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ECG SIGNAL CLASSIFICATION FOR ARRHYTHMIA DETECTION USING DEA AND ELM

[1]SUMANTA KUILA , [2]NAMRATA DHANDA, [3]SUBHANKAR JOARDAR

[1]Haldia Institute of Technology, Department of Computer Science & Engineering, Haldia, India,
[2]Amity University Uttar Pradesh, Amity School of Engineering & Technology, Lucknow, India,
[3]Haldia Institute of Technology, Department of Computer Science & Engineering, Haldia, India,

E-mail: [1]sumanta.kuila@gmail.com, [2]ndhanda510@gmail.com, [3]subhankarranchi@yahoo.co.in

ABSTRACT

The electrical mobility of the human heart is represented by the Electrocardiogram signals. In the modern years the automatic classification of ECG signals has great significance as the cardiologists and the technicians take the decision on heart disease based on automatic classification. The goal of the work is to optimize the total number of hidden neurons by using DEA (Differential Evolution algorithm) and ELM (Extreme Learning Machine) algorithm, which makes the classification of the ECG signals with high rate of accuracy. The extreme learning machine is an application of single feed-forward Neural network whose performance depends on weight, activation function and threshold value of the modeled data. The Pan-Tompkins technique were used here to obtain different characteristics of the ECG data, mainly works with the QRS complex of the ECG signals. The ventricular depolarization is maintained by QRS complex where PR period, ST period, QT period are used to analyze the characteristics properties of the ECG signals. A series of filters are applied here to remove the background noise from the ECG signals which makes quick heart depolarization to get adaptive thresholds to identify the peaks of the signal. The ECG samples were simulated with ELM and then the DEA algorithm was used to optimize the problem for better classification of the ECG data. The performance of the classification was measured and it was compared with other related works. In this work the total accuracy was 96.027% where different numbers of hidden neurons were taken (maximum up to 160) which was tested with conventional ELM.

Keywords:- *Machine Learning , Differential Evolution algorithm, Extreme Learning Machine, Pan Tomkins , Electrocardiogram, Arrhythmia.*

1. INTRODUCTION

The Electrocardiogram signal describes the alternation of human heart. The peak of the signal describes the different critical area of the ECG signal such as QRS complex, P wave , T wave peak. The P wave occurs due to atrial depolarization and the partitions among the peaks creates the QRS complex. Classification and detection of the ECG signals has great significance as by classification and feature extraction of ECG data, the characteristics of human heart condition can be measured by these classification results. The figure (Figure-1) describes a standard ECG signal where several peak intervals are described. Different peak intervals such as P-P , Q-T, S-T, P-R, T-P, P-Q segments describes the normal heart activities.

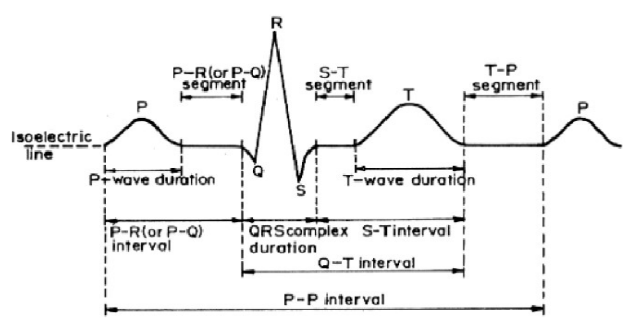

Figure -1 : Different Components and peaks of an ECG signal

The most import segment is QRS complex which represents the quick depolarization of left and right ventricles. The heart disease requires timely diagnosis of the heart condition and the proper treatment if required [1]. The main purpose this work is to create automatic feature extraction and classification mechanism of the ECG signal data, which will help physicians and cardiologists to treat heart arrhythmia properly. Classification of ECG creates effective algorithm to design a computer aided automated ECG detection system. Different classification techniques such as Radial basis function, AdaBoost method, convolutional nueral network, Adaptive neuro-fuzzy, Extreme learning machine, has the ability to create the rapid learning and generalization environment. In this work ECG classification has been done based on ELM systems. In the ELM work several drawbacks were found such as indefinite learning percentage, availabilities of local minima's, overfitting, the number of hidden neuron selection etc. The drawbacks of ELM is optimized by several population based techniques such as Differential Evolutional algorithm, Genetic algorithm, Artificial Bee Colony algorithm, Ant Colony Optimization, Particle Swam Optimization etc. For heart recording the T wave, P wave, QRS complex are the vital section for the recording of heart condition. By processing the heart signal the correct decision regarding the heart diseases are measured by the physicians. In this work machine learning system is used to detect the heart signal and based on that the diagnosis of heart arrhythmia can be done. Here to detect the heart activity correctly the Differential Evolution Algorithm was used with conventional Extreme Learning Machine method[2][3]. The unique portion of our work was the proper utilization of the accuracy to select the number of hidden neurons which was operated with the competent optimization method Differential Evolution algorithm. For proper ECG classification exact feature subtraction is required. The significance of Pan-Tompkins technique is that it works with series of filters to select the frequency content from the quick heart depolarization from where the peaks are detected from adaptive thresholds of filtered signals. Sensitivity, Specificity, Accuracy and F-measure are the issues to check the effectiveness of the computer aided system[4]. The main objective of the work is to increase the performance of the classification and to reduce the disadvantages of the ELM classification by using DEA-ELM to the ECG signals. The classification results are optimized by the number of hidden neurons where DEA based optimization process selects the optimum value for the classification of ECG data[5][6].

2. METHODS

The working methodology can be divided within four working modules, firstly ECG signal data is preprocessed with MIT-BIH Arrhythmia database . The process of preprocessing is operated in two steps as elimination of 60 Hz noise and baseline wondering[7]. The extraction of morphological , statistical and temporal features of the ECG signal is the important step for preprocessing. Classification and optimization are the another two steps by which optimization of the number of hidden neurons by the traditional ELM can be done. The fourth step is to detach the signal into normal and abnormal stages[8].

2.1 Preprocessing

In the ECG signal noise and interference should be removed to get clean ECG data. The ECG data is obtained by taking the potential difference between two points on the surface of the body where these measurements of these surfaces describes different types of noise.

