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Classification of coronary artery disease data sets by using a deep neural network

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Abstract

In this study, a deep neural network classifier is proposed for the classification of coronary artery disease medical data sets. The proposed classifier is tested on reference CAD data sets from the literature and also compared with popular representative classification methods regarding its classification performance. Experimental results show that the deep neural network classifier offers much better accuracy, sensitivity and specificity rates when compared with other methods. The proposed method presents itself as an easily accessible and cost-effective alternative to currently existing methods used for the diagnosis of CAD and it can be applied for easily checking whether a given subject under examination has at least one occluded coronary artery or not.

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Introduction

Today, the diagnosis of some of the major cardiovascular diseases, such as heart rhythm problems, coronary artery diseases (CAD), etc., is generally accomplished by following sophisticated and expensive medical procedures performed in well-equipped hospitals and health institutions. Moreover, these procedures usually require the application of invasive methods by only highly qualified medical experts. Although this approach provides a high degree of accuracy regarding diagnosis, the number of patients having access to this facility is very limited. Hence, the development of a novel, economic and easily accessible method for cardiovascular disease diagnosis is highly desirable.

Different classification methods (1-10), each with its unique advantages and disadvantages, have been presented to diagnose the CAD. While conventional methods such as decision trees (1), naive Bayes (3), etc., have some speed benefits and easily applied to data sets, these methods cannot yield significant classification performance. Therefore, machine learning based classification methods, such as neural network classifiers and fuzzy classifiers (6, 8, 11), have been applied in recent years to classify the CAD data to improve the classification performance.

In recent studies, it has been shown that the deep neural network (DNN) can be successfully employed for complex classification problems (12-19). The DNN based classifiers are very attractive because the accuracy of the classification rate is very high, compared to conventional classifiers. The DNN classifier attempts to produce hidden patterns from the raw data set. Using these hidden patterns rather than using raw features improves the classification performance of the DNN (12). The DNN offers the ability of autoencoders (AEs) to understand feature hierarchies, and the capability of the softmax layer to predict the correct class value, which is actually the diagnosis information for the CAD. Therefore, DNNs may be utilized to classify and diagnose CAD by using proper network topologies and processing strategies.

In this study, we represent a classification strategy for CAD data sets. The proposed

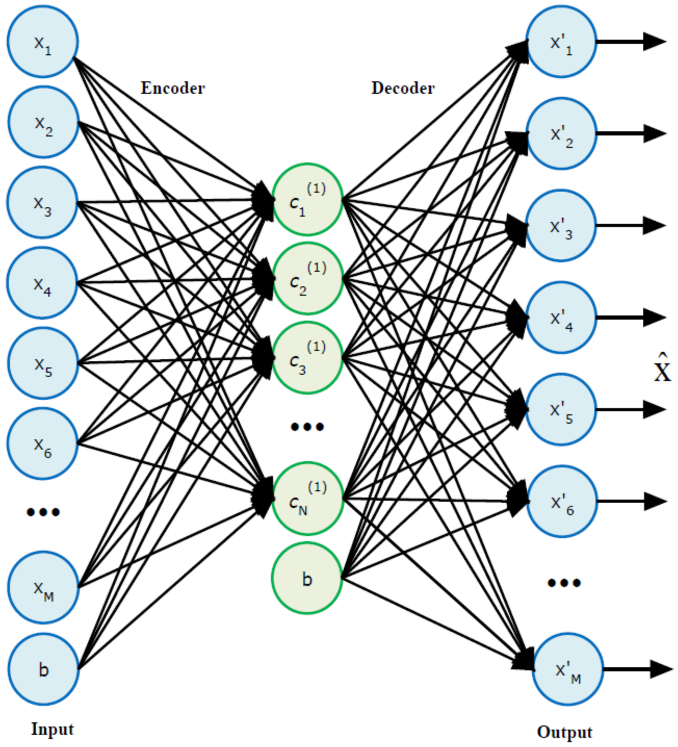

Figure 1. An Autoencoder Network.

strategy depends on a deep neural network classifier constructed by conveniently combining two autoencoders and a softmax classifier. The performance of the proposed classifier is measured by different data sets and also compared with conventional classification methods. Simulation results demonstrate that the proposed method offers superior performance over the competing operators cited in the study and is capable of efficiently classifying 4 different CAD data sets obtained from Data Mining Repository of the University of California, Irvine (UCI) (20).

