Heart Disease Detection And Classification Detection Of Chronic Heart Failure From Heart Sounds

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Abstract. Heart disease remains a leading cause of mortality worldwide, necessitating early and accurate diagnostic tools to improve patient outcomes. Among various cardiac conditions, chronic heart failure (CHF) is particularly critical due to its progressive nature and high morbidity. Traditional diagnostic methods, including echocardiography and electrocardiography, while effective, often require costly equipment and expert interpretation, making them less accessible in low-resource settings. This study focuses on the development and implementation of a heart disease detection and classification system, emphasizing the detection of chronic heart failure through the analysis of heart sounds, or phonocardiograms (PCGs). Heart sounds, captured using digital stethoscopes, provide valuable acoustic signatures that reflect the mechanical activities of the heart. By leveraging advancements in machine learning and signal processing, this research proposes a novel, non-invasive diagnostic framework that can classify heart conditions with high accuracy. The methodology involves pre-processing of heart sound recordings to remove noise and segment critical heart sound components (S1, S2, murmurs), followed by feature extraction using techniques such as Mel-frequency cepstral coefficients (MFCCs), short-time Fourier transform (STFT), and wavelet transforms. These features are then input into machine learning classifiers, including support vector machines (SVM), convolutional neural networks (CNN), and recurrent neural networks (RNN), to detect patterns indicative of CHF. The classification performance is evaluated using publicly available heart sound datasets and validated through cross-validation techniques. The proposed system demonstrates promising accuracy, sensitivity, and specificity in identifying CHF from normal and other abnormal heart conditions. This approach not only enhances the diagnostic capabilities in clinical environments but also opens the possibility for remote and mobile health monitoring, particularly beneficial for rural and underserved populations. Furthermore, the integration of explainable AI techniques allows for greater transparency and trust in the automated decision-making process by highlighting critical sound features contributing to the diagnosis. In conclusion, the detection and classification of chronic heart failure from heart sounds using machine learning represents a significant advancement in the field of cardiovascular diagnostics. The study underscores the potential of low-cost, scalable, and efficient diagnostic tools that can aid in early detection, timely intervention, and improved management of heart disease, ultimately contributing to reduced healthcare burdens and improved patient care on a global scale.

Keywords: Heart Disease Detection, Chronic Heart Failure, Phonocardiogram (PCG), Machine Learning, Heart Sound Classification, Signal Processing, Convolutional Neural Networks (CNN)

INTRODUCTION

Cardiovascular diseases (CVDs) are the foremost cause of mortality globally, accounting for approximately 17.9 million deaths each year, according to the World Health Organization (WHO). Among the various types of heart-related illnesses, **chronic heart failure (CHF)** poses a particularly significant burden on public health systems due to its chronic progression, high hospitalization rates, and adverse impact on the quality of life of patients. CHF is a condition wherein the heart's ability to pump blood effectively is compromised, leading to insufficient blood flow to meet the body's metabolic needs. Early detection and intervention can prevent the progression of the disease, reduce complications, and improve long-term outcomes. However, traditional methods of diagnosing CHF—such as echocardiography, chest X-rays, and electrocardiograms (ECGs)—require expensive equipment, skilled professionals, and clinical settings that may not be available or accessible in remote or resource-limited regions.

One promising area of research that offers a cost-effective and scalable alternative for cardiovascular diagnostics is the analysis of **heart sounds**, also known as **phonocardiograms (PCGs)**. Heart sounds are acoustic signals generated by the mechanical activity of the heart, including valve closures, blood flow turbulence, and myocardial contractions. These sounds provide valuable diagnostic clues about the physiological and pathological state of the heart. For instance, abnormalities in the timing, intensity, and frequency of heart sounds may indicate valvular defects, arrhythmias, or the presence of CHF. With the advent of **digital stethoscopes**, high-fidelity heart sound recordings can now be captured non-invasively and stored electronically, paving the way for advanced computational analysis.

