

## Highlights

### **Rapid auscultation techniques for acute heart failure in ambulance scenarios**

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- An auscultation dataset has been established, containing 2999 recordings from heart failure patients, each with rich annotations, and is publicly accessible on <https://github.com/qiuzhaoyu/AHF-Rapid-Diagnosis>.
- A DenseHF-Net model for diagnosing acute heart failure has been proposed, featuring only 0.33M parameters, making it suitable for rapid auscultation in ambulance scenarios.
- A multi-region fusion auscultation strategy with an accuracy of 99.25% has been proposed, capable of comprehensively analyzing heart sounds from the mitral valve, pulmonary valve, and aortic valve.
- A mitral valve auscultation strategy has been proposed, achieving an accuracy of 92.60% based on 15 seconds of auscultation of the mitral valve.

# Rapid auscultation techniques for acute heart failure in ambulance scenarios

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## ABSTRACT

**Background and Objectives:** Acute Heart Failure (AHF) results in over 26 million hospital admissions worldwide annually, posing a significant global health concern. Currently, AHF diagnosis relies on biochemical markers and echocardiography, which take more than 20 minutes. Auscultation, a quick and non-invasive clinical practice, is used alongside the gold standard. To address the need for rapid clinical AHF diagnosis, this paper presents a model for feature extraction and diagnosis using short heart sound signals.

**Methods:** Discrete wavelet transform was applied for heart sound denoising, and Mel Frequency Cepstrum Coefficients were used for feature extraction. A new DenseHF-Net is proposed for diagnosing heart failure. Additionally, a feature fusion method is introduced for multi-region fusion auscultation, including mitral, aortic, and pulmonic valves, along with an ensemble method for long auscultation in the mitral valve region.

**Results:** An auscultation dataset containing 2999 recordings, each with rich annotations, has been established. The proposed wavelet denoising algorithm achieved a signal-to-noise ratio of 7.8 dB. For multi-region fusion auscultation using DenseHF-Net, the average accuracy reached 99.25%. For mitral valve ensemble auscultation, the average accuracy was 92.60%.

**Conclusions:** The proposed method enables rapid auscultation for AHF, providing accurate results based on a 3-second auscultation recording. While multi-region fusion auscultation achieves high accuracy, mitral valve ensemble auscultation offers a good balance between efficiency and accuracy. This research has the potential to be applied in cardiac auscultation tools for mobile phones, cloud-based systems, or electronic gloves. Data and codes are accessible on <https://github.com/qiuzaoyu/AHF-Rapid-Diagnosis>.

## 1. Introduction

### 1.1. Background

Cardiovascular disease (CVD), including heart failure (HF) and stroke, has become the leading cause of death and disability worldwide [1–4]. The upward trend in the age-standardized rate of CVD is occurring in almost all non-high-income countries [2]. Heart failure is an end-stage in the development of CVD characterized by dysfunction of the contractile/stretching function of the heart. Acute heart failure is a leading cause of emergency hospital admissions, particularly in the elderly population [5, 6]. Acute heart failure (AHF) accounts for more than 26 million hospital admissions each year, with a mortality rate of 20–30% [7]. Emergency procedures for AHF include ambulance response, door-to-balloon, emergency, and ward transfer. Shortening the first two procedures can significantly reduce patient mortality and morbidity [8, 9]. Taking myocardial infarction as an example, which is one of the causes of AHF: the control group reduced ambulance response time by 15.3 minutes and door-to-balloon time by 36 minutes, decreased the length of hospital stay by 6.3 days, lowered the mortality rate by 12.33%, and reduced the rehospitalization rate by 19.69% [9]. Therefore, shortening the door-to-balloon

time in the emergency department for patients with AHF, and even completing the basic disease diagnosis during the ambulance response, can significantly improve the survival rate of patients. However, the traditional process of AHF diagnosis needs to be optimized. While some rapid methods, such as auscultation, are part of clinical examinations, their effectiveness needs further quantitative evaluation.

Traditional AHF diagnosis relies heavily on clinical biochemical trials, and there is a lack of convenient and accurate diagnostic methods, especially for 20% of patients with no history of chronic heart failure (CHF). According to the European Society of Cardiology's AHF First Aid Guidelines, the diagnostic criteria for AHF include clinical evaluation, electrocardiogram (ECG), chest x-ray and imaging techniques, laboratory tests, and echocardiography [10]. The diagnosis of AHF is usually based on the history and physical examination as well as physical tests to assist in the examining of ECG, echocardiography, and biochemical tests of brain natriuretic peptide (BNP) and NT-proBNP. At present, according to ten mainstream NT-proBNP and BNP biochemical detection equipment on the market, the waiting time for BNP results is 9–16 min, and the waiting time for NT-proBNP results is 11–21 min [11]. The ejection fraction obtained by echocardiography is also an important indicator in the preoperative evaluation of AHF [12], which takes about 20–30 minutes for a single examination, including five minutes for equipment location.

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Auscultation, as part of the clinical evaluation, is an effective means of diagnosing heart failure and is recommended by the European Society of Cardiology as class-1 [10]. Heart sounds are produced by the mechanical motion of the heart's dynamic system. They are the sum of various mechanical vibrations caused by the blood movement within the cardiovascular system. Considering the mechanism by which heart sounds are produced, they contain a wealth of information regarding the physiology of the cardiovascular system and are regarded as a visual description of the contractile and stretch function of the heart [4, 13, 14]. Normal heart sounds consist of 4 tones, called first heart sound (S1), second heart sound (S2), third heart sound (S3), and fourth heart sound (S4) in the order during the cardiac cycle. Mitral valve, aortic valve, and pulmonary valve are the three most commonly used auscultation areas. Different from ECG, heart sounds are a manifest of the ventricle's ability to pump blood, which can reflect pathological information better than ECG in a single cardiac cycle. In general, abnormal heart sounds have more background noise, greater S1 amplitude fluctuations and more high-frequency details than normal heart sounds.

