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FA-1D-CNN Implementation to Improve Diagnosis of Heart Disease Risk Level

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Abstract **-** During the last decade heart disease become the leading cause of death around the world. Improving the accuracy of detection of heart disease from readily available biomedical data will enhance possibility of early treatment and low mortality rate.
This paper proposes a heart disease diagnosis system using feature optimization algorithm from firefly algorithm (FA) which is a nature inspired swarm technology and a deep learning technique called convolutional neural network (CNN). The automated diagnosis overcomes the problem of nonstationary and nonlinearity nature of ECG wave. FA performs better by finding the global optima faster than other contemporary nature inspired algorithm such as: genetic algorithm or particle swarm optimization.
The method was trained and tested using two separate clinically available electrocardiogram (ECG) databases against other machine learning algorithm. The correctly classified outcome using FA-CNN is 88.25% with kappa statistics of .703, while 84.26% correctly classified outcome and kappa statistics of .63 was achieved using same approach without using FA.

Keywords**:** Firefly algorithm, Deep learning, Convolutional neural network, Heart disease prediction.

1. Introduction

Cardiovascular disease (CVD) and stroke are the two leading cause of death in the world. About 735,000 people in the U.S. have heart attacks each year, of those about 120,000 die [1]. According to World Health Organization (WHO) approximately 17.7 million people died from CVDs in 2015 [2]. These statistics alone are sufficient to signify the importance of studying cardiovascular activity of human so that necessary measures can be taken to prevent any potential severe consequence. Since many features from heart signal reflect the function of the heart, it is difficult for the physician to quickly and accurately perform diagnosis. Correct early detection of heart disease can provide the chance to patient to take proper medication, lifestyle change or surgery if necessary before it is too late [3]. By employing computerized technologies for heart disease diagnosis, the physician can come to a faster and more accurate conclusion.

Based on soft computing, currently there are several heart disease diagnosis systems being proposed by researchers. Integration of different techniques together to make hybrid models is prominent because they perform better than the use of a single technique [4]-[9]. Many researchers have investigated feature selection for heart disease diagnosis, prominently based on support vector machine (SVM) [8]. SVM classifier was combined with forward feature inclusion [4] and uses multivariable adaptive regression splines to reduce the set of explanatory features [10], then use particle swarm optimization (PSO) [11]. Recently, rough set theory has been used to investigate data dependencies and reduction of data attributes, also greedy heuristics were applied to find attribute reduction as well based on rough set [12], [13]. Though these approaches are fast, but they may work for the heuristic feature selection only [14]-[16]. Meta-heuristic algorithms were applied for attribute reduction based on rough set was also investigated [14]-[16]. Firefly algorithm is one of the recent swarm intelligence techniques that rely on flashing behaviour of fireflies in nature which finds the global optimal solution in the search space and is used to solve many difficult combinational optimization problems [17]. It showed higher success rate than PSO or genetic algorithm because this algorithm is more efficient in finding the global optima [18].
Researchers have utilized several computer-aided heart disease detection methods using clinical data, such as: decision trees [19], support vector machine [20], ensemble machine learning [21], rotation forest classifier [22], K-star algorithm [23], neuro fuzzy classifier [24], Bayesian algorithm[25], artificial neural network (ANN) [26] and rule organization method [27], [28], etc. Most of these approaches use heart rate variability (HRV) as an accurate marker for heart disease, but building HRV based model is time consuming as well as prone to error due to large amount of pre-processing and

manual selection of appropriate features. Among the most ANN based methods which have been researched, several hybrid models are widely adopted in medical diagnosis due to their ability of handling complex linear as well as non-linear models [29]-[32]. Though these ANN-based methods provide useful decision support system to an extent, the attributes for heart disease are generally assumed to have equal contribution. Whereas, there exist several researches providing proof that the heart disease attributes have varying range of contributions to the overall outcome of disease diagnosis [33]-[35]. Deep learning is a representation based learning which consists of one input layer, hidden layers and one output layer. It follows a systematic approach where the network is fed data and automatically learns the necessary framework for classification, whereas multiple hidden layers explain the word “deep” in learning [36]. Using back propagation algorithm, a convolutional neural network (CNN) is one of the most popular neural network techniques [37]. For several decades, CNN has been used in computer vision, analysing healthcare data, medical images, pathological images, MRI and X-ray images, pattern recognition, electron transport proteins etc.[38]-[50].