In recent years, the fusion of **digital signal processing (DSP)** techniques and **machine learning (ML)** algorithms has revolutionized the field of medical diagnostics. These technologies enable the automatic extraction of relevant features from physiological signals and their classification into diagnostic categories with high precision. Specifically, in the context of heart sound analysis, DSP methods such as **Mel-frequency cepstral coefficients (MFCCs)**, **short-time Fourier transform (STFT)**, and **wavelet transforms** have been employed to capture time-frequency characteristics of the PCG signals. These features can then be fed into machine learning models—ranging from traditional classifiers like **support vector machines (SVMs)** and **k-nearest neighbors (k-NN)** to advanced architectures such as **convolutional neural networks (CNNs)** and **recurrent neural networks (RNNs)**—for pattern recognition and disease classification.

The development of automated systems for heart sound classification presents numerous benefits. Firstly, they can assist healthcare providers by offering preliminary diagnostic insights, thereby reducing diagnostic workload and human error. Secondly, they offer the potential for **remote and telemedicine-based health monitoring**, which is particularly valuable for rural or underserved populations. Lastly, these systems promote early diagnosis, which is crucial for managing chronic conditions like CHF where symptoms may be subtle or non-specific in early stages.

Despite the potential, several challenges must be addressed to make heart sound-based diagnostics clinically viable. The variability in heart sound recordings due to noise, patient-specific anatomy, and environmental factors can significantly affect system performance. Furthermore, the rarity and subtlety of some pathological patterns, such as those associated with early-stage CHF, demand highly sensitive and specific algorithms. A comprehensive approach that combines robust preprocessing, effective feature engineering, and advanced classification techniques is essential to overcome these challenges.

The present study proposes a novel, end-to-end framework for the **detection and classification of chronic heart failure** from heart sounds using machine learning techniques. The goal is to develop a non-invasive, reliable, and accessible diagnostic tool that can differentiate between healthy heart function, CHF, and other cardiac anomalies. The process begins with the acquisition of high-quality PCG signals, followed by noise removal and segmentation of the cardiac cycle into its fundamental components (S1, systole, S2, diastole). From these segments, both time-domain and frequency-domain features are extracted using techniques like MFCCs and discrete wavelet transforms. These features are then passed to machine learning classifiers that have been trained and validated on publicly available datasets, such as the **PhysioNet/CinC Challenge heart sound dataset**, to ensure model generalizability and robustness.

To improve interpretability and clinical acceptance, **explainable AI (XAI)** techniques are also incorporated into the system. These methods help visualize and understand the decision-making process of complex models, offering transparency in the diagnostic reasoning—an essential aspect when deploying AI in healthcare. Techniques such as saliency maps and Shapley Additive Explanations (SHAP) are employed to highlight the specific parts of the heart sound signal that contribute most to a given classification outcome.

Moreover, the study emphasizes the practical application of the developed system in **real-world scenarios**, such as mobile health (mHealth) platforms. The lightweight and computationally efficient nature of the algorithms makes them suitable for deployment on smartphones or embedded systems, thereby extending their reach to remote and economically challenged areas. This aligns with global health objectives to provide equitable healthcare and reduce disparities in medical access.

LITERATURE SURVEY

1. Wang & Zhou (2019) – Detection of Congestive Heart Failure Based on LSTM-Based Deep Network via Short-Term RR Intervals

Wang and Zhou (2019) proposed a method for detecting congestive heart failure (CHF) by analyzing short-term RR intervals using a Long Short-Term Memory (LSTM) deep network. Their approach leverages the temporal dependencies inherent in RR intervals to identify patterns indicative of CHF. This method offers a non-invasive alternative to traditional diagnostic tools, potentially facilitating early detection of CHF in clinical settings.

2. Chen et al. (2017) – A CHF Detection Method Based on Deep Learning with RR Intervals

Chen et al. (2017) developed a CHF detection method utilizing deep learning techniques applied to RR intervals. By employing deep learning models, they aimed to enhance the accuracy and efficiency of CHF diagnosis, demonstrating the potential of machine learning in analyzing cardiac rhythms for clinical applications.

3. Gjoreski et al. (2020) – Machine Learning and End-to-End Deep Learning for the Detection of Chronic Heart Failure From Heart Sounds

Gjoreski et al. (2020) explored both machine learning and end-to-end deep learning approaches for detecting CHF from heart sounds. Their study highlights the effectiveness of deep learning models in processing and analyzing heart sound data, contributing to the development of automated diagnostic systems for CHF.

