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Origins of ECG and Evolution of Automated DSP Techniques: A Review

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ABSTRACT Over the years, researchers have studied the evolution of Electrocardiogram (ECG) and the complex classification of cardiovascular diseases. This review focuses on the evolution of the ECG and covers the most recent signal processing schemes with milestones over the last 150 years systematically. Development phases of ECG, ECG leads, portable ECG monitors, Signal Processing schemes and Complex Transformations are discussed. This paper summarizes the development of ECG features detection for cardiac anomalies and the history of the development of ECG monitors, beginning from String Galvanometer. It also discusses the automated detections on ECG, beginning from 1960 to the most recent signal processing techniques. Additionally, this paper provides recommendations for future research directions.

INDEX TERMS Automatic, classification, databases, ECG, Einthoven, evolution, signal processing.

I. INTRODUCTION

In 1902, Dutch scientist Willem Einthoven invented the String Galvanometer to measure the electrical cardiac activity that has become one of the century's most significant contributions. This invention of ElectroCardioGram (ECG) or EleKtrocardioGram (EKG) revolutionizes the diagnoses of cardiovascular anomalies. The history behind the subject covers similar developments occurring with oscillographs and electrometers. Therefore, researchers are interested in knowing the developments of ECG and its origin that led to the global acceptance of one of the most influential research of the century.

The ECG signal's evolution is well studied and reported in [1]–[3]. In [1], the authors discuss ECG background and the development of physiological instrumentation, oscillographs, String Galvanometer and the efforts by Cambridge Scientific Instruments (CSI) company to make ECG monitors practically usable in hospital settings. In [2], the authors discuss Thomas Lewis's role for his efforts to make ECG globally accepted, the development of the String Galvanometer, Cambridge electrocardiograph machine, including the changes in the design for medical use. In [3] authors discuss the exciting history of ECG origin, electrophysiology practice in 19th century, the contribution of Willem Einthoven, String Galvanometer and early definitions of cardiac arrhythmias. It also discusses the American observations of the ECG, the role of Thomas Lewis and the development of Electrocardiography, ECG and Myocardial Infarction (MI), precordial leads, and augmented limb leads, Vectorcardiogram in clinical physiology and the challenges of Electrocardiography. While these reviews focus on the historical development of the ECG, a recent review [4] focuses on various ECG signal processing research development that has occurred during 2000-2020. In [5], authors discuss several automatic detection methods for Myocardial Infarctions in their review. Authors in [6] discussed ECG based detection and prediction models leading to sudden death due to cardiac failure.

This review focuses on the developments in the cardiac health monitoring schemes starting from ECG origin to the most recent ECG signal processing techniques. We have started with the work presented by Willem Einthoven and studied the history behind his work to cover the roadmap of ECG development.

Though the history and evolution of ECG are reported in [1]–[3] to the best of authors' knowledge, no holistic review has been reported in the literature that covers the ECG Evolution, early signal processing techniques, to the most recent techniques in a systematic manner. This review discusses the precursors of ECG, ECG origination, feature detection for cardiac health monitoring, development of electrodes and leads, and the development of bedside monitors

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from the early string galvanometers. We also discuss the signal processing techniques during 60's -90's, various standard databases, electrodes, different cardiac health monitoring schemes, and recent trends in these processing methods. The review also discusses the limitations of existing machine learning and neural network based classifiers. The trade-off between the complexity of signal processing techniques and hardware and software system requirements for real-time systems is also discussed. The shortcomings of utilizing the standard databases, in terms of different demographics, changing definitions of diseases over the period, are some of the critical findings of this review.

We have studied the papers presented by William Einthoven and the pioneering research in this field for the article selection. Further, we have selected the most cited papers from Journals and conferences to follow the timeline of biomedical engineering development for cardiac health monitoring schemes. During the years 2000-2020, abundance of papers can be found in this stream related to front end development for ECG signal acquisition, ECG sensors, ECG electrodes, automatic signal processing with various compression techniques, etc. In this review, we have mainly considered the work related to the automatic signal processing domain. To the best of the authors' knowledge, a broad review in this domain is not presented in the literature covering the history of automatic signal processing development schemes. We have not included the commercial systems available for cardiac health monitoring in the market in this review as the main focus of the work is to determine recent trends in automatic signal processing techniques. Additionally, the hardware of wearable devices is not the focus of the review. Interested readers can find the wearable devices review in [7].

II. ORIGIN OF ELECTROCARDIOGRAM

Advances in oscillographs were significant for the development of ECG as they provided varying means for recording the alternating voltage. The first oscillograph that enabled the recording of electrical variations by Blondel in 1893 is assumed to be the first predecessor of ECG [8]. The electromechanical oscilloscope consisted of a moving part to provide oscillations to detect electrical current passing through it. He offered three probable solutions for the recording of electrical variations. The first approach was based on the moving magnet principle, the second on the moving coil, and the last was to adapt the telephones for recording purposes. He chose the moving magnet approach to record the electrical variations until this time; moving coil galvanometers were exceptional and not used to record the electrical signal variations.

The moving coil principle provided by the Blondel was the second generation of ECG's precursors. Dudell, in 1897 [9] replaced the conventional moving magnets with Phosphor Bronze Strips that utilize the moving coil principle along with a mounted mirror that reflected a beam of light. The reflected beam fell on the photographic plate and

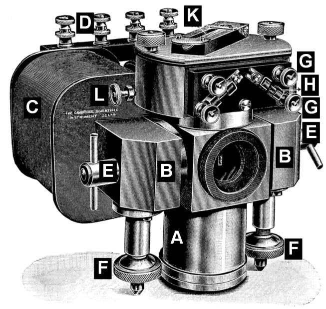


FIGURE 1. Dudells oscillograph (Picture credit: [9]) A is the brass oil bath in which two vibrators are fixed B, core of electromagnet which is excited by two coils C, one of the two coils D, two pairs of terminals for connecting the two coils E, bolts that hold the oil bath in position between the poles of the magnet F, two of three leveling screens (one is hidden behind the oil bath) G, terminals of one vibrator H, fuse K, thermometer with bulb in center of oil bath.

provided a magnified recording of the movement of phosphor bronze strips. Dudell's oscillograph is shown in Fig. 1.

In 1897, Clement Ader developed a Galvanometer [10], this significant invention aimed to boost the telegraphic transmission speed on long cables. The transmission principle was based on fine metal wires with 20 μm diameter, vibrating between the poles of large magnets. This galvanometer by Ader is perceived to be the first string galvanometer. When Willem Einthoven started experiments on recording the heart's electrical activity in 1902, by his String Galvanometer, he was unaware that Clement Ader had already developed a similar system. Notably, the principle of operation for both the galvanometers was the same: a String was employed to record the electrical variation between large poles of magnets. Einthoven's experiment was successful in its own right as later it was observed that Ader's Galvanometer's sensitivity was lower than Einthoven's String Galvanometer. And this would not have been adequate for recording the physiological signals from the human body during the experiments. When Einthoven learned about Ader's String Galvanometer, he credited Ader and the researchers involved in these researches in one of his early papers [11].

By now, several groups were already working on recording the heart's electrical activity both from the signal and physiological point of view. Fig. 2 shows a brief overview of such events during the late 1800s to 1900.

The first known successful event of recording the electrical activity of the heart was performed by Alexander Muirhead between 1869 - 1870 at St. Bartholomew's Hospital in London using the Thomson Siphon Recorder [12], [13] as shown in Fig. 3. It was developed by William Thomson, a Telegraph Engineer. Muirhead recorded the ECG signal only once and after that, he never followed the research on physiological signals.

Much before the Galvanometer experiments, Marey demonstrated theoretically in 1861 that it is possible to use a Capillary Electrometer to measure the electrical activity of the human heart. It was never investigated practically on humans, but the electrical activity of the heart of the

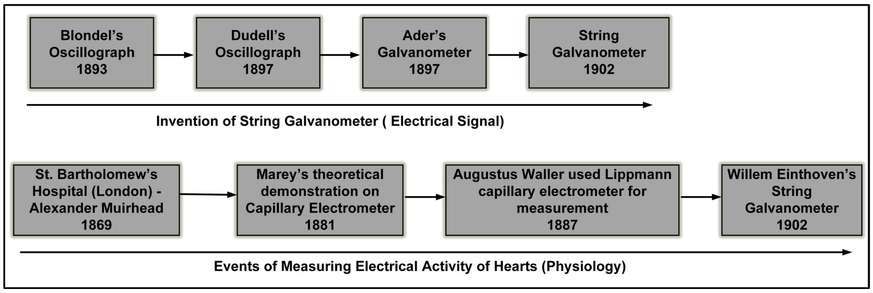


FIGURE 2. **Precursor's of ECG and events of measuring electrical activity of heart till the string galvanometer development for ECG measurement.**

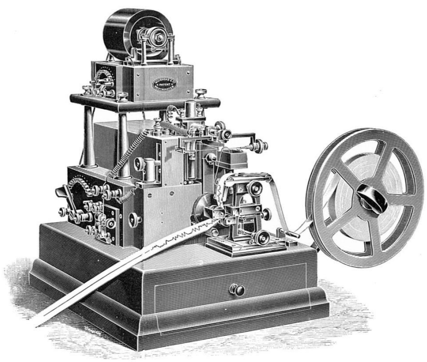


FIGURE 3. **Syphon recorder used by Alexander Muirhead to measure the cardiac activity (Picture credit: [13]).**

frog was demonstrated using the Capillary Electrometer [14], [15]. The electrometer was invented by Gabriel Lipmann in 1872 while working in G. R. Kirchoff's laboratory in Berlin. It was used to detect minor potential differences applied to the thick end filled with mercury and the thin end with the sulphuric acid solution (see Fig.4a).

Around the same period, Augustus D. Waller used Marey's technique and applied it to the exposed hearts of mammals. It led to the successful event of recording the electrical activity of the heart in 1887 using Lipmann Capillary Electrometer [16], [17]. The ECG wave obtained by Waller [18] and the experimental setup at Royal Society [19] is shown in Fig. 4. This event was widely publicized in local London Newspapers. Interestingly after this, he was investigated and tried under the 'Animal Cruelty Act' for his experiments involving his pet dog, Jimmie. Also, Waller himself was not convinced that it could be used widely in the biomedical domain. He went on further and stated, "*I do not imagine that electrocardiography is likely to find any very extensive use in the hospital. . . It can at most be of rare and occasional use to afford a record of some rare anomaly of cardiac action.*" Waller was not the first to use the term "Electrocardiogram," and could not perhaps foresee this as "the future" in Medical Technology and this is one of the reasons that his contributions are not acknowledged widely.

A. WILLEM EINTHOVEN'S STRING GALVANOMETER

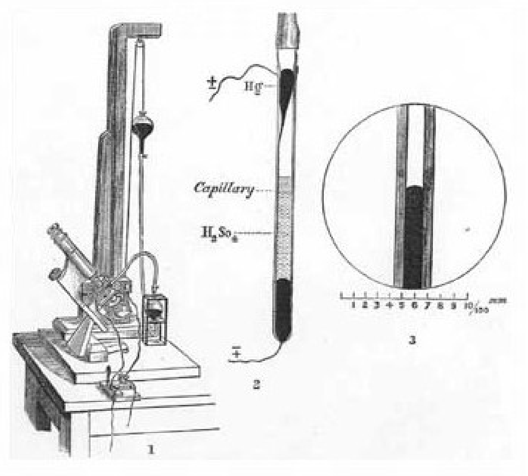
By this time, the most notable research findings were coming out from Willem Einthoven's String Galvanometer experiments [20], [21] that measured cardiac potentials in 1902. His experiments demonstrated that String Galvanometer was easier to use, free from damping, and more sensitive than the Capillary Electrometer. The String Galvanometer is shown in Fig. 5. His contributions revolutionized the biomedical cardiac signal acquisition forever. Einthoven was rightly entitled as the "Father of Modern Electrocardiography".

The first deflections of the cardiac activity were named A, B, C, D by Einthoven *et al.* [22] shown in Fig. 6a. A mathematically corrected version of deflections named as P, Q, R, S, T was superimposed on the former ones shown in Fig. 6a [23]. The naming conventions P, Q, R, S and T are still used to represent an ECG signal as shown in Fig. 6b. The reason for changing the cardiac deflection's name from A, B, C, D to P, Q, R, S and T is still unclear but most likely it may have been done to include the successive points in the ECG tracings [24].

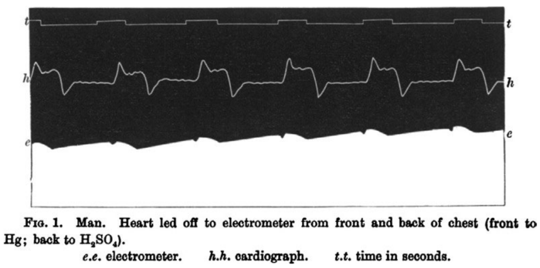
According to Einthoven, in [20], [21], the specifications for the String Galvanometer (Fig. 5a) is described as "*The String Galvanometer is essentially composed of a thin silver-coated quartz filament (about 3μm thick), which is attached like a string in a strong magnetic field. When an electric current is conducted through this quartz filament, the filament reveals a movement that can be observed and photographed using considerable magnification, this movement is similar to the movement of the capillary electrometer. It is possible to regulate the sensitivity of the galvanometer very accurately within broad limits by tightening or loosening the string*".

