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Training feedforward neural network using genetic algorithm to diagnose left ventricular hypertrophy

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ABSTRACT

In this research work, a new technique was proposed for the diagnosis of left ventricular hypertrophy (LVH) from the ECG signal. The advanced imaging techniques can be used to diagnose left ventricular hypertrophy, but it leads to time-consuming and more expensive. This proposed technique overcomes thesef issues and may serve as an efficient tool to diagnose the LVH disease. The LVH causes changes in the patterns of ECG signal which includes R wave, QRS and T wave. This proposed approach identifies the changes in the pattern and extracts the temporal, spatial and statistical features of the ECG signal using windowed filtering technique. These features were applied to the conventional classifier and also to the neural network classifier with the modified weights using a genetic algorithm. The weights were modified by combining the crossover operators such as crossover arithmetic and crossover two-point operator. The results were compared with the various classifiers and the performance of the neural network with the modified weights using a genetic algorithm is outperformed. The accuracy of the weights modified feedforward neural network is 97.5%.

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1. INTRODUCTION

The patients who suffered from left ventricular hypertrophy may lead to the risk of mortality. Sudden cardiac death may also causes because of left ventricular hypertrophy [1]. Left ventricular hypertrophy is arising due to prolonged high blood pressure. The high blood pressure is also called as cardiovascular syndrome [2]. It makes the chamber walls to be thick and it enlarges the chamber. It is also stated that the increase in left ventricular mass leads to changes in the structure of myocardium [3]. The factors influences the LVH disease are age, increase in blood pressure, glucose intolerance and obesity [4]. It alters ventricle repolarization and depolarization which leads to the changes in QRS and T patterns in the ECG signal [5]. The various LVH-ECG criteria were reported which includes Cornell Voltages, Romhillt Estees and Sokolov Lyon (SL) [6]. The ECG is a common method on the account of wide availability [7]. Thus, the electrocardiography can be used as a tool to diagnose LVH in an early stage. The LVH can be diagnosed using imaging modalities with advanced techniques. This method is high priced and the process is delayed. The shortage of financial resources to acquire the echocardiographic facility with skilled personnel is a challenging issue in the hospitals present in the rural area [8]. To overcome

these issues, a suitable algorithm is proposed to diagnose left ventricular hypertrophy using ECG signal. The various Neural Network techniques are widely used to diagnose cardiovascular events [9].

In this research work, the classification of LVH disease is implemented using feedforward neural network with modified weights. The weights were modified by using a crossover operator in a genetic algorithm. Several researchers have utilized a genetic algorithm and a feedforward neural network for signal processing applications. Zeinab Arabasadi et al. proposed a hybrid neural network and genetic algorithm for the diagnosis of heart diseases. The neural network performance was increased by 10% [10]. Arpit Bhardwaj et al proposed a network model for multiclass classification. This algorithm provides a 5% to 8% better result [11]. Kinjal Jadav et al reported that the neural network training may lead to local minima and slow convergence. To overcome this issue author applied a genetic algorithm for global optimization [12]. Zhen-Guo Che et al compared the neural network and genetic algorithm performance and found that the BPN performs better [13].

Janati Idrissi et al. optimized a neural network based on metaheuristic algorithm by formulating multi-objective mathematical function [14]. Ze Li et al. reported a Genetic Algorithm backpropagation network which increases the convergence speed [15]. Hongqiang Li et al. reported the GA-BPNN network for the signal classification it produced very good results [16]. Arpit Bhardwaj et al. developed a new crossover and mutation operator to solve a classification problem [17]. V. S. R. Kumari et al reported that the genetic algorithm optimizes the learning rate to classify arrhythmia disease [18]. Ali Bahadorinia et al. developed a PSO and genetic algorithm-based neural network for the classification of arrhythmias [19]. Mansoura Sekkal et al developed a neuro-genetic algorithm to classify cardiac arrhythmia disease [20]. Manab Kumar Das et al used S transform to extract the features and optimized using a genetic algorithm to obtain a better result [21]. Section 2 explains the dataset, Methodology, ECG pre-processing and ECG signal analyzing and Classification techniques. Further, this article results are discussed and concluded in section 3 and section 4.

