Ensemble Classification System for Detection of Cardiovascular Diseases using Electrocardiogram Signal

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ABSTRACT
Early detection of Myocardial Infarction (MI) and Congestive Heart Failure (CHF) Cardiovascular Diseases (CVDs) are challenging diseases for cardiologist practioners to reduce the mortality rate. This paper deals with the design and development of an automated Ensemble Classification system using optimized Heterogeneous Features set viz. Morphological/Structural and Statistical Non Linear features of Electrocardiogram (ECG) Signal. ECG is non-invasive and vital clinical therapeutic agent deployed for taking intelligent health care prediction of MI and CHF. In this approach, the ensembles of classifiers are performed by taking into account diversity and accuracy of multi classifiers in intelligible hybridization manner with majority voting technique in ECG pattern recognition. Proposed methodology achieved the maximum Accuracy, Sensitivity, Specificity of 99.75%, 99.72%, 99.85% respectively, along with Precision, Recall and F1-Score statistical indices ranging from 0.9 to 1 value, taking into account 300 patient's ECG signals collected from diverse databases. The time required for execution of the system is 0.55 seconds. Computation time is reduced to greater extend with directly evaluation of the features from the ECG signal analyzed on the morphological and statistical domain, so, the detection of R-peaks are eliminated with the proper selection of derivative levels.

General Terms
Cardiovascular Diseases, Myocardial Infarction

Keywords
Ensemble Classification, Electrocardiogram, Heterogeneous Features, Statistical Features.

1. INTRODUCTION
Electrocardiogram (ECG) signal comprises the recording of deviation of bioelectric potential differences with respect to time (duration) and amplitude (voltage) as per each cardiac cycle of .the human heart. ECG acquisition is a non-invasive technique that is easy to operate and recording [1]. ECG provides information about the heart functioning and related cardiovascular scheme. An ECG signal is successive repetitions of the fiducial points "PQRST" as shown in figure 1. At the first, 'P' wave is generated from the straight signal. The deflection in downward side of ng linear wave is recognized as a 'Q' wave. Just after Q wave, a sudden deflection in vertical forms a upward cone shape, indicate as 'R' wave. The small down fluctuation forms 'S' wave. And after a noticeable time the 'T' wave is formed that denotes the end of one segment of the ECG cycle [2]. Congestive heart failure (CHF) is a condition when the heart is becomes weak to generate pressure sufficiently to circulate the blood flow which is needed for human organs functioning. ECG signal deviations in CHF shows R wave height (amplitude) first increases and then decreases in random manner. QRS complex duration changes in either smaller or larger range (QRS>0.1s or QRS<0.09s) and Beats Per Minute (BPM) changes [5].

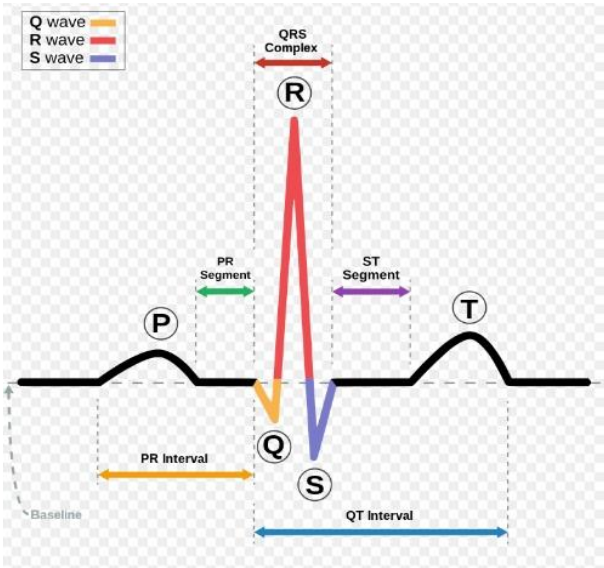

Fig 1: Waveform of a Normal ECG [1]

Myocardial infarction (MI), refers to a heart attack, when heart muscles get damaged due to decrease of blood flow to the heart. Onset of a Myocardial Infarction, multiple changes can be noticed in the pattern of ECG Signal. First, sharp peaked T wave undergoes changes that results in variation of ST dimensions and elevation. ST dynamic elevation increases to ≥0.2 mV in men or ≥ 0.15 mV in women [3-5]. The key motivation behind this work lies to improve the automated detection of CHF and MI using ECG signal processing using machine learning approach in ensemble structure. Manual interpretation of ECG on grid view and diagnosis prominent cardiovascular diseases by medical personnel may not be visualized and relied comprehensively. Hence, the automated computerized model is adopted for reliable and accurate detection of CHF and MI CVD's.