## 1.2. Related works

The current research on digital auscultation technology encompasses aspects such as datasets, signal processing, and diagnostic models.

In terms of datasets, the most commonly utilized dataset is the one established by PhysioNet for the Heart Sound Classification Challenge in 2016 [15], including 665 abnormal heart sounds and 2575 normal heart sounds. Yaseen et al. [16] provided a five-classification dataset of Aortic Stenosis (AS), Mitral Regurgitation (MR), Mitral Stenosis (MS), Mitral Valve Prolapse (MVP) and Normal (N), with 200 cases of each type. Nonetheless, for the development of algorithms aimed at diagnosing a particular medical condition, the current dataset may exhibit limitations in terms of annotation richness. Therefore, to develop rapid diagnostic models for AHF, additional efforts are needed to refine the data and standardize inclusion criteria.

In terms of pre-processing and feature extraction for heart sounds, in Vepa's research [17], heart sound signals were processed based on Short-Time Fourier Transform (STFT) and Discrete Wavelet Transform (DWT). Wu et al. [18] extracted the MFCC components of heart sound signals based on the hidden Markov model (HMM) model. Existing techniques, such as feature extraction based on MFCC, have been highly successful and widely utilized in the processing of heart sounds. However, current heart sound processing techniques are primarily designed for long-duration signals, with some even exceeding 60 seconds, rendering them unsuitable for AHF rapid diagnosis.

In terms of diagnostic models, Rubin [19] used a convolutional neural network (CNN) for heart sound signal classification by time-frequency characteristics. Arora et al. [20] performed transfer learning of heart sound signals based on VIZ, MobileNet, Xception, VGG, ResNet, DenseNet and

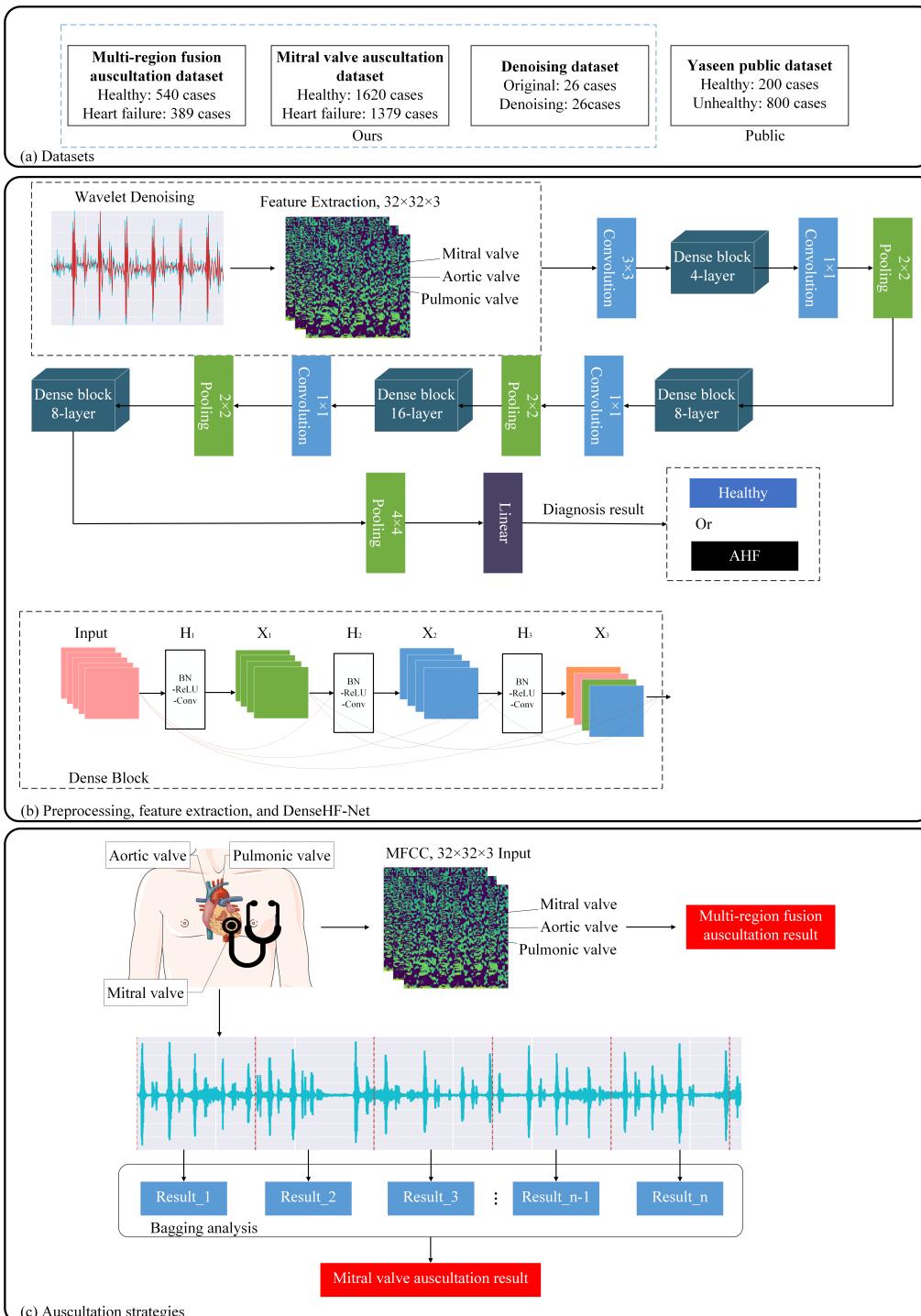
Inception. Scholars such as Li and Shuvo [21, 22] have developed end-to-end lightweight neural networks for clinical mobile devices. The established models are too large in size for rapid diagnosis of AHF. Therefore, we have developed lightweight models and introduced different auscultation strategies for various clinical scenarios.

