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Transfer learning based Chronical Heart Failure Detection from Heart Sounds

Nagidi Prudhvi Raj
PG scholar, Department of MCA, DNR college, Bhimavaram, Andhra Pradesh.
A.NAGA RAJU-
(Assistant Professor), Master of Computer Applications, DNR college, Bhimavaram, Andhra Pradesh.

Abstract: Chronic Heart Failure (CHF) is a major health condition, and early detection is crucial for effective management. In this study, we propose a method for CHF detection using heart sounds, utilizing four different predictive algorithms: (1) a machine learning (ML) approach with Random Forest, (2) a deep learning (DL) model based on a custom Convolutional Neural Network (CNN), (3) a hybrid ML-DL approach combining both techniques, and (4) a transfer learning-based approach using a pretrained VGGish model for feature extraction. The PhysioNet Heart Sound Dataset is used, and the dataset undergoes pre-processing, including noise reduction and feature extraction. The models are then trained and evaluated on the dataset, with the final system predicting CHF from unseen heart sound recordings. Our approach demonstrates a robust framework for leveraging both classical ML and advanced DL techniques for the early detection of CHF, potentially improving patient outcomes through timely intervention.

Keywords: Chronical heart failure, heart sound, deep learning, machine learning, CNN

I. INTRODUCTION

Chronic Heart Failure (CHF) is a progressive condition where the heart fails to pump sufficient blood to meet the body's metabolic needs, even at normal filling pressures. Chronic Heart Failure (CHF) remains a significant global health challenge, marked by the heart's inability to supply sufficient blood to meet the body's demands. This study expands CHF detection using a larger dataset, including six PhysioNet datasets, and integrates end-to-end DL with improved ML methods. It explores heart sound differences between decompensated and recompensated CHF states to develop personalized monitoring models. Early detection can reduce hospitalizations, enhance patient quality of life, and ease healthcare burdens. [1]

Early and accurate detection of CHF is essential to improve patient outcomes and reduce healthcare costs. Heart sounds, recorded as Phonocardiograms (PCGs), contain vital acoustic information that can aid in diagnosing heart conditions. This project leverages advanced deep learning (DL) and machine learning (ML) techniques, including transfer learning, to detect CHF from heart sounds. Phonocardiography can detect distinct changes in heart sounds that occur when heart failure worsens. This project uses a cutting-edge end-to-end aggregate recording model that combines features from both deep learning and machine learning to detect chronic heart failure from phonocardiography (PCG) data. The performance of the proposed ChronicNet model, along with standalone ML and DL models, was also evaluated. [3]

In this study, four different algorithms are employed to predict CHF effectively:

1. **Random Forest (ML Algorithm):** A robust machine learning algorithm used for feature-based classification of heart sounds.
2. **Custom CNN (DL Algorithm):** A convolutional neural network designed specifically to extract spatial and temporal features from PCGs.
3. **ML-DL Hybrid Algorithm:** A combination of ML and DL techniques, integrating the strengths of both approaches for improved prediction accuracy.
4. **DL with Pretrained Layer (Transfer Learning):** The use of a pretrained VGGish layer, known for its efficiency in

audio signal processing, to enhance feature extraction and model performance.

The aim of this project is to explore the potential of transfer learning alongside traditional ML and DL techniques to develop a comprehensive system for CHF detection. Transfer learning enables the model to leverage knowledge from pre-trained audio networks, reducing training time and improving generalization, especially when dealing with limited datasets.

CHF affects over 26 million people globally, with its incidence increasing annually. Despite its significant impact, automatic methods for detecting CHF remain scarce. This study presents a method combining ML and DL using heart sounds, achieving an accuracy of 92.9% on datasets from 947 subjects. [4]

The primary objective is to analyze the effectiveness of these algorithms in predicting CHF and compare their performance. Each algorithm is evaluated for its ability to handle noise, extract meaningful features, and deliver accurate predictions. This project also highlights the integration of transfer learning through the VGGish layer, which provides a robust foundation for processing heart sound signals. The approach demonstrates how pretrained layers can accelerate model development while maintaining high accuracy in detecting CHF.

