

# Feature Extraction and Classification for the Identification of Different Cardiac Arrhythmias using Wavelet-SVM Methodology

# Mayank Kumar Gautam

Department of Electrical Engineering, Rajkiya Engg College, Ambedkar Nagar, India

## ABSTRACT

According to a recent report of world health organization (WHO), an estimated 17.5 million people died from CVDs (cardiovascular diseases) representing 30% of all global deaths (latest available data from website). Electrocardiogram (ECG) is the recording of the electrical activities of the heart and is used to diagnose various cardiovascular diseases. The real source of human calamity is Cardiac issues that are expanding step by step in world. To incredible exertion and analyze the cardiovascular disease, which numerous individuals are utilized diverse sort of portable electrocardiogram (ECG) in remote observing method. ECG Feature Extraction acting a critical part in diagnosing generally of the heart sicknesses. Presently complete inspected has been completely through for highlight extraction of ECG sign dissecting, highlight extricating and taking after that characterizing it have been arranged amid the long-prior time, and here we presented delicate processing procedures. To perceive the current circumstance of the heart Electrocardiography and is a fundamental device however it is a period expending procedure to break down a persistent ECG signal as it might hold a huge number of relentless heart pulsates. As of right now we, change over simple sign to computerized one and after that switch of it, it helps in precisely diagnosing the sign. Point of this paper is to show an identification of some warmth arrhythmias utilizing emerging Wavelet-SVM methodology.

Keywords: ECG, SVM, Wavelet Transform, Feature Extraction and Classification

### I. INTRODUCTION

The electrocardiogram (ECG) is routinely utilized as a part of clinical practice, which portrays the electrical activity of the heart. In physical checkups at healing centers, doctors record the ECG after the patient has practiced to check his/her cardiovascular condition. The Holter ECG recorder is utilized most oftentimes to record the ECG. Doctors apply the gadget to a patient when they have to screen his/her ECG to locate the couple of unusual cycles in the ECG for the duration of the day. Doctors then decipher the states of those waves and buildings. They figure parameters to figure out if the ECG hints at heart malady or not. The parameters are the stature and the interval of every wave, for example, RR interval, PP interval, QT interval, and ST segment. Acknowledgment of the fiducial focuses and counts of the parameters is a dreary routine for the doctor. In this way, there is an

requirement for a programmed ECG earnest acknowledgment framework to decrease the weight of translating the ECG. Cardiovascular arrhythmias result from any aggravation in the rate, normality, and site of cause or conduction of the heart electric motivation [1]. Comprehensively talking, arrhythmias can be isolated into two gatherings. The main gathering incorporates ventricular fibrillation and tachycardia which are lifeundermining and require quick treatment with a defibrillator. Discovery of these arrhythmias is all around examined and effective indicators have been planned with high affectability and specificity [2]-[5]. This study explored the second gathering which incorporates arrhythmias that are not quickly lifedebilitating but rather might oblige treatment to avert further issues. The electrocardiogram (ECG) is an ease, noninvasive, and viable test for arrhythmia examination and has turned into the standard indicative apparatus. A few arrhythmias show up occasionally and up to a

week of ECG action might should be recorded utilizing a Holter ECG screen to effectively catch them. Numerous arrhythmias show as groupings of heartbeats with abnormal timing or ECG morphology. An imperative stride toward recognizing an arrhythmia is the arrangement of heartbeats. The mood of the ECG sign can then be controlled by knowing the arrangement of back to back heartbeats in the sign [6]. Order of heartbeats can be exceptionally tedious and henceforth any computerized handling of the ECG that helps this procedure would be of help and is the center of this study.

Robotized characterization of heartbeats has been beforehand reported by different agents (e.g., [7]–[12]) utilizing an assortment of elements to speak to the ECG and various arrangement strategies. Highlights incorporate ECG morphology [8], [9], pulse interim elements [8]–[11], recurrence based components [7], higher request cumulant highlights [10], Karhunen– Loeve development of ECG morphology [11], and hermite polynomials [12]. Classifiers strategies utilized incorporate straight discriminants [7], back spread neural systems [8]–[10], self-sorting out maps with learning vector quantization [11], and self-arranging systems [12].

