Journal of Cardiovascular Disease Research

ISSN: 0975-3583, 0976-2833 VOL 12, ISSUE 01, 2021

Early Detection of Chronic Heart Failure from Phonocardiography Data: A Machine Learning and Deep Learning Approach

Kalpana K[1], Shirisha[2], Saritha Kunamalla [3]

[1,2,3]Assistant Professor, Department of ECE, Malla Reddy Engineering College and Management Sciences, Hyderabad, Telangana

Abstract

The ability of an experienced physician to detect the progression of chronic heart failure (CHF) primarily relies on patient examination and changes in heart failure biomarkers, determined from blood tests. Unfortunately, the clinical deterioration of a CHF patient often signals a fully developed CHF episode that may necessitate hospitalization. In some cases, distinctive changes in heart sounds can accompany heart failure progression and are detectable through phonocardiography. Leveraging recent advancements in machine learning and deep learning, this project introduces an early detection system for chronic heart failure using phonocardiography (PCG) data. The system utilizes an end-to-end average aggregate recording model that incorporates features extracted from both machine learning and deep learning techniques. The proposed ChronicNet model is compared with individual machine learning and deep learning models, demonstrating its effectiveness in early CHF detection.

Keywords: Chronic Heart Failure, Phonocardiography, Machine Learning, Deep Learning, Early Detection, ChronicNet Model.

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 [1]. 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 [2]. 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 [3]. The goal of this approach is to leverage the strengths of both types of algorithms to improve the accuracy of CHF detection [4]. The process of developing a unified machine learning and deep learning model for CHF detection from PCG data typically involves several steps [5]. 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 [6]. The models are evaluated on the testing set to determine their accuracy in detecting CHF [7]. 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 [8] 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 [9] 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 [10], and ultimately improve outcomes for patients with this condition.

Rest of the paper is organized as follows: Section 2 details about literature survey, section 3 details about the proposed methodology, section 4 details about the results with discussion, and section 5 concludes article with references.

2. Literature Survey

Sreejith, S., S. Rahul, et al. (2016) [11] proposed a system that suggests a framework for measuring the heart rate, temperature and blood pressure of the patient using a wearable gadget and the measured parameters is transmitted to the Bluetooth enabled Android smartphone. The various parameters are analysed and processed by android application at client side. This processed output is transferred to the server side in a periodic interval. Whenever an emergency caring arises, an alert message is forwarded to the various care providers by the client-side application. The use of various wireless technologies like GPS, GPRS, and Bluetooth leads us to monitor the patient remotely. Gjoreski, Martin, et al. (2017) [12] presented a machine-learning method for chronic heart failure detection from heart sounds. This method consists of filtering, segmentation, feature extraction and machine learning. This method was tested with a leave-one-subject-out evaluation technique on data from 122 subjects. Ismail, Shahid, et al. (2023) [13] proposed a technique that relies on signal filtering, time segmentation, spectrogram generation, hybrid classification and finally a voting-based mechanism. It carries out analysis at cycle as well as at signal level. Evaluation of the proposed technique on a challenging public dataset (PASCAL 2011) results in precision, recall and accuracy values of greater than 95% using 5-fold cross validation. Sanei, Saeid, et al. (2011) [14] approached for separation of murmur from heart sound has been suggested. Singular spectrum analysis (SSA) has been adapted to the changes in the statistical properties of the data and effectively used for detection of murmur from single-channel heart sound (HS) signals. Incorporating a cleverly selected a priori within the SSA reconstruction process, results in an accurate separation of normal HS from the murmur segment. Gao, Shan, Yineng Zheng, et al. (2020) [15] proposed a method based on convolutional neural networks (CNN) and heart sounds (HS) is presented for the early diagnosis of LVDD in this paper. A deep convolutional generative adversarial networks (DCGAN) model-based data augmentation (DA) method was proposed to expand a HS database of LVDD for model training. Firstly, the pre-processing of HS signals was performed using the improved wavelet denoising method. Secondly, the logistic regression based hidden semi-Markov model was utilized to segment HS signals, which were subsequently converted into spectrograms for DA using the short-time Fourier transform (STFT). Finally, the proposed method was compared with VGG-16, VGG-19, ResNet-18, ResNet-50, DenseNet-121, and AlexNet in terms of performance for LVDD diagnosis.

