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Genetics For Enhanced Heart Murmur Classification

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Abstract

The recording of the heart's sonic vibrations and blood circulation is PhonoCardioGraphy (PCG), whose signals ensure information regarding performance of heart valves and hence has the potential to detect heart diseases. Automatic murmur classification was studied to help medical diagnoses. Challenges include noisy signals in a time domain. The automated murmur classification process starts with feature extraction followed by feature selection and classification. Feature selection is the first stage in classification where data is represented by feature vectors. It reduces features for consideration later in classification to enhance classifier efficiency. This study proposes a framework to classify PCG, and a Genetic Algorithm(GA) based feature selection is suggested. Experiment results prove the proposed feature selection's efficacy to improve heart murmur classification.

Introduction

PCG the study of heart sounds has many components. PCG-based heart rate measurement is carried out through detection of cardiac pulse peaks. A microphone is used inside a stethoscope's hollow tube to record PCG with 32-bit accuracy and 22050 Hz sampling frequency [1]. Phonocardiogram represents the heart sound recording using a microphone on the chest, to detect low-frequency sound waves [2]. The stethoscope has lost its interest after ECG and PCG techniques discovery, which, apart from cardiac signals quantitative characteristics give their qualitative visual itemized characteristics.

Heart sounds recorded by an electronic stethoscope are converted to digital signals and plotted, and termed PCG signals. Recordings time-frequency plots show that frequency range and murmurs duration increase with stenosis and a second heart sound diminishes with advanced stenosis [3]. Heart sound analysis determines whether captured sound correspond to a healthy or diseased heart [4]. There are two classical heart sounds called first (Lub) and second (Dub) sound. There are also other sounds known as third and fourth sounds detected by graphical recording [5].

A heart murmur occurs between heartbeats. The sound is produced by blood flowing through the heart and is similar to sound, water makes when flowing through a hose [6]. A heart murmur is not an indication that there is something wrong with the heart. Murmurs are continuous sounds that persist during inspiration and expiration though their intensity varies during a respiratory cycle. Murmurs are characterized using onomatopoeia and conventional grading and sorted into 6 predetermined topographic patterns [7].

PCG Pattern recognition is interpreted in two ways. The general definition includes patterns recognition in any PCG dataset type and is called uniform PCG pattern classification. This discriminates heart sound peaks as excitation source for circulation hemodynamic. The other is called adaptive pattern clustering which magnifies and observes spectral characteristics associated with PCG waveform turbulences, differentiating them as clinical diagnostic indices. Modern PCG has led to new cardiac murmurs classification, which better describes them in relation to origin and the heart's total dynamic complex. Classification should enable recognition of the murmur's origin from its description.

Automatic feature extraction depends on accurate knowledge of heart cycles timing [9]. Segmentation into first heart sound (S1), systole, second heart sound (S2) diastole is needed. Systolic and diastolic murmur frequencies are classified according to frequency band with largest power value in the tenth (s) of systole/diastole corresponding to the maximum values of SI/DI. If largest power value is found in one of the two lowest frequency bands (containing frequencies below 125 Hz), a murmur is classified as low-frequency murmur [10].

Feature extraction is the initial transformation to represent measured signals. Features are extracted from a PCG signal in frequency domain to classify signals. Dimensionality reduction retains information important for class discrimination and discards the irrelevant. A classifier with fewer inputs has less adaptive parameters to be determined, leading to a classifier having better generalization properties Feature selection reduces features provided for classification [8]. Of the 3 activities, feature extraction is most critical as particular features available for discrimination directly influence classification task efficacy. Feature selection methods have twoadvantages; the first is to rank and select most important features, where high classification accuracy is achieved if only a features subset with highest rank is used in classification.

Feature subsets increase exponentially with dimensionality increase. Finding an optimal subset is intractable [11] and feature selection related problems are NP-hard. To balance a tradeoff of result optimality and computational efficiency, different search strategies like complete, heuristic, and random search are studied to generate candidate feature subsets for evaluation. A classification situation occurs when an object is assigned to a predefined group or class based on observed attributes and features related to that object [12].