In this paper, we propose an integrated decision support system for heart disease detection based on efficient hyperplane framework with 1D-CNN that utilizes one of the most well-known natural inspired swarm intelligence systems called firefly algorithm (FA). In [51]-[53], combination of FA and 2D-CNN has been applied to medical image analysis to perform diagnosis. In this work, the combination of FA and 1D-CNN of physiological signal to diagnose heart disease is proposed. The proposed approach is significantly less computationally extensive than diagnosis using image analysis.

The 1D-CNN is able to reduce network units using convolution layers. The use of FA-CNN provides faster global optima than other swarm intelligence algorithms [18]. It has superior performance over other classification techniques using physiological signals [54]-[56], which have used 1D CNN only. To our knowledge, this method is the first one to investigate the performance of FA-1D-CNN with physiological signals. The proposed method involves two sequential steps, firstly FA is used to properly rank and optimize the number of features or attributes, and secondly the chosen optimized attributes are applied to train a 1D-CNN classifier using an online dataset (PTB Diagnostic ECG Database) for prediction of heart disease. The performance of the proposed method (FA and 1D-CNN) was evaluated by using a separate dataset called MIT-BIH from physionet.

2. Materials and methods

In section 2.1, the clinical data for heart disease are discussed. In sections 2.2 & 2.3, the background for FA and CNN are provided. In section 2.4, the implementation of FA-CNN is discussed.

2.1. Heart disease dataset

In the study, the PTB Diagnostic ECG Database was used to train and validate, MIT-BIH collected from physionet was utilized to evaluate the performance of the proposed hybrid model identifying heart disease among patients [57]. In PTB dataset there are 549 records for 290 subjects with 52 are healthy. For each record , 180 sample points were collected from randomly chosen beat and from the P,Q,R,S,T points the 10 more segments or interval were also calculated. These 190 features will be input for the firefly algorithm for feature optimization. For evaluate data, from MIT-BIH database 500 randomly selected ECG fragments were used.

2.2. Nature inspired swarm intelligence: Firefly algorithm (FA)

Firefly algorithm is a multimodal optimization algorithm based on flashing characteristics of fireflies in nature. The main assumption is each solution (firefly) moves towards more attractive solutions (fireflies). Since the real firefly behaviour is much more complex and sophisticated it requires some simplified rules to use them in other practical diagnoses. According to Yang who proposed the firefly algorithm [17], fireflies have three major attributes towards other fireflies as principles: 1. Regardless of their sex they are attracted to each other due to being unisex in nature, 2. The brighter they are the more attractive they become, 3. Computation of brightness is based on an objective function, distance between fireflies are inversely proportional to brightness and attractiveness [17], [18].

Firefly algorithm has two parameters: the variation in light intensity and the attractiveness of firefly to each other. The light intensity L(r) changes inversely proportional to square of distance according to following formula in Eq. (1):

$$L(r) = \frac{L_S}{r^2} \tag{1}$$

where, the intensity of the light source is L(r) and the fitness function is LS for a maximization problem. LO is the intensity at the source (r=0), and for a fixed air absorption coefficient "γ", the light intensity L varies with distance "r" as shown in Eq.(2)The combination of effects from inverse square law and the absorption law can be expressed as an approximation as Eq. (3) [17]:

$$L(r) = L_0 e^{-r\gamma} \tag{2}$$

$$L = L_0 e^{-r^2\gamma} \tag{3}$$

The attractiveness A of any firefly is proportional to its light intensity of other fireflies adjacent to and AO is the attractiveness at r=0,

$$A(r) = A_0 e^{-r^2\gamma} \tag{4}$$

The distance d_{ij} between two fireflies i and j at point x_i and x_j in Cartesian coordinate system is:

$$d_{ij} = |x_i - x_j| = \sqrt{\sum_{k=1}^{l} |(x_{ik} - x_{ik})|} \tag{5}$$

The firefly i can travel towards firefly j using Eq. (5), [17]:

$$x_i^{t+1} = x_i^t + A_0 e^{-\gamma r_{ij}^2}(x_j^t - x_i^t) + \alpha\,(rand - .5) \tag{6}$$