2. RESEARCH METHOD

This section is described with the dataset utilized in this study, methodology, signal pre-processing, and feature extraction and classification methods.

2.1. ECG signal dataset

The PTB Diagnostic ECG database is utilized in this work to acquire 12 lead ECG signals of healthy persons and the patients who are affected by left ventricular hypertrophy. This database also contains the ECG signal with bundle branch block, myocarditis, and cardiomyopathy [22]. The sampling frequency of the signal is 1000 Hz.

2.2. Methodology

The Figure 1 shows the flow of proposed work to diagnose left ventricular hypertrophy. It includes feature extraction and classification. The fast Fourier transform was implemented to remove the low frequencies and inverse fast Fourier transform was applied to restore the ECG signal. This was followed by a windowed filter to determine the local maxima. The size of the filter was adjusted and filtering is repeated to identify the peaks present in the signal. The temporal, spectral and statistical features were obtained. These features were fed to the various classifiers to diagnose the LVH disease.

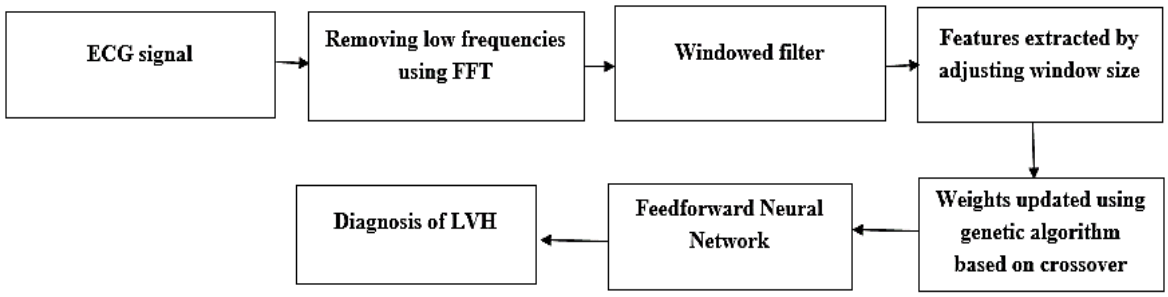

Figure 1. Diagnosis of Left Ventricular Hypertrophy from ECG signal

2.3. ECG signal pre-processing

The ECG signals are corrupted with the artifacts due to other monitoring devices, cables [23]. The elimination of these artifacts is essential to diagnose the disease more accurately. The FFT is implemented to remove the low-frequency noise present in the signal.

2.4. Feature extraction

The essential features that are extracted to diagnose LVH are variance, kurtosis, form factor, average Heart rate, mean RR interval, RR interval root mean square distance, standard deviation, heart rate variability, and power spectral Entropy. In this study, the ECG leads such as Lead I, II and III, aVL, V1 to V6 obtained from the PTB database. The low-frequency signals removed by using a fast Fourier transform. This is followed by an inverse fast Fourier transform to restore the ECG signal as shown in Figure 2.