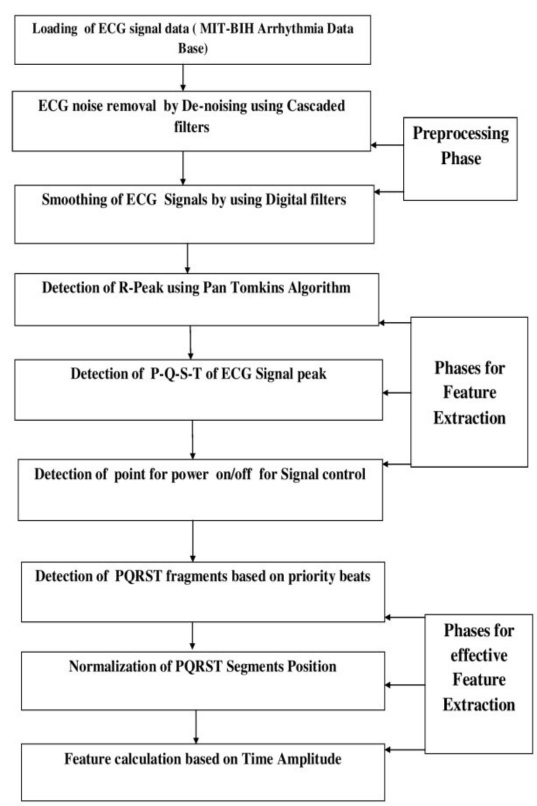

Figure 2 : Procedure For Preprocessing And Feature Extraction [9]

The figure (Figure-2) shows the steps for preprocessing and the effective feature extraction.

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The raw ECG signal contains various distortions noisy components generated from different origins. In this process various frequency components are used in the ECG signal recording and acquisition process. The unwanted changes in the signal may interfere the unique data and may deliver the wrong ECG data.The objective of the ECG preprocessing is to filter and minimize the noise components by which various heart disorders can be measured [9]. The frequency noise is the most important factor for noise source where baseline wandering, interference and muscle noise has significant role for this model.The noise components from the model are filtered by the various denoised methods. The base of evaluation of each method the signal to noise ration of filtered and original signals were considered [10]. The performance of the morphological filter gives the best performance in impulsive noise and baseline wandering band stop filter works good to reduce the noise of narrow band frequency signal. A huge number of unrest noises involved with ECG signal are removed from the above described methods. The system interactions and baseline wondering were the prominent disturbances the ECG signal found for classification. The baseline wondering was corrected by denoising operator and symlet scaling filter[11].

2.2 Feature Extraction

Specific property extraction form the ECG signals is important for the process of classification. After preprocessing the properties of the ECG signals were properly utilized in the stage of feature extraction. The Morphological and Statistical features used to extract the properties were Kurtosis, Skewness, Variance, Minimum, Mean, Maximum, ST interval, QT interval, P wave amplitude, PR interval, QRS complex amplitude. The feature extraction stage works initially with R wave then Pan-Tomkins algorithm was used to detect the QRS complex[12][13] .

2.2.1 Statistical Feature

The statistical features are directly related to every single lead segment of the ECG signal. The working mechanism is such that the ECG signal is initially split into bands then the statistical features are extracted from individual segments which leads to extract the feature vectors. The classification will give more accurate result when the ECG signal pattern will be simplified through the representation of proper features where feature extraction, selection and reduction had significant role. In this stage savaral methods are used to extract several diverse ECG features from the raw data . Statistical characteristics and syntactic descriptions are the two important issues of feature extraction whereas the activity of feature selection is to optimize the feature vector to reduce the size of features so that the most relevant features can be considered. To decrease the dimensionality of the feature vectors statistical measures are used to test and cross validate The selected features of the ECG signal.

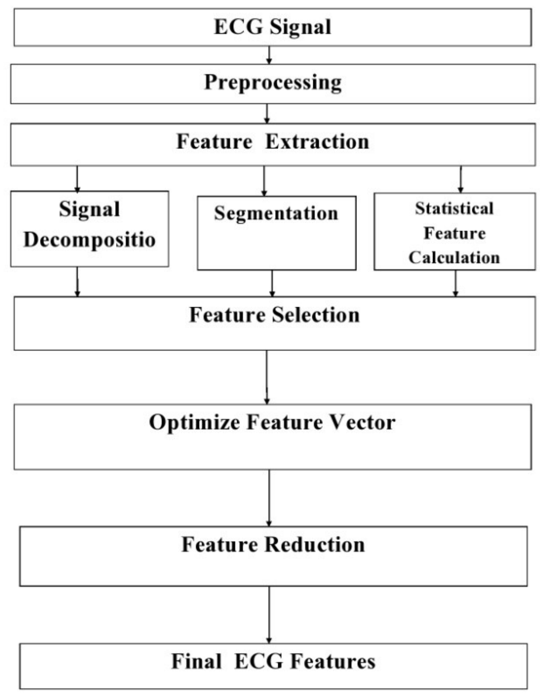

Figure -3 : Procedure to select the final ECG features [14]

The figure (Figure -3) describes the procedure to select the final ECG feature from the feature set. Here in the feature reduction process, it reduces the number of features without losing significant characteristics. Feature reduction helps to decrease the curse of dimensionality which decreases the number of possible dimensions by which time and space complexity of the application increases[15][16].

2.2.2 Morphological Feature

The internal and external features supported by a structured organism as a whole described as

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Morphological features. The repolarization phase of the heart activity mainly controlled by the T-wave section of the heart activity. To estimate the performance of morphological features the relevant feature vectors are tested where wavelet features and morphological features both works in a collaboration for the classification. This classification model uses various R peak positions where the features are selected based on position and value of minimum and maximum deviation of the whole ECG signal components[17][18].

2.2.3 Temporal Feature

Temporal features are the time domain features where the samples are extracted from physical interpritation like time, amplitude, energy of ECG signal. The temporal features claculates the execution time between RR interval, i.e the time interval between current heart beat and previous heart beat[19]. In the experiment total 6 temporal features are used as shown in table (Table-1). It also calculates the time interval between successive correct and false heartbeats. To access temporal and morphological features of the ECG waveform the P-QRS-T components of the ECG waveform are normalized with the vales of beat data such as intercycle baseline values and intercycle time intervals are considered. Some of the features are considered to avoid noise contamination[20].

2.2.4 ECG Features Taken

The most of the data of the ECG generated from the amplitude and intervals generated by P-QRS-T peaks of the signal where QRS, QT and ST creates different features of ECG data. In this experiment total of N features are used. The best fragments are detected at QRS area, ST distance and QT distance.