The remaining of the paper is structured as follows. Section II briefly explains coronary artery diseases and then presents the descriptions of the structures of the autoencoder, the softmax classifier. This section also explains the training procedure of the autoencoder and the DNN. Section III reports the results of the experimental studies performed on CAD data sets. Section IV is the final section and presents the discussions and conclusions.

Method

Heart disease or cardiovascular disease relate to various complications that afflict the heart and the blood vessels in the heart. Angina, heart rhythm problems, heart attack, heart failure, coronary artery disease and heart defects are some examples for the varied types of heart diseases. In particular, CAD is one of the main reasons of disorder and death in the contemporary community (21). CAD is a disease where a waxy substance termed plaque builds up inside the coronary arteries, which carry oxygen-rich blood to the heart muscle (22-25).

The existence of CAD is considered to occur when the narrowing of at least one of the coronary arteries is more than 50%. Coronary angiogram or cardiac catheterization is currently a widespread approach to diagnose the existence of CAD. This approach is highly acceptable however, it is invasive, costly and not available for a large population. Several methods have been applied to diagnose the CAD using less expensive and non-invasive ways such as an electrocardiogram depended analysis, medical image analysis, heart sound analysis, etc. (22).

The proposed method for the coronary heart diseases classification is based on a deep neural network operator constructed by combining a stacked autoencoder (sAE) network with a softmax classifier.

Autoencoder

An autoencoder, which is shown in Fig. 1, is a feed forward artificial neural network that comprises one input layer, one hidden layer and one output layer (26, 27). The internal parameters of the AE is tuned to generate its own input at the output, hence the number of neurons in the output layer is always the same as the number of inputs. The AE has two main parts, namely the encoder and the decoder parts illustrated in **Fig. 1**. The input is defined as $\mathbf{x}$ and the output is defined as $\hat{\mathbf{x}}$. Here, the dimension of the input is M and the number of neurons in the hidden layer is N. The weight matrix $\mathbf{W}$ and the bias vector $\mathbf{b}$ is tuned for training of the network. The objective function of the AE is defined as follows (28):

$$J(\mathbf{W},\mathbf{b}) = \frac{1}{S}\sum_{k=1}^{S} e_k^2 + \frac{\lambda}{2}\|\mathbf{W}\|_2^2 + \beta\sum_{j=1}^{N} KL(\rho||\hat{\rho}_j) \quad [1]$$

