CHAPTER-1

INTRODUCTION

Now a day, a sedentary lifestyle has accumulated, stress and drug use have increased, and individual is prone to heart diseases. As per WHO, cardiovascular illnesses are the main source of death in all individuals worldwide. Cardiovascular disease accounts for 30% of the world's population, with 23.6 million people expected to be still affected by this disease by 2030 [S. Maheshwari et al., 2014]. Then again, a lack of specialists in provincial India leads to improper consultation with a cardiologist. Nonetheless, the Public authority of India is rapidly creating medical services habitats in country regions. Tele-cardiology could be a practical answer to this basic issue. Telecardiology, in light of the Internet of Things (IoT), provides better clinical types of assistance, CVD management, and clinical diagnosis for provincial residents, even during the 'Golden Hour.' Telecardiology driven by the IoT, which also offers tele-ECG, teleconsultations, tele- echocardiography, and online instruction, provides a predominant choice, as a specialist can analyze and facilitate treatment from the metropolis to residents in rural/backward areas. This enables real-time exchange of patient data and examination of ECG statistics. The Internet of Things (IoT) provides a platform for linking medical devices that could capture, analyze and transmit data to specialists and store records with inside the cloud or servers. Arrhythmia is the pathway of compulsive initiation of the heart, leading to SCD. This also results from the abnormalities that happened because of ailment within the electrical framework of the coronary heart and abnormalities because of impulses, or each will also be the purpose for this. With the result of exceptions, the frame can also get hold of the inadequate go with the drifting flow of blood supply, and coronary heart might not paintings properly. These are the symptoms of life-threatening. Normal sinus rhythm (NSR), which happens when there aren't any problems or illnesses inside the P wave, QRS complex, or T wave designs of the ECG signal, is the only heartbeat with no arrhythmias. The classification of arrhythmias, which includes atrial fibrillation, heart block, ventricular atrial fibrillation, supraventricular tachycardia, ventricular atrial fibrillation, and ischemia, is determined by the primary condition of the disease affecting the heart. Arrhythmia classification and detection are dependent on the patterns of coronary heart rhythm. Researchers around the world have developed machine-learning techniques for the classification of arrhythmias. These include support vector machines, K-nearest neighbor, principal component analysis, and machine learning techniques. Several models have been mentioned in the literature: the Gaussian mixture model, linear discriminant analysis, Random Forest, and artificial neural network. ECG wearable tracking structures are also now available; however, these systems are typically evolved for various purposes with little scientific involvement. Therefore, there is still a need for a user-friendly ECG tracking system that may speed up diagnosis and prevent patients from having to drive to the hospital, especially during the Golden Hour. The Internet of Things (IoT) could provide a key solution for developing such an ECG monitoring system.

1.1 Cardiovascular Diseases

Cardiovascular diseases (CVD) are a disease that occurs when a blood vessel in the heart breaks down. WHO (World Health Organization) states that CVD consists of congenital coronary illness, pulmonary embolism and deep vein thrombosis, rheumatic coronary illness, cardiovascular disease, and peripheral arterial disease, all conditions that can occur [V.L. Roger et al., 2012]. All over the world, CVD is a leading cause of morality. In 2013, 17.3 million people died due to CVD, and all over the world, it is 31.5% representing death. By 2030, CVD-related deaths are expected to account for 23.3 million deaths [G.B.D, 2013]. Cardio disease and ischemic heart disease are the reasons for mortality. With time, people are becoming prone to heart diseases because of poor lifestyles, Usage of drugs, and increased stress level. Cardiovascular is becoming the leading cause of mortality, and 34% of all mortality is because of cardiovascular diseases [D. Singh et al., 2012]. With the lack of specialist and a specialist-patient ratio of 1:1700, people cannot access quality-of-life healthcare services. So, the primary task is improving cardiovascular disease management, which is only done by advances in its diagnosis, pretreatment , and proper suggestions to the patient.

1.2 Electrocardiogram (ECG)

An electrocardiogram (ECG) represents the heart's electrical activity. It is a technique for examining the heart's momentary electrical activity. The electrocardiogram (ECG) represents the graph of contraction and expansion activity of the heart tissue [A. Savitzky, M. Golay, 1964]. These ECG variations are acquired by proper electrode arrangement on the chest of the human body. ECG is also used for recording. During recording, ECG provides medical information about the heart's functioning and allows detecting the cardiac variation up to a great extent, which is then used to diagnose angina pectoris, ischemia, arrhythmias, and alters in the shape of the human heart [E. Ostertagova, 2015]. The ECG signal is formed by the depolarization and repolarization of specific cells resulting in the plasma drifting of Na+ and K+ particles. ECG signals require a detection range of 0.1 to 120 Hz, typically in the 2mV range [A. Savitzky, M. Golay, 1964]. The electrocardiogram is obtained using a harmless procedure involving putting electrodes at predetermined areas on the patient's skin [S.C.H. Albricht et al., 2015]. The ECG signal and heartbeat are indicators of the human heart's cardiac health. Any irregularity in the cardia's rhythm or pace and changes to the ECG signal's morphological graph indicate heart arrhythmia. During acquisition in a clinical setting, the ECG signal encounters a variety of artifacts. Power line interference, outer electromagnetic field obstruction, noise brought about by arbitrary body movements and respiratory motion, electrode contact placement, electromyography (EMG), and instrumentation noises are the ones of primary interest. These noises reduce signal quality and frequency resolution and affect the morphology of an ECG signal containing critical information. It is crucial to reduce irritability in the ECG signal and improve accuracy as well as reliability for better diagnosis [W. Brock, J. Lakonishok, 1992].

Numerous procedures have been created to eliminate noise from contaminated ECG signals. The signal is sent first by the low pass, notch filters, then high pass. But these filters are statics. One of the main drawbacks of these static filters is that they further exclude some significant frequency components close to the cut-off frequency. The filter coefficients of static filters are predetermined. Decreasing instrumentation interference with fixed filter coefficients is challenging because the noise's time-varying actions are unknown. Different versatile filtering strategies have been created to conquer the constraints of static filters. Other types of dynamic filters incorporate the versatile Kalman filter, the Wiener filter, and the modified extended Kalman filter. Wavelet-based filters and neural networks are also used to de-noise the ECG signals. Several filters have been implemented in this proposed work to reduce noise in ECG.

1.3 The Heart's Electrical System

There are four chambers in the heart, i.e., two upper chambers known as atrium and atria, whereas two lower chambers are known as ventricles. Because their pumping level is greater, the ventricles are larger and have a thicker wall than the atria. Because the left ventricle pumps blood throughout the body, its wall is thicker than the ventricle at the right, while the ventricle at the right disseminates blood to the pneumonic circuit. Specialized myocardial fiber electrical conduction is also used, facilitating the passage of electrical driving forces and activation of the arteries and ventricular muscle cells, resulting in cyclic contractions of the heart muscle that are synchronized and ordered. The sympathetic nervous system innervates the heart but does not control it. Due to the conduction system's spontaneous activation, it continues to beat even without this stimulus [P.E. Mcsharry et al., 2003]. The sinoatrial (SA) node, the atrio ventricular (AV) node, the Shriek bundle (both ways branches), and the Peripheral Nervous System are shown in Figure 1.1. The sinoatrial (SA) node functions as a normal pacemaker for the heart and has the property of automaticity, which means it does not need to be triggered. Electrical impulses travel from the SA node to the atria, enacting the right and left atriums. When the impulse reaches the atrioventricular node, it gives blood time to move from the atria to the ventricles before delaying the valves, separating them from collapsing. When the electrical stimulation reaches the ventricles, it causes them to contract. The atrioventricular node then sends electrical impulses through the left and right portions of the bundle of His [E.J. Berbari, 2000]. Synchronized contraction of the ventricles requires rapid electrical impulse transmission, which is accomplished by a network of semiconducting sections that join to form the Purkinje network, as shown in Figure 1.1.

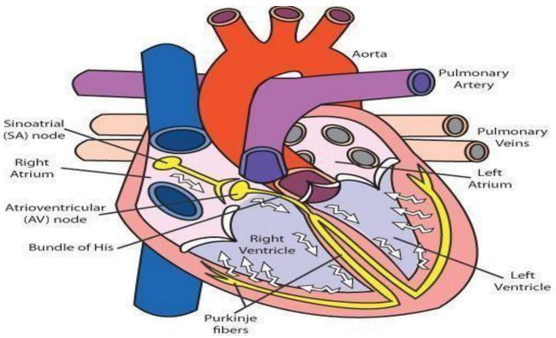


Figure 1.1 Heart's Electrical System [reproduced from http://cdeastcprfirstaid.wikispaces.com]

1.4 Activation of the Heart

The cardiovascular action potential (AP) is a constant going up and down trajectory related to the potential difference between the indoor and outdoor cardiac tissue [R.S. Khandpur, 1992]. This function is carried out via the heart's excitatory and contractile mechanisms. Positive voltage increases across the cell's membrane potential, for example, in the unique excitatory system. Depolarization is a unique characteristic that is independent of external effects. This occurs between the conclusion of one action potential and the start of the next activity potential. The cell membrane's expansion allows the cell potential to approach the threshold potential naturally. When it approaches the threshold, it causes the subsequent muscular contraction, known as the pacemaker potential. Thus, the pacemaker potential drives the self-generated rhythmic firing, known as muscle automaticity. Further, the differentiation of the action potentials allows the different electrical characteristics of the various portions of the heart. The structure of the AP shape changes from cell to cell and varies from place to place. The extended duration of the AP in cardiac cells, which runs between 150 and 300 milliseconds, is a common feature. As a result of the action potential's (an electrical event) ability to synchronize with its muscle contraction, its prolonged length has significant functional consequences (mechanical phenomenon). The AP occurs in the following phases in all other cardiac fibers (ventricular and atrial), as indicated in Figure 1.2.

- Stage 0 is a fast depolarization stage with a rapid and extensive upstroke caused by the increasing Na+ ion entry across the membrane. The slope of this stage represents the most extreme pace of potential change, denoted by dV /dt max. The cardiac myocyte net ionic current is proportional to this slope.
- Stage 1 is a transient repolarization. It happens at the same time as the fast Na+ channels are inactivated. The modest downward deflection is caused by the transitory net apparent current brought about by the entry of K+ and Cl- particles.
- Stage 2 is frequently referred to as the 'plateau' phase. The duration of cardiac cells' action potentials is lengthening during this period. This phase is maintained due to a balance between outward K+ movement and inward Ca2+ migration via L-type calcium ions.
- Stage 3 is a rapid repolarization stage considering the large outpouring of K+ particles from the cell and a lessening in Ca2+ particle influx, rebuilding the cell to its relaxed state.

- Stage 4 is the resting membrane potential. This is due to a distinction in conductivity and ion concentrations across the cell layer. The customary resting film potential of the ventricular myocardium is around -85 to -95 mV.