Our work builds on previous findings by using a larger patient dataset, incorporating six additional PhysioNet datasets, and employing an upgraded end-to-end deep learning method. We also explore personalized monitoring models by analyzing heart sound changes during the transition between decompensated and recompensated stages of CHF, aiming for early diagnosis to prevent hospitalizations and reduce the burden on patients and the healthcare system. [5]

The proposed method in this paper combines Ensembled Transfer Learning and Multiple Kernel Learning (MKL) for atherosclerotic coronary artery disease detection using phonocardiogram (PCG) signals. The approach utilizes deep embeddings from pre-trained CNN models, which are fused with handcrafted features through MKL to improve detection accuracy by optimizing kernel combinations, achieving a significant performance improvement in CAD classification. [6]

This study explores the differences in heart sounds during the transition between the recompensated and decompensated states of CHF, aiming to develop personalized monitoring models. Early detection of worsening CHF could reduce hospitalizations, enhancing patients' quality of life while lowering the financial and logistical burdens on both patients and healthcare systems. [7]

In the proposed paper, the authors use the heart sound dataset from the PhysioNet website, which contains PCG (Phonocardiogram) signal data. From these PCG signals, systolic and diastolic features are extracted for training with classic machine learning (ML) algorithms. Since ML models cannot train directly on raw features, these extracted features are used for training. Additionally, the raw PCG data is trained with deep learning algorithms to capture more complex patterns. To further enhance accuracy, the average recordings from both models are combined and retrained with a third classifier, ultimately improving the overall prediction accuracy. This research showcases the power of combining traditional ML, custom DL, hybrid approaches, and transfer learning for CHF detection. The findings contribute to advancing non-invasive diagnostic solutions, paving the way for improved healthcare outcomes.

II. LITERATURE SURVEY

Chronic Heart Failure (CHF) affects over 26 million people globally, with a rising annual incidence of 2%. This study introduces a method for CHF detection using heart sounds, combining traditional Machine Learning (ML) for expert feature analysis and Deep Learning (DL) for spectro-temporal signal representation. Evaluated on data from 947 subjects, the method achieved a score of 89.3, surpassing the PhysoNet challenge baseline by 9.1, and an aggregated accuracy of 92.9%. Additionally, 15 expert features were identified to distinguish CHF phases with 93.2%

accuracy. These results highlight the potential for automated CHF detection and home-based monitoring to reduce hospitalizations. [1]

This work proposes an ensemble classifier to detect heart abnormalities using Phonocardiogram (PCG) signals for the INTERSPEECH 2018 ComParE Heart Beats SubChallenge. The approach includes a 1D-CNN with time-convolution layers leveraging features from a pre-trained PhysioNet Heart Sound model, unsupervised feature learning via Deep Recurrent Autoencoders, and classification using SVM and LDA. Segment-level features extracted using Low-Level Descriptors (LLD) further enhance performance. The ensemble achieves an 11.13% relative improvement in Unweighted Average Recall (UAR) compared to the best single system. [2]

CHF is a progressive condition where the heart cannot pump blood effectively, leading to insufficient blood flow to the body's tissues and organs. This debilitating condition is increasing at a rate of 2% annually, with 1-2% of the general population and 10% of those aged 65 and above affected. CHF represents a significant financial burden, with approximately 2% of healthcare expenditure directed toward its diagnosis and treatment. Despite advancements in medical and device-based therapies, the 5-year survival rate remains around 50%. Patients with CHF experience fluctuating phases of symptom severity, from stable periods to acute episodes requiring hospitalization. Early detection of worsening CHF is critical to preventing hospitalization, and this project aims to leverage phonocardiography (PCG) to identify these changes. By employing an innovative end-to-end average aggregate recording model that combines ML and DL features, the project seeks to improve the detection of chronic heart failure and assess the performance of both standalone and integrated models. [3]

The proposed method for CHF detection using heart sounds combines classic ML and DL techniques. It was evaluated on 947 subjects across six publicly available datasets and a CHF dataset collected for this study, achieving an accuracy of 92.9% (error of 7.1%). This method identified 15 expert features useful for differentiating between CHF phases, with an accuracy of 93.2%, showing promising results for both detecting healthy subjects and different CHF phases, potentially aiding in home-based monitoring and reducing hospitalizations. [4]

We propose a method for detecting CHF based on heart sounds, combining traditional ML and DL. The method utilizes both expert features for ML and spectro-temporal representations for DL. Tested on recordings from 947 subjects across six public datasets and one CHF dataset, the method achieved a score of 89.3, outperforming the baseline by 9.1 points. With an accuracy of 92.9% and 93.2% for distinguishing CHF phases, the approach shows promise for identifying new CHF patients and enabling home-based monitoring to reduce hospitalizations. [5]

