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Deep Learning based Automatic Heart Disease Detection using ECG Signals

Madhuri Kerappa Gawali[1*], Dr. C. Rambabu[2] Dr Aparna Junnarkar
[1*]Research Scholar, University of Technology, Jaipur, India.
[2*]University of Technology, Jaipur, India. And Professor, [3*] PESMOCEPune
[1*] madhurigawali31@gmail.com

ABSTRACT

For medical and clinical applications automated electrocardiogram (ECG) diagnosis may be very useful aid. We had implemented a deep learning approach in building a system for automatic classification and detection of ECG signals for processing. To detect cardiovascular disease in ECG signals we acquired expertise in convolutional neural network (CNN) by using a training data set of 259,789 ECG signals accumulated from cardiac function rooms in tertiary care hospital with facilities. Database provided availability of more than 4000 ECG signal samples taken from various outpatient ECG examinations gathered through 47 subjects: 22 females and 25 males. For normal class confusion matrix processed out from testing dataset showed 99% accuracy. In “atrial premature beat” class, ECG samples were accurately grouped 100% of time. Lastly, for “premature ventricular contraction” class, ECG segments was correctly segregated 96% of time. Totally, we found an average accuracy in classification of about 98.33%. Specificity (SPC) and sensitivity (SNS) was found to be 98.35% and 98.33% respectively. A novel concept dependent on deep learning and, particularly on a CNN network ensuresoutstandingbehaviour in automated recognition hence helping in prevention of cardiovascular diseases and in some cases pre detection so as to take necessary preventive steps.

KEYWORDS: Deep learning, Electrocardiogram, Heart Disease and CNN.

1. Introduction

According to World Health Organization W.H.O reports, in 2015, estimated 17.7 million individuals were died because of CVD [1]. It denotes 31% of the total estimated death around the world. From the early death of these 17.7 million people in 2015, approximately 82% deaths were reported in under developed or developing countries. There are ample factors that were responsible for CVD. According to WHO reports, these risk factors can be classified as: - Major Changeable Risk Factors, Other Changeable Risk Factors, Non-Changeable Risk Factors and Novel Risk Factors [1]. Changeable risk factors encompass high blood pressure, abnormal blood lipids, use of tobacco, lack of physical exercise and activity, Obesity, junk foods and shortage of fruits and vegetable intake, high saturated fat intake etc. Other changeable risk factors consist of use of certain drugs and hormone replacement treatment, mental stress, lipoprotein, degradation in socio-economic status, Left Ventricular Hypertrophy (LVH), alcohol use, depression etc. Non changeable factors include gender, heredity, age, society background and race etc. Novel risk factors include surplus homocysteine in blood, Anomalous blood thickening etc. CVD can be classified on effect, cause and risk factors [1]. CVDs can be predicted with the analysis of ECG and certain parameters such as age, sex, smoking, drinking, blood pressure, cholesterol, etc. These factors can be analyzed by numerous ways. In the last few years the researchers focused on deep learning algorithms to predict CVD. The deep learning algorithms show a better performance as compare to traditional learning algorithms. The basic reason behind its better performance is that the deep learning algorithms are encouraged by working and organisation of neurons in brains. Broadly deep learning algorithms could be classified inalgorithm of reinforcement learning,unsupervised learning algorithms and supervised learning algorithms and [2].

2. Literature Review

Heart is the key part in the human or animal governing body. Heart is an organ which pumps blood through vessels.

