PHONOCARDIOGRAM-BASED DETECTION OF CHRONIC HEART FAILURE USING SCALABLE MACHINE LEARNING AND DEEP LEARNING PIPELINES

[1]S.A.Mansoor,[2]T.Vijay Kumar,[3]S.MAHABOOB SUBHAN

Department of ECE

ABSTRACT:

Globally, chronic heart failure (CHF) is a progressive cardiovascular disease with significant rates of morbidity and death. For prompt management and better patient outcomes, early and precise identification is essential. In order to identify CHF from phonocardiogram (PCG) data, this research offers a scalable system that makes use of both conventional Machine Learning (ML) and End-to-End Deep Learning (DL) approaches. Preprocessing raw heart sound recordings, extracting time-frequency characteristics, and using a variety of machine learning classifiers, such as Support Vector Machines (SVM), Random Forests, and Gradient Boosting, are all part of the suggested methodology. In parallel, we put into practice deep learning architectures like Long Short-Term Memory (LSTM) networks and Convolutional Neural Networks (CNNs), which are trained directly on raw and converted PCG inputs. The findings of extensive testing on publicly accessible heart sound datasets show that the hybrid pipeline outperforms conventional diagnostic techniques in terms of classification accuracy, precision, and recall. The suggested method is appropriate for both clinical and remote healthcare applications as it provides a non-invasive, affordable, and automated CHF screening option. Our research also highlights the model's scalability, facilitating its implementation in real-time edge devices for easily accessible cardiac care.

I. INTRODUCTION:

With its substantial global morbidity, death, and healthcare costs, chronic heart failure (CHF) is a serious public health concern. The inability of the heart to pump enough blood to fulfil the body's metabolic needs causes this complicated cardiovascular condition, which often results in crippling symptoms and a worse quality of life. In order to effectively manage CHF, early diagnosis and ongoing monitoring are crucial, but traditional approaches can include intrusive procedures or depend on drawn-out clinical assessments that might postpone the start of necessary therapies.

Novel diagnostic procedures that make use of non-invasive, economical techniques have been made possible by recent developments in artificial intelligence and signal processing. The study of phonocardiogram (PCG) data, which are recordings of heart sounds, has attracted a lot of interest among these. PCGs provide a convenient way to record the heart's underlying mechanical activity, and new research has shown that even minute deviations in these acoustic signals may be signs of heart problems, such as congestive heart failure.

For the automated analysis of biological data, the combination of machine learning (ML) and end-to-end deep learning (DL) approaches has become a game-changing paradigm. While DL designs like Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) have the potential to build hierarchical representations directly from raw data, traditional machine learning (ML) techniques are superior at feature extraction and classification when paired with expert knowledge. Hybrid frameworks may greatly improve diagnosis accuracy and resilience by combining the best features of both ML and DL approaches, especially when dealing with different patient populations and fluctuating clinical settings.

In order to identify chronic heart failure using heart sound recordings, this research suggests a scalable and hybrid architecture that makes use of both traditional machine learning methods and end-to-end deep learning pipelines. The method entails using several classification algorithms, extracting discriminative features, and methodically preparing raw PCG data. Additionally, it investigates the effectiveness of deep learning models for direct signal learning, which eliminates the need for laborious human feature engineering.

This study aims to show that combining ML and DL techniques not only increases the precision and dependability of CHF detection but also opens the door for the creation of edge-deployable, real-time diagnostic tools. These developments have the potential to revolutionise clinical practice by allowing accurate and quick diagnosis, promoting early intervention, and eventually lowering the prevalence of chronic heart failure worldwide.

