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Multi-lead ECG heartbeat classification of heart disease based on HOG local feature descriptor

Mohammad Ali Sheikh Beig Goharrizi [a,*], Amir Teimourpour [b], Manijeh Falah [c], Kiavash Hushmandi [d], Mohsen Saberi Isfeedvajani [e]

[a] University of Tehran, Tehran, Iran
[b] Department of Microbiology, High Institute for Research and Education, Tehran, Iran
[c] Atherosclerosis research center, Baqiyatallah University of Medical Sciences, Tehran, Iran
[d] Department of Food Hygiene and Quality Control, Division of Epidemiology & Zoonoses, Faculty of Veterinary Medicine, University of Tehran, Tehran, Iran
[e] Department of Community Medicine, Faculty of Medicine, Baqiyatallah University of Medical Sciences, Tehran, Iran

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ABSTRACT

Introduction: ECG data play an important role in the diagnostics of various cardiovascular diseases. Classification of multi-lead ECG signals could be challenging even for well-trained physicians. In this study we propose a new approach for multi-lead ECG classification.

Method: Five-types of 15-lead ECG data namely healthy control, bundle branch block, cardiomyopathy, Dysrhythmia, and myocardial infarction patients from two types of datasets, 5319 and 6647 heartbeats from Baqiyatallah and PTB Diagnostic ECG database, were used, respectively. One-dimensional total variation regularization was used to denoising ECG data. Heartbeats were extracted by one cardiologist and saved as images with jpg format. Histogram of oriented gradients method was used to extract feature of images. for classification task support vector machine and fully connected neural network were used. Five-fold cross validation was used for validating the models.

Result: For 15-lead ECG PTB Diagnostic database, the best classification models are SVM model with cubic (accuracy: 99.9%, Range: 99.77% - 100%) and quadratic (accuracy: 99.88%, Range: 99.77%-100%) kernel function, for this dataset fully connected accuracy is 99.4% with range of 99.02%- 99.70%. Regarding to the Baqyatallah dataset SVM with cubic (accuracy: 99.83%, Range:99.72%-100%) and quadratic (accuracy: 99.77%, Range: 99.62%-99.9%) were the best classification model and the accuracy for fully connected neural network was 99.1% with the range of 98.59%-99.62% based on HOG descriptors. Expected sigmodal kernel all classification method have accuracy more than 99%.

Discussion: simultaneous use of HOG feature extraction method and appropriate classification algorithm such as SVM or fully connected neural network can classify 15-lead ECG heart-beat for different heart disease with high accuracy and adding other relevant patients' information can be easily done in order to increase the method performance.

Introduction

Cardiovascular diseases (CVDs) are one of the leading causes of morbidity and mortality around the world. Based on previous studies, one-third of all annual death worldwide are caused by CVDs [1,2]. Thus, early detection of CVDs and administrating correct medication is crucial for patients and health system in order to reduce the burden of CVDs. There are different biomedical tests to diagnose CVDs, the systematic methods including blood test [3], Electrocardiogram (abbreviated as ECG or EKG) [4], Holter monitoring [5], echocardiogram [6], cardiac catherization [7], computerized cardiac tomography (CT) scan [8] and cardiac magnetic resonance imaging (MRI) [9]. Based on these diagnosis methods and other patients' health-related conditions, such as clinical profiles and past medical history, a physician diagnoses the patient's problem and decides a therapeutic strategy. Making correct strategy mostly depends on correct diagnosis, and it needs careful and talented physicians along with advance tools and methods.

Electrocardiogram provides electrophysiological information of the heart performance through body mass. this method is one of the simple

* Corresponding author.
E-mail address: msheikhbeig@ut.ac.ir (M.A. Sheikh Beig Goharrizi).

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Abbreviation

ECG	Electrocardiogram
HOG	Histogram of Oriented Gradients
SVM	Support vector machine
CNN	Conventional neural network
CVD	Cardiovascular diseases
CT	Cardiac Tomography
MRI	Magnetic resonance imaging
MI	Myocardial Infarction
ACS	Acute coronary syndrome

and oldest cardiac investigations which is fast, non-invasive, and powerful tool to evaluate and diagnose the risk of various cardiac diseases. More specifically, diagnosing the vast majority of arrhythmia diseases such as myocardial infarction (MI) and acute coronary syndrome (ACS) among other similar diseases are solely depend upon multi-lead ECG. multi-lead ECG data are complex, such that even with relevant clinical information non-trained physicians cannot use this powerful tool efficiently. Furthermore, multi-lead ECG contain information that may not recognized by even well-trained experts. Thus, the use of new technologies to aid physicians to diagnose heart disease gain great interest nowadays. During last two decades, various computer-aided diagnosis system (CADS) has been developed by the researchers to analyze ECG data in order to aid physicians to diagnosis CVDs. the ultimate aim of these CADS is to classify the ECG heartbeats automatically, which is quite hard issue for human eyes, since multi-ECG heartbeat data have low morphological variations and complex structure [10,11].

