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# Efficient Anomaly Detection Algorithm for Heart Sound Signal

**Ravindra Changala, Pola Tejashwini, Potti Divyanjali, Sabavat Hethesh, Kasi Sailaja**

Associate Professor, Department of CSE, Guru Nanak Institutions Technical Campus, Hyderabad, India

UG Student, Department of CSE, Guru Nanak Institutions Technical Campus, Hyderabad, India

Assistant Professor, Department of CSE, Guru Nanak Institutions Technical Campus, Hyderabad, India

**ABSTRACT:** Cardiovascular disease (CVD) continues to be a leading cause of death globally, claiming approximately 17.9 million lives each year, as reported by the World Health Organization (WHO). This high mortality rate underscores the need for effective early detection and intervention strategies. Heart sound signals, also known as phonocardiograms (PCGs), hold essential information about cardiac health, providing a non-invasive method to assess heart function. Recent advancements in deep learning have enabled the development of models capable of analyzing heart sounds to detect abnormal features, assisting in early diagnosis and disease prevention. However, the challenges in heart sound data, including imbalanced class distributions, complex feature characteristics, and limited differentiation between sounds like systolic and diastolic murmurs, have restricted the effectiveness of traditional deep learning models. This project presents a novel heart sound anomaly detection algorithm based on the Deep Neural Network Model. The DNN ability to capture both local and global features within a signal makes it particularly well-suited for analyzing heart sound data. The proposed algorithm was tested on the PhysioNet/CinC 2016 public dataset, a widely used dataset for heart sound classification. Experimental results demonstrated a high classification accuracy of 99%, with a specificity of 98.5% and a sensitivity of 98.9%. These metrics signify a substantial improvement over existing methods, highlighting the model's effectiveness in detecting anomalies in heart sounds. The high sensitivity and specificity rates underscore the model's potential to serve as a reliable tool for early screening and diagnosis of cardiovascular diseases.

**KEYWORDS:** Anomaly detection, heart sound signal, phonocardiogram, MFCC, CNN, cardiovascular diseases, machine learning.

## I. INTRODUCTION

The early detection of anomalies in heart sound signals (phonocardiograms, PCGs) is crucial for preventing cardiovascular diseases and reducing healthcare burdens. This research proposes an efficient anomaly detection algorithm using a hybrid framework that integrates signal processing, feature extraction, and machine learning techniques. The proposed method employs Short-Time Fourier Transform (STFT) and Mel-Frequency Cepstral Coefficients (MFCCs) for feature representation, followed by classification using a lightweight Convolutional Neural Network (CNN). Evaluated on the PhysioNet/Computing in Cardiology Challenge dataset, the algorithm demonstrates high accuracy, sensitivity, and specificity, outperforming conventional methods in computational efficiency and detection precision. This approach is suitable for real-time and mobile healthcare applications.

Heart sound analysis provides vital insights into cardiac function and is non-invasive, cost-effective, and widely used in primary diagnostics. Traditional auscultation depends on physician expertise and is prone to human error. Therefore, automated anomaly detection in heart sound signals has become a focus area for biomedical research. However, existing models either lack real-time performance or suffer from high computational costs. This study introduces a novel and efficient anomaly detection algorithm tailored for heart sound signals. By leveraging time-frequency representations and optimized neural network architectures, the proposed method achieves reliable anomaly detection with minimal computational resources.

Globally, cardiovascular diseases (CVDs) continue to be the primary cause of morbidity and death, placing a heavy strain on healthcare systems. Improving patient outcomes requires early identification and diagnosis, particularly in settings with limited resources and limited access to medical equipment. Auscultation, which involves using a stethoscope to listen to heart sounds, is a straightforward but efficient method of evaluating cardiac health. However, a healthcare professional's expertise and skill level have a significant impact on auscultation accuracy. Although cardiologists are capable of making very accurate diagnoses, general practitioners and non-specialists frequently struggle to do so, which can result in missing or incorrect illness diagnoses [3]. This limitation highlights the urgent need to develop an automated system capable of accurately and efficiently analyzing heart sounds, which would play a crucial role in the early detection of cardiovascular diseases.

