International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

Detection of ECG Wave Components for the Prediction of Acute Coronary Syndrome - Brief Survey

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Submitted: 21/12/2023 **Revised**: 27/01/2024 **Accepted**: 09/02/2024

Abstract: An ACS (Acute Coronary Syndrome) is a term used to define the heart diseases like Heart attacks, Myocardial infarction, and Unstable Angina. The study described the Electrocardiogram is an important tool for measuring human health and disease detection. Electrocardiogram (ECG) signal consist of Components like waves, intervals and segments studied on the basis of time duration and size. PAN and TOMPKINS give the concept of QRS detection in the decade of eighty. Further several researchers developed various algorithms to detect QRS on the basis of derivative, wavelet transforms and other techniques. In this research we survey the progressive methods of detection of electrocardiogram wave components for the prediction of acute coronary syndrome by introducing electrocardiogram signal preprocessing, heartbeat segmentation, feature extraction and learning algorithms used. Additionally we depict some databases which is used for evaluation indicated by The AAMI standards were introduced by AAMI and are described in American National Standard Institute (ANSI/AAMI EC57:1998/(R) 2008) [16] for analyzing and describing the performance effect of cardiac rhythm and ST-segment evaluation algorithms. Sometimes monitoring and analyzing heartbeat ECG records are necessary. Most of the time there is a possibility of inaccuracy in ECG record analysis. This research becomes the alternative. It can provide essential information to doctors to carry out their diagnoses on patients.

***Keywords**: Pre-processing, Segmentation, Feature Extraction,Training, and Testing*

1. Introduction

Electrocardiogram is a non-invasive tool which plays a vital role in routine medical check-ups in intensive care units to monitor the health of patients. An ECG signal defines the electrical action of the heart. ECG signals are graphical information which shows the strength and timing of the electrical action in the heart [1]. Cardiac activities like normal sinus rhythm,

arrhythmia, and blockage are related to functions of different heart sections e.g., atria and ventricular, etc. The variation in the rhythm of heartbeats and morphology of wave components is due to the indifferent behavior of cardiac parts. It helps to diagnose cardiac diseases. Automation of ECG signal analysis and diagnosis technique of diseases like Arrhythmias, Coronary heart diseases, and Heart attacks can be divided into four steps: [2-6].

1. Signal acquisition and Pre- processing
2. Feature Extraction
3. Heartbeat segmentation
4. Training and Testing.

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The electrical signal starts from Right Atrium (sinoatrial node) and then moves towards Right Bundle Atria and Left Atria. The P wave signal recorded in the upper heart chamber. The signal moves from Atria to the Ventricles through the AV node (Atrioventricular). After AV nodes' signal moves along a path known as Bundle of His and then into right bundle branch block (RBBB) and left bundle branch block (LBBB) [8].

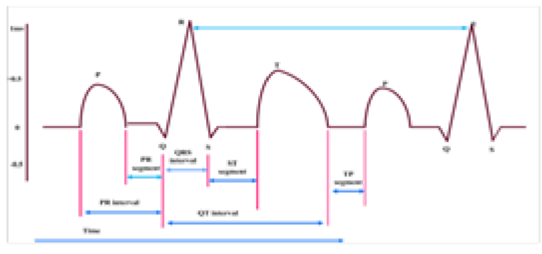

Fig 1: Electrocardiogram signal [85]

A diagrammatic representation of ECG signal in terms of P-Q-R-S-T wave components in an ECG signal as shown in Figure1.

PR Segment: PR segment illustrates the electrical conductivity through the atria and the hold up in the AV node.

QRS wave: Series combination of ‘Q’, ‘R’, and ‘S’ waves are recorded as QRS wave.

T - Wave: T - wave illustrates retrieval of ventricles.

ST-segment: T waves and QRS complexes are connected by the ST segment.

QT- interval: – Time required for ventricles to stimulate and recover.