2. LITERATURE REVIEW
R.K.Tripathy et al. [6] presented the CHF detection by using Stockwell Transform technique and frequency-division to analyze the time-frequency domain of electrocardiogram (ECG) signals. They evaluated the entropy features by making division of frequency sub-band from ECG signal. Similarly, they have adopted the hybrid classifier system involving the mean of Euclidian distances amongst the kNN classifier and class specific sparse representation residual classifier for each

class and achieved accuracy, sensitivity, specificity of the hybrid classifier as 98.78%, 98.48%, 99.09%, respectively. The limitation of this approach is that, they have worked on homogeneous feature set that is time-frequency domain entropy based features. The use of heterogeneous feature sets can enhance the result with same approach. Mihaela Porumb et al. used three convolutions layered CNN without pooling operation thus reduces the computational complexity and achieved 100% accuracy for CHF disease detection [7]. The limitation of the work is that, they have examined only 18 normal and 15 CHF patients ECG signal for analysis. So, analyzing on more new ECG signals from more number of new patients may affect to the accuracy in detection of CHF. U. Swain et al. considered the morphological features for analysis using 12 lead ECG signal for diagnosis of MI. They performed 2-class classification with MI threshold-based regulation of classification. They claimed the accuracy, sensitivity and specificity of 99.93%, 99.97% and 99.30% respectively in MI prediction. In their future work, they proposed to extend this method arrhythmia inculcated with the state-of-the-art smart phones [8]. Kamal Jafarian et al. [9] proposed the automated detection along-with localization of MI disease. They extracted statistical feature from ECG signal using classic-approach of a Discrete Wavelet Transform (DWT) and Principal Component Analysis (PCA) applied on the filtered and pre-processed signals and applied shallow neural network (NN) for classification purpose. They performed proper training and validation on dataset by achieving over 98% accuracy for MI detection and localization using K-fold cross-validation method. The drawback of the mentioned work may lies in computational time of the system as they have used 28 features in MI-prediction and 32 features for MI-localization. A. Dohare [10] proposed detection of MI by extracting clinical morphological features such as P wave duration, QRS complex duration, ST interval duration and QT-interval derivation from sampled beats of 12-lead ECG signal. Initially, they worked on 220 features using support vector classifier (SVM) and achieved the accuracy of classification as 98.33%. Later, they applied the method of Principal Component Analysis (PCA) reduction technique and reduced 220 features to 14-features for MI detection by applying SVM classifier to obtain sensitivity-96.66%, specificity-96.66% and accuracy-96.66% respectively. Here, author used limited dataset as 60 MI patients and 60 Normal patients from only one database Physikalisch-Technische Bundesanstalt (PTB). So, there can be scope to improve MI detection using less numbers of features than 14 features and analyzing more ECG record from diverse database.

In view of findings from Literature Review, the limitations in existing researches are listed as (i) Existing Researchers Extracted ECG signal features by analyzing one aspect of the signal either Structural or Statistical or Entropy domain and focused on individual class using homogeneous (only one type) features set, (ii) Examination and Analysis is done with limited number of records and single line ECG Signals dataset. (iii) Moreover, existing research have used one or more classification algorithms separately to detect the CVD's. (iv) It is observed in some of the studies that proper validation method is not used. (v) Single Classifier Model approach is used to detect CHF or MI.

3. MATERIAL AND METHODOLOGY

The ECG samples retrieved for analysis purpose from four different databases viz. BIDMC Congestive Heart Failure (CHF) Database, Congestive Heart Failure RR Interval Database, PTB Diagnostic ECG Database and Normal Sinus Rhythm (NSR) RR Interval Database [11-13]. Proposed methodology is elaborated in figure 3. The system is consisting of four stages initially starting from pre-processing, processing, post-processing and the Ensemble classification scheme.