The original apparatus weighed around 600 *lbs* and required approximately two rooms for placing it. Provision for cooling the electromagnets was provided with continuous water flow. Saline water in buckets was used as electrodes on the left leg, left arm and right arm locations shown in Fig. 5b.

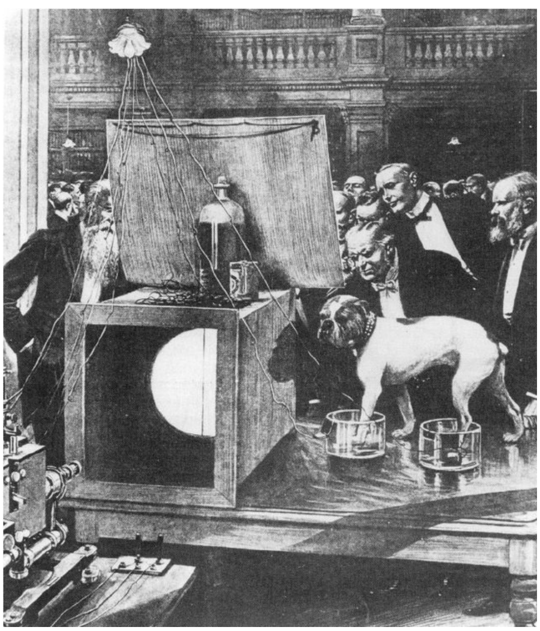
Einthoven demonstrated significant differences in normal and abnormal ECG waveforms in 1906 [25] and 1908 [26]. In the experiments to follow, in 1912 [27], Einthoven investigated and found out that the heart creates a potential difference at different locations and the magnitude and direction of



(a) Capillary Electrometer utilized by A.D. Waller to measure the electrical activity of the heart (Picture Credit: [17])



(b) Cardiac electrical activity obtained by A.D. Waller obtained with Capillary Electrometer Time Scale at Top, Pulse tracing in Centre and Electrocardiogram at Bottom (Picture Credit: [18])



(c) Experiment Demonstration of measuring the electrical activity of heart on A.D. Waller's Pet Dog Jimmie to the Royal Society in London (Illustrated London news May 22^{nd} May 1909) (Picture Credit [19])

FIGURE 4. **Waller's experimentation to measure the electrical activity of heart.**

the current changes at different locations of the heart can be represented by the Einthoven Triangle is shown in Fig. 7.

He demonstrated that Lead I had advantages for judging the T waves, in Lead II peaks were usually larger and Lead III was most suited for the diagnosis of Ventricular hypertrophy[1] of left and right ventricles. He also observed a linear relationship between the three leads that yielded $Lead\ II - Lead\ I = Lead\ III$ to obtain any lead by combining the other two leads.

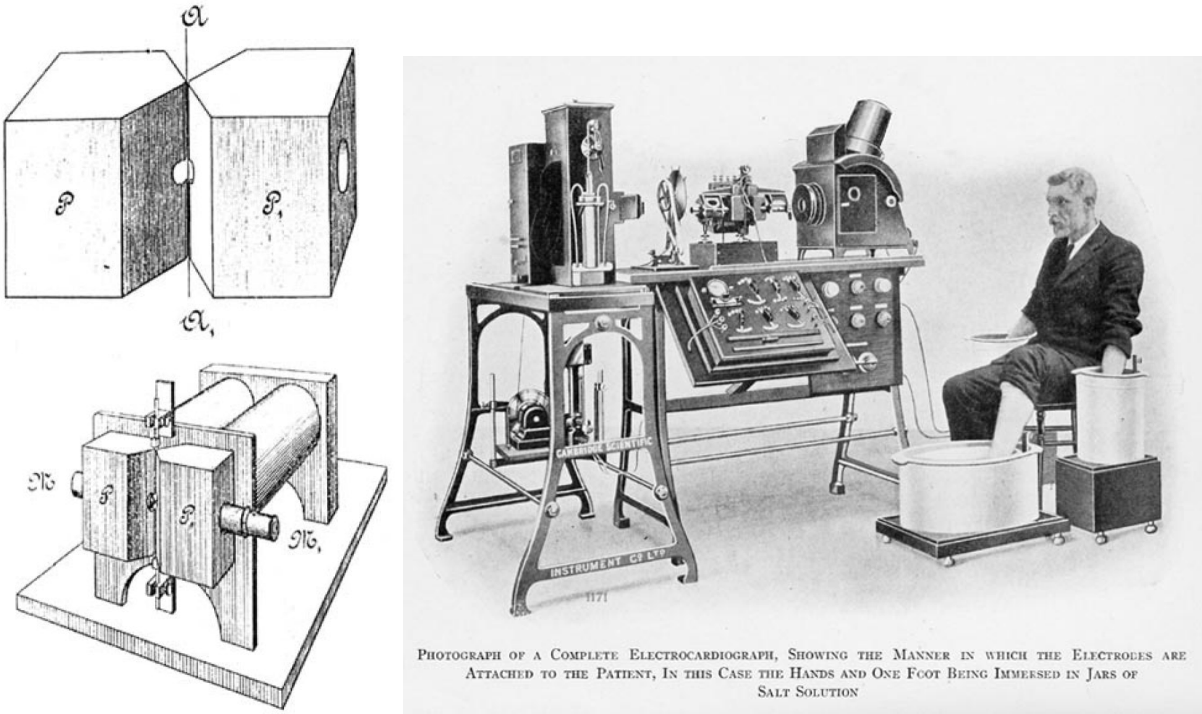
By then, Europe had accepted electrocardiograms and the rest of the world followed. The ECG research mainly evolved into three groups (see Fig. 8): the first group was working to categorize the ECG signals for cardiac conditions: mainly consisted of Physicians; the second group was working on optimizing electrodes and leads, and the third group was working on optimizing the size of string galvanometer and designing portable bedside monitors, mostly technological experts.

B. IMPROVING OF STRING GALVANOMETER TO PORTABLE ECG MONITORS

The need to extend the ECG device to bedside monitors was a deriving factor for Einthoven. In 1903, he approached Cambridge Scientific Instruments Company Limited (CSI) to reduce the String Galvanometer's size to a more practicable form. CSI became interested in the idea and produced their first String Galvanometer around 1905 (Fig. 5b) with 10% royalty fees going to the inventor. The first instrument was sold to MacDonald's laboratory in Sheffield in 1905, the second to J.C. Bose at Presidency College, Calcutta in 1906 and the third to Keith Lucas in Cambridge in 1907. Later, Dudell made some modifications to the original design to reduce the instrument's size, which resulted in a reduced royalty to Einthoven. Edward Schafer of the University of Edinburgh bought the advanced version of the String Galvanometer and was the first to buy the string galvanometer for clinical use in 1908. Subsequently, after world war- I, this ECG machine evolved meant to be placed by the bedside. After a few modifications to the design, Harold Segall designed the instrument [1] that could be carried in two wooden cases, each weighing around 50 lbs. It was the beginning of portable ECG monitors.

The use of vacuum tubes for a reduced form factor and to amplify the electrocardiogram instead of the mechanical amplification by the string galvanometer is said to be used by 1925, reported by both Fye [3] and Parker *et al.* [28]. Subsequent advances in electronic components resulted in the first portable ECG machine by 1928, that was powered by a vehicle battery. This was until the invention of increasingly smaller transistor electronics [3]. More recently, microchips allowed for developing the 12 lead ECG that we are familiar with today. Around 1935, Sunborn Company designed the ECG machine that could be kept in a wooden box weighing

[1] Ventricular hypertrophy is thickening of the walls of a ventricle (lower chamber) of the heart.



(a) String Galvanometer Developed by Einthoven to measure ECG (Picture Credit [20])

(b) Modified String Galvanometer designed by Cambrige Scientific Instrument Limited Picture Credit: [2]

FIGURE 5. **Einthoven's string galvanometer to measure the electrical activity of the heart.**

around 25 lbs [1]. The invention of transistors by the 1960s made the ECG machines portable for use in hospitals and the invention of Holter[2] recorders in 1961 [29] paved these for usage in out of hospital settings.

C. ECG SIGNAL (P WAVE, QRS COMPLEX, T WAVE, J POINT)

Following Einthoven's invention, scientists became interested in this emerging field and started categorizing the signals based on their interpretations. Fig. 9 shows various ECG features such as R-R interval, PR interval, QT interval and ST interval based on P wave, QRS complex, T wave, J point and Baseline level of the signal.

Einthoven, in 1906 categorized normal and abnormal ECGs that were translated by Cardiologist Henry Blackburn [30]. He discussed the first electrocardiographic tracings of atrial fibrillation,[3] premature ventricular contractions,[4] ventricular bigeminy,[5] atrial flutter.[6] The beginning of ECG related research was also demonstrated in an experimental setup that induced heart block in a dog, as shown in Fig.10.

By then, Thomas Lewis, a physician, was convinced about the significance of Einthoven's contribution to determine various heart anomalies. Independently, he concluded that atrial fibrillation is a common cause of arrhythmia and termed as a "clinical condition" [31]. Fig. 11 shows the ECG signal of Atrial Fibrillation case and ECG waves of mother and fetal studied by Lewis [2]. Six major categories of anomalies were also coined by Lewis, namely: sinus arrhythmia, heart block, premature contractions, proximal tachycardia, auricular fibrillation and alteration of the pulse. The ECG machine used by Lewis during 1930 to diagnose the patients is shown in Fig. 12 [32]. In addition, he also explained the terms such as sino auricular node, pacemaker, premature contractions, proximal tachycardia and auricular fibrillation. The contribution of Lewis' research to bridge Einthoven's research was vital and can be understandable by Einthoven's statements after he was awarded the Nobel Prize in 1924.

In his Nobel lecture, Einthoven stated about Lewis, "*I owe you so much. Without your steady and excellent work to which you have devoted a great part of your life there would have been in all probability no question of a Nobel prize for me. You have given to Medicine at least as much as I have*" [33]. Lewis continued working as the world's leading electrocardiographer while Einthoven investigated the theoretical bases for Electrocardiography.

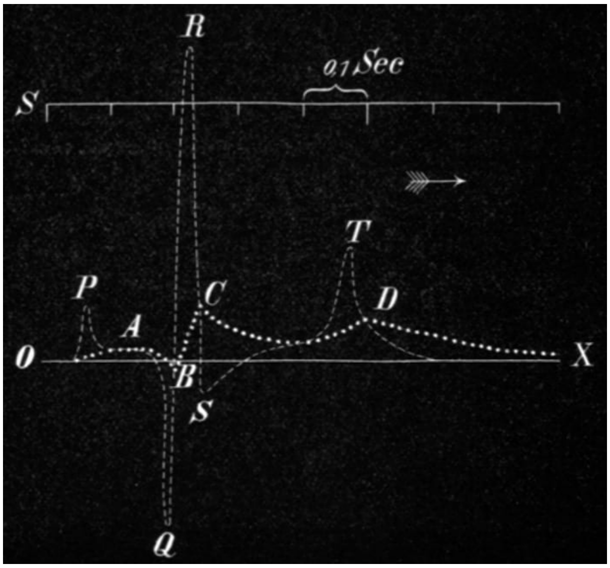
[2]Named on the scientist Norman Jeff Holter who developed it.

[3] Cardiac anomaly where R-R interval is abnormal and P wave is missing at instances.

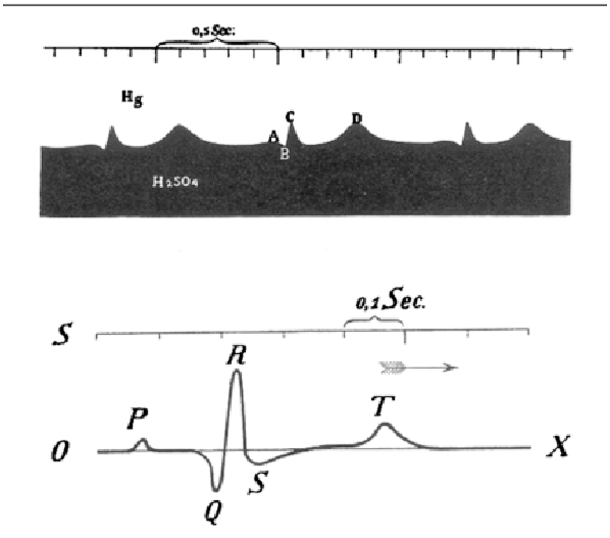
[4]Abnormal heartbeat where contractions begin in the ventricles, instead of Sinoatrial node of heart.

[5]Arrhythmia where there is a pattern of irregular heartbeat and regular heartbeat occurrence.

[6]Type of arrhythmia, where the heart's upper chambers (atria) beat too quickly.



(a) P, Q, R, S and T deflections superimposed on previously known deflections A, B, C and D in the ECG Tracing By Einthoven



(b) First ECG Tracing

FIGURE 6. First ECG tracings provided by Einthoven (Picture credit: [20]).