Das and Ari [12] used S-transform and wavelet transform (WT) feature extraction methods to classify five different heartbeats namely normal beat, ventricular beat, supraventricular beat, fusion beat and unknown beat extracted from MIT-BIH database. The authors used Multilayer perceptron Neural Network (NN) for classification task. Abdullah et al. [10] used eight local feature descriptor namely Binary pattern, frequency decoded LBP, Quaternionic local ranking binary pattern, Binary Gabor Pattern, local phase Quantization, Binarized statistical image features, census transform histogram and pyramid histogram of oriented gradients for extracting features from ECG heartbeat images of five type namely normal beat, left-bundle-branch-block beats, right-bundle-branch-blocks beats, premature-ventricular-contractions beats and paced-beats. For classifying the ECG beats support vector machine were used. In other study conducted by Chen et al. [13] a cascaded classification system was proposed to extract features from multi-lead ECG beat from four different open source databases including MIT-BIH Arrythmia Data base, QT Database, MIT-BIH supraventricular Arrhythmia Database and St.petersburg Institute of Cardiological Technics 12-lead Arrythmia Database. For classification task random forest and multilayer perceptron were used. In other study conducted by Gliner et al. [14] two different deep learning methods including CNN-dig and CNN-im were used to classify images of 12-lead ECG signals of normal sinus, atrial fibrillation, first-degree atrioventricular block, left bundle branch block, right bundle branch block, premature atrial contraction, premature ventricular contraction, ST-segment depression or ST-segment elevation. Beak et al. [15] used a new deep learning algorithm for classification of 12-lead ECG signals for identifying atrial fibrillation during sinus rhythm. Kobat et al. [21] used a 3D shape prismatoid pattern-based method for create feature and using k nearest neighbor (kNN) and SVM as classifier. At another work conducted by Tuncer et al. [22] novel Discrete Wavelet Concatenated Mesh Tree (DW-CMT) and ternary chess pattern (TCP) based ECG signal recognition method is used to diagnose heart beat arrythmias. For other similar work see [22,24,25].

In this paper, we aim to introduce a new approach for classifying 15-lead ECG heartbeat of five types of ECG arrythmia including bundle branch block, cardiomyopathy, Dysrhythmia, and myocardial infarction patients along with healthy control. Histogram of Oriented Gradients (HOG) method is used to extract features from images of multi-lead ECGs signals. we use support vector machine (SVM) and fully connected neural network (NN) method for classification task. For SVM method we considered linear, quadratic, cubic sigmodal and radial kernel function. Our approach is different from Abdullah et al. [10] studies. Because in this study we used different type of local feature descriptor method and we used fully connected neural network method for machine learning. Furthermore, we classify 15-lead ECG signals which is hard for even professional physicians because of complex morphological pattern. The reminder of this paper is as follows; in method section we describe the proposed method in details. The proposed method is applied to two types of datasets and the results is reported in result section. Some discussions are made in the discussion section and the paper is concluded in conclusion section.

Method

In this study, two sets of ECG data are used. The first dataset is gathered from patients in heart ward of Baqiyatallah hospital and the second one is from PTB Diagnostic ECG Database located at https://www.physionet.org/about/database [16] Five-types of ECG data are considered in this study for both datasets, namely normal healthy control, bundle branch block, cardiomyopathy, Dysrhythmia, and myocardial infarction patients. For the Baqiyatallah data, 6647 ECG heartbeat and from the PTB Diagnostic dataset 5319 ECG heartbeats were extracted. Each ECG heartbeat record includes 15 simultaneously measured signals including the conventional 12-leads (i, ii, iii, avr, avl, avf, v1, v2, v3, v4, v5, v6) together with the 3 Frank lead ECGs (vx,vy, vz). Wfdb package in Python software was used to get the PTB Diagnostic ECG data from the physionet; more information about the wfdb package can be found at [17]. the proposed method used in this study could be divided into three phases, including ECG signal preprocessing, Predictor extraction and classification. The workflow of the method is summarized in Fig. 1.

At the preprocessing phase; each ECG signals were denoised by one-dimensional total variation regularization (TVR) method. The total variation of spurious details of a signal is removed in this method, while the essential structural details is preserved. In this method if $y \in \mathbb{R}^N$ be a signal observed in additive noise and $F : \mathbb{R}^N \rightarrow \mathbb{R}$ considered as an objective function then the one-dimensional total variation regularization (TVR) is defined as minimizing function F with respect to $x \in \mathbb{R}^N$,

$$x^* = \operatorname{argmin} \frac{1}{2}\ y - x_2^2 + \lambda \sum_n \phi([D_x]_n)$$

where $\lambda > 0$ is regularization parameter [18]. In Fig. 2 one heartbeat before and after denoising is illustrated. It is evident from Fig. 2 that after denoising the main structure of the heartbeat ECG signal is more obvious. Thus, denoising the heartbeat ECG signal make the heartbeat pattern simple, but we do not loss essential information for the classification task.

