# HARDWARE OPTIMIZATION & CAD SYSTEM OF AN ELECTROCARDIOGRAPH CIRCUIT FOR LEAD II

*Dissertation submitted in partial fulfillment of the requirement for the degree of*

**BACHELOR OF TECHNOLOGY**

**IN**

**ELECTRONICS AND COMMUNICATION ENGINEERING**

By


**Shwetanjali Dubey 121087**
**Ambesh Kumar Singh 121088**
**Akanksha Dhiman 121100**


UNDER THE GUIDANCE OF

**Dr. Shruti Jain**


JAYPEE UNIVERSITY OF INFORMATION TECHNOLOGY, WAKNAGHAT


June 2016

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# DECLARATION BY THE SCHOLAR

We hereby declare that the work reported in the B-Tech Thesis entitled **"HARDWARE OPTIMIZATION & CAD SYSTEM OF AN ELECTROCARDIOGRAPH CIRCUIT FOR LEAD II "** submitted at **Jaypee University of Information Technology, Waknaghat, India,** is an authentic record of our work carried out under the supervision of **Dr. Shruti Jain.** We have not submitted this work elsewhere for any other degree or diploma.

Shwetanjali Dubey (121087)

Ambesh Kumar Singh (121088)

Akanksha Dhiman (121100)

Department of Electronics & Communication

Jaypee University of Information Technology, Waknaghat , India

Date :

# SUPERVISOR'S CERTIFICATE

This is to certify that the work reported in the B-Tech. thesis entitled **"HARDWARE OPTIMIZATION & CAD SYSTEM OF AN ELECTROCARDIOGRAPH CIRCUIT FOR LEAD II "** submitted by **Shwetanjali Dubey (121087), Ambesh Kumar Singh (121088) and Akanksha Dhiman(121100)** at **Jaypee University of Information Technology, Waknaghat , India,** is a bonafied record of their original work carried out under my supervision. This work has not been submitted elsewhere for any other degree or diploma.

Dr. Shruti Jain
**Assistant Professor (Senior Grade)**

Date:

## ACKNOWLEDGEMENT

It is said that gratitude is a virtue. This part is dedicated to special thanks that we would like to deliver to the people who help make possible the fulfillment of this project.

First of all, we would like to thank Dr. Shruti Jain for introducing us to this intriguing research field. Thank you for the motivation and enlightening insights. Without your support and guidance we would not have completed our project. We are especially grateful that you treat us like a friend, respect our decisions and plans, and encourage us with every progress, no matter how humble it is, along the way.

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Shwetanjali Dubey (121087) Ambesh Kumar Singh (121088) Akanksha Dhiman (121100)

# LIST OF ACRONYMS

1. aVF : Augmented Vector Front
2. aVL : Augmented Vector Left
3. aVR : Augmented Vector Right
4. CAD: Computer Aided Design
5. CM: Confusion Matrix
6. CMRR : Common Mode Rejection Ratio
7. ECG / EKG: Electrocardiograph
8. GUI: Graphical User Interface
9. ICA: Individual Classification Accuracy
10. K-NN: K- Nearest Neighbor
11. LA : Left Arm
12. LL : Left Leg
13. OCA: Overall Classification Accuracy
14. RA: Right Arm
15. RF: Radio Frequency
16. RL: Right Leg
17. SSVM: Smooth Support Vector Machine
18. SVM: Smooth Vector Machine

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# ABSTRACT

This thesis provides electronic implementation of electrocardiogram (ECG) circuit by using instrumentation amplifier as bio-potential amplifier in such a manner that it reduces noise, common voltage, DC offset value and RF interference from the existing circuit.

Electrocardiogram (ECG) signal's noise reduction is critical for ECG automatic diagnosis and analysis, and the de-noising result directly affects the accuracy of ECG parameter extraction even the patients' illness diagnosis and analysis. Noise and common voltage can be removed from ECG using driven right leg circuit or by using isolator circuit. DC offset can be removed by using integrator as feedback. By using filters, we can reduce RF interference. In our project, we have used instrumentation amplifier as a bio-potential amplifier.