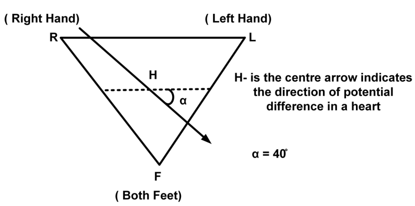


FIGURE 7. Einthoven's triangle to obtain the relationship between lead I, II and III (Picture credit: [27]).

The clinical features of Myocardial Infarction were first published in 1910 by Russian Physicians W P. Obrastzow and N. D. Straschesko. They reported two main findings: prolonged chest discomfort and persistent dyspnea[7] however, these features were not based on ECG tracings. Further, the electrocardiographic features for various diseases were observed as listed below.

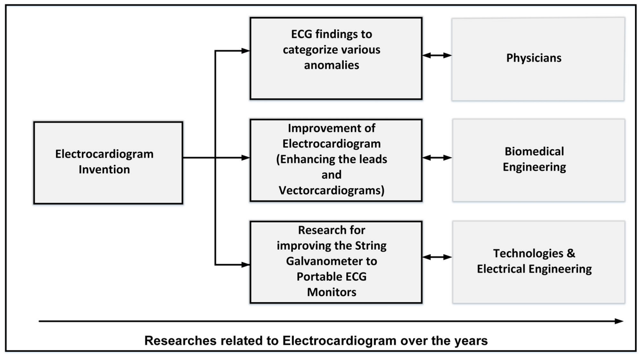


FIGURE 8. Research categorization in the following years after EKG origin.

- 1917- Electrocardiographic features for acute myocardial infarction were first published by Oppenheimer and Marcus Rothschild [34].
- 1920- Harold Pardee reported ST-segment elevation in Lead II, Lead III and T wave inversion features of Myocardial Infarction [35].
- 1924-Woldemar Morbitz found out two different types of second-order Atrioventricular (AV) blocks that are named after him, known as Morbitz type I and type 2 blocks [36].
- 1930- WPW syndrome was described by scientists Wolf, Parkinson and White named after the scientists in which Bundle branch block with short PR interval was discussed [37].
- 1931-1932- Charles Wolferth and Francis Wood reported the electrocardiographic features for the Angina Pectoris[8] after moderate exercise [38], [39].
- 1935- Sylvester McGinn and Paul D. White find features for the cardiac condition, acute pulmonary embolism[9] [40].
- 1939- Richard Langendorf obtained the ECG features for Atrial Infarction [41].
- 1942- Arthur Master, Friedman Rudolph and Dack Simon standardized the two step exercise test also known as the Master two-step for cardiac function [42].
- 1944- Young and Koenig reported the PR Segment deviations for Atrial Infarction condition [43]

The development of such Electrocardiographic features is till date continued.

D. EVOLUTION OF ECG LEADS AND VECTORCARDIOGRAM

Developmental activities were also going to find out the best materials for electrodes. Electrodes are connected to

[7] Shortness of breath or difficulty in breathing.
[8] Angina pectoris is the medical term for chest pain or discomfort due to coronary heart disease. It occurs due to narrowing of arteries due to blockage and also known as ischemia.
[9] It is a blockage of an artery in the lungs.

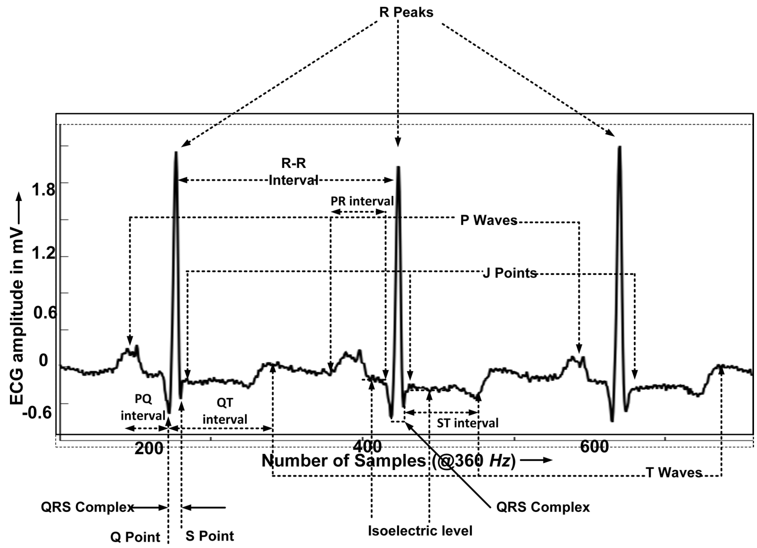


FIGURE 9. **Various features of an ECG signal based on P wave, QRS complex, T wave and J point.**

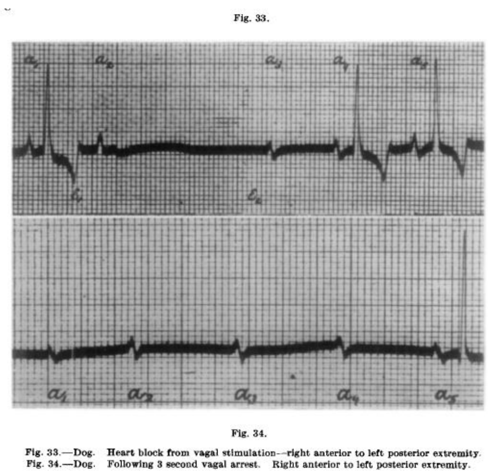
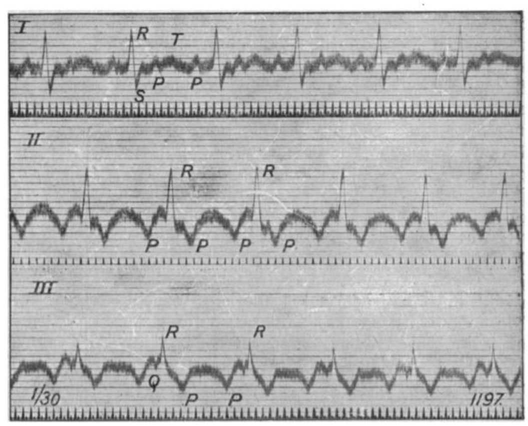
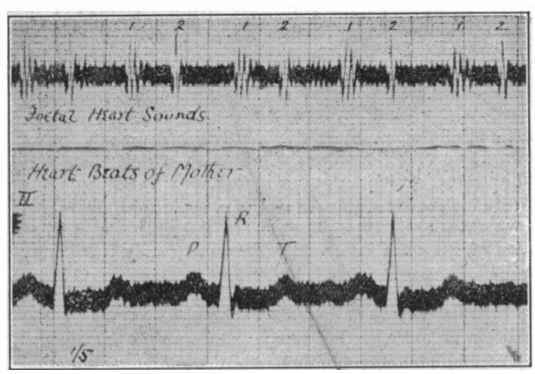


FIGURE 10. **ECG tracings of experimentally induced heart block in a dog by Einthoven to demonstrate role of ECG to determine cardiac anomalies (Picture credit [30]).**



(a) Atrial Fibrillation waveforms by Thomas Lewis



(b) ECG Waves of Mother and Feotal

FIGURE 11. **ECG signals studied by Thomas Lewis (Picture credit: [2]).**

various specific locations on the human body. Electrodes are conductive pads that enable the recording of the electrical activity of the human heart. An 'ECG lead' can be obtained by analyzing the various electrode signals and considering different electrodes' positions. It provides different viewpoints to measure the heart's electrical activity, and it is similar to clicking a picture of the heart from different angles to get a better understanding by the physicians.

Leads may be unipolar or bipolar in nature. In the unipolar leads, the potential difference between any specific electrode and ground terminal is considered. In Bipolar leads, the difference between two electrodes' signal is considered with reference to the ground terminal. Unipolar leads provide the horizontal view of the heart, and bipolar leads provide the heart's frontal view.

In 1893, Einthoven first used the term EKG and studied the graphs using the capillary electrometer. Later he built a string galvanometer based on a 3-electrode EKG machine

FIGURE 12. ECG Machine of Thomas Lewis for checking the patients in the year 1930. Picture from medical exhibits in the science museum, London (Picture credit: [32]).

TABLE 1. ECG and VCG leads and electrodes.

Signal Acquisition	Leads	(Bipolar/ Unipolar/ Vectors)	Number of Electrodes	Location of Electrodes
Standard 12 Lead ECG	I	Bipolar	3	RL, LA, LL
	I, II, III	Bipolar	4	RA, LA, LL, RL
	avl, *avr*, *avf*	Unipolar	4	RA, LA, LL,RL
	(V1, V2, V3 V4, V5, V6)	Unipolar	6	Different anatomical sites on chest
Vectorcardiogram	V_X, V_Y, V_Z	Vectors	7	5 at the transverse plane of chest, BN and LL

^{LL} Left Leg, ^{LA} Left Arm, ^{RA} Right Arm, ^{RL} Right Leg, ^{BN} Back of Neck

in 1902. In the year 1912, Einthoven mathematically reported the Einthoven's triangle [27]. This became the basis for future EKG, Vectorcardiography (VCG) and development of Electrodes and Leads for ECG acquisition (see Fig.13) that is being used till date. Table 1 shows the corresponding number of electrodes and leads for ECG and VCG schemes.

In 1934, Frank Wilson defined an 'indifferent electrode' that was later known as 'Wilson Central Terminal' by connecting the right arm, left leg and left arm with resistances typically $5K\Omega$ [44]. Wilson Central Terminal is an artificially constructed reference for electrocardiography, which is assumed to be at zero potential and steady during the cardiac cycle so that the reference point for unipolar potential remains fixed. It worked as a ground terminal for other unipolar leads. The events that occur during each heartbeat are termed a cardiac cycle that can be divided into two parts: a period of relaxation known as diastole and a period of contraction known as systole. A cardiac cycle on an ECG signal is shown in Fig. 14.

In 1938, the American Heart Association and the Cardiac Society of Great Britain published their recommendation for recording the exploring lead from six sites named V1 through V6 across the precordium [44].

Later, Emanuel Goldberger extended the Wilson Central Terminal with Augmented Unipolar Leads (*avl*, *avr* and *avf*) also known as Goldberger leads for obtaining a detailed view of the frontal plane [45]. Further, in 1953 the general theory of heart vector projection was presented by Frank [46] that provided a mathematical framework where three vectors determined the person's complete cardiac health that confirmed the robustness of the methods used then with a mathematical validation. In the following year, in 1954, the American Heart Association published their recommendation for standardization of 12-lead Electrocardiogram and Vectorcardiogram [47]. Till date, 12 Lead ECG and 3-Lead VCG continues to be the standard of ECG measurement systems.

1) HISTORY OF VCG AND NEED OF VCG IN DIAGNOSIS

The theoretical background for Vectorcardiogram (VCG) was developed by Burger [48] that the heart vector represents the total cardiac electrical dipole strength and direction. This concept was later utilized by Frank [46] to provide a complete electrode configuration known as VCG. It had widespread clinical use till 1960s but, by the year 1987, VCG had been discontinued [49]. It may be attributed to diagnostic performance of ECG was getting better with experienced cardiologists [50]. However, the statistical programs for diagnosis performed better on the VCG signals. The use of VCG was vanishing until the year 1987 when novel methods of obtaining the VCG signals from the 12 Lead ECG signals [51]–[53] were reported. A detailed study of VCG origin and its significance in medical diagnosis can be found in [49].

Various attempts have been made to utilize VCG for the disease diagnosis in recent years (2000-2021) [54]–[60]. In [54], a triggering system that uses the spatial information of the VCG to minimize the effects of magnetic resonance related noise and rejection of arrhythmic premature ventricular depolarizations had also been demonstrated. In [55], detection of various cardiac diseases had been discussed based on VCG signals. Reconstruction of the equivalent heart vector for the QRS complex from limb lead voltages and the VCG parametric space derived from the frontal plane VCG has been used to classify different ECG abnormalities. In [56], authors compared the diagnostic utility of various planar QRS-T angles (ECG signals) to the spatial QRS-T angle (VCG signals) in detecting various cardiac anomalies. Authors derived the VCG signals from ECG signals and concluded that diagnostic accuracy of spatial QRS-T angles was better for detecting coronary artery disease, hypertrophic cardiomyopathy, or left ventricular systolic dysfunction. In [57], authors discussed detection of cardiac ischemia based on VCG signals with a neural network based classifier. Independent Components Analysis and Principal Component Analysis techniques are used for feature dimensionality reduction. It was concluded that VCG is an efficient diagnostic tool for detection of ischemia where ECG signals failed to categorize. In [58], a typical VCG signal on the thorax and its reliability of the detection of the PR-time are analyzed for detecting various cardiac anomalies. In [59], [60], authors discussed techniques to detect posterior myocardial infarction using VCG signals as standard 12 Lead ECG signals do not provide

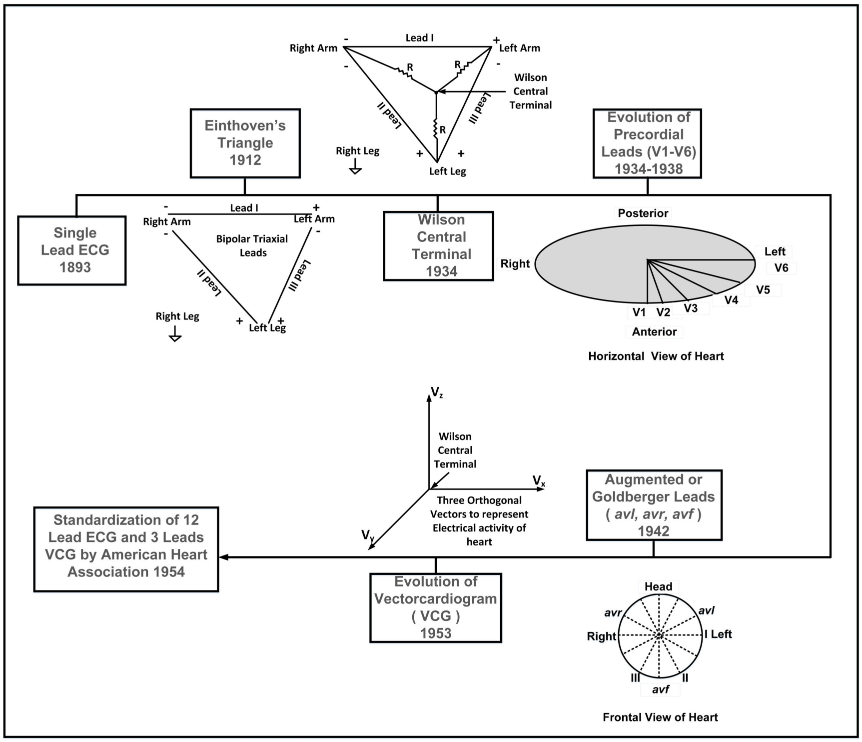


FIGURE 13. Addition of various leads to ECG signals to get a complete 3-D View of heart and development of VCG over the years.