After denoising the multi-lead ECG signal, heartbeat is extracted by a cardiologist (expert), Fig. 3 illustrate how the ECG signal is segmented by cardiologist for one lead of ECG signal, after determination of segments location (red line in Fig. 3) other 14-lead ECG signals have been segmented based on these locations. Finally, the 15 images of each heartbeat corresponding to 15-lead ECG data saved as jpg formated image (480×480 pixel). In Fig. 4, 15 image of one heartbeat corresponding to 15 different ECG channel are presented.

At the second phase, features of each image are extracted by using Histogram of Oriented Gradients (HOG) method. Actually, these features play as predictors role in the third phase (machine learning or classification task). This method is a feature descriptor that is used

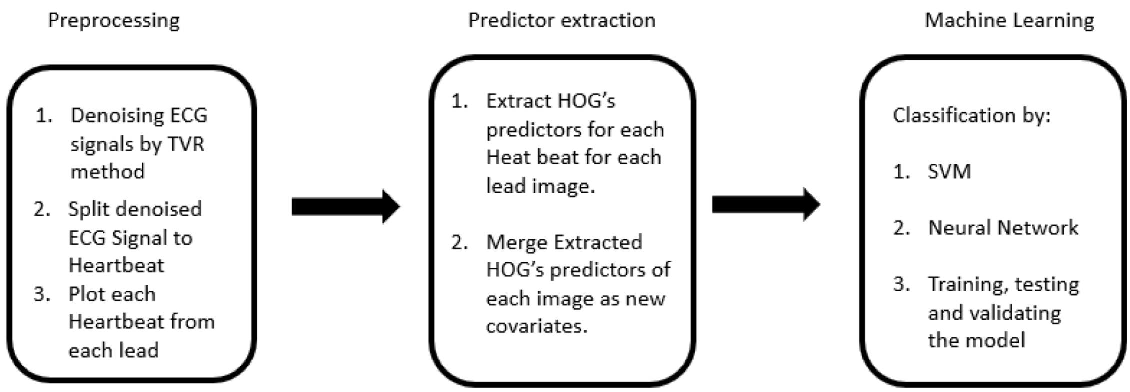

Fig. 1. The workflow of the study.

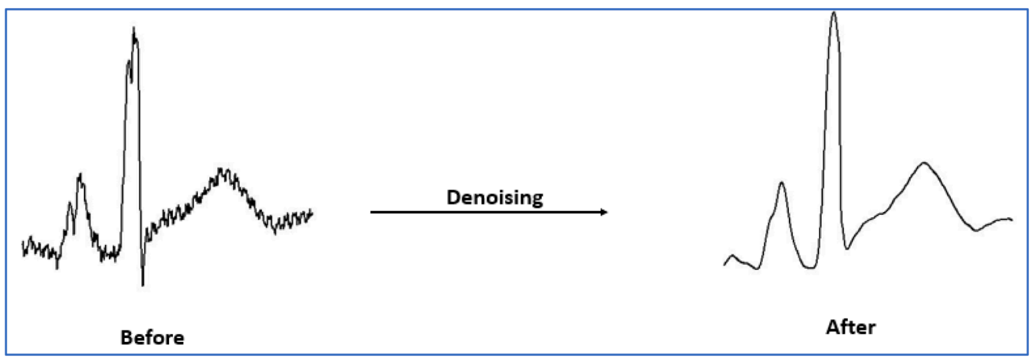

Fig. 2. Heartbeat ECG signal before and after denoising.

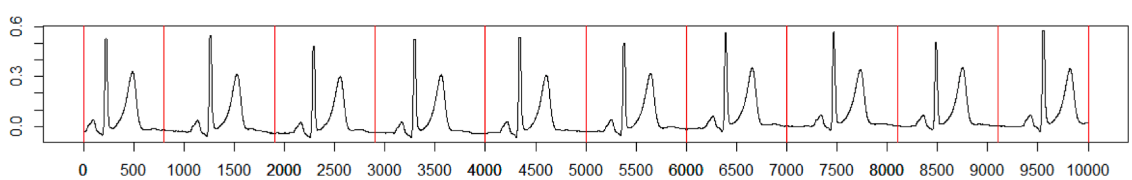

Fig. 3. Segmented one lead of ECG signal by cardiologist (expert), red line determined by cardiologist.

