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Efficient Algorithm for Early Detection of Myocardial Ischemia using PCA based Features

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Abstract

Objective: The purpose of this work is to develop an efficient algorithm for uncovering the myocardial ischemia at early stages from ECG signal using Principal Component Analysis (PCA). **Methods/Statistical Analysis:** The proposed work mainly involves three stages namely denoising, extracting features and classification. The removal of noise from ECG signal is achieved by applying wavelet threshold technique. The extraction of clinically useful features is carried out by selecting ST-T complex from ECG beat samples followed by dimensionality reduction using PCA. These features are fed to MLP, SVM and KNN classifier models for diagnosing myocardial ischemia at early stages. The performance of classifier models are validated with ECG data obtained from physiobank database in terms of performance measures such as classification accuracy, sensitivity and positive prediction accuracy. **Findings**: The comparisons of experimental results have shown that the MLP classifier model has great scope for diagnosing myocardial ischemia at early stages. The MLP classifier model has resulted in classification accuracy of 90.51%, PPA of 93.8% and sensitivity of 96.19%. **Application/Improvements:** The proposed PCA based method has shown an improved accuracy of 90.51% in comparison with classifiers developed by other researchers.

Keywords: Artificial Neural Network, Discrete Wavelet Transform, Principal Component Analysis, Support Vector Machine

1. Introduction

The estimate of World Health Organization (WHO) indicates 17.3 million deaths have taken place worldwide due to the Cardiovascular Disease (CVD). The primary cause of CVD is due to the condition called atherosclerosis, which restricts the oxygenated blood flow to the heart leading to a condition called myocardial ischemia. Myocardial ischemia is characterized by ST-segment deviation and T wave amplitude changes in ECG signal[1]. A short period of myocardial ischemia may lead to reversible effects which lead to the recovery of heart cell. The long time persisting ischemia causes the death of heart cells leading to a heart attack or myocardial infarction. Therefore, there is a great scope to develop a novel and efficient algorithm for early prognosis of myocardial ischemia to prevent unexpected heart attacks and other forms of heart arrhythmia.

In the last few decades, the quest for automatic diagnosis of ischemia resulted in widespread search for techniques to analyze the ECG signal in both time and frequency domain. Abundant techniques are available for feature extraction from ECG signal such as correlation dimension, morphological properties of the P, QRS and T waves, wavelet transform and combined morphological wavelet transform features with temporal features of ECG signal. Extracting the features from ECG signal is helpful in detecting cardiac ischemia, but difficult when the size of the ECG data is huge. Furthermore, manual analysis of ECG signal for detecting ischemia by a physician is very

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time consuming and prone to human error. Very little effort is made towards automated diagnosis of arrhythmia from ECG signal, particularly myocardial ischemia.

In an attempt to diagnose myocardial ischemia automatically, an ANN based ischemic beat classifier was developed, trained and tested with long duration European ST-T change database[2]. The technique of combining wavelet transform and PCA has shown promising performance in choosing best ANN architecture for the classification of arrhythmias[3]. In reference[4], PCA was used for dimensionality reduction of morphological features extracted from ECG and Elman neural network for classifying arrhythmia. The PCA technique is used in diversified applications. One such application is in the area of cognitive radio spectrum sensing techniques[5] for determining the spectrum holes in the network in order to use efficiently the spectrum bandwidth. Also, the weighted PCA algorithm has been applied for image pattern extraction and compression[6]. Further, the PCA technique is used in the process of automatic facial region localization and tracking in video frames through 3D mesh model[7]. An algorithm has been proposed to recognize six arrhythmias from ECG using continuous wavelet transform and PCA with neural network classifier[8]. In this work, PCA was used to reduce the size of the feature vector of ECG signal.

Many methods and algorithms have been proposed, compared and implemented over the past few years to classify arrhythmia from ECG signal. This includes neural network, fuzzy cluster, wavelet transform and principal component analysis. The simple classifiers such as linear discriminants, K-nearest neighbor, complex classifiers including artificial neural network and support vector machine have been extensively used in detecting cardiac arrhythmia. One major issue in neural network classifiers is deciding the optimal number of features sets for training and testing. In the work[9]of predicting ventricular tachycardia by neural network classifier using heart rate variability features, 67% of feature vector is used for training and remainder for testing the neural network classifier. Divisive Artificial Neural Network (DI-ANN) algorithm has been proposed to reduce MSE, which remove the least weighted hidden neurons by searching in sub neuron level[10]. In a study for diagnosing Attention Deficit Hyperactivity Disorder (ADHD), it is experimentally found that the accuracy of MLP algorithm is best compared to the accuracy of SVM classifiers[11]. It is established that an optimal number of 200 exemplars are required for training MLP neural network for maximizing classification accuracy[12]. In another study, neural network modules are cascaded for improving the accuracy of classifiers by aggregating the decisions of one or a few of the members[13]. Authors of all the above papers demonstrated the possibility of classification of ischemia with an accuracy of 70-85 %. For the further improvement of classification accuracy, this research work involves the development of an automated technique for diagnosing myocardial ischemia by integrating PCA with neural network.