To address the challenges of signal processing and diagnostic model in AHF auscultation, our main contributions are:

- An auscultation dataset has been established, containing 2999 recordings from heart failure patients, aiming at addressing the challenges in heart failure auscultation. This dataset encompasses comprehensive information, including diagnostic results, collection area annotations, medical history records, and annotations related to BNP and NT-proBNP. Additionally, this dataset has undergone a rigorous ethical review process and is publicly accessible on <https://github.com/jimmytju/AHF-Rapid-Diagnosis/Database>.
- A wavelet denoising algorithm and a lightweight DenseHF-Net have been developed for short-duration auscultation signals, aiming at rapid diagnosis of acute heart failure. The denoising algorithm proposed in this paper has improved the average signal-to-noise ratio to 7.8 dB. DenseHF-Net has only 3.82M parameters and is easily ported to low-computation scenarios such as mobile terminals.
- We have introduced two auscultation strategies: multi-region fusion auscultation and mitral valve auscultation. Multi-region fusion auscultation is designed for scenarios where long-time auscultation is possible, such as monitoring situations. It utilizes the three most crucial regions, namely, the mitral valve region, aortic valve region, and pulmonic valve region. On the other hand, mitral valve auscultation is specifically designed for rapid diagnosis in cases of heart failure emergencies, focusing solely on the mitral valve auscultation region. It completes the diagnosis within 15 seconds with an accuracy of 94.41%, representing only a 4.94% reduction compared to the multi-region fusion strategy.

## 2. Materials and Methods

Fig. 1 illustrates the methodology employed in this paper. Firstly, in order to address the data scarcity issue in the development of AHF diagnostic models, we have created several datasets. We create a multi-region fusion auscultation dataset, containing 540 healthy cases and 389 heart failure cases. Each case includes three audio recordings corresponding to the mitral valve, aortic valve, and pulmonic valve. Additionally, a mitral valve auscultation dataset is established, containing 1620 healthy cases and 1379 heart failure cases, with each recording lasting between three to five seconds.



**Figure 1: Methodology of the proposed work.** (a) A dataset was built in this paper, including two HF diagnostic subsets, a denoising subset, and a public subset. (b) The layered architecture of the proposed DenseHF-Net contains four Dense blocks. (c) Multi-region fusion auscultation and mitral valve auscultation.

Next, in response to the signal processing and lightweight requirements for rapid AHF diagnosis, we have developed a wavelet denoising algorithm and a lightweight DenseHF-Net. We explore a wavelet denoising algorithm specifically designed for short-duration heart sound signals to reduce noise effectively. Subsequently, we employ the MFCC algorithm to extract one-dimensional

sound signals into two-dimensional image features. Finally, a DenseHF-Net is used to train on the MFCC features.

Two distinct auscultation strategies are introduced in this paper. 1. Multi-region fusion auscultation is designed for scenarios where long-time auscultation is possible, using the fusion characteristics of the mitral valve, aortic valve, and pulmonic valve as input features. 2. Mitral valve auscultation

is specifically designed for AHF rapid diagnosis in cases of ambulances. In the case of mitral valve auscultation lasting more than 10 seconds, an ensemble method is proposed.

## 2.1. Datasets

### 2.1.1. HF auscultation datasets

The heart sound databases were acquired at Tianjin 4th Center Hospital of China between 2021 and 2022. The data were recorded using a 3M™ Littmann® electronic stethoscope 3200, with a sampling rate set at 22kHz. This project was approved by the medical ethics committee of Tianjin 4th Center Hospital of China (No. 2022-T050). All volunteers have signed an informed consent.

Under the guidance of two chief physicians, we collected heart sounds from heart failure patients in various departments to create a pathological dataset. We recruited volunteers among patients diagnosed with heart failure, recorded auscultation at three different regions, and simultaneously documented their gender, age, hospitalization information, medical history, and the latest biochemical markers. Afterward, the chief physicians reviewed the data to exclude samples that had already recovered from heart failure or had unclear signs of heart failure features. Finally, heart sounds from a healthy population were collected in the same manner to serve as a comparison group. As shown in Tab. 2, the HF auscultation dataset consists of a total of 71.6 minutes of heart failure auscultation and 81 minutes of the comparison group auscultation.

The multi-region fusion auscultation dataset comprises 540 healthy cases and 389 cases of heart failure. Each case includes three audio recordings of the mitral valve, aortic valve, and pulmonic valve. To ensure robustness, we established a 10-fold cross-validation database after shuffling.

The mitral valve auscultation dataset consists of 1620 healthy cases and 1379 cases of heart failure, with each case featuring audio recordings lasting three to five seconds. Similar to the previous dataset, we created a 10-fold cross-validation database after shuffling.

### 2.1.2. Denoising dataset

As shown in Fig. 1a, we have created a comparative dataset before and after denoising, encompassing 26 different pathological descriptions. The initial 26 recordings are characterized as noisy signals, encompassing various common abnormal heart sounds. In contrast, the remaining 26 control recordings were subsequently reviewed and verified by two medical professionals to eliminate background noise while preserving all relevant pathological information.

### 2.1.3. Yaseen public dataset

As shown in Fig. 1a, we also use a publicly available Yaseen dataset [16]. This dataset includes Aortic Stenosis (AS), Mitral Regurgitation (MR), Mitral Stenosis (MS), Mitral Valve Prolapse (MVP), and Normal (N). The main purpose is to evaluate the model's generalization ability in diagnosing normal and abnormal heart sounds. We employ 80% training data and 20% testing data. Each case is recorded for a duration of 2 seconds.