We have also made a CAD system which helps the doctor in analyzing whether patient waveform is normal or abnormal. We have used the knowledge of automatic classification of ECG signals with feature selection and extraction techniques. 83 samples of 12 lead systems were collected from various doctors out of whom we have used the lead 2 samples of the ECG waveforms. . In the feature extraction module, for extracting the features morphological feature extraction method was employed. In the classification module we used different classifiers like k-NN, SVM & SSVM. In this thesis, we have accurately classified and differentiated normal and abnormal waveforms. Experiments reveal that the OCA is 71.43%

.

# CHAPTER 1

# INTRODUCTION

## 1.1 BASIC ECG SYSTEM

The electrocardiogram (ECG or EKG) is a graphic recording of electric potentials generated by the heart. The signals are detected by means of metal electrodes attached to the extremities and chest wall and are then amplified and recorded by the electrocardiograph. ECG *leads* actually display the instantaneous *differences* in potential between these electrodes.

The human heart serves as a pump to move blood through vessels called arteries and veins. Blood is carried away from the heart in arteries and is brought back to the heart in veins. The heart is a dual pump, consisting of a two-chambered pump on both the left and right sides. The upper chambers are inputs to the pump and are called atria. The lower chambers of the heart are called ventricles and are the pump outputs.

The conduction system of the heart consists of the sinoatrial node (SA), bundle of His, atrioventricular node (AV), the bundle branches and purkinje fibres. The SA node serves as a pacemaker for the heart and it provides the trigger signal. When the SA node discharges a pulse, then electrical current spreads across the atria causing them to contract. Blood in the atria is forced by the contraction through through the valves to the ventricles [1-3].

The action potential generated in the SA node stimulates the muscle fibres of the myocardium, causing them to contract. When the muscle is in contraction, it is shorter, and the volume of the ventricular chamber is less, so blood is squeezed out. The contraction of so many muscle cells at one time creates a mass electrical signal that can be detected by electrodes placed on the surface of the patient’s chest or the patient’s extremities. This electrical discharge can be mechanically plotted as a function of time, and the resultant waveform is called an electrocardiogram (ECG) [1].