Features	ECG Feature Description
Features based on Time	Time difference between P & R
	Time difference between Q & R
	Time difference between S & R
	Time difference between T & R
	PT time to QS time ratio
	QT time QS time ratio
Features based on Amplitude	Amplitude difference between P & Q
	Amplitude difference between Q & R
	Amplitude difference between R & S
	Amplitude difference between S & T
	STamp to QSamp ratio
	RSamp to QRamp ratio
	STamp to QTamp
Features based on Distance	Distance between P & Q
	Distance between Q & R
	Distance between R & S
	Distance between S & T
	STdis to QSdis Ratio
	RSdis to QRdis Ratio
Features based on Slope	Slope of the line joining P & Q
	Slope of the line joining Q & R
	Slope of the line joining R & S
	Slope of the line joining Q & S
	Slope of the line joining S & T
Features based on Angle	Angle generated by PQR
	Angle generated by QRS
	Angle generated by RST
	Angle generated by RQS
	Angle generated by RSQ
Additional Features	Area of QRS Triangle
	QRS angle to RST angle ratio
	QRS angle to QStime ratio
	RST angle to QTtime ratio
	RQS angle to RTS angle ratio
	QRS area to QRamp ratio

Table 1 : ECG Features Used In The Experiment

In this experiment total of 35 extracted features were used as shown in the table (Table-1). These features were extracted from double layered feed forward neural network with hidden Sigmoid. The vectors can be classified arbitrarily with Softmax output neurons which produces sufficient neurons in the hidden layers[21]. Among the different 35 features some are time, amplitude, distance based, also the slope of joining the peaks, features based on angles were also taken. Some 6 additional miscellaneous features ware taken to reduce the error and produce the clean ECG data.[22][23.]

2.3 Database Used

In this work MIT- BIH arrhythmia database was used. This database is a typical test material used for arrhythmia detection. Originally this database contains 48 half an hour experts containing two-channel ambulatory ECG recordings. In our experiments 14 of the records were used for Pan Tomkins implementations[24]. The whole database is publicly available in PhysioNet. A wide unpredictability of the ECG rhythms and the details of waveform characteristics and morphology are reflected in this database. The accurace ECG data was generated from the ambulatory ECG records by several procedures. That clean accurate data is used for industry and academic research purpose for arrhythmia and various heart disease [25].

3. PAN TOMKINS IMPLEMENTATION

Here Pan Tomkins algorithm was implemented by using Python 3.8.0 to detect QRS peak from the ECG detector. The database used for the simulation was MIT BIH Arrhythmia database and for the testing of the peaks of QRS 14 records were taken from that database. Initially (5-15)hz Bandpass filter was taken. The main activity of the filter is to highlight the QRS complex from where the high frequency noise (0.150 sec/length) . Based on the sampling frequency of the signal the best matched characteristics of the ECG signals were chosen[26][27].

3.1 Decision Rule

The output signal was generated and an pulse shaped waveform appears as signal output. For Pan Tomkins the decision has to take whether the pulses corresponding to the QRS complexes performed satisfactory or not using adaptive thresholding. The fiducial mark is created by the waveform by the set of unit samples of different weights whose main focus is to localize the proposed QRS complex to a single slot of time[28].

3.2 Thresholding

The amplitude of the MWI output was analyzed where this algorithm used two different threshold values namely SIG and NOISE were initialized during very short two seconds training phase which is responsible for the signal quality of the ECG. Threshold was described as THRS .The non zero samples of QRS were classified by CURRENTPEAK where CURRENTPEAK > THRS, where THRS is the location where the signal level components of QRS complex was updated. The signal level was described as SIG and the updated value is calculated as SIG = 0.125× CURRENTPEAK +0.895×SIG ----(1)

if THRS(NOISE) < CURRENTPEAK< THRS(SIG) then the particular location is described as the noise peak where the level of the noise was updated as

NOISE[LEVEL]= 0.125× CURRENTPEAK +0.895× NOISE[LEVEL]--------------------(2)

From these signal and noise levels are estimated and the resulting ECG signal threshold are adjusted as

THRS[SIGNAL] = NOISE[LEVEL] +0.25×(SIG[LEVEL] - NOISE[LEVEL])-------(3)

The noise level is calculated as

THRS[NOISE] = 0.5× THRS[SIGNAL] -----(4)

These steps were taken to decrease the threshold periodically from signal segments by which proper Quality of signal were obtained [29][30].

3.3 Missed QRS complex detection

The above described thresh holding procedure if CURRENTPEAK < THRS , the peak misses the resultant component of the QRS complex. If the thresh hold peak misses with a long span of time then the resulting QRS failed a search back. By this way the number of false negative was minimized. The minimum RR interval time to trigger the search back was 1.66 times than the usual execution time. The interval between THRS[SIGNAL] and THRS[NOISE] described the missed QRS complex of the scenario [31]. The working procedure of the algorithm was that two average RR intervals were taken the first one calculated the average of the last 8 locations of the QRS to adapt of the changing heart rate and the second RR interval represents the mean of the majority portion of regular RR intervals. The irregular heart beat failed to improve detection if the threshold level is lower[32].

3.4 Multiple detection elimination

The detection of QRS complex was not possible if the time interval between two QRS complex exceeds 200ms . The constraints works with a certain duration of the refractory period during which the ventricular depolarization can occur. The generation of QRS complex candidates and the elimination of the physically unfeasibly events reduces the false positive rates[33].

3.5 Discrimination of T wave

The T wave generates when abnormal heart beat found and this occurs when QRS candidate activity found 200ms refractory period whereas the previous period timing of the QRS candidate takes 360ms. Then the Pan Tompkins algorithm determines whether these QRS complexes generated genuine heart beat or not. The main slope of the waveform takes the decision about T wave and QRS complex where a particular slope less than 50% of the earlier QRS complex was considered to became a T wave which for the detection of perfect QRS complex[34][35].

3.6 Experiments done with MIT BIH Arrhythmia Database

The experiment was done with 14 records of MIT BIH arrhythmia database. The Pan Tomkins technique was used upon the database and the graph data were fetched accordingly.