This study proposes a novel approach for Coronary Artery Disease (CAD) detection using phonocardiogram (PCG) signals, combining conventional machine learning with deep learning for improved performance. By utilizing multiple kernel learning (MKL) to fuse deep embeddings transferred from a pre-trained convolutional neural network (CNN) with handcrafted features, the method maximizes the similarity with ideal kernels while minimizing redundancy. When fused with handcrafted features through MKL, the accuracy improves to 91.19% with a kappa of 0.8238, showing the potential for a high-accuracy, non-invasive CAD detection system using easily acquired PCG signals.[6]

This study presents a method for detecting chronic heart failure (CHF) using heart sound data. It combines classic Machine Learning (ML) that utilizes expert features and end-to-end Deep Learning (DL) that processes spectro-temporal representations of heart sounds. Evaluated on 947 subject recordings from multiple datasets, the method achieved an accuracy of 92.9%, surpassing the baseline method from a recent PhysioNet challenge. The model also identified 15 expert features that help differentiate between CHF phases with 93.2% accuracy, showing potential for early CHF detection and the development of home-based monitoring systems to reduce hospitalizations.[7]

III. PROPOSED METHOD

In this project, we aim to predict Chronic Heart Failure (CHF) from heart sounds using four different algorithms. First, we upload the PhysioNet dataset, which contains heart sound recordings from various subjects. The dataset undergoes preprocessing, including noise reduction and feature extraction, to prepare it for model training. We then run the machine learning (ML) algorithm using Random Forest to classify the heart sounds based on extracted features. A custom Convolutional Neural Network (CNN) is also implemented as a deep learning (DL) approach to directly learn from the raw heart sound data, capturing complex patterns in the audio.

Additionally, we combine ML and DL techniques in a hybrid approach, leveraging the strengths of both to improve classification accuracy. For transfer learning, we use a pretrained VGGish model that has been trained on a large dataset of audio signals, and fine-tune it on our heart sound dataset for better feature extraction. Finally, we predict CHF by testing the models on unseen heart sound recordings, providing an end-to-end solution for early CHF detection. This method allows for more accurate and efficient diagnosis by combining traditional ML with advanced deep learning

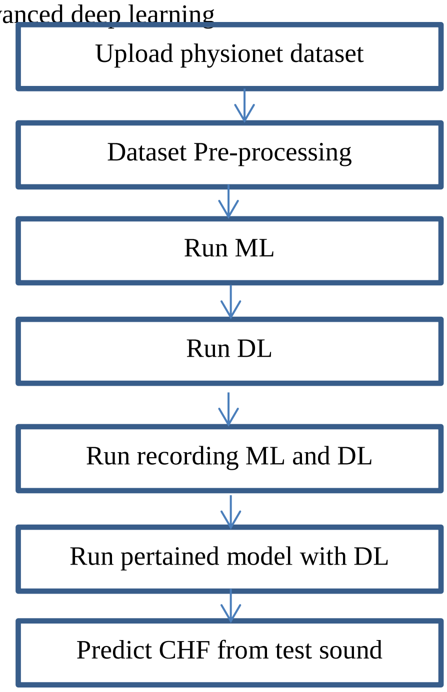

Fig. Flowchart of proposed method

Following are the steps of proposed method

1. **Upload PhysioNet Dataset**:

Load the required dataset from the PhysioNet database, which contains phonocardiogram (PCG) recordings and heart sound data. Ensure the dataset is in the appropriate format and includes relevant labels for CHF detection.

2. **Dataset Pre-processing**:

Clean the dataset by removing noise or irrelevant data. Segment the PCG signals into systolic and diastolic phases if required. Extract features such as frequency, amplitude, or spectro-temporal representations for further analysis.

3. **Run ML (Machine Learning)**:

Train classic ML models such as Random Forest, using expert-engineered features extracted during preprocessing. Evaluate these models on test data for accuracy, precision, recall, etc.

4. **Run DL (Deep Learning)**:

Train deep learning models such as CNNs on spectro-temporal representations of PCG signals. Use end-to-end learning, where the model learns relevant features directly from raw or minimally processed data.

5. **Run Recording ML (Combined ML and DL)**:

Combine the outputs or learned features from both ML and DL models. Train an additional ML model (like ensemble learning) to fuse these features and improve overall accuracy.

6. **Run Pretrained Model with DL**:

Utilize pretrained deep learning models (e.g., ResNet, VGG) on PCG data by transferring their learned embeddings. Fine-tune these models on the

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specific dataset for better performance in detecting CHF.