RR- interval – Time duration recorded between two R peaks of heartbeat. Usually, the frequency and amplitude extent of an Electrocardiogram signal is 0.5 to 100 Hz and 0.2 mV respectively.

P wave: P - wave describes atrial depolarization before the contraction of atrium. The period of the P wave lies between 60ms to 110 ms.

QRS period - QRS complex notify the duration of ‘Ventricular Depolarization’. The high conduction velocity of an electrical impulse produces R peaks of high amplitude. R-peak is the most common standard in the beat detection procedure, due to the high amplitude; it can be differentiated from the noise. QRS wave normally lies within 60 to 100ms time interval.

T- wave: Repolarization of Ventricles is also called as ventricular recovery and it described by the T wave having sharp or bluntly rounded amplitude less than 5mm. T wave lies in between the time interval of 0.10-0.25 seconds. Distressing disease hypercalcemia is interrelated with T-wave anomalies.

P-R Interval: Atrioventricular (AV) node supervises pulse rate, and the node delay energizes the Atrioventricular node. Normally the time duration of PR interval is 0.12 to 20 seconds and any irregularity in P-R - Interval provides early symptoms disorder of undeniable Cardiac Arrhythmias.

ST- Segment: ST segment trailed the QRS complex, where depolarization of both ventricles occurs. The advance ST segment describes the disorder of hypoxia or ventricular ischemia and duration of ST segment is about 0.43 seconds.

QT Intervals: The time duration of QT intervals revealed repolarization and depolarization of signals.

P-P interval analyses the atrial rhythm, whereas the R-R interval analyses the ventricular rhythm. If P-P intervals and RR intervals are uniform throughout the Electrocardiogram then the heart is all right, and if P-P intervals and R-R intervals are not able to maintain uniformity throughout the Electrocardiogram, it is an indication of heart disease [10].

U- Wave: After the ventricular repolarization U-wave followed by the T- wave is hardly detectable as it is having tiny shape. The repolarization of Purkinje fibers illustrated by the U- Waves.

ECG-based Arrhythmia analysis based on two main paradigms, Inter-patient and Intra-patient [8, 9]. The interpretation gives the correct classification of the QRS wave components as True Positive, incorrect classification (non-QRS wave components) as False Positive, and misclassified QRS Wave components as False Negative [9].

The irregularities that reside in the P, QRS, and T waves represent crucial cardiovascular diseases (CVD) like Myocardial Infarction (MI), Ventricular Hypertrophy (VH), & Bundle Branch Block (BBB) etc.

2. Electrocardiogram signal acquisition and Pre-processing

Pre-processing is nothing but the data preparation technique in which a raw ECG signal is converted into a format that is required for further processing Pre-processing includes 1-3 steps. The generalised block diagram is as shown in figure: 2 like linear filtering, nonlinear transformation and decision rules. Linear filtering process comprises Bandpass filter, Derivative and Moving Window Integrator. Nonlinear transformation is used for ECG signal amplitude squaring. T wave discrimination and adaptive thresholds produce ‘Decision Rule Algorithm’. Acquired ECG signal firstly decompress then extract the leads [8, 10-14]. Here we can remove noise, artifacts, and ectopic beats and compute a median beat for each lead [15, 16, 17], to control baseline noise [18] and stable artifacts [19].

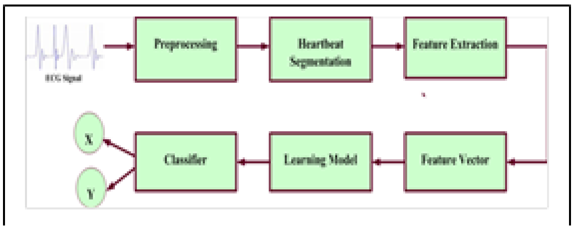

Fig 2: Generalised block diagram

3. Heartbeat segmentation

The heartbeat segmentation is the technique used for the identification of R peak wave or QRS complex while analyzing the accuracy of heartbeat segmentation. Positive predictivity and Sensitivity take into consideration to evaluate the heartbeat segmentation accuracy [20, 21]. Heartbeat segmentation has been studied for more than three decades [22-26].

$$\text{Sensitivity Segmentation} = TP/\,(TP + FN), \quad (1)$$

$$\text{Positive predictivity Segmentation} = TP\,/\,(TP + FP), \quad (2)$$

Where

(TP) True Positive is the analysis of a number of corrected heartbeats.