Wang, Hui, et al (2022) [16] proposed an automatic approach for HF typing based on heart sounds (HS) and convolutional recurrent neural networks, which provides a new non-invasive and convenient way for HF typing. Firstly, the collected HS signals were pre-processed with adaptive wavelet denoising,then, the logistic regression based hidden semi-Markov model was utilized to segment HS frames. For the distinction between normal subjects and the HF patients with preserved ejection fraction or reduced ejection fraction, a model based on convolutional neural network and recurrent neural networkb was built. Beritelli, Francesco, et al (2018) [17] proposed a new approach to heart activity diagnosis based on Gram polynomials and probabilistic neural networks (PNN). Heart disease recognition is based on the analysis of phonocardiogram (PCG) digital sequences. The PNN provides a powerful tool for proper classification of the input data set. The novelty of the proposed approach lies in a powerful feature extraction based on Gram polynomials and the Fourier transform. Zheng, Yineng, et al (2022) [18] studied Complementary ensemble empirical mode decomposition and tunable-Q wavelet transform were used to construct self-adaptive sub-sequences and multi-level sub-band signals for PCG signals. Time-domain, frequency-domain and nonlinear feature extraction were then applied to the original PCG signal, heart sound sub-sequences and sub-band signals to construct multi-scale and multi-domain heart sound features. The features selected via the least absolute shrinkage and selection operator were fed into a machine learning classifier for ACC/AHA HF stage classification. Finally, mainstream machine learning classifiers, including least-squares support vector

ISSN: 0975-3583, 0976-2833 VOL 12, ISSUE 01, 2021

machine (LS-SVM), deep belief network (DBN) and random forest (RF), were compared to determine the optimal model. Liu, Yongmin, Xingming Guo, and Yineng Zheng (2019) [19] proposed a non-invasive method using extreme learning machine and heart sound (HS) characteristics was provided. Firstly, the improved wavelet denoising method was used for signal preprocessing. Then, the logistic regression based hidden semi-Markov model algorithm was utilized to locate the boundary of the first HS and the second HS, therefore, the ratio of diastolic to systolic duration can be calculated. Eleven features were extracted based on multifractal detrended fluctuation analysis to analyze the differences of multifractal behavior of HS between healthy people and HFpEF patients. Afterwards, the statistical analysis was implemented on the extracted HS characteristics to generate the diagnostic feature set. Yang, Siyu, et al (2022) [20] studied a training dataset containing five categories of heart sounds was collected, including normal, mitral stenosis, mitral regurgitation, and aortic stenosis heart sound. A convolutional neural network GoogLeNet and weighted KNN are used to train the models separately. For the model trained by the convolutional neural network, time series heart sound signals are converted into time-frequency scalograms based on continuous wavelet transform to adapt to the architecture of GoogLeNet. For the model trained by weighted KNN, features from the time domain and time-frequency domain are extracted manually.

3. Proposed Methodology

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. Here's a step-by-step approach to detecting CHF from PCG sounds: Figure 1 shows the proposed block diagram.

