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Chronic Heart Failure Detection using ML and CNN

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Abstract
CHF, a grave medical condition that impacts millions of individuals globally, is becoming increasingly prevalent at a rate of 2% every year. Despite the widespread availability of sensors and technologies, automated detection of CHF remains a challenge. In response, this study proposes a new method for CHF detection using heart sounds, which combines traditional machine learning (ML) with convolutional neural networks (CNNs). By analysing recordings of heart sounds, this model can detect subtle changes in the sound patterns that may be difficult for a human to detect. The usefulness of this technique goes beyond identifying CHF in both healthy individuals and patients. The research discovered 15 specialized characteristics that can distinguish between different stages of CHF with an impressive precision of 93.2%. This development offers hope for the development of home-based CHF monitors to prevent hospitalization. This study highlights the importance of combining traditional ML with advanced techniques such as CNNs in improving the accuracy and efficiency of CHF detection. The promising results of this method demonstrate its potential for the detection of fresh CHF cases and the creation of CHF monitoring systems that can be used at home. Further research and development of this method could lead to the development of more effective and accessible CHF detection and monitoring tools.
Keywords: Chronic heart failure, heart sounds, machine learning, convolutional neural networks, PCG

Introduction

Heart failure is a global health issue, affecting millions of people worldwide each year. The chronic form of the condition, known as Chronic Heart Failure (CHF), is characterized by the inability of the heart to efficiently pump blood to the rest of the body, leading to a range of symptoms such as shortness of breath, fatigue, and swelling in the legs and ankles. CHF is a complex condition with various underlying causes and contributing factors, making its diagnosis and management challenging. Therefore, early detection of CHF and monitoring of its progression is crucial for improving patient outcomes and reducing the burden on the healthcare system. Despite the availability of advanced technologies, automated CHF detection methods remain limited. Traditional approaches rely on clinical examination, electrocardiogram, and echocardiography, which can be time-consuming, expensive, and require specialized expertise. As such, there is a need for more efficient and accurate methods for CHF detection. Recent studies have proposed the use of heart sounds, or phonocardiograms (PCG), as a non-invasive and cost-effective alternative for CHF detection. This study builds on this approach and proposes a novel method that combines traditional Machine Learning (ML) with Convolutional Neural Networks (CNNs) to detect CHF from PCG recordings. Moreover, we also investigate the differences in heart sounds during the transition between decompensated and recompensated states of CHF. This investigation aims to develop personalized monitoring models that can detect early signs of CHF worsening, thereby reducing hospitalizations and improving patient quality of life while decreasing the financial and logistical burden on both the patients and the health system. Therefore, the proposed

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method has significant potential for developing home-based CHF monitors and identifying new CHF patients, which can aid in the early detection and treatment of CHF.

Literature Survey

The detection of chronic heart failure (CHF) has been the subject of extensive research, including the use of machine learning (ML) models. Numerous research studies have investigated the potential of machine learning classifiers to identify CHF based on heart sounds. One such study proposed a stack of ML classifiers for CHF detection from heart sounds, achieving a classification accuracy of 85%. Another study examined the economic implications of CHF in the United States and found that it results in significant healthcare costs. In addition, a PhysioNet/Computing in Cardiology Challenge evaluated the classification of normal/abnormal heart sounds, with the best-performing model achieving an F1 score of 0.875. Other studies explored ML models in various applications, including deep neural network-based pedestrian detection, ImageNet classification with deep convolutional neural networks, and the use of residual connections on learning. Natural language processing and probabilistic language models were also studied, as well as the recognition of echolalic autistic child vocalizations using convolutional recurrent neural networks. Bag-of-deep-features were proposed as noise-robust deep feature representations for audio analysis. Finally, deep affect recognition from R-R intervals and the learning of deep physiological models of affect were also explored in different studies. Overall, these studies demonstrate the potential of ML models in detecting CHF and in various other applications. Some of the citations are as follows:

- *Citation*- The project "Machine Learning and End-to-End Deep Learning for the Detection of Chronic Heart Failure from Heart Sounds" aims to develop a system for the automatic detection of chronic heart failure (CHF) from heart sounds using machine learning and deep learning techniques.
  Outcome- This project is a system that can accurately detect CHF from heart sounds, which could potentially be used as a screening tool for early detection of CHF. This system could help healthcare professionals diagnose CHF more quickly and accurately, which could improve patient outcomes and reduce health care costs.

- *Citation*- The project "Chronic heart failure detection from heart sounds using a stack of machine-learning classifiers" The objective of this project is to create a system that can precisely identify chronic heart failure by analyzing heart sounds with the help of machine learning algorithms.
  Outcome- The authors report that their system achieved a high accuracy of 91.2% in detecting chronic heart failure from heart sounds, demonstrating the potential for using machine learning algorithms to assist in the diagnosis of heart conditions.