(FP) False Positive is the analysis of the heartbeats which do not correlate

(FN) False Negative is the analysis of heartbeats which do not execute.

Feature extraction

Feature extraction is nothing but the process of reducing initial raw data set into a new manageable data set, also known as "dimensionality reduction", and the feature is nothing but the statistics extracted through heartbeat to distinguish its class. The heartbeat interval (RR Interval) is the common feature, computed from Cardiac Rhythm studied in most of the literatures.

The different features from cardiac rhythm or electrocardiogram signal's morphology extracted in time domain or frequency domain, or both the R-R interval have a remarkable ability to distinguish the class of heartbeats. Number of researchers developed their techniques using R-R intervals [27- 29]. The variations in R-R interval can be used for noise interference reduction [30].

The classification results improved using normalized RR-interval. [31]. Efficiency of normalized RR features confirm by using feature selection [32]. Some authors develop the methods to determine the distance between fiducial points of heartbeat which is also known as ECG segments or ECG intervals [24]. Various techniques applied on samples directly for dimensionality reduction of feature vector represents the heartbeat as PCA (Principal Component Analysis). [33–35], or ICA Independent Component Analysis [36–38]. Principal Component analysis is a better technique for noise reduction as compared to independent component analysis, whereas independent component analysis is better for feature extraction than principal Component analysis. The combination of principal component analysis technique and independent component analysis technique is more advantages than using independently. [39] KPCA (Kernel Principal Component Analysis) is a better technique to classify heartbeats from electrocardiogram signal than PCA. [40] Kernel Principal Component Analysis has a better performance due to its nonlinear structure. [41] Clustering technique is used to reduce samples to points or clusters, also used to increase the number of features [42]. Morphological features are nothing but the sub-sample of ECG wave [43, 44].

Wavelet transform is the best technique for feature extraction from electrocardiogram signal. [44- 46]. Wavelet transform permits feature extraction in both time and frequency domains [47]. Heartbeats classified as Ventricular Ectopic Beat (VEB) and Supraventricular Ectopic Beat (SVEB) [48]. The Table no 1: summarizes the Comparative study of various features and accuracy calculation

4. Learning algorithms

A learning algorithm is a procedure followed by a machine to carry out the given function anticipated output for a given input. [13, 19, 49]. Machine learning executes the procedure to acquire and scrutinize the input data for expected output in an adequate sequence. The unused data is fed to a learning algorithm; the algorithm reviews the data and upgrades the process for better functioning.

The selection of a suitable machine learning algorithm depends on various aspects, including data size, classification, multiplicity, preciseness, learning period, checkpoints, and many more. The selection of a suitable machine learning algorithm also influenced by the combination of business demands, prerequisites, fact-finding, and time allocated.

Machine learning algorithms are classified as Supervised, Semi-supervised, Unsupervised, and Reinforcement Learning.

Supervised learning: Supervised machine learning algorithm specifies the presence of a supervisor and the use of labeled data. The supervised machine-learning algorithm with valid data encompasses appropriate inputs and outputs and incorporates a method to access these inputs and outputs; find out paradigm in data, get wind of facts from findings, and make predictions for these findings compared with a trained dataset that is already available. The learning process of the algorithm continues it accomplishes preciseness. Supervised machine learning is again categorized as Classification, Regression, and Forecasting.