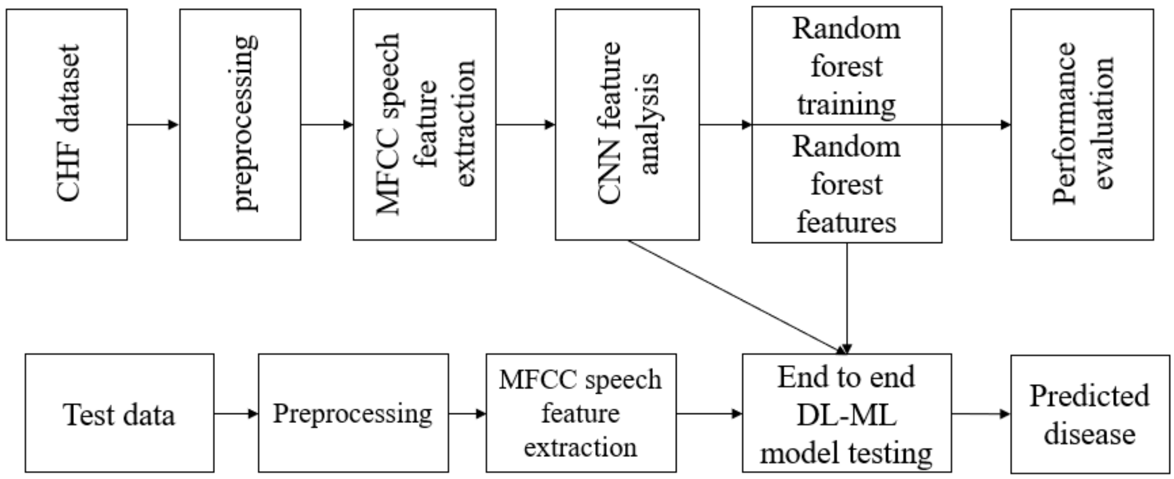


Figure 1. Proposed Block diagram

The following steps are

Step 1: Dataset Preprocessing:

- Collect a dataset of PCG recordings from patients with and without CHF.
- Convert the audio files to a common format, such as WAV.
- Segment the audio recordings into individual heartbeats using an automatic or manual segmentation technique.
- Remove any artifacts or background noise from the recordings.

ISSN: 0975-3583, 0976-2833 VOL 12, ISSUE 01, 2021

- Label the heartbeats as either normal or abnormal (i.e., associated with CHF).

Step 2: Feature Extraction:

- Extract Mel-frequency cepstral coefficients (MFCCs) from each heartbeat using a Fourier transform-based technique.
- Use a sliding window approach to segment the MFCCs into frames of equal length.
- Apply a temporal averaging technique to reduce the dimensionality of the feature set.

Step 3: Feature Analysis:

- Apply a convolutional neural network (CNN) to the MFCC frames to learn a set of discriminative features.
- Train the CNN on the labeled dataset, using a cross-validation approach to avoid overfitting.
- Extract the learned features from the last fully connected layer of the CNN.

Step 4: Classification:

- Use the extracted features as input to a random forest classifier to predict whether a heartbeat is normal or abnormal.
- Train the random forest classifier on the labeled dataset, using a cross-validation approach to optimize hyperparameters and avoid overfitting.
- Evaluate the performance of the classifier on a hold-out test set, using metrics such as accuracy, precision, recall, and F1 score.

By following this approach, it is possible to develop an accurate and reliable system for detecting CHF from PCG sounds. However, it is important to note that the performance of the system may be limited by factors such as the quality and quantity of the dataset, the choice of feature extraction and classification techniques, and the generalization of the model to new patients and recording conditions. Therefore, it is important to carefully design and evaluate the system using appropriate methodologies and benchmarks.

3.1 Preprocessing

Preprocessing the PCG dataset is an essential step in developing a reliable and accurate system for detecting CHF from PCG sounds. Here are some common preprocessing steps that can be performed:

Step 1: Data collection:

- Collect a dataset of PCG recordings from patients with and without CHF.
- Ensure that the dataset covers a range of ages, genders, and ethnicities to ensure the generalizability of the model.
- Verify that the recordings are of good quality, with minimal background noise and no recording artifacts.

Step 2: Data format conversion:

- Convert the PCG recordings to a common format, such as WAV or MP3.
- Ensure that the recordings are of a consistent sampling rate and bit depth.

ISSN: 0975-3583, 0976-2833 VOL 12, ISSUE 01, 2021

Step 3: Heartbeat segmentation:

- Segment the PCG recordings into individual heartbeats.
- This can be done manually by an expert clinician or automatically using algorithms.
- Ensure that the segmentation is accurate, and that no heartbeats are missed or duplicated.

Step 4: Artifact and noise removal:

- Remove any artifacts or background noise from the recordings.
- This can be done using various signal processing techniques, such as filtering, denoising, or wavelet decomposition.
- Ensure that the signal is cleaned without losing important information related to the heartbeats.

Step 5: Labeling:

- Label each heartbeat as either normal or abnormal (i.e., associated with CHF).
- This can be done manually by an expert clinician or automatically using algorithms.
- Ensure that the labeling is accurate, and that no heartbeats are mislabeled.