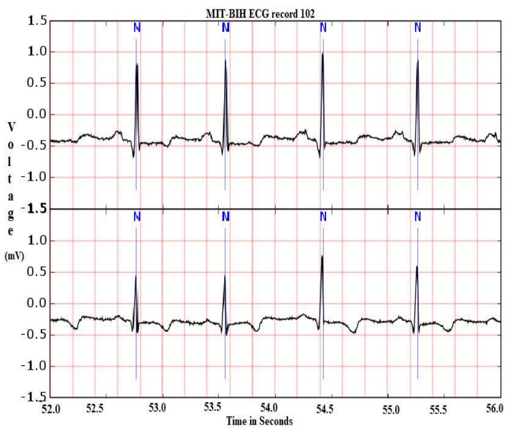

Figure 4 : Sample Record Of MIT- BIH Arrhythmia Database (Record 102)

The figure (Figure 4) shows the outcome of the ECG data after the Pan Tomkins were implemented on the database. The figure is the outcome of record number 102 of the MIT-BIH arrhythmia database. From the ECG graph the time series component was read with respect of time in seconds to voltage and from there the total QRS complex was count to calculate the total accuracy of the ECG dataset[36]. From the experiment total records were taken from each record bit and the values of True Positive (TP), False Positive (FP), False Negative (FN) ,True Negative(TN).

Table 2: Performance Of The Beat Detector Of MIT-BIH Arrhythmia Database

Record number	Total number of Beats	TP	TN	FP	FN
113	650000	548	646958	1249	1249
118	650000	154	645599	2125	2124
215	650000	56	643329	3308	3309
231	650000	334	649191	1238	1239
102	650000	34	645502	2269	2195
210	650000	1348	646092	1298	1302
112	650000	641	645562	1899	1898
203	650000	868	644908	2112	2112
202	650000	49	645980	2084	2089
119	650000	1	646929	1536	1534
115	650000	66	646159	1888	1889
222	650000	640	645669	1848	1843
109	650000	152	645091	2399	2380
102	650000	304	645929	1884	1883

The table (Table-2) describes the performance of the ECG record sets of the MIT-BIH dataset where TP, TN, FP, FN values are given. This confusion matrix checks the performance of the ECG datasets taken from the MIT-BIH Arrhythmia database[37].

4. EXTREME LEARNING MACHINE

ELM is a machine learning technique which works with back propagation(BP) algorithm with feed forward neural network. To optimize the parameters conventional BP algorithm is considered as a traditional first order gradient method. Here local minimum problem and slow convergence decreases the efficiency of the training set and to overcome this problem feed forward neural networks (FNN) with single hidden layer (SLFNs) is used. In comparison of traditional FNN the efficiency of ELM is significantly higher and it has that capacity to achieve optimum solution[38].

For N randomly different samples (x_i , t_i), where $x_i = [\, x_{i1}, x_{i2}, x_{i3}, \ldots\ldots\ldots, x_{in} \,]^T$, and t_t represented as $t_t = [\, t_{i1}, t_{i2}, t_{i3}, \ldots\ldots\ldots, t_{in} \,]^T \in R^m$, standard SLFNs with number of hidden nodes N and activation function g(x) are mathematically expressed as $\sum_{i=1}^{N} \beta i\ \Psi i(x_j) = \sum_{i=1}^{N} \beta i\, \Psi i(w_i.x_j + b_i) = o_j$, --------------------(5)

where j= 1,2…..N and w_i is the weighted vector, represented as $w_i = [w_{i1}, w_{i2}, \ldots\ldots w_{in}]^T$. The weighted vector connects the i_{th} hidden node with output nodes $\beta i = [\, \beta i1, \beta i2, \beta i3 \ldots\ldots\ldots, \beta im]^T$ is described as weight vector which connects the output node and the i_{th} hidden node. The threshold of the i_{th} hidden node is b_i and inner product of w_i and w_j is denoted by $w_i.\ w_j$. In this work the output nodes are chosen linear . The N hidden nodes and the standard SLFNs works with the activation function Ψx appropriates these N number of samples with 0 error means expressed as $\sum_{i=1}^{N} || o_j - t_j || = 0$, i.e the equation suggests that, there exists b_i and $\beta_i .w_j$ such that

$\sum_{i=1}^{N} \beta i\ \Psi(\beta i\,.\,wj\ + bi\ ) = t_j$, j= 1,2…….,N . ----- (6)

Equation (5) & (6) can be written compactly as $H\beta = T$. ----------------------(9)

H comes from the name Huang et al. [A,B] , H is described as neural network output matrix of hidden node where $x_1, x_2, \ldots\ldots x_N$ are the respective inputs[39][40].

5. DIFFERENTIAL EVALUATION ALGORITHM

The Differential Evaluation Algorithm is a population based stochastic method works for global optimization problem. DEA is a heuristic optimization technique based on Genetic Algorithm in terms of operators and operations to provide efficient results. The optimization expressed as D the dimensionality (Symbolized as D vector), NP (Number of population vector), CR(Crossover Rate) and F(Scaling Factor). The population $P_{y,g} = (y_{i,g})$, i=0,1,2….,NP-1, $g=0,1,\ldots\ldots,g_{max}$,

$Y_{i,g} = (y_{j,I,g})$, j= 0,1,……D-1.----------------(8)

Where g denotes the generation counter and D the number of parameters i.e. the dimensionality.

The initialization of the said population described as $y_{j,I,0} = rand_j(0,1).(b_{j,U} - b_{j,L}) + b_{j,L}$ ------(9)

The b_U and b_L indicates the upper and lower bounds of the $x_{i,j}$ parameters vector.

The perturbation of the base vector described as $z_{i,g}$, which was derived by using the difference vector based mutation . $v_{i,g} = z_{i,g} + F\ .(y_{r1,g} - y_{r2,g})$ ---------------------- (10)

This generates the mutation vector $v_{i,g}$. The difference of vector indices r1 and r2 are selected randomly once for each vector. In DE the base vector is such that it is also randomly chosen population vector. For selection DE uses simple one-to-one selection process where $u_{i,g}$ is the trail vector which competes the $y_{i,g}$ target vector. This vector works with lowest objective function to generate next generation g+1 ,

$y_{i,g+1} = u_{i,g}$ if $f(u_{i,g}) \le f(x_{i,g})$, otherwise it is $y_{i,g}$.-------(11)

Some parts of the present chromosome is changed randomly determined amounts by mutation. The changes are determined in proper direction and right quantity to establish the proper goal of mutation[41][42].

6. PROPOSED DEA-ELM ALGORITHM

The proposed algorithm works with the combination of DEA & ELM where convergence comes from the process of Initialization, Mutation, Crossover, Selection respectively.

Step 1: Number of hidden neurons : Nhn
Problity of crossover :Pcr
Number of mutation : Nmu
Number of population taken : Npop

Step 2: The variable parameters bound are taken as Vmin_1, Vmax_1, Vmin_2, Vmax_2.
Transfer function : Tf, The learning iteration initialized with maximum number : Itmax.