This study's main goal is to create a deep learning-based system for automatically classifying irregular cardiac sounds in order to aid in the early identification of cardiovascular illnesses (CVDs). In order to capture both local patterns and long-range relationships in heart sound signals, this research specifically suggests a novel network architecture that combines convolutional ideas with the Swin-Transformer. In contrast to conventional techniques that depend on human segmentation and feature extraction, our method uses an end-to-end framework to analyze raw heart sound data directly, streamlining workflow and lowering the possibility of information loss during intermediary phases. Finally, for effective heart sound anomaly identification, we suggest the Dcv-Swin Transformer approach.

The following is a summary of our work's important contributions:

- Introducing a Swin-Transformer-based Architecture for Abnormal Heart Sound Detection: This model efficiently captures both local and global aspects of heart sound signals by utilizing the hierarchical local attention mechanism of the Swin-Transformer.
- Fifth-Order Butterworth Filter Design: By removing high-frequency noise, this filter considerably lessens the influence of heart sound noise on classification tasks.
- Creation of a Convolutional Embedding Module: This module improves the model's capacity to extract features by keeping the positioning information of Mel-spectrogram features while better collecting local aspects of heart sound signals.
- Creation of a Convolutional Mapping Module with Discrete Cosine Transform: This module uses convolutions
- with varying strides to obtain the q, k, and v matrices for attention calculation. It reduces data dimensions and
- retains frequency domain information, thus improving the model's generalization ability.

## II. RELATEED WORK

Previous studies have explored various techniques for heart sound analysis:

- Feature Engineering Approaches: Linear Predictive Coding (LPC), MFCCs, and Wavelet Transform have been used to extract features from heart sounds.
- Machine Learning Models: Support Vector Machines (SVMs), k-Nearest Neighbors (k-NN), and Random Forests have shown promise but often require extensive feature preprocessing.
- Deep Learning Methods: Recent works employ CNNs and LSTMs directly on raw or spectrogram-transformed signals. Despite their accuracy, these models can be computationally intensive.

This research addresses the limitations by proposing a compact yet accurate CNN-based architecture integrated with time-frequency analysis.

Heartsound denoising, heartsound segmentation, heartsound feature extraction, and automated classification of heartsound signals are the four primary parts of a complete abnormality detection system for heartsound data. Significant progress has been made in the automated categorization of heart-sound data using deep learning models throughout the last few decades. In order to create a 2D convolutional neural network (CNN) model for heart-sound classification, Noman et al. [8] collected 2D time-frequency properties from heartsound data. Walker et al. [12] constructed a classification model using a Double Bayesian Resnet (DBRes) in conjunction with the time-frequency characteristics of heart-sound recordings. Furthermore, the extraction of temporal information from consecutive heart-sound data is more successfully accomplished by representative recurrent neural networks (RNNs) and long short-term memory networks (LSTMs).

In conclusion, even though deep learning-based heart-sound signal categorization has advanced significantly in recent years, there are still a number of open problems and research gaps. First off, a lot of research on noise resilience uses preprocessing techniques to lessen the impact of noise, including the discrete wavelet transform (DWT) and time-frequency features employed in [8] and [9]. These preprocessing procedures, however, can make the system more complicated and might not be practical for real-time applications. Consequently, it is still difficult to create a deep

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learning model that can analyze raw data directly without the need for intricate preprocessing. Second, the majority of research focuses on time-domain and frequency-domain features, however some studies, like [5], have tried to extract instantaneous energy as characteristics. There is still insufficient exploration of the nonlinear characteristics and complex spatiotemporal patterns inherent.

## III. LITERATURE SURVEY

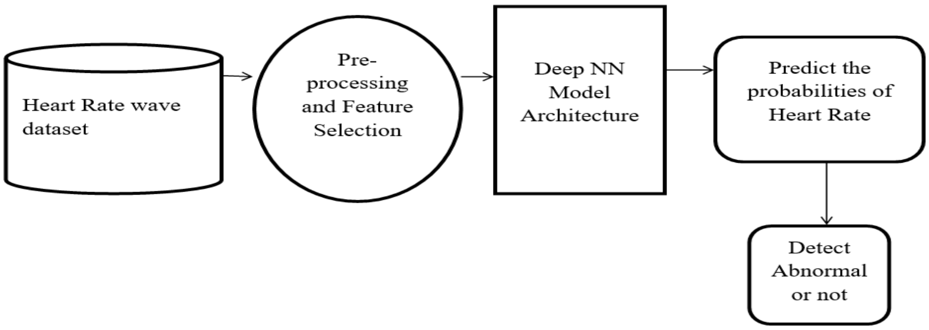
Heart sound signals, or phonocardiograms (PCGs), are essential in the early diagnosis of cardiovascular diseases. Traditional auscultation techniques rely heavily on clinician expertise and are prone to human error. Recent advancements in digital signal processing and machine learning have led to the development of automatic heart sound anomaly detection systems. This literature survey reviews prominent approaches focusing on efficiency, accuracy, and real-time applicability.