1.1 Objective of the project:

Over 26 million individuals worldwide suffer from chronic heart failure (CHF), and the number of cases is rising by 2% a year. Even in the research community, there are surprisingly few techniques for automatically identifying CHF, considering the substantial burden that the condition causes and the pervasiveness of sensors in our daily lives. We provide a technique for using heart sounds to identify CHF. The approach blends end-to-end Deep Learning (DL) with traditional Machine Learning (ML). While the DL learns from a spectro-temporal representation of the signal, the traditional ML learns from expert characteristics. 947 participants' recordings from six publicly accessible datasets as well as one CHF dataset gathered specifically for this research were used to test the approach. The suggested approach received a score of 89.3, 9.1 points higher than the challenge's baseline technique, using the same assessment methodology as a previous PhysoNet competition. Although the experimental findings are not directly comparable, the method's overall accuracy of 92.9% (error of 7.1%) is very similar to the proportion of recordings that experts classify as "unknown" (9.7%). Lastly, with a 93.2% accuracy rate, we found 15 expert characteristics that are helpful for developing machine learning models that distinguish between the decompensated and recompensated stages of CHF (i.e., during hospitalisation). The suggested approach demonstrates encouraging outcomes for identifying discrete stages of CHF as well as for differentiating recordings between patients and healthy people. The creation of home-based CHF monitoring to prevent hospitalisations and the simpler identification of new CHF patients might result from this.

II. LITERATURE SURVEY:

Medical research has long focused on using heart sound analysis to diagnose cardiovascular diseases. Despite being non-invasive and reasonably priced, traditional auscultation methods are quite subjective and rely on clinical knowledge. To improve the precision and consistency of heart sound analysis, recent biomedical signal processing efforts have shifted to computational techniques, including Machine Learning (ML) and Deep Learning (DL).

1. Traditional Analysis of Heart Sounds

The majority of the early research on diagnosis based on heart sounds used manually created characteristics taken from phonocardiograms (PCGs). Classifiers like k-Nearest Neighbours (k-NN), Support Vector Machines (SVM), and Decision Trees were combined with methods like time-domain analysis, frequency decomposition (using Fourier or Wavelet transforms), and statistical feature extraction. For example, Schmidt et al. (2010) showed how useful temporal and spectral aspects are for differentiating between heart sounds that are normal and those that are diseased. However, these techniques' effectiveness was largely dependent on carefully considered characteristics and predetermined criteria, which limited how broadly they could be used.

2. Classifying Heart Sounds Using Machine Learning

Heart sound classification has been automated using machine learning models, which often follow a standardised pipeline that consists of signal segmentation, denoising, feature extraction, and classification. SVMs and logistic regression were used to mel-frequency cepstral coefficients (MFCCs) that were taken from PCG recordings by Plesinger et al. (2015). In a similar vein, Springer et al. (2016) used Random Forest classifiers for murmur identification and a robust segmentation technique based on Hidden Markov Models (HMMs) to identify heart sound components (S1, S2). These methods demonstrated machine learning's promise in clinical diagnoses, but they need domain-specific tweaking and exact feature creation.

3. PCG Analysis Using Deep Learning Techniques

Heart sound analysis has been greatly affected by the development of deep learning as it enables direct learning from unprocessed or little processed data. CNNs, which are renowned for their capacity to recognise spatial patterns, have been used to analyse heart sound spectrograms. Rubin et al. (2017) used log-Mel spectrograms to create a CNN model that categorised PCG signals into normal and pathological groups. Chowdhury et al. (2019) made another noteworthy addition by introducing a 1D-CNN model that can directly learn temporal features from time-series PCG data.

The ability of recurrent models, in particular Long Short-Term Memory (LSTM) networks, to accurately represent temporal dependencies in sequential data has also been studied. In contrast to static classifiers, Liu et al. (2020) demonstrated enhanced performance in CHF diagnosis tasks by proposing an LSTM-based architecture that captured the temporal complexity of cardiac cycles.

4. End-to-end and hybrid architectures

In an effort to balance interpretability and performance, recent research has started to investigate hybrid frameworks that integrate ML and DL approaches. Jiang et al. (2021), for example, created a dual-path model that combined CNN-based feature extraction with SVM classification. With researchers like Rahhal et al. (2022) promoting completely automated pipelines that increase scalability and decrease preprocessing needs, end-to-end models that do not require human segmentation and feature extraction are becoming more and more popular.