Step 6: Dataset splitting:

- Split the dataset into training, validation, and test sets.
- Ensure that each set contains a balanced number of normal and abnormal heartbeats.

By performing these preprocessing steps, the PCG dataset will be ready for feature extraction and classification, which can be performed using various machine learning techniques. It is important to note that the preprocessing steps may vary depending on the specific dataset and research question, and that careful consideration and evaluation should be performed at each step.

3.2 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.

Step 1: The given speech signal is divided into frames (~20 ms). The length of time between successive frames is typically 5-10ms.

Step 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.

Step 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

ISSN: 0975-3583, 0976-2833 VOL 12, ISSUE 01, 2021

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.

Step 4: Mel-scaling and smoothing (pull to right). Mel scale is approximately linear below 1 kHz and logarithmic above 1 kHz.

Step 5: Compute the logarithm of the square magnitude of the output of Mel filter bank.

Step 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.

Step 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.

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

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

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

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.

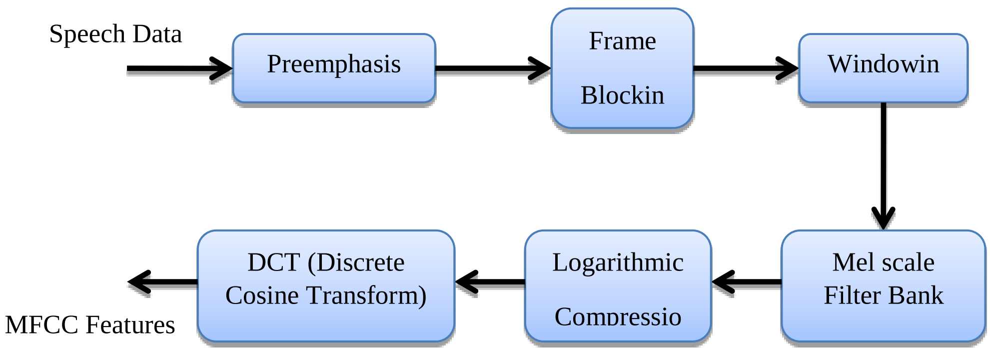


Figure 2. MFCC operation diagram

3.3 CNN model

Journal of Cardiovascular Disease Research

ISSN: 0975-3583, 0976-2833 VOL 12, ISSUE 01, 2021

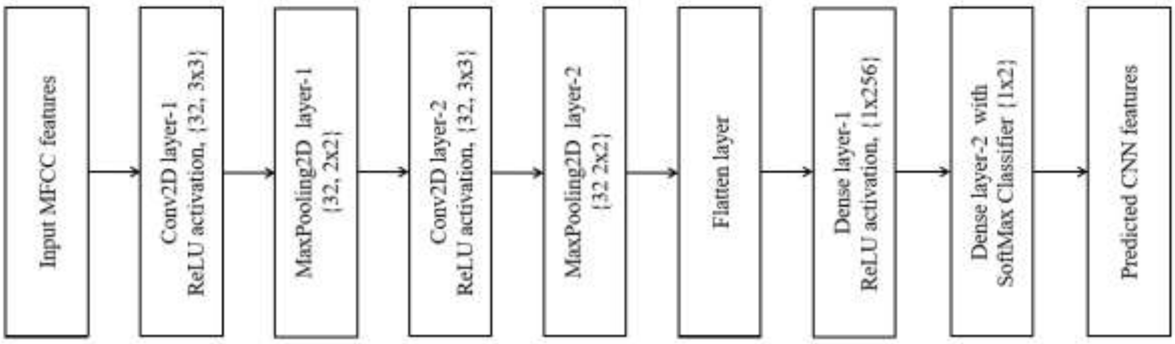


Figure 3. Proposed deep CNN model for feature extraction.

3.3.1 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 4 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 is RGB) and a filter or kernel with similar size of input PCG and can be denoted as $F(k_x, k_y, d)$.