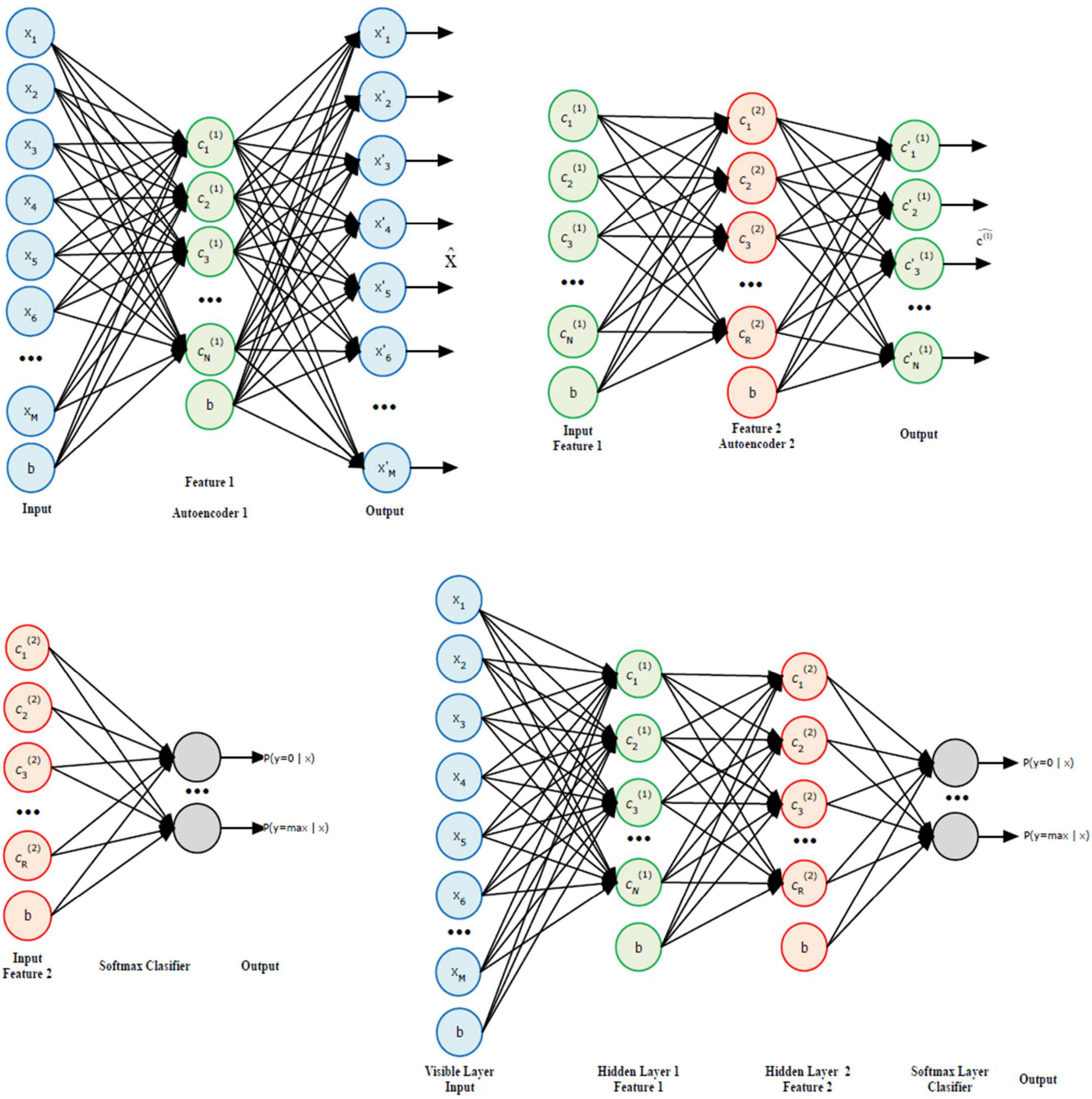

Figure 2. Training of the Deep Neural Network.

where $e_k = \|X^{(k)} - \hat{X}^{(k)}\|$ for $k = 1 \ldots S$ and S is the number of instances. λ is a regularization term used to prevent overfitting. β is the weight of the sparsity penalty term $KL(\rho\|\hat{\rho}_j)$ is Kullback–Leibler divergence (26, 28) given as

$$KL(\rho\|\hat{\rho}_j) = \rho \log \frac{\rho}{\hat{\rho}_j} + (1-\rho) \log \frac{1-\rho}{1-\hat{\rho}_j} \qquad [2]$$

Here, ρ is a constant sparsity parameter and $\hat{\rho}_j$ computed below is the mean activation value of j^{th} neuron in the hidden layer of the autoencoder (28).

$$\hat{\rho}_j = \frac{1}{S} \sum_{i=1}^{S} f_j(\mathbf{x}^{(i)}) \qquad [3]$$

where, f_j *is* the activation function of the j^{th} neuron of the hidden layer.

Softmax

The softmax classifier is a linear classifier performing probability-based logistic regression. It is also called the multinomial logistic regression. The softmax is the advanced version of the logistic regression, which is used to separate two classes. The softmax can be utilized to classify two or more cases as opposed to the logistic regression. The softmax is connected to the sAE as a supervised layer which is employed to classify the learned features (29).

Deep Neural Network

A desired number of the encoder parts of AEs are connected to construct the sAE, which connects to the softmax layer to build the deep neural network (10). The training of the DNN is very complicated and defined as follows:

First, the AEs are trained independently of each other and they are trained with the same input and output in an unsupervised fashion. Their encoder parts are combined to construct the sAE as can be seen in **Fig. 2**.

Secondly, the output of the sAE is fed to the input of the softmax layer, which is trained with labels in a supervised fashion shown in **Fig. 2**.

Finally, the AEs and the softmax layer are combined to build the DNN whose weights are fine-tuned for the last time with a convenient optimization algorithm such as the limited memory BFGS algorithm demonstrated in **Fig. 2**.

Results and Discussion

In this paper, a DNN classifier with two AEs and a softmax layer is proposed for classification of the medical CAD data. The proposed DNN classifier is tested with four benchmark data sets including, Cleveland, Hungarian, Long Beach and Switzerland. These data sets with 7 categorical and 6 numerical attributions summarized in **Table 1** are received from the Data Mining Repository of University of California, Irvine (UCI) (20). The designed DNN classifier attempts to predict whether the subject under investigation has CAD or not by using the features in the CAD data set.

The DNN has many user-supplied parameters, which are heuristically chosen, experimentally validated and summarized in **Table 2**. Several simulations are performed to show the classification performance of the DNN for each data set. The 10-cross validation technique is employed to compare the DNN classifier with the popular classifiers used in the literature. Besides, Limited memory BFGS optimization algorithm is used for all training steps and every simulation is run for 400 iterations for each data set. The training regularization term is set to 0.003. The designed DNN is implemented on a system with Intel i7 2600 3.4 Ghz CPU and 12 GB DDR3 RAM. The performance of the DNN classifier is evaluated over the accuracy rates.

