Classification of Cardiovascular Artery Diseases Using Artificial Neural Network

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Abstract: According to WHO (World Health Organization), 17.9 million people die every year because of Cardiovascular diseases (CVDs) and it accounts for 31% of all global deaths. Hence, the diagnosis of such common and deadly diseases are becoming very critical. In this study, we proposed a method that uses Fisher's Linear Discriminant Analysis (FLDA) for dimension reduction and Artificial Neural Network (ANN) for obtaining an efficient CVD diagnostic model. Performance evaluations based on publicly available datasets show that the accuracy of the proposed method is 97%, which is superior than the state of the art.

Key words: Cardiovascular heart disease, cardiovascular artery disease, machine learning, artificial neural network, linear discriminant analysis, multilayer perceptron neural network.

1. Introduction

Cardiovascular diseases (CVDs) are a group of disorders that occurs in blood vessels and heart. It includes several diseases such as coronary artery disease (CAD), also known as coronary heart disease, which is the most common heart disease all over the world. Angiography is the main diagnostic method for the abnormal narrowing of the heart vessels. Due to its cost and complications, researchers try to find alternative diagnostic methods.

In the literature, several models for classification of various diseases are proposed and implemented by using different methods and techniques. Z-Alizadeh Sani *et al*. [1] have proposed cost-sensitive algorithms using classifiers such as Sequential Minimal Optimization (SMO), k-Nearest neighbors KNN and C4.5 Decision Tree and have obtained 92.09% accuracy on Z-Alizadeh Sani Dataset. Chetna Yadav *et al.* obtained 93.75% accuracy on Z-Alizadeh Sani Dataset using algorithms, such as Improved ARM, SMO, Support Vector Machine (SVM), C4.5, Naïve Bayes and KNN [2]. Frantisek Babic *et al*. have used Decision tree, Naïve Bayes, SVM and Neural Networks to obtain classification model on different heart datasets [3]. They reached to an 86.67% accuracy on Z-Alizadeh Sani Dataset, and a maximum of 89.93% accuracy on UCI Machine Learning Repository Dataset [4]. In terms of CVD diagnosis, there are also several research efforts that make use of Cleveland, Hungarian, Switzerland, Long Beach VA datasets at UCI Machine Learning Repository and they obtain average 86% accuracy [5]-[15]. Researches have also experimented several well known classifiers, ensemble classifiers, feature selection and feature extraction methods[16] on some CVD datasets to improve the diagnosis power [17]. In Table 1, a comparison of CVD diagnosis algorithms is given. Unlike the existing studies, in this study, to generate a robust heart disease diagnostic model, we performed Fisher's Linear Discriminant Analysis (FLDA) for feature dimension reduction and then used Artificial Neural Networks (ANN) after applying hyper parameter optimization. In this research effort, we evaluate the overall performance of our neural network model based on accuracy, precision, recall, F1-score and AUROC measures using stratified 10-fold cross-validation.

This study is organized as follows: In section 2, we introduce the datasets. In section 3, we present the proposed methodology. In section 4, we present performance evaluations. Section 5 concludes the paper.