ECG records of 300 patients are utilized (CHF-46, MI-148, NSR-106) from mentioned diverse databases of PhysioNet for analyzing and implementing our machine learning model. The recorded ECG Signals stored in Comma Separated (.csv) and Data (.data) file format consisting of mentioned patient record. While acquisition of the ECG samples, sampling-frequency was 360Hz per channel with 12-bit resolution fixed over 10 mV Range. ECG signals affected with CHF, MI and NSR are considered as three classes and pre-processed for denoising the signal and then it is segmented in to number of pieces (segments) depend on time scale. Each segment is decomposed into levels by using derivative based system [14]. The non-linear statistical features based on time-frequency domain and related morphological features in time and amplitude scale are extracted and computed. Later, a subset of significant features are selected and optimized to prepare a reliable heterogeneous features set. The performance evaluation of these features is done using Ensemble Classification Scheme taking in to account independent and more accurate classifier in hybridization manner to achieve the best classification result in regards to detection of CHF, MI and NSR classes.

4. FEATURES EXTRACTION

In this work, heterogeneous features are extracted viz. Morphological features and Non-linear Statistical features from ECG signal. The morphological features comprises the structural features belongs to ECG signal which indicates the operational aspects of the heart system. These features include event based phenomenon features such as P-wave duration, QRS complex duration and T-wave duration with respect to time/duration or amplitude/voltage scale. Similarly, non-event phenomenon features comprises to time interval for consecutive event of the ECG such as PQ-segment, QRS-complex duration and ST-segment. Also, we have analyzed the time-frequency domain to extract statistical non-linear features such as RMSSD (Root Mean Square of Successive Differences between normal heartbeat) [15], pNN50 (Percentage of successive RR intervals that differ by more than 50 ms), SDNN (Standard Deviation of RR Interval) [16], Sd1 and Sd2 (Standard Deviation in diagonal to the line of identity) of an ECG signal.

5. RESULTS AND DISCUSSIONS

The main objective of the presented work focused on the detection of CHF and MI cardiovascular diseases based on the duration-amplitude (time-voltage) and statistical analysis from ECG signal domain. The morphological/structural features from event (P,Q,R,S,T fiducial points) and non-event (ST-segment, PQ-segment, QRS complex duration) phenomenon from ECG signal are considered and extracted using Hamilton Segmenter algorithm, Discrete Wavelet Transform and Statistical Indices measure. The Ensemble Classification that belongs to intelligent hybrid classification sub-domain is designed and developed for assessing and evaluating the performance of these heterogeneous features set. To verify and recognize the effectiveness of the proposed system, we made comparison with prior/existing work for CHF and MI detection models and methods. The patient dependent and specific to particular diseases, the 10-fold-cross-validation-approach is accomplished for evaluating the performance of Ensemble Classifier that proves the robustness of the system. The ECG features are given as input to the Ensemble Model, where, the classification is performed using mutually independent and individual classifier models viz. Decision Tree Algorithm (DTC) with entropy and gini criterion [17-19], Support Vector Machine (SVM) having gamma or linear criterion, k-nearest neighbors (KNN) [20]. From this pool of multiple classifier models used, it is being observed that DTC with entropy and gini criterion and SVM [21] with linear criteria are having accuracy of 99.4%, 99.4% and 99.7% respectively in terms of detection of CHF, MI and NSR cardiovascular diseases as shown in figure 2. Hence, Ensemble Model is formulated by considering these three higher accurate classifier models. An ensemble is a group of models bundled together to predict the same set of values. The goal of Ensemble Algorithms is to provide composite predictions of several base predictors over a single predictor to improve accuracy and robustness. The Classifier Ensemble is designed by using following hybrid approaches:

i. **Using different classifiers models:** Introduced diversity by combining different independent individual classifier.
ii. **Using heterogeneous features subsets:** Introduced diversity by training individual classifier with different subset of features.
iii. **Using majority voting technique:** Aggregated the result of individual classifiers to produce final conclusion based on majority voting [18].