Coiflet is used for feature extraction, and feature selection is, using Information Gain (IG) in this study. A GA based feature selection was proposed and compared with statistic feature selection technique using classifiers like kNN, Naïve Bayes, C4.5, and SVM. The rest of the study is organized as follows: Section 2 reviews related work. Section 3 contains methodology. Section 4 discusses results, and section 5 concludes the study.

Related Work

A technique to improve Least Square Support Vector Machine (LSSVM) performance was proposed by Ari et al., [13] for classification of normal/abnormal heart sounds using wavelet-based feature set. In the new technique, Lagrange multiplier based on Least Mean Square (LMS) algorithm, was modified which in turn modified weight vector to reduce classification error. Performance of the new systems was evaluated on 64 heart sounds different recordings, comprising normal and 5 different pathological cases. It was found that the new technique classified heart sounds with higher recognition accuracy than other techniques.

Processing and analysis methods to classify 2 congenital heart defects were used by Dabanlo et al., [14]. Congenital Aortstenosis(AS) is an important congenital valve disease and of septum diseases is Ventricular Septal Defect(VSD). Fuzzy classification of 3 groups of healthy, AS, and VSD patients were managed with PCG.

A complete heart sound analysis system covering segmentation of beat cycles to final determination of heart conditions was presented by Kao and Wei [15]. The heart beat cycle segmentation process included autocorrelation to predict a heartbeat’s cycle time. Experiments were done through a public heart sound database released by the Texas Heart Institute. A highly promising recognition rate was achieved.

A new method of wavelet based envelope extraction algorithms for cardiac sound signal segmentation was presented by Zhong et al., [16]. A new Morlet wavelet based method was proposed to extract the heart sound’s energy envelope. Results showed that the envelope extraction algorithm was more sensitive (morlet detection rate of 88.29% versus 66.77% of Hilbert method) in processing signals with low ratio of signal/noise proving that new method was more robust for heart sound signal detection.

Key PCG features were extracted by Xiao-juan et al., [17] based on slopes of envelop of Hilbert Transfer after moving boundaries with energy envelope segmentation. In this, features extraction’s overall accuracy was 91.95%. Overall accuracy was 91.3%, in results of two-kind classification, better than 85.23% accuracy in 100 features of Shannon Energy Envelope. Results showed that features including clinical signification is significant in enhancing accuracy of PCG classification.

Wavelet Transform was used by Wu et al., [18] to extract PCG envelope involving normal and abnormal ones; the envelope achieved accurate S1 and S2 positions. Results showed that the algorithm has 95% accuracy and strong practicality. But, SVM and Neural Network (NN) train Power Spectral Entropy from mitral stenosis and mitral insufficiency signals respectively where classification capacity reaches high levels indicating that Information Entropy Power Spectrum analyzes abnormal PCG.

To analyze PCG signal, Teager energy operator and autocorrelation function were investigated, and different parameters like S1-Systole and S2-Diastole signals were extracted with their timing and heart rate estimation by Sabir [19]. Results were very optimistic, and the new framework was an automatic PCG analysis procedure that can be implemented in real time for PCG classification. Signals were acquired by MP-36 of BIOPAC Systems, Inc.

A Bio-Medical, Discrete Wavelet Transform (DWT) based system for normal/abnormal heart sound identification useful for heart diseases detection was proposed by Devil et al., [20]. DWT was applied up to 10 levels to extract individual Heart Signal features. One-dimensional feature extraction was got by evaluating parameters like mean energy, variance, standard deviation and maximum entropy. So, proper level of wavelet using best feature could be extracted for Heart Sounds.

Sun et al., [21] proposed an improved EMD-Wavelet algorithm for PCG signal de-noising. Based on PCG signal processing theory, S1/S2 components were extracted by combining improved EMD-Wavelet algorithm and Shannon energy envelope algorithm. By applying a wavelet transform algorithm and EMD for pre-procession, PCG signal was filtered. Experiments on 30 samples illustrated the new algorithm, which revealed that recognition accuracy of S1/S2 components was as high as 99.74%.

A signal processing procedure that identified first and second heart sounds (S1 and S2), extracted systole from diastole, detected and characterized systolic murmur within was described by Ningand Hsieh [22]. Heart sounds identification was facilitated by DWT approximation using Coiflet wavelet and by using indicators that quantify signal activity and strength. Performance of the new procedure was evaluated and proved with clinically recorded systolic murmur episodes.

