International Journal of Innovative Technology and Exploring Engineering (IJITEE)
ISSN: 2278-3075, Volume-9 Issue-12, October 2020

Performance Analysis of ECG Arrhythmia Classification based on Different SVM Methods

Sumanta Kuila, Sayandeep Maity, Suman Kumar Mal, Subhankar Joardar

Abstract*: Heart arrhythmias are the different types of heartbeats which are irregular in nature. In Tachycardia the heartbeat works too fast and in case of Bradycardia it works too slow. In the study of different cardiac conditions automatic detection of heart arrhythmia is done by the classification and feature extraction of Electrocardiogram(ECG) data. Various Support Vector Machine based methods are used to analyze and classify ECG signals for arrhythmia detection. There are several Support Vector Machine (SVM) methods used to classify the ECG data such as one against all, one against one and fuzzy decision function. This classification detects the existence of the arrhythmia and it helps the physicians to treat the heart patient with more accurate way. To train SVM, the MIT BIH Arrhythmia database is used which works with the heart disorder like sinus bradycardy, old inferior myocardial infarction, coronary artery disease, right bundle branch block. All three methods are implemented in proper way, and their rate of accuracy with SVM classifier is optimal when it is processed with the one-against-all method. The data sets of ECG arrhythmia are usually complex in nature, so for the SVM based classification one-against-all method has great impact and will fetch better result.

Keywords*: Arrhythmia, Classification, Electrocardiogram, Feature Extraction, MIT BIH Arrhythmia Database, Support Vector Machine, QRS Complex.

I. INTRODUCTION

Heart disease is a major issue of the human being among different illness. Timely detection and accurate medical treatment of heart problem can save life of human being. The energy of the heart beat comes from an electrical signal which is generated from Sino Atrial node. This node is located at the Atrium which is top of the right chamber of the heart and it is treated as the natural pacemaker of the heart. The circulation of blood throughout the whole body is controlled by the natural pacemaker and any disorder of this causes a serious heart problem[1][2]. The inefficient heart beat creates the disease like arrhythmia which occurs due to abnormal conduction of the cardiac function In general ECG signal are constructed with T wave, QRS complex and T wave. These signal components are denoted by the capital letters ,Q,R,S,T. The important components required to inspect a heart patient is QRS complex, P wave, RR interval and T wave. These parameter changes causes the heart disease and the illness of human being.

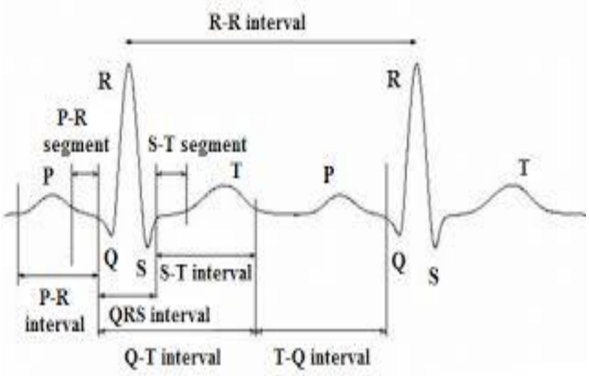

Fig-1: Standard block diagram of an Electrocardiogram Signal

In ECG diagram P,Q,R,S,T components, QRS complex duration, P-R , Q-T, S-T , P-P intervals, T-P, S-T,P-Q segments, P wave, T wave durations are clearly described[3]. The ECG signal shares two most important information the first one measures the time interval and from there it is measured that how long it works with the heart also we can determine the performance of the electrical activity is fast, slow, regular or irregular. The electrical activity of the heart muscle also reflects the stress taken by the heart and it checks the amount of overwork done by the person. Using the ECG recording system the physicians detects heart arrhythmia and from there the ECG waveform morphology was detected. ECG recorders use various mobile and remote health care system and day by day the use of ECG recorder is increasing. The importance of automatic arrhythmia detection and classification is that, the automation decreases the human dependency of the heart treatment and classification and feature extraction makes the diagnosis more accurate[3][4]. To do this operation several classification algorithms are required which reads the ECG patterns and in real time it recognizes different types of arrhythmias. Support vector machine and several other classifiers are used to classify the electrocardiogram beats. Several algorithms have been introduced over several years to develop the automated system which will classify the ECG signals accurately. The researchers used Artificial Neural Network (ANN) to detect the strain of left ventricular portion by classifying the abnormalities of ST-T segment of Electrocardiogram. The use of ANN helps the researchers to detect the QRS and from there the ECG beat classifications can be done.