Step 3 : for i= 1 to Npop
Population(i).Nhn = unidrnd(Vmax_1) ;
Population(i).Tf = unidrnd(Vmax_2);
Population(i).cost = DEA-ELM (Dataset, Type_of_Elm, population(i).Nhs, Tf{population(i).Tf} ,5)
End

Step 4: Mutation
beta = unifrmd(min_beta, max_beta, Var_Size);
y1= population(p).Nhn + beta × (population(q).Nhn-population(r).Nhn)

Step 4 : Crossover
n point crossover
n1=sizeof(x1) ; t(0) = random([1, numel(x1)]
Where x1 considered as hidden neuron
for t=1 ; read the hidden neurons , numel(x1)
if ((t== t(0) && rand <=Pcr
n1(t) =y1(t);
else n1(t) = x1(t) end;
Revise Optimum value
BestValue = BestSolution.Value;
End [43][44]

7. EXPERIMENTAL RESULTS

The experimental results shows the system efficiency values for ECG classification. To do the experiment a total if 192 ECG signals in 14 records are taken as shown in the Pan Tomkins experiments. The experiment was performed using Python 3.9 . The system performance was operated with confusion matrix with efficiency parameters Accuracy(ACC), Specificity(SPE), Sensitivity(SEN) and F-measure. These parameters are measured True Positive (TP), False Positive(FP), True Negative(TN), False

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Negative (FN) where normal ECG signal which are correctly identified described as True Positive. True negative correctly identified abnormal ECG signal. The respective equations are described below [45][46].

ACC = TP+TN/ (TP+TN+FP+FN)-------------(12)
SPE = TN/(TN+FP)-------------------------------(13)
SEN = TP/(TP+FN)-------------------------------(14)
F-measure= 2×TP/(2×TP + FP+FN)------------(15)

7.1 Classifier performance

The classification performance are measured by several DEA-ELM with some of the ELM's parameter . In this experiment 9 numbers of neurons and hidden layers are restricted to single hidden layer and the observations for optimization of parameters are Sigmoid(Sig), Sinus(Sin), Radial Basis(RadBus), Triangular Basis(TriBas), Tangent Sigmoid(TanSig), Log Sigmoid(LogSig), Hard Limit(HarLim). The experiment was done by using hidden neurons of ELM to 30, 50, 65, 80, 105, 125, 150, 160. The below tables (Table 2, Table 3, Table 4) describes the results of accuracy, Sensitivity and Specifity respectively. The efficiency of system proficiency was done by optimizing the hidden neurons as described in the DEA-ELM algorithm. The main goal of the experiment was to test the efficiency of the system and the capacity to optimize the numeral of selected hidden neurons by the proposed DEA-ELM algorithm. Here total of 13 ECG features are taken among which 6 statistical features and 9 morphological features were used to obtain characteristics features. Numeral hidden neurons increases the classification performance by conventional ELM and when DEA also implemented with ELM a robust optimization outcome achieved[47]. The Table (Table -3) shows the results of Accuracy percentage with the ELM optimization parameters with the number of hidden neurons taken. The result obtained with the DEA-ELM algorithm with 350, 500, 900, 950, 1250 number of iterations. The result were tested with different number of iterations to achieve the accurate result. When the number of iteration increases the highest best cost values were obtained. The table (Table -4) shows the value of the Sensitivity of different optimization parameters with the number of hidden neurons taken. Different morphological and temporal statistical features were extracted from the ECG signal employed with the hidden neurons using the optimization features. The table (Table-5) shows the Specificity from the experiment. The proposed DEA-ELM technique worked with MIT-BIH arrhythmia database to optimize the number of hidden neurons. The Recursive Feature Eliminator worked with statistical and morphological features was engaged to decrease the feature space dimension. A total of 35 features were used in the experiment which includes temporal, statistical and morphological features. For feature optimization SFFS (sequential forward floating search) algorithm were used and finally it was implemented to Linear discriminants analysis and Multilayer perceptron.

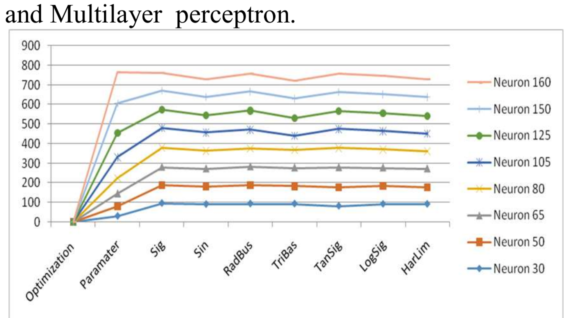

Figure 5: Graphical Representation Of Accuracy Obtained

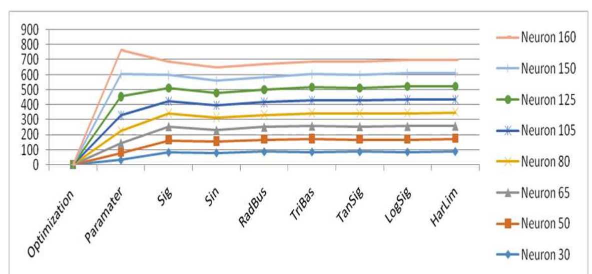

Figure 6: Graphical Representation Of Sensitivity Obtained

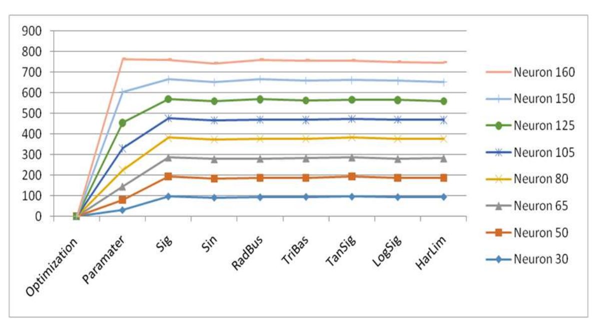

Figure 7 : Graphical Representation Of Specifity Obtained

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Here Figure 5, Figure 6, Figure 7 shows the graphical representation of the performances of Accuracy, Sensitivity and Specificity with optimizing the parameters with the hidden neurons. Based on the proposed DEA-ELM algorithm the performance metric was generated with the MIT-BIH arrhythmia database. The above three graphs shows the comparison of the performances based on 9 optimization parameters and 8 different types of hidden neurons, where the main goal of the study was to improve the classification performance.

