Detection of Congestive Heart Failure using Naive Bayes Classifier

Dipen Deka

*Abstract***:** *Congestive heart failure (CHF) is gradually becoming more prevalent due to the stressed lifestyles in modern life. Accurate detection with lower computational complexity and lower cost of diagnosis is a challenge to the researchers in this domain. In this work, I have proposed an approach using naive Bayes algorithm with a lesser number of significantly discriminating features for differentiating the CHF subjects from the normal subjects. The small size of feature sets enhances the computational efficiency and the choice of strong features improves the accuracy. The features are chosen on the basis of p-value of the 2-sample t-test performed between the two types of subjects. Using the p-value, 6 features are selected to train, validate and test the classifier. Publicly available benchmark PhysioNet datasets for congestive heart failure patients and normal subjects are used to carry out the experimentation. This approach is able to provide 100% classification accuracy as well as sensitivity and specificity of 100% in identifying CHF patients employing Gaussian naive Bayes algorithm.*

*Keywords***:** *Congestive Heart Failure, Time Domain Analysis, Discrete Wavelet Transform, Naive Bayes Classifier,*

I. INTRODUCTION

With the escalation of heart patients all across the world possibly due to stressed life, correct and low cost diagnosis is becoming vital to enable proper treatment. Often people die due to the negligence towards the minor health problems or delayed information about the actual cause of the disease, especially in the underdeveloped countries. Congestive heart failure (CHF) is one type of acute heart syndrome, in which the pumping capacity of the heart gets diminished. This is a degenerative disease observed mostly in the aged people or someone who has suffered earlier from strokes [1-3]. From the literature it can be observed that electrocardiography signal (ECG), echocardiography, heart rate variability (HRV) signals are used to detect the CHF [3, 9-13]. Further, machine learning (ML) advancements have been instrumental in the quality and quick diagnosis of various types of diseases. Machine learning techniques are getting improved continuously to tackle various types of data, like data of very big size, very scanty in size, again some are of nonlinear high dimensional type and so on [4-6]. Machine learning classifiers such as, k-nearest neighbor (KNN), support vector machine (SVM), decision tree (DT), classification and regression tree (CART), naive Bayes network (NB), random forest (RF), convolutional neural network (CNN), and various fuzzy classifiers are widely used in many works to detect different types of heart diseases [1-3,7-13]. Wijbenga et al. [8] have performed an analysis on CHF patients by using parameters including left ventricular ejection fraction (LVEF), HRV triangular index (HTI), systolic pressure, HR and found significant change in these parameters for CHF patients. Arbolishvili et al. [9] have observed depressed HRV in the CHF subjects. Engin [10] compared the CHF data with the normal subject's data by using wavelet transform (WT) based variance measure and detrended fluctuation analysis (DFA) coefficient. He found considerable difference between the readings of CHF patients and normal subjects. However, no ML techniques were used in the works discussed above. Melillo et al. [11] have obtained the specificity of 100.00% and a sensitivity of 89.74% using CART algorithm. For classification, they used long term HRV parameters, named root mean squared differences of successive differences (RMSSD), standard deviance of the averages of every 5 minute segments of normal to normal interval (SDANN), and total power calculation using Lomb-Scargle (LS) periodogram. Kuntamalla and Reddy [12] have used heart rate sequential trend analysis for discriminating the CHF beats from the normal sinus beats. They achieved classification accuracy of 96.68% in differentiating CHF data from normal heart beats data. They improved the accuracy up to 100% using dual scale entropy analysis [13]. Again, Hossen and Al-Ghunaimi [14] have obtained accuracy up to 90% using power spectral distribution based analysis. Isler and Kuntalp [15] used linear discrimination analysis by taking short term HRV features and obtained sensitivity of 86.2% and the specificity of 92.6%. Afterwards, in another work [16], they have combined the short-term time domain parameters and wavelet entropy measure and thus improved the sensitivity and specificity up to 81.8% and 98.1% respectively using KNN classifier. For choosing the best combination of features, they utilized genetic algorithm. Masetic and Subasi [3] have compared the accuracy using different classifier and found 100% accuracy in random forest classifier. They extracted the HRV features by applying autoregressive Burg method. Recently, adopting a different approach, Porumb et al. [17] have taken the ECG signal instead of HRV signal for their analysis and applied CNN classifier to identify the class discriminative regions in ECG to identify the CHF patients. They have obtained 100% accuracy in their classification work. However, ECG is more prone to noise which leads to the requirement of robust noise canceller. On the top of that identifying such discriminative region increases computational complexity. On the other hand deriving HRV signal is very easy. Further, classifiers like ANN, CNN, and RF, SVM techniques are more complex and demanding more computational time. This calls for a simpler but accurate method to identify the CHF cases.