Table 1. Comparison of Existing Studies for Diagnosis of Heart Disease

Reference	**Method**	**K-Fold CV**	**F1-Score**	**Accuracy**	**AUROC**	**Dataset**	**Year**
Alizadehsani *et al.* [1]	SMO	-	-	92.09%	-	Z-Alizadeh Sani	2012
Chetna Yadav *et al.* [2]	Apriori	-	-	93.75%	-	Z-Alizadeh Sani	2015
Frantisek Babic *et al.* [3]	SVM	-	-	86.67%	-	Z-Alizadeh Sani	2017
Kemal Polat *et al.* [5]	Fuzzy+ AIRS+ KNN	15	-	87%	-	Cleveland	2007
My Chau Tu *et al.* [6]	Bagging with Decision Tree	10	-	81.41%	-	UCI Repository	2009
Resul Das *et al.* [7]	ANN Ensemble	-	-	89.01%	-	Cleveland	2009
Shouman *et al.* [8]	Decision Tree	10	-	84.1%	-	Cleveland	2011
Karabulut *et al.* [9]	ANN	10	-	91.2%	0.915	UCI Repository	2012
Shouman *et al.* [10]	KNN	-	-	97.4%	-	UCI Repository	2012
Nahar *et al.* [11]	Apriori, Tertius	-	-	99.38%	-	UCI Repository	2013
Rajalaxmi *et al.* [12]	BABC+Naïve Bayes	-	-	86.4%	-	Cleveland	2014
Randa El-Biary *et al.* [13]	C4.5 Decision Tree	10	-	78.54%	-	Cleveland	2015
Luxmi Verma *et al.* [14]	Multinomial Logistic Regression	-	-	90.28%	-	Cleveland	2016
Frantisek Babic *et al.* [3]	Decision Tree	-	-	73.87%	-	South Africa	2017
Samuel *et al.* [15]	ANN	-	-	91.1%	-	UCI Repository	2017
Our study	**FLDA+ ANN**	**10**	**93%**	**97%**	**0.97**	Z- Alizadeh Sani	**2019**

2. Medical Dataset

In the study, to assess the accuracy of our diagnostic model, we used the popular and publicly available Z-Alizadeh Sani Dataset [18], which contains samples from individuals with cardiovascular heart disease and normal controls. It has 54 features, which are arranged in four categories: demographic, symptom and examination, ECG, laboratory and echo.

The Z-Alizadeh Sani dataset contains 303 samples in which 87 of them are collected from CAD patients and 216 of them are collected from normal individuals. A patient is categorized as CAD, if individual's narrowing of diameter is greater than or equal to 50%, and as normal otherwise.

3. Methodology

In the study, we try to answer whether we can discriminate CAD patients from normal individuals using

54 features. In this respect, we can summarize our study in two steps. Firstly, we tried to reduce the dimension of the feature space that best distinguishes between normal cases and CAD patients as explained in Section 4.1. Secondly, we aimed to classify the disease state of the subjects. For this purpose, we performed hyper-parameter optimization in Artificial Neural Networks as explained in Section 4.2.

3.1. Dimension Reduction Using Fisher's Linear Discriminant Analysis (FLDA)

The idea behind Fisher's Linear Discriminant Analysis (FLDA) [16] is to reduce feature space from a high-dimension to one-dimension to find linear combination of features. As shown in Fig. 1, the data samples are projected into a one-dimensional space that has the best separation of different class types.

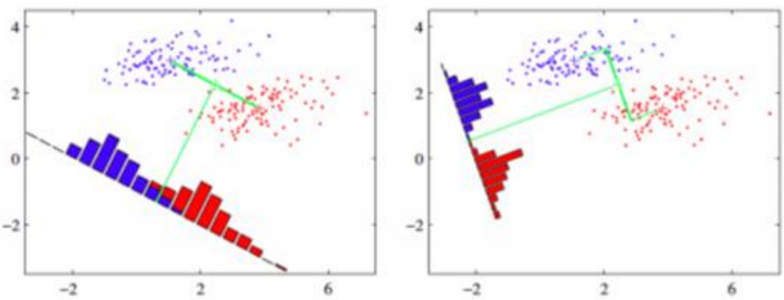

Fig. 1. Illustration of the idea of fisher's linear discriminant analysis [16].

In this study, we use FLDA as a dimension reduction technique. Therefore, we obtain a single feature starting from the set of 54 features, which enables to reduce the computational cost of model training and testing considerably.

3.2. Parameter Optimization and Classification Using Artificial Neural Network (ANN)

Artificial Neural Networks (ANN) is a machine learning method that aims to learn by mimicking the human nervous system. The most commonly used ANN model is the multilayer perceptron, that consists of three layers such as; input, hidden and output layer. The Fig. 2 represents the standard multilayer perceptron architecture that is formed by 3 layers.