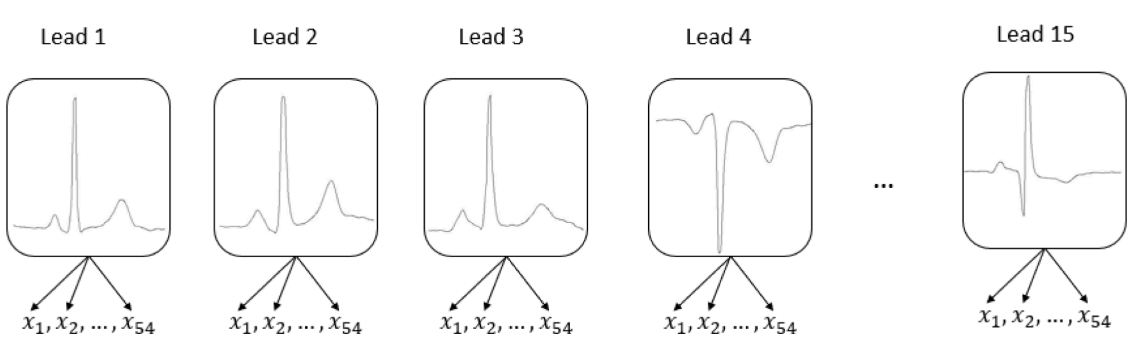

Fig. 4. The generating feature for a heartbeat for different leads (x's are the features extracted by the HOG method from the image of 15 different heartbeats captured by 15 different ECG leads).

widely in computer vision and image processing for the purpose of object detection. The technique counts occurrences of gradient orientation in localized portion of an image [19]. HOG method is applied for each image such that for each heartbeat we have 810 predictor, 54 predictor for each image of ECG channel (Fig. 4).

In the third phase two machine learning methods including SVM and fully connected neural network (NN) are used for classification task. A SVM is a supervised machine learning algorithm that performs classification tasks by constructing a divider or kernel that separates data into categories [23]. The optimal divider is the one which is in equal distance from the boundaries of each group. for SVM machine learning method five kernel function including linear, quadratic, cubic, sigmodal, and radial functions are considered. For the neural network model, we considered one hidden layer, to capture nonlinear relationship, with six nodes (Fig. 5). To evaluate the classification performance of the proposed models, five-fold cross-validation was used.

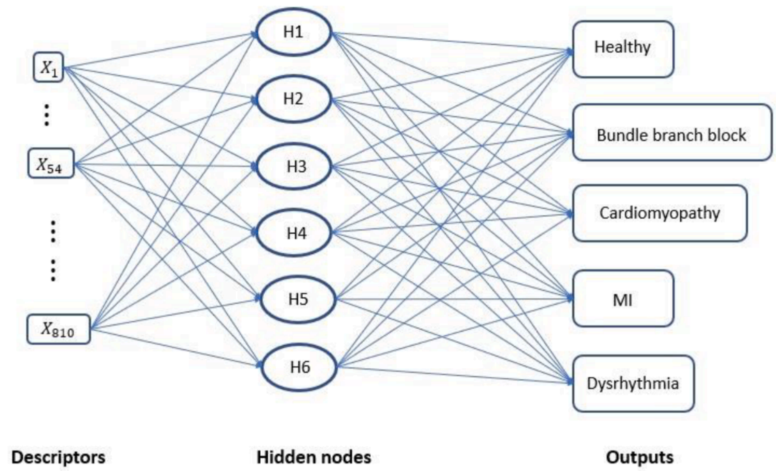

Fig. 5. The structure of Fully Connected Neural Network with one hidden layer and 6 nodes. There are 810 descriptor, 54 descriptors for each lead and there are 15 leads.

The proposed model was coded entirely in R software version (4.0.2). the OpenImageR package was used for importing images and HOG feature extraction. e1071, package was used for conducting SVM and Keras package was used to perform fully connected neural network classification model. Caret package was used to perform cross-validation. cvms package was used to plot confusion matrix. The R code is given at supplementary material.

Results

The mean and standard deviation of the patient's age for the first and second dataset are 62.1 ± 8.7 and 57.2 ± 15.6 years, respectively.

Totally, 6647 and 5319 heartbeats for normal healthy control, bundle branch block, cardiomyopathy, Dysrhythmia, and myocardial infarction patients from PTB Diagnostic ECG Database and Baqiyatallah hospital were considered.

For fully connected neural network the history of training and validation metrics including loss and accuracy by epoch are visualized in Fig. 6 for PTB Diagnostic Dataset, here we considered 2000 epoch and batch size of 100, The loss is plotted on the top panel and the accuracy plotted on the bottom panel.

Form the Fig. 6 we can observed that after 500 epoch the training loss decreases and accuracy increases with every epoch, similar behavior is observed in validation loss and accuracy.