## 2.2. Preprocessing

The preprocessing of heart sound signals aims to depress the noisy background in clinical environments. Wavelet transform is used to decrease the noise of heart sounds based on mother wavelets, such as Haar, db, Coif, Sym, and Biorthogonal (bior). Chen et al. [23] achieved optimal denoising results using the db6 wavelet basis. Zhao et al. [24] reported the best outcomes with the bior5.5 basis. Cheng et al. [25] utilized wavelet-based adaptive algorithms to enhance the denoising of heart signals, resulting in a signal improvement of 12.4 dB compared to the pre-denoising state.

In this paper, we consider three wavelet functions: db6, sym8, and coif5. These wavelet bases are used for the discrete wavelet decomposition of heart sound recordings. Following the decomposition, discrete wavelet reconstruction is performed, with a coefficient shrinkage function applied at a threshold of 20% modulo the maximum hard threshold.

Secondly, in order to determine the coefficient contraction strategy, various coefficient contraction functions are applied during both the discrete wavelet decomposition and reconstruction processes.

We introduce a novel self-adaptive threshold function, as depicted in Eq.(1).

$$f_{self}(x, T) = \begin{cases} e^{\frac{x+T}{2}} - e^{\frac{-x-T}{2}} & x \leq -T \\ 0 & -T \leq x \leq T \\ e^{\frac{x-T}{2}} - e^{\frac{-x+T}{2}} & x \geq T \end{cases} \quad (1)$$

$f_{self}$  has the following three advantages:

- $f_{self}$  satisfies:

$$\lim_{x \rightarrow -T^-} f_{self}(x) = \lim_{x \rightarrow -T^+} f_{self}(x) = 0$$

$$\lim_{x \rightarrow T^-} f_{self}(x) = \lim_{x \rightarrow T^+} f_{self}(x) = 0$$

$f_{self}$  is differentiable at  $x = \pm T$

- $f_{self}$  is odd, with smooth and monotonically increasing curves.
- $f_{self}$  can overcome the problem of discontinuities in the hard threshold function so that the reconstructed signal retains more detailed information after the reconstruction.

We collect statistical data on the average signal-to-noise ratio (SNR) under different coefficient contraction functions and thresholds.

## 2.3. Feature extraction

Feature extraction for heart sound signals aims to reduce the dimensionality of the data, highlight key information, and thereby improve the subsequent data processing and analysis. Mel Spectrum and MFCC have widely employed feature extraction methods in speech recognition. Human perception of frequency is non-linear, with greater sensitivity to low-frequency signals compared to high-frequency

ones. Consequently, frequency conversion is performed according to the equation Eq.(2).

$$Mel(f) = 2595 \ln \left( 1 + \frac{f}{700} \right) \quad (2)$$

To reproduce the Meier scale in the processing of discrete digital signals, the power spectral estimates of the resulting periodic plot are filtered using a Mehr filter bank (usually 26 V-Band Pass filter banks), as shown in Eq.(3).

$$H_m(k) = \begin{cases} \frac{k-f(m-1)}{f(m)-f(m-1)} & f(m-1) \leq k \leq f(m) \\ \frac{f(m+1)-k}{f(m+1)-f(m)} & f(m) \leq k \leq f(m+1) \\ 0 & others \end{cases} \quad (3)$$

Multiply with FFT to get the Mel spectrum:Eq. (4).

$$MelSpec(m) = \sum_{k=f(m-1)}^{f(m+1)} H_m(k) * |X(k)|^2 \quad (4)$$

Calculate the logarithmic energy output of the V-Band Pass filter bank: Eq.(5). Discrete cosine transform (DCT): Eq. (6) to obtain the MFCC coefficient.

$$S(m) = \ln \left( \sum_{k=0}^{N-1} |X_a(k)|^2 H_m(k) \right), 0 \leq m \leq M \quad (5)$$

$$C(n) = \sum_{m=0}^{N-1} S(m) \cos \left( \frac{\pi n(m-0.5)}{M} \right), n = 1, 2, \dots, L \quad (6)$$

The L order refers to the order of the MFCC coefficient, usually 12-16. M is the number of triangular filters.

The MFCC feature design in this paper is defined as Wu et al. [18] and has achieved the same time-frequency extraction effect as Vepa [17], as shown in Fig. 1a.

## 2.4. DenseHF-Net

The common deep learning model architecture for heart sound diagnosis includes Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Long Short-Term Memory networks (LSTM), and Convolutional Neural Network-Long Short-Term Memory network hybrids (CNN-LSTM) [19–22]. This paper focuses on model design specifically tailored for AHF rapid diagnosis, aiming to develop a model that balances lightweight characteristics with accuracy.

We introduce DenseHF-Net, which is based on the CVPR 2017 Best Paper, Dense-Net [28]. To achieve model lightweight, DenseHF-Net employs only four Dense Blocks: DenseBlock-1, DenseBlock-2, DenseBlock-3, and DenseBlock-4. This choice reduces the model's parameter count and computational load while still maintaining a certain level of depth and feature extraction capability. Three transition layers with small compression rates are employed simultaneously to reduce the output channel numbers of the 1x1 convolutional layers, thereby reducing the size of feature

maps. Ultimately, the diagnostic results are obtained after passing through a linear layer. The parameter settings for the three models are detailed in Tab. 1.

The classic ResNet [26] and MobileNet [27] models are also trained for comparison with DenseHF-Net. All input features are resized to 32×32 to make it more convenient for mobile terminals. The parameter numbers of the three models are 0.33M, 42.61M, and 12.24M. The Memory Access Cost (MAC) of the three models are 30.64M, 556.97M, and 46.28M.