An ECG recording of a Healthy Heartbeat can be drawn like this :-

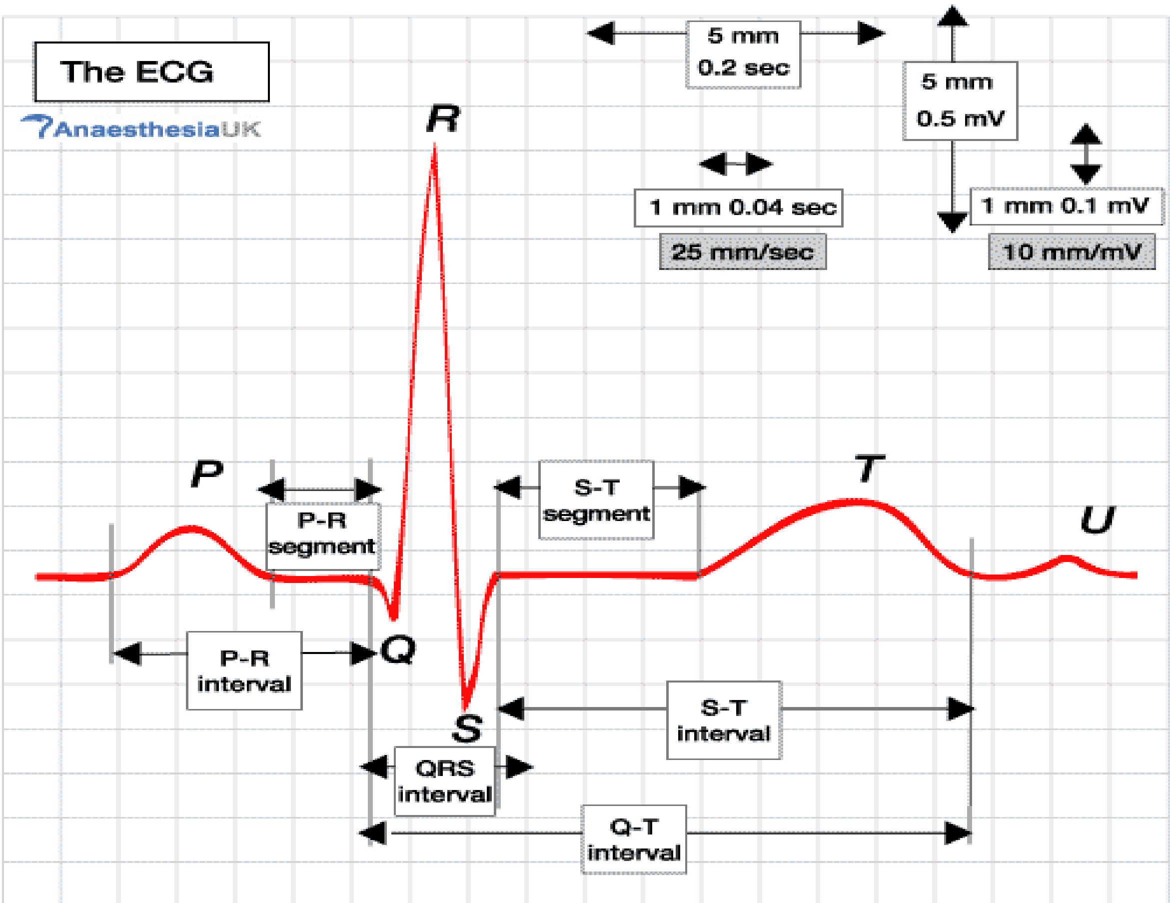



**Fig. 1.1 An ECG Waveform**

The different parts of the ECG waveform are designated by letters P, Q, R, S, T, U.

The **P-wave** indicates **atrial contraction**.

The **QRS complex** indicates **ventricular systole (depaolarization)**.

The **T-wave** indicates **refractory period** (resting for repolarization).

The **U-wave** is hypothesized to be caused by the repolarization of the interventricular septum. They normally have a low amplitude, and even more often completely absent. They always follow the T wave and also follow the same direction in amplitude. If they are too prominent, suspect hypokalemia, hypercalcemia or hyperthyroidism usually [3].

The electrocardiogram is ordinarily recorded on special graph paper which is divided into 1-$mm^2$ gridlike boxes. Since the ECG paper speed is generally 25 mm/s, the smallest (1 mm) horizontal divisions correspond to 0.04 (40 ms), with heavier lines at intervals of 0.20 s (200 ms).

Vertically, the ECG graph measures the amplitude of a given wave or deflection (1 mV = 10 mm with standard calibration).

There are four major ECG intervals: R-R, PR, QRS, and QT  The heart rate (beats per minute) can be readily computed from the interbeat (R-R) interval by dividing the number of large (0.20 s) time units between consecutive R waves into 300 or the number of small (0.04 s) units into 1500.

The **PR interval** measures the time (**normally 120–200 ms**) between atrial and ventricular depolarization, which includes the physiologic delay imposed by stimulation of cells in the AV junction area.

The **QRS interval** (**normally 100-110 ms or less**) reflects the duration of ventricular depolarization.

**The ST segment** requires approximately **50 to 150 ms.**

The **QT interval** includes both ventricular depolarization and repolarization times and varies inversely with the heart rate.

The QRS complex is subdivided into specific deflections or waves. If the initial QRS deflection in a given lead is negative, it is termed a *Q wave*; the first positive deflection is termed an *R wave*. A negative deflection after an R wave is an *S wave*. Lowercase letters (qrs) are used for waves of relatively small amplitude.

### 1.1.1 ECG LEADS

The 12 conventional ECG leads record the difference in potential between electrodes placed on the surface of the body. In standard ECG recording there are five electrodes connected to the patient: *right arm (RA), left arm (LA), left leg (LL), right leg (RL) and* *chest (C)* .These electrodes are connected to the inputs of a differential buffer amplifier through a lead selector switch.

The ECG leads are divided into two groups: **six limb (extremity) leads** and **six chest (precordial) leads**. The **limb** leads record potentials transmitted onto the ***frontal plane*** (**Fig. 1.2 A**), and the **chest** leads record potentials transmitted onto the ***horizontal plane*** (**Fig.1.2 B**).