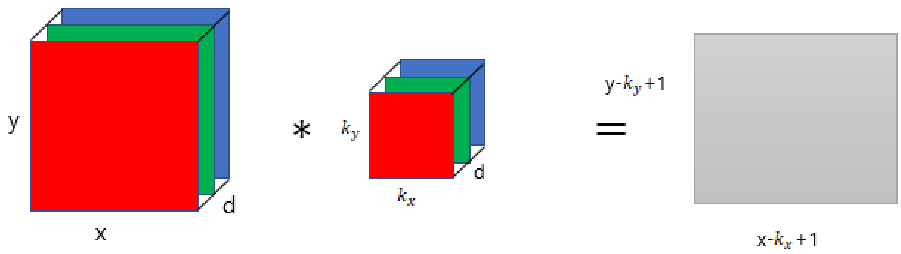


Figure 4. Representation of convolution layer process.

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. 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.

1	1	1	0	0
0	0	1	1	1
1	1	0	0	1
0	0	0	1	1
1	1	1	0	0

5x5 image

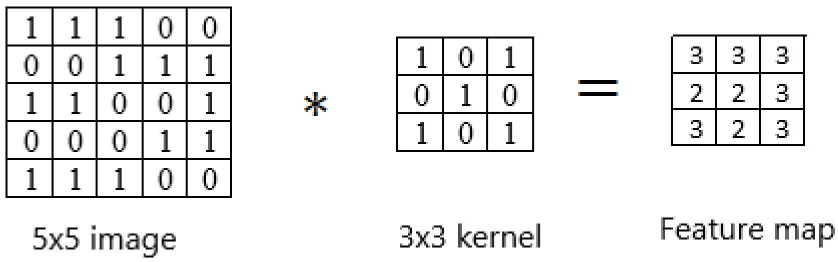
*

1	0	1
0	1	0
1	0	1

3x3 kernel

(a)

ISSN: 0975-3583, 0976-2833 VOL 12, ISSUE 01, 2021



(b)

Figure 5. Example of convolution layer process (a) an PCG with size 5 × 5 is convolving with 3 × 3 kernel (b) Convolved feature map.

3.3.2 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:

$$\mathcal{G}(x) = \max\{0, x\} \tag{3}$$

3.3.3 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.

3.3.4 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.

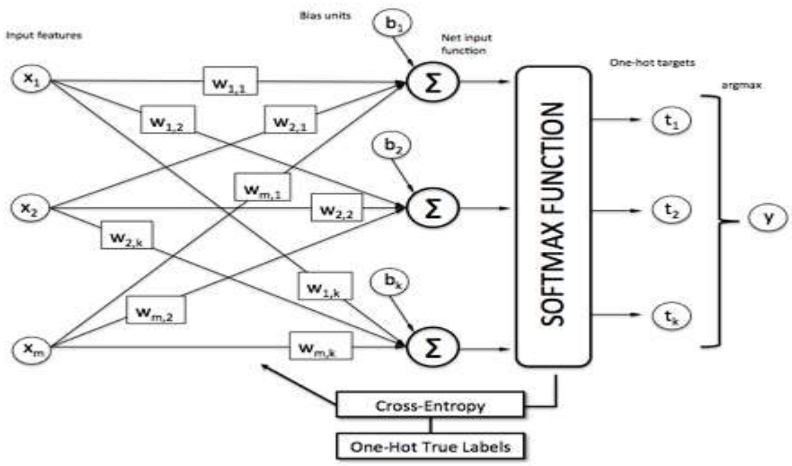


Figure 6. Emotion prediction using SoftMax classifier.

Journal of Cardiovascular Disease Research

ISSN: 0975-3583, 0976-2833 VOL 12, ISSUE 01, 2021

we must predict what is the object that is present in the picture. In the normal case, we predict whether the emotion 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.