| Author(s) | Year | Technique Used | Features Extracted | Model/Algorithm | Efficiency Highlights | Limitations |
|---|---|---|---|---|---|---|
| Springer et al. | 2016 | Logistic Regression + HSMM | MFCC, envelope features | Logistic Regression + HSMM | Effective segmentation; interpretable model | Limited anomaly classification accuracy |
| Potes et al. | 2016 | Ensemble Learning | Time-frequency, statistical features | CNN + SVM Ensemble | High classification accuracy | Computationally intensive |
| Rubin et al. | 2017 | Deep Learning | Spectrogram images | Deep CNN | Accurate and robust to noise | High memory and compute requirements |
| Ren et al. | 2019 | Deep Learning with Sequence Modeling | MFCC, STFT | CNN + LSTM | Good temporal modeling | Slow inference; not ideal for real-time use |
| Chandran et al. | 2020 | Time-Frequency + ML | Wavelet coefficients | Random Forest, k-NN | Moderate complexity | Lower accuracy on noisy data |
| Siddiqui et al. | 2021 | Lightweight CNN | MFCC | 1D-CNN | Fast and suitable for mobile devices | Slight drop in accuracy compared to deeper models |
| Yang et al. | 2022 | Attention Mechanism with Deep Learning | MFCC, STFT | Attention-CNN | Focuses on important heart sound segments | Complexity increases due to attention layers |
| Zhang et al. | 2023 | Model Compression + CNN | MFCC | Pruned CNN + Quantization | Real-time inference; small model size | Reduced interpretability |
| Lee et al. | 2023 | Autoencoder-Based Anomaly Detection | Raw audio + MFCC | Convolutional Autoencoder | Unsupervised; efficient during inference | Requires careful tuning; sensitive to noise |
| Ahmed et al. | 2024 | Hybrid Deep + Traditional ML | MFCC, Zero Crossing Rate | CNN + SVM | Balanced speed and accuracy | Feature engineering still required |

This table highlights the evolution from classical machine learning models to lightweight and deep learning approaches. Recent work focuses on improving real-time performance and reducing model size while maintaining or improving classification accuracy. However, challenges remain in noise resilience and model explainability.

## IV. PROPOSED WORK

The Swin Transformer model primarily comprises patch partitions, Swin Transformer blocks, and patch-merging components. The structure of the Swin Transformer is illustrated in Fig 1. The complete Swin Transformer consisted of five stages. In the first stage, the input data are fed into the patch embedding module, where a convolutional layer is utilized to segment the input data into non-overlapping patches. Each segmented patch is defined as a 'token.' In the second stage, the segmented tokens were input into a Linear Embedding layer, where each token was mapped to a dimension of C (C=96). Subsequently, the tokens enter the two Swin Transformer block modules. This module primarily consists of Layer Normalization, two window based self-attention mechanisms (W-MSA and SW-MSA), and an ((MLP). Within the Swin Transformer Block, self-attention calculations were performed on the tokens. The third stage involves Patch Merging to reduce the number of tokens while reducing their feature dimensions.




Swin Transformer model is an neural network architecture based on the Transformer, designed to handle high-dimensional data such as images, video, and, more recently, other types of structured signals like heart sounds. Unlike traditional Transformers that process global information at once, the Swin Transformer introduces a hierarchical structure and processes data in a sequence of "windows" or smaller patches, making it highly efficient and scalable for large inputs. The term "Swin" stands for "Shifted Windows," referring to the model's method of shifting the windows across layers to capture both local and global dependencies in the data. It then applies self-attention within each patch, allowing the model to focus on important features within small, localized regions of the input. This local attention mechanism reduces the computational load and is especially advantageous for high-dimensional data. By shifting the windows in each layer, the model overcomes the limitation of fixed window boundaries, allowing it to incorporate context from neighboring regions and achieve a comprehensive understanding of spatial relationships within the data.