This paper is structured such that the methodology comprising of ECG signal denoising and segmentation, PCA based feature extraction and classifier models is discussed in Section 2. The results of classifiers for diagnosing myocardial ischemia are highlighted in Section 3. Finally, Section 4 describes the conclusions of the present work.

2. Methodology

Figure 1 depicts the generalized flow chart of the proposed method for diagnosing myocardial ischemia.

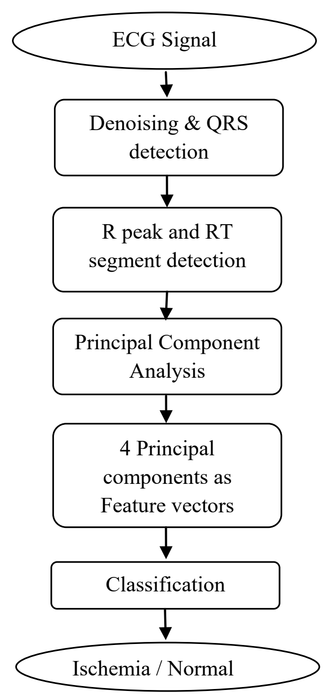

Figure 1. Generalized flow chart for Myocardial Ischemia detection.

The ECG data obtained from European ST-T datasets[14] comprises of various noises and requires to be denoised before feeding to the feature extraction stage. In the proposed method, initially the ECG signal is denoised by applying wavelet thresholding with COIF 2 wavelet function and RIGRSURE soft thresholding rule. Subsequently, the ECG signal is fragmented into separate segment between RR intervals for selecting RT segment from each beat. Further feature extraction is carried by applying PCA on RT segment of ECG beats which reduces the dimensionality of data sets. The features extracted by applying PCA are fed as inputs to classifier models for detecting myocardial ischemia. The optimum choice of classifier is achieved by evaluating its performance indices such as sensitivity, accuracy and positive prediction accuracy. The algorithms were programmed in MATLAB and tested on an IBM compatible personal computer.

2.1 Denoising and Segmentation of ECG Signal

The raw ECG signals acquired from physionet database are usually contaminated with noise which includes baseline wander, electromyogram noise, motion artifact, power line interference and contact noise. Initially in the denoising process, the mean value of each sample is removed to eliminate the offset error. Due to the outstanding performance shown by wavelet based thresholding technique in denoising ECG signal, the proposed method adopts this technique. After repeated analysis, soft wavelet based thresholding technique with COIF2 wavelet function and RIGRSURE thresholding rule is selected for denoising ECG signal. The denoised ECG signals are segmented between R-R intervals since clinically useful information lies in this region.

The segmentation of R-R intervals of ECG signal is carried by QRS complex detection and finding R peak location. This work uses Pan-Tompkins algorithm for QRS detection. The annotation of ECG signal datasets provides the clinical information of normal and ischemic beats. A total of 16 ECG data files are randomly chosen from European ST-T datasets of physiobank database for this work. After slicing the ECG signal for beats between R-R intervals, RT segment is extracted on which PCA is applied to constitute feature vectors.

2.2 PCA Based Feature Extraction Algorithm

In this study, an ECG segment between RR intervals is classified as ischemic or normal. Since the MIT-BIH data set is completely annotated, the RR intervals and the diagnostic information of the ECG signal are exactly known. The sampling frequency of this signal is 250 Hz. The extracted samples between RR intervals has all the information regarding morphological variations in ECG such as ST-segment deviation and T wave amplitude changes, which gives the information of whether the ECG beat is ischemic or normal. The ECG segments between RR intervals of the records in the database were separated into two sets. One set for training and the other set for testing in the classifiers.

The efficient performance of automated diagnosis method for myocardial ischemia requires the dimensionality reduction of massive quantity of data. In the proposed work, PCA is applied on the RT segments of ECG beats samples resulting in vector of Principal components. In this work, the first four PC vectors are chosen and fed as input to the classifier. The selection of only four PC vectors has resulted in dimensionality reduction without major loss of clinically useful information from ECG beat samples. The first two principal components represent the low-frequency component and remaining two principal components denote the high frequency components of RT interval beat segment.

The step by step process of PCA based feature extraction algorithm is indicated below and is developed in MATLAB software.

Step 1: Denoising ECG signal by wavelet thresholding technique and separating RT segment of each ECG beat.

Step 2: The input data matrix for the algorithm is the matrix containing RT-interval samples of segregated ECG beats as discussed in Equation (1).

$$[B_s]_{m\times n} = \begin{bmatrix} \text{Beat(1) RT-intervalsamples} \\ \text{Beat(2) RT-intervalsamples} \\ \bullet \\ \bullet \\ \text{Beat(n) RT-intervalsamples} \end{bmatrix} \quad (1)$$

Each row of B_s matrix corresponds to the RT-interval samples of ECG beat which indicate possible morphological changes of myocardial ischemia. As a result, the rows of B_s matrix are used as a base for computing principal components.