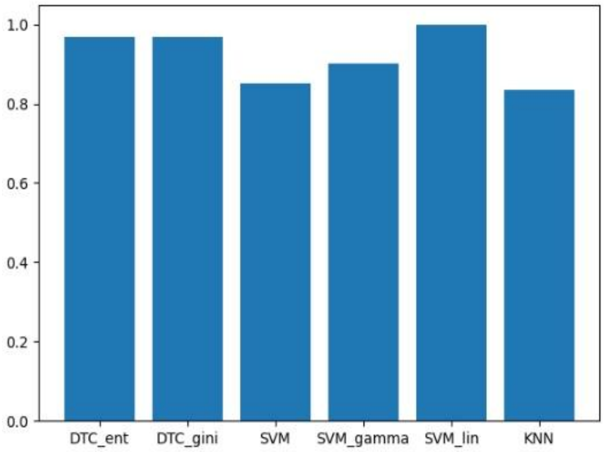

Fig 2: Accuracy of Classifier Models using ECG Features

The confusion matrix generated by Ensemble Model classifier is depicted in figure 3. The mention confusion matrix is a multi-class matrix having CHF, MI and NSR as three classes, hence it comprises of 3x3 matrix. The intersection cell of Actual value and Predicted value of classification model is term as True Positive (TP) [22]. The TP values of each class are present in the matrix diagonally. Here in case of MI class detection, TP is 59 and according to multi-class confusion matrix analytics the cell numbering 5,6,8,9 comprises as True Negative (TN) values for MI class. The cell number 2 and 3 in the same row (Actual) and cell number 4 and 7 in the same column (Predicted) of MI class are considered as False Positive (FP) and False Negative (FN) values respectively.

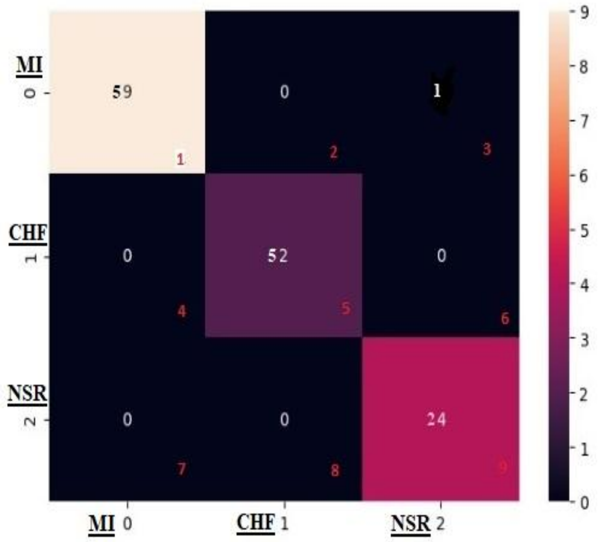

Fig 3: Ensemble Model Classifier Confusion Matrix

To evaluate the performance of the classification, we used the standard statistical indices of accuracy (Acc), sensitivity (Se), and specificity (Spec) derived from four parameters: correctly detected beats (true positives =TP), undetected beats (false negatives = FN), correctly undetected beats (true negatives =TN) and falsely detected beats (false positives = FP). These statistical indices are defined as follows,

Accuracy: It defines how often the model predicts the correct output.

$$Accuracy = \frac{(TP + TN)}{(TP + TN + FP + FN)} * 100$$

Sensitivity: Sensitivity (Sen) is calculated as the number of correct positive predictions divided by the total number of positives.

$$Sensitivity = \frac{TP}{(TP + FN)} * 100$$

Specificity: Specificity (Spec) is calculated as the number of correct negative predictions divided by the total number of negatives.

$$Specificity = \frac{TN}{(TN + FP)} * 100$$

So, on the basis of performance metrics formulas the average result of detection of these three classes is recorded in terms of model performance result having accu-racy, sensi-tivity and speci-ficity of 99.5%, 99.44%, 99.7% respectively as shown in the Table 1.