It provides oxygen and other nutrients by removing metabolic wastes. There are many diseases which may attack the heart. Coronary sickness is a term covering any disorder of the heart. There is a miniature difference between cardiovascular disease and heart disease. Cardiovascular disease describes problems with diseased vessels, structural problems, and blood clots whereas heart disease refers to issues and malformation of Cardiac Valve. Goings from heart-related disease among provincial Indians has beaten those among urbane Indians, as demonstrated by a foreseen report in the lancet. In previous year's enormous study has been done on the CVD using diverse methods. Different learning algorithms such as Naïve Bayes, Bagging and Boosting Algorithms, Support Vector Machine Algorithms, Decision Tree etc. were projected by researchers [3-7]. The outcome shows that deep learning based systems shows higher specificity, accuracy and sensitivity as compared to conventional algorithms. The medical diagnosis comprises physical examination and present indicators in patient, clinical history of patient and laboratory data. There are a number of parameters for critical medical diagnosis of CVD. There are nearly 70-75 analysis parameters for CVD. However, from theses parameters approximately 13 significant parameters are used for analysis purpose. Theses parameters includes ―Sex, Age, Fasting Blood Sugar (FBs),Chest Pain Type (CP),the slope of the peak exercise ST segment (slope), Maximum Heart Rate Achieved (thalach), Maximum Heart Rate Achieved (thal),Resting Electrocardiographic Results (restecg), Number of major vessels coloured by fluoroscopy (ca), Resting Blood Pressure (Trestbps-in mm Hg), ST depression induced by exercise relative to rest (old peak), serum cholesterol (Chol-in mg/dl), exercise induced angina (exang) etc. Datasets are required for learning, training and validation of deep learning algorithms. Researchers use number of datasets of different patients for diagnoses purpose. Datasets for different attributes for analysis can be obtained from:Cleveland Clinic Foundation available at UCI database[8]; Inonu University Faculty of Medicine, Malatya, Turkey; Sahara Hospital, Aurangabad, Maharashtra, India; Massachusetts Institute of Technology (MIT) database; Central Clinical Hospital No. 2 of Russian Railways JSC; Laboratory of Cardiovascular Imaging and Dynamics, Catholic University of Leuven, Leuven, Belgium; Survey conducted by American Heart Association (http://www.heart.org/HEARTORG/Conditions); database available at physionet ; KNHANES-VI conducted by the Korea Centers for Disease Control and Prevention; Congestive Heart Failure(CHF) database of Beth Israel Deaconess Medical Center (BIDMC) andUniversity Clinic Benjamin Franklin'sDepartment of Cardiology, in Germany‖. There are some other datasets also which were used by researchers. The methodology adopted for implementation of deep learning algorithm is: i) Collection of datasets of patients with different attributes for learning, training and validation purpose. ii) Key attributes selection from the set of ―n‖ no. of attributes and iii) Implementation of deep learning algorithms using selected attributes as input. In the last few years, remarkable research was going in the heart disease prediction system using medical diagnosis parameters. Hongmei Yan et al. [9] proposed a Multi-layer perceptron neural network (MLP) model. Dataset (352 individuals) from Southwest Hospital and Dajiang Hospital, Chongqing, P. R. China, was collected for training, learning and validation. Back propagation algorithm was used. For training purpose data sets of 297 patients and for testing purpose data sets of 55 patients were used. Total 38 input attributes were used in MLP model. These were divided in five main categories: gender, age, inducement and history (5 factors),clinical examinations (17 factors), and clinical symptoms (14 in all). 82.9 % classification ratios on trainingset and test set for chronic corpulmonale was achieved. A hybrid approach using neural network and image analysis was proposed by Scott JA et al. [10]. Dataset of 132 patients for neural and image analysis was collected and analysed. The combined system shows 88% sensitivity and 65% specificity for the diagnosis of ischemic heart disease. Fuzzy logic and neural network based approach was proposed by Kemal Polat et al. [11].

The input attributes from dataset were weighted using Fuzzy Logic. ―Artificial Immune Recognition‖ System was used as classifier for analysis heart disease. Database of Cleveland Clinic Foundation available at UCI database was adopted. Total 13 attributes were used for analysis. K-fold (10- fold) cross validation was used. The proposed system attained 92.30% sensitivity and 100% specificity by using AIRS classifier with fuzzy logic based weighted attributes. M. CengizÇolak et al. [12] put forward a Multi-layered perceptron artificial neural network with eight different algorithms. 237 cases were used for testing and training of model (171 for training and 66 for testing). 124 patients were selected for validation. Eight different algorithms were used for analysis: Conjugate Gradients (CGs) of scaled, Levenberg-Marquardt, Polak-Ribiere (PR), Quasi-Newton (BFGS), Fletcher-Reeves (FR), Powell-Beale (PB), Quasi-Newton (one step secant) and Back Propagation (BP). Resul Das et al. [13] proposed Multi-layered perceptron artificial neural network model. 297 cases were analysed from which 70% cases were used for training purpose and 30% were used for validation. The model was based upon multi-layer feed forward neural network and back propagation learning algorithm. The back-propagation learning algorithm uses three variations: ―Pola–Ribiere Conjugate Gradient (CGP), Levenberg–Marquardt (LM) and Scaled Conjugate

