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CHRONICNET: DETECTION OF CHRONIC HEART FAILURE FROM HEART SOUNDS USING INTEGRATED ML AND DL MODELS FOR CARDIAC HEALTH MONITORING

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ABSTRACT

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. Currently, an experienced 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. Therefore, with the usage of recent advancement in machine learning and deep learning models, this project implements the detection of chronic heart failure from phonocardiography (PCG) data using end-to-end average aggregate recording model built with extracted features from both machine learning and deep learning. The proposed ChronicNet model results also compared with individual ML, and DL model.

Keywords: ChronicNet heart, Random Forest, CNN, Classification

1.INTRODUCTION

"The detection of chronic heart failure (CHF) from phonocardiogram (PCG) data using unified machine learning and deep learning models is a promising area of research. PCG data refers to the acoustic signals that are generated by the heart during its normal cycle of contraction and relaxation. This data can be recorded using specialized equipment, and analysed using machine learning and deep learning algorithms to detect CHF.

The use of a unified machine learning and deep learning model for CHF detection from PCG data involves the combination of traditional machine learning techniques, such as logistic regression or support vector machines, with deep learning techniques, such as convolutional neural networks or recurrent neural networks. The goal of this approach is to leverage the strengths of both types of algorithms to improve the accuracy of CHF detection.

The process of developing a unified machine learning and deep learning model for CHF detection from PCG data typically involves several steps. First, the PCG data is pre-processed to remove noise and artifacts, and to extract relevant features such as heart rate, amplitude, and frequency. Then, the data is split into training, validation, and testing sets, and used to train the machine learning and deep learning models. The models are evaluated on the testing set to determine their accuracy in detecting CHF. One advantage of using a unified machine learning and deep learning model for CHF detection from PCG data is that it can help to overcome some of the limitations of traditional machine learning techniques. For example, deep learning algorithms are well-suited to handling complex and high-dimensional data, and can automatically extract relevant features from the PCG signals. However, deep learning algorithms can also be computationally expensive and require large amounts of training data. Overall, the use of a unified machine learning and deep learning model for CHF detection from PCG data is an active area of research with the potential to improve the accuracy of CHF detection, and ultimately improve outcomes for patients with this condition.

2. LITERATURE SURVEY

Gjoreski, Martin, et al (2020) [1] presented a method for CHF detection based on heart sounds. This 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. This 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. This 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.

Gahane, Aroh, and Chinnaiah Kotadi(2022) [2] investigated different approaches for detecting CHF based on the heart sounds produced by the patient. The perception of heart rate, as well as the relationship between heart sounds and cardiovascular disease, are important considerations. The basic techniques used in the processing and interpretation of cardiac signals seem to be de-noising, categorization, extraction, feature extraction, and classification, among others. Because of the emphasis on the usage of Machine Learning (ML) algorithms for analysing heart sounds, classic Machine-Learning (ML) technologies are merged with IoT end-to-end technologies, and both are integrated with a wide range of defined techniques. The primary goal is to examine the many technologies that are comprised of the internet of things that are used to forecast heart attack disease and how they are used. It is not only to explain the existing heart attack prediction, but also to address the aware and monitoring system for the patient who is likely to be suffering from cardiovascular illness.

Shuvo, Samiul Based, et al (2021) [3] proposed CardioXNet, a novel lightweight end-to-end CRNN architecture for automatic detection of five classes of cardiac auscultation namely normal, aortic stenosis, mitral stenosis, mitral regurgitation and mitral valve prolapse using raw PCG signal. The process has been automated by the involvement of two learning phases namely, representation learning and sequence residual learning. Three parallel CNN pathways have been implemented in the representation learning phase to learn the coarse and fine-grained features from the PCG and to explore the salient features from variable receptive fields involving 2D-CNN based squeeze-expansion. Thus, in the representation learning phase, the network extracts efficient time-invariant features and converges with great rapidity. It outperforms any previous works using the same database by a considerable margin. Moreover, the proposed model was tested on PhysioNet/CinC 2016 challenge dataset achieving an accuracy of 86.57%. Finally the model was evaluated on a merged dataset of Github PCG dataset and PhysioNet dataset achieving excellent accuracy of 88.09%. The high accuracy metrics on both primary and secondary dataset combined with a significantly low number of parameters and end-to-end prediction approach makes the proposed network especially suitable for point of care CVD screening in low resource setups using memory constraint mobile devices.

Li, Suyi, et al(2020) [4]. detected techniques play an important role in the prediction of cardiovascular diseases. The latest development of the computer-aided heart sound detection techniques over the last five years has been reviewed. There are mainly the following aspects: the theories of heart sounds and the relationship between heart sounds and cardiovascular diseases; the key technologies used in the processing and analysis of heart sound signals, including denoising, segmentation, feature extraction and classification; with emphasis, the applications of deep learning algorithm in heart sound processing. In the end, some areas for future research in computer-aided heart sound detection techniques are explored, hoping to provide reference to the prediction of cardiovascular diseases.