An automatic method to segment heart sounds applying classification and regression trees was proposed by AmiriandArmano[23]. A diagnostic system, designed and implemented to detect and classify heart diseases was validated with a representative dataset of 116 heart sound signals from healthy/unhealthy medical cases. About 99.14% accuracy, 100% sensitivity, and 98.28% specificity were obtained on a dataset used in experiments.

The problem of accurate heart sounds segmentation within noisy, real-world PCGs using a Hidden Semi-Markov Model (HSMM) was addressed by Springer et al., [24] and extended with use of SVMs for emission probability estimation. A 123 patient's database with over 20,000 labelled heart sounds trained and tested the algorithm. On out-of-sample test data, the new method outperformed earlier methods with 94.9% and 91.0% sensitivities and 95.2% and 90.9% positive predictivities for first and second heart sounds respectively.

Abo-Zahhad et al., [25] proposed a new technique for human identification task based on heart sound signals using feature level fusion based on canonical correlation analysis. For this, a wavelet analysis of the heart sounds based robust pre-processing scheme was introduced. Combining MFCC and DWT, a feature vector was extracted improving system performance by 95.12%. Canonical correlation analysis was applied to feature fusion improving performance of the new system by 99.5%. The results showed significant improvements in the new system's performance over methods using single feature extraction.

A review of wavelet-based ECG compression methods and performances based on findings from experiments using clean and noisy ECG signals was presented by Mani kandan and Dandapat [26]. Different wavelet-based compression methods, pros, and cons were demonstrated based on experimental results. Finally, various practical issues in validation, reconstructed signal quality assessment, and performance comparisons were highlighted by considering future research studies based on a recent digital signal processing technique and computing platform.

Methodology

This section discusses various techniques used in the investigation like Coiflet wavelet for feature extraction and IG for PCG signals feature selection. Different classifiers are discussed, and the new GA based feature selection is presented.

Coiflet Wavelet

Coiflets are Ingrid Daubechies designed discrete wavelets at the request of Ronald Coifman, for scaling functions with vanishing moments [27]. A wavelet is near symmetric, their functions have $N / 3$ vanishing moments, and scaling functions $N / 3 - 1$, and are used in applications with Calderón-Zygmund Operators. Both scaling (low-pass filter) and wavelet functions (High-Pass Filter) are normalised by a factor $1/\sqrt{2}$.

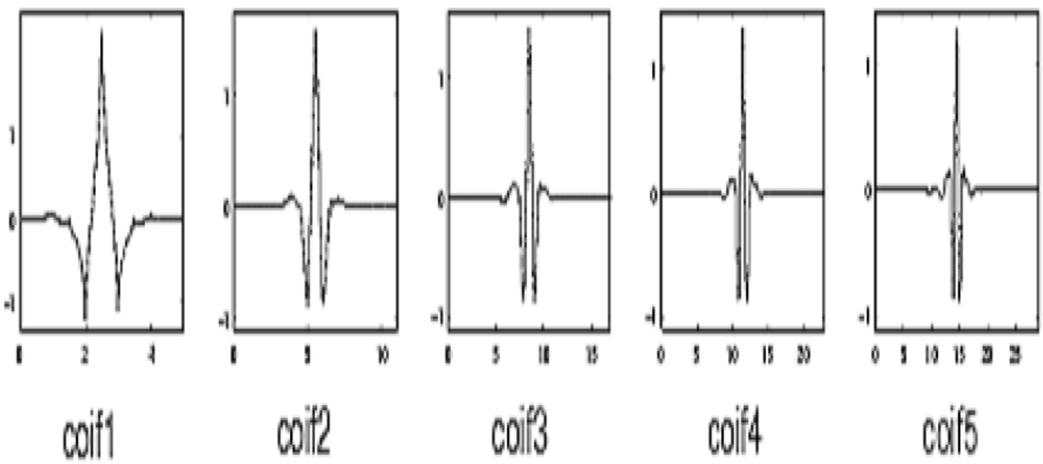

Figure 1: Coiflet Wavelets

A wavelet function has 2N moments equal to 0 and scaling has 2N-1 moments equal to 0 [28]. Both functions have a support of length 6N-1. General characteristics: Compactly supported wavelets with highest number of vanishing moments for phi and psi for a support width. Wavelet coefficients are got by reversing the order of scaling function coefficients and reversing sign of every second one (i.e. C6 wavelet =