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To this end, naive Bayes algorithm is used to test its discrimination power in discerning the CHF patients from normal subjects by extracting features from time domain statistical and discrete wavelet transform (DWT) based analysis. Here, the extracted parameters for both types of data are compared and then their statistical differences were tested. Based on the *p*-value, the features are chosen for NB classifier. Overall, the proposed method provides a simpler, accurate and robust detection of CHF patients.

The remainder of the paper is structured as follows. Section II gives the details of the data used for the work and proposed methodology. In Section III, the findings and its discussion are provided. Finally Section IV concludes the paper.

II. METHODOLOGY

A. Data studied

The RR (R-peak to R-peak of ECG) interval data for the CHF patients and normal subjects are acquired from the benchmark PhysioNet database [18]. The CHF data are retrieved from the Beth Israel Deaconess Medical Center (BIDMC) Congestive Heart Failure Database. The database contains long-term ECG data of 15 subjects (11 men of ages ranging from 22 to 71 years; 4 women, of ages from 54 to 63 years) with major CHF falling under the class 3–4 as per NYHA. The recording of the data were taken before consuming the inotropic agent, milrinone. The ECG signals were sampled at 250 samples/second with 12-bit resolution over a range of ±10 millivolts. The original analog recordings were made at the BIDMC using ambulatory ECG recorders with a bandwidth of approximately 0.1 Hz to 40 Hz.

On the other hand, the control group contains the ECG recordings of normal subjects that are retrieved from the MIT-BIH normal sinus rhythm database. It includes 18 (5 men, of age range 26-45 years, and 13 women, age range 20-50 years) long-term ECG recordings [18]. The subjects were found to have no significant arrhythmias.
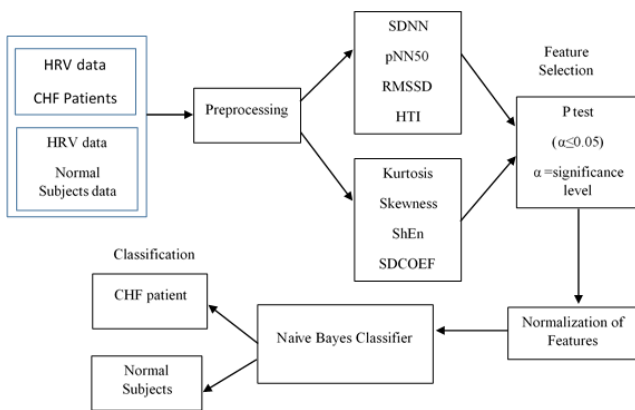
Fig. 1. Block diagram of the proposed methodology

B. Data Preprocessing

The RR interval data for both the CHF and normal subjects were checked for the presence of outliers. The observed outliers were removed from our analysis as it is found to be less than 1%. The dataset are converted to a format where one variable contains the instances of R-peaks and the other variable shows the corresponding RR intervals. The data will be better termed as HRV time series for our proposed analysis.

C. Time domain Parameters for evaluating HRV signal

In this work, the statistical parameters, based on the differences between RR intervals are calculated to observe the pattern of changes in HRV for CHF patients. Time based statistical parameters, namely, standard deviation of normal to normal interval (SDNN), percentage of NN intervals exceeding 50 ms (pNN50), root mean square of successive differences (RMSSD), standard deviation of the averages of NN intervals for 5 minute segments (SDANN) and HRV triangular index (HTI) are calculated from the HRV time series for the acquired datasets. It is to specify that NN intervals means the RR intervals between two normal sinus beats after excluding all the ectopic beats. Then mathematical expressions for calculating these parameters are given in the following equations [19]

$$SDNN = \sqrt{\left(\frac{1}{K}\sum_{k=1}^{K}(RR(k) - \overline{RR})^2\right)} \quad (1)$$

where $\overline{RR}$ indicates the mean value of the RR intervals and K is the total number of *RR* intervals.