Revised Manuscript Received on September 25, 2020.

***** Correspondence Author

Sumanta Kuila *, Dept. of Computer Sc. & Engineering, Haldia Institute of Technology, Haldia-721657, West Bengal, India, smanta.kuila@gmail.com

SayandeepMaity, Dept. of Computer Sc. & Engineering, Haldia Institute of Technology, Haldia-721657,West Bengal, India. sayandeepmaity328@gmail.com

Suman Kumar Mal, Dept. of Computer Sc. & Engineering , Haldia Institute of Technology, Haldia-721657,West Bengal, India. sumank343@gmail.com

Subhankar Joardar, Dept. of Computer Sc. & Engineering, Haldia Institute of Technology, Haldia-721657,West Bengal, India subhankarranchi@yahoo.co.in

The adaptive multilayer perceptron structure is used to model the noise of the non linear background as it augments the QRS complexities which gives much reliable detection[5][6]. Two different classification techniques represents the ECG classification work, the first one is with supervised learning the another is with unsupervised learning. To detect cardiac arrhythmia and also ventricular arrhythmia a fuzzy logic based method is used also by using ANN the visibility of the heart rate is measured by analyzing base ECG signals by which classification of four different cardiac arrhythmias are measured. For the extraordinary performance of classification support vector machine is used and in this work three mostly used and well-known SVM based procedures are used. The standard arrhythmia data sets are used to classify to compare the result sets of the different SVM procedures and this brings the best result among the data set[7].

II. SUPPORT VECTOR MACHINE (SVM)

For binary classification and the mathematical explanation of that classification algorithm SVMs were designed .

Let the training set be explained as S= $\{(x_1, y_1),(x_2, y_2),\ldots,(xl, yl)\}$ where m dimensional attribute vectors are represented as x_i where y_i E {-1, +1}, y_i = -1, and y_i = +1 for class 1 & class 2, respectively, where the SVM classifier is described as follows $D(x) = w^t\Theta(x) + b = 0$ (1)

Here $\Theta(x)$ is described as mapping function , b is a scalar w^t is described as vector in the feature space. The below condition satisfy the decision function.

$$Y_i\,(w^t\Theta(x) + b) > 1$$

For $i = 1,\ldots,l$ (2)

There are various separating hyperplanes and among all of these separating hyper planes the optimal one contains maximal margin between separate two classes and this can be described as

$$\min Z(w, b)_{w,b} = ½\, w^T w \qquad (3)$$

Analyzing the equation (2), assume the training data are separable nonlinearly and the slack variables makes the hard margin constraints more operable. Now introduce slack variable ς_i in

(2) brings the result as follows.

$$Y_i\,(w^t\phi(x_i) + b) \geq 1-\varsigma_I \qquad \text{For } i = 1,\ldots,l \qquad (4)$$

$$\varsigma \geq 0$$

For $i = 1,\ldots,l$ (5)

Now we want to obtain optimal separating hyper plane the equation is minimized and come to the shape

$$\min Z(w, b, \varsigma_i) = ½\, w^t w + \gamma\, 1/2 \sum_{i=1}^{l} \varsigma i \qquad (6)$$

According to the equation (4) & (5) parameter γ defines transaction between minimum classification error and maximum margin.