In spite of gauges prescribed for reporting execution aftereffects of cardiovascular musicality calculations by the Association for the Advancement of Medical Instrumentation (AAMI) [13], [14], just the work in [11] and [12] have used these models. This makes it exceptionally hard to evaluate the relative benefits of the distinctive calculations. The AAMI principles are embraced in this study and our outcomes have been contrasted with those of [11] and [12].

In [11], Hu et al. tweaked a pulse classifier to a particular patient (known as a nearby classifier) and afterward joined it with a worldwide classifier composed from a huge database of ECG signs. The two classifiers were then joined utilizing a blend of specialists (MOE) approach. The nearby classifier requires a cardiologist to clarify a fragment of a patient-particular ECG keeping in mind the end goal to execute the MOE approach. The worldwide classifier accomplished an exactness of 62.2% and the MOE classifier accomplishing 94.0% precision for recognizing ventricular ectopic beats (VEB) from non-VEBs.

Lagerholm et al. [12] depicted a strategy for grouping ECG heartbeats from a recording into 25 bunches and verified that by and large 98.5% of the heartbeats in any one bunch were from the same pulse class. This means a characterization execution of 98.5% if a specialist can effectively distinguish the prevailing beat of a bunch.

AAM I heart beat class	N	S	V	F	Q
Descr iption	Any heartbeat not in the S,V,F or Q class	Supraven tricular ectopic beat	Ventric ular ectopic beat	Fusion beat	Unkno wn beat
	Normal beat (nor)	Atrial prematur e beat (AP)	Premat ure ventricu lar contract ion (PVC)	Fusion of ventric ular and normal beat (fVN)	Paced beat (P)
	Left bundled branch block beat (LBBB)	Aberrated atrial prematur e beat (aAP)	Ventric ular escape beat (VE)		Fusion of paced and normal beat (fPN)
MIT- BIH heartb eat types	Right bundled branch block beat (RBBB)	Nodal (junction al) prematur e beats (NP)			Unclas sified beat (U)
	Atrial escape beats (AE)	Supraven tricular prematur e beat (SP)			
	Nodal (junction al) escape beats (NE)				

# **Table 1.** Mapping the MIT-BIH Arrhythmia DatabaseHeartbeat Types to the AAMI Heartbeat Classes

The AAMI prescribed practice was utilized to consolidate the MIT-BIH pulse sorts into five pulse classes which were utilized as a part of all resulting handling. Every class incorporates heartbeats of one or more sorts as appeared in Table 1. Class N contains beats beginning in the sinus hub (typical and group sorts), class contains branch piece beat S supraventricular ectopic beats (SVEBs), class V contain ventricular ectopic beats (VEBs), class F contains beats that outcome from intertwining typical what's more, VEBs, and class Q contains obscure beats including paced beats.

#### **Database Used**

All ECG information is acquired from MIT-BIH arrhythmia database that contains records of numerous patients with heart inconveniences or variations from the norm. The recurrence of the ECG information was 360HZ. Every record has its separate explanation document that shows the class of the pulse. A solitary channel ECG is gathered and used to calculation assessment. Since there is couple of classes of unusual QRS buildings in one record, we select diverse strange QRS edifices from a few records. Six sorts of QRS buildings showed up every now and again in the database. Along these lines, we for the most part manage six sorts heartbeats which incorporate typical beat(NORMAL), package branch left square beat(LBBB), right package branch piece beat(RBBB), beat(PACE), untimely paced ventricular contraction(PVC) and atrial untimely contraction(APC). In the information preprocessing process, nonstop ECG signals must be isolated into numerous fragments which contain one pulse. Table 2. shows the different beats belonging to different MIT-BIH files used in the study.