Step 3: The covariance matrix computed from the matrix B_s is a square matrix of dimension n x n. Covariance indicates a measure of the relation between the data to be analyzed.

$$[C_s]_{n\times n} = \text{cov}(B_s) = \left(\frac{1}{m-1}\right)[B_s]^T [B_s] \quad (2)$$

Step 4: The coefficients of principal components are realized by the command *pca( )* as in Equation (3).

$$[COEFF, score, latent, tsquared, explained] = pca(Bs) \quad (3)$$

Where, the columns of COEFF contain the principal component coefficients of the covariance matrix C_s. The dimension of COEFF matrix is n-by-n. The columns are in the order of decreasing component variance and LATENT includes the Eigen values of the covariance matrix C_s. The variable EXPLAINED contains the numbers, which describe the percentage of the total variance explained by each principal component. Rows of SCORE represents observations and columns represent components. TSQUARED indicates T-squared statistic for each observation in B_s.

Step 5: For detecting the ST-T wave changes in each beat of ECG signal, the principal components are computed for each beat by using the rows of B_s matrix as base, which is represented as pseudo code in Equation (4)

$$\begin{aligned} & for\ i = 1:n \\ & PCAfirst(1,i) = sum(B_s(i,:).*COEFF(:,1)'); \\ & PCAsecond(1,i) = sum(B_s(i,:).*COEFF(:,2)'); \quad (4) \\ & PCAthird(1,i) = sum(B_s(i,:).*COEFF(:,3)'); \\ & PCAfourth(1,i) = sum(B_s(i,:).*COEFF(:,4)'); \\ & end \end{aligned}$$

Where *PCAfirst, PCAsecond, PCAthird and PCAfourth* are the row vectors representing the principal components characterizing RT segment of all ECG beats of the dataset.

Step 6: The four principal components, which describe the RT segment of first ECG beat, are represented as in Equation (5). These four principal components of ECG beat are used as inputs to the classifiers.

$$\begin{aligned} & principal\ component\_1 = PCAfirst(1) \\ & principal\ component\_2 = PCAsecond(1) \\ & principal\ component\_3 = PCAthird(1) \\ & principal\ component\_4 = PCAfourth(1) \end{aligned} \quad (5)$$

In this work, the selection of only four PC vectors has resulted in dimensionality reduction without major loss of clinically useful information from ECG beat samples.

Step 7: Repeat Step 5 and Step 6 for computing principal components of all the beats of ECG signal.

Step 8: Return all the principal components of ECG beats as input features to classifier models for diagnosing myocardial ischemia.

Step 9: End.

2.3 MLP, SVM and KNN Classifier Models

The general structure of a MLP network is shown in Figure 2. For approximating linear problems, a simple two-layer ANN is employed which consists of an input layer containing input feature vector and output layer containing classes to be isolated. On the other hand, for approximating nonlinear complex systems, additional intermediate layers are employed to handle the complexity of prob-

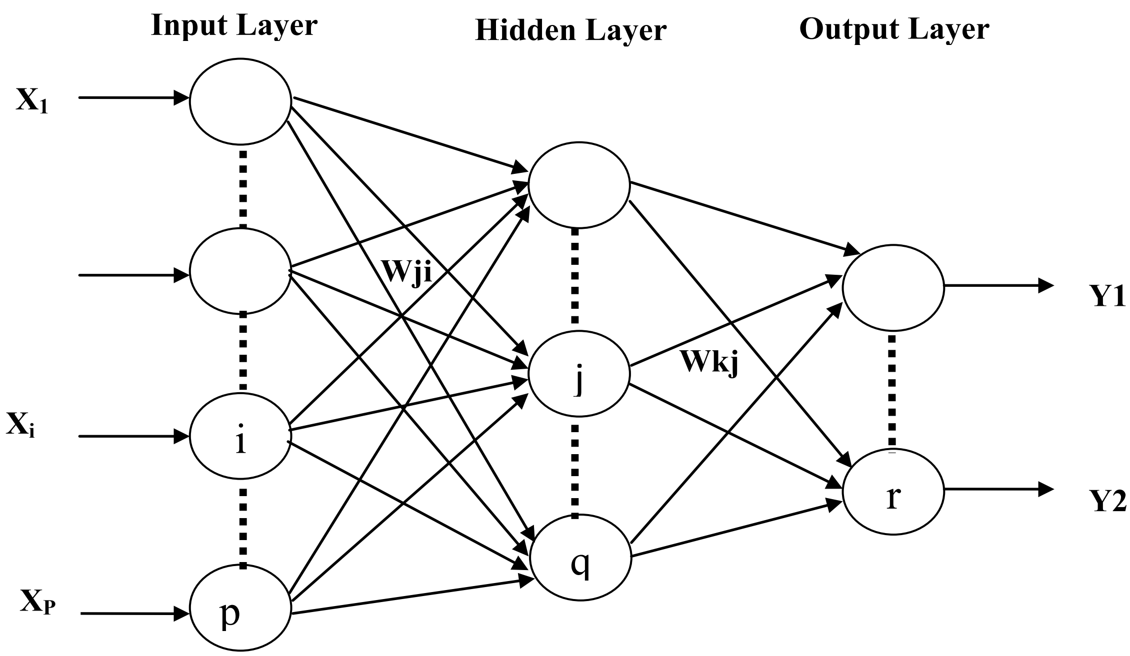

Figure 2. Structure of a MLP network.

lems. However, only one hidden layer may be sufficient to map any input feature vector to output classes to any extent of accuracy. Hence, three-layer ANN architecture is employed in the present work. For arriving at highest recognition accuracy, the number of hidden neurons is varied by trial and error.