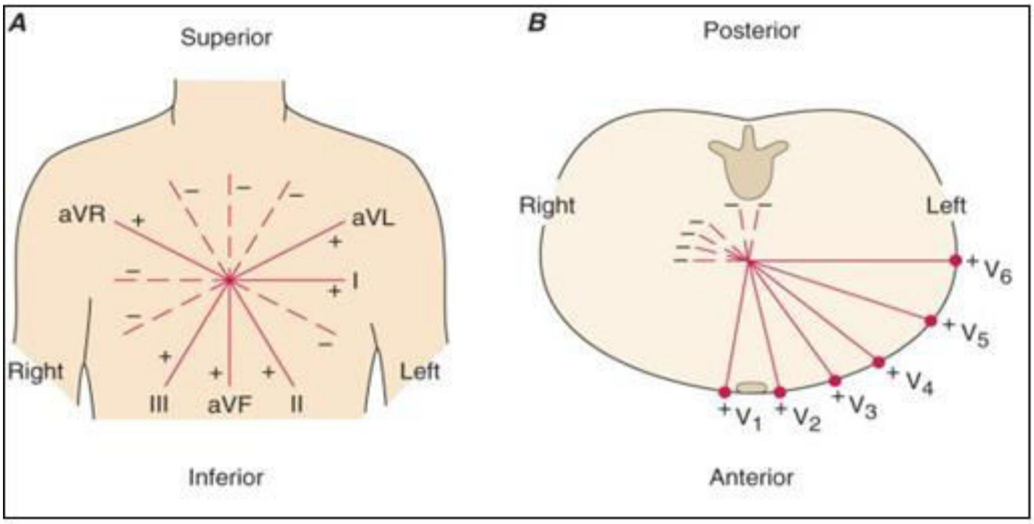



**Fig 1.2 A & B:- Frontal & Horizontal Planes**

The six **limb** leads are further subdivided into **three standard "*bipolar*" *leads* (I, II, and III)**and **three augmented "*unipolar" leads* (aVR, aVL, and aVF)**.

The bipolar limb leads measure the difference in potential between electrodes at two extremities:

1. Lead I = left arm – right arm voltages
2. Lead II = left leg – right arm voltages
3. Lead III = left leg – left arm voltages

