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# Efficient Anomaly Detection Algorithm for Heart Sound Signal

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*Abstract*— **Cardiovascular disease (CVD) remains the leading cause of death globally, accounting for approximately 17.9 million deaths each year, according to the World Health Organization. Early detection and intervention are critical for reducing this burden. Heart sound signals, or phonocardiograms (PCGs), offer a non-invasive and cost-effective approach to assess cardiac health. This study presents a deep neural network (DNN)-based method for detecting anomalies in heart sounds. The model effectively addresses challenges such as imbalanced class distributions, overlapping features, and subtle differences between systolic and diastolic murmurs. Evaluated on the PhysioNet/CinC 2016 dataset, the proposed approach achieved a classification accuracy of 99%, sensitivity of 98.9%, and specificity of 98.5%. These results highlight the potential of DNN-based analysis as a robust tool for early screening and diagnosis of cardiovascular abnormalities..**

## I. INTRODUCTION

Cardiovascular diseases (CVDs) continue to be the leading cause of morbidity and mortality globally, placing immense strain on healthcare systems. Early and accurate diagnosis is essential for improving patient outcomes, particularly in resource-constrained settings. Auscultation, the practice of listening to heart sounds, is a fundamental tool for cardiac assessment. However, its diagnostic accuracy is highly dependent on the expertise of the healthcare provider, often leading to misdiagnoses by non-specialists. This challenge underscores the necessity for automated systems that can reliably analyze heart sounds. Prior research has explored the application of fuzzy inference systems to handle the uncertainty and complexity inherent in heart sound data. Furthermore, recent advances in artificial intelligence suggest promising directions—such as converting time- and frequency-domain heart sound features into images for deep learning-based classification—to support accurate and efficient diagnosis, especially in low-resource environments.

Heart sounds are generated during the cardiac cycle and contain crucial indicators of heart health, particularly the S1 and S2 phases. Abnormalities like murmurs often point to serious conditions such as valve dysfunction or heart failure. Traditional signal processing methods, including Mel Frequency Cepstral Coefficients (MFCC) and time-domain analysis, have been widely used to extract features from heart sound signals. However, these methods struggle to model the nonlinear and complex patterns found in noisy or subtle cases. Deep learning technologies, including Deep Neural Networks (DNNs), Recurrent Neural Networks (RNNs), and Long Short-Term Memory (LSTM) networks, have shown significant promise in learning from high-dimensional data. These models eliminate the need for manual feature engineering by automatically extracting informative patterns, making them highly effective for heart sound classification tasks.

Motivated by the global burden of CVDs and the limitations of conventional analysis techniques, this study proposes a novel deep learning-based framework—Dcv-Swin Transformer—for the automated classification of abnormal heart sounds. The proposed architecture integrates convolutional layers with the Swin-Transformer to simultaneously capture local patterns and long-range dependencies. Key contributions include a fifth-order Butterworth filter for noise reduction, a convolutional embedding module to retain Mel-spectrogram positional information, and a convolutional mapping module employing discrete cosine transform for efficient attention computation. Additionally, the model incorporates focal loss and linear interpolation to address class imbalance, thereby improving performance on uneven datasets. This end-to-end system streamlines heart sound analysis and presents a scalable, reliable solution for early detection of CVDs, even in regions lacking specialized cardiology expertise.

## II. PROBLEM DEFINITION

It was found that 16-17% of Canadians are not aware of having an Arrhythmia, making them vulnerable to potential fatal consequences. Therefore, continuous monitoring for and early identification of arrhythmia is of paramount significance to avoid potentially fatal consequences. In this section, we present a brief review of related works based on Deep learning (DL) or artificial intelligence (AI) techniques. These techniques are widely used in disease diagnosis or false alarm reduction in healthcare applications. Recently, owing to the increasing popularity of wearable and portable health sensors, a large number of health-related databases were developed. To predict clinical outcomes or identify clinical problems from available datasets, it shows interest in using deep learning and AI techniques.