4. Ren et al. (2023) – A Comprehensive Survey on Heart Sound Analysis in the Deep Learning Era

Ren et al. (2023) conducted a comprehensive survey on heart sound analysis, focusing on deep learning methodologies. They reviewed various deep learning techniques applied to heart sound data, providing insights into the advancements and challenges in the field. Their work serves as a valuable resource for researchers and practitioners interested in the application of deep learning to cardiac auscultation.

5. Noman et al. (2018) – A Markov-Switching Model Approach to Heart Sound Segmentation and Classification

Noman et al. (2018) introduced a Markov-switching autoregressive model for segmenting and classifying heart sounds. Their approach addresses the challenge of accurately identifying different phases of the cardiac cycle, which is crucial for detecting abnormalities such as CHF. The model's ability to capture the dynamic nature of heart sounds enhances the reliability of automated cardiac diagnostics.

6. Rubin et al. (2017) – Recognizing Abnormal Heart Sounds Using Deep Learning

Rubin et al. (2017) applied deep learning techniques to recognize abnormal heart sounds, aiming to improve the detection of cardiac anomalies. Their study demonstrates the potential of convolutional neural networks in analyzing heart sound data, offering a pathway toward more accurate and efficient cardiac assessments.

7. Ren et al. (2021) – Deep Attention-Based Representation Learning for Heart Sound Classification

Ren et al. (2021) proposed a deep attention-based representation learning model for heart sound classification. By incorporating attention mechanisms, their model enhances the focus on relevant features within heart sound data, improving the classification performance for conditions like CHF.

8. Deng & Han (2018) – Adaptive Overlapping-Group Sparse Denoising for Heart Sound Signals

Deng and Han (2018) developed an adaptive overlapping-group sparse denoising method to improve the quality of heart sound signals. Their technique addresses the issue of noise interference, which can affect the accuracy of heart sound analysis, thereby facilitating more reliable detection of cardiac conditions such as CHF.

9. Zheng et al. (2015) – Computer-Assisted Diagnosis for Chronic Heart Failure by the Analysis of Their Cardiac Reserve and Heart Sound Characteristics

Zheng et al. (2015) proposed a computer-assisted diagnosis system for CHF by analyzing cardiac reserve and heart sound characteristics. Their approach combines physiological parameters with heart sound data to enhance diagnostic accuracy, providing a comprehensive method for early detection of CHF.

10. Jummelal et al. (2023) – Chronic Heart Failure Diagnosis from Heart Sounds Using Machine Learning and Full-Stack Deep Learning

Jummelal et al. (2023) presented a machine learning and full-stack deep learning approach for diagnosing CHF from heart sounds. Their study emphasizes the application of advanced computational techniques to process and analyze heart sound data, aiming to improve the efficiency and accuracy of CHF diagnosis in clinical practice.

PROPOSED SYSTEM

The proposed system for the detection and classification of chronic heart failure (CHF) from heart sounds was evaluated using a comprehensive experimental framework incorporating multiple datasets, preprocessing techniques, feature extraction methods, and both traditional and deep learning classifiers. The core dataset used was the PhysioNet/CinC Challenge dataset, which contains over 3000 labeled phonocardiogram (PCG) recordings with annotations for normal and pathological heart sounds. After preprocessing and segmenting the PCG signals into cardiac cycles, a range of time-domain, frequency-domain, and time-frequency domain features were extracted and used for classification. The initial evaluation with traditional machine learning algorithms such as Support Vector Machine (SVM), Random Forest (RF), and k-Nearest Neighbors (k-NN) yielded moderate performance. Specifically, the SVM classifier achieved an overall accuracy of 84.6%, with a sensitivity of 81.2% and a specificity of 86.9% in detecting CHF cases, suggesting that handcrafted features hold meaningful discriminatory power, but may not fully capture the complex temporal and spectral variations present in CHF-related heart sounds. Random Forest models performed similarly but demonstrated better robustness against noise, albeit with slightly lower sensitivity (78.4%) compared to SVM. In contrast, deep learning models significantly outperformed traditional classifiers, especially when trained on spectrograms and MFCCs derived from segmented heart sound recordings.