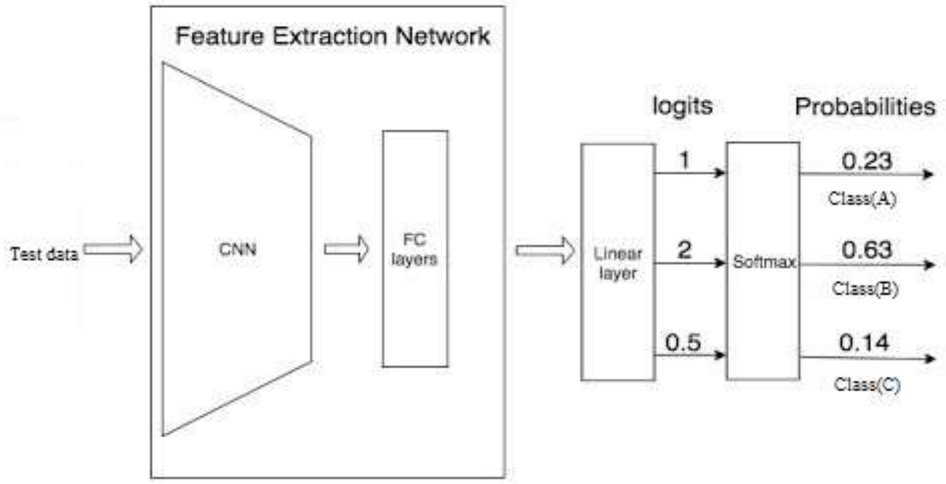


Figure7. Example of SoftMax classifier.

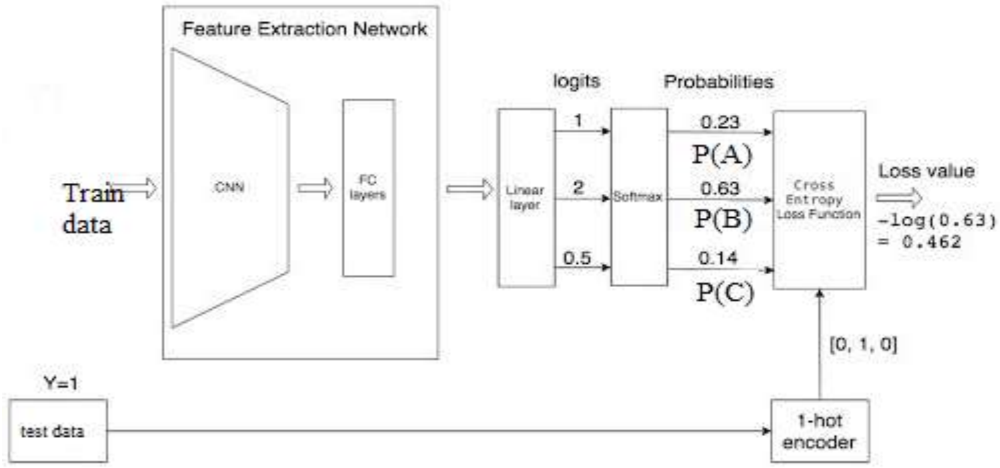


Figure 8. Example of SoftMax classifier with test data.

ISSN: 0975-3583, 0976-2833 VOL 12, ISSUE 01, 2021

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: -

$$LOSS = np.sum(-Y \ * \ np.log(Y\_pred)) \tag{4}$$

3.4 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.

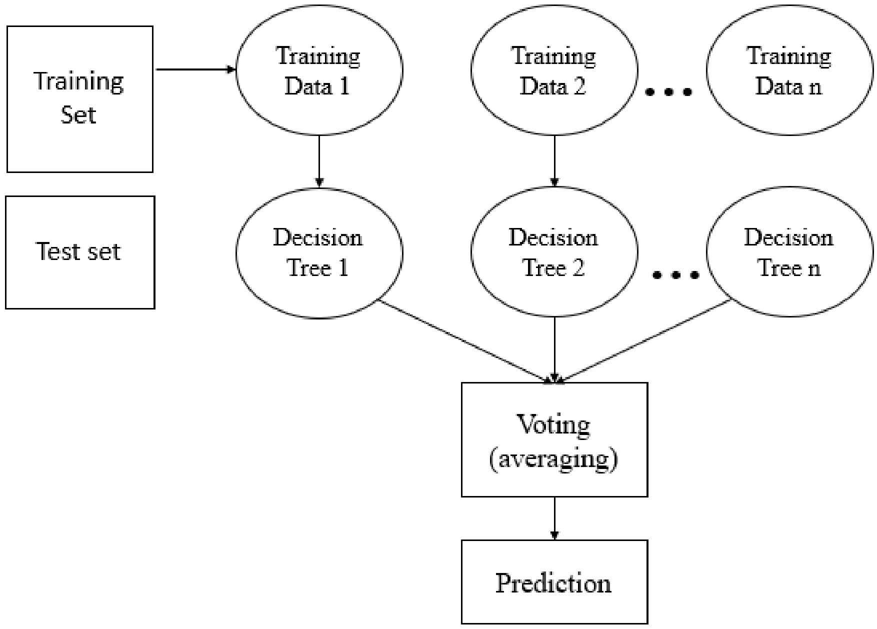


Figure 9. Random Forest algorithm

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.