- *Citation*- The project "A reevaluation of the costs of heart failure and its implications for allocation of health resources in the United States" aims to update and refine estimates of the economic burden of heart failure in the United States, and to analyze the implications for allocation of health resources.
  Outcome- The study highlights the need for more effective management and prevention strategies for heart failure, and the importance of allocating healthcare resources appropriately to address this growing problem.

- *Citation-* The project "Classification of normal and abnormal heart sound recordings" aims to develop a system for accurately classifying heart sound recordings as either normal or abnormal using machine learning algorithms.
  Outcome- The study demonstrated the potential of machine learning techniques in assisting with the diagnosis of heart conditions based on heart sounds, which could improve the accuracy and efficiency of diagnosis and ultimately lead to improved patient outcomes.

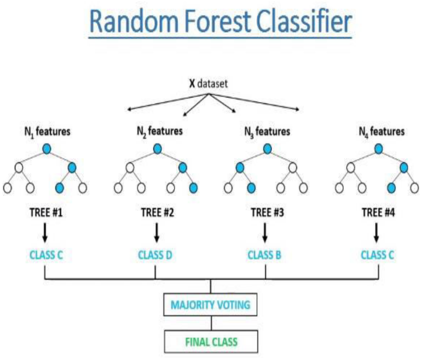
Proposed System

The proposed system aims to combine two machine learning techniques, Random Forest and Convolutional Neural Networks (CNN), to detect Chronic Heart Failure (CHF) from heart sounds. The system uses heart sound recordings as input data, which are first pre-processed to extract relevant features. These features are then fed into both the Random Forest and CNN models for training. The Random Forest model is trained on the extracted features and used for the classification of normal and abnormal heart sounds. The output of the Random Forest model is then used as input to the CNN model, which is trained to identify the specific characteristics of heart sounds associated with CHF. The CNN model is used to detect subtle changes in heart sounds that may not be detected by the Random Forest model. During the testing phase, the heart sound recordings are fed into the pre-trained Random Forest model for classification into normal or abnormal heart sounds. The output of the Random Forest model is then fed into the pre-trained CNN model, which identifies the specific characteristics of heart sounds associated with CHF. The final output of the system is a binary classification of normal or abnormal heart sounds with respect to CHF. The proposed system has several potential benefits. Firstly, it combines the strengths of both Random Forest and CNN models to improve the accuracy of CHF detection. Secondly, the use of pre-processing techniques and feature extraction can help to reduce the dimensionality of the input data and improve the efficiency of the system. Finally, the proposed system has the potential to improve the accuracy and efficiency of CHF detection.

Algorithm

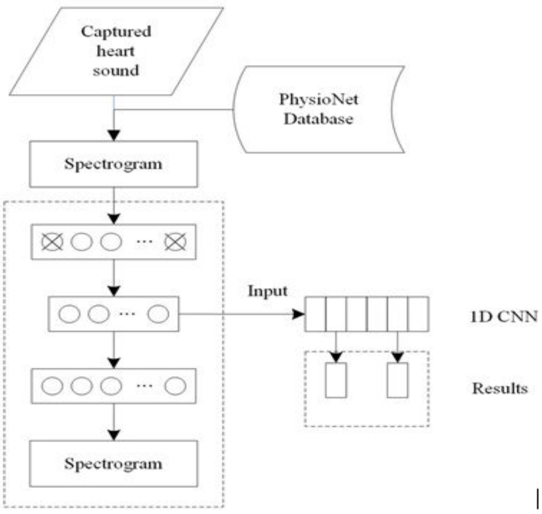
RANDOM FOREST

Random forest is a type of machine learning algorithm that is used for classification and regression tasks. It belongs to the category of ensemble methods, which combine the results of multiple decision trees to improve the accuracy of predictions. In a random forest, a large number of decision trees are trained on random subsets of the data, and each tree produces a prediction. The final prediction of the random forest is the average of the predictions of all the individual trees. Random forests are commonly used in applications such as image classification, speech recognition, and bioinformatics. They have also been applied to medical diagnosis and prognosis tasks, including detecting heart failure, diabetes, and cancer. Overall, random forest is a powerful machine learning algorithm that can produce accurate predictions in a wide range of applications.



CNN

In a CNN architecture for audio data, the first layer is typically a 1D convolutional layer that applies a set of filters to the audio signal. The filter bank can be designed to extract frequency features that can capture the different frequency components of the audio signal. The output of the convolutional layer is then passed through a nonlinear activation function, such as ReLU, to introduce nonlinearity in the model. This is followed by a pooling layer that reduces the dimensionality of the feature map. The convolutional and pooling layers can be stacked to create multiple layers of feature extraction. The final layers are typically fully connected layers that perform classification or regression based on the extracted features. During training, the CNN adjusts the weights of the neurons using backpropagation and gradient descent to minimize the error between the predicted and actual labels. CNNs have shown to be effective in audio processing tasks such as speech recognition, music classification, and environmental sound recognition.