The SVM classifier segregates the two classes of datasets by computing a hyper plane of maximum margin between them. The present work uses various kernel functions for detecting the most optimised one. KNN classifier classifies the two datasets by computing Euclidean distance d and a positive integer K.

3. Results and Discussions

The proposed technique has been tested with ECG dataset selected from European ST-T datasets of physionet database. The ECG signal was decomposed at level 4 using discrete wavelet transform. Figure 3 shows the simulated results obtained by application of threshold denoising technique and QRS detection applied over the record e0603 as explained in Section 2.1

Feature extraction is carried by applying PCA on RT segment of ECG beats which reduces the dimensionality of data sets. In the proposed work, PCA is applied on the samples of denoised ECG beats resulting in vector of Principal components as discussed in Section 2.2. Table 1 shows the extracted principal components from RT interval segments of normal and ischemic beats of an exemplary record from European ST-T database.

Figure 4 depicts the shape of four PCA projections. Figure 5 illustrates that RT interval segment can be reconstructed with these four PCA projections that represent the total signal energy without the loss of clinically useful information.

A total of 3108 ECG beats across 16 data files of MIT-BIH database is used for cross-validating the algorithm. The ECG beats are randomly partitioned such that 2424 ECG beats for training set, 404 ECG beats for validation set and 280 beats for test set.

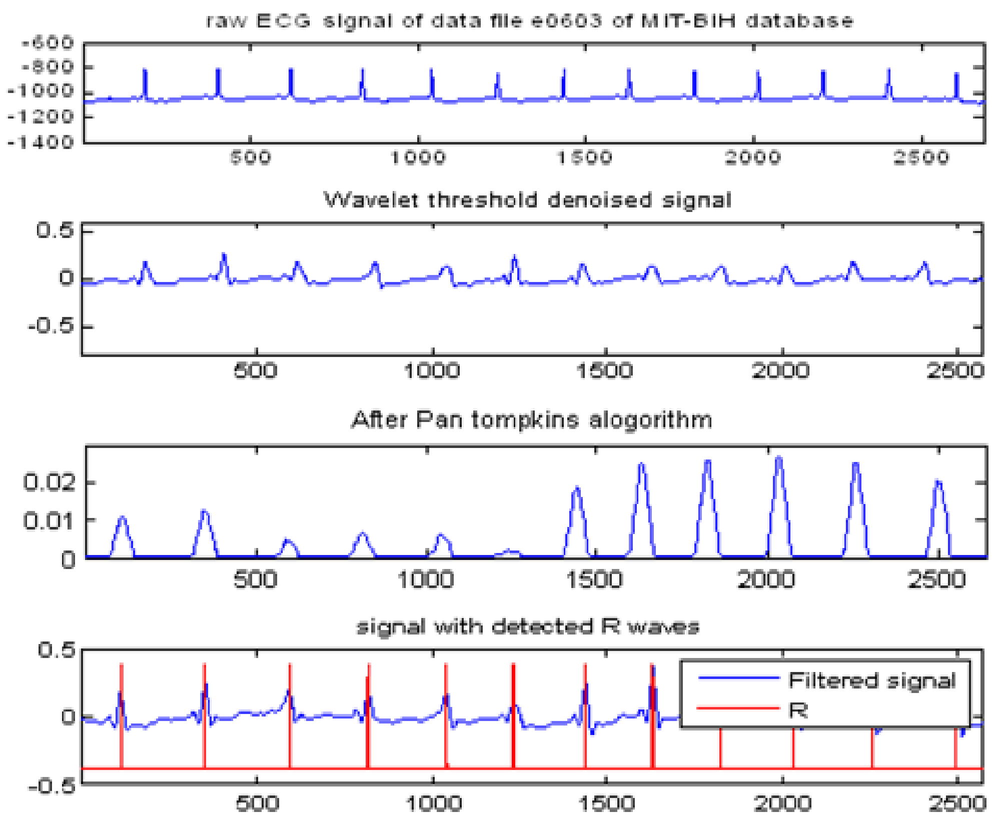

Figure 3. ECG signal (e0603) denoising and R peak detection stages.