1. Classification is a machine learning program that identifies the category of new findings.
2. Regression is a machine learning technique that forecasts the output as a continuous numerical value.
3. Forecasting refers to the predictive algorithm based on former and existing data for future outcomes.

5.1 Support Vector Machine algorithm

(SVM) is an example of "Supervised Learning Model" which scrutinizes utilized data for the analysis of Classification and Regression. SVM is a well-significant classifier for Electrocardiogram based irregular heartbeat classification approach. SVM rectifies the disparity of The Massachusetts Institute of Technology – Beth Israel Hospital Arrhythmia Database (MIT-BIH) database and describes the assured values [50]. Numerous practices with SVM modifications carry forward like a composite

Fuzzy theory to accomplish Support Vector Machine classification [51], incorporate with composite classifiers

Sr. No	Reference	Author	Year	Features	Classifier	Accuracy %
1.	[8]	P. de. Chazal et.al.	2004	ECG Intervals, Morphological	Weighted LD	83
2.	[9]	G. de. Lannoy	2012	RR Intervals, Morphological ECG segments HBF and HOS	Weighted CRF	85
3.	[10]	Soria et.al.	2009	RR Intervals Morphological +FFS,VCG	Weighted LD	90
4.	[11]	G. de. Lannoy, et.al.	2010	ECG Intervals, Morphological HOS, HBF Coefficients	Weighted SVM	83
5.	[12]	K. S. Park, et.al.	2008	HOS and HBF	Hierarchical SVM	85
6.	[13]	Mar et.al.	2011	Temporal, Morphological, Statistical + SFFS	Weighted LD MLP	89
7.	[14]	Zhang et.al.		RR Intervals, Morphological ECG Intervals and segments	Combined SVM	86
8.	[17]	C. Ye, et.al.	2012	RR Intervals, Morphological Wavelet, ICA, PCA	SVM	86.4
9.	[18]	Y Bazi, et.al.	2013	Morphological, Wavelet	SVM, IWKLR,DTSVM	97 (DS1) 92 (DS2)
10.	[30]	C. Ye, et.al.	2010	Morphological, Dynamic	Random Selection	96.5
11.	Proposed Research			Time Domain features, RR Intervals, Morphological	Support Vector Machine	---

[52], genetic algorithms compound controlled Fuzzy Support Vector Machine (FSVM) [53], and Least Squares Support Vector Machine (LSVM) [54].

5.2 Semi-supervised learning: Semi-supervised learning algorithms handle both labeled data and unlabelled data.

5.3 Unsupervised learning: In an Unsupervised machine-learning algorithm there is no supervisor and valid data encompasses appropriate inputs and outputs. In unsupervised machine learning, the learning algorithm learns by itself using the dataset's computational complex algorithm with less accuracy.

5.4 Reinforcement learning: Reinforcement machine learning algorithm is a key element in efficient learning techniques. Reinforcement machine learning is a feedback-based model with trail, specifications, and terminal value that learns from previous common and popular experiences.

5.5 Artificial neural network: (ANN) is a computational method which shows the tendency of nerve cells to perform a function in the human brain and Multi-layer Perceptrons (MLP) and Probabilistic Neural Networks (PNN) are used to classify arrhythmia [58-59]. Designs constructed with Multilayer Perceptrons are weak and less efficient as compared to Probabilistic Neural networks [3]. A composite neuro-fuzzy network was put forward to, improve its appearance and minimize the training time of Multilayer Perceptrons [59-62].

5.6 Random decision forests: Random decision forests or random forests machine learning algorithm is a set of collective learning techniques that combines different algorithms to achieve better performance for Classification, Regression, and other tasks. Every classifier alone is less strong, but when tie up with others, can generate a better outcome. The structure of the 'decision tree' (flow diagram like a tree, or step-by-step determination) algorithm looks like a tree that starts with an input set at the top [63- 65] which proceeds step by step towards the foot of the tree, with specified variables of segmented data into compressed data.