{−0.022140543057, 0.102859456942, 0.544281086116, −1.205718913884, 0.477859456942, 0.102859456942}). This looks, mathematically, like $B_k = (-1)^k C_{N-1-k}$ where k is coefficient index, B is a wavelet coefficient and C a scaling function coefficient. N is wavelet index, i.e. 6 for C6 [29].

Information Gain (IG)

IG measures quantity of information in bits about class prediction if only information available is presence of a feature and corresponding class distribution [30]. IG is an impurity-based criterion using entropy measure (origin from information theory) as impurity measure [31],

$$InformationGain(a_i, S) = Entropy(y, S) - \sum_{v_{i,j} \in dom(a_i)} \frac{\left|\sigma_{a_i = v_{i,j}} S\right|}{|S|} . Entropy(y, \sigma_{a_i = v_{i,j}} S)$$

Where

$$Entropy(y, S) = \sum_{c_j \in dom(y)} -\frac{\left|\sigma_{y=c_j} S\right|}{|S|} . \log_2 \frac{\left|\sigma_{y=c_j} S\right|}{|S|}$$

Proposed Genetic Algorithm (GA) based Feature Selection

GA is a general adaptive optimization search methodology based on direct analogy to Darwinian natural selection and genetics in biological systems. It is a promising alternative to traditional heuristic methods. Based on Darwinian principle ‘survival of the fittest’, GA works with candidate solutions set called a population and gets an optimal solution after iterative computations [32]. GA evaluates an individual’s fitness, i.e. solution quality through fitness function.

Fitter chromosomes have higher probability to go to next generation or to be chosen to the recombination pool using tournament selection. If a population’s fittest individual/chromosome cannot meet the requirement, successive populations are reproduced to provide alternate solutions [33]. Crossover and mutation functions are main operators which randomly transform chromosomes impacting fitness value finally. Evolution will not stop till acceptable results are got. Associated with the exploitation and exploration search characteristics, GA deals with large search spaces and so has less chance to get local optimal solution than other algorithms.

GA is a powerful feature selection tool, when original feature set dimensions are large. Reducing feature space dimensions reduces computational complexity and increases classifiers estimated performance [34]. GA’s are easily applied to a feature selection problem given a set Y having cardinality equal to N, a subset X of Y (X ⊆ Y) is represented by a binary vector b having N elements whose i-th element is set to 1 if i-th feature is included in X, otherwise 0. Besides the solution encoding simplicity, GA’s suit these classes of problems as search in exponential space is hard as interactions among features are highly complex and strongly nonlinear [35].

Naïve Bayes Classifier

Naive Bayes classifier is a classification method based on the assumption of conditional independence between different variables in a dataset given a class.

Following notation, being X, Y, and Z random variables, $X \perp Y \mid Z$ for "X is conditionally independent on Y given Z". Naive Bayes model in this notation states that [36]

$$\forall i, j\ 1 \leq i, j \leq n;\ A_i \perp A_j \mid C$$

Bayes theorem in probability theory relates conditional/marginal probabilities of 2 random events. It computes posterior probabilities of given observations. Let x = (x^1, x^2, ...,x^d) be a d-dimensional instance with no class label, the goal is building a classifier to predict its unknown class label based on Bayes theorem. Let C = {C_1,C_2, . . . ,C_K} be set of class labels. P(C_k) is prior probability of C_k (k = 1, 2, ...,K) that are inferred before new evidence; P(x|C_k) be conditional probability of seeing evidence x if hypothesis C_k is true. A technique to construct such classifiers to use Bayes' theorem to get [37]:

$$P(C_k \mid x) = \frac{P(x \mid C_k) P(C_k)}{\sum_{k'} P(x \mid C_{k'}) P(C_{k'})}$$

K Nearest Neighbor (KNN)

kNN is a simple algorithm storing all cases and classifying new ones based on similarity measure [38]. kNN classification rules are generated by training samples without additional data. kNN classification algorithm predicts test sample's category according to k training samples which are nearest to test sample and determine it to that category with largest category probability [39]. kNN is a non-parametric classification method broadly classified 2 types 1) structure less NN techniques 2) structure based NN techniques.