Experimental environment system: Ubuntu 18.04; CPU: Intel(R) Core(TM) i7-9700K CPU @ 3.60GHz; GPU: NVIDIA GeForce RTX 3090 with 24G VRAM; CUDA Version: 11.4; Pytorch Version:1.10.

## 2.5. Auscultation strategies

The multi-region fusion auscultation strategy is designed for AHF diagnosis in hospitals, with the aim of reducing the door-to-balloon time. Then to reduce the mortality rate and rehospitalization rate of HF patients [9]. Heart sound signals are synchronously collected from three regions, including the mitral valve region, aortic valve region, and pulmonic valve region.

The processing pipeline includes three main steps:

1. Applying wavelet transform to the three channels of heart sound to reduce noise.
2. Feature extraction using the MFCC.
3. Fusion of the three MFCC feature sets to produce input of the same dimension as that of the mitral valve auscultation.

The mitral valve auscultation strategy is designed for emergency medical services (EMS) or general screening scenarios, with a stronger emphasis on convenience, aiming to complete the diagnosis within 15 seconds.

As shown in Fig. 1c, for mitral valve auscultation durations exceeding 10 seconds, there arises the need to address the challenge of reducing false positive diagnoses. To tackle this issue, this research paper introduces an ensemble learning method as a strategic approach.

$$\begin{aligned} Result_i &= \max_{\alpha_i} Softmax(\alpha_i) \\ &= \max_{\alpha_i} \frac{\exp(\alpha_i)}{\sum_{i=1}^n \exp(\alpha_i)} \end{aligned} \quad (7)$$

Eq.7 is used to calculate the diagnostic results for a single fragment.  $\alpha_i$  represents the model output.  $Result_i$  is 0 for healthy and 1 for heart failure.

$$Output = Result_1 \vee Result_2 \vee \dots \vee Result_n \quad (8)$$

Eq.8 represents the result of a one-to-one OR operation applied to auscultation segments, designed to minimize the occurrence of false positives. Here, 'n' denotes the number of fragments, typically set to 3.

**Table 1**  
Models parameter setting

DenseHF-Net (ours)			ResNet-18 [26]			MobileNetV1-28 [27]		
Layer	Filters	Output	Layer	Filters	Output	Layer	Filters	Output
Feature Map	$[3 \times 3, 24] \times 1$	$32 \times 32$	Feature Map	$[3 \times 3, 64] \times 1$	$32 \times 32$	Feature Map	$[3 \times 3, 32] \times 1$	$30 \times 30$
Dense Block	$[1 \times 1, 48] \times 4$	$32 \times 32$	Conv2_x	$[3 \times 3, 64] \times 2$	$32 \times 32$	Conv_dw,pw	$[3 \times 3, 32] \times 1$	$30 \times 30$
Transition	$[1 \times 1, conv]$ $[2 \times 2, pool]$	$16 \times 16$	Conv3_x	$[3 \times 3, 128] \times 2$	$16 \times 16$	Conv_dw,pw	$[3 \times 3, 64] \times 1$	$15 \times 15$
Dense Block	$[1 \times 1, 48] \times 8$	$16 \times 16$	Conv4_x	$[3 \times 3, 256] \times 2$	$8 \times 8$	Conv_dw,pw	$[3 \times 3, 128] \times 1$	$15 \times 15$
Transition	$[1 \times 1, conv]$ $[2 \times 2, pool]$	$8 \times 8$	Conv5_x	$[3 \times 3, 512] \times 2$	$4 \times 4$	Conv_dw,pw	$[3 \times 3, 128] \times 1$	$8 \times 8$
Dense Block	$[1 \times 1, 48] \times 16$	$8 \times 8$	Pooling	$4 \times 4$	$1 \times 1 \times 512$	Conv_dw,pw	$[3 \times 3, 256] \times 1$	$8 \times 8$
Transition	$[1 \times 1, conv]$ $[2 \times 2, pool]$	$4 \times 4$	Linear		$1 \times 2$	Conv_dw,pw	$[3 \times 3, 256] \times 1$	$4 \times 4$
Dense Block	$[1 \times 1, 48] \times 8$	$4 \times 4$				Conv_dw,pw	$[3 \times 3, 512] \times 5$	$4 \times 4$
Pooling	$4 \times 4$	$1 \times 1 \times 384$				Conv_dw,pw	$[3 \times 3, 512] \times 1$	$2 \times 2$
Linear		$1 \times 2$				Conv_dw,pw	$[3 \times 3, 1024] \times 1$	$2 \times 2$
						Pooling	$2 \times 2$	$1 \times 1 \times 1024$
						Linear		$1 \times 2$

### 3. Results

#### 3.1. Datasets

Tab. 2 shows the details of the dataset in this paper. The details include the age and gender composition of auscultation volunteers, and case descriptions for the denoising dataset. Auscultation dataset contains 2999 recordings from heart failure patients, each with rich annotations, and are publicly accessible on <https://github.com/qiuzhaoyu/AHF-Rapid-Diagnosis/tree/main/Database>.

#### 3.2. Preprocessing

Firstly, we conduct an analysis to determine the average SNR under various combinations of wavelet bases and decomposition layers, using a coefficient shrinkage function based on the 20% modulo maximum hard threshold. The results of this analysis are presented in Fig. 2, which clearly indicates that the Sym8 base at the 7-layer decomposition level yields the most effective denoising results among the tested methods.

Secondly, we further investigate the average SNR across different shrinkage functions and threshold values while maintaining the sym8 base at the 7-layer decomposition level. Our findings indicate that the use of the 20% modulo maximum with the  $f_{self}$  threshold function emerged as the optimal denoising method.