7. Predict CHF from test sound:

Use the trained model (ML, DL, or the combined approach) to predict CHF status for unseen test recordings. Input the test sound data into the model, ensuring it has undergone the same pre-processing steps as the training data. Obtain the output, which classifies the heart sound as healthy or indicative of CHF, and evaluate predictions against the ground truth labels.

In this project we used heart sounds for prediction of heart failure. We used 4 different algorithms for prediction of heart failure. The algorithms used are a) ML algorithm (random Forest) b) DL algorithm (Custom CNN) c) ML-DL hybrid algorithm d) DL with pretrained layer (vggish layer)

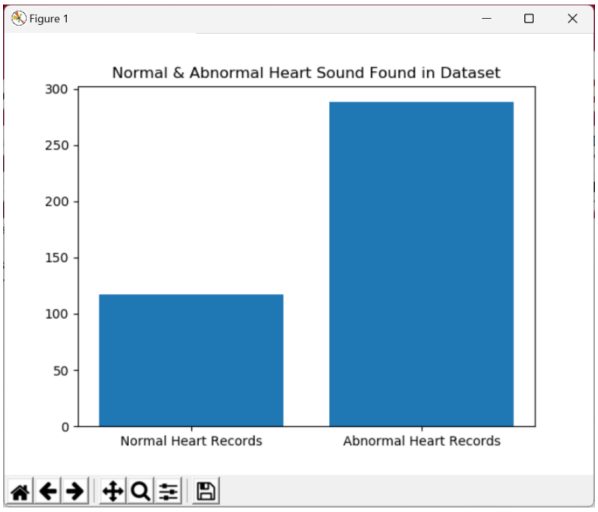


Fig. Heart sound images available in dataset

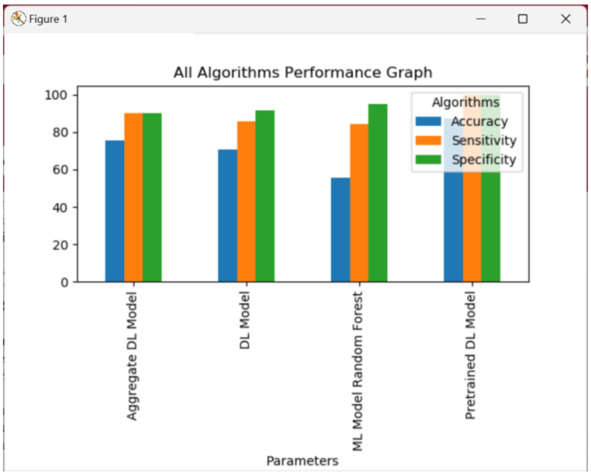
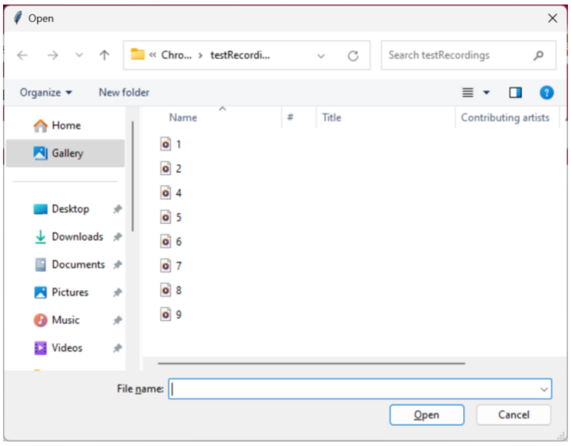


Fig. Performance analysis of different algorithms

It is observed that proposed model , pretrained with DL for chronical heart failure prediction from heart sound gives better performance than previous algorithms such as ML , DL and ML_DL hybrid algorithm.



Predict the chronical Heart Disease from test speech samples

Fig. Predicted as Normal Heart Sound

Fig. Predicted as Abnormal Heart Sound

IV. CONCLUSION

This study presents a comprehensive approach for Chronic Heart Failure detection from heart sounds using a combination of machine learning and deep learning techniques. By incorporating various algorithms, including Random Forest, Custom CNN, ML-DL hybrid models, and pretrained VGGish-based transfer learning, the proposed system provides a flexible and accurate method for predicting CHF. The experimental results show that combining traditional and advanced methods improves prediction accuracy and robustness. This approach holds significant potential for clinical applications, enabling early diagnosis and personalized monitoring, ultimately leading to better patient management and reduced healthcare costs. Future work could explore further model refinements and real-time application integration to facilitate practical use in healthcare settings.

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