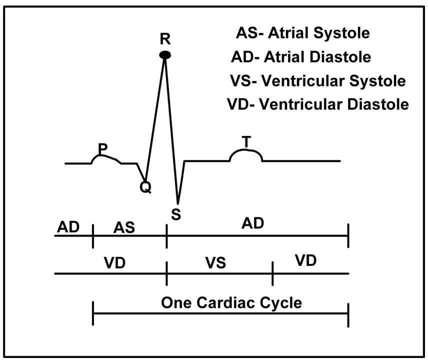


FIGURE 14. Representation of a cardiac cycle.

this information. Weighted support vector machine [59] and discriminative multiscale eigenfeatures [60] from the stationary wavelet transform subband matrices is utilized for classification purpose.

VCG signals have lesser information content than the standard 12 Lead ECG signals [49]. However, it has shown to be beneficial for detecting cardiac conditions by automated statistical methods. In certain typical cardiac conditions, for example, posterior myocardial infarction VCG signals provide more diagnostic features than standard 12 Lead ECG signals that are inefficient. Still, 12 lead ECG signals are significantly more diverse compared to VCG signals for automated detection schemes. We can even utilize the same electrode configuration to obtain VCG by utilizing various conversion matrices [51]–[53]. It could be interesting to look into various aspects of utilizing VCG signals efficiently.

2) TYPES OF ECG ELECTRODES

ECG electrodes are the conductors to obtain the electrical signals of heart activity and are connected to specific body locations. During the invention of the String Galvanometer, Einthoven utilized the saline water buckets as Electrodes. Nowadays, Silver - Silver Chloride (Ag- AgCl) are primarily used to obtain ECG signals. These electrodes are connected with the electrolyte gel on the skin to increase conductivity, hence known as wet electrodes. An electrolyte is usually composed of a salt solution gel material. Ag- AgCl electrodes are widely used in conventional schemes as these types of electrodes provide a high signal to noise ratio, but there are some disadvantages associated with these types of electrodes. Some patients seem to be allergic to these gels, and the hairs on the skin make it difficult to apply for some cases. Also, the wet electrodes are not comfortable for long term ECG monitoring [61].

Electrodes can be categorized as active and passive electrodes. In the active electrodes, the pre-amplification module is immediately after the conductive material between the skin and the electrode and is present to enhance the signal-to-noise ratio. The passive electrodes provide a direct connection between the metal layer and the processing unit. Various other types of electrodes are also reported in the literature and are compared with the conventional wet Ag-AgCl electrodes [62]–[73]. A list of other types of electrodes recently reported in the literature is given- below:

Gel less ECG Electrode [62]: This work discussed the grip-style dry electrodes for ECG measurement during physical activity and presented an innovative design for a portable ECG amplifier that mitigates some of the pre-identified issues of electrodes.

Capacitive Electrodes for noncontact ECG monitoring [63], [64]: The noncontact capacitive electrodes can obtain ECG signals through clothes and implemented with the real-time denoising algorithm.

Carbon Nanotube (CNT)/Polydimethylsiloxane (PDMS) composite-based dry electrodes [65]: In this work, the CNT/PDMS composite-based dry ECG electrodes were readily connected to the conventional ECG devices, and showed its long-term wearable monitoring capability and robustness to motion and sweat.

Esophageal Electrodes for long term monitoring based on Titanium Nitride (TiN) and iridium oxide (IrOx) [66]: This work discussed the advantages of esophageal electrodes over wet and dry electrodes for long term monitoring without the need of electrolyte gels. The TiN and IrOx are identified as suitable materials for esophageal electrodes that are superior to the standardized surface skin-electrode concerning signal distortions, and thus, it might help prolong conventional ECG recordings maintaining high-quality signals.

Underwater Electrodes based on Carbon Black Powder (CB) and Polydimethylsiloxane (PDMS) [67]: In this work, hydrophobic electrodes that provide all morphological waveforms without distortion of an ECG signal for both dry and water-immersed conditions was discussed.

Dry Metal Electrodes [68]: The wearable multi-lead electrocardiogram (ECG) recorder suggested that dry metal electrodes provide a comfortable sensation, less skin-irritating, easy clean surfaces, reusable capability and more durability compared to conventional ECG electrodes.

Dry textile-based electrodes, needle array electrodes and silver-coated surface electrodes [69]: The three types of dry electrodes, viz. textile electrodes, needle array electrodes and Silver coated surface electrodes, were fabricated and tested for acquisition of ECG signals. The dry electrodes were fabricated as active electrodes and recording from the dry electrodes are compared to that of the wet electrodes.

Carbon Based Electrodes for Wearable Applications [70]: The flexible dry electrodes for long-term biosignal monitoring were designed by mixing carbon nanofibers (CNFs) in biocompatible-elastomer (MED6015).

Silver Nanowire based Dry Electrode [71]: The silver nanowire (AgNW)-based dry electrodes were fabricated for noninvasive and wearable ECG sensing.

Garment type electrode [72]: The multi-channel telemeter and garment-type electrodes were developed that exhibited a sufficient R-wave detection rate in four positions

Poly(3,4-ethylenedioxythiophene) Polystyrene Sulfonate (PEDOT:PSS) and PDMS coated cotton fabric electrode [73]: A flexible electroconductive textile material was developed by coating PEDOT: PSS/PDMS on cotton fabric via flat screen printing. The coated fabric was utilized as ECG electrodes and compared with the conventional electrodes.

3) ECG COMPRESSION

ECG data compression techniques reduce the computational cost for any system by removing redundant information and retaining essential parameters of the signal. Efficient compression techniques significantly reduce the storage and transmission requirement for any portable system and can optimize its performance [74].

ECG compression can be classified into lossy, lossless, direct, transformation-based, prediction-based, 1D and 2D techniques. Lossy techniques are capable of achieving higher compression ratios at the cost of reconstruction errors. On the other hand, lossless compression offers lower compression ratios but allows for nearly perfect signal reconstruction. In biomedical signal processing, lossless compression techniques are preferred over the lossy ones [74] because, for clinical applications, loss of information could prove fatal.

Additionally, compression techniques can also be classified into direct and transformation based approaches. In direct compression, the time domain signals are compressed, while in the transformation methods, the signal is converted to the frequency domain using Fourier transform or the time-frequency domain using WT. Various Prediction based models [75], [76] are reported in the literature that provide comparatively higher compression ratios. Various 2-D ECG compression techniques [77]–[79] are also discussed for achieving the optimum results.

Various compression techniques are developed in the last few years [82]–[89]. In [82], an ECG compression technique using unsupervised dictionary learning titled CULT was reported. The algorithm expanded its dictionary upon the arrival of any unseen pattern and used discrete cosine transformation to make it immune to incoming noise. In [83], a sparse encoding algorithm consisting of two subcategories based on geometry-based methods and WT based iterative thresholding was reported. In [84] an energy-efficient novel block-sparsity-based multichannel ECG compression scheme that utilizes spatiotemporal correlation and multi-scale information of the signal using wavelet transform of the signal was reported. In [85], a deep learning technique based on a convolutional auto-encoder is applied to achieve ECG signal compression without any independent encoding method. In [86], a linear method based on the sparsity of the ECG signal and compressed sensing was used to achieve compression in real time. In the recovery phase, authors utilized an efficient method known as the Kronecker technique. The system implementation was based on full-adder/subtractor (FAS) and shift registers, without using any external processor or training algorithm. References [87] discusses a lossy compression algorithm based on fast wavelet transformation that provided insignificant delay for the compression at low level distortion of the signal. In [88], empirical mode decomposition and wavelet transformation to compress the ECG signal was discussed. References [89] utilize the 2D Discrete Cosine Transform coefficient and iterative JPEG2000 encoding for compression purposes that proved efficient.

Interesting readers can find a detailed review of lossless ECG compression techniques in [80] and wavelet based ECG compression techniques in [81].

III. CARDIAC HEALTH MONITORING SCHEMES

Other streams of cardiac health monitoring that are also of interest to researchers are PhonoCardioGraphy (PCG), BallistoCardioGraphy (BCG), ApexCardioGraphy (ACG), SeismoCardioGraphy (SCG) and KinetoCardioGraphy (KCG).

Phonocardiogram is a plot of high fidelity recording of the sounds made by the heart. Monitoring and recording equipment for PCG was developed during 1930- 1940s and was standardized around 1950 [90]. PCG originated in an attempt to time the occurrence of heart sounds in a cardiac cycle. The acquisition system of PCG, similar to ECG, consists of low noise amplifiers and filters. As this review focuses only on the ECG and related signal processing schemes, the interested reader may refer to more details regarding PCG in [90]–[92]. Ballistocardiogram measures the Ballistic forces (Mechanical Forces) generated by the heart and is a noninvasive method based on the measurement of the body motion generated by the blood's ejection at each cardiac cycle [93]. Apexcardiogram was first described by Marey [94]. The curves of the apexcardiogram display all consecutive phases of the cardiac cycle; contraction-and-emptying and relaxation-and-filling. The apex cardiogram's waveform is caused primarily by movements of the left ventricle against the chest wall. Thus, it is a translation of the sequence of hemodynamic events occurring in the underlying left ventricle [95]. Seismocardiogram (SCG) is the recording of body vibrations induced by the heartbeat. SCG contains information on cardiac mechanics, in particular, heart sounds and cardiac outputs [96]. Kinetocardiography (KCG) records indicate movements as the result of the motions of the heart and utilize only the low-frequency motions (0–30 Hz) [97].

Though these methods by themselves are interesting, none evolved to match the process of ECG methods.

IV. COMPUTERIZED AUTOMATED DETECTIONS ON ECG FOR CARDIAC HEALTH MONITORING IN EARLY YEARS [60'S–90'S]

By 1961, Norman Jeff Holter had designed the Holter [29] for continuous ECG monitoring in hospitals. Holter designed a backpack recorder that weighed 75 lbs and it was able to record and transmit ECG signals to the hospitals for further evaluation. It became a landmark invention for the automatic detection and transmission of biomedical signals, specifically ECG signals.

A new era had ushered for automated computerized detection. The first automated classification on 20 clinically normal individuals on magnetic tape recorders to store a 1-minute recording of each subject [98] were utilized. In 1965, average transient computing based on average response computing techniques was presented to extract the ECG signal from the noisy records such as exercise stress test results in [99]. In 1966, the system was developed for online computer monitoring of critically ill patients [100]. This system provided continuous monitoring for various health parameters such as ECG, systolic and diastolic blood pressure, pulse rate, temperature readings at various parts of the body, manual inputs from the user, etc., within the hospital setting due to the high form factor of the system. The system was used at the California Shock Research Unit for clinical management of seriously ill patients. The system provided online acquisition, processing and display of the data. In 1967, Vector Cardio Graph (VCG) was used to separate normal and Left Ventricular Hypertrophy (LVH) on subjects [101]. Four different techniques were utilized for categorization, such as sum of amplitude measurement, vector differences, weighted vector differences and class separating differences. Two hundred subjects' samples were utilized for obtaining the results out of which 100 were LVH Samples and 100 were normal subjects (case-control study). In a similar year, another work [102] was presented to analyze the normal subjects' frontal leads to expand the conventional amplitude and time base factor.

By 1968 advanced mathematical concepts from signals and systems viz Contour Analysis were used to categorize the normal and abnormal ECG Rhythms [103]. Around 2000 samples were subjected to an automated contour plot and the results were compared with the physician's results to determine the accuracy of the technique.