Finally, the average SNR of the denoising algorithm proposed in this paper is 7.8 dB.

#### 3.3. Multi-region fusion auscultation

The quality of models refers to Eq.9: Accuracy (Acc), Eq.10: Sensitivity (Se), Eq.11: Specificity (Sp) and Eq.12: F1-Score.

$$Acc = \frac{TP + TN}{TP + FP + TN + FN} \quad (9)$$

$$Se = \frac{TP}{TP + FN} \quad (10)$$

$$Sp = \frac{TN}{TN + FP} \quad (11)$$

$$F1 - Score = 2 \times \frac{Se \times Sp}{Se + Sp} \quad (12)$$

Tab.3 presents the classification results on the HF-Diagnosis dataset and the public Yassen dataset, comparing the performance of three models: DenseHF-Net, ResNet-18, and MobileNetV1-28.

DenseHF-Net achieves the highest accuracy ( $99.25\% \pm 0.71\%$ ) and specificity ( $99.44\% \pm 0.75\%$ ), demonstrating strong classification performance with an F1-score of  $99.10\% \pm 0.64\%$ . In comparison, ResNet-18 has an accuracy of  $98.71\% \pm 1.26\%$  with lower specificity ( $98.10\% \pm 2.68\%$ ), though its sensitivity is close to DenseHF-Net. MobileNetV1-28 excels in sensitivity ( $100.00\% \pm 0.00\%$ )

**Table 2**

The details of the dataset information.

HF datasets			
Group	Age( $\bar{x} \pm sd$ )	Sex	Length(min)
Healthy	24	Male	27.0
Healthy	26 ± 2	Female	54.0
HF	72.6 ± 12.0	Male	34.8
HF	77.9 ± 11.1	Female	36.8

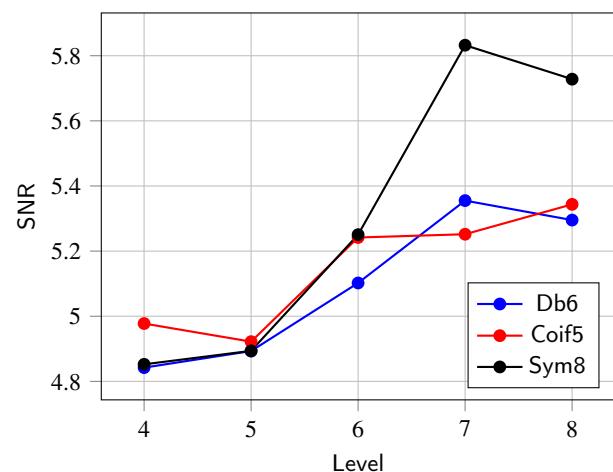
Denoising dataset		Length(s)
Description		Length(s)
Systolic murmur		68
Functional aortic stenosis		4
Musical noise		23
Organic mitral regurgitation		59
Functional mitral stenosis		9
Organic mitral stenosis		9
Diplogue		39
Paradoxically divided		13
Varied S1		23
Weak S1		3
Split S1		4
Strong S1		6
Weak S2		29
Split S2		12
Ventricular septal defect		9
Open flap sound		10
Late contraction		9
Relative mitral regurgitation		4
Sinus bradycardia		7
Sinus tachycardia		4
Functional pulmonary regurgitation		3
Pulmonary stenosis		67
Diastolic tetra tone		15
Continuous murmur		15
Overlapping galloping sound		9
Pendulum sound		6

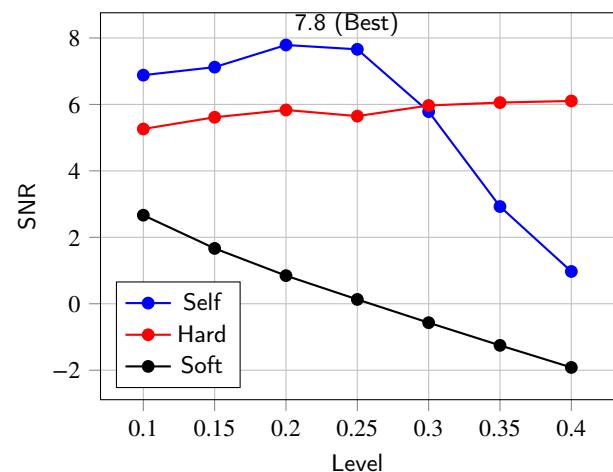
Yaseen dataset		Number
Description		Number
Aortic Stenosis		200
Mitral Regurgitation		200
Mitral Stenosis		200
Mitral Valve Prolapse		200
Normal		200

but has slightly lower specificity ( $97.95\% \pm 1.54\%$ ), with overall performance similar to DenseHF-Net. In summary, DenseHF-Net offers the best balance between sensitivity and specificity, making it the preferred model for HF-Diagnosis tasks.

Fig.3 provides a comprehensive overview of the average performance across the mitral valve auscultation dataset. Notably, ResNet-18 and MobileNetV1-28 exhibit comparable performance, while DenseHF-Net exhibits the most rapid rate of improvement. Importantly, all three models exhibit effective convergence of the loss function. It is



(a) Choice of base and levels



(b) Choice of threshold parameters

**Figure 2: Wavelet denoising of short signal.** (a) Best: wavelet denoising with sym8 base at 7-layer decomposition. (b) Best: wavelet denoising with 20% modulo maximum  $f_{self}$ .

worth highlighting that both ResNet-18 and MobileNetV1-28 demonstrate similar performance trends, with DenseHF-Net demonstrating the fastest convergence among them.