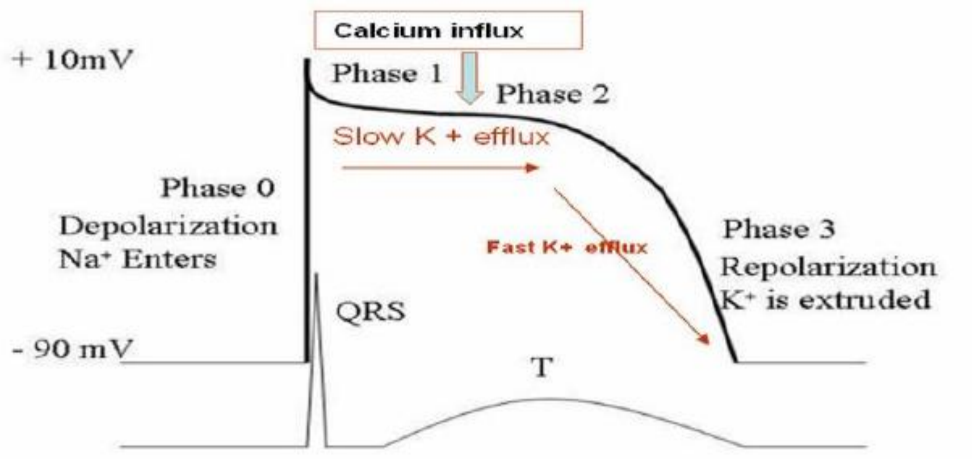


Figure 1.2 Simple model of a cardio-myocyte action potential [reproduced from https://drsvenkatesan.wordpress.com]

1.5 Electrocardiogram Generation and Action Potential Propagation

The propagation of electrical stimulation through the heart forms action potentials (APs) at variable temporal and spatial intervals, changing the electrical potential at the body surface. The ECG reflects all estimated body surface area AP gradients during the cardiac cycle. Figure 1.3 depicts the geometry of several APs that correlate to different heart tissue types. The last ECG signal found by adding these APs at a specific area on the body is represented in Figure 1.3 [W.F. Ganong et al., 2005].

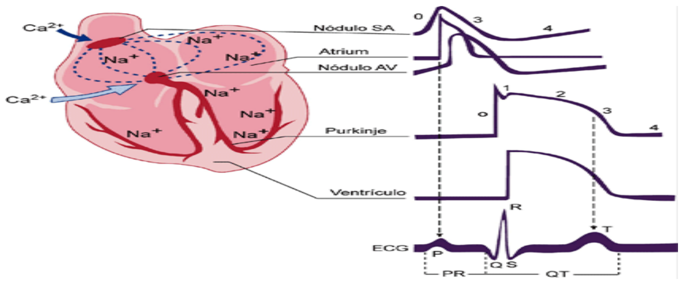


Figure 1.3 Generations of ECG [reproduced with permission from W.F. Ganong et al, 2005]

1.6 Standard 12-Lead ECG System

A probe is a pair of electrodes placed at unique physical locations on the human body to evidence the heart's activity as a graph. Each wire comprises a negative (-) electrode and a positive (+) electrode. The conventional 12-lead ECG framework includes three bipolar leads, three enhanced unipolar leads, and six chests (precordial) leads, as shown in Figure 1.4 and Table 1.1. The polarity of electrodes can be changed using the switch on the ECG machine known as the 'lead selector.' Using a 'lead selector' on the ECG machine, one can change the polarity of electrodes. This helps get the various lead selections without moving the lead cables or electrodes [E.L. Frank, 1956]. The descriptions of the 12 lead frameworks are as follows: The potential difference between the positive and negative poles is recorded by bipolar leads.

a) To record the electrical potential, unipolar leads use a solitary probing cathode.
b) Unipolar appendage leads record potentials between aVR (right arm), aVL (left arm), and aVF(left leg).

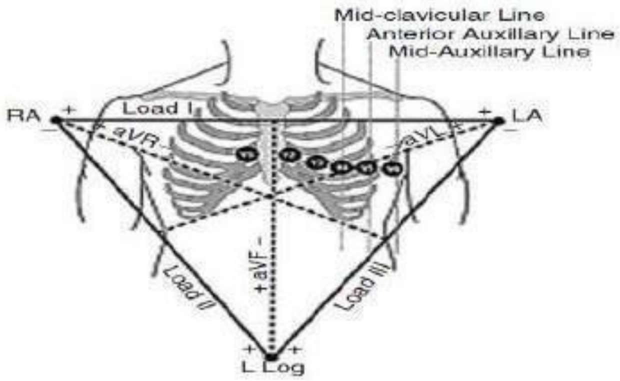


Figure 1.4 12-lead ECG system [reproduced from http://rtboardreview.com/public/equipment_room/ecg.htm]

Table 1.1 a typical 12-lead ECG system

Standard leads	Limb Leads	Chest Leads
BipolarLeads	UnipolarLeads	Unipolar leads
Lead I	Avr	V1
Lead II	Avl	V2
Lead III	Avf	V3
		V4
		V5
		V6

1.6.1 Einthoven Lead

Lead III measures the difference in potential between the left leg and the left arm. Lead II picks up the potential between the left leg and the right arm. I monitor potentials in both arms, i.e., the left arm and right arm, as I lead.

V6 is located in the midaxillary line.

V5: on the 5th rib, the anterior axillary line

V4: is the 5th intercostal gap.

V3: the area between the second electrode and fourth electrode

V2: left Sternal edge, 4th intercostal space

V1: Right Sternal edge, 4th intercostal space

When distinct waveform morphological information is required, only a few electrodes are necessary to diagnose the heart rhythm. Ten electrodes are often utilized for acquisition. In this case, six leads are put on the chest, whereas four are placed on the furthest points.

1.7 ECG Features

A number of features were evaluated using the ECG waveform. Each characteristic, independently and collaboratively, is extremely valuable for recognizing the situation of the heart. The ECG waveform comprises the P wave, the QRS complex, and the T wave, as shown in Figure 1.5. A typical ECG waveform contains complexes, segments, waves, and intervals marked as a voltage on the upward hub v/s time on the level pivot. A complex is formed when two waveforms are used together. In comparison, a segment is an isoelectric line, flat and straight. An interval is a complex waveform linked to a section. Positive deflection refers to all ECG tracings above the zero baseline, while negative deflection refers to tracings below the zero baseline.

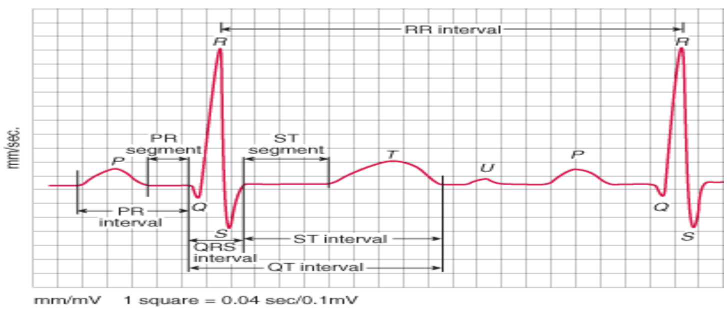


Figure 1.5 A human ECG signal during one cardiac cycle [reproduced from http://www.datasci.com/solutions/cardiovascular/ecg-research]

The following are the ECG features [M. Singh, 2010; D.J. Bronzino, 2000].

P wave: This waveform is delivered because of depolarization of the atrial. The electrical vector is routed from the SA hub to the AV hub and extends from the right chamber to one of the side chambers. In ECG, this is addressed by the P wave. Its duration is around 80ms.

QRS complex: It reflect the rapid depolarization of the right ventricle and left ventricle. Because the ventricles have a lot bigger bulk than the atria, the QRS complex is much more appropriate than the P wave. The range of a typical QRS complex lies between 80 to 100ms. This demonstrates the way that this type of wave accumulation is suggested as a QRS complex.

T wave: It refers to ventricle repolarization. The time elapsed between the earliest beginning stage of the QRS complex and the peak of the T wave referred as the absolute refractory period. The second half of the T wave is called the relatively refractory period. The T wave is generally positive and has a length of 150-350 ms.

RR interval: It is the time span between an R-wave and the succeeding R-wave. The duration of heart beat is of 60 and 100bpm. Its range is between 0.6 and 1.2 seconds.

PR interval: It is the time span stretch among the initial points of both the P wave and QRS complex waveform. The PR span addresses the time the electrical signal takes to travel between the SA node to the AV node and through the ventricles. It's the most accurate estimation of the AV hub work. Its duration is between 120 and 200 milliseconds.

PR segment: It links both the waves, i.e., the P wave and the complex QRS wave. The impulse vector is from the AV node to the Bundle of his to the bundle branches, and then to the Purkinje fibers. This electrical activity does not produce a contraction directly and travels down towards the ventricles. It lasts between 50 and 120 milliseconds.

J Point: It is the point where QRS complex wave ends and the ST segment starts. It is used to measure ST elevation or elevation.

ST segment: It connects the complex QRS and T waves and represents depolarized ventricles. The ST magnitude calculates the variation from the TP or PQ segment (Iso-electric line) at point J.

ST interval: It calculates the time taken while travelling between the beginning of point J to the end of the T wave. It endures 320 milliseconds.

QT interval: It is employed to measure the beginning of QRS wave to the end of T wave. It is minor, but if it persists, it increases the risk of sudden death and arrhythmia. The duration for a heart rate of 60 bpm is up to 420ms.

1.8 Artifacts in the ECG Signal

The fluctuation in ECG tracings is an ECG artifact. Normal segments or components of the ECG are distorting due to artifacts. The term artifact is related to the word artificial, frequently used to describe something that is not real. An artifact is a term used in electrocardiography to describe something not created by the heart. These can include electrical interference from outside of the body, outside factors, poor electrode contact, and recording machine malfunction, among other things Artifacts are quite common, and understanding them is essential for avoiding ischemia misunderstanding [F.A. Clifford, 2006].

1.8.1 Cause of Artifacts

The noises can be caused by the person's movement or through electrical or embedded devices in the body, such as a deep brain stimulator. The most common motion-induced artifacts are shivering and tremors. ECG abnormalities can also cause by simple activities like combing or brushing one's hair. Similarly, power lines interference, frequency identification, and medical equipment are external sources of ECG artifacts. Various equipment, such as leads, electrodes, amplifiers, and filters, might alter ECG measurement systems in operating rooms and intensive care units (ICUs). Hemo-filtration devices, electro cautery, and transcutaneous nerve stimulators are examples of common equipment that might generate ECG artifacts [J.G. Webster, 2009; L. Schamroth, 2009].

Noise that comes from somewhere other than the patient's room

a) Electrostatic sources

b) Radio frequency interference

c) Electromagnetic induction

Patient Electrode Contact Noise

a) Mechanical movement of recording electrodes

b) Polarization of electrodes distorts ECG

Noise Originating from the Patient

a) Muscle artifact

b) Electromyogram

1.8.2 Characteristics of the Artifact

The person or all Electrocardiogram elements, such as the P, QRS, T waves, and PQ, TP, and ST segments, can be distorted by artifacts on the ECG. These artifacts can sometimes be mistaken for certain arrhythmias. It is very difficult to distinguish between artifact frequency and these artifact changes from actual alterations to prevent misdiagnosis. For instance, ST fragment elevation and ST fragment depression can be misdiagnosed for myocardial infarction if baseline wandering alters the ST segments. The MIT-BIH database can misdiagnose arrhythmias if artifacts present in this dataset.