Miotto, Riccardo, et al.(2018) [5] provided new effective paradigms to obtain end-to-end learning models from complex data. They reviewed the recent literature on applying deep learning technologies to advance the health care domain. Based on the analyzed work, we suggest that deep learning approaches could be the vehicle for translating big biomedical data into improved human health. However, they also note limitations and needs for improved methods development and applications, especially in terms of ease-of-understanding for domain experts and citizen scientists.They discuss such challenges and suggest developing holistic and meaningful interpretable architectures to bridge deep learning models and human interpretability.

Allugunti, Viswanatha Reddy[6] provided an efficient answer to the problem of making decisions and accurate forecasts. This application of machine learning strategies is making significant headway in the medical sector.They presented, a unique technique to machine learning is proposed for the purpose of predicting cardiac disease. The PhysioNet Dataset was utilised for the study that was proposed, and data mining algorithms like regression and classification were utilised. Support Vector Machine, Decision Tree and Random Forest are both the machine learning approaches that are utilised here. The cutting-edge strategy for the machine learning model has been devised. Support Vector Machine, Random Forest, Decision Tree, and the Hybrid model (Hybrid of SVM, RF and DT) are the four types of machine learning algorithms that are utilised in the implementation process. The accuracy level of the heart disease prediction model using the hybrid model was found to be 88.7 percent based on the results of the experiments. The user's input parameter will be utilised to predict heart illness, which will be done with a model that is a hybrid of Decision Tree and Random Forest. This interface is built to acquire the user's input parameter.

Zubair, Muhammad (2021) [7] detected sounds S1 and S2, the features like envelograms, Mel frequency cepstral coefficients (MFCC), kurtosis, etc., of these sounds are extracted. These features are used for the classification of normal and abnormal heart sounds, which leads to an increase in computational complexity. They had proposed a fully automated algorithm to localize heart sounds using K-means clustering. The K-means clustering model can differentiate between the primitive heart sounds like S1, S2, S3, S4 and the rest of the insignificant sounds like murmurs without requiring the excessive pre-processing of data. The peaks detected from the noisy data are validated by implementing five classification models with 30 fold cross-validation. These models have been implemented on a publicly available PhysioNet/Cinc challenge 2016 database. Lastly, to classify between normal and abnormal heart sounds, the localized labelled peaks from all the datasets were fed as an input to the various classifiers such as support vector machine (SVM), K-nearest neighbours (KNN)

Valera, HH Alvarez, and M. Luštrek (2022) [8] investigated chronic heart failure (HF) diagnosis with the application of machine learning (ML) approaches. They simulated the procedure that is followed in clinical practice, as the models they built are based on various combinations of feature categories, e.g., clinical features, echocardiogram, and laboratory findings. We also investigated the incremental value of each feature type. The total number of subjects utilized was 422. An ML approach is proposed, comprising of feature selection, handling class imbalance, and classification steps. The results for HF diagnosis were quite satisfactory with a high accuracy (91.23%), sensitivity (93.83%), and specificity (89.62%) when features from all categories were utilized. The results remained quite high, even in cases where single feature types were employed.

3.PROPOSED METHOD

3.1 Overview

Chronic heart failure (CHF) is a serious condition that requires early detection and treatment to prevent its progression. One way to detect CHF is by analyzing the phonocardiogram (PCG) sounds using machine learning techniques

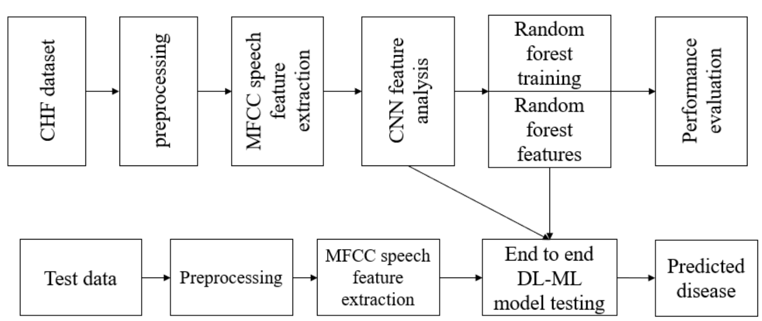


Figure 1. Proposed block diagram.

3.1 MFCC feature extraction

Pre-emphasis is the initial stage of extraction. It is the process of boosting the energy in high frequency. It is done because the spectrum for voice segments has more energy at lower frequencies than higher frequencies. This is called spectral tilt which is caused by the nature of the glottal pulse. Boosting high-frequency energy gives more info to Acoustic Model which improves phone recognition performance. MFCC can be extracted by following method.