Tab.3 also presents the results obtained from the Yaseen dataset. DenseHF-Net, ResNet-18, and MobileNetV1-28 typically reached convergence around 50 epochs. The AS diagnosis exhibits the best performance, with sensitivity and specificity exceeding 82% across all three models. For MS and MR, all three models achieve correct diagnoses, with sensitivity and specificity exceeding 87% in both ResNet-18 and MobileNetV1-28. However, MVP diagnosis by DenseHF-Net yields suboptimal results, with a specificity of only 30% and an F1-Score of only 45.88%.

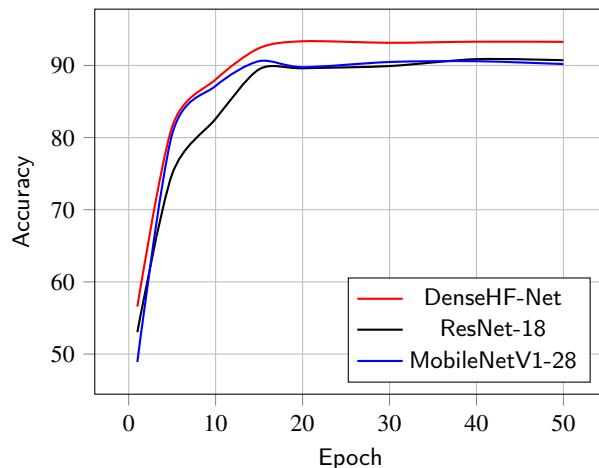
### 3.4. Mitral valve auscultation

For mitral valve auscultation, DenseHF-Net demonstrates the best performance with an accuracy of  $92.60\% \pm 1.11\%$ , along with a good balance between sensitivity ( $92.68\% \pm 0.88\%$ ) and specificity ( $92.53\% \pm 2.08\%$ ), as

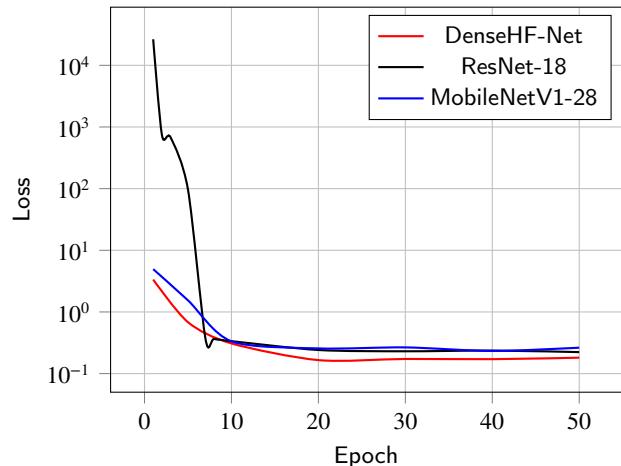
**Table 3**

Classification results of HF-Diagnosis dataset and public Yassen Dataset.

Multi-region fusion auscultation results												
DenseHF-Net(ours)	Average $\pm$ sd	ResNet-18	Average $\pm$ sd									
Acc(%)	99.25 $\pm$ 0.71	Acc(%)	98.71 $\pm$ 1.26									
Se(%)	98.97 $\pm$ 1.22	Se(%)	99.09 $\pm$ 0.92									
Sp(%)	99.44 $\pm$ 0.75	Sp(%)	98.10 $\pm$ 2.68									
F1 – Score(%)	99.10 $\pm$ 0.64	F1 – Score(%)	98.59 $\pm$ 1.49									
Mitral valve auscultation results												
DenseHF-Net(ours)	Average $\pm$ sd	ResNet-18	Average $\pm$ sd									
Acc(%)	92.60 $\pm$ 1.11	Acc(%)	91.33 $\pm$ 2.48									
Se(%)	92.68 $\pm$ 0.88	Se(%)	92.32 $\pm$ 2.59									
Sp(%)	92.53 $\pm$ 2.08	Sp(%)	90.20 $\pm$ 4.49									
F1 – Score(%)	92.01 $\pm$ 2.15	F1 – Score(%)	91.17 $\pm$ 2.58									
Yaseen dataset results												
DenseHF-Net(ours)		ResNet-18										
	AS	MR	MS	MVP	AS	MR	MS	MVP	AS	MR	MS	MVP
Acc(%)	91.25	58.75	75.00	63.75	92.50	88.75	95.00	83.75	82.50	92.50	85.00	88.75
Se(%)	90.00	97.50	75.00	97.50	95.00	80.00	90.00	80.00	87.50	87.50	87.50	87.50
Sp(%)	92.50	20.00	75.00	30.00	90.00	97.50	100.00	87.50	77.50	97.50	82.50	90.00
F1 – Score(%)	91.23	33.19	75.00	45.88	92.43	87.89	94.74	83.58	82.20	92.23	84.93	88.73



(a) Mitral valve auscultation testing accuracy.



(b) Mitral valve auscultation testing loss value.

**Figure 3: Average 10-fold CV history. (a)** Average testing accuracy of three models. **(b)** Average testing loss of three models (without augmentation).

shown in Tab.3. In comparison, ResNet-18 has slightly lower accuracy ( $91.33\% \pm 2.48\%$ ), with competitive sensitivity ( $92.32\% \pm 2.59\%$ ) but lower specificity ( $90.20\% \pm 4.49\%$ ), indicating a higher rate of false positives. MobileNetV1-28 shows the lowest accuracy ( $90.73\% \pm 1.80\%$ ) and the least balanced performance in terms of sensitivity ( $90.68\% \pm 2.49\%$ ) and specificity ( $90.80\% \pm 2.97\%$ ).

Overall, DenseHF-Net is the most effective model for mitral valve auscultation, offering superior accuracy and a better balance between sensitivity and specificity, making it the preferred choice among the three models.