ISSN: 0975-3583, 0976-2833 VOL 12, ISSUE 01, 2021

4.Results and discussion

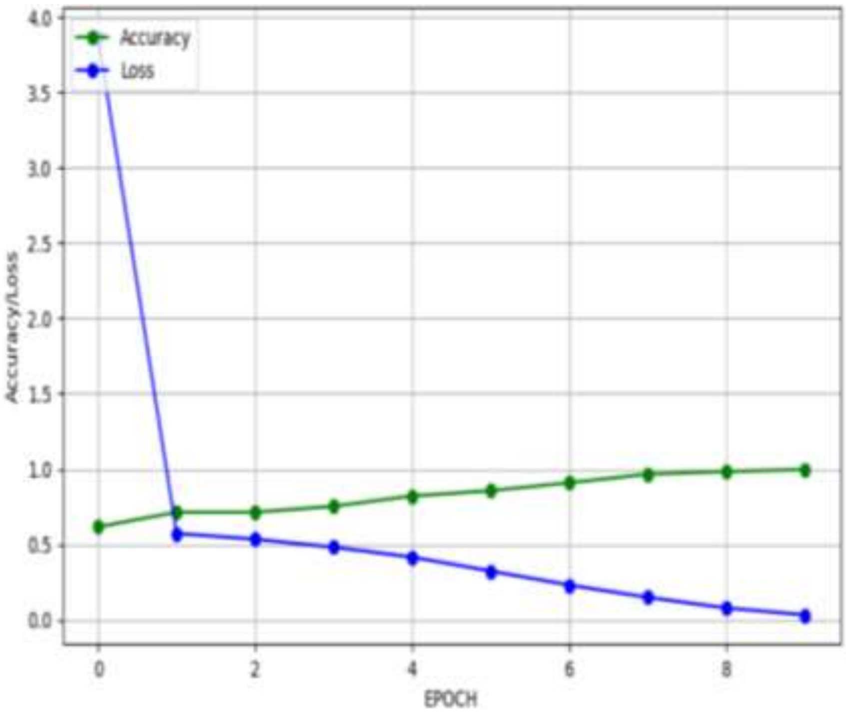


Figure 10. Accuracy graph.

In Figure 10, 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. Table 1 compares the segmentation performance of different approaches to the proposed method. The first column contains performance methods. The second column contains the performance estimation during the Random Forest method. The third column contains the performance estimation during the Proposed Average Aggregate Model method. Finally, last column the performance estimation during Deep learning is presented.

Table 1. Performance of Comparison.

Methods	Random Forest	Deep Learning Model	Proposed Average Aggregate Model
Accuracy	87.65432	93.90243	96.34146
Sensitivity	87.5	100.0	100.0
Specificity	87.719298	91.07142	94.91525

5. Conclusion

At this time, an experienced physician is able to detect the worsening of HF by performing a physical examination on the patient and by observing characteristic changes in the patient's heart failure biomarkers, which can be determined from the blood of the patient. The clinical deterioration of a patient with CHF indicates, unfortunately, that we are most likely already dealing with a fully developed CHF episode that will most likely require hospitalisation. In addition, the progression of heart failure in some patients is accompanied by characteristic changes in heart sounds, which can be

ISSN: 0975-3583, 0976-2833 VOL 12, ISSUE 01, 2021

detected using phonocardiography. These changes can be heard. As a result, this project implements the detection of chronic heart failure from phonocardiography (PCG) data using an end-to-end average aggregate recording model that was built with extracted features from both machine learning and deep learning. The advancements in machine learning and deep learning models that have been made in recent years are being utilised in this project. In addition, the results of the proposed ChronicNet model were compared with those of individual ML and DL models.