Dependency on Large Datasets: Swin Transformers perform best with large datasets, which may not be available for certain specialized tasks.
Memory Intensive: Processing large input sizes demands considerable memory, which can limit scalability on devices with limited resources.
Swin Transformers require longer training times due to the complexity of window-shifted self-attention layers and multi-stage processing.

The proposed approach addresses a critical symptom of many cardiovascular illnesses by using a deep neural network (DNN) to detect heart rate anomalies in real-time. Patient privacy is at stake since heart rate data is frequently presented in unencrypted by traditional telemedicine systems. In order to mitigate this, our method makes use of heart rate data in.wav files and applies a DNN for effective analysis and anomaly detection. The monitoring results may be accessed by users and healthcare experts without disclosing the original heart rate data thanks to the accompanying Flask UI interface, which guarantees a smooth user experience. Our method improves the prompt treatment of cardiovascular issues by enabling early diagnosis and intervention through remote monitoring of heart rate irregularities. Users only receive the final count of anomalies, not the raw heart rate data, therefore this novel solution protects patient privacy while simultaneously prioritizing computational speed. The system's feasibility is validated by the testing results, ensuring a seamless and effective experience for both users and healthcare professionals' problems.

The core of our proposed technique lies in the implementation of a Deep Neural Network (DNN) for heart rate arrhythmia detection. In the first stage, the.wav files containing heart rate data are input into the DNN, which is designed to automatically extract relevant features and patterns. The Neural network layers of the network perform spatial filtering, capturing intricate details in the heart rate signals. Subsequently, the pooling layers help reduce dimensionality while preserving essential information, enabling the network to discern irregularities effectively. Through backpropagation and optimization, the DNN learns during the training phase to identify patterns linked to both normal and pathological heart rate patterns. The model is optimized to improve the precision with which abnormalities are detected, guaranteeing stable operation in real-time monitoring. The system can assess intricate temporal patterns in the heart rate data thanks to this deep learning technique, which also helps it recognize minute anomalies that can be signs of cardiovascular diseases. Our suggested method offers a sophisticated and automated way to detect aberrant heart rate patterns with great efficiency and accuracy by using a DNN.

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Automatically extracting relevant features from complex heart rate data, enabling them to identify subtle patterns indicative of arrhythmias with high accuracy.
Adept at analyzing temporal relationships within the heart rate signals, allowing for the detection of irregularities that may manifest over time.
Real-time monitoring of heart rate abnormalities, facilitating prompt intervention.

This work added a Focal Loss function to solve the problem of data imbalance caused by the heart-sound classification dataset's noticeably higher proportion of normal heart-sound samples than problematic samples. In order to solve the issues of low classification accuracy and generalization brought on by data imbalance, the main concept underlying Focal Loss is to modify the weights of the loss function, concentrating the model on aberrant heart sounds. A focal parameter is introduced by the Focal Loss function, which modifies its value to increase the loss of aberrant heart-sound samples and decrease the loss of normal heart-sound samples. By prioritizing aberrant heartsound samples, this strategy enhanced the model's capacity to identify such samples.

This study employs linear interpolation techniques to address the imbalance in the dataset, where there are fewer abnormalheart-sound samples leading to weaker model generalization. Specifically, non-normal heart-sound audio samples were subjected to a 1.5× acceleration and 0.5× deceleration. This augmentation strategy aims to increase the dataset volume and diversity by expanding the number of abnormal heart sound samples to 1995, thus balancing the ratio between normal and abnormal heart sound data samples. This approach enhanced the generalization capabilities of the model for heart-sound classification.