Table- 3: *The Accuracy Obtained With Optimization Parameter With Hidden Neurons*

Optimization Paramater	Number of Hidden Neurons Taken for Accuracy(%)							
	30	**50**	**65**	**80**	**105**	**125**	**150**	**160**
Sig	95.45	93.54	91.69	98.56	99.23	96.13	95.21	92.13
Sin	90.34	92.56	89.53	91.23	92.15	90.59	91.12	90.29
RadBus	93.12	95.21	94.99	92.13	94.46	99.34	95.34	94.12
TriBas	92.56	91.34	93.59	92.49	69.29	93.28	96.38	93.99
TanSig	81.34	98.45	99.54	99.23	95.65	94.39	95.16	94.39
LogSig	91.45	93.56	92.56	93.45	92.19	93.69	94.19	95.23
HarLim	91.34	88.45	92.56	89.35	89.34	92.13	93.46	92.89

Table 4*: The Sensitivity Obtained With Optimization Parameter With Hidden Neurons*

Optimization Paramater	Number of Hidden Neurons Taken for Sensitivity(%)							
	30	**50**	**65**	**80**	**105**	**125**	**150**	**160**
Sig	81.5	82.3	93.4	84.6	83.5	87.5	86.23	88.12
Sin	78.23	77.28	76.34	83.12	82.15	84.17	83.67	85.12
RadBus	85.12	84.13	83.54	82.19	83.27	84.18	83.26	84.25
TriBas	84.28	87.13	88.23	87.15	86.23	86.19	85.67	84.29
TanSig	85.23	84.28	87.45	86.19	85.38	86.45	87.17	86.34
LogSig	84.27	86.38	87.59	88.45	87.13	89.23	87.48	88.28
HarLim	87.18	86.34	87.48	88.96	86.45	87.29	88.78	87.65

Table 5*: The Specifity Obtained With Optimization Parameter With Hidden Neurons*

Optimization Paramater	Number of Hidden Neurons Taken for Specifity(%)							
	30	**50**	**65**	**80**	**105**	**125**	**150**	**160**
Sig	97.34	96.23	93.45	94.23	95.45	93.34	95.34	96.34
Sin	91.23	92.56	95.34	93.23	94.56	93.67	91.65	93.56
RadBus	93.45	94.32	93.41	94.56	95.42	97.49	98.11	93.63
TriBas	95.41	93.38	94.61	93.28	92.62	94.39	97.54	98.45
TanSig	96.45	97.65	93.45	94.41	92.56	93.27	94.36	95.23
LogSig	94.24	93.38	92.56	95.61	94.52	94.67	93.37	94.32
HarLim	95.23	93.23	94.51	93.23	92.17	92.16	91.34	95.21

Table 6: The Overall Performance Obtained With The Hidden Neurons

Sl. No.	**Performance Parameters**	**Value**
1	Total Accuracy	**96.027**
2	Total Recall	88.083
3	Total Specificity	97.616
4	Total Precision	88.083
5	Total	92.452

The table (Table 6) shows the overall performance with the hidden neurons where both true positive rate and false positive rate were also calculated to get overall accuracy, recall, specificity and precision. The values are shown here. The classification performance were increased by implementing the idea of several temporal and deep learning methods. Accuracy does not produce detailed information about the problem but it consider whether the specific model is trained correctly or not. Here the percentage of accuracy describes how much the model is correct for future use. The number of relevant documents generated by the search has a ratio of total number of existing documents is described as recall. In this study the recall is 88.083% , which shows the database is relatively clean. There is converse relationship between recall and precession and it has the possibilities to increase cost of one while reducing the cost of other. The values of recall and precision does not come as isolated instead it depends on each other. The accuracy of this study gives satisfactory result.

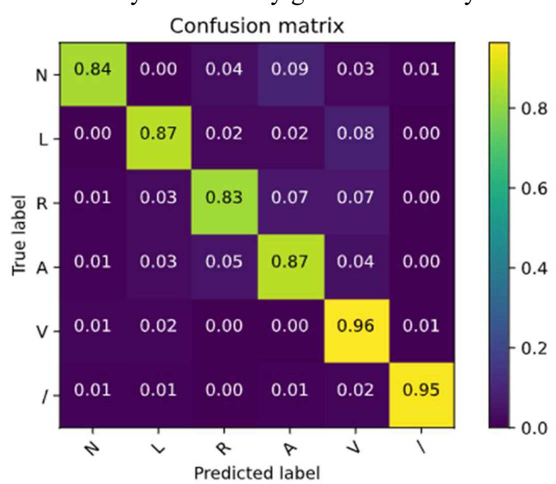

Figure 8: The Confusion Matrix Shows The True Label And Predicted Label

The figure (Figure 8) is the confusion matrix which describes the performances of the classification model on the set of test and train data from the MIT-BIH arrhythmia dataset. This confusion matrix can also treated as error matrix as specific accuracy based on the performance of the algorithm was shown here. Summary of predicted result of the classification problem and the outcome of the validate data set and test data are pictorially represented here. The predicted class represents each row of the matrix and actual class is represented by each column of the matrix. The table is filled with correct and incorrect predictions. The classification model shows the classification accuracy which defines how often the classification model predicts the accurate output. Analyzing the performance of the confusion matrix the heart arrhythmia can be predicted by the dataset taken from the database. The accuracy measure shows the probability of arrhythmia of a particular patient of the whose cardiac data was investigated and tested.

Table 7 : Comparison With The Other Similar Works

Different Work	Database Used	Types of Feature	Classifier	Total Accuracy(%)
A. Dikera, E. Avcib et. al. [31]	PTB Diagnostic DB	Statistical & Morphological	ELM & DEA	97.5
T.Mar, S.Zaunseder et. al. [35]	MIT-BIH Arrhythmia	Statistical, Morphological & Statistical	LDA,SVM, MLP	90.2
A.Diker,Z. Comert et. al. [4]	PTB Diagnostic DB	Statistical & Morphological	k-NN, ANN & SVM	80.6
E.Pasolli ,F.Melgani, et. al. [24]	MIT-BIH Arrhythmia	Morphological & Temporal	k-NN, SVM	83.4
V.Bhagyalakshmi , R.V.Pujeri, et. al. [19]	MIT-BIH Arrhythmia	Gobar	GB-SVNN	96.96
. Md.N. Dar, M.U. Akram, et. al. [16]	ECG-ID Database	Morphological	Single Nearest Neighbor	82.30
C.K Chen, C.L Lin, et. al. [17]	MIT-BIH Arrhythmia	Statistical, Morphological & Statistical	BPNN with Chaotic features	91.03
R. D. Labati, E. Munoz, et. al. [18]	PTB Diagnostic DB	Morphological & Statistical	Deep CNN	97.4