5.7 A decision tree: A decision tree is a data flow diagram structured as a tree - shape that uses a bifurcating technique to emphasize all the possibilities of decision. Every node in the tree constitutes a test on a specified variable and every branch is the result of that particular test [63- 65].

5.8 The K-Nearest-Neighbour algorithm: The K-Nearest-Neighbour algorithm evaluates the group members belonging to a data point. K Means Clustering algorithm is another example of 'Unsupervised learning' which utilizes to classify untagged data, i.e., undefined data groups the variable K depicts the number of groups. Then it works repetitively to allocate every data point of the K group depending on the features assigned.

5.9 Clustering: Clustering associates classified database interpretation. It is useful for segmentation of data into different cluster to evaluate each data set to perceive patterns [64-68]. Naivy Bayes Classifier is found on the basis of 'Bayes' theorem. It classifies each and every value differently using Probability. The Naivy Bayes Classifier algorithm permits to imagine a classification or categorization that depends on a given set of attributes. The core class of regression is nothing but the linear regression which permits the valid interrelation connecting two unbroken variables, algorithm related to fitting a straight line in the data [68].The probability event turning up which depends on the past data supplied, evaluated and targeted by logistic regression. Logistic regression utilized to mask a 'Binary Conditional Variable", having 0 and 1 values, which characterize the end result. Logistic regression is a classifying algorithm related to a fitting curve in the data [69].

5.10 Linear Discriminants: Linear Discriminants are an analytical approach that depends on the discriminant functions. The Association for the Advancement of Medical Instrumentation (AAMI) recommended linear discriminants as classifiers. Support Vector Machine and Multilayer Probabilistic require more training time as compared to Linear Discriminants classifiers, as it is not repetitive. Just describes the classification model and enumerates demographic from the trained data. Various methods for irregular heartbeat classification have evolved using other data mining and machine learning algorithms.

The Hidden Markov model: The Hidden Markov Model is a statistical model in which detected parameters are used to find out unseen (i.e., hidden) parameters [66-69].

Hyper box classifiers were scrutinized for the recognition and categorization of heartbeats in an electrocardiogram which is important in the prognosis of cardiac dysfunction [70].

Optimum-path Forest classifier is identical to the Nearest Neighbours classifier when all training samples are used as the first model [71, 72]. Conditional random fields are acute mimics used for anticipating series [27]. Rules-based models operate based on a cause-and-effect approach [73-75].

Dimension reduction: Dimension diminution minimizes the number of variables being considered to discover required information.

Databases and the AAMI Standard

The AAMI standards were introduced by AAMI and are described in American National Standard Institute (ANSI/AAMI EC57:1998/(R) 2008) [16] for reporting and testing the attainment impact of cardiac rhythm and ST-segment evaluation algorithms. The obligation to carry out the assessment makes sure the assessments are duplicable and approximate. The standard re commends the use of 5 databases.

- The Massachusetts Institute of Technology Beth Israel Hospital Arrhythmia Database (48 records of 30min each) (MIT-BIH).
- The European Society of Cardiology ST-T Database (90records of 2h each) (EDB).
- The American Heart Association Database for Evaluation of Ventricular Arrhythmia Detectors (80 records of 35min each); (AHA).
- The Creighton University Sustained Ventricular Arrhythmia Database (35 records of 8min each) (CU).

- The Noise Stress Test Database (12 records of ECG of 30min each, plus 3 records with noise excess) (NST).
- The most indicative dataset for arrhythmia is the MIT-BIH [76]. The ANSI/AAMI EC57:1998/(R) 2008 standard also describes the interpretation that one should be done in the databases.

QRS wave pulls out during ventricular depolarization or systole of the heart. The exact detection of QRS wave has been implemented using various techniques like Derivative based Methods (DM), Transform based methods like Hilbert Transform, Wavelet Transform, Digital Filters (DF), Entropy method, Difference Operation Method, Neural Network (NN) etc.