NN50=Total number of consecutive NN intervals whose differences is more than 50 ms.

$$pNN50 = \frac{NN50}{Total\ number\ of\ NN\ intervals} \times 100\% \quad (2)$$

$$RMSSD = \frac{1}{K-1}\sqrt{\sum_{k=1}^{K-1}[RR(k+1) - RR(k)]^2} \quad (3)$$

$$SDANN = \sqrt{\left(\frac{1}{L-1}\sum_{l=1}^{L-1}\left(\overline{SEG(l+1)} - \overline{SEG(l)}\right)^2\right)} \quad (4)$$

where L is the number of 5 min segments in whole HRV time series and $\overline{SEG}(l)$ is the average of the NN intervals in a 5 min segment.

and *HTI* is the ratio of the integration of the density distribution of the NN intervals by the maximum value of density distribution.

D. Discrete Wavelet Transform (DWT)

DWT is a discrete version of a time-frequency analysis technique which basically filters a signal by a set of high pass filters (HPF) and low pass filters (LPF) [20,21]. It is suitable for analyzing non-stationary signals since it provides a more localized time-frequency analysis. The increase in the decomposition level provides the information of more detailed (high frequency) components of a signal. The scaling function provides the coarse information, whereas the wavelet function, also known by mother wavelet gives the detailed information of a signal to be analyzed.

If $(\psi)_{l,m}(n)$ is a wavelet function, the DWT of a signal x[n] is given by

$$W_\psi(l,m) = \frac{1}{\sqrt{M}}\sum_{n=1}^{N}x[n]2^{l/2}\,\psi(2^l n - m) \quad (5)$$

where *l* and *m* are scaling and translation parameter respectively. The scaling parameter can be expanded or contracted to have the frequency or time localized analysis as per requirement. For better analysis of a signal, orthonormal wavelet basis function should be smooth and regular. Further the property of compact support is very desirable for leakage free spectral analysis.

For our analysis 'db4' wavelet member of Daubechies family with 4th level of decomposition is chosen considering the smoothness, compact support properties of db4. Here, the vanishing moment and decomposition level is chosen in such a way to reduce the computation cost as well as to maintain the desired accuracy. Since HRV signal spectra lies up to 0.4 Hz, 4th level of decomposition will be sufficient in our case. We have calculated the Shannon entropy (ShEn) [22], kurtosis, skewness [21], and the standard deviation of the 3rd level detail component coefficients as the features to be trained in the naive Bayes classifier.

E. Naive Bayes Classifier

Naive Bayes classifier is governed by Bayes' theorem, which is based on a key idea that all the features derived from a dataset are independent of the other features [23,24]. This is actually a conditional probability model, which provides the probability of identifying a class (C_k) for a given vector random variable (X) with its vector of feature values (x_i), as given by [24]

$$P(C = C_k | X = x_i) = P(C = C_k) \times \frac{P(X=x_i | C=C_k)}{P(X=x_i)} \qquad (6)$$

where $P(X = x_i | C = C_k)$ is the class-conditional probability and the Bayes discriminant function can be given by Eq. 7.

$$D(x) = arg \max_{C_k} P(X = x_i \mid C = C_k) P(C = C_k) \qquad (7)$$

For the classification purpose, Gaussian naïve Bayes model is employed. In this model, for a particular class C_k, the feature vector data (x_i) are considered to be following normal distribution. From the trained feature vector, x_i, the classifier will compute the mean ($\bar{x}_i$) and variance ($\sigma_k{}^2$) for the class C_k sample. Then for a test data (p_k), the probability distribution of p_k given a class C_k is given by Eq. 8.

$$P(x_i = p_k | C_k) = \frac{1}{\sqrt{2\pi\sigma_k{}^2}} e^{-\frac{v_k - \bar{x}_i}{2\sigma_k{}^2}} \qquad (8)$$

It is to mention here that the simplicity and efficacy of this algorithm for small datasets drive me to use it for discerning CHF patients.

F. Statistical Significance Test

In this work, statistical significance test plays an important role, as only the significant features/parameters based on p-value are fed to the classifier. This approach reduces the computational cost as well as enhance the accuracy of classification. 2-sample *t*-test is applied between the CHF patients and the normal subjects for all the individual features. Those features whose p-value is less than 5% are considered as significantly discriminative. For that purpose, initially the t-statistic has to be calculated and then of *p*-value is obtained from the reading *t*-value and degree of freedom (DF) [25]. I have used IBM SPSS statistic 20 software to obtain the *t*- and *p*-value. However, their computations are given below:

$$t = \frac{\overline{X_A} - \overline{X_B}}{\sqrt{\frac{\sigma_{X_A}{}^2 + \sigma_{X_B}{}^2}{N}}} \qquad (9)$$

where X_A and X_B are the readings of a parameter for the CHF and normal subjects respectively and σ indicates the standard deviation. From the size of the dataset, the DF can be obtained as DF=N-1, where N is the number of observations. Finally p-value can be obtained by using t-statistic chart for the corresponding DF [25].