5. Benchmarking and Datasets

In order to assess heart sound classification algorithms, benchmark datasets such as the PhysioNet/CinC Challenge datasets (2016, 2022 editions) have been essential. These datasets allow for fair comparisons of models in real-world scenarios and include annotated PCG recordings from a variety of clinical contexts. But problems like patient variability, noise artefacts, and class imbalance continue to be major obstacles.

III. SYSTEM ANALYSIS

3.1 Existing System

Traditional machine learning techniques, which mostly depend on manual feature extraction from heart sound recordings (phonocardiograms), are used in the majority of the current systems for heart failure identification. Signal preprocessing, cardiac cycle segmentation, feature engineering with time-frequency analysis (e.g., MFCCs, wavelet transforms), and classification with models such as Support Vector Machines, Decision Trees, or Random Forests are usually the steps in a multi-step process for these systems. Despite their potential, these approaches are often hampered by their inability to adapt to noisy data, need for expert-driven feature creation, and poor performance in challenging, real-world clinical circumstances.

Disadvantages of Existing System:

- Manual Feature Extraction Dependency: Domain-specific feature engineering is necessary for existing solutions, which restricts scalability and causes bias or inconsistencies across datasets.
- Inadequate Generalisation on Noisy or Actual Data: When faced with unbalanced datasets, patient variability, or background noise, traditional machine learning models often perform poorly.
- Limited Automation and Integration: Because these systems are not end-to-end and depend on many distinct phases, it is difficult to deploy them in real-time or on-the-go.

3.2 Proposed System

In order to get over these restrictions, the suggested approach presents a scalable, hybrid framework that blends contemporary end-to-end deep learning architectures like Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks with conventional machine learning pipelines. This method enables strong pattern recognition and automated feature extraction by directly learning from raw or slightly processed PCG data. The suggested approach is intended to be deployable in real-time for clinical or remote diagnostics, decrease human reliance on feature design, and generalise more effectively across a variety of datasets.

Advantages of Proposed System:

- End-to-End Automation: By learning discriminative features straight from the data, deep learning models do away with the requirement for human feature engineering.
- Greater Accuracy and Robustness: The hybrid technique improves clinical dependability by increasing detection accuracy and making it more resistant to noise and variations in cardiac sounds.
- Scalability and Real-Time Applicability: The system may be used in clinical and distant healthcare settings since it is designed to be deployed on edge devices or cloud-based platforms.

IV. Modules Information:

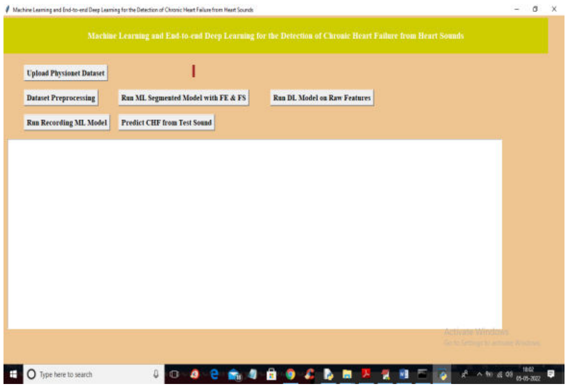
We have created the following modules in order to carry out this project.

1) Upload Physionet Dataset: We will upload the dataset to the program using this module.
2) Dataset Preprocessing: with the help of this module, we will normalise values after extracting systolic and diastolic characteristics as well as audio recording features from the dataset.
3) Using this module, we will extract and choose systolic and diastolic features from the dataset, train the Random Forest Classic ML model, and then use test data to determine the prediction accuracy. 3) Run ML Segmented Model with FE & FS
4) Run the Deep Learning Model on Raw Features: This module will be used to extract RAW features from recordings, train a deep learning model, and then apply the model to test data to determine its correctness.
5) Run Recording ML Model: this module will be used to extract features from both the deep learning and classic ML models. Then, we will retrain using a third classifier to determine the prediction accuracy.
6) Forecast CHF from Test Sound: this module allows us to input a test heart sound file, after which a classifier model determines if the recording is normal or