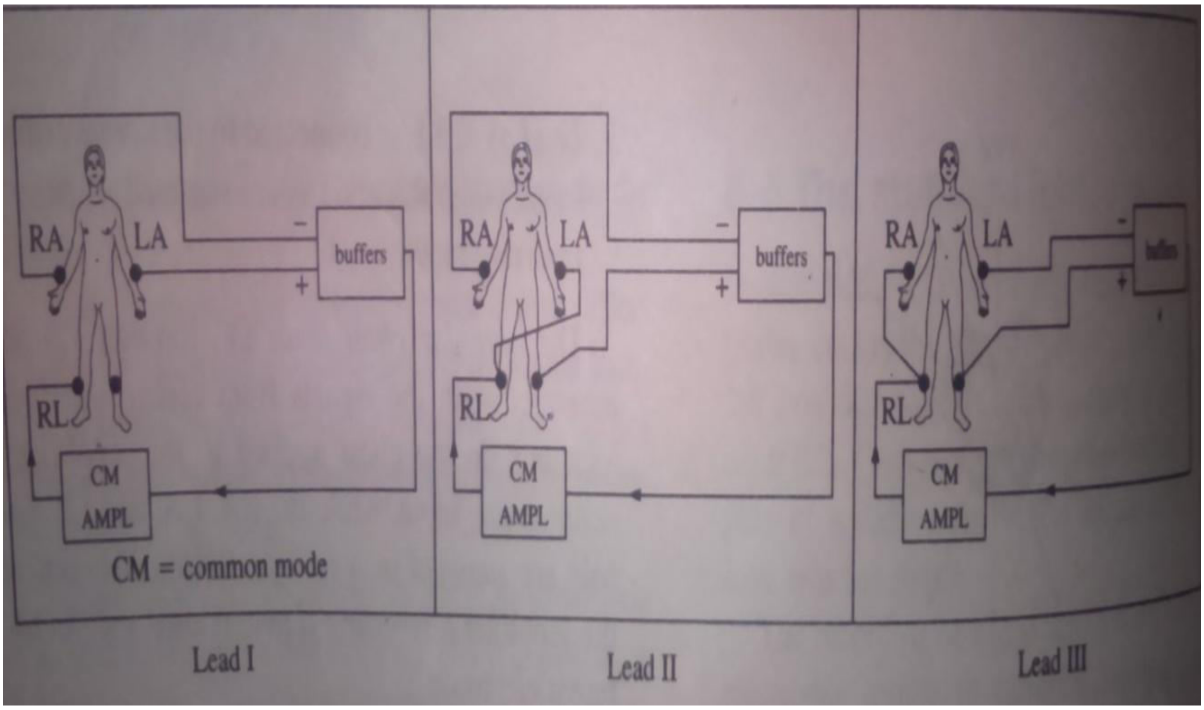



**Fig 1.3: Position of bipolar limb leads on body [1]**

The unipolar leads also known as the augmented limb leads, measure the voltage (V) at one locus relative to an electrode (called the *central terminal* or *indifferent electrode*) that has approximately zero potential. In all three augmented leads, the signals from two limbs are summed in a resistor network and then aplied to the amplifier's inverting input, while the signal from the remaining limb electrode is applied to the noninverting input.

i) Lead aVR: RA is connected to the noninverting input, while LA and LL are summed at the inverting input.
ii) Lead aVL: LA is connected to the noninverting input, while RA and LL are summed at the inverting input.
iii) Lead aVF: LL is connected to the noninverting input, while RA and LA are summed at the inverting input.

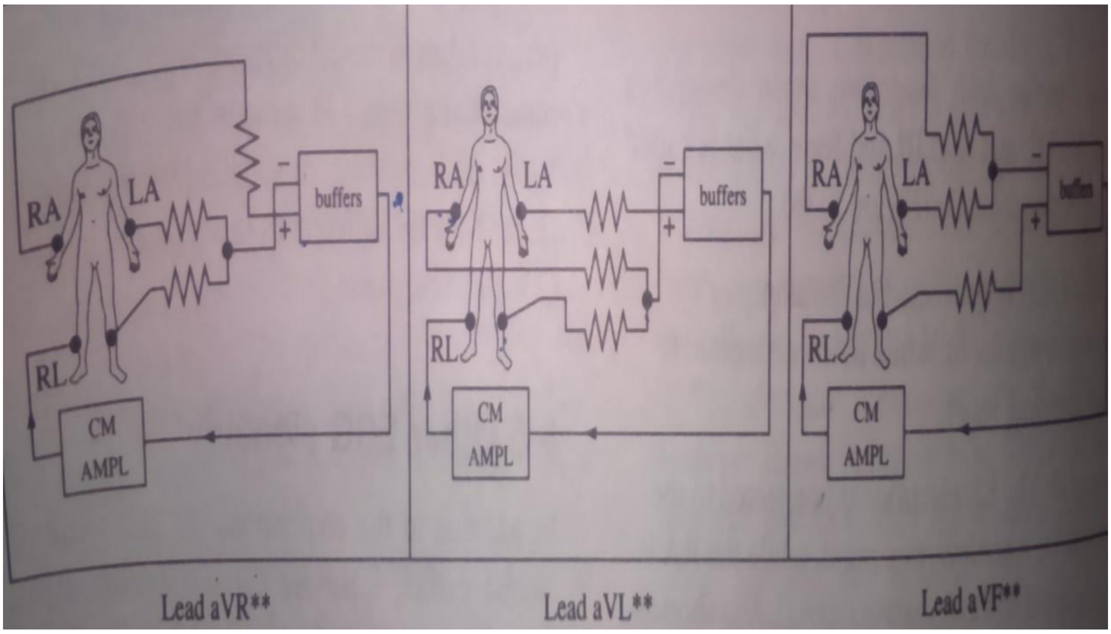



**Fig 1.4 : Position of unipolar limb leads on body [1]**

The unipolar chest leads ($V_1$ through $V_6$) are measured with the signals from certain specified locations on the chest applied to the amplifier's non inverting input, while the RA, LA, and LL signals are summed in a resistor Wilson network at the amplifier's inverting inputs.

