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Detection of Chronic Heart Failure Using Ml & Dl

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ABSTRACT: 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 academic community, there are surprisingly few approaches for automatically identifying CHF, considering the substantial burden that CHF presents and the widespread use of sensors in our daily life. We describe a cardiac sound-based technique for CHF detection. 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 standard ML learns from expert characteristics. 947 participants' recordings from six publicly accessible datasets and one CHF dataset that was gathered specifically for this research were used to assess the approach. Utilising the same assessment technique as a previous PhysoNet challenge, the suggested approach obtained a score of 89.3, surpassing the challenge's baseline method by 9.1. The total accuracy of the approach is 92.9% (error of 7.1%); while there is a lack of direct comparability between the experimental and method findings, this error rate is similar to the proportion of recordings that experts have classified as "unknown" (9.7%). Ultimately, with an accuracy of 93.2%, we discovered 15 expert characteristics that are helpful for developing machine learning models that distinguish between CHF phases—that is, the decompensated phase during hospitalisation and the recompensated phase. The suggested approach demonstrates encouraging outcomes for the identification of discrete stages of CHF as well as for the differentiation of recordings between patients and healthy people. This could facilitate the identification of newly diagnosed CHF patients and facilitate the creation of CHF monitors that can be used at home to prevent hospital stays.

1. INTRODUCTION:

Chronic heart failure (CHF) is a chronic, progressive condition underscored by the heart's inability to supply enough perfusion to target tissues and organs at the physiological filling pressures to meet their metabolic demands. CHF has reached epidemic proportions in the population, as its incidence is increasing by 2% annually. In the developed world, CHF affects 1-2% of the total population and 10% of people older than 65 years. Currently, the diagnosis and treatment of CHF uses approximately 2% of the annual healthcare budget. In absolute terms, the USA spent approximately 35 billion USD to treat CHF in 2018 alone, and the costs are expected to double in the next 10 years . Despite the progress in medical- and device-based treatment approaches in the last decades, the overall prognosis of CHF is still dismal, as 5-year survival rate of this population is only approximately 50%. In the typical clinical course of CHF, we observe alternating episodes of compensated phases, when the patient feels well and does not display symptoms and signs of fluid overload, and decompensated phases, when symptoms and signs of systemic fluid overload (such as breathlessness, orthopnea, peripheral edema, liver congestion, pulmonary edema) can easily be observed. During the latter episodes, patients often require hospital admission to receive treatment with intravenous medications (diuretics, inotropes) to achieve a successful negative fluid balance and return to the compensation state. Early detection of HF worsening would allow a treating physician to adjust the patient's medical management on an outpatient basis in a timely manner and thus avoid the need for a hospital admission. Currently, anexperienced physician can detect the worsening of HF by examining the patient and by characteristic changes in the patient's heart failure biomarkers, which are determined from the patient's blood. Unfortunately, clinical worsening of a CHF patient likely means that we are already dealing with a fully developed CHF episode that will most likely require a hospital admission. Additionally, in some patients, characteristic changes in heart sounds can accompany heart failure worsening and can be heard using phonocardiography. An example of a phonocardiogram (PCG) recording of a healthy subject is presented. In healthy subjects, 2 heart sounds are typically heard (called S1 and S2). S1 is caused by the closure of the mitral valve and ventricular wall in the early systole, S2 is caused by the closure of the aortic and pulmonary valves at the beginning of the diastole. Here, the interval between S1 and S2 is called systole, i.e., the contraction phase of the cardiac cycle, and the interval between S2 and S1 is called diastole, i.e., the relaxation phase of the cardiac cycle. Additional heart sounds (such as S3 and S4) can be heard in certain cardiac conditions and are never regarded as normal. In the case of CHF (in the course of decompensation), we can often hear a third sound (S3) that typically appears 0.1-0.2 s after the second sound, i.e., S2. Recently, it has been demonstrated that some physiological parameters, such as the occurrence of additional heart sounds or increased blood pressure in the pulmonary circulation, already start to appear several weeks before the CHF patient develops a clinically evident decompensation episode. This is also an important therapeutic window where outpatient-based treatment interventions can reverse CHF deterioration and return the patient to the compensated state without the need for a hospital admission. In recent years, many studies have proposed MachineLearning (ML) approaches for the automatic detection of different heart conditions using PCG signals recorded with a digital stethoscope . Nevertheless, methods that explicitly focus on CHF detection are quite scarce. The typical ML pipeline for the detection of different heart conditions is as follows: segmentation of the signals by detecting the "typical" heart sounds (i.e., S1 and S2), denoising of the signals, extracting individual frequency-domain and time-domain features, and learning a feature-based ML model (e.g., using ML algorithms, such as Random Forest or Support Vector Machine - SVM) that is capable of classifying healthy vs. unhealthy sounds. Most of the features currently used are based on medical and audio/signal analysis knowledgeHowever, a PCG recording that sounds unhealthy to one expert may sound healthy to another one; therefore, doctors never diagnose a CHF patient using only heart sounds, but rather use a holistic view of the patient instead (i.e., extensive medical history, blood pressure, laboratory tests, etc.). This uncertainty is one reason why 9.7% of the recordings in the recent PhysioNet cardiology challenge were actually labeled as "unknown" by experts, while the rest of the recordings were labeled as healthy or unhealthy. The recent advancements in Deep Learning (DL) suggest that end-to-end learning (i.e., ML models that learn directly from the raw data and no features are needed) can outperform the classic, feature-based ML. For example, DL has achieved breakthrough performance in tasks such as pattern recognition problems , image processing , natural language processing , speech and audio processing , and sensor data processing . For CHF detection, a successful combination of classic ML and end-to-end DL can outperform each single approach. The classic ML approach learns from a large body of expert-defined features, and the DL approach learns both from a time-domain (the raw PCG signal) representation of the signal and a temporaldomain representation (the spectrogram) of the signal. This approach was successful in our previous study of human activity recognition from smartphone sensor data . In addition to distinguishing the CHF patients and healthy individuals, we focus on detecting the CHF state (compensated vs. decompensated) based on the analysis of heart sound recordings. Our work builds upon the initial studies, where we demonstrated that it is possible to distinguish between healthy individuals and patients in a decompensated CHF episode using a stack of machinelearning classifiers and expert features, showing promising results on a limited dataset . We expand upon this approach using a considerably larger patient dataset, including six additional PhysioNet datasets, and an improved ML method that uses end-to-end DL. Furthermore, we investigate the differences in the heart sounds during the transition between the decompensated and recompensated states of CHF, with the aim of developing personalized monitoring models. Early detection of the worsening of CHF has the potential to reduce hospitalizations due to the worsening of the condition, which both improves the quality of life of patients and decreases the financial and logistic burden on the patient and the health system