**Table 2:** Samples of ECG used for training and testing.

Class	Beat	No. of Beats	MIT-BIH
Label	Туре	Used	File
		2230	100
		1860	101
1	N	2080	103
		1730	113
		1950	115
		1510	123
		2490	109
2	LBBB	2120	111
		1450	207
		2000	214
		2160	118
3	RBBB	1530	124
		1820	212

		1250	231
5	PVC	990	208
		830	233
		380	209
8	APC	90	220
		70	223
		1380	232
9	Paced	2070	107
		1540	217

## **II. METHODS AND MATERIAL**

# Methodology for feature extraction and classification

The stages of a computerized framework suitable for pulse grouping which depends on the results of this study which comprises of three stages: a preprocessing stage, a handling stage, and a characterization stage. The digitized ECG is connected at the information to the preprocessing stage. The preprocessing stage uses a sifting unit to evacuate ancient rarity signals from the ECG signal. These signs incorporate gauge meander, power line impedance, and high-recurrence clamor. The handling stage comprises of pulse identification highlight extraction modules. The and pulse recognition module endeavors to find all heartbeats. The element extraction module is worried with framing a vector of estimations (highlight vector) from every pulse that are handled by the classifier stage. The element extraction modules are required on the grounds that, despite the fact that it is workable for the grouping stage to handle the ECG tests specifically, more prominent grouping execution is frequently accomplished if a littler number of separating components (than the quantity of ECG tests) are initially extricated from the ECG. The arrangement stage contains SVM-Wavelet classifier units which select one of the required classes in light of the information highlight vector. The classifier units ordinarily contain parameters which are set amid the framework advancement to enhance the grouping execution. A combiner then unites the choices of the classifier units to frame the last choice of the framework. The modules framing these stages are talked about in more detail beneath. The modules forming these stages are discussed in more detail below.

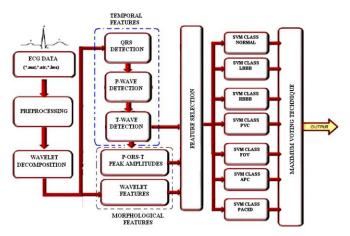


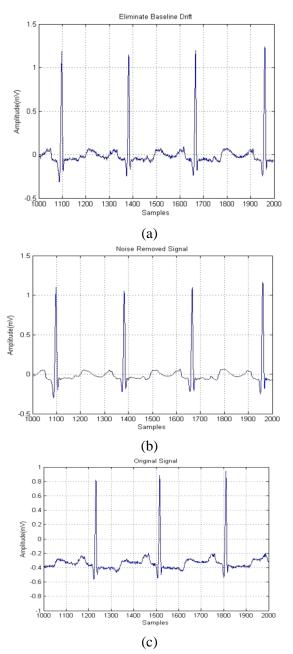
Figure 1. Structure of purposed ECG signal processing approach.

#### **Pre-processing of Signal**

ECG signal intrinsically contains of different kind of undesirable noise and artifacts impacts like baseline drift, noise f the electrode contact, polarization noise, the inward speaker noise, noise because of movement of the muscles, and motor artifacts. The movement of electrodes instigated artifacts noise. Along these lines in order to make original ECG signal prepared for feature extraction step, we should evacuate baseline wander and take out above noise.

We propose to utilize wavelet filtering to filter the ECG signal since this method is suitable for processing the R-peak areas without change of the shape or position of the original signal. As per the past exploratory information, with an aim to upgrade the signal to be separating, we should consider these two criteria: sampling frequency of the signal and the learning that a large portion of the noises are situated outside of the frequency interval between 1.5 Hz to 50 Hz [13]. For this reason, we utilize a band pass filter (BPF) Equations which is being developed by a high pass filter (HPF) with cutoff frequency of 1.5 Hz. This filter disposes of benchmark varieties. The yield of this channel is course with a LPF with cutoff frequency.