Table 1. Four principal components extracted from ECG beats of ECG record e0603

ECG Beat types	Beat No.	Principal Components (PCs)			
		PC1	PC2	PC3	PC4
Normal Beats	Beat 1	-0.407	0.4259	0.4821	0.3207
	Beat 2	-0.0814	-0.1809	0.4672	0.2491
	Beat 3	-0.1264	0.2101	0.6088	0.3189
	Beat 4	-0.1071	-0.1327	0.6302	0.2817
	Beat 5	-0.2308	-0.1355	0.6528	0.288
	Beat 6	-0.2271	-0.0214	0.6843	0.2921
	Beat 7	-0.2436	-0.0752	0.7186	0.2501
	Beat 8	-0.1771	-0.1296	0.6929	0.245
	Beat 9	-0.1204	-0.1357	0.6062	0.2617
	Beat 10	-0.0444	0.3443	0.536	0.3181

Table 1 Continued

Cardiac Ischemic Beats	Beat 1	0.0659	0.1947	0.6185	0.3307
	Beat 2	-0.0464	0.0223	0.6655	0.3092
	Beat 3	-0.2734	-0.066	-0.0763	0.0319
	Beat 4	0.3825	-0.2781	0.5279	0.2759
	Beat 5	-0.4743	-0.3207	0.4281	0.3392
	Beat 6	-0.2902	0.3749	0.6394	0.3737
	Beat 7	-0.0208	-0.1956	0.6989	0.3445
	Beat 8	-0.4165	-0.2437	0.526	0.3126
	Beat 9	-0.1909	-0.0147	0.7635	0.3619
	Beat 10	0.1003	-0.1821	0.6846	0.3834

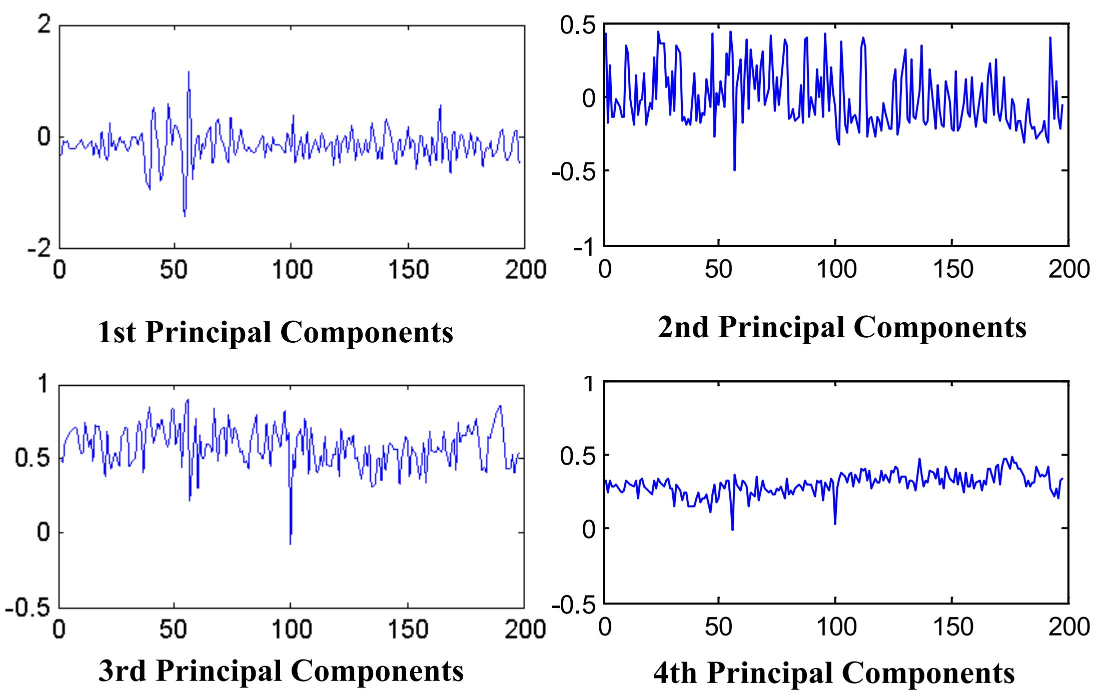

Figure 4. The PCA projections of four principal components.