G. Performance Metrics

For performance evaluation of the classifier, generally the data is cross validated using either *k*-fold validation, hold out or leave one out technique. The suitability of these techniques are based on the size of the dataset and the demand of speed and accuracy. Leave one out is a very rigorous process, which selects only one sample for test, while putting the other samples for training. This leads to high computational cost. In this work, 10-fold cross validation technique is used to derive the performance metrics such as accuracy, sensitivity, specificity. In 10-fold cross validation method, whole samples are divided into 10 equal parts, from which one part is kept for testing, while the rest 90% samples are fed into the classifier for training. Based on the outcome of cross validation, the accuracy, sensitivity, specificity and receiver operating characteristic (ROC) are obtained from the data. The parameter accuracy can be defined as the ratio of summation of true positive and true negative to the total number of events, as given by [26]

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \qquad (10)$$

where TP, stands for true positive, which means the presence of an event in both prediction and actual is true.
TN, stands for true negative, which means the absence of an event is true for both prediction and actual.
FP, stands for false positive, which means that an occurrence of an event is predicted but actually the event does not occur. and FN, stands for false negative, which means that the absence of the occurrence of an event is predicted but actually the event does occur.

Accuracy cannot be sufficient to depict the true picture of a model, the information about false positive and false negative events are required to judge the performance of classifier model. Sensitivity of a classifier provides the information about FN events, and it is the given by [26].

$$Sensitivity = \frac{TP}{TP + FN} \qquad (11)$$

Again, specificity can be defined as the ratio of the true negative assessment to the actual negative events [26].

$$Sensitivity = \frac{TN}{TN + FP} \qquad (12)$$

Besides these metrics, ROC is very important for the assessment of a classifier model because a classifier can be considered as perfectly discriminative, if above a certain threshold, all the abnormal population would come down to zero and below that threshold, all the normal population come down to zero [27]. This ROC characteristics is actually obtained from the plot between specificity (true negative rate) in the x-axis and sensitivity (also known as true positive rate) along y-axis. The absolutely discriminative classifier characteristic will pass though (0, 1) coordinate. In other way as the area under this curve (AUC) increases, the performance of a classifier improves.

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III. RESULTS AND DISCUSSION

To perform the classification task, 11 numbers of CHF subjects from the BIDMC CHF database and 11 numbers of normal subjects from MIT-BIH normal sinus rhythm database are considered. The time domain statistical parameters, SDNN, pNN50, RMSSD, HTI parameters and the DWT based parameters, kurtosis, skewness, Shannon entropy and SD of the wavelet coefficients of 3rd level detail

components are obtained from the simulations on MATLAB R2018a environment. Before, time and frequency based evaluations, the outliers in the data are removed. In Table- I, the normalized readings of the HRV parameters for 7 CHF patients and 7 normal subjects are shown. This is done because, fitting the data of 11 CHF and 11 normal subjects in a table takes lots of space. Besides that our motive is to evaluate the *p*-value for the data, so the indicated *p*-value is taken from the whole 22 subjects as used in this work.

Table- I: Normalized readings of HRV features and their *p*-values for CHF patients and Normal subjects