The performance of SVM with five kernel functions including linear, quadratic, cubic, sigmodal and radial along with fully connected neural network model is reported in Table 1. In this table the performance is measured as accuracy based on mean of the results of five-fold cross validation.

Regarding to the results of PTB Diagnostic ECG Database reported in Table 1, SVM model with cubic and quadratic kernel have better performance in comparison with other models, such that the average

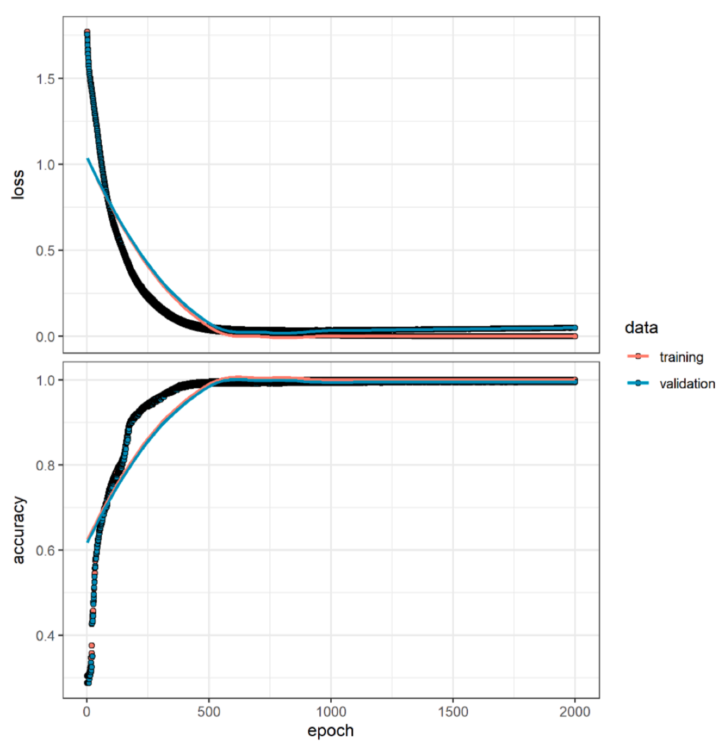

Fig. 6. The History of training and validation metrics, loss and accuracy, for fully connected neural network based on PTB Diagnostic dataset.

Table 1
Classification performance accuracy for SVM with 5 different kernel functions and fully connected neural network for classifying 15-lead ECG Heartbeat Based on HOG descriptor method.

Data set	Classification Method	Accuracy*	Range
Baqyatallah	Neural network	99.1%	98.59%–99.62%
	SVM Linear	99.53%	99.53%–100%
	SVM Quadratic	99.77%	99.62%–99.9%
	SVM Cubic	99.83%	99.72%–100%
	SVM Sigmodal	82.19%	79.79%–84.77%
	SVM radial	99.72%	99.53%–99.91%
PTB Diagnostic ECG Database	Neural network	99.4%	99.02%–99.70%
	SVM Linear	99.86%	99.77%- 100%
	SVM Quadratic	99.88%	99.77%–100%
	SVM Cubic	99.9%	99.77%–100%
	SVM Sigmodal	81.24%	80.3%–81.95%
	SVM Radial	99.8%	99.70%–100

*Average of five-fold cross validation.

accuracy of cubic and quadratic kernel is 99.9% (Range: 99.77%–100%) and 99.88% (99.77%–100%), respectively. in overall, except SVM with sigmodal kernel other models including fully connected neural network, linear, quadratic, cubic and sigmodal SVM models have accuracy above 99%.

The confusion matrix of the cubic and quadratic along with neural network are depicted in Figs. 7-9. These confusion matrices are plotted based on the aggregated results of five-fold cross-validation result in Table 1.

Regarding to the confusion matrix reported in Fig. 7, for Myocardial infarction disease totally from 2012 heartbeat, SVM model with cubic kernel function correctly classified 2008 heartbeat (99.8% accuracy). For Dysrhythmia disease from 1137 heartbeats SVM with cubic kernel