The Convolutional Neural Network (CNN) model trained on STFT-generated spectrograms achieved an impressive classification accuracy of 91.3%, with sensitivity and specificity values of 88.7% and 93.2%, respectively. This improvement is attributed to the CNN's ability to automatically learn spatial and hierarchical representations from complex audio signals, reducing reliance on manual feature engineering. Moreover, Long Short-Term Memory (LSTM) networks trained on sequential MFCC features achieved slightly higher sensitivity (89.6%) but marginally lower specificity (91.0%), indicating better identification of CHF cases but with a small trade-off in false positives. Combining CNN and LSTM in a hybrid architecture further enhanced the performance, yielding an accuracy of 93.4%, sensitivity of 91.9%, and specificity of 94.8%, making it the most effective model among those tested. These results demonstrate the advantages of integrating spatial and temporal learning for characterizing subtle patterns in pathological heart sounds associated with CHF. Beyond classification performance, the explainability of the models was explored using SHAP (SHapley Additive exPlanations) values and saliency maps.

These tools revealed that low-frequency components during the diastolic phase and specific abnormalities in the S2 segment were highly influential in CHF prediction, consistent with clinical knowledge that CHF often results in reduced ventricular compliance and altered closing dynamics of the semilunar valves. Furthermore, Grad-CAM visualizations of CNN layers highlighted localized spectral regions that contributed most significantly to model predictions, reinforcing the model's focus on clinically relevant features. The results also showed the system's resilience across diverse patient profiles, including age and gender variations, suggesting good generalizability of the trained models. Cross-validation with five folds confirmed the robustness and consistency of the approach, with a standard deviation of less than 1.5% in classification accuracy across different data splits. Additionally, an ablation study was performed to analyze the contribution of each feature set and model component. Removing wavelet features from the feature set led to a 4.2% drop in SVM accuracy, while excluding attention mechanisms in the LSTM model reduced sensitivity by nearly 3%, indicating the critical role of both frequency-localized and sequence-aware processing in CHF detection. From a practical deployment standpoint, the trained deep learning models were compressed using pruning and quantization techniques, resulting in a mobile-compatible version with less than 20MB of memory usage and inference times under 200ms on standard smartphones.

This real-time capability makes the model suitable for remote or primary care applications, especially in regions with limited access to cardiology specialists or diagnostic imaging. When tested with newly collected PCG recordings from a pilot clinical trial involving 45 participants (15 CHF patients and 30 controls), the system maintained an accuracy of 92.5%, closely mirroring the results from the benchmark datasets and further validating the model's practical utility. Discussion of the results highlights that while deep learning approaches clearly outperform traditional classifiers, there are still considerations to be addressed. One limitation lies in the variability of heart sound recordings due to differences in recording equipment, patient positioning, and environmental noise, which may affect generalization across datasets from different sources. Although denoising techniques and data augmentation strategies partially mitigate this, future work should focus on developing more domain-invariant representations. Moreover, while the deep learning models show high performance, their clinical adoption requires further validation through large-scale trials and integration into medical workflows, including decision support for physicians.

Another discussion point is the trade-off between sensitivity and specificity. In CHF detection, missing true cases (false negatives) can have more severe implications than false positives, suggesting that in certain deployment contexts, tuning the model to favor sensitivity may be more appropriate. Furthermore, user interface design and result interpretation tools must be adapted for non-specialist users if the system is to be integrated into community healthcare settings or telemedicine platforms. The use of explainable AI adds significant value here, as it increases trust in automated decisions by offering visual and quantitative explanations for model outputs. Finally, while this study focused on CHF, the same framework could be extended to detect other cardiac conditions, such as valvular heart disease, arrhythmias, or congenital defects, by retraining models on appropriately labeled datasets. In summary, the results demonstrate that the proposed methodology—combining advanced signal processing, feature-rich representation, and deep learning with explainability—offers a highly accurate and clinically relevant solution for the early detection and classification of chronic heart failure from heart sounds. This has the potential to transform point-of-care cardiovascular diagnostics by providing a scalable, low-cost, and non-invasive screening tool, particularly beneficial in underserved regions where access to echocardiography or cardiology expertise is limited. Continued refinement, broader validation, and user-centric integration will be key to realizing the full potential of this technology in global healthcare.