Table 1: Class-wise Evaluation of Ensemble Model

Predicted Class	Confusion Matrix Metric Values		Model Performance Evaluation
MI (Class-0)	TP = 59 (Index 1)	TN = 76 (Index 5,6,8,9)	**Accuracy =** (135/136)*100 = 99.26% **Sensitivity =** (59/60)*100 = 98.33% **Specificity =** (76/76)*100 = 100%
	FP = 0 (Index 4,7)	FN = 1 (Index 2,3)	

CHF (Class-1)	TP = 52 (Index 5)	TN = 84 (Index 1,3,7,9)	**Accuracy** = (136/136)*100 = 100% **Sensitivity** = (52/52)*100 = 100% **Specificity** = (84/84)*100 = 100%
	FP = 0 (Index 2,8)	FN = 0 (Index 4,6)	
NSR (Class-2)	TP = 24 (Index 9)	TN = 111 (Index 1,2,4,5)	**Accuracy** = (135/136)*100 = 99.26% **Sensitivity** = (24/24)*100 = 100% **Specificity** = (111/112)*100 = 99.10%
	FP = 1 (Index 3,6)	FN = 0 (Index 7,8)	

To verify the effectiveness of the present method, the patient specific cross-validation approach is accomplished for evaluating the performance of Multi-Model Ensemble classifier. In patient specific cross-validation approach, the ECG instances from a particular patient are used for the testing of the classifier, whereas the remaining ECG instances from the other patients and NSR based ECG instances are used for the training. The individual classification accuracy values for the ECG features for different CHF and MI patients are shown in Table 2. The performance of ensemble model is computed for each individual feature by considering one group as test dataset and remaining nine groups as training dataset in 10-fold cross validation. It is observed that features in fold1 to fold5 with ensemble classifier have higher performance for the detection of CHF and MI. We have used a feature selection technique Chi-squared test which is a statistical hypothesis test used in the analysis of contingency tables when the sample sizes are large. In simpler terms, this test is primarily used to examine whether two categorical variables (two dimensions of the contingency table) are independent in influencing the test statistic to reduce the computational complexity of the classifier. A total of 09 features are optimized and selected out of total 13 features using Chi-squared method, which are used as the input to ensemble classifiers. The performance of classifiers is evaluated by considering feature selection techniques for hold-out, and 10-fold cross-validation schemes, because, at 10^{th} group of dataset, the performance of the ensemble model is found to be constant and linear. It is evident that there are very small variations in the accuracy in each fold of cross-validation.

Table 2: Performance of Ensemble Classifier Model-1 using Morphological Features (4 Features) and 10-fold cross validation

Features	Measure	Fold -1	Fold-2	Fold -3	Fold-4	Fold -5	Fold-6	Fold-7	Fold -8	Fold-9	Fold-10	Average
BPM	Accuracy	100	99.5	99.6	99.6	99	99.3	99.5	99.6	99	99.16	99.44
QR Duration		99.3	99.5	99.5	99.3	99.9	99.6	99.5	99.5	99.3	99.66	99.53
RS Duration		99	99.7	99.9	99.6	99.9	99.5	99.6	99.9	99.8	99.99	99.72
QRS Duration		100	100	99.6	99.3	99.6	99.6	99.3	99.5	99.9	99.66	99.67

6. CONCLUSIONS

- In order to prevail over the manual interpretation of ECG signal, this research has developed an automated system using a Ensemble Classification approach with optimized heterogeneous features set viz. Morphological and Non Linear statistical features of ECG to detect Congestive Heart (CHF) and Myocardial Infarction (MI) cardiovascular diseases.
- The Methodology yielded maximum Accu-racy, Sensi-tivity and Speci-ficity of 99.75%, 99.72% and 99.85% respectively, along with Precision, Recall and F1-Score statistical indices ranging from 0.9 to1 values, taking into account 300 patient's signals collected from diverse databases. The time required for execution of the system is 0.55 seconds which is reduced to greater extent, as separate R-peak detection not needed.
- Moreover, the designed ensemble classifier is the hybridization of multiple independent and different classifiers, hence the tested results are more accurate and reliable compared to individual classifier.
- The patient relevant 10-fold-cross-validation statistical technique is accomplished for evaluating the performance. Thus, the model is more robust in detection of CHF and MI Cardiovascular Diseases.
- The research work will be helpful to medical practioners (cardiologist) in aid to early and accurate diagnosis of CHF and MI cardiovascular diseases which will lead to further medical treatment and possible survival of the patient.
- This research may be extended to detect various CVD's with maximize classification performance results and using multiple ensemble models with minimum number of

heterogeneous features to reduce the computational load by analyzing the ECG signal from various domains including time-frequency domain.

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