The scale and sort of the mother function parameters are particular to every filter. Along these lines, the programmed figure of ideal scale for high pass sifting when the examining frequency is 256 is equivalent to request 6. The ideal scale request for the low pass filtering is equivalent to order 2. The consequences of above steps are being appeared in the following ECG record Figure 2.



**Figure 2.** Preprocessing results taken on record 100.dat from MIT-BIH cardiac arrhythmia database (a) original signal, (b) baseline elimination, (c) removal of noise

#### **B. QRS Detection**

Every ECG cycle is basically comprised of a P-wave which is been compared to the atrial depolarization phase of ECG cycle, a QRS complex which is being related to the ventricular depolarization phase of ECG cycle and a T wave which is point to the fast repolarization of the ventricles. A typical ECG signal and its time intervals are appeared in Figure 3.

The greater part of the clinically features which are helpful for symptomatic the illness can be found in the time interval between segments of ECG and the estimation of the signal sufficiency. For instance, the Q-T highlight is utilized to acknowledgment one risky ailment, the Long Q-T Syndrome (LQTS), which is capable of thousand passings every year [14]. The state of T wave is a basic component and it is key to distinguish it effectively since reversed T waves can be brought on as an impact of a genuine infection named coronary ischemia [15].Designing a calculation in order to extricate the features of ECG naturally is hard since ECG signal has a period variation conduct. As an aftereffect of these signal properties, we confront with various physiological limitations and the presence of noise.

Lately a few calculations have been proposed for discovery those features. In [16] they acquainted a technique with concentrate wavelet features and utilized SVM for order. In their purposed strategy, the order is done without totally distinguish ECG parts. Castro et al. presented a technique that utilized wavelet based features and characterize different type of irregular heartbeats [17]. Tadejko and Rakowski proposed a calculation which depends on computational morphology [18]. Their fundamental objective is the evaluation of different programmed classifiers for location of confusion in the ECG. In [18] they proposed a strategy to concentrate highlight from ECG in view of a multi determination wavelet transform. To start with, they expel commotion from ECG signal by tossing the coefficient which brought on noise. In next step, they identify QRS buildings and by utilizing them the begin and end of every wave part is resolved. They survey proposed strategy on a few records taken in the account from MIT-BIH Cardiac Arrhythmia Database of ECG records.

We have proposed a strategy for acknowledgment of time interval and sufficiency of different wave parts of ECG in the current thesis for the evaluation of peaks. In the First phase of our methodology, the R-peak is recognizing precisely. For this reason we utilized wavelet. In the second stage, the other ECG parts are recognized by utilizing a neighborhood seeks around the distinguished R-peak. We can abridge this methodology:

The area of the R-wave has been recognized by utilizing wavelet transform.

# C. R-Peaks Detection

The discovery of R-peak is the initial step of feature extraction. For this reason, we utilized DWT because of its capacity to perceive distinctive areas of the waves precisely. So also to the preprocessing, we apply the same strides in order to fig the scale as well as the pickup the mother capacity. We have the QRS complex sign as a data which has the frequencies somewhere around 5Hz and 15Hz, so we select size of request 4 and pick the Db4 mother wavelet. The Db4 wavelet is exceptionally prominent for the discovery and area of R peaks because of the solid likeness of its shape to the ECG signal. Our technique is sorted out in the accompanying steps. By performing wavelet decomposition, we down examining the information. Thus, the measure of pointless data is decreased however the segment of QRS is not changed.

In order to evaluate the focused area of renowned R wave peak, firstly we pick the areas which their sufficiency is more noteworthy than 60% of the maximum estimation of the entire data signal. Since, we expel the commotion from the sign in the past step; it is helpful for R-peak identification.

Since we break down the sign into fourth level, the Rpeak area in the adjusted sign is no less than 0.25 of the R-peak area in the original signal. So as to locate the real area of R-wave we should change over the established positions by duplicating them with 4. Another vital point is that R-peak area in changed sign is not precisely on the original signal at a size of 4. Position of the sign will change amid the down examining, so we should to do neighbourhoods seek around the R-peak which computed in past part. The interval of this pursuit can be restricted to a window of  $\pm 20$  samples.