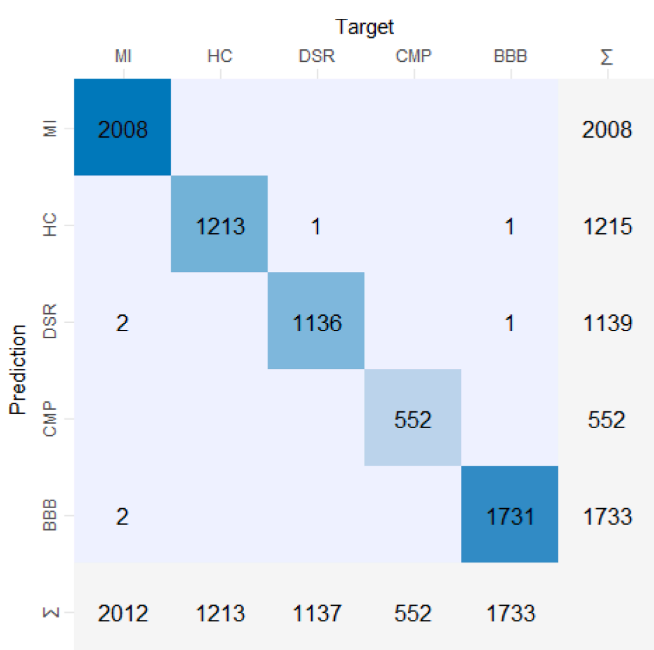

Fig. 7. Confusion matric of SVM with Cubic kernel function based on PTB Diagnostic dataset. in this figure MI, HC, DSR, CMP, BBB represents Myocardial infarction, Healthy control, Dysrhythmia, Cardiomyopathy and Bundle Branch Block, respectively.

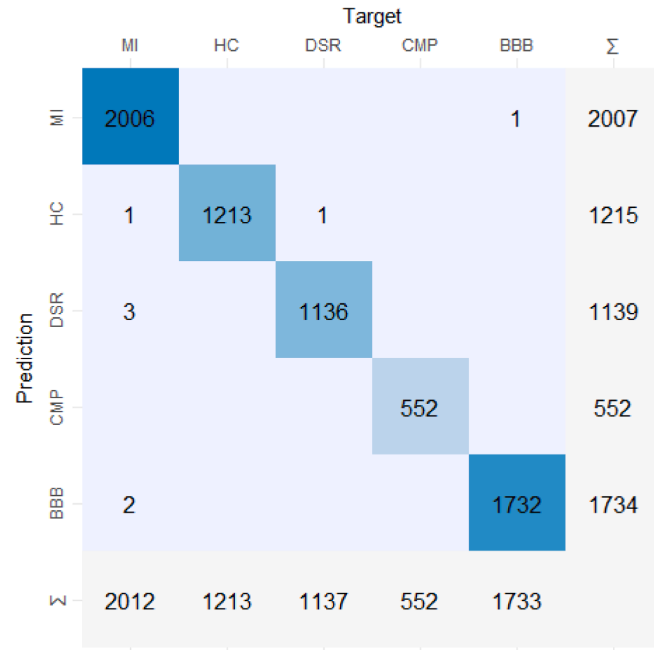

Fig. 8. Confusion matric of SVM with Quadratic kernel function based on PTB Diagnostic dataset. in this figure MI, HC, DSR, CMP, BBB represents Myocardial infarction, Healthy control, Dysrhythmia, Cardiomyopathy and Bundle Branch Block, respectively.

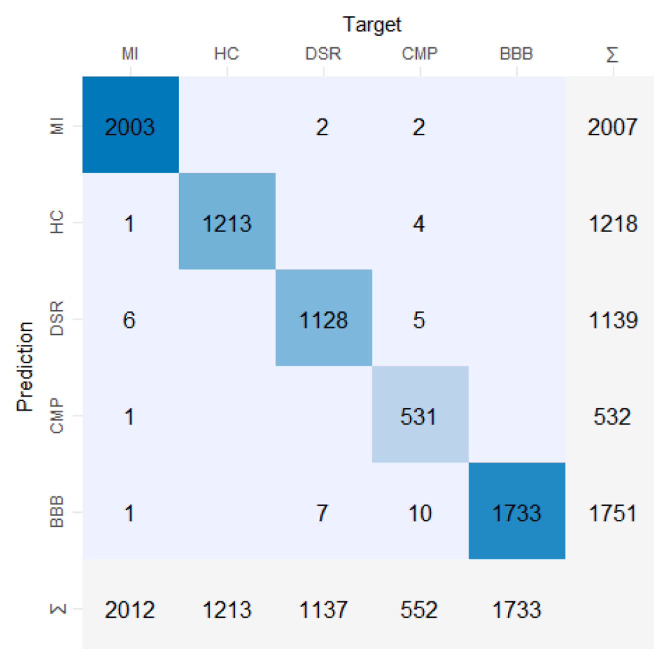

Fig. 9. Confusion matric of fully connected neural network based on PTB Diagnostic dataset. in this figure MI, HC, DSR, CMP, BBB represents Myocardial infarction, Healthy control, Dysrhythmia, Cardiomyopathy and Bundle Branch Block, respectively.

correctly classified 1136 heartbeats (99.91% accuracy) and for Bundle Branch Block disease from 1733 heartbeats 1731 heartbeats were correctly classified (99.88% accuracy). For Healthy control and Cardiomyopathy heartbeat SVM with cubic kernel could classified perfectly.