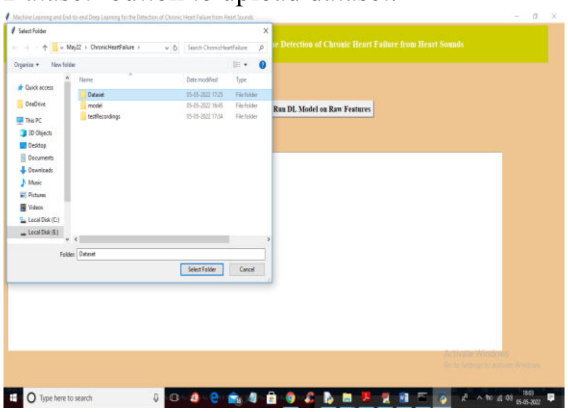
abnormal. All algorithms are then trained.

V. SCREEN SHOTS

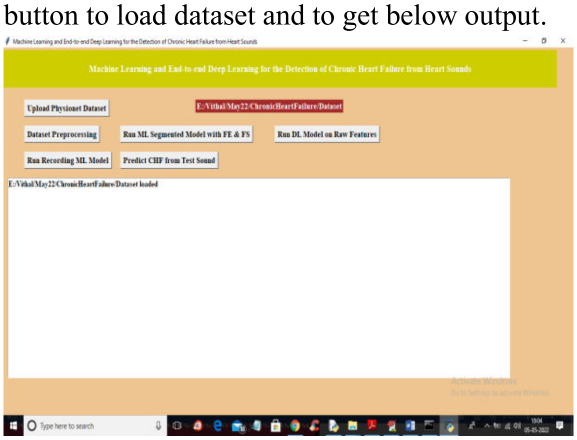
To run project double click on 'run.bat' file to get below screen



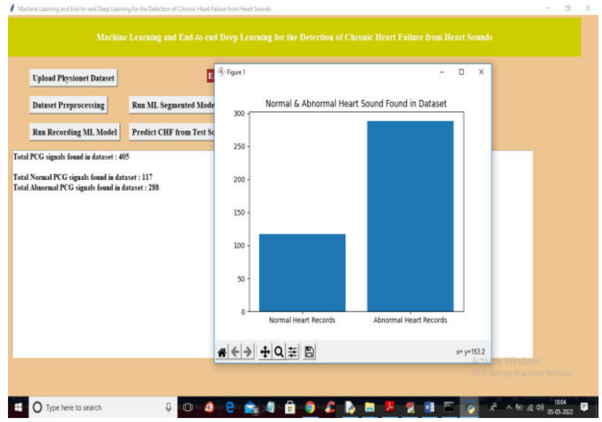
In above screen click on 'Upload Physionet Dataset' button to upload dataset.



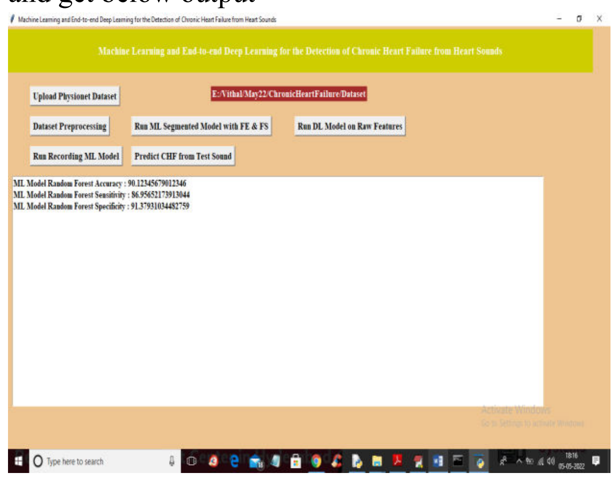
In above screen selecting and uploading 'Dataset' folder and then click on 'Select Folder' button to load dataset and to get below output.