By 1970, the online Real Time algorithms for ECG waveforms were started to developed [104], that provided the information whenever the values were exceeded beyond the predefined limits for a single lead ECG signal.

In 1971, both 12 lead ECG and 3 Lead VCG techniques were considered standard methods of monitoring and around 1100 patients for the automated detections were obtained [105], [106]. This study suggested no appreciable differences from automated techniques obtained from 3 Lead VCG and 12 Lead ECG data inputs. It also concluded that 3 Lead VCG data was sufficient for automated detections as it saved the computing time and emphasized VCG as preferable for automated detections. Although VCG became famous for automated detections, it never became popular for physicians due to the nonstandardized lead configuration, and the other reason is medical doctors are accustomed to using 12 lead ECG in clinical applications [107]. VCG can be obtained by 12 lead ECG signals but this field also requires more attention from the researchers.

In 1973, a research based on clustering techniques [108] for pattern recognition. The categorization was based on the clusters defined by the human operators. If the values fall outside the boundary limits of clusters the human invention was requested. The system was semiautomated and classified the QRS complexes of the ECG signal. In 1974, another research work [109] was published for QRS and premature

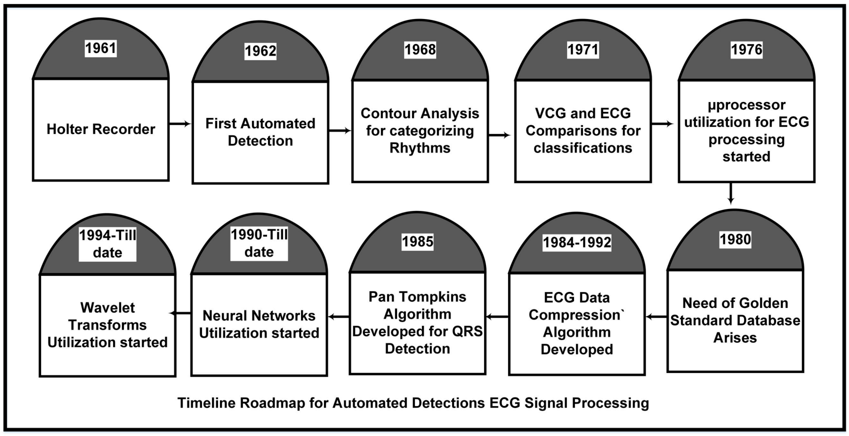


FIGURE 15. Milestones of ECG signal processing in the initial years.

ventricular beat detection for a continuous real time ECG signal. However, the authors were not convinced of its widespread use and specified that it was limited for specific research purposes.

Around the similar year, μprocessors were made available for automatic analysis in biomedical engineering. The first reported use of μprocessor for Ambulatory ECG monitoring is believed to be around 1976 [110], [111]. These were μprocessors powered bedside ECG monitors and became an important milestone in automated ECG methods due to transformation in the research methodology. Various papers were reported [112]–[117] during the same period that provided the μprocessors based systems for Ambulatory ECG Monitoring.

Until 1980's, all these automated detection algorithms and methods were based on separate databases. So, there was a need for a standard database as the results were invariably data-dependent. Literature [118]–[120] suggests that various attempts to obtain the Gold Standard database for comparison begun. Around 1983, MIT and Beth Israel Hospital Arrhythmia Laboratory released the data obtained from Holter tapes patients between 1975 and 1979 [119]. It later became a standard database and is used till date. The databases [121]–[141] available on Physiobank for automated processing schemes comparisons are shown in Table 2. PhysioBank is a large and growing archive of well-characterized digital recordings of physiologic signals and related data for the biomedical research community. In this paper, only ECG and relevant signals databases are considered. The databases provide the annotations for quantification of ECG waves (Truth values for P, QRS and T waves to be compared with automated generated results) and the diagnosis of various diseases confirmed by cardiologists. Except this, some of the databases also provide information for compression tests and signal to noise ratio information of the signal. These standard databases continue to be the gold standard of ECG processing research.

Research related to Holter Tapes' automated analysis with μcomputers and Automated Holter Scanning were published during 1983 [142]. The system consisted of two μcomputers to detect QRS durations for arrhythmias of 24 hours recorded on Holter tapes. It determined the heart rate variability and PVC counts, a method used till date. Around the same year, another method of QRS complex detection was presented in [143]. In this method, the QRS complex was represented by a single positive pulse along with onset and end of it, by a dynamic threshold technique that utilized the time domain features. But, the results of the method was provided on the simulated ECG data as a software based technique.

A portable μcomputer based Arrhythmia Monitor was designed [117] for storing 16 *seconds* arrhythmia intervals. The major difference of this system with Holter tapes was that it did not store any normal rhythm data and was advantageous in terms of memory utilization. The system was able to provide continuous and long term monitoring for high-risk patients. In 1987, filter design was illustrated in [144] for biomedical signal processing techniques. The filters were implemented for the ECG signals and quantization of filter coefficients was used to design various filters with its implementation on 8 bit μprocessor.

These μprocessor-based systems became the interest of researchers with databases available to them and the evolution of data compression techniques. The processing of various data compression techniques also evolved rapidly as processing the 12 Lead ECG data for automated methods was computationally expensive. The compression techniques further minimized redundant information present in the original signal and helped the system practically feasible. These methods are believed to have early beginnings during 1968 and continued in later years (1984- 1992) as cited in various works [145]–[149].

Various data compression algorithms as Turning Point Algorithms [115], FAN algorithm [150], AZTEC Algorithm [148], CORTES algorithm [146], Fast Walsh Transform [151] and SLOPE algorithm [152] are discussed. One of the main concerns in biomedical data reconstruction was the clinical acceptability of these signals. During the data compression, the requirement for lossless information and the

TABLE 2. Some of the ECG databases available on Physionet website.

Reference	Database	Specifications	Number of Records	Abbreviations
[121]	MIT-BIH Arrhythmia	2- Channel Ambulatory ECG with R peak Annotations	48	MITDB
[122]	MIT-BIH Arrhythmia with P Wave Annotations	Contains P-waveannotations for 12 signals from MITDB	12	PWAVE
[123]	MIT-BIH Atrial Fibrillation	25 long-term ECG recordings with Atrial Fibrillation	25	AFDB
[124]	MIT-BIH ECG Compression Test	Short ECG recordings to pose challenges for ECG compressors	168	CDB
[125]	MIT-BIH Long-Term ECG	Long-term ECG recordings with manually reviewed beat annotations	7	LTDB
[126]	MIT-BIH Malignant Ventricular, Ectopy	Recordings of Ventricular Fibrillation, Flutter and Tachycardia	22	VFDB
[127]	MIT-BIH Noise Stress Test	Recordings of different SNR data and Typical noises in Ambulatory ECG	12+3	NSTDB
[125]	MIT-BIH Normal Sinus Rhythm	Long term Normal Sinus Rhythm	18	NSRDB
[128]	MIT-BIH Polysomnographic	Multiple physiologic signals during sleep	18	SLPDB
[129]	MIT-BIH ST Change	Recordings of varying length during exercise stress tests and with transient ST depressions	28	STDB
[130]	MIT-BIH Supraventricular Arrhythmia	Recordings of Supraventricular arrhythmias	78	SVDB
[131]	QT	With onset, peak, and end markers for P, QRS, T, and U waves annotations	100	QTDB
[132]	Physikalisch-Technische Bundesanstalt	15 Leads data for various cardiac conditions specifically MI	549	PTB
[125]	St Petersburg INCART 12 lead Arrhythmia	12 standard leads annotated recordings extracted from 32 Holter records	75	INCARTDB
[133]	European ST-T	ST segment change and T wave change episodes included	90	EDB
[125]	Common Standard of Electrocardiography	collection of short (12- or 15-lead) recordings	1000	CSE
[134]	Combined measurement of ECG, Breathing & Seismocardiograms	ECG, SCG and Breathing signals of healthy subjects	20	CEBSDB
[135]	WECG	Wrist ECG of healthy subjects	30	WECG
[136]	FANTASIA	ECG and respiration signals during supine resting	40	FANTASIA
[137]	Apnea-ECG	Annotated nighttime ECG recordings	90	APNEA-ECG
[138]	PAF Prediction Challenge	consists of training and testing data for Proxymal Atrial Fibrillation detection	50-Training 50- Testing	AFPDB
[139]	CAP Sleep Database	polysomnographic recordings registered at sleep disorders	108	CAPSDB
[140]	MIT-BIH Malignant Ventricular Arrhythmia Database	ECG recordings of subjects with Ventricular flutter, tachycardia and fibrillation	22	MVADB
[141]	Creighton University Ventricular Tachyarrhythmia Database	ECG recordings of subjects with Ventricular flutter, tachycardia with Ventricular flutter, tachycardia	35	CUVTDB

removal of repeated or redundant signals proved a challenge. The data reduction techniques provided viable options for storing or processing large amounts of data with lower storage requirements and became successful.

Following this, Pan and Tompkins proposed the seminal algorithm for QRS detection [153] for normal and abnormal waveforms. This algorithm provided accuracy of more than 99% for QRS detection and revolutionized the means for arrhythmia monitoring. The algorithm also provided the ideal means for heart rate variability measurements in real-time processing and reporting various cardiac conditions and diseases. In 1987, another research [154] provided the preliminary heart rate variability (HRV) analysis by using the autoregressive modeling techniques and power spectral density estimates. For the QRS detection, it followed the classical technique by obtaining the derivative of the ECG signal followed by adaptive thresholding. After obtaining the R-R interval information, it discriminated the normal and pathological subjects by utilizing the autoregressive modeling and power spectral density estimates. In 1988, two methods for detecting the QRS complexes were discussed in [155] based on the length transformation and energy transformation of the signal. In both the methods QRS complexes of the signals were enhanced and other components of the signal were suppressed significantly and detection accuracy for QRS complexes was found out be over 99%.

Around 1989, research on connectionist systems, better known as neural networks for diagnostic purposes, was proposed. Neural networks were first used for ECG signal processing during 1990 for diagnostics [156]–[162], categorization and QRS detections and proved interesting. The application of neural networks also proved to be advantageous in classifications and detections with extended computations. Over the years, such artificial intelligence algorithms were extended towards categorizing normal and abnormal waveforms and pattern matching. During 1992, detection of QRS complexes for very noisy signals was demonstrated using neural networks [160]. This work used a multilayer perceptron neural network as an adaptive whitening filter instead of a typical linear filter.

Another work on the QRS template matching was updated by ANN recognition algorithm was discussed in [161]. Several hidden layers in multilayer perceptron with eigenvalue decomposition method to classify the signals available in MIT/BIH database were provided in [162] and the technique was also patient adaptable. Although the neural networks provided better detection accuracy than the conventional classification (based on thresholding and empirical values), the computations requirements for such systems were high and often difficult to realize on customized hardware.

In [163], authors discussed the utilization of Wavelet Transform (WT) for ECG analysis and compression techniques. The research presented a preliminary investigation into its application to the study of both ECG and heart rate variability data. Further, WTs were also studied that provided time and frequency analysis for the ECG signals discussed in [164]–[168]. The authors suggested that wavelet transforms' efficiency measures were comparatively higher than conventional methods [164], [165]. The timeline for the signal processing is shown in Fig. 15.

V. ECG SIGNAL PROCESSING IN RECENT YEARS [90-TILL DATE]

ECG signal processing is classified into four major subcategories: acquisition of ECG signal, preprocessing, feature points selection and classifier selection. Fig. 16 shows various steps of standard ECG signal processing steps.

The ECG signal is obtained through publicly available databases or various ECG acquisition methods. The number of leads for ECG data can be chosen according to the application of the system. So, the ECG input to the system may be a single lead ECG signal, Bipolar three lead signal, standard 12 Lead ECG signal or the 3 Lead VCG signal.

The preprocessing step is the initial step before the feature selection process. The preprocessing stages usually denoise the ECG signal affected by various kinds of noises such as baseline wandering, power line interference, electromyogram noise *etc.* [169]. In some of these cases, filters are employed at this level to consider a particular band of frequencies. The introduction of the preprocessing stage before feature selection leads to more accurate results. However, we found out that the signal quality assurance before the preprocessing stage is mostly missing from most of the researches. Various noise removal or preprocessing techniques for the ECG signal are discussed in [170], interested readers may have a look at it.

In the subsequent step, the signal features, namely temporal, spectral or time-frequency are selected. The original ECG signal is in the time domain, and for converting it to other domains, various transforms such as Fourier transform or wavelet transforms are needed. In some of the cases, statistical information regarding the signal is also considered.

After the feature selection, classifiers are implemented to categorize the signals. These classifiers may be empirical, thresholding, machine learning or a deep neural network. Based on the results of classifiers, detection of the disease or diagnosis is usually done.

In literature, time domain [171]–[182], frequency domain methods [183]–[196] or time frequency domain methods [197]–[213] are classified with the empirical, thresholding based, machine learning or deep neural network approaches. In this report, the papers are classified according to feature point selection or the classifiers scheme discussed in the work.