# **D.** T Wave Detection

Discovering T-wave in ECG signal is the most confused errand. Outlining a method for recognizing Twave is troublesome since it has a time variation practices. By checking the ECG waveform somebody can see that the T-wave is situated as the interval which has largest amplitude in the middle of S and the center of the R-R interval. In this manner, the starting interval for T began from S-wave and completed at the center purpose of the R-R interval. • T-wave Onset detection

Another critical point in analyzing the ECG signal is the begin purpose of T-wave or Ton since it is utilized as a bolster (support) point for deciding the extremity of T which can be positive, negative or leveled (flat). Presence of negative or level T waves in ECG demonstrates a genuine illness, the heart ischemia. The looking area is beginning from the S-wave in addition to little balance till T-wave and Ton is a point with min value in this interval.

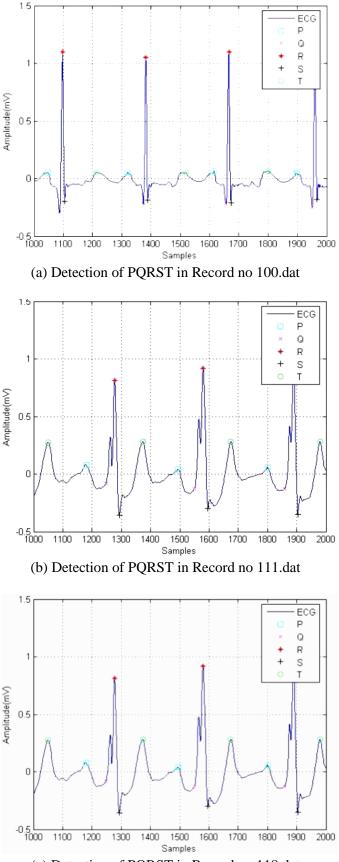
T-wave end detection

Identification of end purpose of T-wave, Toff, is another troublesome errand in this area since there is still discourse between experts about it. The best properties for distinguish Toff is finding the point which has the most minimal amplitude after T inside of a constrained extent. For this reason, it is important to make the signal smooth. We can do it by including past estimations of the sign to it. In the event that a point in abundance is bigger than the amplitude's of all the past 3 samples, it can be think about as a Toff point.

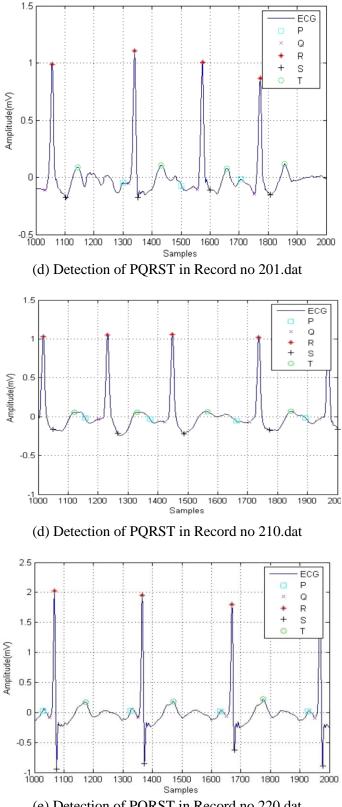
Table 3 condenses the search intervals used to discover ECG segments. It demonstrates the records of the begin and the end scopes of the search [19]. The aftereffects of usage of PQRS discovery calculation for some ECG records from MIT-BIH database are appeared in Figure 4

Wave type taken	Start	Stop	Type of Interval
Р	0.7*R_R(i)-7	Qon(i)-12	max
Q	R_R(i)-25	R_R(i)-7	min
Qon	Q(i)-12	Q(i)-5	max
s	R(i)+6	R_R(i)/5-10	min
Ton	0.7*(T(i)-S(i))	T(i)-10	min
r	S(i)+15	R_R(i)/2	max

Table 6	Table for Searching of Intervals	
Tauc -	Table for Sedicinity of Intervals	



(c) Detection of PQRST in Record no 118.dat



(e) Detection of PQRST in Record no 220.dat

Figure 3. Detection results of PQRST in (a) record 100.dat, (b) record 111.dat, (c) record 118.dat, (d) record 201.dat, (e) record 210.dat, (f) record 220.dat taken in account from MIT-BIH arrhythmia database of ECG records.