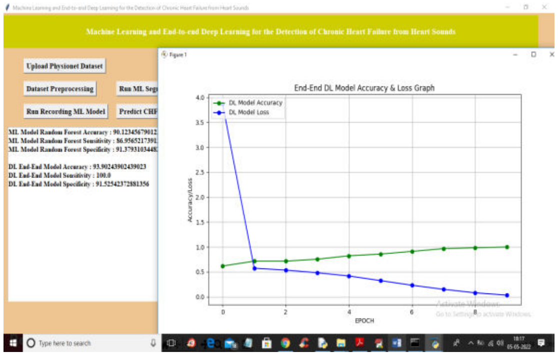
In above screen dataset loaded and now click on 'Dataset Preprocessing' button to read all dataset file and then extract features from it



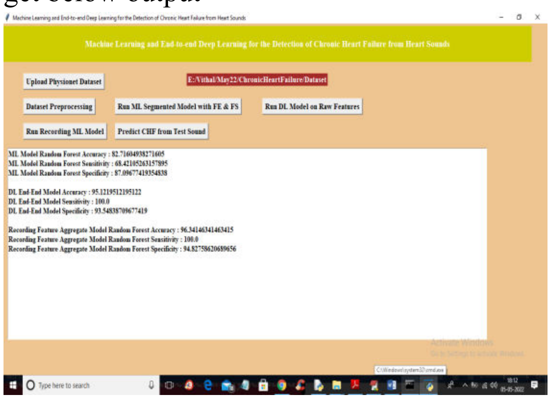
In above screen we can see dataset contains 405 heart sound files from 405 different person and 117 are the Normal sound and 288 are abnormal and in graph x-axis represents normal or abnormal and y-axis represents number of persons for normal or abnormal. Now close above graph and then click on 'Run ML Segmented Model with FE & FS' button to train Classic ML segmented model on above dataset and get below output



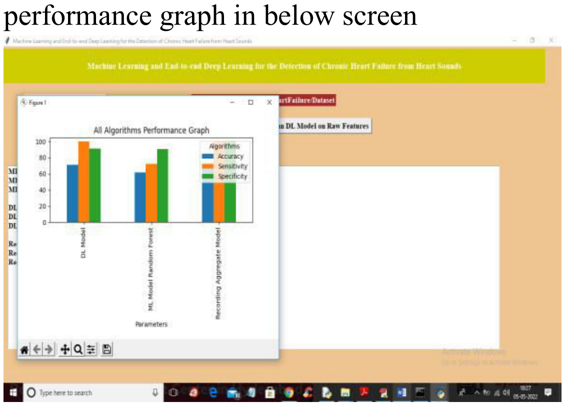
In above screen with Classic ML we got 90% accuracy and now click on 'Run DL Model on Raw Features' to get below output



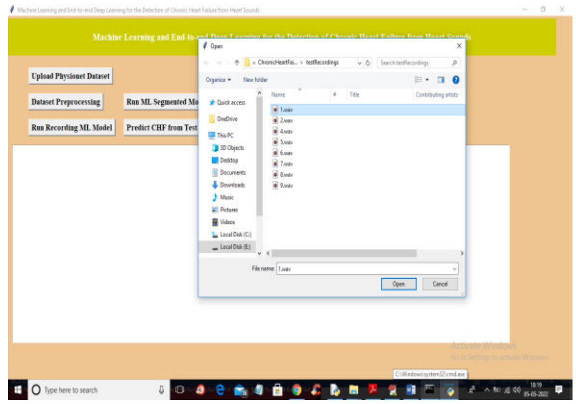
In above screen with DL model we got 93% accuracy and in graph x-axis represents epoch or iterations and y-axis represents accuracy or loss values and green line represents accuracy and blue line represents LOSS and we can see with each increasing epoch accuracy got increase and loss got decrease and now close above graph and then click on 'Run Recording Model' button to get below output