Whole data is classified into training and test sample data in structure less NN techniques. Distance is evaluated from training point to sample point, and a point with lowest distance is called nearest neighbor. Structure based NN techniques are based on data structures like Orthogonal Structure Tree (OST), k-d tree, ball tree, axis tree, nearest future line, and central line. Nearest neighbor classification is used when all attributes are continuous. The classification process steps are [40]:

1) Determine a suitable distance metric.
2) Find k nearest neighbors using selected distance metric.
3) Find plurality class of k-nearest neighbors.
4) Assign, that class to sample, to be classified.

C4.5 algorithm

C4.5 is an algorithm to induce classification rules as a decision tree. As an ID3extension, default criterion in choosing splitting attributes in C4.5 is information gain ratio [41]. Instead of using information gain as in ID3, information gain ratio avoids bias of selecting attributes with values. Splitting ceases, when instances to be split, are below a threshold. Error–based pruning is done after growing phase. C4.5 handles numeric attributes. It induces a training set incorporating missing values using corrected gain ratio criteria [31].

Support Vector Machine (SVM)

SVM deals with pattern classification meaning this algorithm is used for classifying different patterns. The idea behind SVM is an optimal hyper plane construction, used for classification of linearly separable patterns. Optimal hyper plane is a hyper plane chosen from a set of hyper planes to classify patterns which increase the hyper plane margin i.e. distance from hyper plane to nearest point of a patterns. SVM's objective is maximizing the margin so that it correctly classifies given patterns i.e. larger the margin size more correctly are patterns classified.

SVM are systems using a linear functions hypothesis space in high dimensional feature space, trained with a learning algorithm from optimization theory that implements a learning bias from statistical learning theory. SVM became famous when, using pixel maps as input it ensures accuracy comparable to sophisticated NN with elaborate handwriting recognition task features. It is also used for applications, like hand writing analysis and face analysis and specially for pattern classification/regression based applications.

Experimental Results

The system was evaluated using heart sounds corresponding to four different heart conditions: normal, Mitral Valve Prolapse (MVP), Ventricular Septal Defect (VSD), and Pulmonary Stenosis (PS). 325 signals consisting of 150 normal heart sound, 75 MVP, 50 VSD and 50 PS. Features are extracted using Coiflet. The experiments conducted to evaluate the efficacy of feature selection methods:IG and proposed GA based feature selection with various classifiers. The table 1 shows the results achieved for classification accuracy, precision, recall and f-measure.

Table 1: Results

Techniques	Classification Accuracy	Precision	Recall	F-Measure
IG_Naive_Bayes	83.38	0.8064	0.8133	0.809835
IG_C4.5	84.62	0.8179	0.8333	0.825528
IG_KNN	81.85	0.7963	0.7967	0.7965
GA_Naïve Bayes	87.69	0.8508	0.875	0.86273
GA_KNN	87.08	0.8455	0.8717	0.8584
GA_C4.5	88.31	0.8602	0.8833	0.871597
GA_SVM	88.92	0.8652	0.8933	0.879025