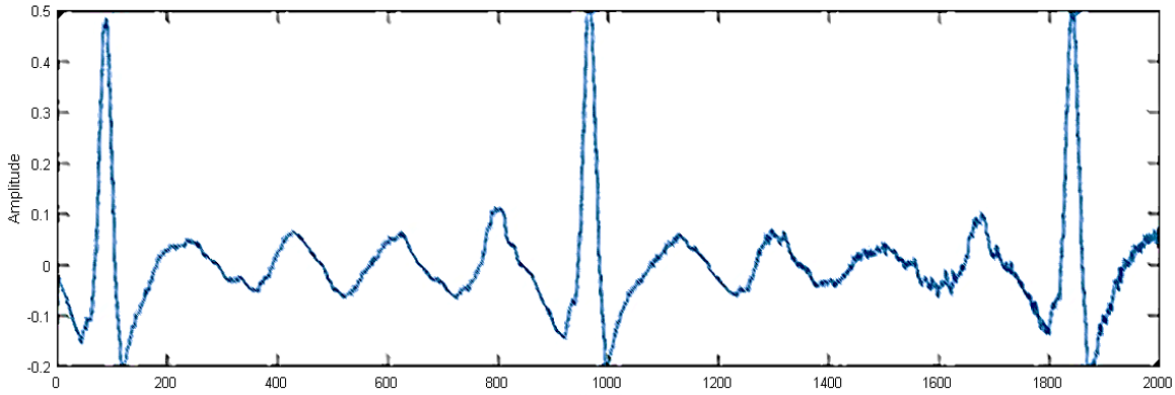

Figure 2. ECG signal after applying FFT

This is followed by a windowed filtering technique to find the local maxima. This helps to find the peaks of the signal. The window sizes were adjusted filtering is applied to the signal to extract features such as kurtosis, form factor, average Heart rate, mean RR interval, RR interval root mean square distance, standard deviation, heart rate variability, and power spectral Entropy. This is further applied to the various classifier to diagnose the disease.

2.5. Classification

In this research work, classifier includes K-nearest neighbor (KNN), support vector machine (SVM), feedforward network and modified weight feedforward network was employed for diagnosis and classification of LVH.

2.5.1. Support vector machine

This classifier segregates the feature by plotting the hyperplane that separates all the features of one class to another. SVM employs mapping to convert nonlinear features to high dimensions [24]. The SVM is analyzed using the Gaussian kernel function in this work [25]. The advantage is that it is flexible. It supports complex models. This function is utilized by the equation is;

$$k(x,y) = \frac{e^{-\|x-y\|^2}}{2^2} \quad (1)$$

2.5.2. K-Nearest neighbor classifier

The classifier K-nearest neighbor is an instant based learning method [26]. It is considered to be effective, to decrease the misclassification of error, when there is a large number of components in the training set [27]. During classification, a group of 'k' features from the training set are proposed that are close to the features that are to be tested [28]. The classifier performance is based on the value K and distance metrics. In this study, these values are implemented by cross-validation for the assessment of classification accuracy [27]. For testing, a single data sample is employed for validation and remaining K-1 data samples are used for training [27]. This is repeated a K time with each of the k data samples.

2.5.3. Feedforward neural network with genetic algorithm

This work proposed that the genetic algorithm is employed to train the feed-forward neural network. The classification was employed using the Levenberg-Marquart network, a scaled conjugate gradient backpropagation neural network. The total number of neurons presented in the hidden layer is 12, 15, and 20. The trial and error method is implemented for the selection of neurons in the hidden layer. In the output layer, one neuron was employed to diagnose the LVH based ECG signal. 70% of the dataset is implemented for training and 15% of the dataset is used for validation and the last 15% of data is used for testing.

This performance of these classifiers was compared with the neural network classifier with the modified weights. In this research work, the weights of the feedforward neural networks were updated based on the genetic algorithm. In a genetic algorithm, a population is considered as a weight. The chromosomes are prescribed by using an objective function. This is followed by a selection of two chromosomes to perform the genetic operation. The offspring is generated which alters the initial population. This is repeated until the desired output is achieved. The objective function is stated as a normalized mean square error.

$$e(x)= (Oi-ti)^2 \quad (2)$$

$$F(x) = \frac{mean(e(x))}{mean(variance(Oi)} \quad (3)$$

Where Oi represents the desired output, ti represents output obtained from net.

ALGORITHM

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Step 1: The size of the weight matrix is defined and considered as a population.
Step 2: Population set is produced. Each component present in this set represents weights.
This weight depends on the number of layers in the network [29].
Step 3: Every matrix of weights is applied to the fitness function.
Step 4: The weight matrix with the best solution is chosen for the modification.
Step 5: Genetic operations mainly based on crossover and mutation. This process creates new
offspring.
Step 6: Crossover operator:
In this work crossover arithmetic and the crossover, two-point is implemented to generate
new offspring. The obtained results were taken and the new offspring is generated which is
followed by mutation.
The crossover arithmetic is a linear combination of two parents who are selected randomly.
The crossover two-point copied values based on the two points. In-between these two points
the genes get swapped. The weights are further computed with the formula (X+X1)/3.
Where X represents the weights obtained from the crossover arithmetic and X1 represents
the weights obtained from the crossover two-point.
Step 7: Stopping criteria is based on the number of generations and the convergence rate
the network reaches the objective.
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Thus feedforward neural network was implemented by adjusting the weights of neural networks using a genetic algorithm.