Regarding to the confusion matrix reported in Fig. 8, Healthy control and Cardiomyopathy had perfect classification by SVM model with quadratic kernel function, but for Myocardial infarction from 2012 heartbeat SVM model with quadratic kernel function correctly classified 2006 heartbeat (99.7% accuracy) and for Dysrhythmia from 1137 heartbeat 1136 heartbeats were correctly classified (99.91% accuracy) and finally for 1733 heartbeats of Bundle Brunch Block disease model classified 1732 heartbeats correctly (99.94% accuracy).

Finally, with regard to the fully connected neural network confusion matrix reported in Fig. 9, this classification model classified Healthy control and Bundle Bunch Block perfectly, but for Myocardial infarction disease from 2012 heartbeat 2003 heartbeats classified correctly (99.55% accuracy) and for Dysrhythmia from 1137 heartbeats 1128 heartbeats were classified correctly (99.21% accuracy) and for Cardiomyopathy disease from 552 heartbeat 531 heartbeats were correctly classified (96.2% accuracy).

Based on final model developed by PTB diagnose data set we used Baqyatallah dataset to evaluate the performance of those trained model. Similarly, we observed that the cubic and quadratic kernel function have better performance for the Baqyatallah dataset, in comparison to the other kernel function. Also, the average amount of accuracy for all method except SVM with sigmodal kernel function were above 99%. The accuracy of fully connected neural network model is 99.1% (Range: 98.59%, 99.62%) (Table 1).

Confusion matrices for neural network, cubic and quadratic SVM model for Baqyatallah dataset is illustrated in Figs. 10-12 with accuracy of 99.1% , 99.77% and 99.83% , respectively.

Discussion

In this study, a method is introduced to classified 15-lead ECG heartbeat of five different types. The introduced method is based on Histogram of Oriented Gradients (HOG) method, this method is widely used for computer vision and object detection in computer science. This method is similar to Edge orientation Histograms, scale-invariant feature transform (SIFT) descriptor, and shape contexts. The concept of HOG method was first described by Robert K. McConnell in 1986. Later in 2005, the usage of HOG became widespread when Navneet Dalat first introduced HOG features in his PhD thesis under Bill Triggs at

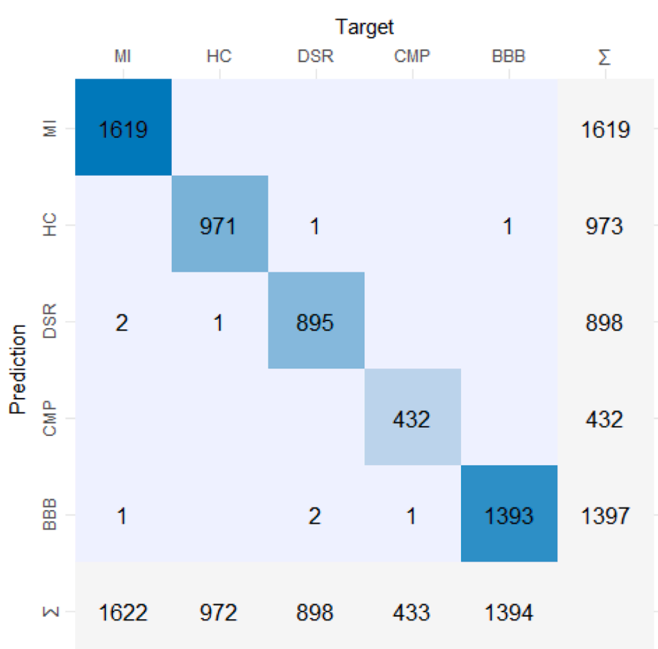

Fig. 10. Confusion matric of SVM with Cubic kernel function based on Baqyatallah dataset. in this figure MI, HC, DSR, CMP, BBB represents Myocardial infarction, Healthy control, Dysrhythmia, Cardiomyopathy and Bundle Branch Block, respectively.