1.8.3 Types of Artifacts

(a) Baseline wanders

The position of the zero line (PQ or TP segment) in the ECG changes during baseline wandering, as shown in Figure 1.6. This phenomenon is most likely caused by the movement of the patient, wire movement during capturing, filthy lead cables or electrodes, and weak electrodes.

Figure 1.6: Baseline wander Noise [reproduced from http://www.mauvila.com/ECG/ecg_artifact.htm]

(b) Muscle Tremor

The heart is not the only part of the human body that produces new organs. The ECG is combined wh seemingly random activity when human skeletal muscles suffer tremors. The amplitude of this artifact is minimal, and it resembles an isoelectric line. Muscle tremors are usually much subtler than the one depicted in Figure 1.7.

Figure 1.7 Muscle Tremor Noise [reproduced from http://www.mauvila.com/ECG/ecg_artifact.htm]

1.8.4 Removal of Artifacts

To achieve correct and sufficient delineation of ECG data, which is then used for isoelectric reference identification and ST segment categorization, artifact removal (pre-processing) is used. During recording, the artifacts mentioned above are frequently observed. It is critical to perceive artifacts frequencies and distinguish these artifacts changes from real changes to avoid misdiagnosis. Various approaches for eliminating baseline wander and muscle tremors have been developed with either linear or nonlinear architectures. Time-based, frequency-based, time-frequency-based, and nonlinear approaches are the four categories in which these methods are classified. The advantages and disadvantages of the above-mentioned methods can be evaluated in [R.J. Martis et al., 2011]. The multi-resolution analysis is a time-frequency-based strategy known as wavelet transform, in which the larger scale incorporates lower recurrence modules and the lower scale contains higher recurrence parts of the signals being analyzed. The wavelet transform can distinguish between two signals with the same magnitude on the spectrum. As a result, wavelet transforms via wavelet coefficients thresholding is better appropriate for analyzing non-stationary ECG signals [H.Y. Lin et al., 2014]. After eliminating wavelet coefficients compared to noise frequencies, there are no negative impacts on the morphological features of the original ECG signal.

1.9 Overview of Arrhythmias

The electrical activity of the heart is studied via electrocardiography. The electrocardiogram (ECG) is a faithful record of the origin and propagation of the electric potential through cardiac muscles. It is monitored by placing sensors at the subject's limb extremities [S. Scheidt, 1984]. As shown in Figure 1.8, the electrocardiogram (ECG) is a faithful record of the origin and propagation of the electric potential through cardiac muscles. It is used to diagnose heart diseases as a typical signal of cardiac physiology. Three electrical components in the cardiac cycle represent the activation and deactivation of the heart's atria, ventricles, and blood-pumping chambers. The atria contract during diastole to fill the ventricles, which subsequently contrxact during systole to give blood to the lungs and systemic circulation. A wave of depolarization extending through the muscular walls of the atria and ventricles closely coordinates the contraction of these chambers. The depolarization wave is an electrical current that spreads across the heart and reflects charge transport across myocyte membranes. Following contraction, cardiac muscle returns to rest, accompanied by a reversal of charge transport across myocyte membranes; this second wave of electrical activity is called cardiac repolarization. The ECG machine's leads detect and record these two waves of cardiac electrical activity. The depolarization wave spreads through the heart in a highly predictable fashion, and understanding the pattern of cardiac depolarization spread is necessary for understanding the ECG readout [M.J. Goldman, 1986].

A P wave is created by atrial depolarization, while the QRS complex is produced by ventricular depolarization. The resultant diffuse deflection of a T wave is caused by ventricular repolarization. The QRS complex's terminology can be confusing but basic. Any positive deflection above the isoelectric line inside the QRS complex is called an R wave. An S wave is a negative deflection that occurs after a R wave. On the other hand, the first deflection of the QRS complex is referred to as a Q wave [M.J. Goldman, 1986]. The ST segment is part of the ECG recording that connects the QRS complex's end to the T wave's start.

For biological systems to function properly, computer technology is an essential component. New approaches to the fundamental challenges of modeling the behavior of biological systems have emerged due to the enormous expansion of high-performance computing techniques in constructing useful and accurate models of biological systems in recent years. The significance of biological time series analysis, which typically reveals dynamical complexity, has long been recognized in nonlinear analysis. Several features have been proposed to uncover hidden key dynamical aspects of the signals. Nonlinear dynamical approaches have been used in various fields, including medicine and biology [F.H. Netter, 1971]. In 2004 [F.H. Netter, 1971], nonlinear methods were used to access physiological information, such as heart rate, brain waves, renal blood flow, arterial pressure, EEG, and breathing signals. The time variation of the underlying process's common statistical properties is computed in most methods for analyzing its time-varying spectral characteristics [F.H. Netter, 1971]. However, conventional methods need to account for the nonlinearity of the process. In contrast, fractal analysis, which is used to analyze electrocardiogram (ECG) signals, allows processing these signals effectively and generating higher-order statistics.

The ECG signal, which is generated by the heart muscle, is an electrical signal sensed on the body's skin surface. This bio-signal exhibits self-identification similar to fractal shapes and is non-stationary. It could provide present disease signs or even warnings about impending diseases. The signs may be present at all times or appear at random intervals across the period. However, studying a set of irregularities in a large dataset is difficult. It is troublesome and tedious to gather much information in a few hours. Therefore, computer-based analytical methods for comprehensive data analysis and classification over extended daytime periods can be useful in diagnostics. The potential difference between the two electromagnetic field sites reflects the ECG signal. The shape of the ECG signal and the cyclic repeating of its characteristic elements, such as the P-QRS-T complex, provide crucial information about the heart's electrical conduction system. We can gain information by analyzing ECG signals recorded concurrently at various places in the human body. Heart-related diagnostic information is critical. It is concerned with the heart's electrical qualities and its morphological and mechanical features. The ECG signal is an electric signal produced directly by the cardiac muscle cells. The information contained in the ECG signal is closely tied to the signal's source, namely the heart.

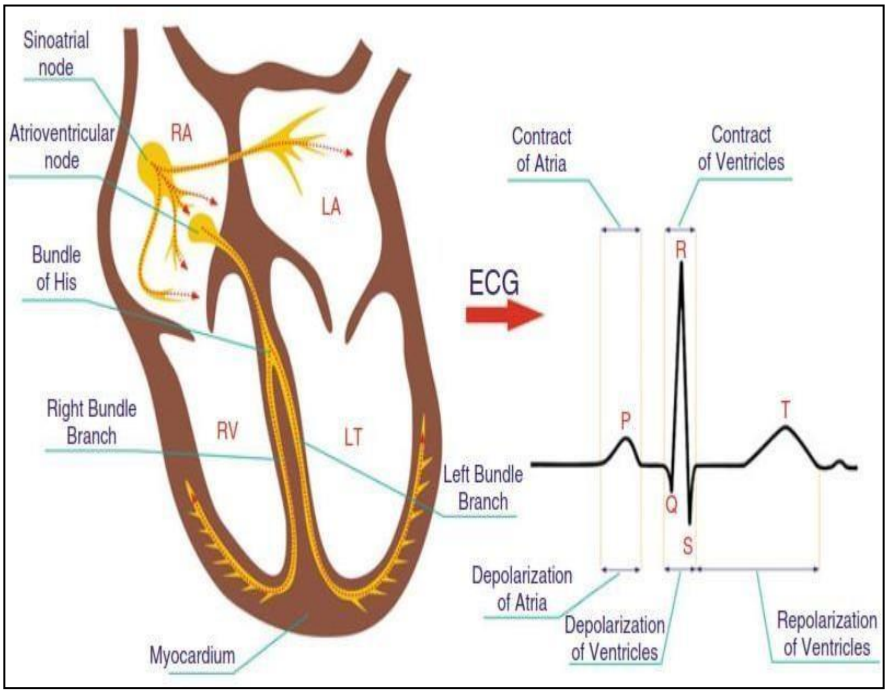


Figure 1.8 Depolarization wave propagation in the cardiac muscle

[Reproduced from M.J. Goldman et.al, 1986]

ECG signals are a difference in electric potentials between two places inside the heart, on its surface, or a human body surface. The potential difference is correlated with the voltage measured between two points where measurements were made. This voltage corresponds to the ECG signal's amplitude as recorded by the two-pole (two-electrode) system. A two-electrode set-up called an ECG lead records the ECG signal. An electrocardiogram records an ECG signal on paper or an electronic data carrier.

Although biologists have typically portrayed heartbeats as sine waves, scientists have realized that fractal geometry is a superior way to describe them [M.J. Turner, 2000]. The ECG signals are fractal, oscillating on the edge of chaos and order. Heart failure can occur if the rhythm is too regular, but a heart attack can occur if it is too irregular. Fractals are a novel field of mathematics and art that may be described as "rough or fragmented geometric patterns that can be split into parts, each of which is (at least roughly) a reduced-size duplicate of the whole" [B.B. Mandelbro, 1982].

1.9.1 ECG Signal Properties in Arrhythmias

One of the most well-known biological signals is the ECG. They present a variety of obstacles during registration, processing, and analysis due to their nature. For instance, biological signals have the property of being non-stationary. ECG recordings and individual variations in a person's noise tolerance can disclose all these characteristics. A typical ECG signal (viewed as normal) that reflects the electrical activity of the heart muscle during a single heart evolution was defined for ECG diagnostics figure 1.9 [S. Scheidt, 1984] shows the segments, locations, and parameters employed to capture the signal's essence. The links between the shape and dimensions of a signal and the functioning of the heart are frequently articulated in terms of linguistic claims, leading to some logical expressions in medical diagnostics. For example, phrases like "extended R wave" and "reduced R wave." QT interval," "unclear Q wave," elevated ST segment," "low T wave," etc. The expert cardiologist creates their model of the process, which is linguistically described. The approach is built on acquired knowledge and experience [S. Scheidt, 1984] fashion. The model is formed based on gained knowledge and experience [S. Scheidt, 1984].