1) The given speech signal is divided into frames (~20 ms). The length of time between successive frames is typically 5-10ms.
2) Hamming window is used to multiply the above frames to maintain the continuity of the signal. Application of hamming window avoids Gibbs phenomenon. Hamming window is multiplied to every frame of the signal to maintain the continuity in the start and stop point of frame and to avoid hasty changes at end point. Further, hamming window is applied to each frame to collect the closest frequency component together.
3) Mel spectrum is obtained by applying Mel-scale filter bank on DFT power spectrum. Mel-filter concentrates more on the significant part of the spectrum to get data values. Mel-filter bank is a series of triangular band pass filters similar to the human auditory system. The filter bank consists of overlapping filters. Each filter output is the sum of the energy of certain frequency bands. Higher sensitivity of the human ear to lower frequencies is modeled with this procedure. The energy within the frame is also an important feature to be obtained. Compute the logarithm of the square magnitude of the output of Mel-filter bank. Human response to signal level is logarithm. Humans are less sensitive to small changes in energy at high energy than small changes at low energy. Logarithm compresses dynamic range of values.
4) Mel-scaling and smoothing (pull to right). Mel scale is approximately linear below 1 kHz and logarithmic above 1 kHz.
5) Compute the logarithm of the square magnitude of the output of Mel filter bank.
6) DCT is further stage in MFCC which converts the frequency domain signal into time domain and minimizes the redundancy in data which may neglect the smaller temporal variations in the signal. Mel-cepstrum is obtained by applying DCT on the logarithm of the mel-spectrum. DCT is used to reduce the number of feature dimensions. It reduces spectral correlation between filter bank coefficients. Low dimensionality and 17 uncorrelated features are desirable for any statistical classifier. The cepstral coefficients do not capture the energy. So, it is necessary to add energy feature. Thus twelve (12) Mel Frequency Cepstral Coefficients plus one (1) energy coefficient are extracted. These thirteen (13) features are generally known as base features.
7) Obtain MFCC features.

The MFCC i.e. frequency transformed to the cepstral coefficients and the cepstral coefficients transformed to the MFCC by using the equation.

$$mel(f) = 2595 \times \log 10 \left(1 + \frac{f}{700}\right) \qquad (13)$$

Where f denotes the frequency in Hz The Step followed to compute MFCC. The MFCC features are estimated by using the following equation.

$$C_n = \sum_{n=1}^{K} (logS_k) \left[n\left(K - \frac{1}{2}\right)\frac{\pi}{K}\right] where n = 1,2, \ldots . . K \qquad (14)$$

Here, K represents the number of Mel cepstral coefficient, C0 is left out of the DCT because it represents the mean value of the input speech signal which contains no significant speech related information. For each of the frames (approx. 20 ms) of speech that has overlapped, an acoustic vector consisting of MFCC is computed. This set of coefficients represents as well as recognize the characteristics of the speech.

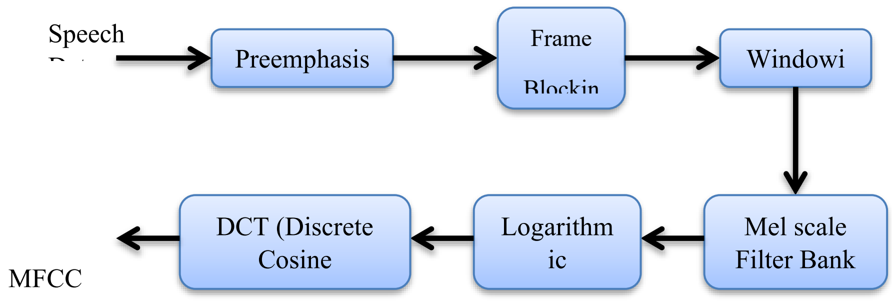


Figure 2: MFCC operation diagram

3.2 CNN model

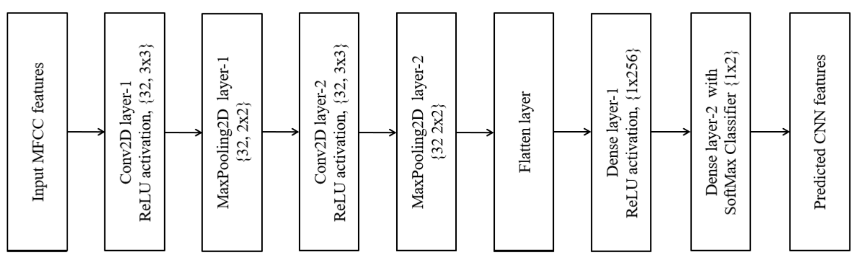


Figure 3: Proposed deep CNN model for feature extraction

Convolution layer:

According to the facts, training and testing of -CNN involves in allowing every source PCG via a succession of convolution layers by a kernel or filter, rectified linear unit (ReLU), max pooling, fully connected layer and utilize SoftMax layer with classification layer to categorize the objects with probabilistic values ranging from [0,1]. Convolution layer as depicted in Figure 8 is the primary layer to extract the features from a source PCG and maintains the relationship between pixels by learning the features of PCG by employing tiny blocks of source data. It's a mathematical function which considers two inputs like source PCG $I(x, y, d)$ where x and y denotes the spatial coordinates i.e., number of rows and columns. d is denoted as dimension of an PCG (here $d = 3$, since the source PCG and a filter or kernel with similar size of input PCG and can be denoted as $F\left(k_x, k_y, d\right)$.

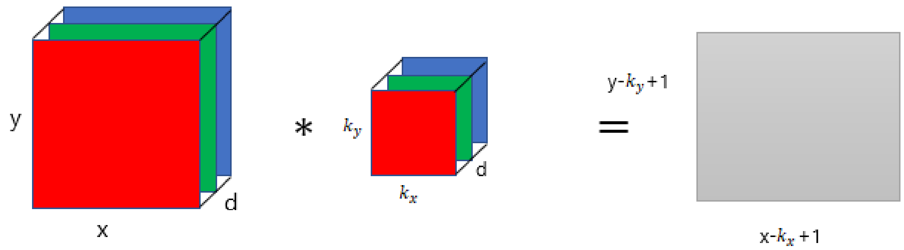
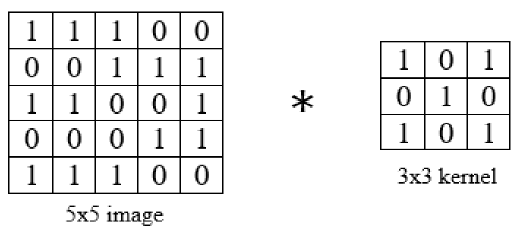
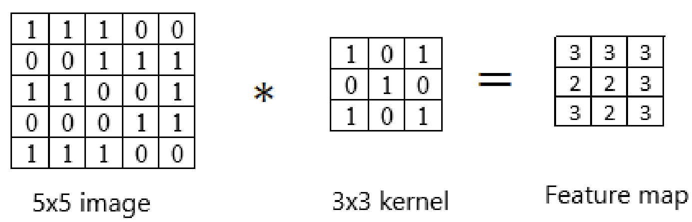


Figure 4: Representation of convolution layer process.

The output obtained from convolution process of input PCG and filter has a size of $C\left((x - k_x + 1), (y - k_y + 1), 1\right)$, which is referred as feature map. An example of convolution procedure is demonstrated in Figure 5.2. Let us assume an input PCG with a size of 5×5 and the filter having the size of 3×3. The feature map of input PCG is obtained by multiplying the input PCG values with the filter values as given in Figure 9.



(a)



(b)

Figure 5: Example of convolution layer process (a) an PCG with size $\mathbf{5} \times \mathbf{5}$ is convolving with $\mathbf{3} \times \mathbf{3}$ kernel (b) Convolved feature map.

3.2.1 ReLU layer

Networks those utilizes the rectifier operation for the hidden layers are cited as rectified linear unit (ReLU). This ReLU function $\mathcal{G}(\cdot)$ is a simple computation that returns the value given as input directly if the value of input is greater than zero else returns zero. This can be represented as mathematically using the function $max(\cdot)$ over the set of 0 and the input x as follows:

$$\mathcal{G}(x) = \max\{0, x\}$$

3.2.2 Max pooing layer

This layer mitigates the number of parameters when there are larger size PCGs. This can be called as subsampling or down sampling that mitigates the dimensionality of every feature map by preserving the important information. Max pooling considers the maximum element form the rectified feature map.

3.2.3 SoftMax classifier

Generally, as seen in the above picture SoftMax function is added at the end of the output since it is the place where the nodes are meet finally and thus, they can be classified. Here, X is the input of all the models and the layers between X and Y are the hidden layers and the data is passed from X to all the layers and Received by Y. Suppose, we have 10 classes, and we predict for which class the given input belongs to. So, for this what we do is allot each class with a particular predicted output. Which means that we have 10 outputs corresponding to 10 different class and predict the class by the highest probability it has.