We first evaluate the proposed method on the Cleveland data set which includes 303 subjects with 13 features. The features are normalized and rescaled between 0 and 1. It can be observed from **Table 3** that the DNN classifier has the best performance among the other methods used in this paper, which are representative popular classification methods from the literature.

Table 1. Summary of the attributions

Age	Age in years
Sex	1=Male; 0=Female
Cp	Chest pain type
Trestbps	Resting blood pressure
Chol	Serum cholesterol
Fbs	Fasting blood sugar
restecg	Resting electrocardiographic results
thalach	Maximum heart rate achieved
exang	Exercise induced angina (1 = yes; 0 = no)
oldpeak	ST depression induced by exercise relative to rest
slope	The slope of the peak exercise ST segment
ca	Number of major vessels (0-3) colored by flourosopy
thal	3 = normal; 6 = fixed defect; 7 = reversable defect
Class	The estimated attribute

Table 2. Parameter lists

			Cleveland	Hungarian	Switzerland	LongBeach
Training	Autoencoder	*Training Algorithm*	L-BFGS	L-BFGS	L-BFGS	L-BFGS
		The activation function	Sigmoid	Sigmoid	Sigmoid	Sigmoid
		The number of the neuron	4 - 4	4 - 4	4 - 4	4 - 4
		Sparsity term (*p*)	0.4-0.1	0.5-0.1	0.4-0.4	0.2-0.2
		The weight of the sparsity (β)	4-1	2-4	2-1	3-3
		Regularization term (λ)	0.003	0.003	0.003	0.003
		Iteration	400	400	400	400
	Softmax	*Training Algorithm*	L-BFGS	L-BFGS	L-BFGS	L-BFGS
		Regularization term (λ)	0.0001	0.0001	0.0001	0.0001
		Iteration	400	400	400	400
Fine-Tuning	DNN	*Training algorithm*	L-BFGS	L-BFGS	L-BFGS	L-BFGS
		The activation function	Sigmoid	Sigmoid	Sigmoid	Sigmoid
		regularization term (λ)	0.0001	0.0001	0.0001	0.0001
		Iteration	400	400	400	400

Table 3. Comparison of the methods for the Cleveland data set

Methods	AR(%)	Methods	AR(%)
J48 (1)	76.5	DecisionTable (5)	83.3
IBK (1)	76.9	NaiveBayes (5)	83.3
PART (1)	81.5	SMO (5)	83.3
NPC (2)	81.5	AdaBoostM1 (1)	83.5
AdaBoostM1 (5)	82.2	Bagging (5)	83.7
Dagging (5)	82.2	Logistic (5)	83.7
FT (5)	82.2	MultiClassClassifier (5)	83.7
LMT (5)	82.2	RandomForest (5)	83.7
RandomCommittee (5)	82.2	DAM (5)	83.7
RandomSubSpace (5)	82.2	RBFNetwork (5)	84
SimpleLogistic (5)	82.2	SMO (1)	84.4
DTNB (5)	82.5	HNPC (minumum) (3)	84.4
RotationForest (5)	82.5	HNPC (product) (3)	85
NaiveBayesSimple (5)	82.9	**Designed DNN**	**85.2**

We then repeat the same experiments on three different data sets of the CAD. The first experiment is conducted on the Hungarian data set where 261 subjects with 13 attributions are available. The results are listed in **Table 4** and demonstrate that the DNN classifier is the best classifier. The second experiment is performed on the Long Beach data set with 200 subjects with 13 features. As it can be seen from **Table 5**, the DNN classifier has the best performance of all, compared to the remaining 7 classification methods. The last experiment is conducted on the Switzerland data set which contains 123 samples with 13 features. We compare the proposed DNN with both the state-of-the-art methods including support vector machine (SVM), k-neighbors (KNN), decision three (DT) and some conventional methods from the literature. The obtained results with the highest accuracy rates (AR) are shown in **Table 6**.