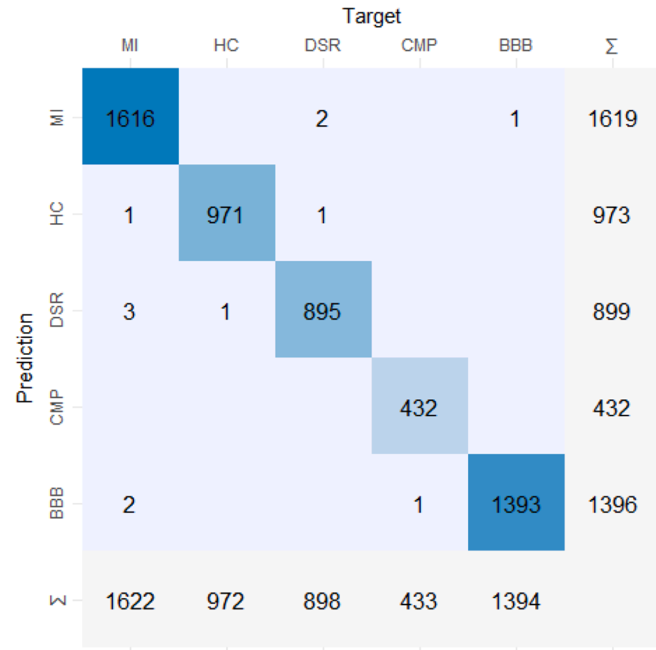

Fig. 11. Confusion matric of SVM with quadratic kernel function based on Baqyatallah dataset. in this figure MI, HC, DSR, CMP, BBB represents Myocardial infarction, Healthy control, Dysrhythmia, Cardiomyopathy and Bundle Branch Block, respectively.

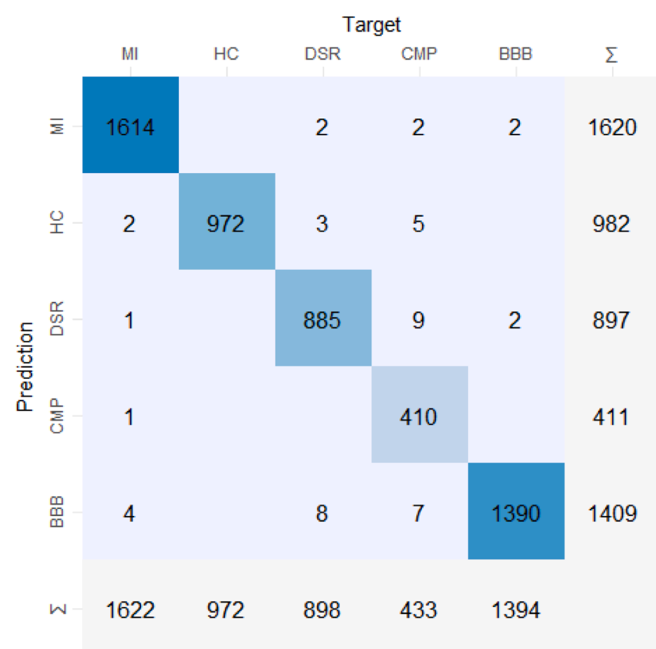

Fig. 12. Confusion matric of fully connected neural network based on Baqyatallah dataset. in this figure MI, HC, DSR, CMP, BBB represents Myocardial infarction, Healthy control, Dysrhythmia, Cardiomyopathy and Bundle Branch Block, respectively.

French National Institute for research in computer science and automation (INRIA). Furthermore, two types of machines learning namely support vector machine and fully connected neural network were considered for classification. For support vector machine learning method five types of kernels were considered namely linear, quadratic, cubic, sigmodal and radial. In fully connected neural network machine learning one hidden layer with 6 nodes were consider. Considering one hidden layer enable the model to capture nonlinear relationship. The proposed method was applied to two types of datasets, the first dataset is from heart disease of Baqyatallah and the second dataset is from PTB Diagnostics database.

We observed that the accuracy of the all considered machine learning methods are more than 80%. More specifically, SVM machine learning method with cubic and quadratic kernel had higher performance in comparison to others. such that, the accuracy of these two methods were more than 99%. According to the findings of this study, simultaneous use of HOG feature extraction method and SVM with cubic or quadratic or fully connected neural network can classify 15-lead ECG heart-beat for different heart disease with high accuracy. The performance of our study is similar to the performance reported in Abdullah et al. [10] study, in contrast to the Abdullah study we used 15-lead ECG heartbeat. Regarding to the multi-lead ECG classification, our approach is as best as the accuracy reported in Gliner et al. [14] study where the reported accuracy for 12-lead ECGs were 98% for CNN-dig and CNN-ima method. Our approach showed better performance in comparison to method introduced by Cia et al. [20].

The limitation of the proposed method in this study is as follows:

- Not fully automatic.
- Not including other patients' information

In this study the heartbeat should be extracted by an expert (cardiologist). the method could be improved by extracting heartbeat fully automatic. Also, the performance of the method could be improved easily by adding other relevant patients' information such as patients past medical history and their clinical profiles to the machine learning phase. These limitations could be coved in future studies.

The benefit of our method is:

- Fast
- Easy to implement

In comparison with fully connected neural network, SVM method had faster and more accurate performance. Also, our method is easy to implement with high accuracy.

Conclusion

The proposed method introduced in this study can be used to assist cardiologists to diagnose different types of heart disease with high accuracy just based on routine patients' ECGs signals. HOGs method along with SVM and NN machine learning method could classify 15-lead ECG signals with high accuracy.

Statements of ethical approval

This study was approved by the Ethical committee of Baqyatallah university of medical sciences, with the ethical code: IR.BMSU.BAQ. REC.1399.010

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.cmpbup.2023.100093.

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