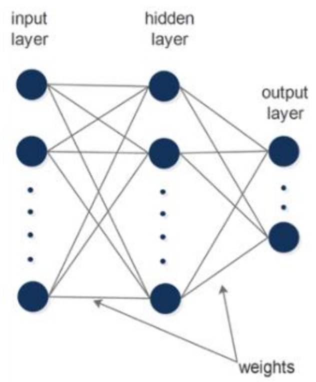

Fig. 2. Illustration of a neural network model.

In single layer perceptron (SLP), hidden layer is positioned between input and output layers and allow modeling nonlinear mappings through their activation functions. The number of hidden layers and the number of neurons in a hidden layer are among the hyper-parameters that define the complexity of a neural network.

In this research, we used L_2 regularization and set learning rate of L_2 regularization (beta) to 0.01. We also set number of hidden layer size to 1. We used ADAM Optimizer as an optimizer and we set its momentum parameters beta1 and beta2 to 0.97 and 0.99 based on our experience. Because of small number of samples, we set batch size to 4. “tanh” function is used as the activation function and in weight initializing step “leCun uniform” approach is used. We optimized the following hyper-parameters by using 10-fold cross validation and doing grid-search;

- Number of training epochs [2,4,6,8…30]
- Hidden neuron size [3,5,7,9,11]
- Learning rate [0.05,0.1,0.3,0.5]

4. Results

We employed Fisher’s Linear Discriminant Analysis (FLDA) for feature dimension reduction followed by Artificial Neural Networks (ANN) to obtain a CAD diagnostic model. We used Z-Alizadeh Sani Dataset which is publicly available and popular in this field. The data is reduced to one dimension by FLDA, which enabled us to achieve remarkable results both in terms of computation time and various performance evaluations metrics, such as accuracy, F1-score and AUROC.

An artificial neural network can perform well through an effective selection of hyper-parameters. In this respect, we performed hyper parameter optimization and obtained the best parameters, i.e., number of training epochs, hidden layer size and learning rate. As a result, we obtain optimum hyper parameters for each 10 folds as follows;

- Optimum learning rate = [0.05, 0.1, 0.3, 0.1, 0.5, 0.3, 0.3, 0.3, 0.1, 0.1]
- Optimum Epoch = [15,13,16,17,14,8,14,16,13,16]
- Hidden neuron size = [3, 5, 4, 3, 5, 5, 4, 4, 3, 4]

In this study, although we have a symmetric dataset, it has an uneven distribution of class labels. Therefore, to evaluate the overall performance of our classification model, we considered different metrics in addition to the overall accuracy. We summarize our results in Table 3 and Fig. 4. includes the accuracy, F1-score and AUROC measures of each fold of the 10-fold stratified cross-validation experiment that we explain in section 4.2. The accuracy metrics obtained from each fold are then averaged. In this study, using 10-fold cross-validation led to 93–97% diagnostic accuracy, 86-100% Precision, 66-96% Recall, 80-96% F1-Score and 83-99% AUROC using machine learning models. We performed also SVM, Random Forest, Logitboost and XGBoost machine learning algorithms. Table 3 includes this experiments on Z-Alizadeh Sani Dataset. We optimized all hyper parameters of this classification algorithms using “Grid Search” and “Randomized Search” from scikit-learn [19] python library. All experiments in this work are carried out using scikit-learn python library as well. As a result, we reached to a significant accuracy, which is 97% and higher than that of the existing studies on Z-Alizadeh Sani dataset, a F1-score 93% and an AUROC of 97%.