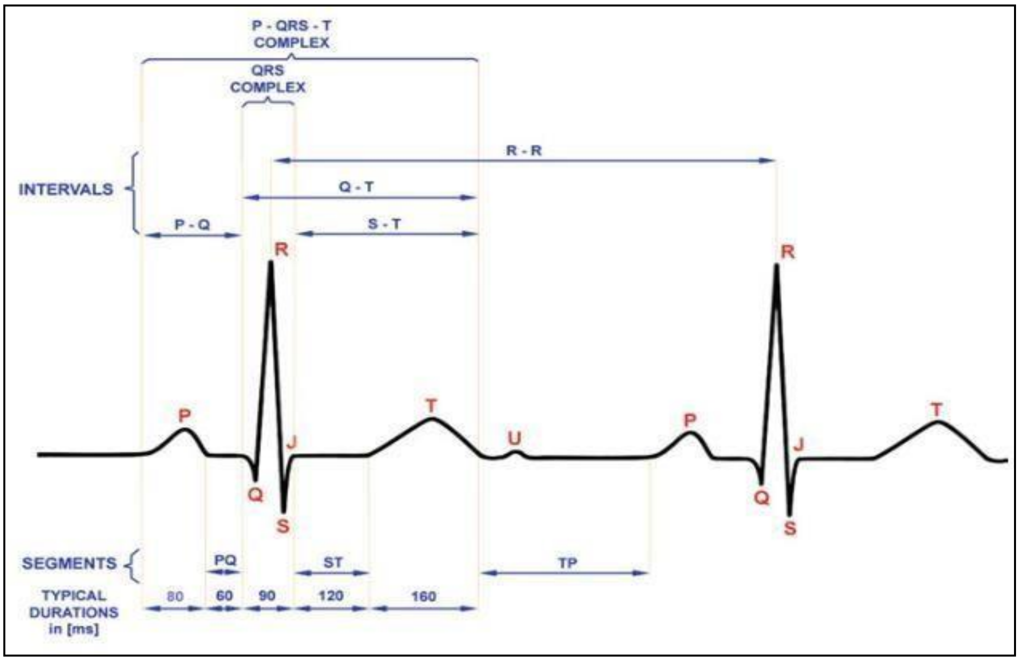


Figure 1.9 Typical shape of ECG signal and its essential waves

[Reproduced from M.J. Goldman et.al, 1986]

1.9.2 Electrocardiogram of the heart: Normal vs. Abnormal

The sinus node causes cardiac activity in a healthy heart, resulting in a normal sinus rhythm. This is easily detected by noting that the three deflections, P-QRS-T, are distinct and follow this order, as shown in Figure 1.10 [M.J. Goldman, 1986]. If the frequency of the sinus rhythm is between 60 and 100 beats per minute, it is considered normal [M.J. Goldman, 1986].

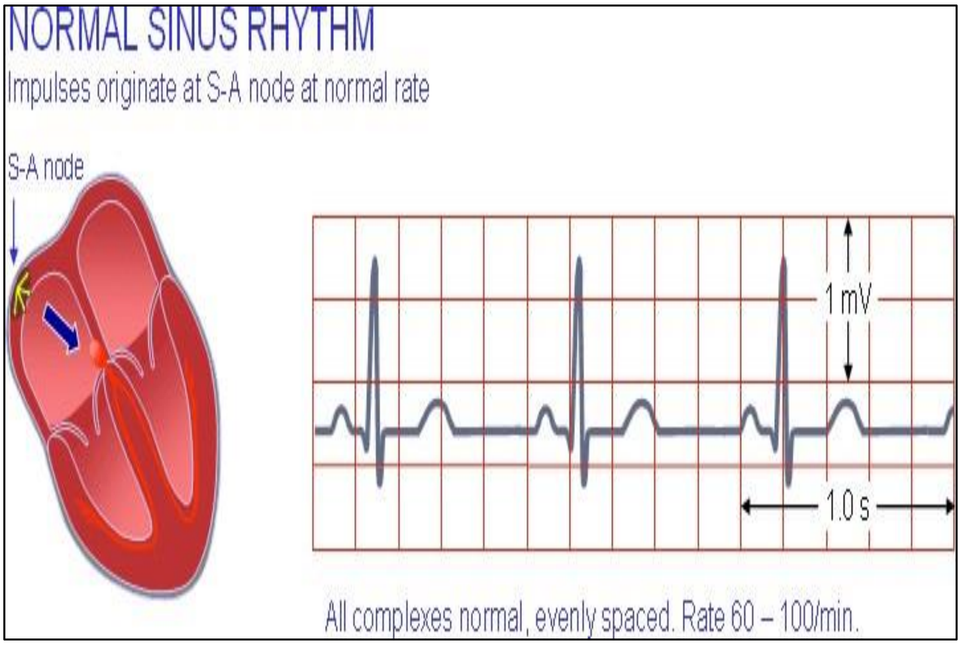


Figure 1.10 A sinus rhythm in its natural state

[reproduced from M.J. Goldman et.al, 1986]

An arrhythmia is a disturbance in the heart's rhythm or heartbeat pattern. The heart can beat abnormally slowly, too quickly, with additional beats, or erratically [M.J. Goldman, 1986]. Some kinds of cardiac arrhythmia are listed below, briefly describing their characteristics.

1.9.3 Problem Definition of Arrhythmias

ECG is vital in cardiology because it includes simple, low-cost methods for diagnosing heart problems that are extremely relevant to the patient's life. Cardiac rhythm disruption is one of the pathological changes detected by ECG (or arrhythmia). Arrhythmia is thought to be the cause of life-threatening illnesses. As a result, detecting abnormalities in intensive care patients is critical. As a result, the presence of automatic ECG analysis and abnormality detection is extremely beneficial, as it will assist clinical staff in the absence of doctors and doctors in diagnosing and acting faster in emergencies. Designing a low-cost, high-performance, easy-to-use ECG instrument with various diagnostic functions is a global pursuit.

1.9.4 Various types of Arrhythmias

1.9.4.1 Ventricular Arrhythmias

In ventricular arrhythmias, ventricular activation does not start at the AV node or does not proceed correctly in the ventricles. If the activation travels through the conduction system to the ventricles are nearly instantly activated, and the activation front moves radially toward the outer walls, the inner ventricle walls will be activated. The QRS complex only lasts a short time as a result. It takes longer for the activation front to travel throughout the ventricular mass if the ventricular conduction system is disrupted or ventricular activation begins far from the AV node. A QRS interval is a requirement for proper ventricular activity of less than 0.1 seconds. A QRS interval of more than 0.1 seconds implies abnormal cardiac activity [M.J. Goldman, 1986]. Examples of ventricular arrhythmias include premature ventricular contractions (PVCs), ventricular tachycardia (VT), and ventricular fibrillation (VF).

1.9.4.2 Supra-ventricular Arrhythmias

Incorporate supraventricular tachycardia (SVT), atrial flutter (AFL), Wolff Parkinson White syndrome (WPW), supra-ventricular premature, atrial fibrillation (AF), supra-ventricular premature. Irregularities of heartbeats occur due to several factors. The main cause of arrhythmias is different types of heart disease, i.e., high blood pressure, hemochromatosis [M.T. Keating and M.C. Sanguinetti, 2001; B.E. Pueyo, J.P. Martánez, and P. Laguna, 2009]. In addition, these irregularities are caused by alcohol, stress, caffeine, and snuff. Various techniques are used to properly detect arrhythmias, i.e., Electrophysiology study (EPS), Holter monitoring, and ECG. A non-invasive method is used to detect arrhythmias, i.e., ECG (Electrocardiogram). It is a gadget used to quantify the electrical working of the human heart [M. Singh, 2010]. The first step in treating arrhythmia is to use antiarrhythmic drugs, for example, calcium channel blockers, beta-blockers, digitalis, and other secondary treatments of arrhythmias, which are trans-catheter interventions, surgery in emergency cases and implantable devices.

1.9.4.3 Premature Ventricular Contraction (PVC)

Figure 1.11 [M.J. Goldman, 1986] shows an abnormally early ventricular contraction known as a premature ventricular contraction. It has a supraventricular origin if it originates in the atrium or the AV node. This supraventricular arrhythmia produces a complex that lasts less than 0.1 seconds. The QRS complex is aberrant and lasts longer than 0.1 seconds if the origin is in the ventricular muscle. The P-wave is usually not connected with it [S. Scheidt, 1984].

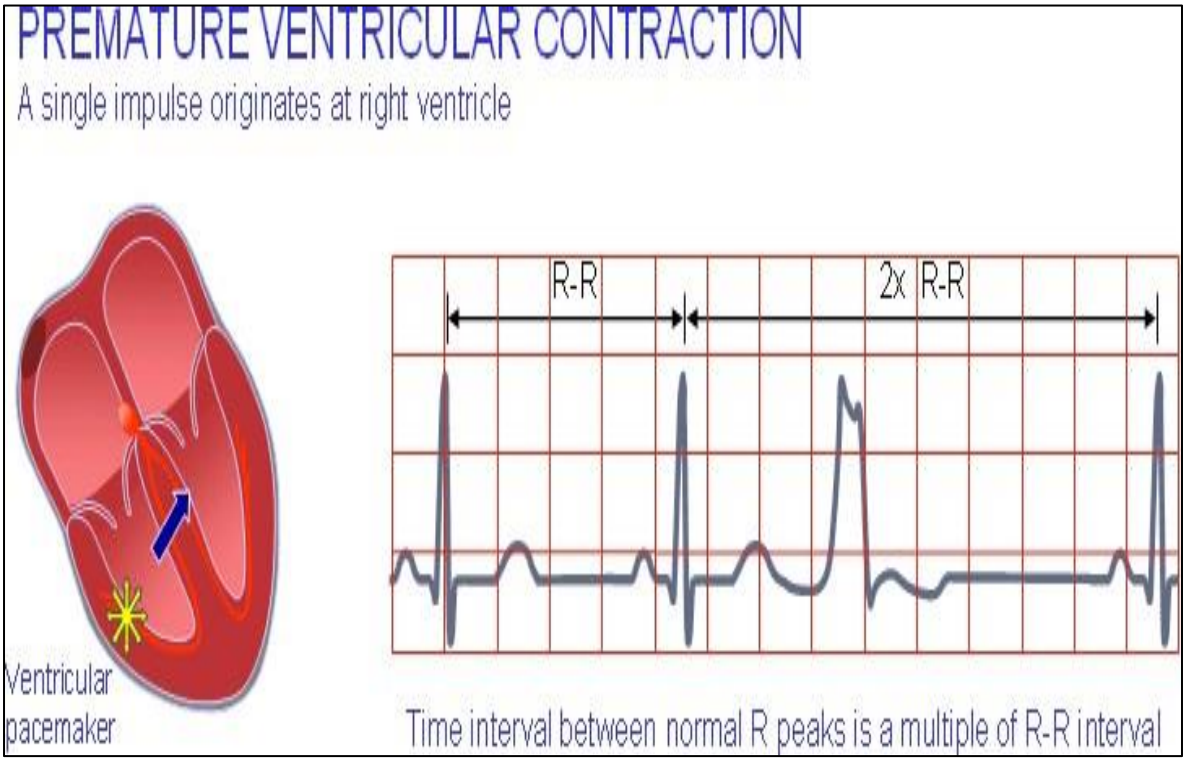


Figure 1.11 Premature Ventricular [reproduced from M.J. Goldman et.al, 1986]

1.9.4.4 Atrial Premature (AP)

Atrial premature complexes (PACs) are premature contractions of the atrium that can cause arrhythmias or odd heartbeat sensations. Palpitations are irregularly timed heartbeats that are either too fast, slow, or both. PACs occur when your heart beats prematurely or early in the heart cycle (Cincinnati Children's) [M.T. Keating and M.C. Sanguinetti, 2001]. The sensation that your heart has skipped a beat or that your heartbeat has briefly stalled is caused by PACs. PACs do happen from time to time, and you should be aware of them.