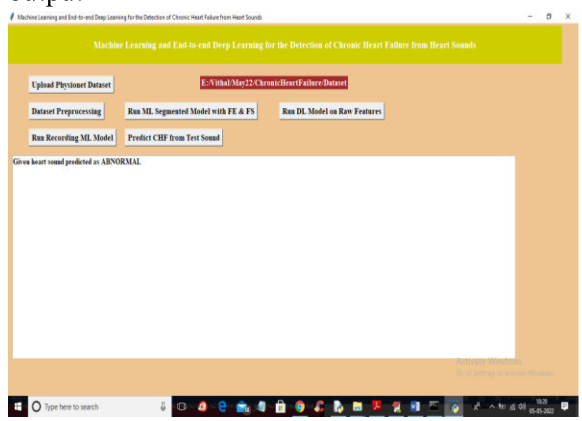
In above screen with recording model we got 96% accuracy and we can see all algorithms performance graph in below screen



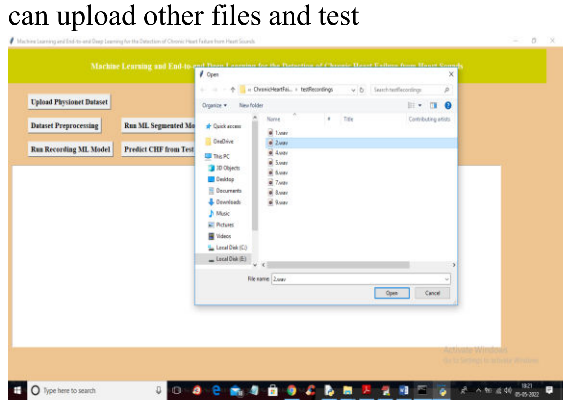
In above graph x-axis represents algorithm names and y-axis represents accuracy, sensitivity and specificity and in all algorithms Recording model has got high accuracy. Now close above graph and then click on 'Predict CHF from Test Sound' button to upload test sound file and get predicted output as Normal or Abnormal



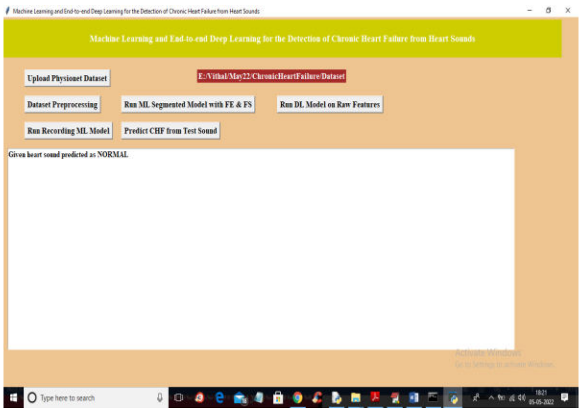
In above screen selecting and uploading '1.wav' file and then click on 'Open' button to get below output



In above screen uploaded heart sound file predicted as ABNORMAL and similarly you can upload other files and test



For 2.wav' file below is the output



VI. CONCLUSION:

In this work, a hybrid strategy that combines end-to-end Deep Learning (DL) models with conventional Machine Learning (ML) approaches is presented for the identification of Chronic Heart Failure (CHF). Using the rich acoustic information found in heart sounds (phonocardiograms), the suggested approach shows how automated and intelligent diagnostic techniques might help with CHF screening and early identification. Our methodology improves scalability, accuracy, and real-time application by using deep neural networks to learn meaningful representations directly from raw or barely processed data, in contrast to current systems that rely mostly on handcrafted features and multi-step preparation.

Our evaluation's findings show that the suggested model performs better than traditional methods in terms of classification accuracy, noise resistance, and patient profile adaptability. Additionally, the system's architecture makes it possible to incorporate it into mobile health platforms or portable diagnostic equipment, providing an affordable, non-invasive option for broad implementation—particularly in environments with low resources.

In conclusion, by addressing significant shortcomings of existing systems and putting forward a unique, scalable method for CHF diagnosis, this study adds to the expanding corpus of work on intelligent cardiovascular diagnostics. In order to facilitate real-world adoption, future work will concentrate on growing the dataset, adding multimodal signals (such as ECG), enhancing model interpretability, and testing the system in clinical settings.

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