The signal processing schemes can also be classified into hardware based, software based or hardware-software based approaches. In the software processing schemes, the computational load does not pose a constraint on the system. Therefore, complex processing schemes are often used to obtain results that provide comparatively more accurate results. However, in the Real-Time system for resource-constrained regions, the computational load does matter and poses a real challenge for the battery-driven systems, deployment and relevance. Hence, for automated detections, there must always be a tradeoff between performance and resource requirements. The performance matrices of the system is defined in terms of True Positives (TP), False Positives (FP), True Negatives (TN), False Negatives (FN), Accuracy(Acc), False Detection Rate (FDR), Sensitivity (Se), Specificity (Sp), Positive Predictivity (PPV), Error Rate (ER), Efficiency of Recognition (EOR), Classification Rate (CR), Classification Error Rate (CER), False Acceptance Rate (FAR), False Rejection Rate (FRR) and Detection Error Rate (DER) etc. Various research works are classified in the following subsections based on their feature point selection strategy or the classification scheme.

A. FEATURE POINTS SELECTION

Feature point selection is a crucial stage as it requires the tradeoff between the system complexity, accuracy and battery requirements for the system. Processing techniques may vary from the simple morphological features capturing to complex transformations. Features may be from the time domain, frequency domain, or a mix of both as in the time-frequency domain. Researches related to the field are listed and compared in the following subsections.

1) TIME DOMAIN

The time domain processing or the temporal domain feature extraction allows the processing in discrete samples. With the evolution of μprocessors around 1974, the conversion of continuous signals to discrete ones became usual, so the signals were also usable by μprocessors. It was easier to convert the discrete signals again back to analog [145].

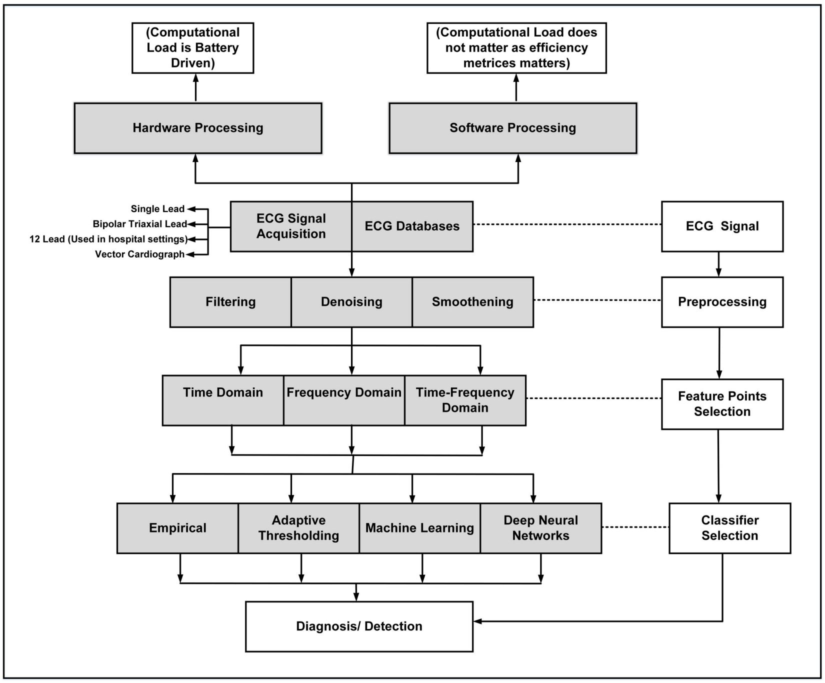


FIGURE 16. Recent ECG signal processing trends categorized into ECG signal acquisition, preprocessing, feature point selection and classifiers sections.

TABLE 3. Literature comparison based on time domain features of ECG signals.

Reference	Research Orientation	Database	Classifiers	Performance
[171]	Real Time QRS Detection	MITDB	Combined Adaptive Thresholding	Se%= 99.69, Sp%= 99.66 (Algorithm1) Se%= 99.74 Sp%= 99.65 (Algorithm2)
[173]	QRS Complex Detection	MITDB	Difference Operation Method	FDR %= 0.19
[174]	R peak detection Algorithm	PTB	ECG double difference and RR interval processing	Se %= 99.8
[175]	ECG feature Extraction	QTDB, PTB	Time Domain Gradient based classification	-
[176], [177]	P and T wave Detection	MITDB	Based on two moving average filters Dynamic event related thresholding	Se %= 98.05, PPV%=97.11 (P wave) Se %= 99.86, PPV%=99.65 (T wave)
[178]–[180]	Disease diagnostic algorithm based on forward search	INCARTDB PTB and QTDB	Decision Logics and Empirical Classifiers	FDR %=0.69, 0.69, 0.34 & 1.72 for BBB, Hypertrophy, Arrhythmia MI
[181], [182]	Disease diagnostic algorithm	MITDB	Decision Logics and Empirical Classifiers	FDR %=1.289%, PPV %= 99.293, Se%=99.492 (QRS Detection)

Table 3 shows the literature based on various time domain methods, in [171], authors discussed two algorithms for QRS detection; the first algorithm detects the current beat while the second algorithm has an RR interval analysis component. Authors in [172] discussed noise filtering, QRS detection, Wave Delineation and Data Compression of the ECG signal in time domain.

Authors utilized the difference operation method for QRS complex detection in two stages in [173]. The first stage was to find the R point by applying the difference equation to an ECG signal and the second stage looked at Q and S points based on the R point to find the QRS complex. By doing so, Q and S point detection efficiency was dependent on the R peak detection algorithm. In [174], authors utilized the squared double-difference signal of ECG signals to detect the R peaks and the results are provided only for the normal cases. In [175], authors utilized a time-domain morphology and gradient-based approach based on a combination of extrema detection and slope information, using adaptive thresholding for ECG features extraction. The main limitation of this algorithm was that its robustness not tested against baseline wandering variations. In [176], [177], authors determined the P and T waves of ECG signal using two moving average filters that provided the dynamic event-related thresholding by utilizing the signal's QRS information. Then the results were compared against the annotations provided by the cardiologists on the MITDB database. Further, in [178]–[180] authors extracted the ECG features and classified various ECG anomalies based on the 12 Lead ECG signal. The advantage of this algorithm was forward search processing; it lowers the memory requirement in real-time processing. Similarly, in [181], [182] authors detected various ECG features required for the classification of ECG anomalies. The results of real time system were not reported in the work.

TABLE 4. Literature comparison based on frequency domain features of ECG signals.

Reference	Research Orientation	Database	Classifiers	Performance
[183]	Determination of bandwidth of ECG by applying Fourier Transform	10 normal ECGs Database- Unknown	-	Waveform- Amplitude 0-200 Hz Waveform duration- 0-60Hz
[184]	Determination of maximum frequency components in P, QRS and T waves	Healthy subjects' ECG Database- Unknown		F_{max} P wave = 55Hz, QRS-complex = 65 Hz, T wave-25 Hz
[185]	Power spectrum Analysis of HRV for Sudden Cardiac Death	18 subjects ECG recordings Database-Unknown	-	
[186]	Ventricular Arrhythmia (VF), Artifacts (A) and Series of complexes of aberrant morphology (CAM)	55 ECG recordings Database- Unknown	various spectral features	VF Sp= 70% Se= 100 % CAM Sp= 100% Se=86 % A Sp= 100% Se=92%
[187]	Frequency Analysis of ECG for Tachycardia Detection	Bipolar Leads Unknown Database	Maximum Entropy Method based on Autoregressive model	-
[188]	P, QRS and T wave detection of ECG signal	locally acquired ECG signals and MITDB	Discrete Fourier Transform	-
[189]	Ventricular Fibrillation duration Detection in swine and humans	Unknown	Frequency domain Features such as median frequency	Estimation = 82.9 %
[190]	Prediction of Counter shock therapy's success by fourier transform of the signal	26 patient's ECG Unknown Databse	Dominant frequency, median frequency and amplitude	Se%= 100 - -
[191]	ECG spectrum feature for classification of arrhythmia	MITDB	Frequency domain features	Approximate pobablity of error 0.0%
[192]	Method for removing artifacts	Real Time ECG obtained from Smartex system	Convolutive Indepent Component Analysis model	-
[193]	Frequency domain Analysis	MITDB and SVDB	Auto Associative Neural Networks	-
[194]	Detection of Power line interference	12000 ECG Signals of 10 sec duration	Power Spectral Density	FP Rate= 0.1%
[195]	HRV and Breath to Breath Interval Analysis	5 female and 6 male subjects Unknown Database	Auto Regressive Moving Average Model for Spectral Analysis	peak amplitude (0.15-0.40 Hz) band > frequency (0.04-0.15 Hz) band
[196]	Disease Diagnosis in Frequency domain	MITDB	Frequency based Neural Networks	80% lesser ECG diagnosis time at 5% Accuracy lose compared to temporal methods

In conclusion, temporal features such as RR, PR, QT interval, ST deviations were utilized to provide the diagnostic results. Various filtering methods such as differentiator, moving average filter, low pass, high pass etc. have been utilized to obtain ECG signals' feature points. The time domain methods are of prime importance as the cardiologist detects the heart's anomalies using 12- Lead ECG signal in the time domain that provides synergistic efforts between doctors and engineers towards automated detection systems.

2) FREQUENCY DOMAIN

Research on the frequency domain processing of ECG signals started around the 1970s. During the initial years, the researchers focused on obtaining the frequency band amplitude information related to ECG signals such as the band of QRS complex, P wave and T wave [183], [184] *etc.*

The features required for diagnosis are primarily temporal and statistical information, as developed by cardiologists. Hence, ECG signal processing based on only spectral information is rare compared to the time domain and time-frequency methods. The frequency domain methods are shown in Table 4. As can be seen in [185], [187], [191]–[193] research, results were not available in terms of standard performance matrices, which makes it quite difficult for comparison. In [186], the ECG signals were classified in different categories namely ventricular fibrillation and flutter (VF), Artifacts (A), series of complexes of aberrant morphology (CAM) and one unknown category by utilizing the spectral features of the ECG signal. However, the ECG data used for the purpose consisted of only 55 ECG signals from an unknown database. In [188] authors detected the QRS, P and T waves of the ECG signals by application of discrete Fourier transform on the ECG signals, acquired locally and from MITDB. The delineated components were evaluated visually and by computing the normalized mean square error between the original and recreated signal. In [189] authors detected the duration of ventricular fibrillation in swine and humans using the frequency domain features of ECG signal. In [190] determination of countershock (Medical Procedure) success was done by obtaining the Fourier transform of ECG signal and it was concluded that the median frequency, dominant frequency and amplitude of the signal could predict the success or failure of the procedure.

In [194], authors determined the power line interference, a common source of noise in the ECG signal that leads to imprecise measurements of the ECG wave durations and amplitudes. In [195] authors determined the heart rate variability using spectral analysis. However, the results were not validated on any standard databases. In [196], authors detected anomalies of ECG signal by utilizing the frequency domain features and the results were compared with the temporal methods.

Frequency domain features are essential to obtain the complete analysis for the signal. However, the disease diagnosis requires the utilization of temporal features as most of the features for cardiac anomalies were developed by cardiologists and physicians accustomed to time domain signals.

TABLE 5. Literature comparison based on time-frequency domain features of ECG signals.

Reference	Research Orientation	Database	Classifiers	Performance
[197]	Arrhythmia Detection in ECG utilizing WT	Pigs ECG signals	-	-
[198]	Compression of ECG using WT	MITDB	-	% Root Mean Square Difference=1.18 (1 dataset)
[199]	Compression of ECG using WT	MITDB	-	Bit Error Rate= 10^{-15} (3 datasets) % Reduction Transmission Time= 72.7
[200]	Compression of ECG using WT	MITDB	-	% Root Mean Square Difference=1.08 (1 dataset)
[201]	Single Lead ECG delineation system	EDB, CSE, MITDB	Multiscale Approach	Se%= 99.66, PPV%= 99.56 (ST-T, CSE) Se% and PPV% = over 99.8
[202]	ECG QRS Detection using Multiresolution WT	MITDB	Two wavelet filters (D4 and D6) for QRS detection	Se%=99.18 ± 2.75 PPV%= 98.00 ± 4.45
[203]	Personal Identity Verification with WT of ECG Signal	QTDB	Euclidean distance measure for verification	False Acceptance Rate = 0.83%(N) and 12.50% (Ab) False Rejection Rate = 0.86%(N) & 5.11%(Ab) (N=Normal Ab= Abnormal)
[204]	Denoising of ECG and QRS Detection	MITDB	Adaptive Thresholding on DWT	Se= 99.71% Sp=99.72% DER = 0.52%
[205]	Cross WT for classification and analysis of ECG signals	PTB	Parameter obtained from XWT wavelet cross spectrum and wavelet coherence	Acc%=97.6, Se%= 97.3 Sp%= 98.8
[206]	Wavelet based ECG Signal Compression	MITDB, SVDB	Wavelet threshold	CD=100% based
[207]	Low-Complexity ECG Feature Extraction	QTDB, PTB, a Non commercial Database	DWT with Haar and mother wavelet functions	$2.423N + 214(+)\ and\ 1.093N + 12(\times)$ for $(N \leq 861)$ $2.553N + 102(+) and 1.093N + 10(\times)$ $for (N > 861)$ (N= number of input samples)
[208]	Wavelet based ECG detector	MITDB	Soft-threshold algorithm	Detection Error-Rate%= 0.196
[209]	ECG Recording and R-Peak Detection Based on WT	MITDB	R peak detection with a FIR filter	Se%= 99.72, PPV%=99.49 Data Reduction =13.68 $\times$
[210]	ECG-Based Biometric Human Identification	CEBSDB, WECG, NSRDB, STDB, AFDB, VFDB FANTASIA, MITDB	Multiresolution convolutional neural network	Average Identification Rate % = 93.5
[211]	ECG Abnormality Detection	MITDB and real time data	Support Vector Machine	Maximum Accuracy= 96%
[212]	Time- Frequency domain coronary artery disease detection	St. Petersburg and FANTASIA	Random tree and J48 decision tree for time frquency domain features	Acc%= 99.93
[213]	Wavelet based ECG signal signal classification and arrhythmia analysis	MITDB, NSTDB	Hidden Markov Model based classifier	Acc%= 99.7%