7. Classification of QRS Detection techniques

- QRS detection techniques based on Derivative
- QRS detection techniques based on Wavelet Transforms
- Other Approaches for QRS detection

7.1 QRS Detection techniques based on derivative

Derivative filters is used to acquire the slope prominent features and the heart signal artifacts are removed using digital filters for the detection of QRS waves, J. Pan and Tompkins [21] introduced a real-time QRS detection algorithm using the features of waveform like amplitude, width, and slope. Filter available for this research is fast, real-time and recursive. In cases zeros present on the unit circle of z-plane get cancelled by poles. The researchers make use of cascaded low-pass and high-pass filters to achieve 3db passband. In this algorithm a real time filter applied with microprocessor at the pre-processing stage to remove noise, a 5-point derivation method to obtain waveform slope and by squaring function is extracted by non-linear amplification. Low – pass filter. The transfer function of 2nd order low pass filter.

The threshold technique is employed at the output stage to recognize the QRS complexes. This version has greater Detection Error Rate (DER) and is incapable of detecting the heartbeats correctly. P.S. Hamilton and J. S. Tompkins [77] developed decision rules on the basis of threshold logic to increase accuracy standard for heartbeat detection and improved the Pre-processing phase using digital filtering and optimization techniques. This technique minimized the detection error rate with time error. To overcome the difficulty of time error and detection of R peak of the ECG waveform D. Benitez [78] introduced the Hilbert Transform method and Kaiser-Bessel window to remove artifacts from the arrhythmia dataset. The QRS complexes evaluated by using adaptive threshold technique along with the zero-crossing technique. N.M. Arzeno [79] modified Hilbert Transform Method by using hybridization of Hilbert transform and secondary threshold technique. The researcher presented a novel technique to enhance the automatically generated threshold performance with a squared function.

7.2 QRS Detection techniques based on wavelet transform

C. Li. C Zheng [5] introduced an algorithm to decompose the waves into a frequency and time component and peak detection. The zero-crossing technique was used for the detection of the small amplitude QRS wave, due to the low Detection Error Rate (DER). The author of [5] proposed two criteria wavelets transform (WT) and Entropy Criteria (EC). Wavelet Transform differentiates low and high entropies. The lack of certainty present in the signal is detected by the Entropy Criterion. The process of elimination of unwanted low signals is known as the Entropy Criteria –Wavelet Transform (EC-WT) technique. The ECG wave components detected is as shown in figure 1, ‘positive R’ waves marked in upward direction similarly ‘negative R’ waves marked in downward directions. ‘Q’ mark indicates the beginning of QRS Complex and the ‘S’ mark indicates the ending location of QRS Complex. S. Rekik [80] introduced a global entropy criterion to enhance the performances of the technique presented in [5]. The proposed research resolves the adjustable thresholds problem for R wave detection.

The multi-time-dependent new entropy technique is introduced by S. Farashi [81] to detect QRS wave components in electrocardiogram signal in the approach of [5]. Undecimated Wavelet Transform (UWT) and thresholding technique used to detect QRS, and improved by using the local entropy method, which is important to detect the irregularity present in a QRS complex.

