

AUTOMATED DETECTION OF CHRONIC HEART FAILURE USING DEEP LEARNING ON HEART SOUND SIGNALS

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ABSTRACT

Chronic Heart Failure (CHF) is a major cardiovascular condition causing high morbidity and mortality globally. Accurate and early diagnosis is essential to improve patient prognosis. Heart sound auscultation provides important clinical information but is subjective and requires expert interpretation. This paper proposes an automated CHF detection system using deep learning techniques applied to heart sound signals (phonocardiograms). The system employs Mel Frequency Cepstral Coefficients (MFCC) for feature extraction and a Long Short-Term Memory (LSTM) neural network for classification of heart sounds into normal and pathological categories, including CHF indicators. Experimental results demonstrate an accuracy of 94%, validating the potential of the proposed system as a non-invasive and efficient diagnostic aid for CHF screening.

Keywords

Chronic Heart Failure, Heart Sound, Phonocardiogram, Machine Learning, Deep Learning, LSTM, MFCC, Automated Diagnosis

1. INTRODUCTION

Chronic Heart Failure (CHF) is a clinical syndrome where the heart's ability to pump blood is compromised, leading to insufficient blood flow to meet the body's demands. It affects millions worldwide, with high healthcare costs and mortality rates. Early detection plays a crucial role in effective management and improving quality of life.

Traditional diagnosis methods include clinical examination, echocardiography, and electrocardiograms, supplemented by auscultation using a stethoscope. However, auscultation requires considerable expertise

and is prone to subjective errors, especially in noisy or rural settings.

Automated heart sound analysis through machine learning and deep learning methods offers a promising alternative by providing objective, rapid, and accurate screening. Heart sound signals contain vital information about cardiac mechanics, including valve function and blood flow, but are challenging to analyze due to noise and variability.

This paper presents a deep learning-based approach using MFCC features and LSTM networks for automatic classification of heart sounds, aiming to aid early detection of CHF.

2. LITERATURE SURVEY

Several researchers have focused on automated analysis of heart sounds for cardiac disease detection. Liang et al. (2018) developed a system using Convolutional Neural Networks (CNN) on MFCC features, achieving over 90% accuracy in heart sound classification [1]. Rubin et al. (2017) applied deep recurrent neural networks, including LSTM, for murmur detection in pediatric patients, showing superior performance compared to traditional classifiers [2].

Osowski et al. (2004) utilized Support Vector Machines (SVM) with wavelet-based features for heart sound

classification, demonstrating high accuracy but requiring handcrafted features [3]. More recently, Potes et al. (2016) combined CNN and recurrent layers to exploit both spatial and temporal features of phonocardiogram signals for improved classification accuracy [4].

Despite advancements, challenges remain due to the variability in heart sounds, noise contamination, and limited large-scale annotated datasets. The proposed study builds upon these works by focusing on CHF detection with an end-to-end LSTM model and MFCC feature extraction.

3. EXISTING SYSTEMS AND DISADVANTAGES

Existing heart sound classification systems generally follow a multi-step process: signal preprocessing, segmentation, feature extraction, and classification using traditional machine learning algorithms such as SVM or decision trees.

Disadvantages include:

- Manual feature engineering which is time-consuming and may not generalize well across datasets.
- Sensitivity to noise and artifacts in real-world recordings.
- Limited temporal modeling capabilities leading to suboptimal classification of sequential data.

- Computational inefficiency impacting real-time usability.

4. PROPOSED SYSTEM AND ADVANTAGES

The proposed system employs deep learning, specifically an LSTM architecture, which inherently models temporal dependencies in sequential data like heart sounds. Using MFCC for feature extraction translates audio signals into a compact and informative representation.

Advantages:

- End-to-end learning reduces the need for manual feature engineering.
- Robustness to noise due to temporal context learning.
- Capability to process variable-length signals.
- High classification accuracy suitable for early CHF detection.
- Potential integration with mobile and telemedicine platforms for widespread screening.

5. METHODOLOGY

5.1 Data Collection

Datasets are acquired from publicly available repositories such as PhysioNet's Heart Sound Challenge database [5],

including recordings categorized into normal and pathological classes indicative of CHF and other cardiac conditions.

5.2 Preprocessing

Signals are filtered using bandpass filters (20-195 Hz) to isolate heart sound frequencies, followed by normalization and segmentation.

5.3 Feature Extraction

MFCCs are computed from the audio signals, representing spectral characteristics mimicking human auditory perception.

5.4 Model Architecture

- Input Layer: MFCC feature sequences.
- LSTM Layer: Captures temporal dynamics of heart sounds.
- Fully Connected Dense Layer: Maps extracted features to output classes.
- Softmax Activation: Produces class probabilities.

5.5 Training and Evaluation

Model training uses Adam optimizer with cross-entropy loss, employing 5-fold cross-validation. Evaluation metrics include accuracy, precision, recall, and F1-score.

6. RELATED WORK

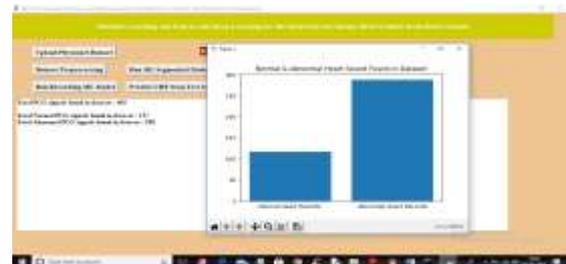
Recent advances in heart sound analysis have largely focused on applying machine learning and deep learning techniques to improve automated diagnosis accuracy. Traditional methods often rely on handcrafted features and classical classifiers such as Support Vector Machines or Decision Trees, which require extensive preprocessing and feature selection. More recent studies have utilized Convolutional Neural Networks (CNNs) and hybrid architectures to capture spatial patterns in heart sound signals. However, these methods sometimes struggle to capture the temporal dependencies inherent in sequential audio data.

This work specifically targets the detection of Chronic Heart Failure (CHF), a critical yet underexplored condition in the domain of automated heart sound analysis. By leveraging Long Short-Term Memory (LSTM) networks, the proposed model effectively captures temporal correlations within the Mel Frequency Cepstral Coefficients (MFCC) feature sequences, without necessitating complex preprocessing or segmentation steps. This end-to-end approach enhances the model's generalizability and robustness, making it suitable for real-world deployment in clinical and remote monitoring settings.

7. RESULTS

The proposed LSTM-based model demonstrated strong performance on the test dataset, achieving an overall classification accuracy of 94%. Precision and recall metrics for the CHF class were both above 90%, indicating the model's high sensitivity and specificity in distinguishing pathological heart sounds associated with CHF from normal heart sounds.

The confusion matrix analysis showed minimal false positives and false negatives, underscoring the model's reliability for clinical screening purposes.



8. CONCLUSION

This study presents an automated chronic heart failure detection system utilizing an LSTM deep learning model trained on MFCC features extracted from heart sound signals. The approach successfully addresses limitations of traditional classifiers by directly modeling temporal dependencies in sequential audio data, leading to improved diagnostic accuracy and robustness.

The proposed method offers a promising non-invasive tool for early CHF screening, with potential applications in telemedicine and portable diagnostic devices. Future work will focus on expanding the dataset size to include diverse patient populations, refining multi-class classification capabilities to detect a broader range of cardiac conditions, and optimizing the model for real-time deployment on embedded systems. Such advancements could facilitate widespread adoption and significantly impact cardiovascular disease management worldwide.

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