Premature heartbeats are common, and they are usually harmful. PACs can occasionally signal a major heart problem, such as life-threatening arrhythmias. An atrial complex or contraction occurs when a premature heartbeat develops in the heart's upper chambers. Premature heartbeats can also develop in the heart's lower chambers. Ventricular complexes are what they're called. Both types of premature beats have the same causes and symptoms. Figure 1.12 [M.J. Goldman, 1986] depicts atrio-ventricular and ventricular hypertrophy.

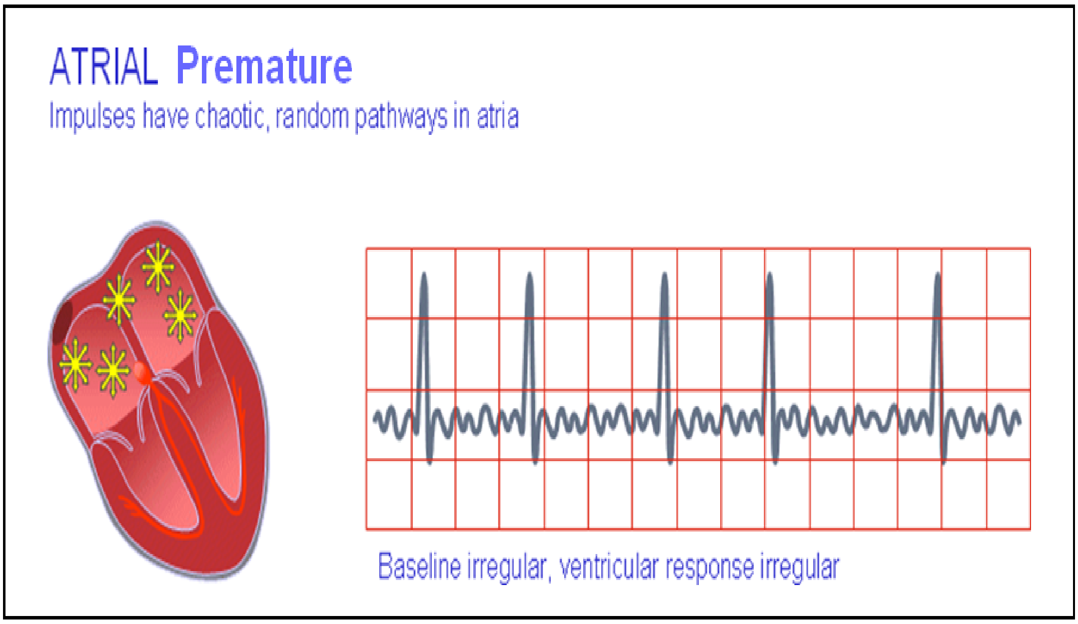


Figure 1.12 Atrial Premature [Reproduced from M.J. Goldman et.al, 1986]

1.9.4.5 Bundle-Branch Block

Bundle-Branch Block is a conduction deficiency in the bundle branches or indirect contact of the left bundle branch. The progression of activation from the atria to the ventricles is entirely blocked if both bundle branches are blocked simultaneously; this is known as a third-degree atrio-ventricular block. Because of the left or right Bundle-Branch Block, the ventricle must wait for the opposing ventricle to initiate activation. Following that, activation is done fully on a cell-by-cell basis. Because the conduction system, which initiates early activity at numerous places, is not involved, the activation process via normal pathways is substantially delayed. As a result, bizarrely formed QRS complexes with excessively lengthy duration emerge.

1.9.4.5.1 Right Bundle Branch Block (RBBB)

If the right bundle branch is damaged and the electrical impulse cannot reach the right ventricle, activation is sent from the left ventricle to the right ventricle. It subsequently passes through the right ventricular and septal muscle mass. Of course, this process is slower than through the conduction system, resulting in a QRS complex that is longer than 0.1 second. The time criterion for the QRS-complex in the right Bundle-Branch Block (RBBB), left Bundle-Branch Block (LBBB) and left Bundle-Branch Block (LBBB) is usually >0.12 s [S. Scheidt, 1984]. The electrical forces of the right ventricle are hidden by the bigger sources emanating from the activation of the left ventricle during normal activation.

Activation of the right ventricle is so delayed in the right Bundle-Branch Block (RBBB) that it occurs after activating the left ventricle. (In normal circumstances, the left ventricle is activated). Figure 1.13 [M.J. Goldman, 1986] shows the right bundle-branch block.

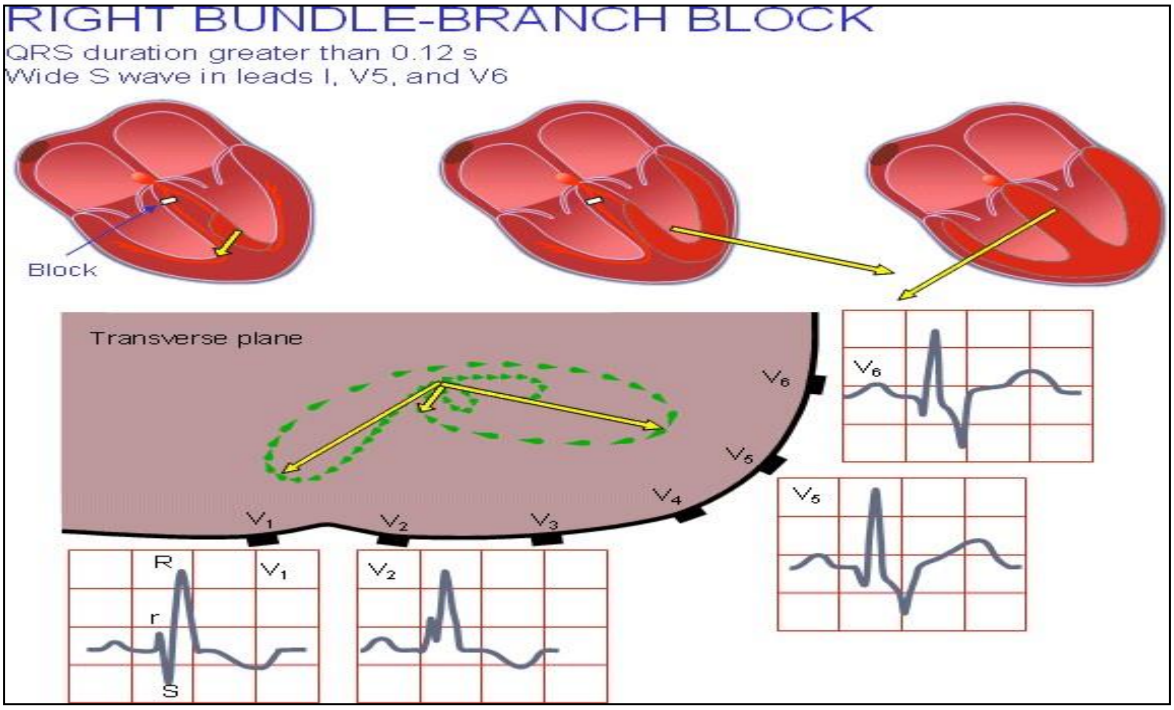


Figure 1.13 Right bundle-branch block

[Reproduced from M.J. Goldman et.al, 1986]

1.9.4.5.2 Left Bundle Branch Block (LBBB)

The scenario is similar in the left Bundle-Branch Block (LBBB), but activation occurs the opposite way in the right Bundle-Branch Block (RBBB). For the QRS-complex, the duration threshold for the complete block is 0.12 s or more [M.J. Goldman, 1986]. The polarities of the signals are often normal in LBBB because the activation wavefront travels in a more or less normal direction. Because of the abnormal sites of initiation of the left ventricular activation front and the presence of normal right ventricular activation, the outcome is complicated, and the electric heart vector makes a slower and larger loop to the left, resulting in a broad and tall R-wave, as shown in Figure 1.14 [M.J. Goldman, 1986].

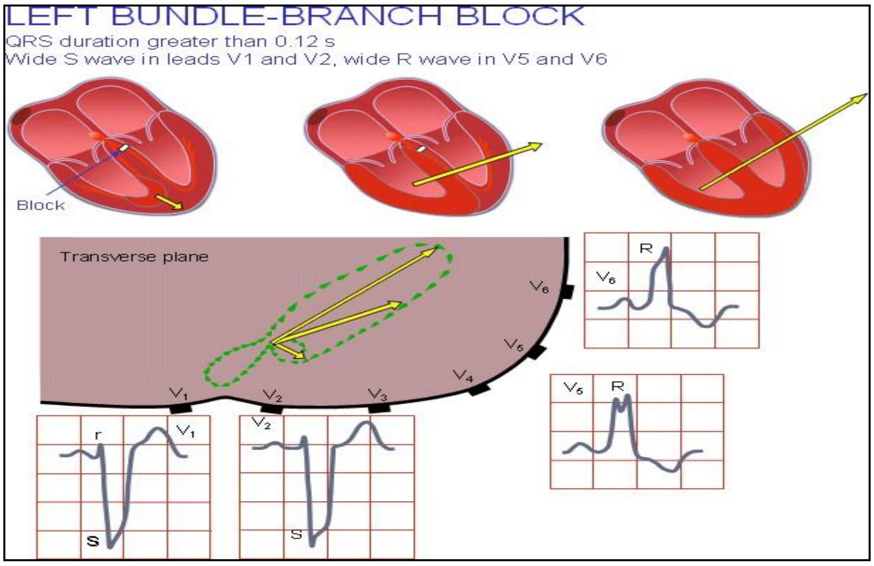


Figure 1.14 Left bundle-branch block [Reproduced from M.J. Goldman et.al, 1986]

1.10 Ischemia

Another type of heart disease is ischemia (I). When there is an increase in blood flow, and supplementation of the nutrient is not properly reached to some parts of the body, then this problem usually occurs. The development of this problem may lead to getting 70% of heart cells blocked and also produce symptoms of ischemia that reduce exercise tolerance [C.R. Conti et al., 2012; G. Gupta, 2010]. Ischemia may lead to chronic problems that deteriorate the heart. If the blood flow properly reaches the heart's cells, the ischemia problem gets reversible; if not, ischemia becomes irreversible, and tissue cells die [F.S. Barnes, 2006]. Due to ischemia, heart attacks and stroke problems take place. It also affects bloody stool and even intestinal rupture, intestines, resulting in abdominal pain. Additionally, it has a negative impact because it increases the risk of losing hands and feet. Ischemia can be taken place without or with chest pain. If ischemia occurs without any symptoms, it is called silent ischemia, i.e., the reason for this is stress, emotional, mental or hectic schedule. If ischemia occurs by chest pain, then it is called angina pectoris. Angina pectoris caused by myocardial ischemia [J. Garcia, 2000]. Identifying this issue and people who have it and have experienced tightness, weight, or discomfort is crucial. According to ref [P.H. Stone, 2013], angina discomfort starts below the breastbone and spreads to the shoulder, neck, arm, and mouth. Angina is divided into two categories:

a) **Stable Angina:** When the heart is working very difficult, stable angina appears, and the heart requires more oxygen than narrowed arteries deliver.

b) **Unstable Angina:** When the heart's cells suddenly stop pumping due to blood clots forming in the coronary arteries, unstable angina occurs. Unstable angina indicates stroke/ heart attack. It can occur in rest conditions or light activity.