1.1 Objective of the project:

Chronic heart failure (CHF) affects over 26 million of people worldwide, and its incidence is increasing by 2% annually. Despite the significant burden that CHF poses and despite the ubiquity of sensors in our lives, methods for automatically detecting CHF are surprisingly scarce, even in the research community. We present a method for CHF detection based on heart sounds. The method combines classic Machine-Learning (ML) and end-to-end Deep Learning (DL). The classic ML learns from expert features, and the DL learns from a spectro-temporal representation of the signal. The method was evaluated on recordings from 947 subjects from six publicly available datasets and one CHF dataset that was collected for this study. Using the same evaluation method as a recent PhysoNet challenge, the proposed method achieved a score of 89.3, which is 9.1 higher than the challenge's baseline method. The method's aggregated accuracy is 92.9% (error of 7.1%); while the experimental results are not directly comparable, this error rate is relatively close to the percentage of recordings labeled as "unknown" by experts (9.7%). Finally, we identified 15 expert features that are useful for building ML models to differentiate between CHF phases (i.e., in the decompensated phase during hospitalization and in the recompensated phase) with an accuracy of 93.2%. The proposed method shows promising results both for the distinction of recordings between healthy subjects and patients and for the detection of different CHF phases. This may lead to the easier identification of new CHF patients and the development of home-based CHF monitors for avoiding hospitalizations.

2. LITERATURE SURVEY:

"Chronic heart failure detection from heart sounds using a stack of machine-learning classifiers,"

Chronic heart failure represents a global pandemic, currently affecting over 26 million of patients worldwide. It is a major contributor in the death rate of patients with cardiovascular diseases and results in more than 1 million hospitalizations annually in Europe and North America. Methods for chronic heart failure detection can be utilized to act preventive, improve early diagnosis and avoid hospitalizations or even life-threatening situations, thus highly enhance the quality of patient's life. In this paper, we present a machine-learning method for chronic heart failure detection from heart sounds. The method consists of: filtering, segmentation, feature extraction and machine learning. The method was tested with a leave-one-subject-out evaluation technique on data from 122 subjects, gathered in the study. The method achieved 96% accuracy, outperforming a majority classifier for 15 percentage points. More specifically, it detects (recalls) 87% of the chronic heart failure subjects with a precision of 87%. The study confirmed that advanced machine learning applied on real-life sounds recorded with an unobtrusive digital stethoscope can be used for chronic heart failure detection.