The first part of Eq. (6) denotes the current location of firefly i, the second term is used to determine the attractiveness (A) of a firefly towards a neighbouring firefly, and the third term indicates the random walk of a firefly. When the firefly i does not find an attractive firefly j nearby, then it will go for a random walk using the third part of Eq. (6), where α is a randomization parameter and rand ([0, 1]) function generator. FA is controlled by three parameters: the randomization parameter α, the absorption coefficient γ and the attractiveness A. FA shows two distinguished asymptotic behaviour, when γ is zero, A becomes AO and when γ becomes infinity, the second part in Eq. (6) vanishes and the firefly movement becomes a random walk

2.3. Convolutional neural network

In convolutional neural network are similar to artificial neural network (ANN) in a way that they are also comprised of neurons that self-optimize through learning. There is an input layer, a number of hidden layers and an output layer in both cases. The major difference between them is that in CNN only the last layer is fully connected, but in ANN all the layers are fully connected. Also, in CNN the hidden layers are named differently due to their functionality such as: convolution layer, the rectified linear unit, pooling layer, etc. In Fig.1 a common architecture of convolutional neural network comprised of the layers is shown.

Conventional 2D CNN are used to implement pattern recognition or classification of mostly images, an alternative version which is 1D CNNs are useful with 1D signals due to reasons such as: simplification of matrix operation by replacing it with array operation in back propagation (BP). 1D CNN has shallower architecture than the 2D counterpart, 2D CNN requires cloud computing or GPU, while 1D CNN can be implemented using a standard computer, due to the low computational requirement of 1D CNN. This network is well suited for real time and low cost applications. Three consecutive CNN layers of a 1D CNN is shown in fig. 2.

The 1D CNN filter kernel size is 3 and sub sampling factor is 2 where kth neuron in the hidden layer ‘l’ first goes through sequence of convolutions, which later passes through the activation function ‘f’ after that is the sub-sampling operation. In 2D CNN the array is replaced by matrix of kernel and feature maps. Next, the CNN layers process the raw data and extract only features which are used in classification in next layers which are fully connected. The reason behind being less computational than 2D is that 1D CNN does a sequence of 1D convolution which is simply linear weighted sum of two 1D arrays. In each CNN layer, the 1D forward propagation is expressed as in (7):

$$x_k^l = b_k^l + \sum_{i=1}^{N_{l-1}} conv1D\,(w_{ik}^{l-1}, s_i^{l-1}) \tag{7}$$

$$E_p = MSE\,\left(t^p, [y_1^L, \dots, y_{N_L}^L]'\right) = \sum_{i=1}^{N_L} (y_i^L - t_i^p)^2 \tag{8}$$

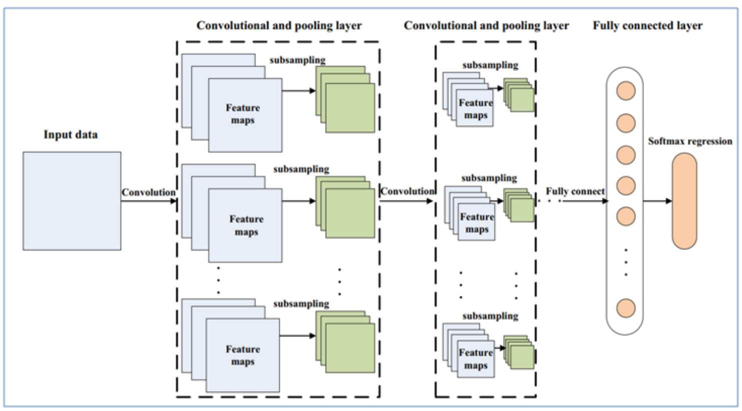

Fig. 1: Convolutional neural network architecture [61].