1.10.1 Causes of Ischemia

In the development of ischemia, there are some risk factors or reasons involved, as follows [P.H. Stone, 2013]

Sickle cell anemia

- Tremendously low blood pressure
- Blood clots
- Ventricular tachycardia
- Atherosclerosis
- Compression of blood vessels
- Congenital heart defects

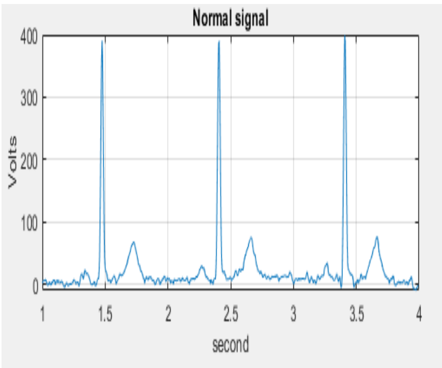
1.10.2 Ischemia Symptoms

In most cases, chest pain (angina) is a common symptom of ischemia. The main symptoms of cardiac ischemia are as follows [P.H. Stone, 2013]

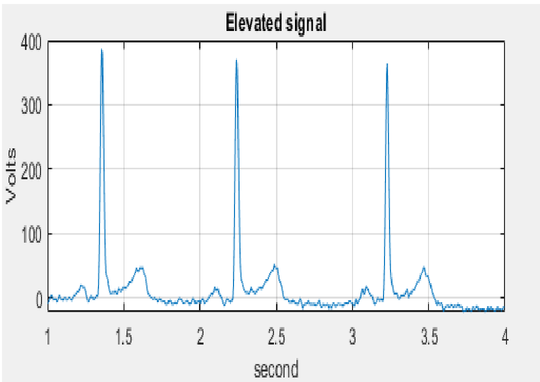
- Chest torment, this is ended up to the back, neck, jaw, arm and shoulder
- Excessive sweating
- Limited physical abilities
- Shortness of breath
- Dizziness with or without vomiting
- Fast heartbeat or abnormal heart rhythms

1.10.3 Myocardial Infarction

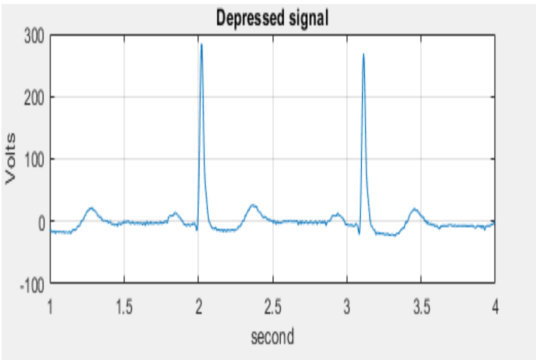
The main ECG change brought about by myocardial ischemia is ST deviation (rise or gloom) on the skin. This is because of obstruction in cardiac function in the ischemia phase compared to the normal zone due to K+ generation. This causes the cell potential to depolarize, resulting in ST deviation. The ST deviation has been widely employed during physical stress and silent ischemic events to indicate myocardial ischemia. The magnitudes of sub-endocardial and associated transmural potential gradients impact ST deviation measurement throughout infraction. [A. Goldberger, 1981; J. Park, 2012; A. Smrdel and F. Jager, 2011]. The raising and depression of the ST section about an isoelectric determine whether there is myocardial infarction in the area where the lead has been installed. Transmural (sub-epicardial) ischemia is associated with raised ST fragments (episodes), while sub-epicardial ischemia (episodes) is characterized by regular ST segments (episodes), an example shown in Figure 1.15. In individuals with sub-endocardial ischemia, depressed ST segments (episodes) develop. STEMI (Raised ST-segment myocardial infarction) happens when blood coagulation impedes a heart valve, resulting in all affected heart muscle death. An increase in the ST segment characterizes ECG alterations. The least severe kind of myocardial infarction is NSTEMI (non-ST segment elevation myocardial infarction). Because the blood clot only partially blocks the blood supply to the heart, just a portion of the heart muscle affected by the artery dies in NSTEMI. In many of the more extreme conditions of cardiac arrest (STEMI), NSTEMI doesn't bring about a noticeable rise in the ST section but does cause a characteristic depression and T-wave inversion. Because the coronary artery is completely stopped, the ST segment elevation implies significant cardiac muscle injury.



(a)



(b)



(c)

Figure 1.15 (a) Normal ST section (b) Elevated ST segment (c) Depressed ST segment

1.10.4 Graphical view of Ischemia

In most situations, the isoelectric line has a similar electric potential to the ST portion of a normal ECG, i.e., the TP segment. The electric potential of the ST fragment changes about the isoelectric line potential of the TP fragment when oxidative stress occurs.

Injury current in cardiac cells is the main cause of ST segment deviation. When a coronary artery is blocked by cholesterol or clotting, it results in ischemia, which causes some myocytes to be intolerant to depolarization or to repolarize more quickly than nearby myocytes. Transmural ischemia patients have raised ST sections, though sub-endocardial ischemia patients have discouraged ST fragments [A. Goldberger, 1981]. In figure 1.16, the shaded zone depicts the location of myocardial ischemia (transmural or sub-endocardial).

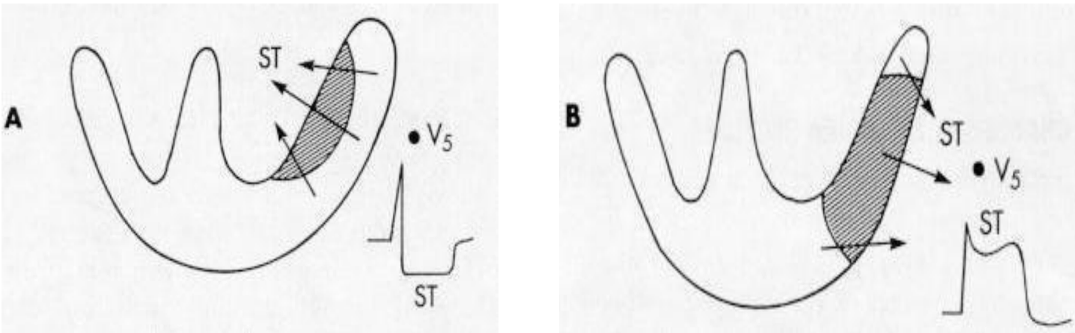


Figure 1.16 The Ischemic Zone's Geographical Location a) Subendocardial ischemia b) Transmural ischemia [reproduced from http://aiyisheng.org/Electrocardiograph.htm

1.10.5 The Ischemic Zone's Geographical Location

Using leads, ECG changes can be used to pinpoint ischemia areas. ST portion elevation in at least one precordial lead through V1-V6 and lead-I and lead a VL indicates anterior wall transmural ischemia. Leads II, III, and a VF show changes in inferior wall ischemia. There is ischemia in the posterior surface, which is discovered.

Subendocardial ischemia (indirect ST segment depression) in leads V1–V3 [A.S. Fauci et al., 2008]. Certain inferior wall myocardial infarctions exhibit persistent and reflexive ST segment discomfort in these scenarios. But for the time being, ST-segment elevation, which is typically caused by ventricular ischemia and may be observed in the proper, makes it simpler to determine.

1.10.6 Differentiation between Ischemia, Infarction and Necrosis

The electrocardiogram (ECG) is a significant method for tracking myocardial infarction and necrosis. These are most commonly caused by a coronary artery obstruction caused by the breakage of a susceptible thrombus, an unstable accumulation of cholesterol plaques and lipids found in the arterial wall. This happens when the blood supply to part of the heart is cut off, resulting in the death of some cardiac cells. Ischemia, the shortage of oxygen to cells, can cause infarction or death of cardiac tissue if ignored over a long enough period [G. Gupta, 2010; M.S. Sabatini, 2000]. On the other hand, areas of necrosis are electrically silent, suggesting that they are generally not depolarized. According to [E.B. Hanna and D.L. Glancy, 2011], myocardial infarction (often stroke) is characterized by anomalies in the ST segment and T waves, which can be controlled by the development of Q waves (necrosis).

[A. Smrdel and F. Jager, 2011] Pathological Q waves frequently represent necrosis. A different criterion has been developed to identify Q waves having pathogenic relevance from those without. However, the ECG may be normal or vague in a patient with ischemia or infarction. In this study, particular ST segments (such as elevation and depression) are also examined for ischemia identification. It's additionally vital to recall that ECG anomalies aren't the only way to determine whether you have infarction, ischemia, or necrosis. When ECG abnormalities are present, they can be caused by ischemia without infarction or non-ischemic illnesses like intense pericarditis. As a result, ischemia, infarction, and necrosis can be detected using a combination of clinical and laboratory testing and different electrocardiogram (ECG) changes [K. Matsumura et.al, 1998].

1.11 Literature Survey

A brief overview of some of the methodologies that have been developed during the past 20 to 25 years is provided below:

J.M. Belmont and L.F. Mattioli et al. (1995) proposed an electronic stethoscope and reliable inter-observer for pediatric telecardiology. The pediatric cardiologists used an acoustic (AS) stethoscope and an electronic stethoscope (E.S.) for the detection of electrocardiogram (ECG) and the evaluation of cardiac disease and heart sounds.

Researchers achieved the results with accuracy is 92%, specificity is 97%, and sensitivity is 88%.

J. Belmont and L.F. Mattioli (2003) investigated that accuracy and reliability can be obtained using a wide-bandwidth electronic stethoscope. Similar results can be achieved through a narrow-bandwidth telephonic stethoscope (T.S.), better than a wide-bandwidth electronic stethoscope. Authors achieved the results, i.e. specificity is 100%, and sensitivity is 94%.

S.W. Chen et al. (2006) authors suggested a basic moving average-based computing technique for detection of QRS,. The algorithm's output was then compared to databases on arrhythmias maintained by the MIT-BIH. This method achieved a detection rate of roughly 99.5% and was dependable even with poor signal quality. In addition to signal pre-processing, the detection algorithm used a wavelet-based de-noising technique to lower the noise level in the ECG data effectively.

F. Hu, M. Jiang et al. (2007) proposed a Telecardiology Sensor Networks (TSN) technique based on the wireless interconnection of small ECG sensors. By using TSN, there is no workforce required. The real-time information of the entire patient is available in this system without any error. It also provides the facility of security against information malicious attacks and stealing.

M.B. Velasco et al. (2008) author proposed a technique for removing noises using the EMD (Empirical Mode Decomposition) technique and provided both qualitative and quantitative findings. For the EMD to effectively eliminate high-frequency noise and baseline wandering, more than just a simple partial summation of IMF is used.