“Classification of normal/abnormal heart sound recordings: the PhysioNet/Computing in Cardiology Challenge 2016,”

In the past few decades heart sound signals (i.e., phono-cardiograms or PCGs) have been widely studied. Automated heart sound segmentation and classification techniques have the potential to screen for pathologies in a variety of clinical applications. However, comparative analyses of algorithms in the literature have been hindered by the lack of a large and open database of heart sound recordings. The PhysioNet/Computing in Cardiology (CinC) Challenge 2016 addresses this issue by assembling the largest public heart sound database, aggregated from eight sources obtained by seven independent research groups around the world. The database includes 4,430 recordings taken from 1,072 subjects, totalling 233,512 heart sounds collected from both healthy subjects and patients with a variety of conditions such as heart valve disease and coronary artery disease. These recordings were collected using heterogeneous equipment in both clinical and nonclinical (such as in-home visits). The length of recording varied from several seconds to several minutes. Additional data provided include subject demographics (age and gender), recording information (number per patient, body location, and length of recording), synchronously recorded signals (such as ECG), sampling frequency and sensor type used. Participants were asked to classify recordings as normal, abnormal, or not possible to evaluate (noisy/uncertain). The overall score for an entry was based on a weighted sensitivity and specificity score with respect to manual expert annotations. A brief description of a baseline classification method is provided, including a description of open source code, which has been provided in association with the Challenge. The open source code provided a score of 0.71 (Se=0.65 Sp=0.76). During the official phase of the competition, a total of 48 teams submitted 348 open source entries, with a highest score of 0.86 (Se=0.94 Sp=0.78).

"Speed up deep neural network based pedestrian detection by sharing features across multi-scale models,"

Deep neural networks (DNNs) have now demonstrated state-of-the-art detection performance on pedestrian datasets. However, because of their high computational complexity, detection efficiency is still a frustrating problem even with the help of Graphics Processing Units (GPUs). To improve detection efficiency, this paper proposes to share features across a group of DNNs that correspond to pedestrian models of different sizes. By sharing features, the computational burden for extracting features from an image pyramid can be significantly reduced. Simultaneously, we can detect pedestrians of several different scales on one single layer of an image pyramid. Furthermore, the improvement of detection efficiency is achieved with negligible loss of detection accuracy. Experimental results demonstrate the robustness and efficiency of the proposed algorithm.

“ImageNet classification with deep convolutional neural networks,”

We trained a large, deep convolutional neural network to classify the 1.3 million high-resolution images in the LSVRC-2010 ImageNet training set into the 1000 different classes. On the test data, we achieved top-1 and top-5 error rates of 39.7\% and 18.9\% which is considerably better than the previous state-of-the-art results. The neural network, which has 60 million parameters and 500,000 neurons, consists of five convolutional layers, some of which are followed by max-pooling layers, and two globally connected layers with a final 1000-way softmax. To make training faster, we used non-saturating neurons and a very efficient GPU implementation of convolutional nets. To reduce overfitting in the globally connected layers we employed a new regularization method that proved to be very effective.

"Inception-v4, inception-ResNet and the impact of residual connections on learning,"

Very deep convolutional networks have been central to the largest advances in image recognition performance in recent years. One example is the Inception architecture that has been shown to achieve very good performance at relatively low computational cost. Recently, the introduction of residual connections in conjunction with a more traditional architecture has yielded state-of-the-art performance in the 2015 ILSVRC challenge; its performance was similar to the latest generation Inception-v3 network. This raises the question: Are there any benefits to combining Inception architectures with residual connections? Here we give clear empirical evidence that training with residual connections accelerates the training of Inception networks significantly. There is also some evidence of residual Inception networks outperforming similarly expensive Inception networks without residual connections by a thin margin. We also present several new streamlined architectures for both residual and non-residual Inception networks. These variations improve the single-frame recognition performance on the ILSVRC 2012 classification task significantly. We further demonstrate how proper activation scaling stabilizes the training of very wide residual Inception networks. With an ensemble of three residual and one Inception-v4 networks, we achieve 3.08% top-5 error on the test set of the ImageNet classification (CLS) challenge.