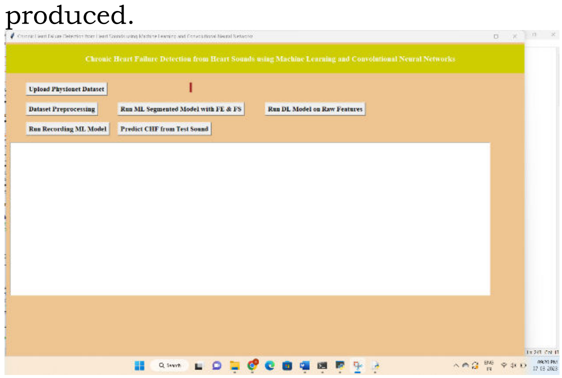


Dataset

The heart sound recordings were collected from different locations on the body. The typical four locations are aortic area, pulmonic area, tricuspid area and mitral area, but could be one of nine different locations. In both training and test sets, heart sound recordings were divided into two types: normal and abnormal heart sound recordings. The normal recordings were from healthy subjects and the abnormal ones were from patients with a confirmed cardiac diagnosis. The patients suffer from a variety of illnesses (which we do not provide on a case-by-case basis), but typically they are heart valve defects and coronary artery disease patients. Heart valve defects include mitral valve prolapse, mitral regurgitation, aortic stenosis and valvular surgery. All the recordings from the patients were generally labeled as abnormal. We do not provide more specific classification for these abnormal recordings. Please note that both training and test sets are unbalanced, i.e., the number of normal recordings does not equal that of abnormal recordings. You will have to consider this when you train and test your algorithms. Both healthy subjects and pathological patients include both children and adults. Each subject/patient may have contributed between one and six heart sound recordings. The recordings last from several seconds to up to more than one hundred seconds. All recordings have been resampled to 2,000 Hz and have been provided as .wav format. Each recording contains only one PCG lead. Please note that due to the uncontrolled environment of the recordings, many recordings are corrupted by various noise sources, such as talking, stethoscope motion, breathing and intestinal sounds. Some recordings were difficult or even impossible to classify as normal or abnormal.

Results and Discussion

Run ChronicHeartDetection.py file in the location where all code files exist. It opens an interface and further, results are produced.



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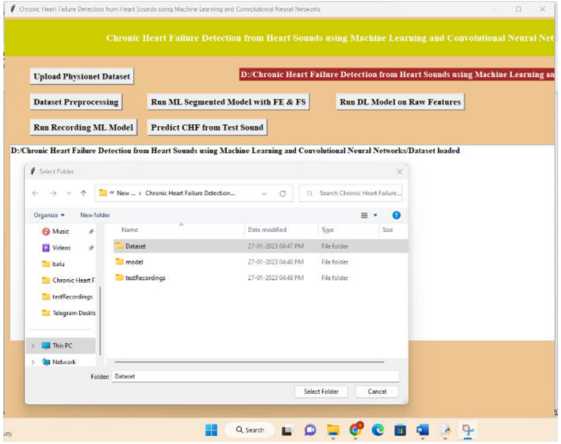