Fig. 4 illustrates a comparative analysis of two different auscultation strategies, as represented by the respective confusion matrices. Both strategies focus on the detection accuracy of mitral valve abnormalities. The confusion matrices in Fig. 4b and Fig. 4a summarize the performance outcomes, including True Positives, True Negatives, False Positives, and False Negatives.

In the first strategy (Fig. 4b), the model achieved a high sensitivity of 92.68% and specificity of 92.53%, with a balanced F1 score of 92.01%. The second strategy (Fig. 4a) demonstrated even higher accuracy, achieving a sensitivity of 98.97% and a specificity of 99.44%, leading to an F1 score of 99.10%.

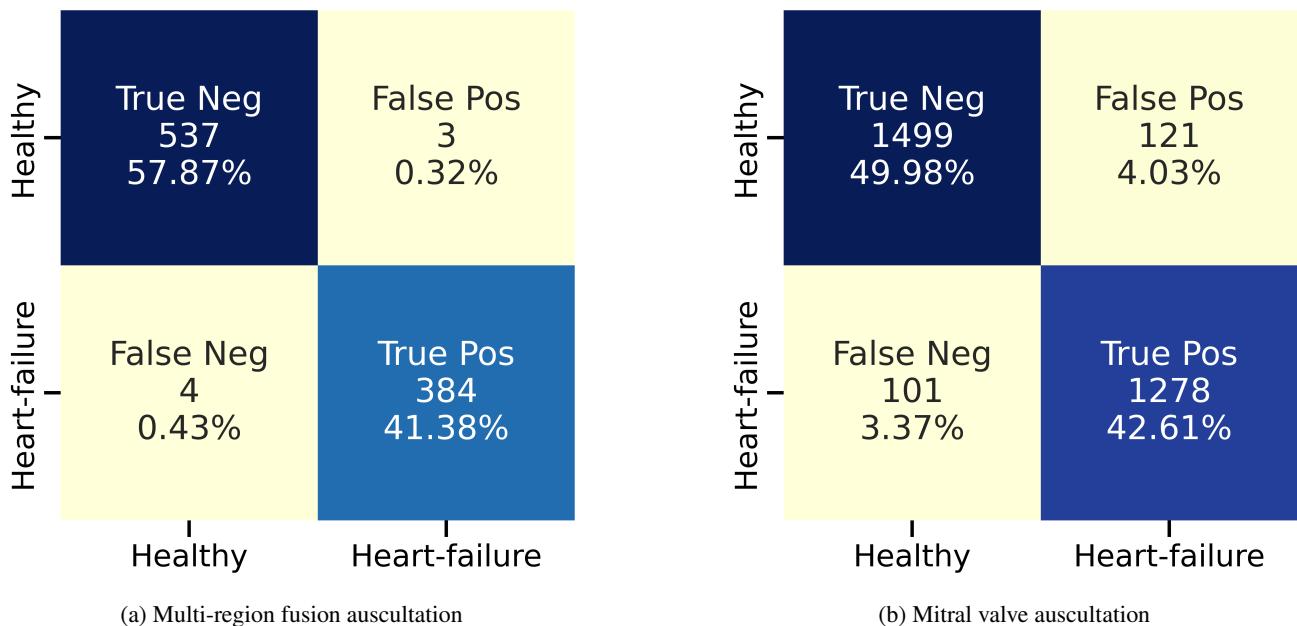


Figure 4: Comparison of two auscultation strategies

### 3.5. Ablation Study

Table 3 presents the results of the ablation study, using Params, FLOPs, MACs, and ten-fold cross-validation accuracy as evaluation metrics. DenseHF-Net strikes a balance between computational efficiency and performance, with 0.33 million parameters, 61.29 million FLOPs, and 30.64 million MACs, achieving an accuracy of 93.47%.

When wavelet-denoising was not applied, the accuracy dropped to 93.26%, indicating that wavelet-denoising has a certain positive impact on model performance. Similarly, using Mel-spectrum features resulted in a significant decrease in accuracy to 90.77%, highlighting the crucial role of feature selection in maintaining high performance.

Adjusting the compression rate showed a clear trade-off between model complexity and accuracy. As the compression rate increased from 30% to 70%, the number of parameters, FLOPs, and MACs also increased, leading to a slight improvement in accuracy. However, the highest accuracy (95.1%) was achieved without compression, which also resulted in the highest computational cost, underscoring the need to balance accuracy and efficiency.

Finally, increasing the number of blocks in the network further raised the number of parameters, FLOPs, and MACs. When the block numbers were set to 8, 16, 32, 16, the accuracy reached 94.74%. This indicates that while deeper networks may offer higher accuracy, they also significantly increase the computational burden, which could be a limiting factor in real-time or resource-constrained applications.

In the final configuration, DenseHF-Net employed a 10% compression rate and block numbers of 4, 8, 16, and 8. This configuration was chosen to prune the model as much as possible while maintaining performance, making it more

suitable for emergency scenarios such as use in ambulances.

**Table 4**  
Ablation Study Results

Ablation Condition	Params (M)	FLOPs (M)	MACs (M)	Accuracy (%)
<b>DenseHF-Net</b>	0.33	61.29	30.64	92.60
Without wavelet-denoising	0.33	61.29	30.64	92.26
Feature input: Mel-spectrum	0.33	61.29	30.64	90.77
Compression rate: 30%	0.39	67.01	33.50	93.87
Compression rate: 50%	0.47	74.13	37.06	93.91
Compression rate: 70%	0.57	82.42	41.21	94.01
Without compression	0.78	98.84	49.42	95.10
Blocks numbers: 6 12 24 16	0.99	132.64	66.32	94.35
Blocks numbers: 8 16 32 16	1.47	201.76	100.88	94.74

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