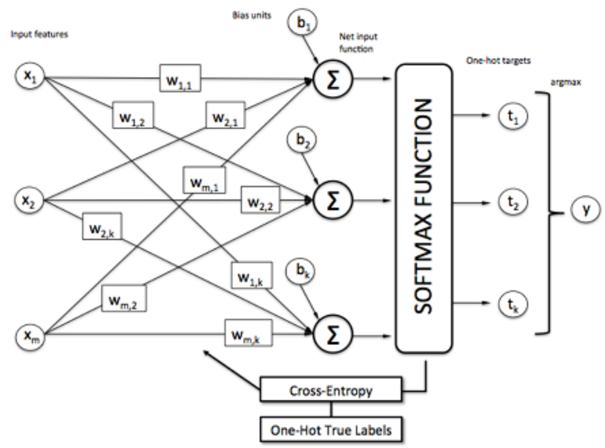


Figure 6: SoftMax classifier.

In Figure 6, and we must predict what is the object that is present in the picture. In the normal case, we predict whether the heart failure is A. But in this case, we must predict what is the object that is present in the picture. This is the place where softmax comes in handy. As the model is already trained on some data. So, as soon as the picture is given, the model processes the pictures, send it to the hidden layers and then finally send to softmax for classifying the picture. The softmax uses a One-Hot encoding Technique to calculate the cross-entropy loss and get the max. One-Hot Encoding is the technique that is used to categorize the data. In the previous example, if softmax predicts that the object is class A then the One-Hot Encoding for:

Class A will be [1 0 0]

Class B will be [0 1 0]

Class C will be [0 0 1]

From the diagram, we see that the predictions are occurred. But generally, we don't know the predictions. But the machine must choose the correct predicted object. So, for machine to identify an object correctly, it uses a function called cross-entropy function. So, we choose more similar value by using the below cross-entropy formula.

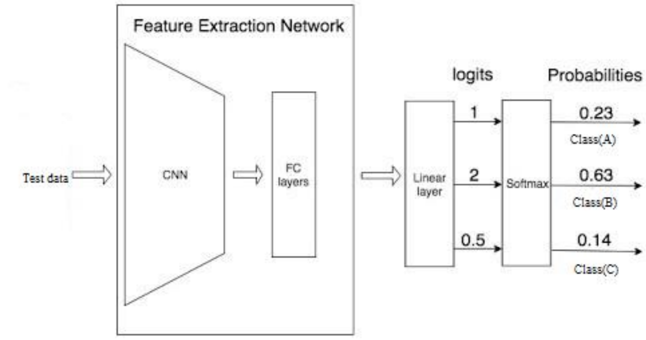


Figure 7: Example of SoftMax classifier.

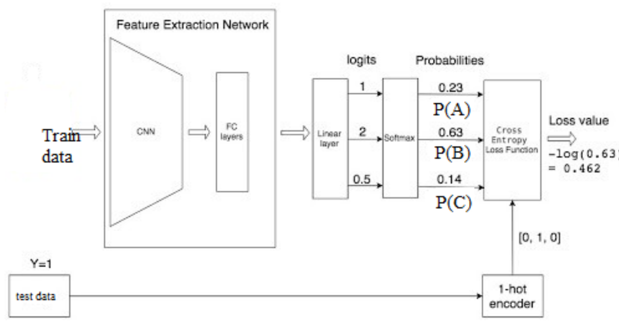


Figure 8: Example of SoftMax classifier with test data.

In the above example we see that 0.462 is the loss of the function for class specific classifier. In the same way, we find loss for remaining classifiers. The lowest the loss function, the better the prediction is. The mathematical representation for loss function can be represented as: -

$$LOSS = np.sum(-Y \ * \ np.log(Y\_pred))$$

3.3 Random Forest classifier

Random Forest is a popular machine learning algorithm that belongs to the supervised learning technique. It can be used for both Classification and Regression problems in ML. It is based on the concept of ensemble learning, which is a process of combining multiple classifiers to solve a complex problem and to improve the performance of the model. As the name suggests, "Random Forest is a classifier that contains a number of decision trees on various subsets of the given dataset and takes the average to improve the predictive accuracy of that dataset." Instead of relying on one decision tree, the random forest takes the prediction from each tree and based on the majority votes of predictions, and it predicts the final output. The greater number of trees in the forest leads to higher accuracy and prevents the problem of overfitting.

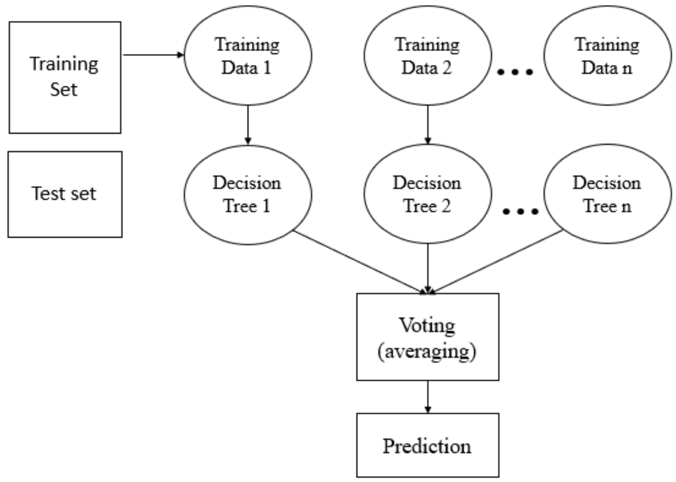


Figure 9: Random Forest algorithm

Random Forest algorithm

Step 1: In Random Forest n number of random records are taken from the data set having k number of records.