3) TIME-FREQUENCY DOMAIN

Time-frequency domain methods utilize the time as well as frequency space for obtaining the features simultaneously. The most popular technique in this domain is Wavelet Transform (WT) and the ECG signal processing using the same is discussed in [197]–[214]. The advantage of using WT over Fourier transform is that Fourier Transform of a signal provides the information regarding the frequency and its magnitude; however, it cannot provide frequency information for a localized signal in time. To overcome the poor time resolution of the Fourier transform, Short Time Fourier Transform (STFT) has been developed. It provides the time-frequency representation of the signal. In the Wavelet Transform signal's different frequency components are analyzed at different time resolutions, also known as multiresolution analysis [215]. The multiresolution analysis capability of WT makes it suitable for biomedical signal processing schemes [214]. Various researches for WT and other time-frequency schemes are given in Table 5. Denoising techniques for an ECG signal using new wavelet- and wavelet packet-based schemes were discussed with simulated noises in [216]. Various WT techniques such as Cross Wavelet Transform (XWT) [205], Continuous Wavelet Transform (CWT) [197] and Discrete Wavelet Transform (DWT) [199]–[203], [205], [207], [210]–[212] are employed in literature.

In [197], authors report the detection of the arrhythmias in the ECG signals of pigs. WT was utilized for the compression of ECG signal in [198]–[200]. The main reason for utilizing WT for the compression is because it transforms the signal's energy into fewer transform coefficients. So, most of the transform coefficients with lower energy can be discarded [217]. It is an efficient and flexible scheme for compression [218]. Authors in [201], [202], [207], [209] detected various features such as R peaks, QRS complex using WT. In [203]–[205], [208], [210]–[212] authors classified the ECG signals by utilizing the wavelet coefficients as features. In [206] two algorithms were presented based on wavelets for real-time ECG signal compression. The authors achieved the correct diagnosis (CD) values up to 100% for various compression ratios. In [213], authors have discussed a method for ECG signal classification and analysis that utilizes wavelet based information as the input. This method followed a three-stage procedure for analyzing ECG signals starting with noise suppression and then wavelet-based feature extraction and classification stages.

The Wavelet Transform has certain disadvantages as it becomes computationally intensive for finer resolution. Discrete Wavelet Transform (DWT) offers fast computations due to the discretization of wavelets as the minimum energy transform coefficients are discarded at the cost of efficiency of the system [215].

4) COMPARISON OF TIME DOMAIN, FREQUENCY DOMAIN AND TIME-FREQUENCY DOMAIN FEATURES FOR AUTOMATED DETECTIONS

The time domain, frequency domain and time-frequency domain methods are used for various specific applications. The temporal or time domain features such as R-R interval, QT interval, ST-T interval and PR duration are of prime importance because the cardiologists are accustomed to such features from standard 12 Lead ECG signal. However, applying preprocessing methods on the ECG signals for automated detections may alter certain features such as ST segment elevation and depression of the ECG signal that could lead to false outcomes. Hence, the time domain methods require careful preprocessing to improve the accuracy.

The frequency domain features such as power spectral density and frequency bands for a particular section of the signal helps in implementing the filters for delineation. However, the classification that is based on frequency domain features is infrequent and requires more attention.

WT is the most common and widely used for the time-frequency methods. References [197]–[213] discuss automated classification and compression methods based on WT. Continuous WT based methods are computationally expensive for portable systems. Preferred discrete WT offers faster computations at the cost of efficiency.

It is to be noted that the system is dependent on the classifier following the feature point selection. Therefore, it is difficult to compare these methods based on feature selection methods only.

B. CLASSIFIERS

The classification stage considers the extracted feature points from the previous stage and classifies the signal into different categories by using empirical, adaptive and constant threshold-based, machine learning based and deep neural networks based classifiers. The conventional empirical classifiers are generally based on the medical observations for the particular field. Thresholding based or decision logic-based approach is based on defined logical rules, *e.g.* R-R interval, ST interval *etc.*

The machine learning based approaches based on multivariate statistical pattern recognition have a widespread utilization in biomedical signal processing. These methods utilize correlation analysis, regression techniques and template matching to identify abnormal patterns or a particular class of signals [219], [220]. However, as these statistical methods move towards greater accuracy, the computational cost for the system also increases. The most popular techniques are deep neural networks also known as ANN consists of multiple hidden layers between the input and output layers [221]. Each layer consists of neurons with different weights and biases. The neurons can pass the information to other neurons in other layers. The backpropagation technique provides feedback and updates the weight associated with neurons offering supervised and unsupervised learning. The deep learning technique offers more accuracy to the system at the cost of increased system complexity, which may be a serious challenge for battery operated portable systems.

Support Vector Machine (SVM) is also widely used for classification of different types of signals. It provides a supervised learning method to optimize the gap between two different categories of training sets. Another type of classifier is Convolutional Neural Networks (CNN) is a particular type of feed-forward neural network. It represents the input data in the form of multidimensional arrays and consists of three layers: convolution, pooling, and fully connected.

Recent developments in deep neural networks are widespread, with the latest techniques discussed in [221] are Recurrent Neural Networks (RNN), Convolution Neural Networks (CNN) and other generative models such as Autoencoders and Generative Adversarial Network (GAN). In the following subsection, we have selected the literature mainly focusing on classification schemes based on machine learning and neural network approaches for ECG signal processing. The reason for selecting only the classifier based on machine learning of deep learning approaches is the widespread utilization of these techniques compared to the other techniques.

1) MACHINE LEARNING AND DEEP LEARNING TECHNIQUES BASED CLASSIFIERS

This section categorizes (shown in Table 6 and Table 7) various researches based on machine learning and deep learning techniques for classification.

In [222], authors provided the customized ECG classifier with patient-specific data based on an unsupervised learning technique. The method's limitation was that it required the development of a local classifier for each patient with patient-specific data. In [223], authors detected the QRS complexes of 12 Lead ECG signals available in CSE dataset -3 with supervised learning of ANN. The backpropagation algorithm has been used to train the system and to update the weight and biases of neural networks.

Authors in [224], utilized the ANN for arrhythmia classification, ischemia detection, and recognition of chronic myocardial diseases. It used both static and recurrent ANN with preprocessing and postprocessing that defined the dimensions of input features for neural networks.

TABLE 6. Literature comparison for machine learning and deep learning techniques based ECG classification.

Ref.	Research Orientation	Database	Classifiers	Performance
[222]	ANN Based Classification	MITDB	Self organizing maps ,learning vector quantization, mixture-of-experts (Patient Adaption) (Unsupervised Learning)	CR %= 94.0, Se%= 82.6, PPV%= 77.0, Sp% = 97.1
[223]	QRS Complex detection of 12 Lead ECG signal	CSE	Artificial Neural Network	Se %= 99.11
[224]	Arrhythmia classification, ischemia detection, & recognition of chronic myocardial diseases	MITDB, CSE, EDB	Static and Recurrent Artificial Neural Networks	-
[225]	Clustering of various ECG complexes using Hermite Basis functions features	MITDB	Unsupervised self organized Neural networks	CER%=1.5
[226]	Recognition and classification of different type of heart beats	MITDB	C-means and Gustafson-Kessel algorithms with fuzzy hybrid neural network	ER %= 2.55 (Training) ER%= 3.94 (Testing)
[227]	On-Line Arrhythmic Heart Beat Recognition Using Hermite Polynomials	MITDB	Hermite coefficients features to Fuzzy Neural Networks	EOR%=96 (Testing)
[228]	Higher Order Statistics (HOS) and Hermite Preprocessing (HP) Features for Automatic classification	MITDB	Support Vector Machine	ER%= 6.28 (HOS) (Testing) ER % = 5.43 (HP) (Testing)
[229]	Automatic Classification of Heart Beats using morphology and heart rate interval features	MITDB	Classifier based on Linear Discriminants	SVEB Se%= 75.9, , PPV%= 38.5 FP %= 4.7 VEB, Se%= 77.7, PPV%=81.9, FP %= 1.2
[230]	Classification of ECG on Personal Digital Assistant	MITDB	Decision Tree or J48 Classifier	Acc%= 100 (Critical Arrhythmias) Acc%=97.95 (Arrhythmias), Acc% = 95 (Arrhythmias before Critical cases)
[231]	Time, frequency and statistical features utilization for Anomalies Detection	MITDB	Two-stage feed forward neural network	Highest Recognition Rate= 93%
[232]	Personalized ECG classification on Hermite Coefficients and R-R interval features	MITDB	Block Based Neural Networks	SVEB Detection Acc%= 96.6 VEB Detection Acc%= 98.1
[233]	ECG classification based on automatically detected features	MITDB	Support Vector Machine with Particle Swarm Optimization	Detection Acc%= 89.72
[234]	ECG compression and and Classification	MITDB	Principal Component Analysis	classification Rate%=90
[235]	Sleep Apnea screening using temporal and spectral features	APNEA- ECG	KNN and Neural networks (NN) supervised learning	KNN-Acc%=88, Se%= 85, Sp%=90, NN-Acc%= 88, Se%= 89,Sp%=86
[236]	Local Fractal Dimension based Arrhythmia Classification	MITDB	PSDFE and VFE	PSDFE Se%= 95.6, Sp%=99.4 VFE Se%= 92.8, Sp%=98.8
[237]	ECG Arrhythmia classification by Temporal, Statistical, Morphological features selection	MITDB	Linear Discriminant(LD) MLP Neural Networks with Sequential Forward Floating Search (SFFS)	LD (SFFS), Acc%=84.6 MLP(SFFS) Acc%= 89
[238]	Personalized ECG Telemonitoring and classification	MITDB	Artificial Neural Networks with 30 Neurons	Acc% =98.82 (Training) Acc%= 63.92 (Testing)
[239]	PSO Wavelet based features utilization for signal classification	MITDB	Support Vector Machine	Se%=91.75, Sp%=96.14 PPV%=74.26
[240]	DWT based morphological features utilization for abnormality detection	MITDB	BPN, FFN and MLP based ANN	Acc%= 100
[241]	Real-Time Patient Specific ECG Classification	MITDB	1-D Convolution Neural Networks	SVEB Acc%= 99 VEB Acc%=97.6
[242]	Personalized Heart Beat classification on long term ECG	MITDB	Parallel general regression neural network	Classification Acc%= 95 (Database) Acc%= 88 (Real Time)
[243]	Atrial Fibrillation detection on automatically detected features	AFPDB	Convolution Neural Networks with Deep Learning	Precision% = 90.65
[244]	Arrhythmia Classification	MITDB	Wavelet sequence based deep on bidirectional LSTM network	Recognition performance =99.39%
[245]	ECG signal classification	Unknown	PCA and KNN with auto regressive modelling	Acc%= upto 100
[246]	Arrhythmia Classification	MITDB	Deep 1-D and 2-D Convolution Neural Networks(CNN)	Acc%=99 (2-D CNN) Acc%=90.93 (1-D CNN)
[247]	Arrhythmia Classification with LSTM based auto-encoder network	MITDB	Support Vector Machine	Acc%= 99.74, Sp%= 99.84, Se%= 99.35

$^{*}\,SVEB$ Supraventricular Ectopic Beat, ^{VEB} Ventricular Ectopic Beat

Authors in [225] utilized an unsupervised learning clustering scheme for the classification using Hermite functions based features of QRS complexes. The limitation was that it did not provide signal quality information in the input vector's self-organizing maps. Authors in [226], used a beat recognition and classifier based on a supervised learning scheme that

TABLE 7. Literature comparison for machine learning and deep learning techniques based ECG classification in last 2-3 years.