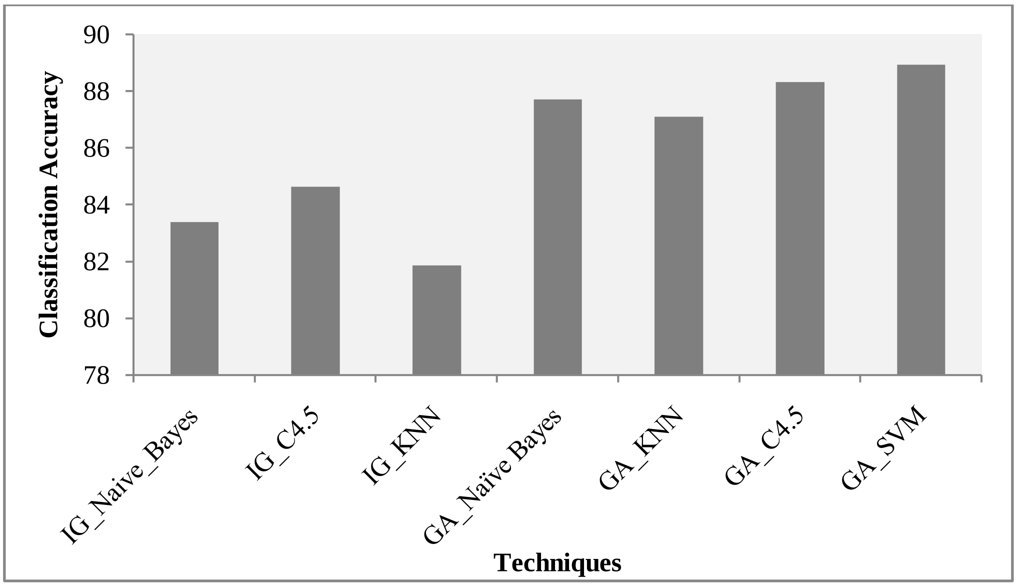

Figure 2: Classification Accuracy

Figure 2 shows the classification accuracy. It is observed from the figure that the GA based feature selection with Naïve Bayes improved classification accuracy by 5.0389% when compared with IG with Naïve Bayes. GA based feature selection with kNN increased accuracy by 6.196% than IG with kNN.

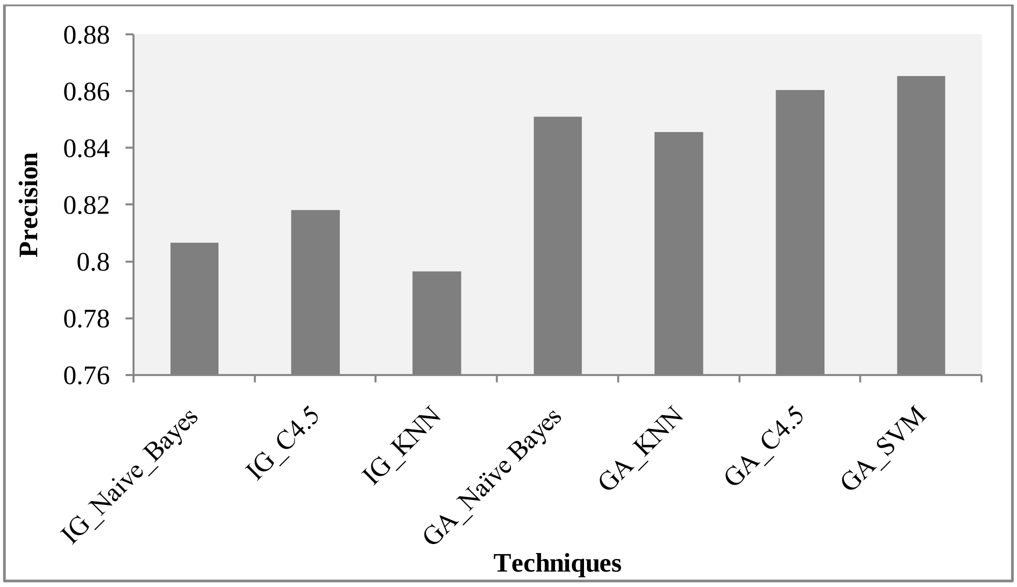

Figure 3: Precision

From the above figure 3, the GA based feature selection with Naïve Bayes increased precision by 5.36% while comparing with IG with Naïve Bayes.