Gradient (SCG)‖. They achieved classification accuracy 89.01%, sensitivity 80.95% and specificity 95.91%. Shaikh Abdul Hannan[14] proposed a prediction system based on RBF NN for analysis. The author collects 300 heart patients' data was collected from Sahara Hospital, Aurangabad, India. 225 patients' data was used for training and 75 patients data was used for testing. Their prediction model shows an accuracy of 97%. The review shows that neural network model can be used to attain improved sensitivity, accuracy and selectivity. In [15] Nazar Elfadil and Intisar Ibrahim proposed a prediction model based on Power spectral estimation and neural network approach. Dataset for training and testing purpose was collected from Massachusetts Institute of Technology (MIT) database. Unsupervised learning approach was used in prediction model. Multi-layer perceptron was used for training and for clustering K-means algorithm was used for clustering. The system shows Specificity of 96.7%, Sensitivity of 89.1% and Accuracy of 92.9%. Applying deep learning, various authors proposed different methods for prediction of CVD based on medical diagnosis [16-26].

3. CNN BASED CLASSIFICATION OF HEART DISEASES

3.1 Adaptation of CNN GeneralArchitecture and Characteristics

In processing of information data that has well known grid like topologies Convolutional neural networks, or CNNs, are a special type of neural network. For examples which include time-series data, that can be thought as an 1-D grid collecting samples at periodic interval of time, image detailed information, which can be considered as a 2-D grid of pixels. General architecture and characteristics of such network are explained in [27], where only difference is rate of sample applied. Current study as well as in [28], rate of sample rate is found to be 44.1 kHz in place of 8 kHz.

Major constituents of deep convolutional neural network is:

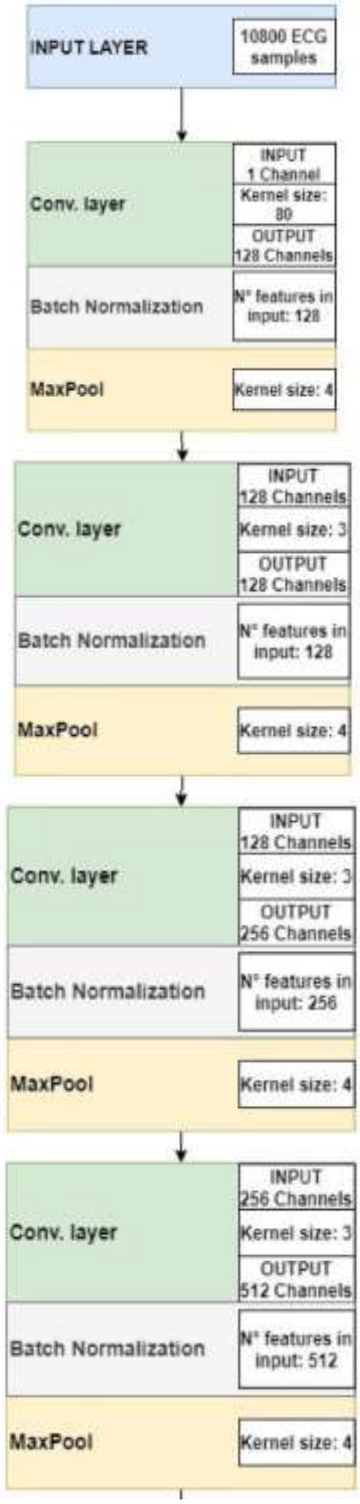
1. Convolution layers of ID;
2. Layers of Batch normalization;
3. Layers of ReLU (Rectified Linear Units) ;
4. Layers of Pooling;
5. Softmax.

In first convolution, application of convolutional kernel consisting of 80 elements wasdone in regardsto subsequent convolution layers was set to 3. This is done with an aim of decreasing computational expenditure.Batch normalization was carried out after each convolution, for avoiding explosion of parameters and phenomenon of vanishing gradients. It had permitted training deep networks and was usedpost every convolutional layer and before conducting ReLU (rectified linear activation function). Height of pooling in CNN which is placed before RELU had decreased issues of information over fitting by network, by taking input size by half actual input.This net performed a single AvgPool and then a LogSofMaxsoftmax, Contrary to pre-existing CNN that were using fully joined neurons as an output layer, cascaded by natural logarithm log (softmax (x)). Structure of proposed network is shown below in table.