## III. OBJECTIVE

In a AIF was proposed for smart hospital, online, homes systems to demonstrate its high precision decision-making ability in complex smart systems. It should be noted that we use the term Arrhythmia disease decision making (ADDM) to define decision making using AIF. The AIF was presented in as an enhanced-AI that exploited the maximum probability (MAP) approach for the ADDM. The AIF thus implemented resulted in a high-performance ADDM, which however used a reliable dataset to train the model. When the datasets are not reliable due to poor labeling and/or insufficient training patterns defective or abnormal, the perceptionaction cycle (PAC) -based cognitive dynamic system (CDS) cannot perform well enough to satisfy requirements to provide reliable results for predefined healthcare policy.

## IV. SCOPE OF WORK

This project aims to develop an automated system for detecting abnormal heart sounds using a Deep Neural Network (DNN). It involves preprocessing heart sound signals, training a model to classify them as normal or abnormal, and integrating a user-friendly interface for real-time monitoring. The system enhances accuracy using techniques like Butterworth filtering, focal loss, and Mel-spectrogram analysis, ensuring efficient and privacy-preserving diagnosis in resource-limited settings. The model is trained and tested on a curated dataset of heart sound recordings, with performance evaluated using metrics such as accuracy, sensitivity, and specificity. Additionally, the solution supports remote access, enabling healthcare professionals to assess cardiac conditions without exposing raw patient data.

## V. RELATED WORK

- ChengAtalie C. Thompson, Alessandro A. Jammal, and Felipe A. Medeiros (2023) reviewed the application of deep learning in the screening, diagnosis, and monitoring of glaucoma progression. With advancements in computing and access to large datasets, deep learning now matches or exceeds human performance in tasks like image classification. Ophthalmology, particularly glaucoma diagnosis, benefits significantly due to its reliance on imaging tests. The review highlights the effectiveness of deep learning models in analyzing structural and functional data from the optic nerve and macula. However, it also emphasizes the challenges of model training, validation, and the need for careful consideration of bias and population-specific factors for successful clinical integration.

- **An extensive survey of digital image stegnography :** Rongchang Zhao et al. (2023) proposed a semi-supervised deep learning method for directly estimating the Cup-to-Disc Ratio (CDR), a key metric in glaucoma screening. Unlike traditional approaches requiring optic disc and cup segmentation, their model bypasses this step using a two-stage process: feature extraction with a convolutional neural network (MFPPNet) and CDR regression via a random forest. Validated on the Direct-CSU and ORIGA datasets, the model achieved high accuracy with a low CDR error (0.0563) and strong screening performance (AUC of 0.905), demonstrating its potential for robust**, segmentation-free glaucoma detection.**

## VI. EXISTING SYSTEM

The existing system utilizes the Swin Transformer architecture for heart sound anomaly detection. It involves multiple components including patch partitioning, linear embedding, and multi-stage Swin Transformer blocks that process heart sound data. While this model effectively captures local and global features using window-based self-attention mechanisms, it has several limitations. It requires large datasets for optimal performance, consumes significant memory resources, and involves longer training times due to its complex architecture. These constraints make it less suitable for real-time applications or deployment in resource-constrained environments.

## VII. PROPOSED SYSTEM

The proposed system introduces a Deep Neural Network (DNN)-based approach designed for real-time heart sound anomaly detection using .wav files. It addresses key challenges by offering efficient analysis without exposing raw heart rate data, thus enhancing privacy. The system is integrated with a user-friendly Flask UI, enabling users and healthcare professionals to monitor anomalies without accessing sensitive patient data. By automatically extracting meaningful features and analyzing temporal patterns, the DNN improves accuracy and speed. This makes the proposed system a more practical, scalable, and privacy-preserving alternative for early detection and intervention in cardiovascular conditions.