The optimization problem is represented by a convex quadratic program which can be easily solved by using the method of Lagrange multiplier. The parameters of Lagrange multipliers are α_i and β_i (i=1,2,….l), the function of Lagrangian function can be described as $L(w,b,\alpha_i, \varsigma_i, \beta_i) = Z(w, b, \varsigma_i) - \sum_{i-1}^{l} \alpha i\, \{y_i\,[w^T \phi(x_i) + b]-1+\varsigma_i\} - \sum_{i-1}^{l} \beta i\, \varsigma_I$ (7)

Now apply Kuhn tracker theorem here we are getting the optimized solution using Lagrangian function, which is as follows $w = \sum_{i-1}^{l} \alpha i\; y_i\phi(x_i)$ (8)

The training examples which contains the non zero Lagrangian coefficients ($\alpha_{i,}$) are described as support vector. Here training examples are initiated as (x_i , y_i). The α_i coefficient can be found by solving the convex quadratic problem and the outcome is as

$$\max\ [-1/2 \sum_{i=1}^{l}\sum_{j=1}^{l} y_i y_j\ (\phi(x_i)^T.\ \phi(x_i))\alpha_i,\alpha_j + \sum_{i=1}^{l} \alpha i \qquad (9)$$

Which is explained as

$$\sum_{i=1}^{l} \alpha_i y_j = 0 \qquad l=1,2,\ldots.l \qquad (10)$$

$$0 <= \alpha_I <= \gamma, \qquad i= 1,2\ldots.l \qquad (11)$$

Then substitute (8) to (1) the final classification can be obtained. Here the new input x, f(x) can be approximated by calculating the equation (12). If f(x) >0, the samples belongs to class 1 otherwise the samples belongs to class 2.

$$f(x) = \{ \sum_{i=1}^{l} \alpha i y i\ .(\phi(x_i)^T.\phi(x))+b\} \qquad (12)$$

where

$$\mathrm{sgn}(x) = \begin{cases} 1, x > 0 \\ 0x \leq 0 \end{cases}$$

The equation (12) describes the inner product pair wise in the feature space where it may be computed by the original data set which uses the kernel function as described (12) & (13).

The kernel function can be implemented as

$$K(x,x_{i)=}\ (\phi(x_i)^T.\ \phi(x_i) \qquad (13)$$

These kennel functions which include redial basis functions and polynomial kernel functions works together for the optimized output[8][9][10]. Then the function can be described as,

$$f(x) = \mathrm{sgn}\{\sum_{i=1}^{l} \alpha i y i\ .K(x_i,x)+b\} \qquad (14)$$

III. ALGORITHM OF MULTICLASS CLASSIFICATION

The main objective of multiclass classification is that it operates every observations of the k class. Here FDF, one-against-one and one-against-all methods will be discussed and analyzed.

Assume that $S=\{(x_1,y_1),(x_2,y_2),\ldots\ldots\ldots(x_i,y_i)\}$ be the training data, where $x_i \in R^m$ and $y_i \in (1,2,\ldots\ldots k)$.

In the case of one-against-one method determines $k(k$-1)/2 classifiers which will support k-class problems. The proposed optimal hyper plane which will support SVM with class i against that if the class j is described as

$D_{ij}(x) = w^T\phi(x) + b_{ij} = 0,$

$I<j$, $1<j<= k$, $1<=i<k$

Where vector described in the feature space is denoted as w^T_{ij} . b_{ij} is described as scalar and $\phi(x)$ is a mapping function[11][12].

The below equation describes the optimal hyper plane orientation and it is explained as

$D_{ij}(x) = - D_{ij}(x)$ (15)

Now from the above equations the following methods can be explained[13][14].

1.1 One against One

For this method the input vector , the method can be explained as

$$D_i(x) = \sum_{j\neq i\ j=1}^{k} sgn\,(Dij\,(x)) \qquad (16)$$

And also the classifier x activates the equation into the class [15][16].

$$\arg\ \max(D_i(x))\ ,\ i=1\ldots.k \qquad (17)$$

1.2 Fuzzy Decision Function

In the Fuzzy Decision Function method, first the input vector x is taken. m_{ij} (x) $(i,j$ = 1,2,3….k) is the 1-D membership function in which the directions of orthogonal optimal separating hyper plane $D_{ij}(x) = 0$.