Table 1. Proposed network's structure

SAMPLES OF ECG	**10,800's INPUT Vectors**		
FIRST LAYER	Conv1D (1, 128, 80, 4): 1 channelsinput 128 channelsoutput kernel_size 80 stride 4	BatchNorm1D (128): N_features: 128	MaxPool1D: kernel_size 4
SECOND LAYER	Conv1D (128, 128, 3): input 128 channels output 128 channels kernel_size 4	BatchNorm1D (128): N_features: 128	MaxPool1D: kernel_size 4
THIRD LAYER	Conv1D (128, 256, 3): input 128 channels output 256 channels kernel_size 4	BatchNorm1D (256): N_features: 256	MaxPool1D: kernel_size 4
FOURTH LAYER	Conv1D (256, 512, 3):	BatchNorm1D (512):	MaxPool1D:

	input 256 channels output 512 channels kernel_size 4	N_features: 512	kernel_size 4
LAYER AT OUTPUT	AvgPool1D (30): kernel_size 30	Linear (512, num_classes): input 1 _ 512output num_classes: 3	Log Softmax



First Layer

Second Layer

Third Layer

Fourth Layer

Layer at Output

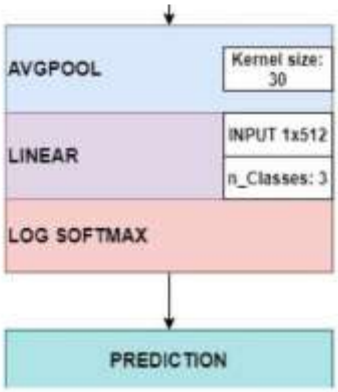


Figure 1. Architecture of Convolutional neural network.

Representation of features can classified and extracted by deep neural networks, rather than performing these two functions separately. ECG recording were sent to CNN network as input after being processed,for classification of pathologies by means of ECG signalbased on convolutional neural networks (CNN) into three classes: premature ventricular contraction, atrial premature beat and normal.

3.2 Testing and Training/Validation Dataset

Input of Neural network constitutes of 30-s segments where each second of ECG's recording is equal to 360 samples, out of 10,800 samples.

Following classes is presented by dataset:

- "Normal" class, constituting 1421 ECG segments;
- Class of "Premature ventricular contraction" that includes 335 ECG samples;
- 133 ECG segments belongings to "Atrial premature beat" class.

Dataset was thenclassified in two separate datasets, observe Figure 2 below:

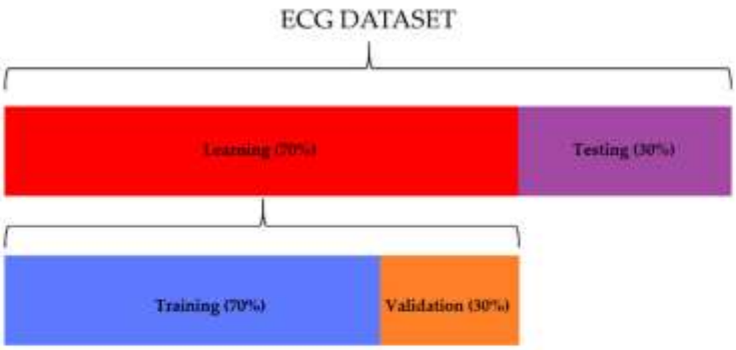


Figure 2. Classification of ECG segments utilized inTesting (30%) and learning (70%). For validation of networkthirty percent of learning dataset were applied.

Testing set, consisting of 40 segments for the atrial premature beat class 426 segments for the normal class and 101 segments for the premature ventricular contraction class. Validation/Training set, contain 93 segments for atrial premature beat class 995 segments for normal class, 234 segments for premature ventricular contraction class, and. The 70% of this set was used for the training, and the other 30% was used for the testing. Primarily, as input, network was trained by putting information concerning to training set then in order to evaluate performance of neural network (percentage of loss and accuracy) it was validated using validation set. Finally, with accuracy estimation, robustness of neural network to data external to the training/validation set, testing set was used verify and validate.

