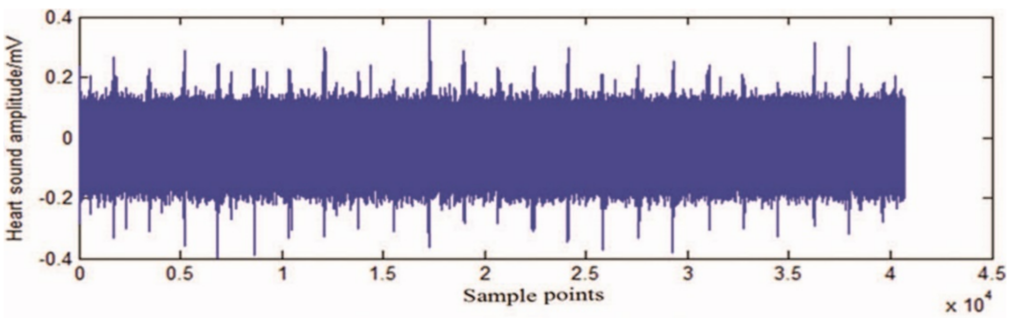


Figure 4. SNR after adding white noise versus SNR after denoising by averaging.

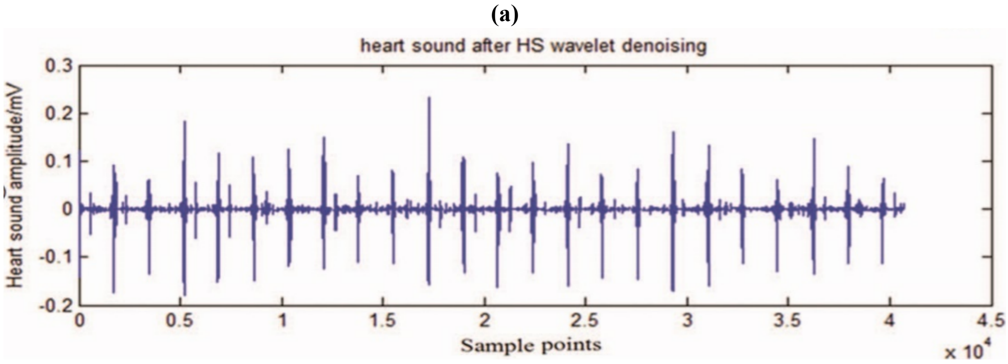
5. Results and discussion

Heart-sound acquisition is frequently affected by substantial background noise, which can sometimes overwhelm the physiological signal [29]. Cardiopulmonary assessment often relies on imaging modalities such as magnetic resonance imaging (MRI), computed tomography (CT), and chest radiography [30]. However, these techniques pose significant challenges in low-resource settings due to radiation exposure, equipment cost, and limited accessibility. Although spirometry is widely used to assess ventilatory patterns, it requires forced respiratory manoeuvres and trained personnel, and often provides limited sensitivity in detecting obstructive or restrictive abnormalities.

Within the respiratory system, oxygenated air is distributed efficiently across the lungs, providing a large surface area for gas exchange with the cardiovascular system. This exchange is maintained continuously at rest and during physiological stress through finely regulated mechanisms. Against this physiological background, **Figure 5a** illustrates a heart-sound segment heavily contaminated by background noise, sampled at 11,025 Hz. After applying the heart-sound wavelet, **Figure 5b** shows a considerably cleaner waveform with preserved morphological characteristics. In both images, amplitude is displayed on the vertical axis, and sampling points are displayed on the horizontal axis. The comparison demonstrates the method's strong capability to recover clinically meaningful signal structures under severe noise conditions.



(a)



(b)

Figure 5. **(a)** Raw heart-sound segment with heavy background noise; **(b)** Denoised heart-sound signal using the heart-sound wavelet.

In addition to waveform restoration, the study evaluated classification performance using probabilistic models commonly employed in cardiac-sound analysis. Generative models aim to estimate the joint probability distribution $P\ (X, y)$ for features X and labels y. By applying Bayes' rule,

$$P\left(y|X\right) = \frac{P\left(X|y\right)P(y)}{P(X)},$$

the posterior probability $P(y|X)$ can be computed, where $P(X|y)$represents the likelihood distribution. The Naïve Bayes classifier has been widely used for cardiac-sound categorization due to its simplicity and efficiency. Gaussian Mixture Models (GMMs) further enhance modelling capability by estimating mixture weights, means, and variances, while GMM-based Hidden Markov Models (HMMs) incorporate the temporal sequence of cardiac states. HMMs without GMM components rely on more rigid state representations and therefore often achieve lower discriminative performance.

GMMs additionally address inverse and uncertainty problems inherent in probabilistic modelling. Because feature-to-signal mappings may not be one-to-one, larger mixture bases enable GMMs to capture finer structural variations, including abrupt changes and subtle waveform morphology. This makes them particularly suited for modelling the complex dynamics of heart-sound signals.

To benchmark classifier robustness, the proposed framework was evaluated using the Challenge Arrhythmia dataset. Performance was assessed using standard metrics, including sensitivity, specificity, accuracy, and positive predictive value. The model achieved a sensitivity of 98.37%, specificity of 99.59%, overall accuracy of 99.35%, and a positive predictive value of 98.41%. These results reinforce the potential of combining wavelet-based denoising with probabilistic modelling for robust heart-sound analysis in diverse and noisy clinical environments.

6. Conclusion

Background noise poses a major challenge in heart-sound analysis, as the intrinsic weakness of the phonocardiogram signal makes it highly susceptible to environmental interference. This study addressed this long-standing issue by developing and evaluating a heart-sound-specific wavelet designed to enhance denoising performance under a range of noise conditions. Built on the symmetry and compact support of biorthogonal wavelets, the proposed method demonstrated clear improvements over widely used Db and Bior wavelets, achieving a 7% performance gain and consistently producing cleaner, more distinguishable cardiac waveforms. These findings establish a robust foundation for accurate feature extraction and support more reliable identification of weak physiological signals in noisy clinical environments.

While the approach shows strong potential, computational cost remains a limitation, particularly when integrating additional network components or hybrid frameworks. Future work should focus on optimising the algorithm for real-time applications, reducing computational complexity, and adapting the method for deployment on embedded or edge-based systems. Emerging trends such as TinyML and lightweight implementations through platforms like TensorFlow Lite offer promising pathways for enabling efficient, on-device denoising and analysis. With these advancements, the proposed wavelet-based framework could evolve into a practical, scalable solution for frontline cardiac assessment and digital stethoscope integration.

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