Now it is described as $m_{ij}(x) = \begin{cases} 1 \\ D_{ij}(x), \end{cases}$ $1 \leq D_{ij}(x)$, otherwise .

From the equation the deduced function comes as the membership function $m_i(x)$ are explained by

$m_i(x) = \min (m_{ij}(x))$, $j = 1\ldots k$ (18)

by using the equation (18) , the specified sample x is classified into the exact class[17][18]

$\arg \max(m_i(x))$ $i = 1\ldots k$ (19)

1.3 One Against All

In the case of a k class problem, one against all method helps to construct the k Support Vector Machine models. All of the training examples are implemented on i_{th} SVM where i_{th} class holds the positive level and all other remaining examples are implemented with negative levels. Final output produced by one against all method is the highest output value which is the class corresponds to SVM[19][20].

Now consider the optimization problem of (3) to (5) and by solving it with all the related training samples with the data set the following decision function is generated with i_{th} SVM is $D_i(x) = w^T\phi(x) + b_i$

In this equation the input vector x is used to assign to the class which maps to the largest value of the corresponding decision function applied to SVM[21]. The final class of x will be implemented as

$X = \arg \max (D_i(x))$ $i = 1\ldots k$

IV. PROCEDURE RELATED TO DATASET

The standard dataset here used is MIT BIH arrhythmia dataset. This has total 310 ECG recordings where 90 persons are involved, where each of the recording contains ECG lead which is recorded for twenty seconds, With 500 Hz, 12-bit resolution over a nominal range of 10mV. The database works with 493 instances where 253 attributes are used of which 231 attributes are characterized as linear values and the remaining are treated as nominal. Many zero valued and missing value columns makes the database imperative to resize and preprocess the dataset which makes the dataset relevant and reliable. So missing values or the all zero components are removed from the dataset. Here the dataset uses a total of 389 instances and related 159 attributes. which is distributed among 6 classes where 1 class indicated as normal ECG , the class belongs to 2 to 5 are designated as different arrhythmia class, remaining class 6 refer to unclassified classes[22][23].

The below table (Table -1) describes different arrhythmia classes and the number of instances which belongs to each of the classes of the dataset described above.

Table 1 :Number of instances in the dataset of Arrhythmia classes

Class	Name of Class	Total No. of Instances
1	Normal class	248
2	Changes in Ischemia	35
3	Myocardial Infraction	17
4	Sinus bradycardia	22
5	Right bundle branch block	46
6	Others	21

In this experiment the SVM based methods used were trained by almost fifty percent of the total dataset. This dataset were chosen from main database where all classes are properly taken in the logical percentage. For testing purpose the remaining dataset from the main database is used. Below table (Table-2) shows the training and testing datasets representing each of the individual class.

Table 2 : Testing and Training datasets of the different classes

Data	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Total
Initial	248	35	17	22	46	21	389
Train	124	17	9	11	23	11	195
Test	124	18	8	11	23	10	194

Here SVM based methods are used by Gaussian kernel[24][25]. Now here σ is denoted as kernel parameter and λ is denoted as regularization parameter . The data are empirically optimized and shown in Table 3 & Table 4. Now the error rate is minimized and the dataset is validated which brings the best accuracy rate. The accuracy rate is determined in terms of percentage which ensures better classification of the datasets used for arrhythmia detection[26]. The below table (Table 3) describes the rate of accuracy (in %) with respect to the value of the kernel parameter σ.

Table 3 : The accuracy rate with respect to the value of σ

No	σ	OAO	FDF	OAA
1	2^{-3}	63.56	63.32	63.18
2	2^{-2}	62.99	61.53	62.17
3	2^{-1}	62.37	62.45	62.19
4	2^{-4}	63.86	61.67	63.12
5	2^{6}	63.46	61.91	69.17
6	2^{5}	64.23	62.56	64.19
7	2^{1}	65.32	63.41	65.19
8	2^{3}	64.12	63.21	64.78
9	2^{2}	68.34	62.34	73.23
10	2^{1}	62.34	60.23	61.25
11	2^{5}	64.32	60.43	61.61
12	2^{7}	67.45	62.19	63.28
13	2^{2}	65.63	61.56	63.78

Below the table (Table 4) describes the rate of accuracy (in %) with respect to λ value where the best value of σ is taken as a reference and the calculation is done according to its reference.