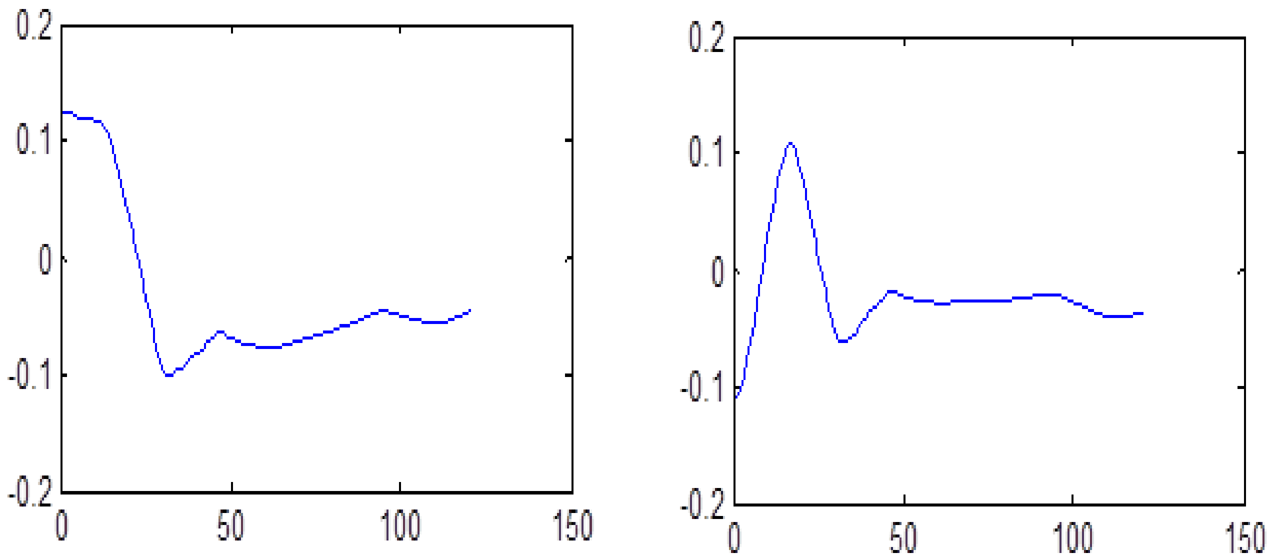

Figure 5. Original and reconstructed rt segment of ecg signal

The comparison of accuracy of classifier models is depicted in Table 2. The results of classifier models for each dataset shown in Table 3 indicates that the MLP neural network trained with Levenberg Marquardt back propagation algorithm was efficient in detecting ischemic beats with a highest classification accuracy of 90.51%. Figure 6 shows the comparison of performance indices of classifier models, which ensures the fact that MLP neural network model detects myocardial ischemia with highest accuracy. Figure 7 shows the variation of accuracy of classifier models for each input data files from MIT-BIH database, which confirms that the MLP classifier provides highest accuracy in majority of data files.

Table 2. Average classification accuracy of classifier models

Classifier Models	Kernel	Accuracy (%)
MLP	-	90.51
	RBF	73.4
SVM	Polynomial	76.59
	Linear	67.02
KNN	-	78.1

Table 3. Results of classifiers over the datasets

ECG Record	MLP Classifier (12 Hidden Neurons)			SVM Classifier (Polynomial kernel)			KNN Classifier		
	Sensitivity (%)	Accuracy (%)	PPA (%)	Sensitivity (%)	Accuracy (%)	PPA (%)	Sensitivity (%)	Accuracy (%)	PPA (%)
e0103	81.82	69.23	81.82	84.62	80	91.67	85.71	70.37	78.26
e0104	84.62	80	91.67	80	70.59	85.71	84	70.79	81.82
e0108	93.75	94.12	100	94.12	94.74	100	94.05	93.55	98.75
e0127	92.31	80	85.71	60	58.82	90	87.67	88.16	100
e0133	100	100	100	93.33	94.12	100	85.07	71.43	80.28
e0147	100	87.5	87.5	75	72.22	92.31	86.9	83.15	94.81
e0155	100	93.75	93.75	81.25	77.78	92.86	86.25	81.4	93.24
e0166	100	100	100	73.33	76.47	100	84.81	84.81	100
e0204	92.86	81.25	86.67	75	72.22	92.31	86.3	76.47	86.3
e0211	100	93.33	93.33	73.33	70.59	91.67	85.92	81.82	93.85
e0304	100	94.12	94.12	82.35	84.21	100	87.36	78.57	88.37
e0403	100	93.75	93.75	87.5	83.33	93.33	83.33	56.47	61.64
e0411	100	93.75	93.75	75	66.67	85.71	84.13	66.27	74.65
e0501	100	93.75	93.75	66.67	70.59	100	84.06	74.68	86.57
e0602	87.5	87.5	100	81.25	77.78	92.86	86.42	81.82	93.33
e0603	100	100	100	70.59	73.68	100	87.76	87.76	100
Average	**96.19**	**90.51**	**93.8**	**78.4**	**76.6**	**94.23**	**86.43**	**78.1**	**88.34**

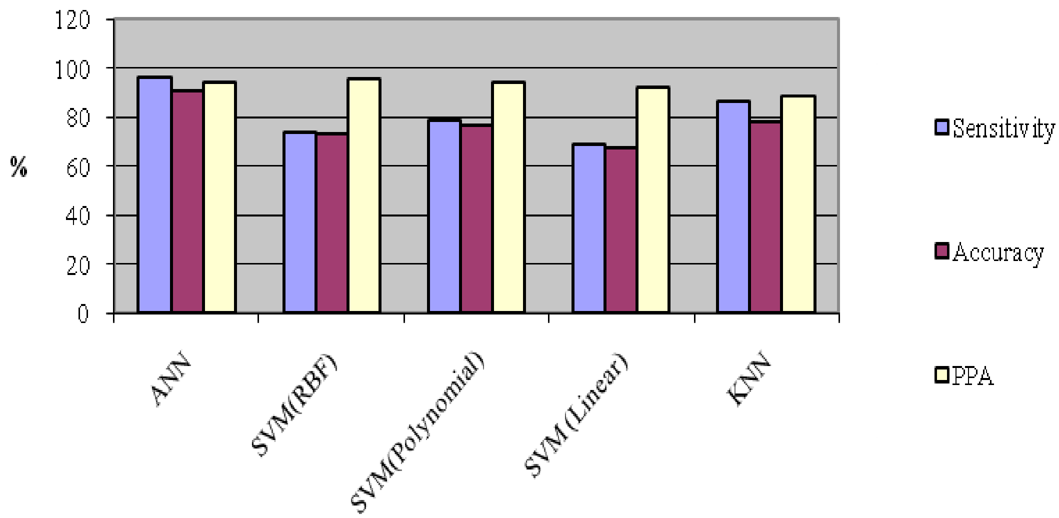

Figure 6. Performance comparisons of classifier models.