Table 3. Evaluation Results Based on Some Machine Learning Algorithms Using 10-Fold Cross Validation after Applying **FLDA** Feature Extraction Method and Hyper Parameter Optimization
(**FE**: Feature Extraction, **FM**: F-Measure, **AUC**: Area Under ROC Curve, **ACC**: Accuracy)

Method	FE	Optimization	k-Fold CV	Precision	Recall	FM	AUC	ACC
SVM (with ‘linear’ kernel)	**FLDA**	Grid search	10	95%	94%	94%	0.96	%92
SVM (with ‘rbf’ kernel)	**FLDA**	Grid search	10	94	95%	94%	0.89	%92
Random Forest	**FLDA**	Grid search	10	91%	90%	90%	0.96	%86
Logitboost (bl:RandomForest)	**FLDA**	Grid search	10	91%	90%	90%	0.96	%86

Logitboost(bl:AdaboostRegressor)	**FLDA**	Grid search	10	94%	94%	94%	0.89	%91
XGBoost	**FLDA**	Randomized S.	10	94%	94%	94%	0.93	%92
ANN	**FLDA**	**Grid search**	**10**	**93%**	**93%**	**93%**	**0.97**	**97%**

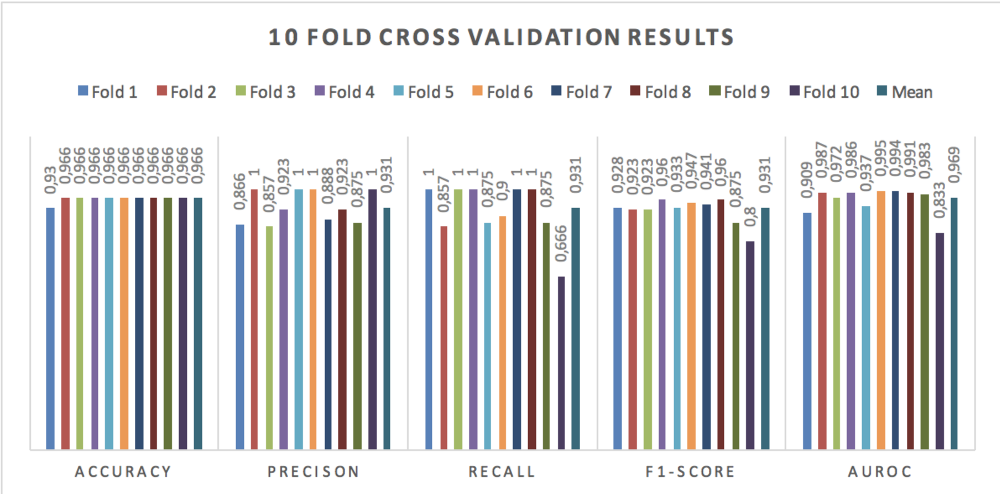

Fig. 4. Performance evaluation metrics of FLDA and ANN obtained by performing a 10-fold cross validation experiment on Z-Alizadeh Sani heart disease dataset.

5. Conclusion and Future Work

Cardiovascular heart diseases are one of the critical health challenges in recent years. In this respect, many researches have carried out studies to diagnose and predict heart diseases. In this research effort, we evaluate the overall performance of our neural network model based on Accuracy, Precision, Recall, F1-score and AUROC measures using stratified 10-fold cross-validation. Based on the evaluation metrics used, we obtained a higher classification accuracy than the existing studies on Z-Alizadeh Sani Dataset.

The results show that Artificial Neural Network (ANN) models provided a greater and reliable diagnostic accuracy compared to the other state of the art machine learning algorithms, such as Random Forest, Decision Tree, SMO, SVM, Naïve Bayes, KNN, in detecting cardiovascular artery disease in individuals [1]-[15]. As a future work, we are planning to apply the proposed method on different datasets.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

All authors had conducted the research and approved the final version.

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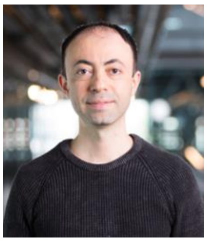

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