7.3 QRS Detection techniques using other approaches

L.D. Sharma [82] proposed the Savitzky-Goley filter used to denoise the signal and root mean square method for detection of beat. P. Phukpattarpant [83] proposed an algorithm to enhance SNR (signal-to-noise) ratio. At the initial stage of pre-processing a quadratic filter is utilized and at the decision making stage an adaptive threshold is utilized. M. Marino [84] designed an algorithm to differentiate QRS and Non-QRS waves by utilizing and two envelopment filters and K-mean clustering. It depends on distance metrics types and k value and obtained greater performance than the existing methodologies. Arbateni [85] proposed a new method by using ANN (Artificial Neural Network) to overcome these dependencies using a whitening filter (WF) and squaring and moving average filter (SAMAF). A matched filter is used along with Radial Basis Function (RBF) based Whitening Filter to reduce Signal to Noise Ratio by using the ANN technique better performance was achieved but required higher training data which in turn increased computational complexity. T. Sharma [86] proposed a new QRS detecting algorithm in online and offline procedures. The thresholding method was utilized to form the envelopes and the Weighted Total Variation (WTV) method to reduce the noise. Y, li. X. Tang [87] proposed another QRS detection technique based on a vector cardiogram, in which QRS peak is detected using the phase space reconstruction, and unwanted signals removed by Matched filtering. Higher accuracy gained by proposed algorithm with respected state art algorithm. Hou, Zhngjie [88] introduced a new QRS detection algorithm using box scoring time series calculations. Chin and Wen-Long [89] designed a QRS detection algorithm by using the

maximum likelihood estimation and variance method. Y.C. Yeh [90] proposed a new QRS detection algorithm to achieve faster performance. This technique is simpler more reliable as compare to wavelet based and derivative-based methods, it is due to the low computation. R Peak is located using different equations in QRS detection method. S and Q peaks detected using R peaks. Various pre-processing filters are used to enhance QRS - complex.

8. Applications

- Electrocardiogram is a bioelectric signal generated due to hearts electrical activity. ECG has an important role in monitoring patient's health in intensive care units and routine medical checkups. The irregularities that reside in the P, QRS, and T waves represent crucial cardiovascular diseases (CVD) like Myocardial Infarction (MI), Ventricular Hypertrophy (VH), & Bundle Branch Block (BBB) etc.
- Electrocardiogram identifies the rhythm disturbances, imbalance of electrolytes and abnormalities in conduction.
- Also provides the information about heart chamber size and heart position in the chest.
- It is extensively used by a cardiologist to access the condition of the heart.
- Also used for diagnosing and progression of pericarditis and myocardial infraction and ischamic diseases.
- The function of artificial pacemakers can be evaluated.
- The automation of the detection of ECG results in reducing the burden of a cardiologist.

9. Comparison of Various QRS Detection Algorithms

This section covers a comprehensive interpretation of the published study related to the proposed research with a clear objective; Table no. 2 shows the literature review of Various QRS Detection Algorithms has been carried out from the year 1985 to 2019. Figure 3: summarizes the Positive productivity evaluations of various studies using different techniques. It summarizes the pre-processing techniques used to remove noise, artifacts, and ectopic beats. It summarizes the decision rule, pre-processing stage and methods implemented by different researchers. The table summarizes the performance parameters and their values. The literature survey is helpful in perceiving the research gaps and their essentials

Table 2: Comparison of Various QRS Detection Algorithms

Sr. No.	Author	Year	References	Techniques used			Performance Parameters				
				Pre-processing Stage	Decision Rule	Total Beats	DER%	FP	FN	Se%	PPV%
1	Chin, Wen-Long, et al.	2019	[89]	BPF	Variance–Based Detection.	-------	-------	164	156	99.86	99.85
2	Hou,Zhongjie et al.	2018	[88]	Matched Filtering	Phase Space Reconstruction	110008	0.19	73	140	99.87	99.93
3	Y.Li,X Tang et al.	2018	[87]	Box scoring calculation	Box scoring time-series	109494	1.24	610	748	99.32	99.45