Step 2: Individual decision trees are constructed for each sample.

Step 3: Each decision tree will generate an output.

Step 4: Final output is considered based on Majority Voting or Averaging for Classification and regression respectively.

Important Features of Random Forest

- **Diversity-** Not all attributes/variables/features are considered while making an individual tree, each tree is different.
- **Immune to the curse of dimensionality-** Since each tree does not consider all the features, the feature space is reduced.
- **Parallelization-**Each tree is created independently out of different data and attributes. This means that we can make full use of the CPU to build random forests.
- **Train-Test split-** In a random forest we don't have to segregate the data for train and test as there will always be 30% of the data which is not seen by the decision tree.
- **Stability-** Stability arises because the result is based on majority voting/ averaging.

3.4.1 Assumptions for Random Forest

Since the random forest combines multiple trees to predict the class of the dataset, it is possible that some decision trees may predict the correct output, while others may not. But together, all the trees predict the correct output. Therefore, below are two assumptions for a better Random forest classifier:

- There should be some actual values in the feature variable of the dataset so that the classifier can predict accurate results rather than a guessed result.
- The predictions from each tree must have very low correlations.

Below are some points that explain why we should use the Random Forest algorithm

- It takes less training time as compared to other algorithms.
- It predicts output with high accuracy, even for the large dataset it runs efficiently.
- It can also maintain accuracy when a large proportion of data is missing.

3.4.2 Types of Ensembles

Before understanding the working of the random forest, we must look into the ensemble technique. Ensemble simply means combining multiple models. Thus, a collection of models is used to make predictions rather than an individual model. Ensemble uses two types of methods:

Bagging– It creates a different training subset from sample training data with replacement & the final output is based on majority voting. For example, Random Forest. Bagging, also known as Bootstrap Aggregation is the ensemble technique used by random forest. Bagging chooses a random sample from the data set. Hence each model is generated from the samples (Bootstrap Samples) provided by the Original Data with replacement known as row sampling. This step of row sampling with replacement is called bootstrap. Now each model is trained independently which generates results. The final output is based on majority voting after combining the results of all models. This step which involves combining all the results and generating output based on majority voting is known as aggregation.

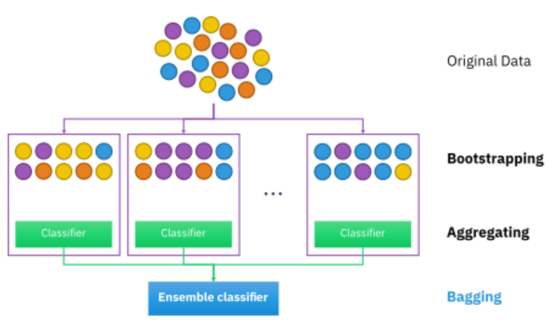


Figure 10: RF Classifier analysis.

Boosting– It combines weak learners into strong learners by creating sequential models such that the final model has the highest accuracy. For example, ADA BOOST, XG BOOST.

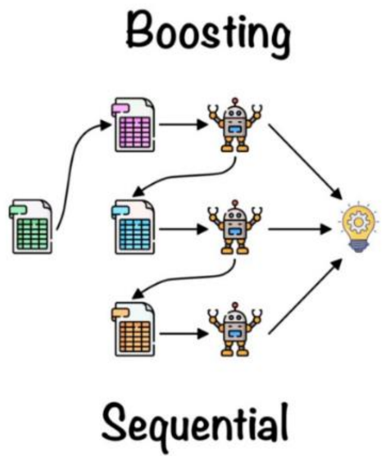


Figure 11: Boosting RF Classifier.

4.RESULTS

Figure 12: Upload of Physionet Dataset in the Chronic Heart Failure GUI.