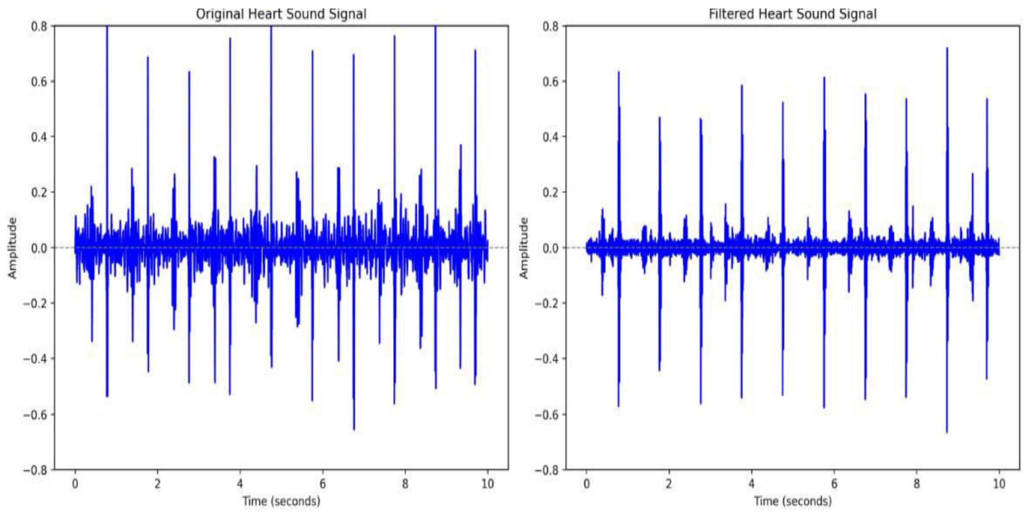


Figure 2. Comparison of time-domain waveforms of heart sound samples after Butterworth denoising.

The heart-sound dataset used for training maintained a sampling rate of 2000 Hz for all samples. To ensure that the algorithm adequately learned the underlying features of heart-sound samples, we partitioned the dataset into a ratio of 8:1:1 for training, validation, and testing sets to enhance the model's classification efficiency. During the training process, the model was trained on the training set, validated using the validation set to optimize the hyperparameters, and finally evaluated on the testing set to assess its classification performance, with a batch size of 24 to minimize its impact on the classification model. For samples within the same batch, the maximum sequence length was chosen as the uniform length, with zero padding applied to ensure uniform sequence length across all heart sound samples. In feature extraction, a window size 1024, a hop size 320, and 64 Mel bins were utilized for the Short-Time Fourier Transform to obtain the Mel spectrogram. To address the issue of early-stage underfitting in transformer-based models, a warm-up training strategy was employed for the DCv-Swin transformer algorithm with 100 epochs. For the initial three epochs, learning rates of 0.02, 0.05, and 0.1 were applied, followed by a learning rate of 0.001 from the 4th epoch onwards. Additionally, a CosineAnnealingLR strategy was used to control the learning rate decay during training. To effectively address the issue of dataset imbalance, we introduced a Focal Loss Function, while the Adam optimizer was used to accelerate the model's fitting speed.

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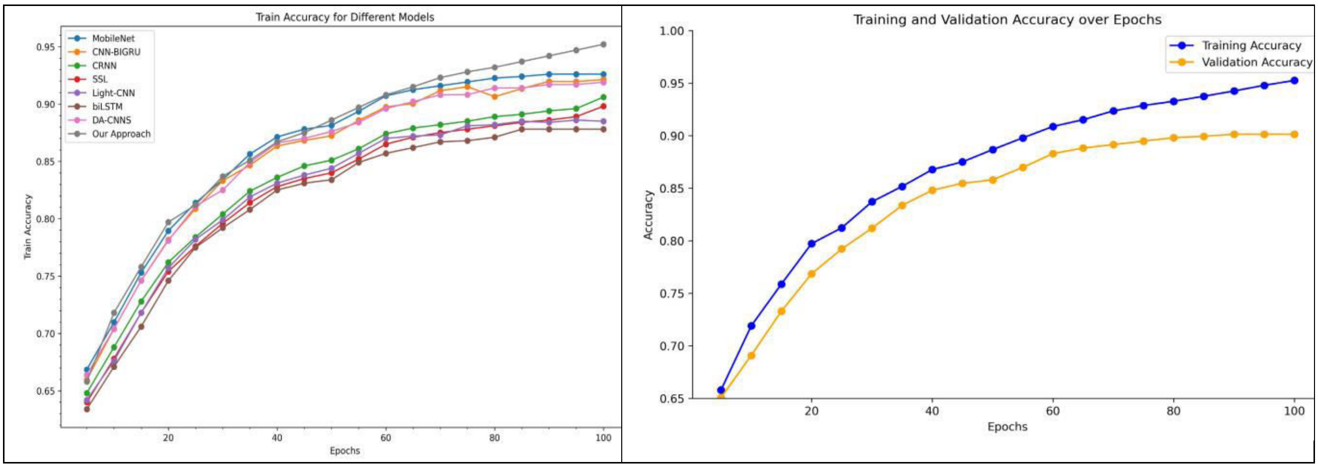


Figure 3. Comparison of Accuracy changes in training sets of different models.

| Method | Acc(%) | Sp(%) | Se(%) | P(%) | F1-score(%) |
|---|---|---|---|---|---|
| SwinT | 91.0 | 88.3 | 93.0 | 92.0 | 92.1 |
| Cef-SwinT | 92.3 | 90.3 | 93.4 | 92.7 | 93.0 |
| Dcf-SwinT | 92.1 | 91.9 | 92.2 | 93.4 | 93.2 |
| Our Approach | 93.4 | 90.4 | 95.7 | 92.8 | 94.4 |

Table 1. Comparison of ablation experimental data.