"Recent trends in deep learning based natural language processing,"

Deep learning methods employ multiple processing layers to learn hierarchical representations of data, and have produced state-of-the-art results in many domains. Recently, a variety of model designs and methods have blossomed in the context of natural language processing (NLP). In this paper, we review significant deep learning related models and methods that have been employed for numerous NLP tasks and provide a walk-through of their evolution. We also summarize, compare and contrast the various models and put forward a detailed understanding of the past, present and future of deep learning in NLP.

"A neural probabilistic language model,"

A goal of statistical language modeling is to learn the joint probability function of sequences of words in a language. This is intrinsically difficult because of the curse of dimensionality: a word sequence on which the model will be tested is likely to be different from all the word sequences seen during training. Traditional but very successful approaches based on n-grams obtain generalization by concatenating very short overlapping sequences seen in the training set. We propose to fight the curse of dimensionality by learning a distributed representation for words which allows each training sentence to inform the model about an exponential number of semantically neighboring sentences. The model learns simultaneously (1) a distributed representation for each word along with (2) the probability function for word sequences, expressed in terms of these representations. Generalization is obtained because a sequence of words that has never been seen before gets high probability if it is made of words that are similar (in the sense of having a nearby representation) to words forming an already seen sentence. Training such large models (with millions of parameters) within a reasonable time is itself a significant challenge. We report on experiments using neural networks for the probability function, showing on two text corpora that the proposed approach significantly improves on state-of-the-art n-gram models, and that the proposed approach allows to take advantage of longer contexts.

3. SYSTEM ANALYSIS

SYSTEM ARCHITECTURE

3.1 Existing System

Chronic heart failure (CHF) affects over 26 million of people worldwide, and its incidence is increasing by 2% annually. Despite the significant burden that CHF poses and despite the ubiquity of sensors in our lives, methods for automatically detecting CHF are surprisingly scarce, even in the research community

Disadvantages of Existing System:

- Less Accuracy
- A soft first heart sound is present in congestive heart failure or with prolonged atrioventricular (AV) conduction

3.2 Proposed System

Chronic heart failure (CHF) is a chronic, progressive condition underscored by the heart’s inability to supply enough perfusion to target tissues and organs at the physiological filling pressures to meet their metabolic demands [1]. CHF has reached epidemic proportions in the population, as its incidence is increasing by 2% annually. In the developed world, CHF affects 1-2% of the total population and 10% of people older than 65 years. Currently, the diagnosis and treatment of CHF uses approximately 2% of the annual healthcare budget

Advantages of Proposed System:

- High Accuracy.
- For emergency department patients with shortness of breath and a risk of heart failure, physicians usually grab one thing first: a stethoscope.
- It allows them to hear the S3, an abnormal third sound in the heart's rhythm strongly associated with cardiac disease and heart failure.

Modules Information:

To implement this project we have designed following modules

1. Upload Physionet Dataset: using this module we will upload dataset to application

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2. Dataset Preprocessing: using this module we will extract audio recording features and systolic and diastolic features from dataset and then normalize values
3. Run ML Segmented Model with FE & FS: using this module we will extract and select systolic and diastolic features from dataset and then train with Random Forest Classic ML model and then apply test data to calculate its prediction accuracy
4. Run DL Model on Raw Features: using this module we will extract RAW features from recording and then train with deep learning model and then this model will be applied on test data to calculate its accuracy
5. Run Recording ML Model: using this module we will extract features from Classic ML model and deep learning model and then retrain with 3rd classifier to get its prediction accuracy
6. Predict CHF from Test Sound: using this module we will upload Test Heart Sound file and then classifier model will predict weather given recording file is Normal or Abnormal

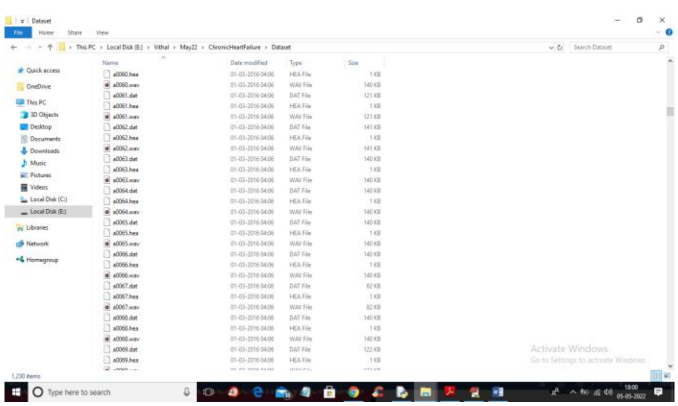
4. SCREENSHOTS:

Due to chronic heart failure many peoples are losing their lives worldwide and to reduce this lives lost we need to have expert physicians and sometime if such experts not available then it's difficult to save life and to overcome from such issue author of this paper is combining different algorithms such as Classic Random Forest and End-End Deep Learning model and then extracting features from both algorithms and then retraining with Random forest by taking AVERAGE Aggregate Recording features from Classic ML and end - end deep learning models. Average Aggregate Recording model giving better accuracy compare to other algorithms.

In propose paper author is using heart sound dataset from PHYSIONET website and this dataset contains PCG signals data and we are extracting systolic and diastolic features from this PCG signals and training with Classic ML algorithms and then PCG recording voice data will get trained with deep learning algorithm.

ML cannot train on RAW features so we are extracting systolic and diastolic features from PCG RAW data and training with Classic ML and then Raw features get trained with Deep learning. From both models we will extract average recordings and then retrain with 3rd classifier which will give more accuracy.

Below is the dataset screen used in this project



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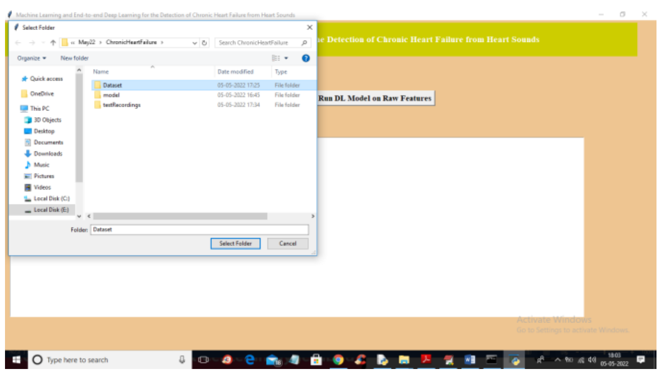
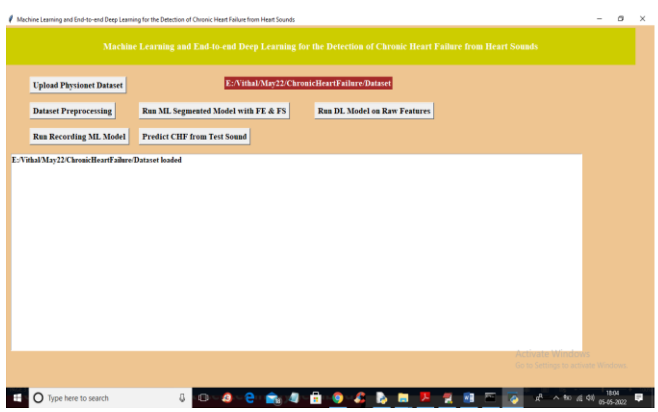
In above screen we have 3 files where .hea file contains class label as Normal or Abnormal and .dat file contains PCG signals and .wav file contains heart sound recording and by using all files we will train all algorithms

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

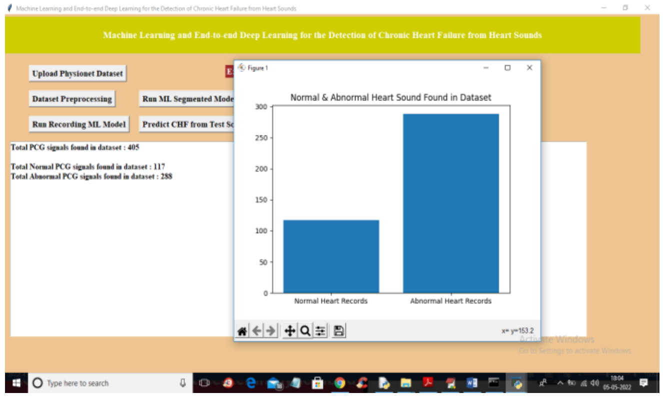
In above screen click on 'Upload Physionet Dataset' button to upload dataset