Parameters	CHF 01	CHF 02	CHF 03	CHF 04	CHF 05	CHF 06	CHF 07	Normal 1	Normal 2	Normal 3	Normal 4	Normal 5	Normal 6	Normal 7	p-value
SDNN	0.38	0.25	0.23	0.11	0.08	0.40	0.31	0.61	0.81	0.44	0.24	0.80	0.62	0.33	0.0097*
pNN50	0.01	0.14	0.16	0.08	0.03	1.00	0.08	0.09	0.14	0.14	0.13	0.35	0.26	0.19	0.674
RMSSD	0.14	0.72	0.24	0.19	0.04	0.99	0.73	0.14	0.78	0.18	0.11	0.61	0.28	0.20	0.71
HTI	0.20	0.07	0.14	0.03	0.07	0.26	0.05	0.22	0.24	0.45	0.09	0.26	0.28	0.12	0.0375*
SDANN	0.28	0.08	0.15	0.10	0.13	0.13	0.13	0.42	0.73	0.34	0.18	0.28	0.48	0.15	0.013*
ShEn	0.03	0.04	0.06	0.02	0.00	0.05	0.04	0.42	0.41	0.23	0.23	0.75	1.00	0.59	0.00015*
SD_DWT	0.07	0.05	0.12	0.03	0.00	0.11	0.08	0.32	1.00	0.22	0.19	0.52	0.63	0.43	0.0014*
Kurtosis	0.09	0.03	0.04	0.24	0.28	0.02	0.10	0.02	0.05	0.01	0.02	0.01	0.00	0.00	0.0474*
Skewness	0.95	0.90	0.96	0.91	0.90	0.94	0.96	0.93	0.93	0.91	0.95	0.95	0.95	0.91	0.2337
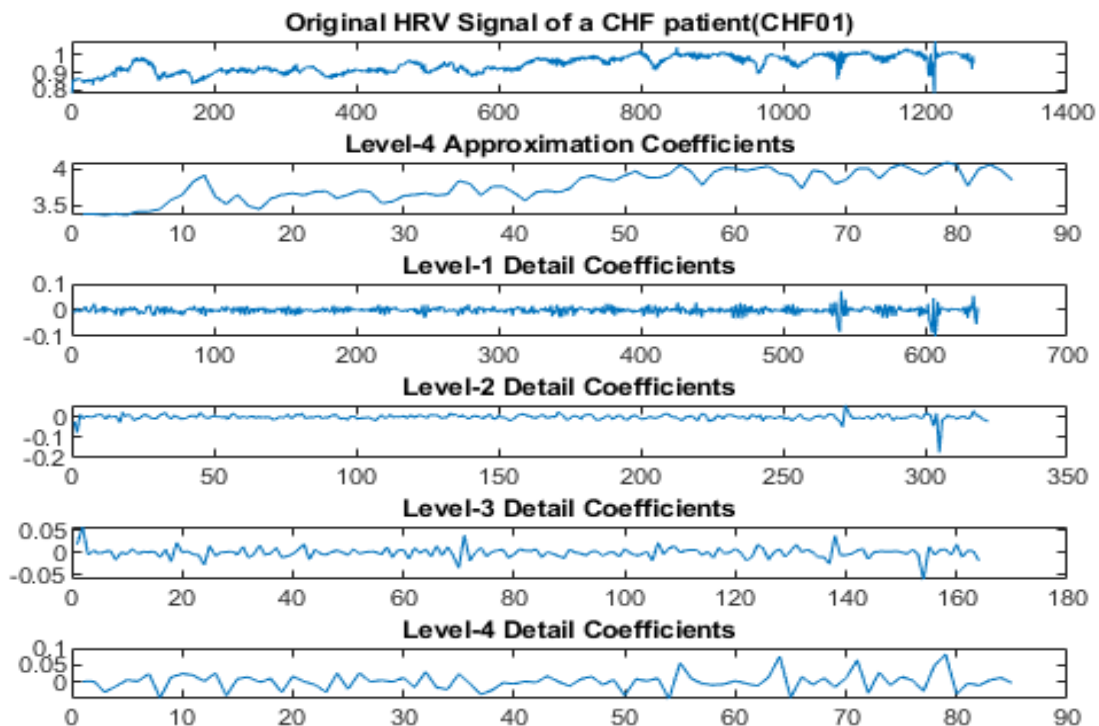
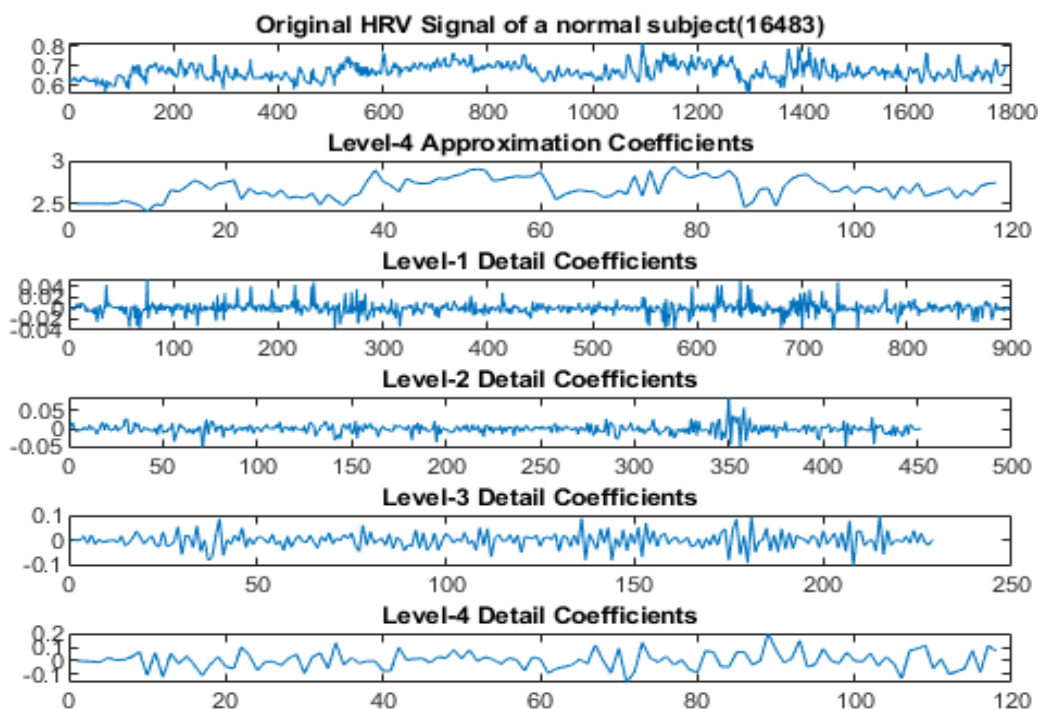**Fig. 2. DWT coefficients for a CHF01 patient**