4. METHODS

For the purposes of performance evaluation as mentioned earlier, said research is utilized for PhysioNet database, typically based on ECG signals implemented as a reference database for automated segregation of cardiac pathologies. Out of such dataset, information related in testing and learning of neural network was receivedfor evaluation of classification accuracy of this technique. This precision showed that network performed with good classification of two groups which concerns in heart disease (premature ventricular contraction and atrial premature beat) and another relating to good state of health. It was possible in assessing proposed method, depending on results achieved from confusion matrix, when applied with statistical classification functions [29]: True positive ratio (TPR), also known as sensitivity, came to be called as true negative ratio (TNR) too, false positive ratio (FPR) also known asFall – Out andrate of test accuracy.

Therefore, it became easy in defining meaning of each statistical classification parameter mentioned before: percentage of ECG recordings was indicated by sensitivity that belongs to a certain category and correctly grouped in that class; how often classifier could classify ECG recordings not belonging to that category was evaluated by specificity ; ECG recordings were considered to belong to a specific category was shown by Fall–Out, however, in real sense, they dint took active participation in it; false discovery ratio indicated that ECG recordings were not considered to belong to a specific category but that, in reality, they were part of it; F1 score took into account precision and recovery of test, where precision was the number of true positives (TP) divided by the number of all positive results, i.e., true positives (TP) plus false positives (FP); while recovery was ratio of number of true positives (TP) to number of all tests that could have been positive, means true positives (TP) added false negatives (FN) too.

Following equations co-relate to classification functions mentioned earlier described.

$$\mathrm{TPR} = \frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FN}}, \tag{1}$$

$$\mathrm{TNR} = \frac{\mathrm{TN}}{\mathrm{FP}+\mathrm{TN}}, \tag{2}$$

$$\mathrm{FPR} = 1 - \mathrm{TNR}, \tag{3}$$

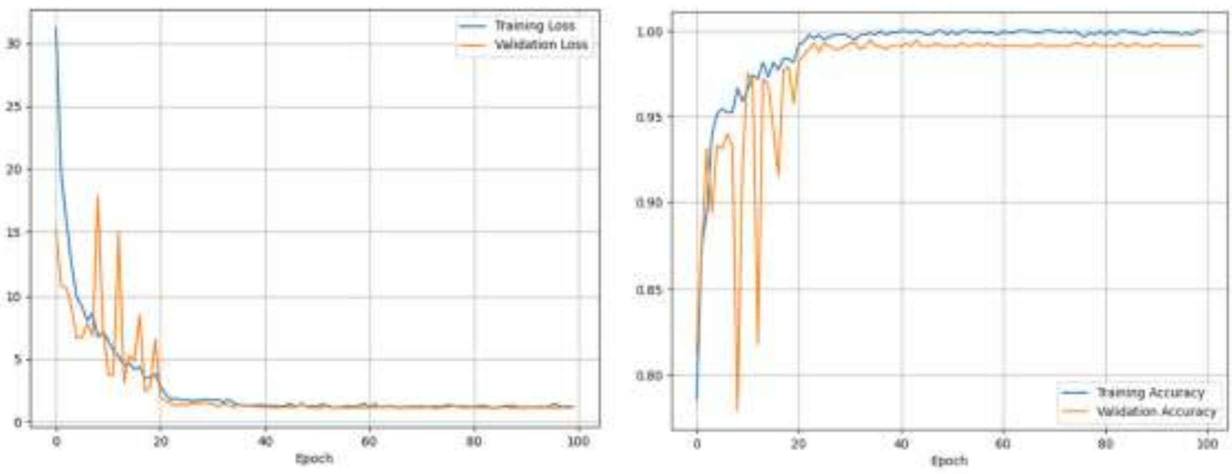
$$\mathrm{FDR} = \frac{\mathrm{FP}}{\mathrm{FP}+\mathrm{TP}}, \tag{4}$$

$$\mathrm{F}_1 = \frac{2\mathrm{TP}}{2\mathrm{TP}+\mathrm{FP}+\mathrm{FN}}. \tag{5}$$

5. ANALYSIS OF PERFORMANCE

5.1 Test Results

In this section, outcome of validation and subsequent training of neural network are explained and discussed. Figure 3a and 3b shows progression of training and validation loss and progress of training and validation accuracy, respectively. Asshown in graphs, after 100 epochs, validation and training losses stabilized at a measured value approximate to zero (Figure 3a), whereas stability stands for training and validation accuracy stabilized is at 100%.These information were very enthusiastic, as it is known that there was a good percentage of accuracy in categorizationof three groupsas explained above.Accuracy obtained with testing set was assessed so as to measure behaviour of CNN network with ECG sequences external to training dataset. Relative confusion matrix is as shown in Figure 4.An average classification accuracy level of 98.33% is highlighted by matrix. Outcome thus recieved in form of statistical parameters depicted in Table 2.