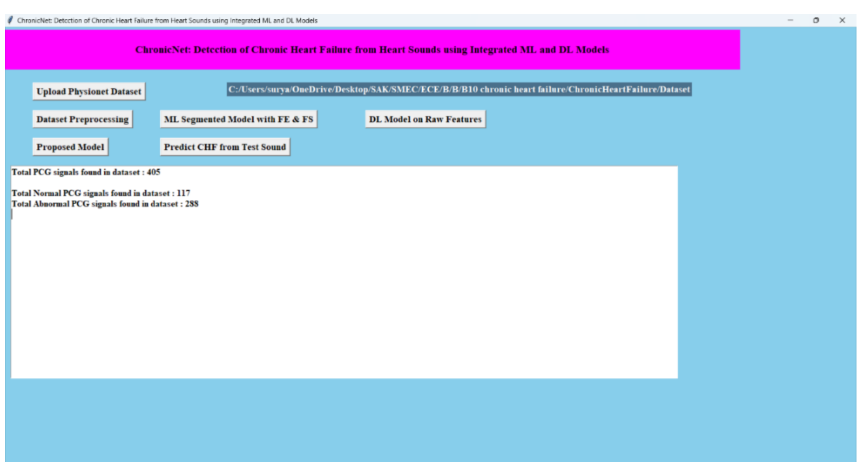


Figure 13: Preprocessing of the uploaded dataset.

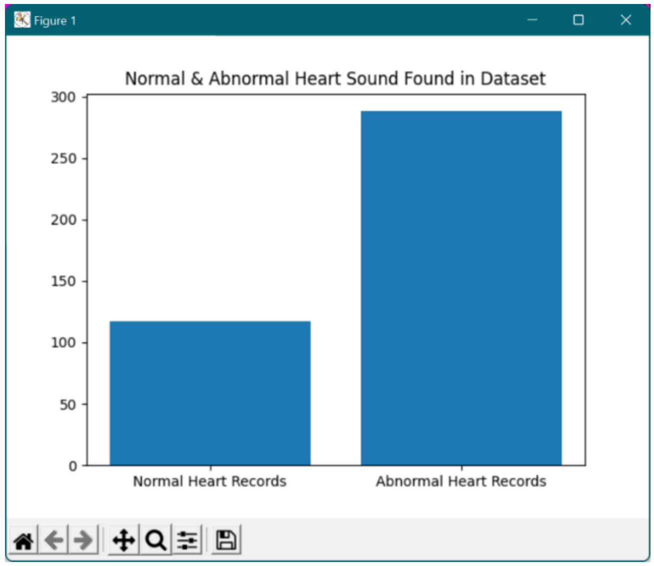


Figure 14: Count plot for count of each label.

figure 14 The 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.

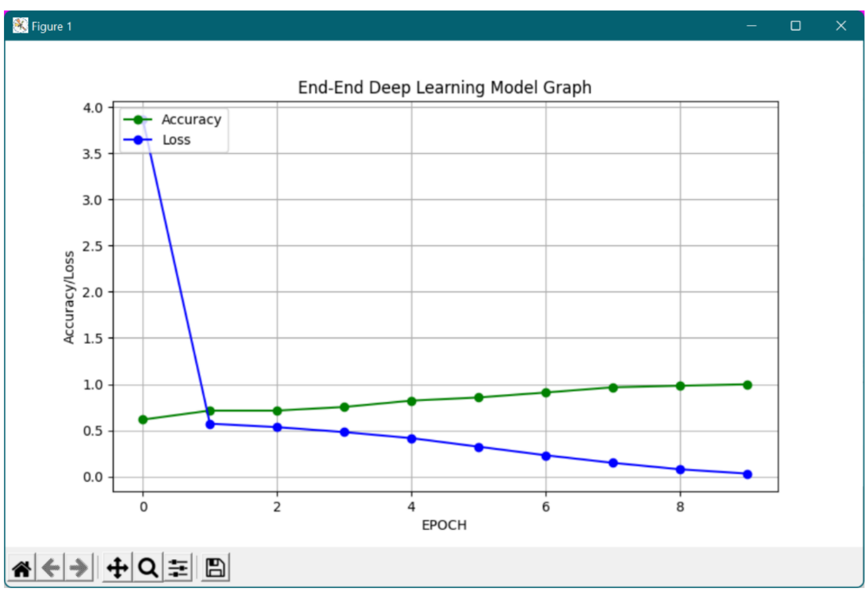


Figure 15: Presents performance evaluation of CNN model per epoch.

Figure 15 The screen with DL model, we got 93.9% 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.