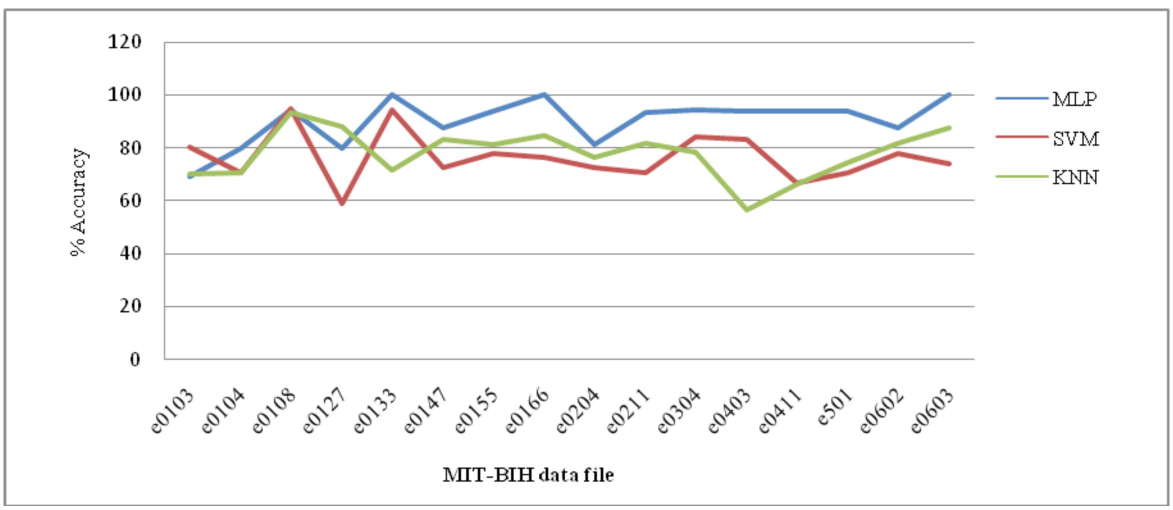

Figure 7. Variation of accuracy of classifier models over the data sets.

Figure 8 shows the variation of performance indices for MLP architecture with different numbers of hidden neurons, which infers that the MLP architecture with 12 hidden neurons detects the ischemic beats with highest classification accuracy. Figure 9 shows the variation of MSE with different architectures of MLP over the ECG records of MIT-BIH data base. The graph indicates that the variation of MSE of MLP neural network with 12 hidden neurons is minimum compared to other architectures.

Figure 8. Comparison of performances measures of different MLP architectures.

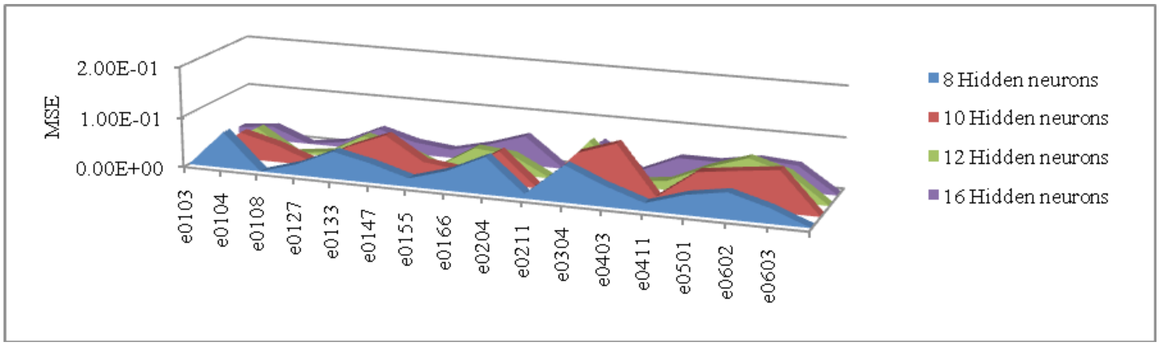

Figure 9. Comparison of Mean Squared Error of different MLP architectures.

From Table 4, it is evidential that the proposed PCA based method outperforms in terms of classification accuracy in comparison with classifiers developed by other researchers.

4. Conclusion

This paper demonstrated a novel and efficient algorithm for early detection of myocardial ischemia by using PCA with neural network. The feature vector is generated by fragmenting ST segment between RR intervals of ECG beats and reducing its dimension by PCA. In this work, three classifier models are used for diagnosing myocardial ischemia by detecting ischemic beats. The ANN classifier model with 12 hidden neurons showed classification accuracy of 90.51%, PPA of 93.8% and sensitivity of 96.19%, which is considerably high in comparison with other classifier models. The work also depicts efficacy of PCA as dimensionality reduction tool in improving the accuracy of diagnosis of myocardial ischemia.