Table 4 : The accuracy rate with respect to the value of λ taking the best σ value

No	λ	OAO	FDF	OAA
1	2^{-2}	68.68	62.45	62.12
2	2^{-4}	67.51	61.39	63.32
3	2^{-3}	66.41	61.45	64.91
4	2^{-2}	68.45	62.36	63.43
5	2^{4}	69.39	62.71	65.32
6	2^{0}	68.23	63.56	64.29
7	2^{3}	69.32	64.41	65.23
8	2^{2}	69.12	64.28	65.78
9	2^{4}	69.34	63.14	66.23
10	2^{3}	68.35	62.27	65.25
11	2^{6}	69.32	63.49	64.61
12	2^{7}	68.48	63.20	65.28
13	2^{8}	69.23	62.36	64.38

V. PERFORMANCE COMPARISON

Now consider the performance comparison among various SVM methods using arrhythmia classification results of the ECG database. The result shows that one against all algorithm shows the accuracy rate with highest percentage. The different σ values helps to classify the dataset which is used to train and optimize the system. The highest percentage of accuracy rate was chosen and fixed by σ value. After that various λ values helps the system to converge and classify. The different range of values used for λ and σ where $\lambda = [2^{-4}, 2^{-3}, 2^{-2}, \ldots\ldots, 2^{7}, 2^{8}]$ and $\sigma = [2^{-4}, 2^{-3}, 2^{-2}, \ldots\ldots, 2^{7}, 2^{8}]$. The research shows that the accuracy and the performance of one-against-all method is better than one-against-one method in the classification of ECG data. It is also fact that the result could vary time to time with different dataset. The study shows that FDF performs constant and relatively poor classification results upon the ECG data. The potential improvement of the performance we have to remove the ambiguity from the database where the FDF method works with σ value . The result clearly shows that the highest accuracy comes from OAO method but the as the gap is minimum, every time it is difficult to calculate the highest accuracy rate among different methods[27][28]. In the dataset the activity of a particular class depends the use of maximum share of the instances and the presence of the instances have the direct impact on classification. Here the OAO method gives the highest result on ECG datasets performing with the distribution in more uniform way and thereby it ensures better training and outcome of the said system[29].

VI. CONCLUSION

The goal of the paper is to present and discuss the classification of ECG arrhythmia with various widely used and popular methods based on SVM. Several popular classification techniques such as fuzzy- decision- function (FDF), one-against-one (OAO), one-against-all (OAA) are used to classify and distinguish between absence and presence of ventricular arrhythmia for cardiac system where classification is done by one among the six groups. Among the several classifiers the performance of SVM is relatively better. It can work with small learning data and still can deliver strong performance. From the obtained result it is clear that OAA is the best method for the classification of arrhythmia in ECG. So OAA method can be implemented to other standard datasets also for the classification and to get the best result.