(a) (b)

Figure 3. (a) Training and validation losses, (b) training and validation accuracy

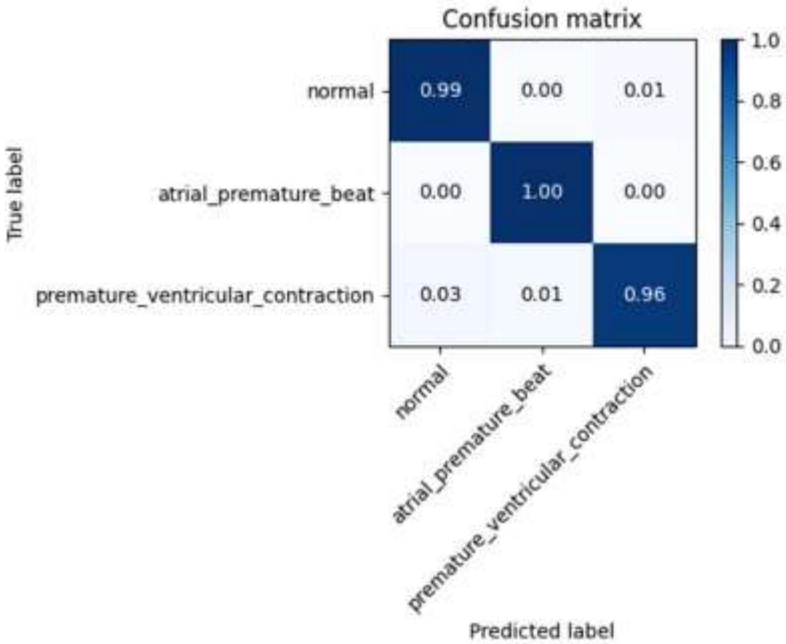


Figure 4. Confusion Matrix for “testing set”.

Table 2. Overall values of accuracy TPR, TNR, TPR, TDR, and F1 score

α	Class	TPR	TNR	FPR	FDR	F1 Score
1	Normal	99.0%	97.1%	2.9%	1%	98.0%
2	Atrial premature beat	100%	99.0%	1.0%	0%	99.5%
3	Premature ventricular contraction	96.0%	98.96%	1.04%	4%	97.5%
Mean Accuracy	98.33%	98.33%	98.35%	1.65%	1.66%	98.33%

5.2 Analysis Cross-Validation

This section involved discussion of we have explained techniques that was used for cross-validation of information, that were applied achieve reliable prediction of generalization error of this method, or how CNN network performs on information except learning data.

Specially, cross-validationK-fold [30] were utilized in these research that consist randomly segregating training dataset in k parts by not reintegrating: K-1 parts was applied for training this method, and some part were used for testing purposes. This process was frequently done k times to obtain k models and behavioural assessment.

Then, average performance of these models was evaluated depending on various independent subsections to get an estimate of behaviour that was least sensitive to partitioning of training information.

As cross-validationk-fold is a repetitive sampling without reintegration method, benefits of such concept is that every sample point would be a part of test and training datasets only one time, that gives an estimate of lower variance estimate in template performance.

For such research, training dataset was subdivided into ten constituents that is K = 10, and through ten iterations, one part was used as a test set for model evaluation and 9 parts was utilised for training. Additionally, estimated behaviour E_i (for instance, precission of classification) of every part were then applied in evaluating average estimated performance E of models. Concept of k-fold cross-validation technique is shown in Figure 5. Standard deviation andaverage accuracy for model utilized in this research were found to be 96.8 $\pm$ 1.2%.