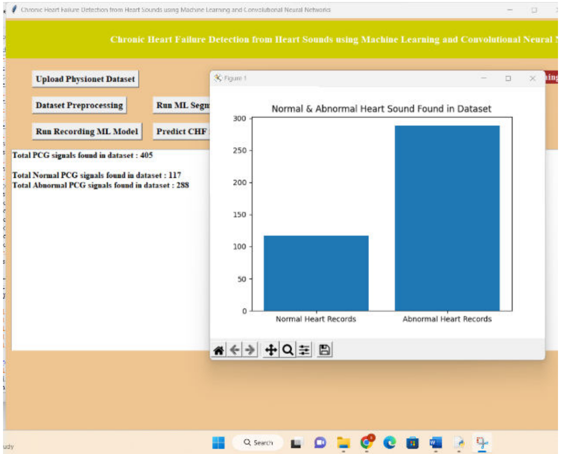

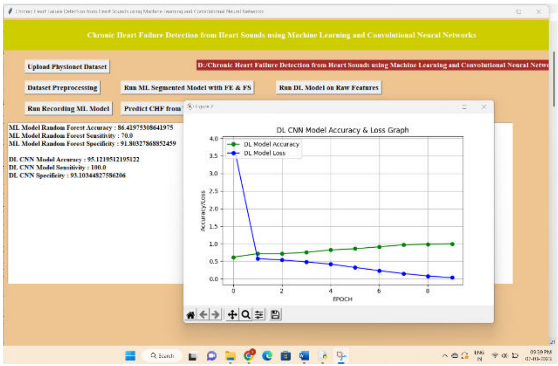

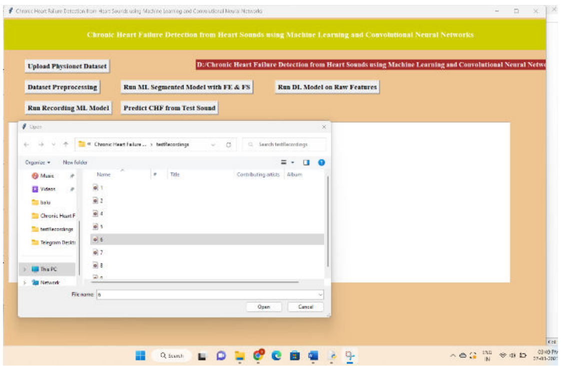

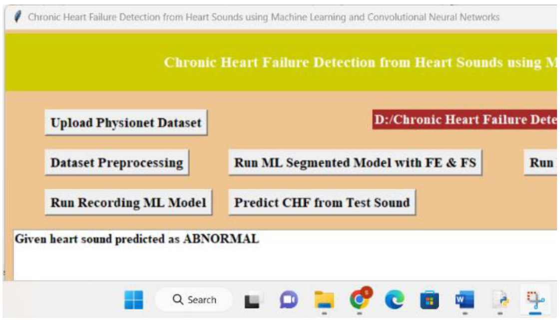

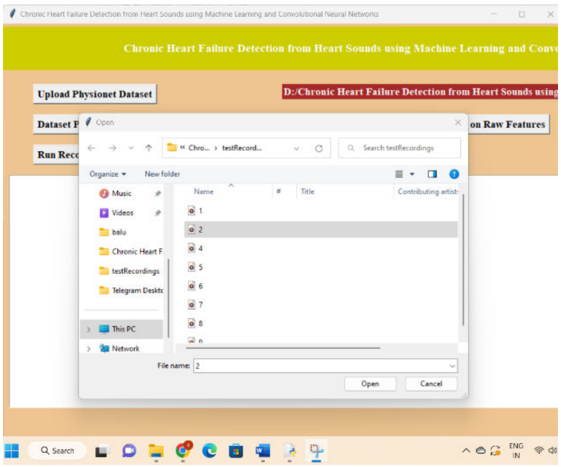

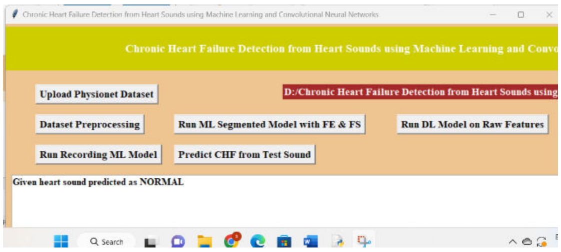

To implement our CHF detection system, we have designed several modules. Firstly, the "Upload Physionet Dataset" module allows us to upload the dataset to our application. Secondly, the "Dataset Preprocessing" module extracts audio recording features, systolic and diastolic features from the dataset, and normalizes their values. Thirdly, the "Run ML Segmented Model with FE & FS" module extracts and selects systolic and diastolic features from the dataset, trains them with a Random Forest Classic ML model, and then applies test data to calculate the model's prediction accuracy. Fourthly, the "Run CNN Model on Raw Features" module extracts RAW features from the recording, trains them with a CNN model, and then applies the model to test data to calculate its accuracy. Fifthly, the "Run Recording ML Model" module extracts features from both the Classic ML model and the deep learning model, retrains them with a third classifier, and then calculates its prediction accuracy. Finally, the "Predict CHF from Test Sound" module enables us to upload a test heart sound file and then use the classifier model to predict whether the given recording file is normal or abnormal.

Conclusion

In this study, a novel method for CHF detection from PCG audio recordings was proposed, which combines classic ML and CNN. The classic ML component learns from a large body of expert-defined features while the CNN component learns from both the time-domain and spectral representation of the signal. The proposed method was evaluated on our own dataset for CHF detection and six publicly available PhysioNet datasets used for the recent PhysioNet Cardiology Challenge. The results showed that the proposed method achieved the best performance compared to the challenge baseline methods. The study also demonstrated that the proposed method is quite robust and useful for detecting different types of heart-sound classification problems, as long as domain-specific labeled data are provided. Moreover, personalized models for detecting different CHF phases were explored. The study identified 15 features that have different distributions depending on the phase. By using just two of these features, a simple and transparent decision tree classifier was built that is capable of distinguishing between the recompensated and the decompensated phases with an accuracy of 93.2%. These results are very encouraging and represent a solid base for further development of personalized models. To the best of our knowledge, this is the first study to address such a problem.

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