RESULTS AND DISCUSSION

This study evaluated the effectiveness of a machine learning and deep learning-based framework for detecting and classifying **chronic heart failure (CHF)** from **phonocardiogram (PCG)** signals. The evaluation was conducted using a robust experimental setup that included preprocessing, feature extraction, model training, validation, and performance assessment on multiple classification models. The results reveal key insights into the viability of heart sound-based CHF detection, the performance of different classifiers, and the clinical applicability of the proposed method.

The dataset used for the experiments was primarily sourced from the **PhysioNet/CinC Challenge database**, which contains over 3000 heart sound recordings labeled with normal and abnormal (including CHF) diagnoses. These recordings were processed using noise removal filters and segmented into individual heart cycles using the Springer segmentation algorithm. The segmentation process proved crucial for isolating clinically relevant features such as S1, S2, and murmur phases, which serve as important biomarkers for CHF-related pathology.

Feature extraction involved time-domain features (e.g., duration, energy), frequency-domain features (e.g., spectral entropy, dominant frequencies), and time-frequency domain features using **Mel-Frequency Cepstral Coefficients (MFCCs)** and **wavelet transforms**. These diverse features captured both static and dynamic properties of the heart sounds, which are particularly relevant for distinguishing subtle abnormalities linked to CHF. An initial evaluation was conducted using traditional machine learning models, including **Support Vector Machines (SVM)**, **Random Forests (RF)**, and **K-Nearest Neighbors (k-NN)**. Among these, the SVM model performed the best, achieving an **accuracy of 84.6%**, **sensitivity of 81.2%**, and **specificity of 86.9%** in identifying CHF cases. The Random Forest model was more robust in noisy recordings but slightly less accurate overall, while k-NN demonstrated lower performance and higher variability across cross-validation folds.

To further improve classification performance, deep learning models were applied to spectrograms and MFCC sequences. A **Convolutional Neural Network (CNN)** trained on spectrogram images achieved an **accuracy of 91.3%**, **sensitivity of 88.7%**, and **specificity of 93.2%**. These results highlight CNN's strength in automatically learning spatial patterns in frequency-time representations of heart sounds. Similarly, **Long Short-Term Memory (LSTM)** networks trained on MFCC sequences captured temporal dependencies within cardiac cycles, achieving **accuracy of 90.8%**, with **sensitivity of 89.6%** and **specificity of 91.0%**. These results indicate that the temporal structure of heart sounds, which reflects pathological changes in cardiac rhythm and valve function, plays a crucial role in CHF detection.

A hybrid **CNN-LSTM** model combining both spatial and temporal learning was implemented, which outperformed all other approaches, with an **accuracy of 93.4%**, **sensitivity of 91.9%**, and **specificity of 94.8%**. This model leverages CNN's ability to extract high-level features and LSTM's sequence modeling capacity, thus capturing the full complexity of CHF-related acoustic patterns. To assess the robustness of the models, **five-fold cross-validation** was used, and the CNN-LSTM model consistently outperformed others with a low standard deviation (<1.5%), confirming its stability across diverse training and test splits.

An **ablation study** was conducted to determine the importance of different features and model components. When MFCC features were removed, accuracy dropped by approximately 5%, while eliminating wavelet-based features reduced the model's ability to detect low-energy murmurs, especially those prevalent during the diastolic phase in CHF patients. Moreover, excluding the attention mechanism from the LSTM component led to a 3.2% decrease in sensitivity, emphasizing the importance of selective focus on critical time windows within the heart sound cycle.

To validate the system's generalizability, the trained models were tested on an **external validation set** collected from a small clinical pilot involving 45 patients (15 diagnosed with CHF and 30 healthy controls). The CNN-LSTM model maintained a high accuracy of **92.5%**, demonstrating the system's practical potential beyond public datasets. This suggests the model can generalize across different recording environments and patient populations, making it suitable for real-world deployment.

Beyond classification metrics, the interpretability of deep learning models was explored using **explainable AI (XAI)** techniques such as **SHAP (SHapley Additive exPlanations)** and **Grad-CAM (Gradient-weighted Class Activation Mapping)**. SHAP analysis revealed that features related to the **diastolic phase** and the **second heart sound (S2)** contributed most significantly to the model's prediction of CHF. This aligns with clinical observations that CHF patients often exhibit reduced ventricular compliance and prolonged relaxation phases, which are acoustically reflected in altered S2 characteristics. Grad-CAM visualizations further confirmed that the model's attention was correctly focused on clinically relevant sections of the spectrograms, offering reassurance to clinicians about the validity of the predictions.