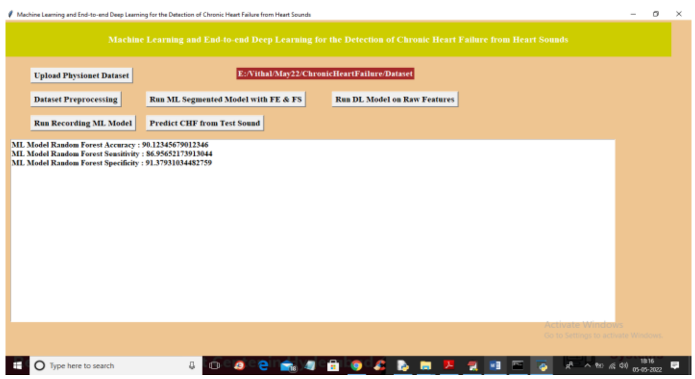
In above screen selecting and uploading 'Dataset' folder and then click on 'Select Folder' button to load dataset and to get below output



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

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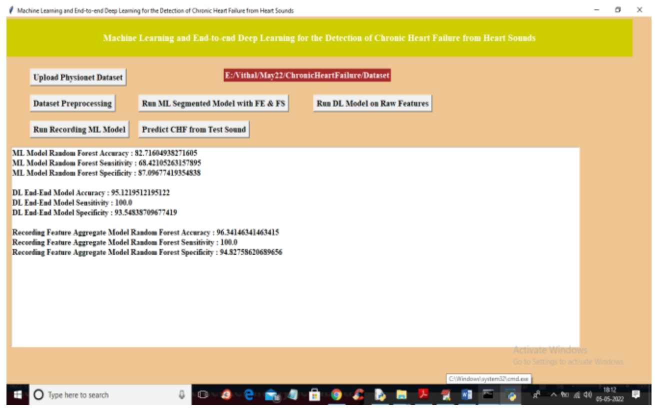
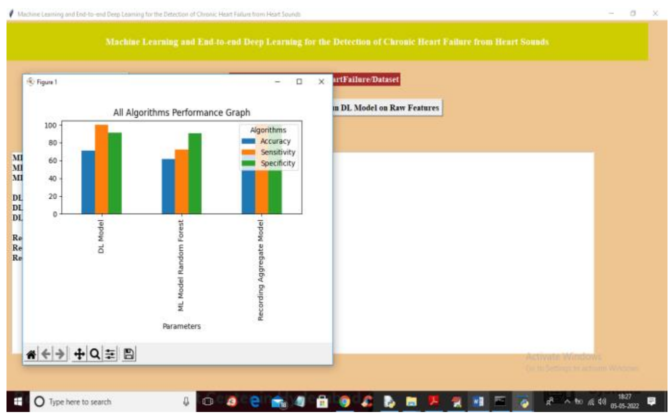
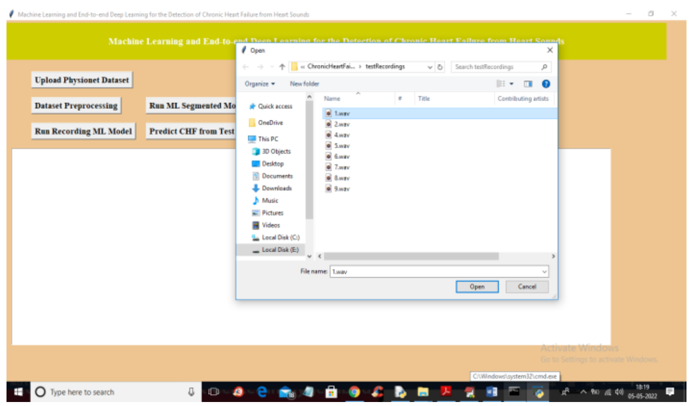


In above screen with recording model we got 96% accuracy and we can see all algorithms performance graph in below screen