# **III. RESULTS AND DISCUSSION Calculation of Accuacy**

Table 4. Detec	tion of Accura	acy for	Different	Туре
of Arrhythmia	on MIT-BIH	Arrhyth	mia Datał	base

Types of	Model
Arrhythmias	Accuracy
Ν	94.16%
APB	99.04%
LBBB	98.50%
RBBB	92.33%
PVC	99.97%
Fusion of V and N	99.51%
PB (Paced Beat)	99.63%
Average	97.59%

As we talked about some time recently, different specialists utilized different sort of techniques for ECG characterization, for example, Combining KNN and DWT [15], MLP and VQ [16] and SOM with SVD [18]. Their framework execution is appeared in Table 5.

As should be obvious, there are numerous elements and reasons cause the examination between our own framework results and theirs off base. For instance the quantity of chose arrhythmia by every scientist is differed to the others, likewise the chose records or even the quantity of removed beat from a particular record for preparing and testing are not specified unmistakably. In any case our framework results are tantamount with the others [19] [20] [21].

Table 5. Comparisons of Different Methods and Proposed Method for ECG Classification

Method	No. of beat type	Accuracy (%)
KNN-DWT Method	4 beat type	96.65%
Neuro-Fuzzy Method	4 beat type	98%
MLP-VQ Method	2 beat type	96.80%
SOM-SVD Method	3 beat type	92.20%
Wavelet-SVM Method (Proposed Method)	7 beat type	97.59%

#### **IV.CONCLUSION**

The essential interest of this research is the classification of Normal, LBBB, RBBB, APC, PVC, Paced Beats etc cardiac arrhythmias utilizing DWT and SVM classifier, and the results have been examined in points of interest in this section. Few parameters have been examined in the study, which are the estimations of vitality, greatest, least, mean and standard deviation of level 4 DWT detail coefficients. The outcomes show that by utilizing DWT and SVM, the characterization of Normal, LBBB, RBBB, APC, PVC, Paced Beats etc can be classified; consequently the essential objective of this study is accomplished. The simulation results about demonstrate that the class of coronary illness is all around predicted utilizing DWT and SVM system and the system functioning admirably since it accomplish the 97.59% of arrangement accuracy rate. This result demonstrates that it has some potential and had been observed to be effective in cardiac disease diagnosis.

#### V. ACKNOWLEDGMENT

This work is supported by University Grant Commission (UGC), New Delhi, India under Major Research Project (MRP) scheme. This work has been carried out in the Department of Electrical Engineering at MMM University of Technology, Gorakhpur, India.

#### **VI.REFERENCES**

- M. S. Thaler, The Only EKG Book You'll Ever Need, 3rd ed. Philadelphia, PA: Lippincott Williams & Wilkins, 1999.
- [2] K. Minami, H. Nakajima, and T. Toyoshima, "Real-time discrimination of ventricular tachyarrhythmia with Fourier-transform neural network," IEEE Trans. Biomed. Eng., vol. 46, pp. 179–185, Feb. 1999.
- [3] S. Evans, H. Hastings, and M. Bodenheimer, "Differentiation of beats of ventricular and sinus origin using a self-training neural network," PACE, vol. 17, pp. 611–626, 1994.
- [4] R. Clayton, A. Murray, and R. Campbell, "Recognition of ventricular fibrillation using neural networks," Med. Biol. Eng. Comput., vol. 32, pp. 217–220, 1994.
- [5] S. Barro, R. Ruiz, D. Cabello, and J. Mira, "Algorithmic sequential decision- making in the frequency domain for life threatening ventricular arrhythmias and imitative artefacts: A diagnostic system," J. Biomed. Eng., vol. 11, pp. 320–328, 1989.
- [6] J. A. Kastor, Arrhythmias, 2nd ed. London, U.K.: W.B. Saunders, 1994.
- [7] L. Senhadji, G. Carrault, J. J. Bellanger, and G. Passariello, "Comparing wavelet transforms for recognizing cardiac patterns," IEEE Eng. Med. Biol. Mag., vol. 14, pp. 167–173, Mar.–Apr. 1995.
- [8] T. H. Yeap, F. Johnson, and M. Rachniowski, "ECG beat classification by a neural network," in Proc. Annu. Int. Conf. IEEE Engineering Medicine and Biology Soc., 1990, pp. 1457–1458.