X. Tan, L Shu, et. al. [23]	MIT-BIH Arrhythmia	Morphological & Temporal	Quantum Neural Network (QNN)	91.70
K. K. Patro, P.R. Kumar , et. al. [22]	ECG ID database	Statistical , Morphological & Temporal	ANN, SVM, K-NN	93.7
Proposed Study*	MIT-BIH Arrhythmia	Statistical , Morphological & Temporal	DEA-ELM	96.027

The table (Table 7) describes the different comparative study of similar type of works. The comparative study works with database used, different types of features used, different classifier taken and the overall accuracy achieved by the classifier with the respective databases. Most of the research work produces the accuracy 90% and above. The popular data base MIT-BIH arrhythmia database was used by most of the research work, apart from that several research work done with PTB Diagnostic and ECG-ID database. The types of features and the classifiers taken for the studies are also given in the table (Table 7). In our study we have works new classifier DEA-ELM, whereas other studies used the traditional classifiers like ANN, K-NN, SVM etc. In this study three types of features are used, Statistical, Morphological and Temporal, whereas other studies used any two of that.

8. CONCLUSION

In this work the proposed algorithm was implemented with MIT-BIH arrhythmia database for feature extraction and classification of ECG data to detect heart arrhythmia . Here the new technique was developed by integrating Extreme Learning Machine with Differential evolution algorithm which had worked different morphological and temporal features. The performance metric was generated by analyzing the automated ECG signal data with the DEA-ELM method, feature type, classes, MIT-BIH arrhythmia database, the hidden neurons with several optimization parameters. The total accuracy achieved from the result were 96.027, using 14 records from the MIT-BIH arrhythmia dataset. The goal of this paper was to analyze and classify records from the ECG database to diagnose different heart diseases particularly heart arrhythmia. The number of hidden neurons of ELM was optimized by the DEA method.

REFERENCES:

[1] Y. N. Singh, S. K. Singh, "Evaluation of Electrocardiogram for Biometric Authentication", Journal of Information Security, January 2012, pp.39-48.

[2] L. Biel, O. Petersson, L.P. Philipson Wide, “ECG Analysis: a new approach in human identification", IEEE Transaction Instrumental Meaurements, VOL. 50, NO. 3, 2001, pp. 808–812.

[3] Y. Gahi, A. Lamrani, A. Zoglat, M. Guennoun, B. Kapralos, "Biometric Identification System Based on Electrocardiogram Data", New Technologies, Mobility and Security NTMS '08, 2008, pp. 1-5.

[4] A.Diker,Z. Comert ,E.Avcl, "A Diagnostic Model for Identification of Myocardial Infarction from Electrocardiography Signals" Bitlis Eren University Journal of Science and Technology, VOL.7, NO.2, 2017, pp.132–139.

[5] G. B. Huang, L. Chen, "Extreme learning machine: Theory and applications", Neurocomputing, VOL. 70, NO. 1-3, Dec. 2006, pp. 489–501.

[6] Y. Qian, M. Ye, J. Zhou, "Hyperspectral image classification based on structural sparse logistic regression and three dimensional wavelet texture features", IEEE Transactions on Geoscience and Remote Sensing, VOL. 51, NO. 4, April 2013, pp. 2276–2291.

[7] Physionet, "Physiobank Archives" , Massachusetts Institute of Technology, Cambridge,2011. http://www.physionet.org/physiobank/database

[8] M. Kaur, A. S. Arora, "Classification of ECG signals using LDA with factor analysis method as feature reduction technique", Journal of Medical Engineering & Technology, VOL. 36, NO. 8, 2012, pp. 411–420.

[9] Kiran Kumar Patro and P.Rajesh Kumar, "Effective Feature Extraction of ECG for Biometric Application", 7th International Conference on Advances in Computing & Communications, August 2017,Cochin, India, Procedia Computer Science 115 (2017), Elsevier, pp.296–306.

[10] T. Saramaki, Y. Neuvo, S. K. Mitra,"Design of computationally efficient interpolated FIR filters" ,IEEE Transactions on Circuits and Systems, VOL. 5, NO. 1, January 1988, pp. 70-88.

[11] R. Ganguli, "Noise and Outlier removal from Jet Engine Health Signals using Weighted FIR Median Hybrid Filters", Mechanical Systems and Signal processing,VOL. 16, NO. 6, January 2002, pp. 967-978.

[12] Kiran Kumar Patro and P.Rajesh Kumar, "Effective Feature Extraction of ECG for Biometric Application", 7th International Conference on Advances in Computing & Communications, August 2017, Cochin, India, Procedia Computer Science 115 (2017), Elsevier, pp.296–306.

[13] J. Rodrigues, D. Belo, H. Gamboa, "Noise detection on ECG based on agglomerative clustering of morphological features," Computers in Biology and Medicine, vol. 87, pp. 322–334, 2017.

[14] T. N. Alotaiby ,S.R. Alrshoud,S. A. Alshebeili, L. M. Aljafar," ECG-Based Subject Identification Using Statistical Features and Random Forest", Journal of Sensors , Article ID 6751932, VOL 2019.

[15] L. Marsanova, M. Ronzhina , R. Smisek, M. Vítek, A. Nemcova, L. Smital, M. Novakova,"ECG features and methods for automatic classification of ventricular premature and ischemic heartbeats: A comprehensive experimental study", Scientific Reports, September 2017, www.nature.com/scientificreports/.

[16] Md.N. Dar, M.U. Akram, S.A Khan, "ECG Biometric identification for general population using Multiresolution analysis of DWT based features", 2nd International Conference on Information and Cyber forensics (InfoSec), 2015, pp.05-10.

[17] C.K Chen, C.L Lin, S.L Lin, Y.M Chiu, C.T Chaing, "A Chaotic theoritical approach to ecg based identity recognition", Computational Intelligence Magazine, IEEE, VOL.9, NO.1, 2014, pp.53-63.

[18] R. D. Labati, E. Munoz, V. Piuri, R. Sassi, F. Scotti, "Deep-ECG: convolutional neural networks for ECG biometric recognition", Pattern Recognition Letters, VOL. 126, 2019,pp. 78–85.

[19] A. Kaveh, W. Chung, "Temporal and spectral features of single lead ECG for human identification",2013 IEEE Workshop on Biometry , Napoli, Italy,September 2013.

[20] M. K. Das, Samit Ari, "ECG Beats Classification Using Mixture of Features", International Scholarly Research Notices, Hindawi Publishing Corporation, VOL 2014, Article ID 178436.