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

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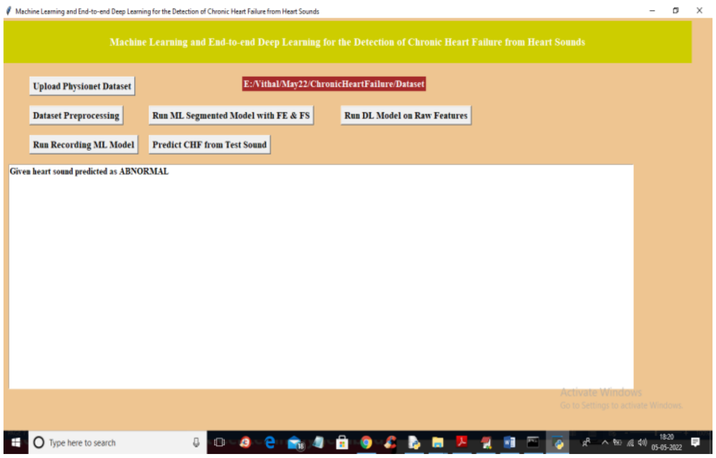
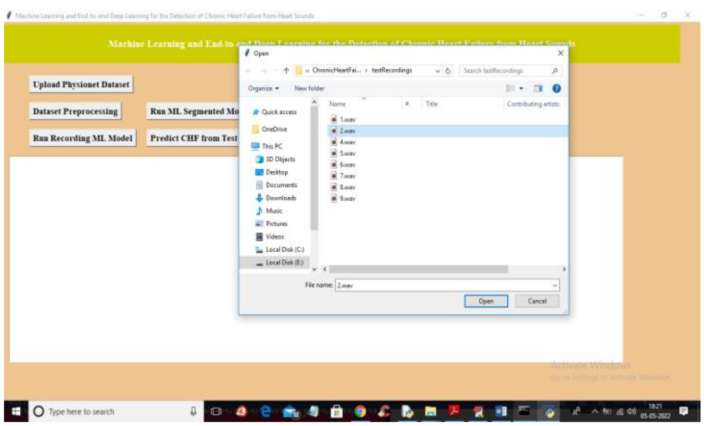
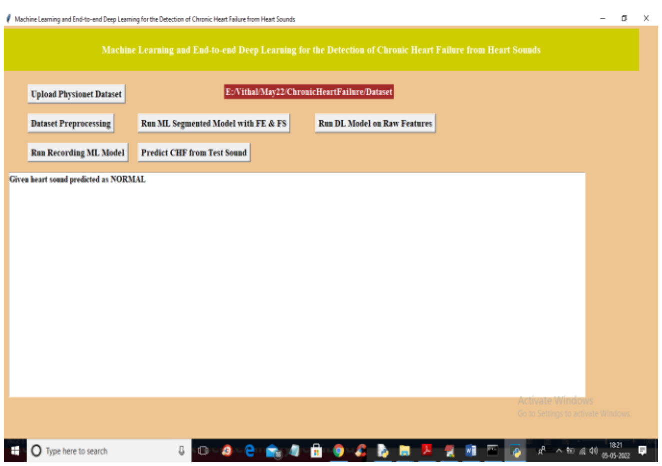


In above screen uploaded heart sound file predicted as ABNORMAL and similarly you can upload other files and test



For 2.wav’ file below is the output



5. CONCLUSION:

Our research introduced a new technique for detecting CHF in PCG audio recordings. The approach blends end-to-end DL with traditional ML. While the DL learns from both the spectral and time-domain representations of the signal—that is, the raw PCG signal—classical ML learns from a vast corpus of expert-defined features. We assessed the approach using six publicly accessible PhysioNet datasets that were used for the most recent PhysioNet Cardiology Challenge in addition to our own dataset for the diagnosis of CHF. We were able to thoroughly assess the method's performance on related domains thanks to the challenge datasets. Our technique outperforms the challenge baseline methods, according on assessment findings across all datasets (see the PhysioNet experiments section). As long as domain-specific labelled data are provided, the majority of these datasets are labelled for various heart-related conditions, and the PCG audio is recorded from a variety of body positions in most of the datasets (e.g., aortic area, pulmonic area, tricuspid area, and mitral area). These facts strongly suggest that the proposed method is quite robust and useful for detecting various heart-sound classification problems, not just CHF detection. In conclusion, we went beyond classifying patients as healthy vs sick and investigated personalised models for identifying distinct stages of CHF, such as the decompensated phase (i.e., when the patient requires medical treatment) and the recompensated phase (i.e., when the patient feels good). Fifteen traits were found, whose distributions vary depending on the phase. We constructed a straightforward and transparent decision tree classifier (refer to Fig. 3) using only two of these characteristics. This classifier can identify between the recompensated and the decompensated phases with an accuracy of 93.2%, as determined by a LOSO assessment. We feel that these findings are highly promising and constitute a good foundation for continued development of personalised models, even if we are conscious that there is a danger of overfitting in these final tests, particularly given the dataset comprises only 44 samples. To the best of our knowledge, no prior research has tackled this particular issue.

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