- [9] Y. H. Hu,W. J. Tompkins, J. L. Urrusti, and V. X. Afonso, "Applications of artificial neural networks for ECG signal detection and classification," J. Electrocardiol., vol. 26, pp. 66–73, 1993.
- [10] S. Osowski and T. L. Linh, "ECG beat recognition using fuzzy hybrid neural network," IEEE Trans. Biomed. Eng., vol. 48, pp. 1265–1271, Nov. 2001.
- [11] Y. H. Hu, S. Palreddy, and W. J. Tompkins, "A patientadaptable ECG beat classifier using a mixture of experts approach," IEEE Trans. Biomed. Eng., vol. 44, pp. 891– 900, Sept. 1997.
- [12] M. Lagerholm, C. Peterson, G. Braccini, L. Edenbrandt, and L. Sornmo, "Clustering ECG complexes using hermite functions and self-organizing maps," IEEE Trans. Biomed. Eng., vol. 47, pp. 838–848, July 2000.
- [13] Gokhale, P. S., "ECG Signal De-noising using Discrete Wavelet Transform for removal of 50Hz PLI noise", International Journal of Emerging Technology and Advanced Engineering, Vol. 2, pp. 81-85, 2012.
- [14] Thakor, N. V., Zhu, Y. S, & Pan, K. Y., "Ventricular tachycardia and fibrillation detection by a sequential hypothesis testing algorithm", IEEE Transactions on Biomedical Engineering, Vol. 37, p. 837-843, 1990.
- [15] Al Qawasmi, A. R., & Daqrouq, K., "ECG Signal Enhancement Using Wavelet Transform", WSEAS Trans on Biology and Biomedecine, Vol. 7, pp. 62-72, 2010.
- [16] Gautam, R., & Sharmar, A., "Detection of QRS complexes of ECG recording based on Wavelet Transform using MATLAB", International Journal of Engineering Science and Technology, Vol. 2, pp. 3038-3044, 2010.
- [17] Sumathi, S., & Sanavullah, M. Y., "Comparative Study of QRS Complex Detection in ECG Based on Discrete Wavelet", International Journal of Recent Trends in Engineering, Vol. 2, pp. 273-277, 2009.
- [18] Priyadarshini, B., Ranjan, R. K., & Rajeev A., "Determining ECG characteristics using wavelet transforms", International Journal of Engineering Research & Technology (IJERT), Vol. 1, 2012.
- [19] Sasikala, P., & Wahidabanu, R., "Robust R Peak and QRS detection in Electrocardiogram using Wavelet Transform", (IJACSA) International Journal of Advanced Computer Science and Applications, Vol. 1, No.6, 2010.
- [20] Senhadji, L., Carrault, G., Bellanger, J. J., & Passariello, G., "Comparing wavelet transforms for recognizing cardiac patterns", IEEE Engineering in Medicine and Biology Magazine, vol. 14, p. 167-173, 1995.
- [21]Gautam, Mayank Kumar, "Performance Analysis of ECG Signal Using by Wavelet Transform, Independent Component Analysis and Fast Fourier Transform", IJSRCSEIT, vol. 1, pp. 95-98, Sept-Oct.2016.