Table 4. Comparison of classification accuracies obtained by other methods

Method	% Accuracy
Fuzzy Inference systems for ECG stress signals[15]	80
WT of heart sounds using ANN[16]	85
Multi-parametric measure of HRV[17]	72.5-84.6
EMD-Teager energy operator with BPNN[18]	85
SVM with BPSO and GA for CAD detection[19]	81.46
SVM with PCA for CAD diagnosis[20]	79.71
Linear and nonlinear features and MLP[21]	89.5
Ischemia detection using PCA and MLP (Proposed)	**90.51**

5. Acknowledgments

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6. References

1. Papaloukas C, Fotiadis D, Likas A, Michalis L. Automated methods for ischemia detection in long duration ECGs. Cardiovascular Reviews and Reports. 2003; 24(6):313–20.
2. Papaloukas C, Fotiadis DI. An ischemia detection method based on artificial neural network. Artificial Intelligence in Medicine. 2002; 24(2):167–78.
3. Silipo R, Marchesi C. Artificial neural networks for automatic ECG analysis. Signal Processing. 1998; 46(5):1417–25.
4. Mohamad FN, Ali MSAM, Jahidin AH, Saaid MF, Noor MZH. Principal component analysis and arrhythmia recognition using Elman neural network. Proceedings of 4th IEEE Control and System Graduate Research Colloquium; 2013. p. 141–6.
5. Sindhubargavi R, Sindhu MY, Saravanan. Spectrum sensing using energy detection technique for cognitive radio networks using PCA technique. Indian Journal of Science and Technology. 2014 Apr; 7(4S):40–5.
6. Garg P, Kumar D. Image pattern extraction and compression using pixel neighborhood and weighted PCA algorithm. Indian Journal of Science and Technology. 2016 Jul; 9(28):1–5.
7. Rashida B, Rabbani MA. An automatic facial localization tracking identification biometric system through PCA and wavelet distribution in 3D Mesh Environment. Indian Journal of Science and Technology. 2016 Aug; 9(32):1–13.
8. Ghorbanian P, Ghaffari A, Jalali A, Nataraj C. Heart arrhythmia detection using continuous wavelet transform and principal component analysis with neural network classifier. Computing in cardiology. IEEE; USA. 2010 Sep. p. 669–72.
9. Joo S, Choi K, Huh SJ. Prediction of ventricular tachycardia by neural network using parameters of heart rate variability. IEEE Computing in Cardiology. 2010 Sep; 26(5):585–8.
10. Monika P, Venkatesan D. DI-ANN clustering algorithm for pruning in MLP neural network. Indian Journal of Science and Technology. 2015 Jul; 8(16):1–6.

11. Radhamani E, Krishnaveni K. Diagnosis and evaluation of ADHD using MLP and SVM Classifiers. Indian Journal of Science and Technology. 2016 May; 9(19):1–7.
12. Ghongade RB, Ghatol AA. Deciding optimal number of exemplars for designing an ECG pattern classifier using MLP. Indian Journal of Science and Technology. 2009 Apr; 2(4):40–2.
13. Javadi M, Ebrahimpour R, Sajedin A, Faridi S, Zakemejad S. Improving ECG classification accuracy using an ensemble of neural network modules. PLOS One. 2011 Oct; 6(10):1–13.
14. Physiobank, Physiotoolkit and Physionet: Components of a new research resource for complex physiologic signals. Available from: http://circ.ahajournals.org/cgi/content/full/101/23/e215
15. Arafat S, Dohrmann M, Skubic M. Classification of coronary artery disease stress ECGs using uncertainty modelling. Proceedings of ICSC Congress on Computational Intelligence Methods and Applications; USA. 2005.
16. Karimi M, Amirfattahi R, Sadri S, Marvasti SA. Noninvasive detection and classification of coronary artery occlusions using wavelet analysis of heart sounds with neural networks. Proceedings of the 3rd IEE International Seminar on Medical Applications of Signal Processing; London. 2005. p. 117–20.
17. Kim WS, Jin SH, Park YK, Choi HM. A study on development of muti-parametric measure of HRV diagnosing cardiovascular disease. Proceedings of World Congress on Medical Physics and Biomedical Engineering; Springer, Korea. 2007. p. 3480–3.
18. Zhao Z, Ma C. An intelligent system for noninvasive diagnosis of coronary artery disease with EMD-TEO and BP neural network. IEEE, International Workshop on Geoscience and Remote Sensing and International Workshop on Education Technology and Training; Shanghai. 2008. p. 631–5.
19. Babaoglu I, Findik O, Ulker E. A comparison of feature selection models utilizing binary particle swarm optimization and genetic algorithm in determining coronary artery disease using SVM. Expert Systems Applications. 2010 Apr; 37(4):3177–83.
20. Babaoglu I, Findik O, Bayrak M. Effects of principal component analysis on assessment of coronary artery diseases using SVM. Expert Systems Applications. 2010 Mar; 37(3):2182–5.
21. Dua S, Du X, Sree SV, Ahamed TVI. Novel classification of coronary artery disease using heart rate variability analysis. Journal of Mechanics in Medicine and Biology. 2012; 12(04):1–19.