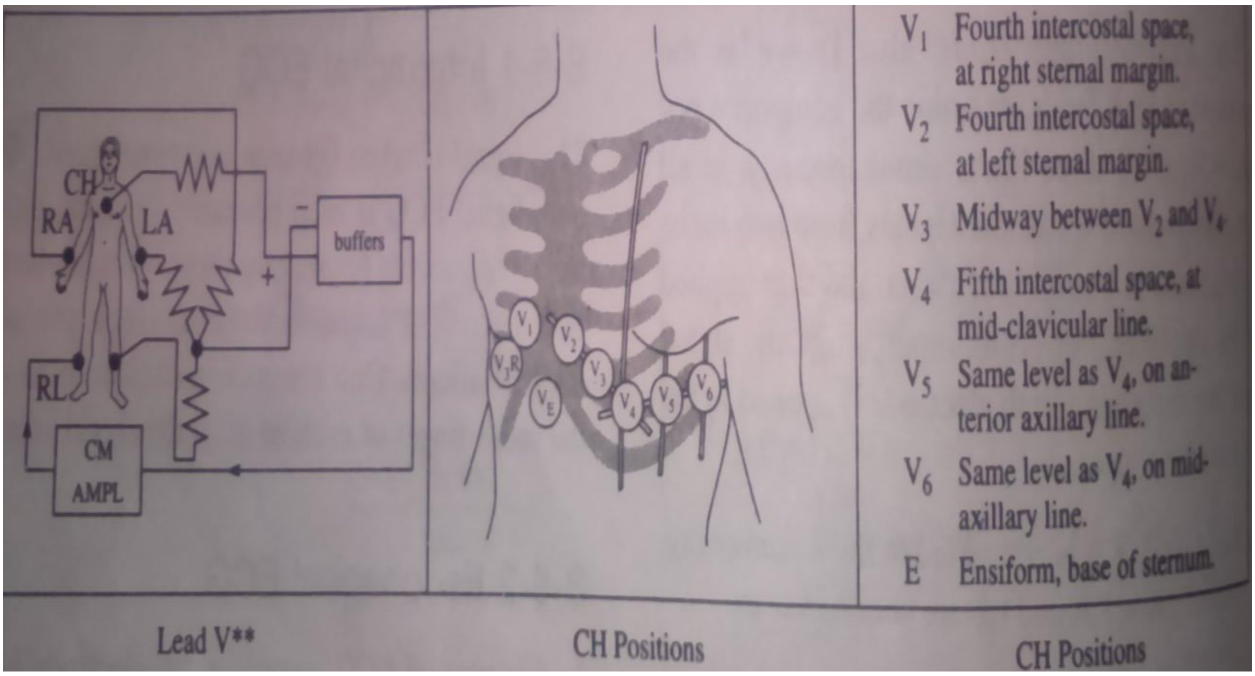



**Fig.1.5: Position of unipolar chest leads on body [1]**

Together, the frontal and horizontal plane electrodes provide a three-dimensional representation of cardiac electrical activity. Each lead can be likened to a different camera angle "looking" at the same events—atrial and ventricular depolarization and repolarization—from different spatial orientations.

The ECG leads are configured so that a positive (upright) deflection is recorded in a lead if a wave of depolarization spreads toward the positive pole of that lead, and a negative deflection if the wave spreads toward the negative pole. If the mean orientation of the depolarization vector is at right angles to a given lead axis, a biphasic (equally positive and negative) deflection will be recorded.

### 1.1.2 DESCRIPTION OF AN ECG WAVE

**P Wave :-** The normal atrial depolarization vector is oriented downward and toward the subject's left, reflecting the spread of depolarization from the sinus node to the right and then the left atrial myocardium. Since this vector points toward the positive pole of lead II and toward the negative pole of lead aVR, the normal P wave will be positive in lead II and negative in lead aVR. By contrast, activation of the atria from an ectopic pacemaker in the lower part of either atrium or in the AV junction region may produce retrograde P waves (negative in lead II, positive in lead aVR). The normal P wave in lead $V_1$ may be biphasic with a positive component reflecting right atrial depolarization, followed by a small (<1 $mm^2$) negative component reflecting left atrial depolarization.