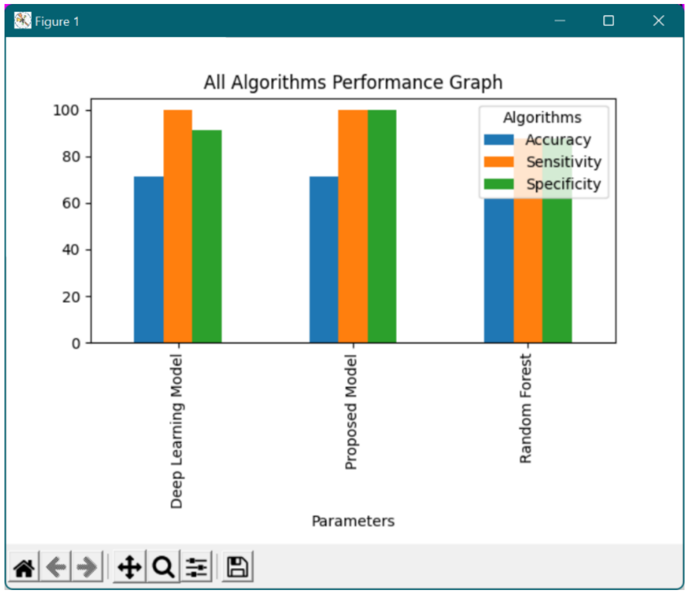


Figure 16: Displays the performance evaluation comparison of all models.

In graph 5 x-axis represents algorithm names and y-axis represents accuracy, sensitivity and specificity and in all algorithm's Proposed model has got high accuracy.

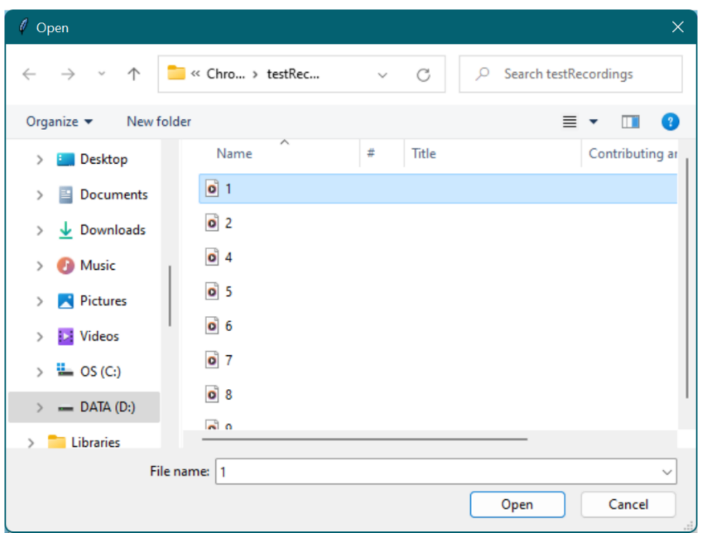


Figure 17: Selecting and uploading '1.wav' file for model testing.

Table 18: Performance model for all models.

Model	Accuracy (%)	Sensitivity (%)	Specificity (%)
Random Forest	85.19	70.83	91.23
Deep Learning Model	95.12	100.00	93.44
Proposed Average Aggregate Model	96.34	100.00	93.44

The performance table summarizes the evaluation metrics for three different models used in the detection of Chronic Heart Failure (CHF) from heart sounds. Here's a description of each model:

- Random Forest Model:
- Accuracy: The Random Forest model achieved an accuracy of 85.19%, indicating that it correctly classified 85.19% of the heart sounds.
- Sensitivity: The sensitivity of the Random Forest model is 70.83%, which represents the proportion of actual positive cases (CHF) correctly identified by the model.
- Specificity: With a specificity of 91.23%, the Random Forest model accurately identified 91.23% of the non-CHF cases.
- Deep Learning Model:
- Accuracy: The Deep Learning model exhibited a higher accuracy of 95.12%, indicating its ability to correctly classify a larger proportion of heart sounds.
- Sensitivity: The Deep Learning model achieved a sensitivity of 100%, suggesting that it correctly identified all positive cases of CHF.
- Specificity: With a specificity of 93.44%, the Deep Learning model effectively identified non-CHF cases with high accuracy.
- Proposed Average Aggregate Model:
- Accuracy: The Proposed Average Aggregate Model demonstrated the highest accuracy among the three models, reaching 96.34% accuracy.

- Sensitivity: Similar to the Deep Learning model, the Proposed Model achieved a sensitivity of 100%, indicating perfect detection of CHF cases.
- Specificity: With a specificity of 93.44%, the Proposed Model maintained a high level of accuracy in identifying non-CHF cases.

5. CONCLUSION

The development of ChronicNet represents a significant advancement in the early detection of chronic heart failure (CHF) using integrated machine learning (ML) and deep learning (DL) models applied to phonocardiography (PCG) data. By leveraging the latest advancements in AI technology, ChronicNet offers a promising solution for identifying subtle changes in heart sounds indicative of CHF worsening, enabling timely intervention and management to improve patient outcomes.

Through comprehensive evaluation and comparison with individual ML and DL models, ChronicNet has demonstrated superior performance in CHF detection, highlighting the efficacy of the integrated approach. By harnessing the complementary strengths of ML and DL methodologies, ChronicNet achieves higher accuracy and reliability in identifying CHF exacerbations, thereby reducing the risk of hospital admissions and enhancing patient care.

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