References

[1]. Gjoreski, Martin, et al. "Machine learning and end-to-end deep learning for the detection of chronic heart failure from heart sounds." Ieee Access 8 (2020): 20313-20324.

[2]. Gahane, Aroh, and Chinnaiah Kotadi. "An Analytical Review of Heart Failure Detection based on Machine Learning." 2022 Second International Conference on Artificial Intelligence and Smart Energy (ICAIS). IEEE, 2022.

[3]. Shuvo, Samiul Based, et al. "CardioXNet: A novel lightweight deep learning framework for cardiovascular disease classification using heart sound recordings." IEEE Access 9 (2021): 36955-36967.

[4]. Li, Suyi, et al. "A review of computer-aided heart sound detection techniques." BioMed research international 2020 (2020).

[5]. Miotto, Riccardo, et al. "Deep learning for healthcare: review, opportunities and challenges." Briefings in bioinformatics 19.6 (2018): 1236-1246.

[6]. Allugunti, Viswanatha Reddy. "Heart disease diagnosis and prediction based on hybrid machine learning model."

[7]. Zubair, Muhammad. "A Peak Detection Algorithm for Localization and Classification of Heart Sounds in PCG Signals using K-means Clustering." (2021).

[8]. Valera, HH Alvarez, and M. Luštrek. "Machine Learning Models for Detection of Decompensation in Chronic Heart Failure Using Heart Sounds." Workshops at 18th International Conference on Intelligent Environments (IE2022). Vol. 31. IOS Press, 2022.

[9]. Ravi, Rohit, and P. Madhavan (2022) "Prediction of Cardiovascular Disease using Machine Learning Algorithms." 2022 International Conference on Communications, Information, Electronic and Energy Systems (CIEES). IEEE, 2022.

[10]. Susic, D., Gregor Poglajen, and Anton Gradišek. "Machine learning models for detection of decompensation in chronic heart failure using heart sounds." Proceedings of the Workshops at 18th International Conference on Intelligent Environments (IE2022). Amsterdam: IOS Press, 2022.

[11]. Sreejith, S., S. Rahul, and R. C. Jisha. "A real time patient monitoring system for heart disease prediction using random forest algorithm 2016.

[12]. Gjoreski, Martin, et al. "Chronic heart failure detection from heart sounds using a stack of machine-learning classifiers." 2017 International Conference on Intelligent Environments (IE). IEEE, 2017.

[13]. Ismail, Shahid, et al. "PCG classification through spectrogram using transfer learning." Biomedical Signal Processing and Control 79 (2023): 104075.

[14]. Sanei, Saeid, Mansoureh Ghodsi, and Hossein Hassani. "An adaptive singular spectrum analysis approach to murmur detection from heart sounds." Medical engineering & physics 33.3 (2011)

[15]. Gao, Shan, Yineng Zheng, and Xingming Guo. "Gated recurrent unit-based heart sound analysis for heart failure screening." Biomedical engineering online 19 (2020): 1-17.

[16]. Wang, Hui, et al. "An automatic approach for heart failure typing based on heart sounds and convolutional recurrent neural networks." Physical and Engineering Sciences in Medicine 45.2 (2022): 475-485.

[17]. Beritelli, Francesco, et al. "Automatic heart activity diagnosis based on Gram polynomials and probabilistic neural networks." Biomedical engineering letters 8 (2018): 77-85.

[18]. Zheng, Yineng, et al. "A multi-scale and multi-domain heart sound feature-based machine learning model for ACC/AHA heart failure stage classification." Physiological Measurement 43.6 (2022): 065002.

[19]. Liu, Yongmin, Xingming Guo, and Yineng Zheng. "An automatic approach using ELM classifier for HFpEF identification based on heart sound characteristics." Journal of medical systems 43 (2019): 1-8.

[20]. Yang, Siyu, et al. "Fast Abnormal Heart Sound Detection Method Based on Multi-struct Neural Network." 2022 7th International Conference on Intelligent Computing and Signal Processing (ICSP). IEEE, 2022.