Fig. 3. DWT coefficients for a normal subject

It can be observed from the table that the parameters, pNN50, RMSSD, and skewness does not yield significant differences between the CHF and normal subjects. On the other hand, DWT based parameters ShEn and standard deviation of the DWT coefficients of 3rd level detail component have provided strikingly significant difference. When the data of these two parameters are fed to naive Bayes classifier, the accuracy has improved radically. Further from Fig. 1 and Fig. 2, the difference between the wavelet coefficients are clearly visible.

Table- II: Comparison of accuracy with other works

Authors	Methods	Accuracy (%)
Isler et al. (2007) [16]	k-NN using HRV signal	96
Hossen and Al-Ghunaimi (2008) [14]	Soft decision tecnique on HRV signal	88.6
Kuntamalla and Reddy (2010) [12]	Sequential trend anlysis	96.68
Melillo et al. (2011) [11]	CART using HRV signal	96
Masetic et al. (2016) [3]	Random forest algorithm using HRV signal	100
Acharya et al. (2019) [7]	CNN using Very short 2 sec ECG signal	98
Porumb et al. (2020) [17]	CNN using raw ECG	100
This proposed work	**Naive Bayes method using HRV signal**	**100**

The ROC characteristic for the proposed classification model is shown in Fig. 4, which shows the perfect discriminative characteristic for the studied data.
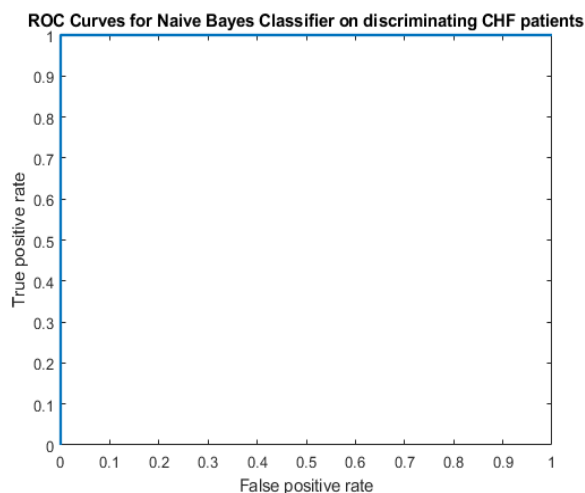

Fig. 4. ROC curve of naïve Bayes classifier in discriminating CHF patients from normal subjects

IV. CONCLUSION

The proposed method is performing the classification based on only 6 parameters, from the *p-value* assessment which enhances the accuracy as well as the computational efficiency. Besides that, naive Bayes method works very well for small datasets which suits this work, as the number of datasets are quite limited. Another main advantage of naive Bayes, which outweighs other competitive random forest, KNN, SVM algorithms is its simple algorithm. Overall, accuracy, sensitivity, specificity of 100% is achieved in this work.

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