Table 4. Comparison of the methods for the Hungarian data set

Methods	AR(%)
genfis2 (8)	39.5
Rough-Fuzzy Classifier (8)	42.4
NNBDSS (7)	46.4
WFR and DTR (10)	49.9
FBCDSS (7)	50.5
ABM1 (6)	76.8
J48 (6)	78.2
Random Forest (6)	80.7
Bagging (6)	81.9
SMO (6)	82
Naive Bayes (6)	82.8
Designed DNN	**83.5**

Table 5. Comparison of the methods for the Long Beach data set

Methods	AR(%)
dT	68.4
Elastic net (9)	80.1[a]
Lasso (9)	80.4[a]
KNN	81.1
SCAD (9)	81.2[a]
L1=2 (9)	81.6[a]
MCP (9)	81.8[a]
SVM	83.4
Designed DNN	**84**

a: mean of 50 runs

Table 6. Comparison of the methods for the Switzerland data set

Methods	AR(%)
WFR and DTR (10)	52.2
Genfis2 (8)	62.3
Rough-Fuzzy Classifier (8)	79.8
DT	86.5
KNN	88.5
SVM	92.2
Designed DNN	**92.2**

All results show that the proposed method is very efficient classifier to classify the CAD data sets. The classification performance of the proposed method remains same for different data sets and different conditions. This show us proposed method can be used to diagnose CAD for the different data sets, which may be obtained from different patients.

The performance of medical diagnostic techniques is often measured by metrics of accuracy, sensitivity and specificity. Therefore, the accuracy, sensitivity, and specificity of the Cleveland and Hungarian data sets are evaluated for one run where data sets are divided into two groups as 70% for training and 30% for testing. The sensitivity, and specificity (30) are not evaluated for Long Beach and Switzerland due to limited number of negative samples. The sensitivity of the test is defined as the rate of subjects with the CAD who test positive. Specificity is the rate of subjects not having the CAD who test negative. The obtained results, which are listed in **Table 7**, shows that the DNN classifier is very efficient classifier to detect the CAD. As it can be seen from **Fig. 3** and **Fig. 4**, the confusion matrices plotted for the Cleveland and Hungarian data sets show the effectiveness of the proposed classifier.

Table 7. The accuracy, sensitivity, and specificity of the Cleveland and Hungarian data sets

	Accuracy	Sensitivity	Specificity
Cleveland	87.640	97.67	78.26
Hungarian	89.744	92.73	82.61

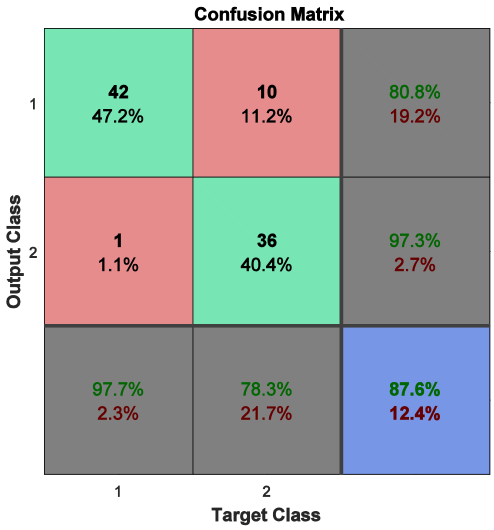

Figure 3. Confusion matrix of the Cleveland data set.

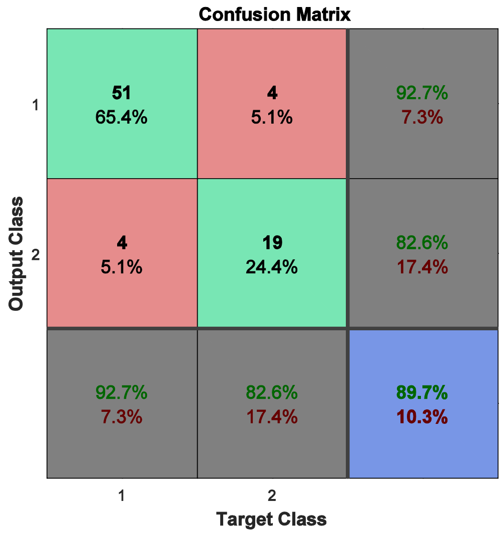

Figure 4. Confusion matrix of the Hungarian data set.

Conclusion

In this study, we proposed a DNN based classifier for classification of CAD data sets for the purpose of diagnosing CAD. The method is tested on the Cleveland, Hungarian, Long Beach and Switzerland data sets from the literature. Experimental results show that the proposed method offers the highest classification accuracy among the methods included in the experiments. It is concluded that the proposed DNN based classifier can efficiently be used to classify medical CAD data sets for the purpose of the diagnosis of CAD.

Conflict of interest statement

The authors declare that there is not any conflict of interest and that they alone are responsible for the content and writing of this article.

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