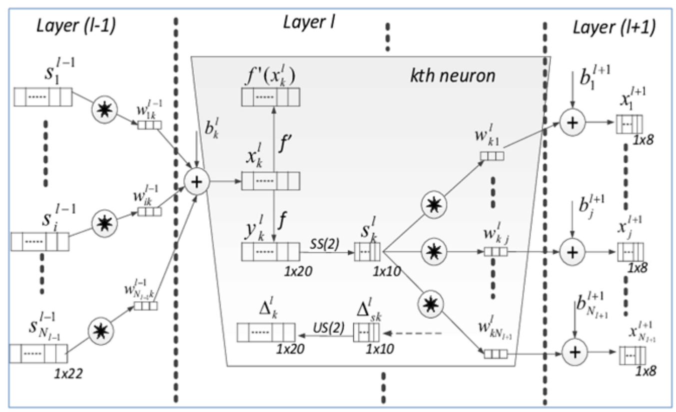

Fig. 2: Three consecutive hidden CNN layers of a 1D CNN [62].

Where, x_k^l is as input, b_k^l is bias of k^{th} neuron at layer ‘l’, s_i^{l-1} is the output of i^{th} neuron at layer l-1, w_{ik}^{l-1} is the kernel from the i^{th} neuron at layer l-1 to the k^{th} neuron at layer l. if the t^p is the target and $[y_1^L, \dots, y_{N_L}^L]'$ is the output vector respectively, the mean-squared error (MSE) can be obtained in (8) . From the first multi-layer perceptron (MLP) to the last convolutional neural network layer, the regular back propagation is done as in equation (9),

$$\frac{\partial E}{\partial s_k^l} = \Delta S_k^l = \sum_{i=1}^{N_{l+1}} \frac{\partial E}{\partial x_i^{l+1}} \frac{\partial x_i^{l+1}}{\partial s_k^l} = \sum_{i=1}^{N_{l+1}} \Delta_i^{l+1} w_{ki}^l \tag{9}$$

2.4. Implementation of FA-CNN

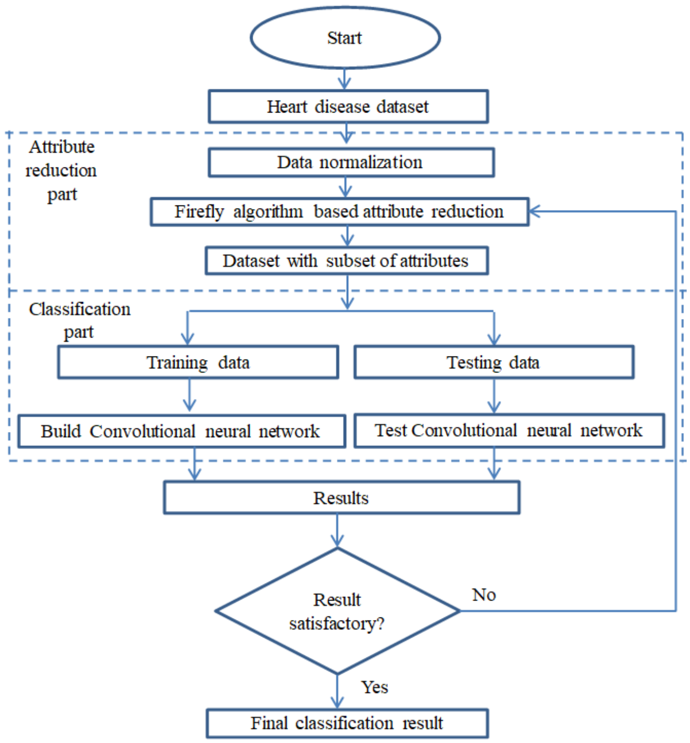

Fig. 3: Whole FA-CNN system for heart disease diagnosis.

In fig.3, the whole disease diagnosis system is shown. The system begins with putting the dataset through normalization and FA for optimized set of features.

Normalization is applied to avoid numerical difficulties during computation process so feature with greater range does not dominate the features with smaller range. Next, FA process started with two steps: exploitation and diversification. Using Eq. (6), the movement of a feature (firefly) is decided and on other side the diversification is done by changing the parameter γ and A. When γ=0 then A=A_O in that case the value of A is the largest possible and the solution moves towards other solution with largest possible leap so the diversification is minimum, while the exploitation is maximum. On the other hand when γ is infinity then A=0, so each feature (solution) moves in a random way so there is no exploitation at all.