3. RESULTS AND ANALYSIS

In this research work, the fast Fourier transform was applied to the signals to eliminate lower frequencies. This is followed by inverse fast Fourier transform to restore the ECG signal. Further, the windowed filter was implemented to find local maxima. The peaks of the signals were identified. The window size is adjusted and again filter applied to find the peaks. It improves the quality of the filtering. The features extracted from this study includes variance, kurtosis, form factor, average Heart rate, mean RR interval, RR interval root mean square distance, standard deviation, heart rate variability, and power spectral entropy. This acquired features fed to the various classifiers to determine LVH based ECG signal from the healthy individual ECG signal.

The 432 ECG signals acquired from the database which includes both LVH and healthy ECG signals. The total features obtained from this study were (432x12=5184 features). These features were applied to the classifiers such as SVM, KNN, Levenberg-Marquardt neural network (LM NN), scaled conjugate gradient neural network (SCG NN), and weights modified feedforward neural networks using GA. This experiment shows the potency of modified GA based feedforward neural network. In GA, the crossover operator was implemented which includes arithmetic crossover and two-point crossover to create a new offspring. Further new weights obtained by combining the weights from these crossover operators.

To determine the constructiveness of extracted features, a receiver-operating characteristic analysis was implemented. The area under the curve (AUC) denotes the goodness of fit [30]. The allocation of feature vectors is similar in two classes for the AUC value is 0.5 [30]. The allocation of features of two classes does not overlap with each other for the AUC value is 1 [30]. This value is more than 0.5 then the guessing model is good. In this work, the fivefold cross-validation scheme is employed for the training and testing of classifiers. The parameters such as sensitivity, specificity, and accuracy are evaluated to identify the performance of the classifier. These parameters are judged by identifying true positives, true negatives, false positives, and false negative values. The TP is true positive which indicates the number of events matched and FN is false negative which indicates the number of events that are not recognized [31]. The FP is false positive which represents the number of events that are not matched and true negative (TN) represents the events that are exactly recognized as not defectives [31]. Table 1 shows the classifier performance evaluated in terms of sensitivity, specificity, accuracy and area under the curve.

Table 1. Performance of the classifiers

Classifiers	Number of neurons	Sensitivity (%)	Specificity (%)	Accuracy (%)	AUC
SVM	-	86.1	92	90.7	0.90
KNN	-	85.1	93.3	91.4	0.91
LM NN	12	89.8	98.8	96.5	0.96
LM NN	15	79.6	96.9	92.6	0.92
LM NN	20	69.4	91.4	85.9	0.86
SC NN	12	43.5	96.6	83.3	0.83
SC NN	15	49.1	96.9	85.0	0.85
SC NN	20	72.2	96.6	90.5	0.90
LM NN weights optimized using GA	12	85.2	98.5	95.1	0.95
LM NN weights optimized using GA	15	84.3	96.6	93.5	0.93
LM NN weights optimized using GA	20	93.5	98.8	97.5	0.97
SCG NN weights optimized using GA	12	37	98.1	82.9	0.83
SCG NN weights optimized using GA	15	62	98.1	83.1	0.83
SCG NN weights optimized using GA	20	60.2	97.8	83.3	0.83

The feedforward NNs were trained with 12, 15 and 20 hidden neurons. The results show that the accuracy of LM NN with modified weights is increased than the LM NN without modified weights. The accuracy of the Levenberg-Marquardt neural network (LM NN) shows better results than scaled conjugate gradient neural network (SCG NN). The accuracy of SVM and KNN is low as compared to LM NN feedforward neural network with modified weights.

4. CONCLUSION

In the current scenario, various imaging modality techniques used to diagnose LVH. But this leads to a delay in treatment and high cost. Hence, the diagnosis of LVH using an ECG signal is a necessary part of effective treatment. This study involves the analysis of temporal, spectral and statistical features of ECG signal. The classification of disease with LVH compared with SVM, KNN and various feedforward neural networks with and without modified weights. In this work, Genetic algorithm was implemented to optimize the weights of feedforward NN. The weights modified based on the crossover operator. Thus, it proves that the Levenberg-Marquardt NN weights optimized using GA perform better than another classifier to diagnose LVH.

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