[21] A.Gupta, B. Thomas, "Neural Network based indicative ECG Classification", 5th IEEE international Conference (Confluence), 2014, pp.277-279.

[22] K. K. Patro , P.R. Kumar, "Machine Learning Classification Approaches for Biometric Recognition System using ECG Signals", Journal of Engineering Science and Technology Review, December 2017, pp 1-8.

[23] X. Tan, L Shu, "Classification of Electrocardiogram signal with RS and Quantum Neural Networks", International Journal of Multimedia and Ubiquitous Engineering , VOL.9, NO.2,2014 ,pp.363-372.

[24] G. B. Moody, R. G. Mark, "The impact of the MIT-BIH arrhythmia database", IEEE Engineering in Medicine and Biology Magazine, VOL. 20, NO.3 , 2001, pp. 45–50.

[25] S. Kuila, N. Dhanda, S. Joardar, "Feature Extraction and classification of MIT-BIH Arrhythmia Database", 2nd International Conference on Communication, Devices and Computing , Haldia Institute of Technology, March 14-15, 2019, Springer proceeding (LNEE) , VOL. 602, pp. 417-427.

[26] J. Pan, W. J. Tompkins, "A Real Time QRS Detection Algorithm," IEEE Transactions on Biomedical Engineering, Vol. 33, No. 3, 1985, pp. 230-236.

[27] J. M. Irvin, S. A. Israel, "A Sequential Procedure for Individual Identity Verification Using ECG", EURASIP Journal on Advances in Signal Processing, VOL. 2009, 2009, Article ID: 243215, pp. 1-13.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

[28] T. W. Shen, W. J. Tompkins, Y. H. Hu, "One-Lead ECG for Identity Verification", Proceedings of the Second Joint EMBS/BMES Conference, Houston, 23-26 October, 2002, pp. 62-63.

[29] R. J. Martis, U. R. Acharya, L. C. Min, "ECG beat classification using PCA, LDA, ICA and discrete wavelet transform", Biomedical Signal Processing and Control, VOL. 8, NO. 5, 2013, pp. 437–448.

[30] V.Bhagyalakshmi , R.V.Pujeri,G.D. Devanagavi, "GB-SVNN: Genetic BAT assisted support vector neural network for arrhythmia classification using ECG signals", Journal of King Saud University, Computer Inf Sci 2018.

[31] Z. Zidelmal, A. Amirou, M. Adnane, A. Belouchrani, "QRS detection based on wavelet coefficients", Computer Methods and Programs in Biomedicine, VOL. 107, NO. 3, 2012 ,pp. 490–496.

[32] A. E. Curtin, K. V. Burns, A. J. Bank, T. I. Netoff, "QRS complex detection and measurement algorithms for multichannel ECGs in cardiac resynchronization therapy patients", Journal of Translational Engineering in Health and Medicine, VOL. 6, 2018, pp. 1–11.

[33] D. B. Saadi, G. Tanev, M. Flintrup, A. Osmanagic, "Automatic real-time embedded QRS complex detection for a novel patch type electrocardiogram recorder", IEEE Journal of Translational Engineering in Health and Medicine, 2015 , VOL. 3, pp. 1–12.

[34] U. R. Acharya, H. Fujita, S. L. Oh, Y. Hagiwara, "Application of deep convolutional neural network for automated detection of myocardial infarction using ECG signals", Information Sciences, VOL. 415, 2017, pp. 190–198.

[35] E.Pasolli , F.Melgani, "Genetic algorithm-based method for mitigating label noise issue in ECG signal classification", Biomed Signal Process Control, VOL 19, 2015; pp.130–136.

[36] S. Kuila, N. Dhanda, S. Joardar, "Feature extraction of electrocardiogram signal using machine learning classification", International Journal of Electrical and Computer Engineering (IJECE), Vol. 10, No. 6, December 2020, pp. 6598-6605.

[37] S. Dutta, A. Chatterjee, S Munshi, "Correlation technique and least square support vector machine combine for frequency domain based ECG beat classification", Medical Engineering & Physics 32(10), 2010, pp.1161–1169.

[38] G.B. Huang, Y.Q. Chen, H.A. Babri, "Classification ability of single hidden layer feed forward neural networks", IEEE Transactions Neural Networks and Learning System, VOL. 11, NO. 3, 2000, pp.799–801.

[39] X.Liu, C. Gao, P. Li, "A comparative analysis of support vector machines and extreme learning machines", Neural Networks 33: pp.58-66.

[40] G.B Huang , Q.Y Zhu , C.K Siew , "Extreme learning machine: a new learning scheme of feed forward neural networks" , Proceedings of international joint conference on neural networks, (IJCNN2004), VOL 2, NO. 25–29, pp. 985–990.

[41] W.A. Yang, Q. Zhou, K.L. Tsui, " Differential evolution based feature selection and parameter optimization for extreme learning machine in tool wear estimation", International Journal of Production Research, VOL 54, NO. 15, 2016, pp. 4703–4721.

[42] Y. Bazi, "Differential evolution extreme learning machine for the classification of hyper spectral images" IEEE Geoscience and Remote Sensing Letters , VOL. 11, NO. 6, 2014, pp. 1066–1070.

[43] A. Dikera, E. Avcib, E.Tanyildizib, M. Gedikpinarc, "A novel ECG signal classification method using DEA-ELM", Elsevier , Medical Hypotheses 136 (2020) 109515.

[44] N. Alajlan, Y. Bazi, F. Melgani, R. R. Yager, "Fusion of supervised and unsupervised learning paradigms for improved classification of hyper spectral images," Information Sciences, Elsevier, VOL. 217, December 2012 ,pp. 39–55.

[45] A. Diker, Z. Comert, E. Avci, S.Velappan, "Intelligent system based on Genetic Algorithm and support vector machine for detection of myocardial infarction from ECG signals", 2018 , 26th Signal Processing and Communications Applications Conference, pp. 1–4.

[46] P.Guo, W.Cheng, Y.Wang, "Hybrid evolutionary algorithm with extreme machine learning fitness function evaluation for two-stage capacitated facility location problems", Expert Systems with Applications, Elsevier, VOL. 71, NO. 1, 2017 ,pp. 57 – 68.
[47] T.Mar, S.Zaunseder ,J.P Martinez , M.Llamedo , R.Poll, "Optimization of ECG classification by means of feature selection" IEEE Transactions on Biomedical Engineering, VOL.58, NO.8, 2011, pp. 2168–2177.