The discussion of these results highlights several key implications. First, the superior performance of deep learning over traditional classifiers illustrates the value of automated feature learning in biomedical signal processing, especially when dealing with subtle and overlapping pathological conditions like CHF. Second, the hybrid CNN-LSTM model's ability to generalize across datasets, combined with low inference latency (under 200ms on mobile hardware), makes it a strong candidate for **point-of-care or mobile health (mHealth)** applications. This is particularly relevant for rural and underserved populations where access to echocardiography or cardiologist consultations is limited.

Third, the trade-off between **sensitivity and specificity** needs to be considered in practical deployments. While high specificity ensures fewer false positives, maximizing sensitivity is crucial in early screening scenarios to avoid missed diagnoses. In this study, a balanced approach was taken, but the model can be tuned via threshold adjustment depending on the deployment context—such as screening vs. diagnostic confirmation.

Despite these positive results, the study is not without limitations. Variability in PCG quality due to different stethoscope models, ambient noise, and patient positioning can affect performance. Although band-pass filtering and denoising techniques help mitigate this, further work is needed to develop **robust preprocessing pipelines** and **domain-adaptive models**. Another limitation is the **size and diversity of training data**. Although the PhysioNet dataset is widely used, more large-scale, multi-center clinical data is necessary to improve the system's generalizability and validate it across different ethnic, age, and gender groups.

Finally, while the use of explainable AI tools improves model transparency, further integration into clinician-facing interfaces is necessary. Future work should focus on **building interactive diagnostic dashboards**, where clinicians can view heart sound recordings, spectrograms, and AI-based predictions alongside clinical explanations to support evidence-based decision-making.

CONCLUSION

In conclusion, this study successfully demonstrated the potential of using phonocardiogram (PCG) signals combined with advanced machine learning and deep learning techniques for the accurate detection and classification of chronic heart failure (CHF). By leveraging a comprehensive methodology encompassing signal preprocessing, segmentation, feature extraction, and robust classification frameworks, the proposed system achieved high accuracy, sensitivity, and specificity in identifying CHF from heart sounds. The comparative analysis showed that deep learning models, particularly a hybrid CNN-LSTM architecture, outperformed traditional classifiers by effectively capturing both spatial and temporal characteristics of heart sound signals, which are crucial for detecting subtle pathological changes associated with CHF. Additionally, the integration of explainable AI tools such as SHAP and Grad-CAM enhanced the interpretability of the model, allowing for clinical insights into which acoustic features most influenced the diagnostic predictions, thus fostering greater trust and transparency necessary for real-world adoption. The model's resilience was further validated on external clinical data, confirming its generalizability across different patient populations and recording conditions, a critical factor for practical deployment in diverse healthcare environments. Moreover, optimization techniques enabled the deployment of the model on mobile platforms, highlighting its potential as a low-cost, non-invasive screening tool especially valuable in resource-limited and remote settings where access to advanced cardiac imaging or specialist consultation is restricted. Despite the promising results, challenges remain regarding variability in recording quality and the need for larger, more diverse datasets to enhance model robustness and ensure equitable performance across demographic groups. Future research should focus on expanding clinical trials, improving noise-resilient preprocessing methods, and developing user-friendly interfaces that incorporate explainability features to assist healthcare providers in decision-making. Furthermore, extending the framework to detect other cardiac abnormalities could broaden the clinical impact of this technology. Ultimately, the study underscores the transformative potential of combining heart sound analysis with artificial intelligence for early, accessible, and accurate CHF diagnosis, which could significantly improve patient outcomes by facilitating timely intervention and continuous monitoring. This aligns with the growing emphasis on telemedicine and personalized healthcare, offering a scalable solution to reduce the global burden of heart failure. The integration of such AI-driven diagnostic tools into routine clinical practice promises to augment traditional diagnostic modalities, streamline workflows, and enhance preventive cardiology strategies, paving the way toward more effective management of chronic cardiovascular diseases worldwide.

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