**QRS Complex :-** Normal ventricular depolarization proceeds as a rapid, continuous spread of activation wavefronts. This complex process can be divided into two major, sequential phases, and each phase can be represented by a mean vector. The first phase is depolarization of the interventricular septum from the left to the right and anteriorly (vector 1). The second results from the simultaneous depolarization of the right and left ventricles; it is normally dominated by the more massive left ventricle, so that vector 2 points leftward and posteriorly. Therefore, a right precordial lead ($V_1$) will record this biphasic depolarization process with a small positive deflection (septal r wave) followed by a larger negative deflection (S wave). A left precordial lead, e.g. $V_6$, will record the same sequence with a small negative deflection (septal q wave) followed by a relatively tall positive deflection (R wave). Intermediate leads show a relative increase in R-wave amplitude (normal R-wave progression) and a decrease in S-wave amplitude progressing across the chest from the right to left. The precordial lead where the R and S waves are of approximately equal amplitude is referred to as the *transition zone* (usually $V_3$ or $V_4$). The QRS pattern in the extremity leads may vary considerably from one normal subject to another depending on the *electrical axis* of the QRS, which describes the mean orientation of the QRS vector with reference to the six frontal plane leads. Normally, the QRS axis ranges from –30° to +100°. An axis more negative than –30° is referred to as *left axis deviation*, while an axis more positive than +100° is referred to as *right axis deviation*. Left axis deviation may occur as a normal variant but is more commonly associated with left ventricular hypertrophy, a block in the anterior fascicle of the left bundle system (left anterior fascicular block or hemiblock), or inferior myocardial infarction. Right axis deviation may also occur as a normal variant (particularly in children and young adults); as a spurious finding due to reversal of the left and right arm electrodes; or in conditions such as right ventricular overload (acute or chronic), infarction of the lateral wall of the left ventricle, dextrocardia, left pneumothorax, or left posterior fascicular block.

**T Wave and U Wave :-** Normally, the mean T-wave vector is oriented roughly concordant with the mean QRS vector (within about 45° in the frontal plane). Since depolarization and repolarization are electrically opposite processes, this normal QRS–T-wave vector concordance indicates that repolarization must normally proceed in the reverse direction from depolarization (i.e., from ventricular epicardium to endocardium). The normal U wave is a small, rounded deflection (≤ 1 mm) that follows the T wave and usually has the same polarity as the T wave. An abnormal increase in U-wave amplitude is most commonly due to drugs (e.g., dofetilide, amiodarone, sotalol, quinidine, procainamide, disopyramide) or to hypokalemia. Inversion of the U wave in the precordial leads is abnormal and may be a subtle sign of ischemia.

### 1.1.3 CLINICAL INTERPRETATION OF THE ECG

Accurate analysis of ECGs requires thoroughness and care. The patient's age, gender, and clinical status should always be taken into account. For example, T-wave inversions in leads $V_1$–$V_3$ are more likely to represent a normal variant in a healthy young adult woman ("persistent juvenile T-wave pattern") than in an elderly man with chest discomfort. Similarly, the likelihood that ST-segment depression during exercise testing represents ischemia depends partly on the prior probability of coronary artery disease.

Many mistakes in ECG interpretation are errors of omission. Therefore, a systematic approach is essential. The following 14 points should be analyzed carefully in every ECG: (1) standardization (calibration) and technical features (including lead placement and artifacts); (2) rhythm; (3) heart rate; (4) PR interval/AV conduction; (5) QRS interval; (6) $QT/QT_c$ interval; (7) mean QRS electrical axis; (8) P waves; (9) QRS voltages; (10) precordial R-wave progression; (11) abnormal Q waves; (12) ST segments; (13) T waves; (14) U waves.

An electrocardiogram (ECG or EKG) is the measurement and graphical representation of electrical signals associated with the human heart. Applications of an ECG range from monitoring heart rate, heartbeat, heart rhythm to the diagnosis of specific heart conditions.

All ECGs pick up heart signals through electrodes connected externally to specific locations on the body i.e. arms and legs. Then the body generates the heart signals which are of few milli volts amplitudes. The specific locations of the electrodes allow the heart's electrical activity to be viewed from different angles, each of which is displayed as a channel on the ECG printout. The channels are commonly referred to as "leads" and the number of leads varies from 1 to 12 depending on the application .12-lead ECG are recorded using right arm ,left arm ,left leg, right leg ,and chest electrodes. They comprise a combination of electrodes . Bipolar limb leads derive signals from electrodes on the limbs, and are designated as leads I (RA to LA), II (RA to LL), and III (LA to LL). Unipolar leads are designated as aVR, aVL, and aVF, and can be designed by connecting RA, LA and LL respectively to non-inverting terminal and remaining two electrodes to inverting terminal of IA. The remaining six leads, V1, V2,…V6, are chest leads. In this paper we are using lead I ECG system.