ECG featured before optimizations were 180 feature points from each segment of 500 records, adding with 10 more feature from intervals. From the ranking of firefly algorithm 24 feature were selected as input for the CNN so the convergence and reliability increases.

In this work, the proposed convolutional neural network consists of 6 layers including 2 convolutional layers, 2 max pooling layers and 2 fully-connected layers. In every convolution layer, the layers are convolved with the respective kernel (4 for 1st convolution layer, 3 for 2nd convolution layer). The objective of max pooling is to reduce the number of features, the stride for convolution and max-pooling layers are 1 and 2 respectively. The fully connected output layers have output neurons as 8 and 2, respectively. Ten-fold cross validation [63] has been applied, where the total patient number is divided into 10 equal clusters in random, where 9 were used to train for the proposed model and 1 to validate the diagnosis effectiveness. MIT-BIH database were used to evaluate the performance of the convolution neural network.

3. Performance Evaluation

To provide a comparison among classification techniques the following evaluation parameters were used: correctly classified, incorrectly classified, kappa statistics, mean absolute error, true positive (TP) rate, false positive (FP) rate, precision, recall and F-measure. Kappa statistics (K_S) is defined as ratio of (Observed agreement-Expected agreement) and (1-Expected agreement).

So when two measurements agree by chance, the K_S is zero and when two measurements agree perfectly the K_S value is 1.0. True positive rate when the model correctly predicts the positive class similarly, the false positive rate is an outcome when the model incorrectly predicts the positive class. The formula for precision, recall and accuracy are given as : Precision = (TP/TP+FP), Recall = (TP/TP+FN), Accuracy = (True positive +True negative)/Total outcome and F-Measure = 2*(precision*recall) / (precision + recall).

In table1, a comparison of statistical parameters related to the performance evaluation among the common classification techniques and the proposed method is shown. High precision means that an algorithm returned substantially more relevant results than irrelevant ones, while high recall means that an algorithm returned most of the relevant results.

Table. 1: A comparison among classification techniques performance

Classifier	Precision	Recall	F-measure
Proposed method	0.853	0.867	0.860
Proposed method without FA	0.828	0.832	0.830
Random Forest	0.78	0.805	0.792
ANN	0.813	0.814	0.813
Logistic regression	0.774	0.783	0.778

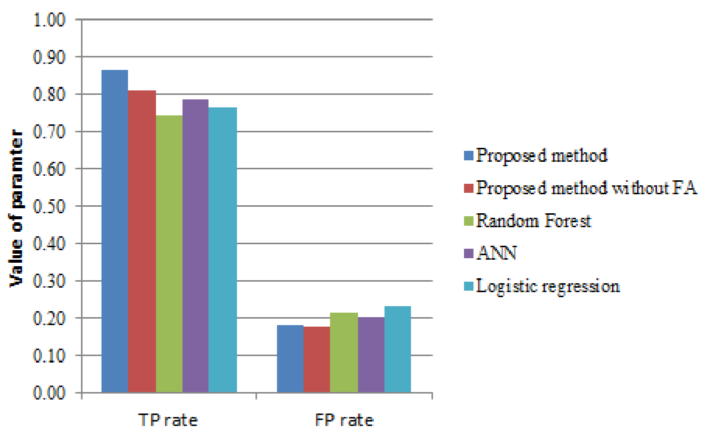

Fig. 4: The TP and FP comparison among classifier.

In Fig.4, the comparison of techniques with true positive and false positive predicted diagnosis is shown. All the results confirm that the proposed FA-CNN method outperforms the other machine learning techniques for detecting heart disease in terms of common statistical parameters.

4. Conclusions and future work

A new classification algorithm model using physiological information was proposed. The model is a combination of firefly algorithm, a nature inspired swarm intelligence algorithm, and 1D convolutional neural network. The proposed FA-CNN model has been trained and tested using dataset containing physiological information of patient about their heart disease. Using common statistical performance evaluation parameters, the proposed method performs better than the other common machine learning classification techniques in detecting heart disease. Future work will focus on making the proposed model more robust, with improvement in correctly predicting outcomes and better optimization of the feature set to make the system perform faster.

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