S.S. Mehta, D.A. Shete et al. (2010) proposed a straightforward K-means clustering approach was suggested by for the identification of the QRS complex in ECG data. The algorithm's detection rate was 98.66% when applied to dataset-3 of the CSE multi-lead measurement library.

Z. Eddine, H. Slimane et al. (2010) developed an EMD-based technique to recognize QRS complexes. As is common knowledge, its analysis includes pre-processing, conditioning, and post-processing of the ECG signal. Compared to other methodologies, the results from all 48 ECGs from the MIT/BIH collection provide a highly interesting interpretation.

S. Pal and M. Mitra (2010) proposed that due to the significance of the EMD-based QRS complex detection algorithm for cardiological diagnosis employing the PTB diagnostic database, the MIT-BIH arrhythmia database was used for the test. A favourable rate of 98.67% was achieved for identifying the R peak and 99.88% and 99.04%, respectively, for the sensitivity and specificity of the QRS complex recognition.

A.K. Manocha and M. Singh (2011) described a new algorithm for detecting ischemia. The performance parameter for identifying ischemia can be evaluated through sensitivity (Se) and positive predictivity (+P). The authors of this paper achieved positive predictivity and sensitivity of ST-segment in ECG results of 90-92 and 87-89.

C.S. Shen, W.C. Kao et al. (2012) considered several features in the preliminary stage. However, only a small subset of those features was used as the classifier's input. A unique classifier incorporating K-means clustering, one-against-one SVMs, and a modified majority voting method was used to achieve an average recognition rate of 98.92%.

A. Daamouche, L. Hamami et al. (2012) suggested that using a polyphase wavelet and particle swarm optimization together is more effective and stable than using two ordinary wavelets (Daubechies and Symlet).

H. Xia, I. Asif et al. (2013) presented a cloud-computing-based real-time continuous monitoring system. The cloud computing procedure aims to collect medical information and transmit it to highly skilled specialist doctors for treatment, especially in rural areas.

M. Eligendi et al. (2013), an automatic QRS detecting algorithm now in use, has high detection rates and incredibly low error rates. To establish the new trend toward battery-powered ECG devices and analyses ambulatory ECG signals in a manner that is both effective and time-efficient, these methods emphasize the machine-learning approach and require appropriate computer resources.

A. Mukherjee and K.K. Ghosh (2013) indicated that the accuracy of QRS complex recognition and the speed of ECG signal processing utilizing continuous wavelet transform (CWT) has improved. Additionally, they conclude that the CWT-based QRS complex detection approach for peak identification is significantly superior to discrete wavelet transform (DWT).

A. Huang, C. Chen et al. (2014) proposed a system named WE-CARE. In this system, a tool known as m-Health is mainly employed for the recognizable proof of coronary illness. In this paper, researchers employed two algorithms that give high detection rate characteristics of ECG signals. For the T wave, the detection rate is 97.7%, and for the QRS complex is 99.3%.

M. Vijayavanan, V. Rathikarani et al. (2014) suggested a method that uses morphological features and a probabilistic neural network classifier to obtain a total classification accuracy of 96.5%. This technique can be used to determine the difference between a normal ECG signal and an arrhythmia signal.

S. Rohini, R. Menaka (2014) suggested distinguishing between normal and aberrant signals. For preprocessing and feature extraction, the fast Fourier transform was used extensively. Backpropagation neural networks were then used as a classifier.

R. Tafreshi, A. Jaleel et al. (2014) A novel algorithm with a first derivative, second derivative, and adaptive threshold was presented to classify waveforms. Performance is also enhanced by spatial and temporal coherence along a single lead and throughout the 12 leads. The designed algorithm had a 99.06% overall sensitivity and a 98.89% positive predictive accuracy when evaluated on 50 healthy volunteers and 50 myocardial infarction patients.

K. Vimala (2014) In various studies, the focus was on the human stress component to identify arrhythmias. The signal was dissected using a discrete wavelet transform, and a hidden Markov model was employed for classification. The classification of ventricular arrhythmia has an accuracy of 93.18%.

X. Wu, C.H. Chu et al. (2014) developed a smartphone-based algorithm for the identification of cardiovascular disease. Basic curve length was used to extract features, and a simple heuristic model based on intermediate data like R-peak amplitude and R-R interval was used to identify probable R-peaks and subsequently exclude fake R-peaks. With a false detection rate of 0.22%, they were able to achieve a sensitivity of 99.88% and a prediction accuracy of 99.90%.

D. Sadhukhan et al. (2015) proposed a technique based on discrete Fourier transform coefficients to reduce medical data. Two strategies have been proposed for the selection of these coefficients. The first is fixed, and the second is adaptive. The fixed strategy depends on fixed bandwidth, and an adaptive strategy depends on the output parameter of the signal. In this paper, researchers achieved the results in terms of compression ratio for the fixed strategy, which is 14.67 and for the adaptive strategy, which is 16.58, with better signal quality.

R. Rodriguez, A. Mexicano et al. (2015) Using a unique methodology, Hilbert transforms, adaptive threshold technique, and PCA for feature extraction, it was possible to detect the QRS complex with a sensitivity of 96.28% and a positive predictivity of 99.71%.

F. Yasmeen, M.A. Mallick et al. (2015) applied the data-driven empirical mode decomposition technique, nonlinear transformation, and adaptive thresholding for the QRS complex detection and reported an average error of 0.21%.

M.M.A. Rahhal et al. (2016) stated that, compared to the prior work with a deep learning strategy for active classification of the ECG data, their method demonstrates a considerable improvement in accuracy with minimal expert interaction and quick online retraining.

A. Kumar and M. Singh (2016) presented an algorithm based on window characterization to identify ischemia episodes. Techniques are used to make this determination, i.e. form factor, kurtosis and coefficient of variation (COV). The researchers obtained positive predictivity (+P) results, 96.89%, and sensitivity (Se), 97.71%.

L. Marsanoval and M. Ronzhina et al. (2017) proposed a technique for categorizing various types of rhythms of the heart, i.e. ischemic and non-ischemic. It is critical to recognize previous history occasions in ECG for monitoring and diagnosis of patients. In this research work, researchers also developed a method for data calculation.

W. Alsaadi and A. Serener (2017) proposed a technique for improving the parameter of the ECG signal via a multipath Rayleigh fading channel. In this paper, the authors explained MIMO antenna technology for improving performance up to 18 dB. For more improvement of ECG signal performance, the DVB-S2 (digital video broadcasting –satellite version2) technique is preferred because it has more advantages as compared to DVB-T(digital video broadcasting–terrestrial (DVB-T)

S.C. Bollepalli et al. (2017) presented an algorithm based on ultra-low-cost dictionary-based real-time continuous heartbeat monitoring. Using this algorithm, the heartbeat can be detected accurately and transmitted after compression. This technique has the advantage it reduces the burden on doctors.

M. Kumar, R.B. Pachori et al. (2017) depicted a procedure given wavelet transform for detecting a heartbeat. The heartbeat is decomposed into small parts in this technique, and sample entropy (SEnt) is calculated using a back propagation neural network (BPNN), random forest (RF), J48 decision tree, least-squares support vector machine (LS-SVM) classifiers. After using the least-squares supports vector machine (LS-SVM), the highest accuracy can be achieved up to 99.31%.

C.K. Roopa and B.S. Harish (2017) proposed an artificial technique-based technique for evaluating ECG signals. This paper employs various techniques to detect a patient's heartbeat, including decision trees, support vector machines, artificial neural networks, rough set theory, fuzzy logic, and genetic and hybrid approach.

F. Gao, S. Thiebes et al. (2018) presented a solution for detecting health problems utilizing the cloud computing principle. The cloud computing methodology lets Clients store and access clinical data from different areas. The authors developed a taxonomy that generates a scheme for providing a cloud platform to healthcare patients.

G. Molinari, M. Molinari et al. (2018) presented the application of telecardiology, and it uses teleconsultation features, which avoids unnecessary travelling for patients and doctors. In this paper, the authors obtained the results with an accuracy of 86.9% sensitivity of 97.4%.

E. Andrès, S. Talha et al. (2018) suggested a new project based on telemedicine. This paper uses artificial intelligence to diagnose cardiac issues in a rural zone. In worst conditions, telemedicine projects are used for the detection of heart problems with results i.e., positive and negatively predictive of 90% and 100%, sensitivity is 100%, and specificity is 72%

A. Sulthana, M.Z.U. Rahman et al. (2018) presented a Kalman filter for noise cancellation or eliminating errors in ECG signals. Using this filter, the highest accuracy can be achieved. In this research work, the author explained various techniques for high-quality ECG signals, combining various least-mean-square (LMS) algorithms.

T. Tariq, A. Abbas et al. (2019) invented a bracelet with various sensors that continuously monitor the patient. If a patient's breathing exceeds a certain threshold, the doctor will make recommendations to the patient right away. This bracelet aids in uploading data to the website to preserve the patient's history. The authors of this paper used a machine learning tool to analyse ECG medical data.

A. Zamanifar and E. Nazemi (2019) proposed a model based on the tree-structured network for monitoring the patient's health status and predicting medical information. In this paper, the authors also explained the application of the Internet of Things (IoT) and achieved an accuracy of 83%. This method is very useful for the detection of the current status of the patient.

M.A.G. Santos, R. Munoz et al. (2020) proposed a method which consists of digital medical monitoring devices based on Internet of Things (IoT) conditions. The researchers of this research work also explained the approach of cloud computing. Users can store and access medical information using the cloud computing concept. In this research work, a machine learning technique is also used to detect heart diseases accurately.

T.H. Nguyen, T.N Nguyen et al. (2020) proposed a deep learning framework for heart disease classification in an IoTs-based system. ECG data collected from ECG sensors of measure devices are sent to one computer for processing. In this system, the authors achieved better results than the state of artworks.

X. Xu, H. Liu et al. (2020) authors designed a Holter data CNN heartbeat classifier based on coupled- a convolution layer structure and adopting the dropout mechanism. It was proved experimentally that the overall accuracy of the classification could reach 99.43%, while the sensitivity and positive predictivity are 99.2% and 99.4%, respectively.

G. Chen, M. Chen et al. (2020) proposed an algorithm for delineating P wave, QRS complex, and T wave developed using twelve-lead signals. QRS detector identifies the locations of QRS complexes in each lead, and then false QRS locations are removed by taking other leads into account.

G. Xu (2020) In this paper, a new ECG quality IoT-assisted signal analysis framework for applications of cardiac health surveillance is introduced. This paper provides an ECG-SSA (Singular Spectrum Analysis) methodology for the automated evaluation of the quality of ECG signals obtained in the sense of patient and physical activity.

W.L. Chin and C.C. Chang (2020) authors proposed QRS detection problem is revisited by proposing a new Bayesian model for QRS detection in real-time. To this, a new algorithm with two stages is proposed to reduce the complexity incurred from the original ML approach without manually adjusting any parameters. The accuracy level of the proposed approach is comparable to state-of-the-art works.

J.S. Huang and B. Q. Chen (2020) authors proposed an ECG arrhythmia classification method using maximal overlap wavelet packet transform and fast compression residual convolutional neural networks. ECG signals from five different types were obtained from the MIT-BIH arrhythmia database after the sage of the FCResNet model author achieved an average accuracy of 98.79%.