4	S. Rekik, et al.	2017	[80]	WT	Zero-Crossing LM maximum	86995	0.14	89	34	99.94	99.99
5	T.Sharma et al.	2017	[86]	Wavelet Transform	Envelopment Filter	109494	0.23	165	156	99.86	99.85
6	L.D.Sharma et al.	2016	[82]	Undecimate WT	Segment Specific Thresholding	109488	0.39	163	273	99.75	99.85
7	S.Farshi et al.	2016	[81]	Median and SG Filter	RMS of Signal	109965	0.39	163	273	99.75	99.85
8	M. Merino et al.	2015	[84]	Quadratic Filter	Adaptive Threshold	86899	0.15	210	202	99.82	99.81
9	P.Phukpattarpant et al.	2015	[83]	Envelopment Filter	K-mean Clustering	109483	0.38	131	71	99.82	99.81
10	K. Arbateni et al.	2014	[85]	Whitening Filter	Adaptive Thresholding	109273	0.28	109	210	99.82	99.81
11	Y.C. Yeh et al.	2008	[90]	HT	Based on RMS Segment	116137	0.19	836	775	99.29	99.24
12	N.M. Arzeno et al.	2008	[67]	Digital Filter (method I)	Threshold-based logic	108499	1.58	758	957	99.13	99.36
13	N.M. Arzeno et al.	2008	[79]	Digital Filter (method II)	Threshold-based logic	109099	0.69	405	354	99.68	99.63
14	D. Benitez et al.	2000	[78]	FIR Filter using KBW	Zero-Crossing	2139	0.35	187	203	99.81	99.83
15	C.Li C Zheng et al.	1995	[5]	Wavelet Transform	Zero-Crossing Point	116137	0.15	65	112	99.9	99.94
16	P.S. Hamilton et al.	1986	[77]	Linear and Non-Linear Digital Filter	Thresholding	109267	2.91	248	340	99.69	99.77
17	J. Pan, et al.	1985	[21]	BPF	Thresholding	116137	0.71	507	277	99.75	99.54
18	S.Modak et al.	2021	[91]	Band Pass Filter	Multi-level thresholding	109494	0.25	169	103	99.8	99.91
FP: False Positive FN: False Negative Se: Sensitivity PPV: Positive Predictivity DER: Detection Error Rate											

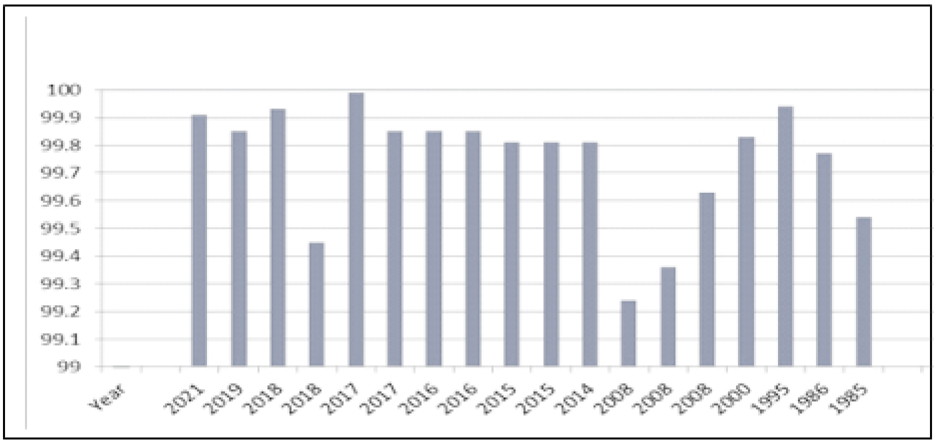

Fig: 3 Positive productivity evaluations of vario

10. Conclusions

In recent years it seems that biomedical signal processing is a considerable & widespread research field. The present study gives a brief review of ECG signal processing and it proposes the design of ECG signal processing to find out the required wave components of ECG Signal. Various research studies are available by distinct researchers in this area. The researchers enforced online gateway to collect the ECG dataset from MIT-BIH. The researchers used numerous techniques to remove noise artifacts and ectopic beats and evaluate the median. The researchers implemented various techniques based on derivative, transforms, digital filters, entropy, neural network, and difference operation method for the exact detection of QRS wave. The comprehensive study of recognized and newest literature helps the forthcoming researchers to find out the research gaps. Distinct objectives are framed for proposed research based on the research gap. The proposed method will classify the wave components for detecting acute coronary syndrome**.**

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