Ref.	Research Orientation	Database	Classifiers	Performance
[248]	Myocardial Infarction severity stages classification	PTB	Multi-lead Diagnostic based Attentional Recurrent Neural Network	Detection Acc%= 97.79
[249]	Multi-class Arrhythmia detection from 12-lead varied-length ECG	China Physiological Signal Challenge DB [253]	Attention-based time-incremental Convolutional neural networks	Classification Acc%= 81.2
[251]	Arrhythmia Classification	MITDB	Deep genetic ensemble of classifiers	Acc%= 99.37
[252]	Automatic diagnosis of 12 Lead ECG	CODE	Deep Neural Networks	Sp above 99% F1 Score above 80%
[254]	Insomnia identification using antisymmetric biorthogonal wavelet filter with ECG	CAPSDB	KNN & Support Vector Machine (Supervised Learning)	Highest classification Acc%= 97.87
[255]	ECG Arrhythmia Classification	MITDB, MVADB AFDB & CUVTDB	Recurrence Plot, Convolutional Neural Networks	Testing Acc%= 98.41 ± 0.11)(Second stage) 95.3 ± 1.27 (first stage)
[256]	P, QRS and T detection using deep learning techniques	QTDB	Convolutional neural networks and LSTM	Se%= 97.95 Precison%= 95.68
[257]	Arrhythmia Classification	MITDB	Manta ray foraging optimization with Support Vector Machine	Acc%=98.26

$^{*}CODE$ more than 2 million labeled exams analyzed by the Telehealth Network of Minas Gerais and collected under the scope of the Clinical Outcomes in Digital Electrocardiology (CODE) in Brazil

utilized fuzzy hybrid neural network and higher-order statistics features as inputs. In [227], authors utilized Hermite basis function expansion of the QRS complexes of ECG waveforms and modified Takagi-Sugeno-Kang neuro-fuzzy network for heartbeat recognition and classification based on a supervised learning scheme. In [228], authors utilized a popular supervised machine learning approach known as Support Vector Machine (SVM) for the recognition purpose. The input features in the method were obtained by two methods, namely higher-order statistics (HOS) and Hermite characterization of the QRS complex. In [229], authors classified the ECG data into three categories, namely normal beat, ventricular ectopic beat (VEB), supraventricular ectopic beat (SVEB). The classification was based on a statistical classifier model utilizing a supervised learning scheme. The limitation of the technique was that heartbeat fiducial points were manually annotated. In [230], authors provided supervised learning based on a decision tree based classifier algorithm to be implemented on a personal digital assistant (PDA). But, the algorithm was not implemented in a real time environment as the PDA was meant only for a system demonstration. In [231], authors used features such as ST segment area, R-S interval, ST-slope, R-T interval, QRS area, Q-T interval, R-wave amplitude, heart beat rate and four statistical features QRS energy, mean of the power spectral density, auto-correlation coefficient and signal histogram were applied to signal stage and two stage feed forward neural networks for the anomalies detection.

In [232], authors used supervised learning that required block based neural networks as classifiers. It utilizes Hermite coefficients and R-R intervals as input features to classify SVEB and VEB.

Authors in [233] utilized the supervised particle swarm optimization (PSO) with the SVM classifier on the automatically detected features. In [234], authors compressed the ECG signal using local extreme extraction, adaptive hysteretic filtering and Lempel-Ziv-Welch (LZW) coding. The reconstructed waveform was verified with frequent normal and pathological cardiac beats using a multilayer perceptron neural network trained with original cardiac patterns and tested with reconstructed ones. In [235], authors did the screen apnea screening using the time domain and frequency domain features. It used two approaches, namely K-nearest neighbor (KNN) (clustering or unsupervised technique) and neural networks that offer the supervised learning scheme. The limitation of the method was that it was unable to detect isolated apneas and other physiological and pathological events during sleep, such as cyclic alternating pattern and periodic leg movements that could affect the classifier's efficacy. In [236] authors used local fractal dimension (LFD) of neighboring sample points of ECG signal segments are used as the features. Two different methods used for estimating the LFD, namely power spectral density based fractal dimension estimator (PSDFE) and variance based fractal dimension estimator (VFE). In [237], authors obtained the ECG features set with sequential forward floating search algorithm based on linear discriminants. The most suitable subset was again evaluated with a multilayer perceptron Neural network as a supervised learning scheme. The selection of suitable features led to complexity reduction for the system. In [238], mobile-cloud based ECG monitoring scheme was compared with the mobile-based systems. The system utilized the supervised ANN for classification. In [239], Particle Swarm Optimization (PSO) based wavelets are applied to the SVM for categorizing various ECG signals. In [240], three neural network classifiers, Back Propagation Network (BPN), Feed Forward Network (FFN) and Multilayered Perceptron (MLP) were utilized for ECG anomalies detection. In [241], authors classified the ECG signals into SVEB and VEB with the supervised 1-D Convolutional Neural networks and the patient-specific data. The method's limitation was that the dedicated CNN was trained for an individual patient and often posed a challenge in the Real-time environment. In [242], authors designed a personalized heartbeat classification model for long ECG Signals and implemented the system with parallel general regression neural network (GRNN). Further to this, they implemented an online-learning module into the parallel GRNN for the real-time personalized automatic classification on the Holter ECG data. In [243], authors implemented various machine learning schemes such as end-to-end CNN, KNN, linear SVM, Gaussian kernel SVM, and Multilayer perceptron classifiers for categorizing the paroxysmal atrial fibrillation cases and concluded that integration of convolution neural network as a feature extractor with other conventional neural network-based classification methods provided better results. In [244], bidirectional long-short term memory networks based wavelet sequences called DBLSTM were used for categorizing various arrhythmic signals such as Normal Sinus Rhythm (NSR), Ventricular Premature Contraction (VPC), Paced Beat (PB), Left Bundle Branch Block (LBBB), and Right Bundle Branch Block (RBBB) available in the MITDB Database. However, the work did not validate the results under the noisy input conditions. In [245], authors used KNN and Principal Component Analysis (PCA) classifier techniques with autoregressive modeling schemes to categorize Atrial Tachycardia, Premature Atrial Contractions and Sinus Arrhythmia.

In [246], authors converted the time domain ECG signals into time-frequency domain spectrogram by utilizing Short-time Fourier transform and the spectrogram was utilized as the input to 2-D and 1-D convolution neural network for the arrhythmia classification on the MITDB database. In [247], authors integrated a long short-term memory based auto-encoder (LTSM-AE) network for features learning with an SVM for ECG arrhythmias classification and followed a supervised learning scheme. In [248], authors developed a system to categorize the severity stages of Myocardial Infarction condition and utilized an attention-based recurrent neural network for automated diagnosis of the three MI severity stages by processing the 12 Lead ECG data. The work's limitation was that it addressed only the classification of MI severity stages, not the diagnosis of the conditions.

An arrhythmia detection from a 12-lead varied-length ECG using Attention-based Time-Incremental Convolutional Neural Network was presented in [249]. The method was validated on the China Physiological Signal Challenge Database [250], which consists of atrial fibrillation, first-degree atrioventricular block, left bundle branch block, right bundle branch block, premature atrial contraction, premature ventricular contraction, ST-segment depression and ST-segment elevation signals with varied length. References [251] discussed arrhythmia detection using a deep genetic ensemble of classifiers. For determining the ECG features, the spectral power density was estimated based on Welch's method and discrete Fourier transform to obtain other useful features. References [252] presented a method for automatic diagnosis of the 12-lead ECG using a deep neural network. The performance for the system was validated on a large dataset consisting of more than 2 million subjects [253]. 98% data has been utilized to train the system, and the remaining 2% has been used to test the system. References [254] identified the sleep disorders with only ECG signals by utilizing optimal antisymmetric biorthogonal wavelet filter banks. It has categorized the signals using supervised machine learning approaches and outperformed the other methods based on other physiological signals. In [255], ECG arrhythmia classification has been done by using Convolutional Neural Networks and recurrence plots. The 1-D ECG data has been converted to 2-D recurrence plots and further utilized the classification of arrhythmias that has been validated using publicly available databases. In [256], authors detected the P wave, QRS complex and T waves of an ECG signal using the Long Short Term Memory (LSTM) combined with the Convolutional Neural Networks by utilizing the temporal features. In [257], a hybrid ECG arrhythmia classification algorithm termed Manta Ray Foraging Optimization with SVM is proposed to automatically determine the relevant features of Local Binary Patterns, Higher Order Statistics, wavelet and magnitude values for categorizing the ECG signals.

As can be seen in the works mentioned above, most of the methods utilize the databases as the input signal and are processed as a software-based approach. Most systems offered good efficiency with the increment in computational load. The methods generally adopted the supervised learning schemes for the classification on the databases that added constraint on the system level implementation because for the real time data, the system needs to be trained on real time ECG data.

VI. DISCUSSION AND CONCLUSION

This review provides insight into the invention of ECG, global acceptance of ECG, the evolution of leads, and the system's transformation from the huge String galvanometer to portable monitors in hospital settings.

Additionally, it offers a view on the earlier ECG signal processing schemes to the most recent ones. The signal processing can be categorized mainly into four steps: acquiring the ECG signal, preprocessing of ECG signal, feature extraction in different domains, and classification schemes. The research challenges of current ECG processing trends are discussed below.

A. PRESENT RESEARCH CHALLENGES

1. The machine learning, deep learning techniques and wavelet transforms are designed on the software processing domains that pose a constraint for the real time systems.

2. The researchers utilized the databases available on Physionet for data acquisition that are old dated. For example, the widely used MIT-BIH arrhythmia database was recorded during 1975-1980. Over the last 40 years, various standard definitions for the diseases changed according to various standards viz., American Heart Association(AHA), European Society of Cardiology (ESC) *etc*. Therefore, the use of the annotations provided in the database for comparing the results

with the automatic means remains slightly questionable. Improvements of annotations with the recent standards and inclusion of most recent databases may lead to more accuracy.

3. Lead uniformity is missing with the automatic methods discussed. For example, the MIT-BIH arrhythmia database provides the MLII lead and V5 leads and other databases such as PTB provides the 15 Lead data. Some of the methods are tested on the 12 Lead data and others are on 2 Lead data.

4. The literature does not utilize patients information (age, gender, previous medical history *etc.*) provided with the dataset that can add additional variables for the classifiers and can lead to more efficient systems, according to the European society of cardiology.

5. Utilization of supervised learning classifiers is suitable to obtain results on the databases. For system implementation, the data needs to be trained and tested based on the actual data and that is a challenge in the case of supervised learning schemes.

6. The demographics conditions of the countries or regions may vary; hence the algorithm developed to diagnose for a specific region of people must be adaptable to these conditions, which can be validated particularly with the locally obtained database. The standard/existing databases do not address this.

B. TECHNOLOGY INNOVATIONS AND FUTURE ROADMAP

This review also concludes that researchers could explore the possible improvements in the system's quality for field deployment. Fig. 17 shows possible directions (shaded) that needs more attention.

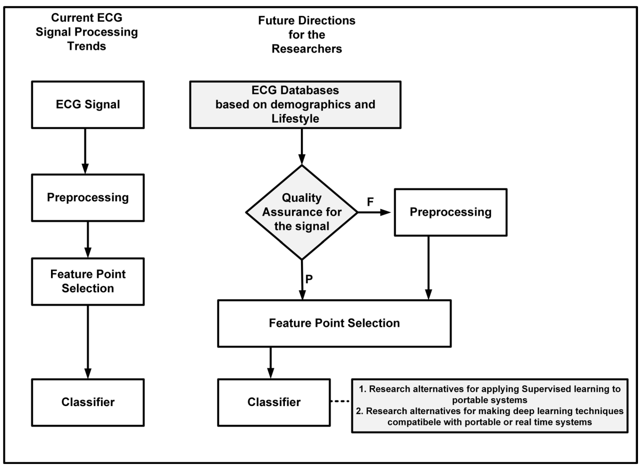


FIGURE 17. Future directions for researchers in the ECG signal processing domain. Gray areas represent the dimensions where future researchers can look into to fill the Gaps in the current research trends.

1. The validation of the system with the locally developed database may provide better accuracy in real time environment as cardiac diseases are highly dependent on individual lifestyle and eating habits. Researchers' focus is needed to develop the databases according to the demographics where we need to implement the system.

2. Signal quality assurance is the way forward for the researchers. However, some methods employ the preprocessing or denoising techniques to remove the random noises existing in the ECG signal, but the effects of such techniques on the ECG features are not discussed and these techniques are employed without assuring the quality of the signal as an application of such techniques may alter the essential parameters present in the signal. Hence, we propose that the signal quality assurance stage after the signal acquisition stage may be beneficial as if the signal quality is passed, then there is no need to preprocess the signal and if it fails, there must be a preprocessing stage to autocorrect the signal.

3. Research alternatives for the application of supervised learning techniques to portable systems must be studied. In this review, we found out that recent ECG signal processing techniques mainly utilize the machine learning approaches based on supervised learning techniques on the available databases by utilizing the time domain, frequency domain, time-frequency domain, and statistical features. The problem associated with the methods is that it requires the annotations or the truth values for testing the systems that create the problem for the implementation of the system in the real time scenario when the ECG signal is obtained locally with the sensors as the system must be trained with the similar ECG data.

Computational loads in Hardware settings need to be studied for the computationally exhaustive deep learning techniques to make them compatible with real-time systems.

4. The significance of VCG, needs to be studied further for automatic detections. Some of the earlier researches [5], [105], [106] shows the significance of VCG over the ECG signal, but it is still not a popular choice among researchers. The reason may be the doctors are accustomed to the 12 Lead ECG signals. Comparative studies of ECG and VCG based methods may open the doors for a new dimension in this domain.

5. Further to this, adding the parameters such as demographics and other user specific parameters could lead to more efficient and accurate systems.

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