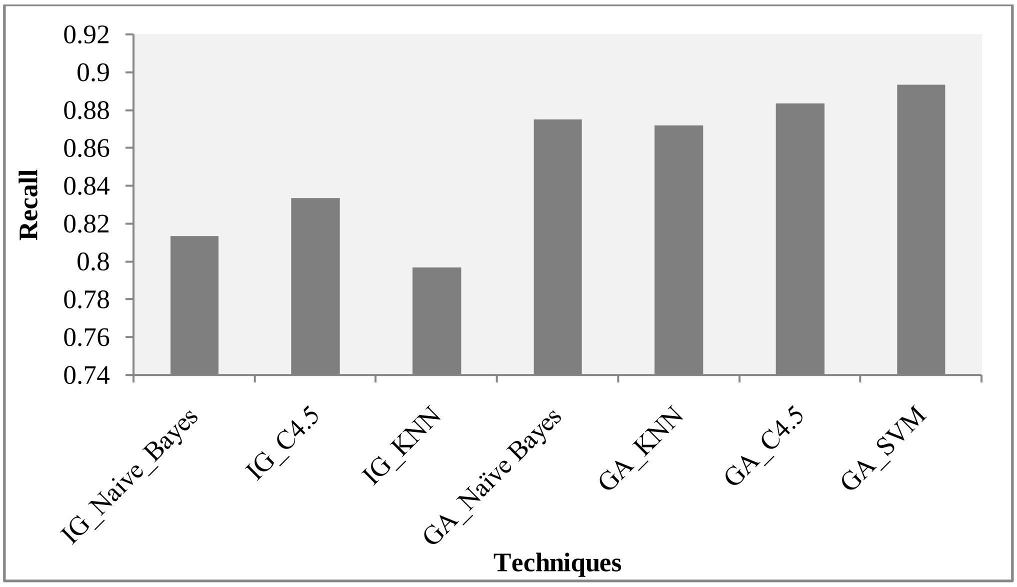

Figure 4: Recall

The figure 4 shows that the GA with C4.5 improved recall by 8.26% when compared with IG with C4.5 algorithm.

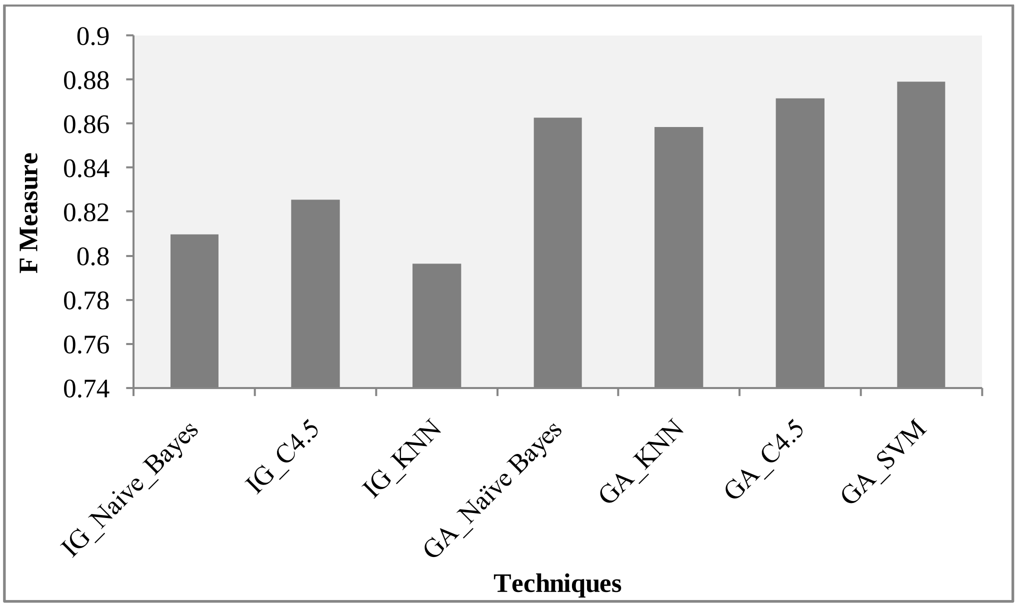

Figure 5: F-Measure

The figure 5 shows that the F-measure is increased by 7.48% with GA based feature selection with kNN when compared to IG with kNN.

Conclusion

PCG signals are heart sound signals carrying tremendous information about the heart's condition.. By analyzing signals, early heart diseases detection and diagnosis is made as it is a major cause of fatality globally. This study proposes a GA based feature selection to improve heart murmur classification. Experiments were undertaken with IG and the new method with different classifiers. Results proved that the new GA based feature selection performed better than IG.

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