REFERENCES

1. E. J. d. S.Luz,W. R.Schwartz ,G.C.Chavez, D.Menotti, "Analysis of Human Electrocardiogram for Biometric Recognition", EURASIP Journal on Advances in Signal Processing Volume 2008, Article ID 148658, pp.1-11.
2. J.S.Wang, W.C. Chiang, Y.T. C.Yang, Y.L. Hsu, "An Effective ECG Arrhythmia Classification Algorithm", International Conference on Intelligent Computing, ICIC 2011 Bio-Inspired Computing and Applications, pp 545-550.
3. Z. Wu, X. Ding, G. Zhang, "A Novel Method for Classification of ECG Arrhythmias Using Deep Belief Networks", International Journal of Computational Intelligence and Applications, Vol. 15, No. 04, 2016, pp 1-13
4. E.J. d. S. Luz, , T. M. Nunes, , V. H.C. Albuquerque, , J. P. Papa, D. Menotti, "ECG arrhythmia classification based on optimum-path forest", Expert Systems with Applications, Elsevier, Vol. 40, 2013, pp 3561-3573.
5. S.S. Qurraie , R. G. Afkhami , "ECG arrhythmia classification using time frequency distribution techniques", Biomed Eng Letters, November 2017.
6. A. Ullah , S. M. Anwar , M. Bilal, R. M. Mehmood , "Classification of Arrhythmia by Using Deep Learning with 2-D ECG Spectral Image Representation" , Remote Sensing, MDPI, 2020, pp 1-14.
7. S. Nikan, F. G.Sridhar, M. Bauer, "Pattern Recognition Application in ECG Arrhythmia Classification", 10th International Joint Conference on Biomedical Engineering Systems and Technologies (BIOSTEC 2017), pp. 48-56.
8. M. H. Song, J. Lee, S. P. Cho, K. J. Lee, S. K. Yoo, "Support Vector Machine Based Arrhythmia Classification Using Reduced Features" , International Journal of Control, Automation, and Systems, vol. 3, no. 4, December 2005 ,pp. 571-579.
9. A. Turnip, M. I. Rizqywan, D. E. Kusumandari, M.Turnip, P. Sihombing, "Classification of ECG signal with Support Vector Machine Method for Arrhythmia Detection", Journal of Physics: Conf. Series 970, 2018, pp. 1-8.
10. S. Karpagachelvi, M. Arthanari, M.Sivakumar," Classification of Electrocardiogram Signals
with Support Vector Machine and Relevance Vector Machine", International Journal of Engineering Science and Technology, Vol. 2(11), 2010, pp. 6511-6520.
11. M. H. Song, J. Lee, S. P. Cho, K. J. Lee, S. K. Yoo, "Support Vector Machine Based Arrhythmia Classification Using Reduced Features", International Journal of Control, Automation, and Systems, vol. 3, no. 4, December 2005, pp. 571-579.
12. E. D. Ubeyli, "ECG beats classification using multiclass support vector machines with error correcting output codes",Digital Signal Processing, Elsevier, 2007, pp. 675–684.
13. D. Tsujinishi, S. Abe, "Fuzzy least squares support vector machines for multiclass problems", Neural Networks , Elsevier Science Ltd, 2003, pp.785–792.
14. D. S. Palacios, C. Ferri, M. J. R.Quintana, "Improving Performance of Multiclass Classification by Inducing Class Hierarchies", International Conference on Computational Science, ICCS 2017, 12-14 June 2017,Procedia Computer Science 108C (Science Direct), pp.1692–1701.
15. B. Liu, Zhifeng Hao, Eric C. C. Tsang, " Nesting One-Against-One Algorithm Based on SVMs for Pattern Classification", IEEE transactions on neural network, Vol. 19, No. 12, December 2008, pp. 2044-2052.
16. R. Debnath, N. Takahide, H. Takahashi, "A decision based one-against-one method for multi-class support vector machine", Pattern Analysis Applications, Springer-Verlag London Limited, 2004, pp. 164–175.
17. C.F. Lin ,S.D.Wang, "Fuzzy Support Vector Machines", IEEE Transactions on neural networks, Vol. 13, No. 2, March 2002, pp. 464-471.
18. U. R. Acharya, P. S. Bhat, S.S. Iyengar, A. Rao, S. Dua, "Classification of heart rate data using artifcial neural network and fuzzy equivalence relation", Pattern Recognition, Elsevier Science Ltd, 2003, pp.61 – 68.
19. M. Arun Kumar, M. Gopal, "Reduced one-against-all method for multiclass SVM classification", Expert Systems with Applications, Elsevier , 2011, pp. 14238-14248.
20. Yi Liu, Y. F. Zheng,"One-Against-All Multi-Class SVM Classification Using Reliability Measures", IEEE Xplore, January 2005, pp. 1-4.
21. G. d. Lannoy, D. Francois, M. Verleysen, "Class-Specific Feature Selection for One-Against-All Multiclass SVMs" ESANN 2011 proceedings, European Symposium on Artificial Neural Networks, Computational Intelligence , 27-29 April 2011, pp. 263-268.
22. S. Kuila, N. Dhanda, S. Joardar, "Feature Extraction and Classification of MIT-BIH Arrhythmia Database", Proceedings of the 2nd International Conference on Communication, Devices and Computing, Springer LNEE, March 2019, Haldia, pp. 417-427.
23. G.B. Moody, R.G Mark, "MIT-BIH Arrhythmia Database",IEEE Eng in Med and Biol, May-June 2001, Version: 1.0.0 , pp. 45-50.
24. P. Sahoo,A. K. Behera, M. K. Pandia, "On the Study of GRBF and Polynomial Kernel Based Support Vector Machine in Web Logs" , 1st International Conference on Emerging Trends and Applications in Computer Science, IEEE explore, September 2013.
25. V. A. Afentoulis, K.I. Lioufi, " SVM classification with linear and RBF kernels", Vasileios Apostolidis-Afentoulis University of Macedonia, July 2015, pp. 1-7.