M. Wu and Y. Lu (2021) authors pay more attention to specific micro-classes, namely the Normal, Left Bundle Branch Block, Right Bundle Branch Block, Atrial Premature Beats, and Premature Ventricular Beats using CNN. The CNN network has relatively higher accuracy. The proposed CNN network shows an outstanding overall classification accuracy of 97.41%, sensitivity of 97.05%, specificity of 99.35%, and a positive prediction rate of 97.21%.

A. Tyagi and R. Mehra (2021) in this paper, an intellectual heartbeats classification model for the diagnosis of heart disease from Electrocardiography (ECG) signal using the Hybridization of Convolution Neural Network (CNN) with Grasshopper Optimization Algorithm (GOA) is proposed. Grasshopper Optimization Algorithm (GOA)based on the feature selection approach is designed with a novel fitness function that aids in attaining better classification accuracy. The author achieved the accuracy from the proposed Heartbeats Classification Model is 99.58%.

F.S. Butt and L.L. Blunda (2021) author proposed ECG signals that can be utilized alone to distinguish different activities and fall from no-fall activities by combining wavelet transform and transfer learning. The transfer learning models learned as efficiently and accurately as any other convolutional neural network trained from scratch. The authors achieved an accuracy of 98.02%.

B.M. Mathunjwa and Y.T. Lin (2021) this research aimed to design a new deep learning method for effectively classifying arrhythmia using 2-second segments of 2D recurrence plot images of ECG signals. The authors achieved the testing accuracy for the five-fold cross-validation was 95.3 % ± 1.27 % and 98.41% ± 0.11% in the first and second stages, respectively.

D.K. Atal and M. Singh (2021) author proposed the automatic method of arrhythmia classification, which is performed using a Bat-Rider Optimization algorithm based on deep convolutional neural networks (BaROA-based DCNN). The author achieved the results like maximal values of 93.19%, 95%, and 93% for accuracy, sensitivity, and specificity.

I. Monedero (2022) author demonstrated a product, a fully operational skilled system that uses conventional 12-lead ECGs to identify 13 different diseases accurately. This technology significantly advances the current state of the art in three ways: (a) the variety of disorders it can diagnose; (b) the use of five leads for more accurate wave identification and measurement; and (c) a revolutionary noise indicator that assesses the ECG signal's overall quality. The expert validated the system and found it to be 80.8% reliable.

R. Morello, F. Ruffa et al. (2022) The current paper aims to explain the project and creation of an Electrocardiogram tracking system that can detect particular heart diseases by modifying the analysis method for the patient being observed. The system can function independently by giving the final assessment to the patient via a set of LEDs. Additionally, an IoT- based framework enables the system to post-process and further analyses data by sharing it with a distant physician in golden -time or storing it as a Holter monitor in an FTP directory. The system is divided into two parts: the digital one, utilizing the National Instrumentation MyRIO, digitizes the signal and evaluates it in golden time to identify potential heart diseases (bradycardia, tachycardia, infarction, and ischemia).

R. Srivastava, B. Kumar et al. (2022) This research presented probabilistic neural network-based arrhythmia categorization and hardware configuration. The ECG was normalized to classify the arrhythmia accurately, and a special collection of ECG features, including spectral entropy, 4th-order autoregressive coefficient, and heart rate, was extracted. First on MATLAB, then on FPGA with Xilinx System Generation, PNN segmentation of arrhythmia was accomplished with an excellent average accuracy of 98.27% for eight classes of ECG.

G. Kuldeep and Qi Zhang (2022) In this study, authors developed the MPCC technique, which combines compressive sensing based on cloud computing with multi-class encryption to protect user privacy. MPCC enables the web to carry out computationally intensive sparse signal recovery without affecting data privacy. For statistical decryption using digital energy datasets and data anonymization using electrocardiogram (ECG) datasets and pictures, three different MPCC variants have been developed. It is demonstrated through a theoretical security study of the MPCC scheme that it is computationally impossible to defeat the suggested scheme. Furthermore, it is demonstrated that ciphertext-only attacks can compromise modern multi-class encryption methods.

R.A. Alharbey, S. Alsubhi et al. (2022) The continuous wavelet transform (CWT) was employed in this study to identify ECG arrhythmias. The natural rhythms were as follows: Atrioventricular (AV), supra-ventricular (SV), and normal cardiac rhythm (NC) arrhythmias were selected for detection and testing of the suggested approach. The MIT-BIH database's Natural signals were used for testing. The continuous wavelet transform was linked to the standard deviation (SD) and Shannon entropy

(SE) for the feature extraction stage. A safe threshold has been proposed to distinguish between the various arrhythmias for classification.

B.M. Mathunjwa and Y.T. Lin (2022) authors proposed an efficient electrocardiogram (ECG) recurrence plot (RP)-based algorithm for classifying arrhythmias that can be used in portable devices provided in this study. The MIT-BIH Atrial Fibrillation Database, the MIT-BIH Arrhythmia Database, the MIT-BIH Malignant Ventricular Ectopy Database, and the Creighton University Ventricular Tachyarrhythmia Database were all employed in this work. The method was tested using 5-fold cross-validation, which enhanced the outcomes compared to earlier research, yielding first and second-stage average accuracy, sensitivity, positive predictive values, and F1-scores of 97.21%, 98.36%, 96.49%, and 97.92%, respectively.

L.C.N. Kouekeu, Y. Mohamadou et al. (2022) The ECG signal strength and trend are used to inform a novel embedded QRS complex identification algorithm proposed in this paper. The technique uses two thresholds based on the signal trend and a calculated capacitive level to record signal strength and determine the location of the R-peak. The beginning of the QRS complex is then determined using the location of the end of the R-peak and the slope to the ECG curve. The algorithm produced average F1 scores of 99.75%, 99.84%, 97.39%, and 86.63% on the MIT-BIH Arrhythmia test.

Y. Liu, H. Zhang et al. (2023) Multichannel ECG signal diagnosis and categorization have been successfully automated using deep learning. However, several significant difficulties still need to be solved, such as high training resource requirements, memory requirements, and high training resource prices. Additionally, deploying mobile-embedded health detection sensors to pick up multichannel signals, particularly 12-channel ones, is difficult. Contrarily, single-channel signals, including single-channel ECG signals, are rather simple to find.

M. Karri and C.S. Rao (2023) suggested a technique based on the Long Short-Term Memory (LSTM) neural network for the classification of Arrhythmia. The embedded system extracts the ECG signal, which is then employed in subsequent steps. Second, threshold levels through DSM and DWT are used to detect the QRS complex/R peak, respectively. Thirdly, an LSTM is used to classify arrhythmias using the hybridized extracted characteristics. For each of the four metrics, the algorithm achieved 99.64%, 99.15%, 99.87%, and 98.18%, respectively.

Mohd. Maroof Siddiqui (2023) author proposed an IoT-based ECG recording has the potential to transform cardiac care by providing individualised insights into heart health, early identification of cardiac issues, and continuous monitoring. This area is being advanced by breakthroughs in technology, data management, and analytics. **Atiaf A. Rawi and Murtada K. Elbashi (2023)** The aim of this paper is to test the effectiveness of deep learning (DL)-based methods (Inception, MobileNet, LeNet, AlexNet, VGG16, and ResNet50) using three large 12-lead ECG datasets. The define-by-run technique is used to build the most efficient DL model using the tree-structured Parzen estimator (TPE) algorithm. Results show that the proposed methods achieve high accuracy and precision in classifying ECG abnormalities for large datasets, with the best results being 97.89% accuracy and 90.83% precision.

A.A.R. Bellfield and S.O. Martorell (2024) authors suggested three different data formats suitable for ECG analysis: Signal ECGs, Image ECGs, and Extracted Signal ECGs. Two ECG arrangements and two data subsets were compared: one with well-separated classes (best-case scenario) and the other with more noise and less certain diagnoses. The findings suggest that Signal ECG data should be prioritized for ML modeling when available.

A Eleyan and E. Alboghbaish (2024) the accurate and automated detection of irregularities in ECG signals is paramount for patients' well-being. To address this, a deep-learning system leveraging convolutional neural networks (CNNs) and long short-term memory networks (LSTMs) was developed in this paper to predict various heart irregularities associated with different heart diseases. Results demonstrated that the FFT+CNN–LSTM approach surpassed other machine learning and deep learning models in both scenarios, achieving accuracies of 97.6% (five classes) and 99.20% (three classes) respectively.

1.12 Our Contributions

- We contribute in this proposed work is that we have employed a variant of DES, i.e., Triple-Data encryption standards (3-DES) and water cycle optimization algorithms. One-time padding (OTP) key is required for the encryption-authentication approach.

- The water cycle optimization technique produced a 56-bit one-time padding key. The triple DES employs the DES algorithm 3 times. For encryption and decryption, the triple-DES has 3 keys of 56 bits, and the key size is 168 bits.

- The 56-bit DES key was not sufficient to encrypt the sensitive data. So, to overcome this problem, triple DES is an easy way to expand the key size without using a novel algorithm.

- Triple DES affects the key size by applying the algorithm with three different keys three times in a row. The key K1(first key) is utilized for the encryption of data, K2 (second key) is employed to decode the encrypted data, and the third key, K3, is used to encrypt the output of K2.

- Triple data encryption standards (3-DES) target to provide a general-purpose technique for increasing the data encryption standards key size that prevents threats without requiring the development of a new block encryption algorithm.

- The Internet of Things is important in developing Medicare healthcare systems for the widening rural population. As a detection device for heart problems, the ECG tracking system performs a vital role. This system simulates evaluating a Portable Point of Care (POC) scheme at a low cost for detecting heart patients.

- In the literature Survey, we have seen less value of sensitivity, specificity, and productivity. If it is not improved, we cannot predict heart disease properly in real-time.

1.13 Organization of the Thesis

The entire thesis has been divided into six chapters. A summary of each of them is provided below:

Chapter 1 describes the significance of ECG monitoring, arrhythmia, and ischemia.

This chapter also provides a general overview of the research problem; encryption, security, optimization and the internet of things are given. It also includes the methodology adopted to implement different proposed algorithms.

Chapter 2 describes the resources and methods covering the database description and mathematical background of multi-resolution wavelet transform and maximal overlap wavelet packet transforms.

Chapter 3 discusses research gaps & objectives.

Chapter 4 discusses the methodology and detailed operating procedure of proposed method for data cryptographic algorithms, data decryption and authentication, water cycle optimization (WCO), characterization data encryption standard (DES), encryption and decryption of triple DES, components of IoT systems, modified iso-electric energy function (MIEEF) for ischemia detection, deviation in region of interest (ROI) and ST-segment assessment, algorithm for myocardial infarction (MI) beat characterization.

Chapter 5 focuses on validating results for eliminating artifacts, a delineation technique for the characteristic points of ECG and a developed method, features extraction, and classification using Deep learned Convolution neural network.

Chapter 6 summarizes all the major findings of the research work. Prospects and scope in the field are also included in this chapter.