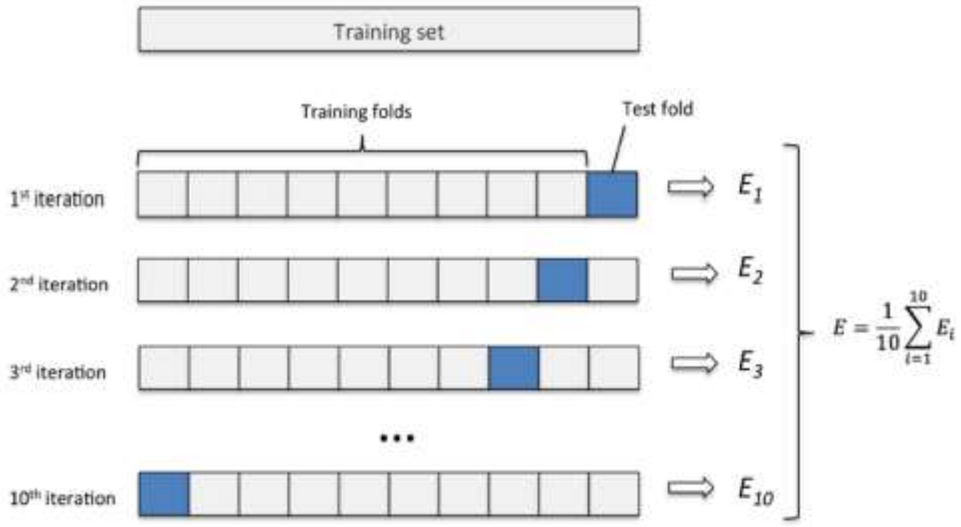


Figure 5. K-fold cross-validation method with subdivision of the training set into k = 10 parts

Comparison between our method and other techniques in form of feature extraction(FE) is shown in Table 3, statistical classification accuracy, system's accuracy and model used. After this, variation amongststate-of-the-art and this work have been talked about.In [31 32], researchers applied extraction ofR-peak (RP) and decision tree (DT) as its characteristic and does not implement convolutional neural networks (CNN) , howeverrather feed-forward neural network (FFNN)and discrete wavelet transformation (DWT). Writer stated that an average accuracy of 96.56% and87.66% respectively, whereas, in our research 98.1% was an average accuracy. This outcome wasmore comparatively to that of result proposed in [31, 32].

Distinguishingly tosuggested approaches in [31 - 36], our technique had more groupingperformances. Concerning to concept as put forth in [36] , it is proved that they exhibit comparative behavior, but they have applied additional concealed layers than as shown in our study, with an effective risein computation expenditure. moreover, using wavelet transformationthey did a preprocessing of information,which enforce extra computational investment. In perspective to structure of neural network in [36], particularly five layers (one full connection layer,two down sampling layers,andtwo convolution layers) additional to output layer generated by Softmax were applied in classification;but, we used separate structure (formerlymentioned), that were more dynamic to phenomenon of "vanishing gradients".

Table 3. Comparison between the proposed method and those previously studied.

Method	FE	Model	ACC	TPR	TNR	FPR	FDR
Ranjan et al. [32]	RP	FFNN	87.66%	94.04%	76.21%	5.96%	23.79%
Sridhar et al. [31]	DT	DWT	96.56%	90.87%	98.45%	9.13%	1.55%

Beritelli et al. [33]		PNN	96.53%	93.1%	100%		
Acharya et al. [34]	RP	11-layer CNN	95.22%	95,49%	94.19%		
Savalia et al. [35]		MLP/5-layer CNN	88.7%/83.5%				
Li et al. [36]	Wavelet transform	6-layer CNN	97.5%				
Proposed method		5-layer CNN	98.33%	98.33%	98.35%	1.65%	1.66%

6. Conclusion

Depending on recent and innovative CNN networks this paper suggested an automated heart disease recognition technique. Proposed method had low complexity and high accuracy of implementation. To capture distinctive characteristics of given heart disease in ECG signal diaspora this concept harnessed significance of deep learning. By implementing “validation set”, proposed techniques produced following results:

- mean accuracy of 98.33%;
- sensitivity of 98.33% ;
- specificity of 98.35% ;
- false positive ratio of 1.65%;
- false negative ratio 1.66%;
- F1 score of 98.33%.

By Contrasting and comparing different techniques, we could confirm that method used in current paper produced considerably good behaviour than those of state-of-the-art techniques.

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