26. H. Song, Z. Ding, C. Guo, Z. Li, H. Xia, "Research on Combination Kernel Function of Support Vector Machine", International Conference on Computer Science and Software Engineering, 2008, IEEE Computer Society, pp.838-841.
27. S. Abe, "Analysis of Multiclass Support Vector Machines", Proc. International Conference on Computational Intelligence for Modelling Control and Automation, January 2003, pp.385-396.
28. J. A. Nasiri , M. Naghibzadeh , H. S. Yazdi , B. Naghibzadeh, "ECG Arrhythmia Classification with Support Vector Machines and Genetic Algorithm", Third UKSim European Symposium on Computer Modeling and Simulation, 2009, pp. 187-192.
29. John C. Platt, Nello Cristianini, John Shawe-Taylor, "Large Margin DAGs for Multiclass Classification", Advances in Neural Information Processing Systems, 1999, pp.547-553.

AUTHORS PROFILE

Mr. Sumanta Kuila is currently working as an Assistant Professor in the Department of Computer Science & Engineering, Haldia Institute of Technology, Haldia-721657, India. He has 16 years of experience in the field of Computer Science & Engineering. He is doing Ph.D in Computer Science & Engineering from Amity University Uttar Pradesh, Lucknow campus. He did his masters (M.E) from west Bengal University of Technology in 2005. He has done 6 Technical certifications (Sun & Oracle) on Java/J2EE & Web Technology. His current research interest includes Machine Learning, Data Analytics, Big Data, Internet of Things etc.

Mr. SayandeepMaity is currently a student of Haldia Institute of Technology, Haldia-721657, India, pursuing Bachelor of Technology in Computer Science and Engineering. He completed his Secondary and Higher Secondary from St. Xaviers School, Haldia in 2015 and 2017 respectively. He has 3 Technical certifications (IBM) on Python and Data Science. His current research interest includes Machine Learning, Data Science, Data Analysis, Artificial Intelligence, etc.

Suman Kumar Mal is currently pursuing his Bachelor's Degree in Computer Science and Engineering from Haldia Institute of Technology, Haldia-721657. He has completed his secondary and higher secondary school from Holy Cross School, Bokaro-827010. He has a Professional Certification in Data Science from IBM.His research interests are in the field of Data Science, Machine Learning and Decentralized Applications.

Dr. Subhankar Joardar is presently Professor & Head in the Department of Computer Science and Engineering, Haldia Institute of Technology, Haldia-721657, India. He received his Ph.D degree from Birla Institute of Technology, Mesra, Ranchi, India in 2016. He did his masters (M. Tech and MCA) both from BIT, Mesra, Ranchi in 2009 and 2002 respectively. He has published more than 14 technical papers in the referred journals/conferences. He has served as Organizing Chair of international conference (ICITAM 2017). He is also Program Committee member of International Conferences (ICCDC 2019). He is a member of Computer Society of India. His current research interests include Swarm intelligence, Routing in Mobile Ad Hoc Networks, Machine Learning.