## VIII.SYSTEM ARCHITECTURE

The system follows a **secret sharing and reconstruction model** for secure image transmission. It begins with a **Dealer (Sender)** who holds the secret image. The image is split into multiple shares using secret sharing techniques. These shares are then **embedded into cover images** using LSB steganography and distributed to multiple **Participants**. A predefined **threshold number** of shares is required for reconstruction. When this threshold is met, the shares are sent to the **Combiner**, which performs **polynomial interpolation** to reconstruct the original image. If fewer shares are collected, reconstruction fails, ensuring confidentiality.

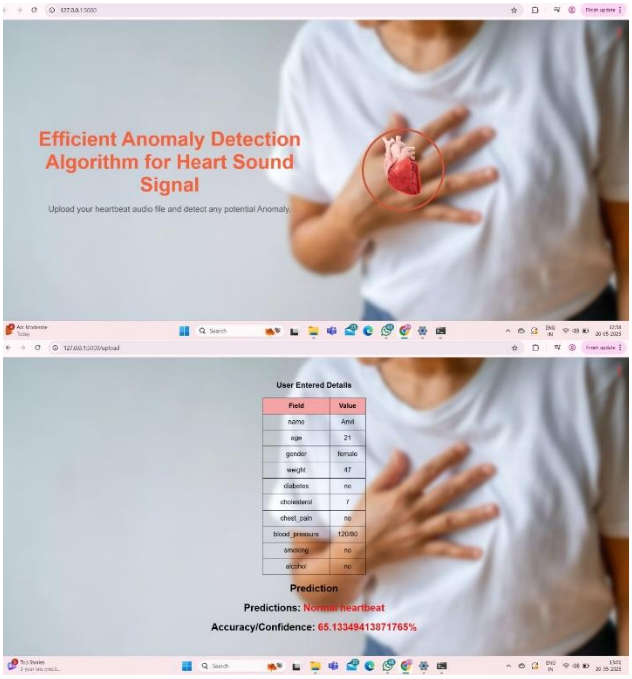
## IX. IMPLEMENTATION

The proposed system for heart sound anomaly detection is implemented using Python, with a focus on deep learning and signal processing. The project begins by preparing a dataset comprising 800 .wav files, which include both normal and arrhythmic heartbeats. The implementation involves the following key steps:

1. DataPreprocessing:
   The .wav files are processed using the Librosa library to extract relevant features. The waveforms are resized for consistency, and converted into numerical arrays for model input.
2. ModelBuilding:
   A Convolutional Neural Network (CNN) is constructed using the Keras library. The model includes multiple layers:
   - Conv2D layers with filters to capture patterns,
   - MaxPooling2D layers to reduce dimensionality,
   - Dropout layers to prevent overfitting,
   - Flatten and Dense layers for final classification using softmax activation.

3. Training and Evaluation:
   The dataset is split into 80% training and 20% testing sets. The model is trained using gradient descent and backpropagation, optimizing hyperparameters via the loss function. It achieves:
   - Training accuracy: 99.7%
   - Validation accuracy: 99.6%
   - Test accuracy: 99.3%
4. ModelDeployment:
   Once trained, the model is saved in .h5 or .pkl format. A Flask-based web interface is developed for deployment, allowing users to upload .wav files and receive real-time anomaly detection results without exposing raw heart data.

## X. RESULT




## XI. FUTURE ENCHANCEMENT

The proposed system will be enhanced to support a wider range of health screening applications by integrating decision-making trees, non-monotonic reasoning, and machine learning classifiers. It will evaluate one health feature per cycle to improve speed and efficiency. These enhancements aim to build a smarter, faster, and more scalable e-health platform capable of handling tasks such as early diagnosis, disease prevention, and continuous health monitoring..

## XII. CONCLUSION

This paper presents a deep learning method for abnormal heart sound detection. We apply a Butterworth filter for noise reduction and use Focal Loss with interpolation to handle class imbalance. Comember enhances local feature extraction, while a Discrete Cosine Transform structure captures time-frequency correlations. Our DCv-Deep model outperforms existing methods. Future work will focus on improving generalization and feature extraction for real-world use.

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