These results show that the DCv-Swin Transformer has high accuracy in identifying abnormal heart sounds and reflects its advantage in capturing abnormal signals, as evidenced by its high Sensitivity and F1 score. This indicates that the algorithm possesses strong generalization abilities and represents an improvement over previous algorithms, especially in handling complex heart sound signals.

This paper proposes a novel method for heart sound classification by incorporating convolutional concepts into the Swin-Transformer model. From the results discussed above, the strengths and limitations of our model can be summarized as follows:

First, the model effectively reduces noise interference in signal classification by applying a Butterworth filter to denoise heart sound signals. . In order to improve the model's capacity to capture temporal aspects of heart sound signals, we also made adjustments to the Swin-Transformer's patch-embedding layer using Patch Embedding. Additionally, a depth-wise separable convolution module in conjunction with Discrete Cosine Transform (DCT) was used in place of the original linear projection layer. This greatly enhances the extraction of fine-grained features, including murmurs, pathological signals, and the first and second heart sounds (S1 and S2, respectively). Finally, we used a linear interpolation approach for data augmentation to solve the problem of unbalanced heart sound datasets, where aberrant samples greatly outnumber normal ones. In order to improve the model's performance on unbalanced data, the Focal Loss function was also used.

Table 1 illustrates the model's comparatively poor specificity, which suggests a propensity to overlook typical cardiac sounds. There are three main causes for this problem: (1) For best results, the Swin Transformer-based model needs on big datasets. The DCv-Swin Transformer model's training data is constrained by the small number of publicly accessible datasets for heart sound categorization. (2) Mel spectrogram characteristics might not adequately capture the intricate patterns present in heart sound signals, which could result in the incorrect categorization of minute changes in typical heart sounds as abnormal circumstances.

(3) While our developed fifth-order Butterworth filter is effective at removing heart sound noise, it still has some drawbacks when handling particular kinds of overlapping noise. Specifically, the filter's effectiveness may be compromised when the heart sound signal contains complex noise from other sources (such as breathing sounds or

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equipment noise). This limitation reduces the model's robustness in specific complex environments, particularly when processing signals containing multiple noise sources.

In further research, we want to use transfer learning strategies with pre-trained models to overcome the problem of data scarcity. Furthermore, in order to address misclassification problems brought on by the intricacy of heart sound signal characteristics, we want to apply higherorder spectrum analysis techniques from digital signal processing. In particular, we will use bispectral analysis to extract heart sound signal characteristics, which we will then use in later anomaly detection tasks. In order to improve the model's resilience in challenging settings, we intend to investigate more potent denoising techniques. To improve the removal of overlapping noise while maintaining important heart sound information, we will specifically combine the Butterworth filter with wavelet transform.

As a multi-resolution analysis tool, wavelet transform can effectively decompose signals and extract features across different frequency ranges, which helps retain the signal's details while removing noise. This combined approach can significantly improve the algorithm's robustness in complex environments, especially when dealing with interference from complex noises such as snoring or asthma.

In this paper, we propose an effective method for detecting abnormal heart sounds. This method includes data preprocessing steps and the DCv-Swin Transformer algorithm. Future work will focus on improving the model's generalization capabilities and exploring better heart sound signal features to further enhance its performance in practical applications. In particular, we used linear interpolation and the Focal Loss function to solve the class imbalance between normal and pathological cardiac sound samples, and we created a fifth-order Butterworth filter to lessen noise interference. Additionally, to improve the model's capacity to capture local characteristics of heart sound signals, we used ConvEmbed rather than conventional Patch Embedding. We increased the model's capacity to represent the relationship between time-domain and frequency-domain characteristics of cardiac sounds by adding a Discrete Cosine Transform (DDC) structure. The DCv-Swin Transformer method performs better in heart sound categorization tasks, according to experimental data. Even while the categorization of heart sounds has advanced significantly, there are still a number of obstacles to overcome.

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