The basic design of a bio-potential amplifier consists of an instrumentation amplifier. The amplifier should possess several characteristics, including high amplification, high input impedance, high common mode rejection ratio (CMRR) and the ability to reject electrical interference, all of which are needed for the measurement of these biopotentials.

## 1.2 CAD SYSTEM

The automatic classification of ECG signal has gained so much importance over the few decades. Apart from saving the lives of thousands, it helps cardiologist make decisions about heart signals more accurately and easily. The ECG is a biometric signal, which records the heart's electrical activity versus time; therefore it is an important diagnostic tool for assessing heart function. The use of computerized analysis of easily obtainable ECG waveforms can considerably reduce the doctor's workload.

**Computer-aided detection (CADe)**, also called **computer-aided diagnosis (CADx)**, are procedures in medicine that assist doctors in the interpretation of medical images. Imaging techniques in X-ray, MRI, and ECG diagnostics yield a great deal of information, which the radiologist has to analyze and evaluate comprehensively in a short time. CAD systems help scan digital images, *e.g.* from computed tomography, for typical appearances and to highlight conspicuous sections, such as possible diseases.

CAD is an interdisciplinary technology combining elements of artificial intelligence and computer vision with radiological image processing. A typical application is the detection of a tumor. For instance, some hospitals use CAD to support preventive medical check-ups in mammography (diagnosis of breast cancer), the detection of polyps in the colon, andlung cancer. Computer-aided detection (CADe) systems are usually confined to marking conspicuous structures and sections. Computer-aided diagnosis (CADx) systems evaluate the conspicuous structures.

CAD systems seek to highlight suspicious structures. Today's CAD systems cannot detect 100% of pathological changes. The hit rate (sensitivity) can be up to 90% depending on system and application. A correct hit is termed a True Positive (TP), while the incorrect marking of healthy sections constitutes a False Positive (FP). The less FPs indicated, the higher the specificity is. A low specificity reduces the acceptance of the CAD system because the user has to identify all of these wrong hits.

# CHAPTER 2

# LITERATURE REVIEW

In this chapter, various research papers are viewed, what was their purpose.

## 2.1 HARDWARE REVIEW

1. **Raman Gupta , Sandeep Singh , Kashish Garg , Shruti Jain "Indigenous Design of Electronic Circuit for Electrocardiograph" Vol. 3, Issue 5, May 2014 [4]**

This paper provides electronic implementation of electrocardiograph (ECG) circuit by using instrumentation amplifier (IA) as bio-potential amplifier in such a manner which reduces noise, common voltage, DC offset value and RF interference from the existing circuit.Noise and common voltage can be removed from ECG using driven right leg circuit or by using isolator circuit [4]. DC offset can be removed by using integrator as feedback. In the differential amplifier part of IA, we can add single resistance, T-network or inverter circuit with integrator to improve impulse response. By using filters, we can reduce RF interference. In this paper, we have used instrumentation amplifier as a bio-potential amplifier.

This paper explains the several techniques to reduce noise and to increase CMRR by using driven right leg circuit. With the help of high pass filter with gain G, we can reduce DC offset. RF interference can be reduced by filtering.

2. **Jyoti Athiya, International Journal of Engineering Science and Technology(IJEST)"AN IMPROVED ECG SIGNAL ACQUISITION SYSTEM THROUGH CMOS TECHNOLOGY" Vol. 4 No.03 March 2012 [5]**

This paper presents the design and realization of low power, high gain PC based system for ECG and data acquisition of a patient's heart condition. The advantage of this system is the use of standard CMOS process which will reduce the complexity and cost of the manufacturer. The system consists of three subsystems. Operational Amplifier based Pre-amplifier, ADC and USB interface device. High gain around 85 dB, low power dissipation of typically 0.683 mW and 61.5 degree phase-margin for stable closed loop operations were achieved. All design and simulation were done using Tanner Tool 0.5 μm technology.This paper has detailed the design of a CMOS process based ECG acquisition system using high speed Flash Type ADC. The design has determined that the circuit gain is 85 dB and power dissipation is 0.693mW. The circuit has good immunity from noise; good frequency response, improved phase margin (61.5 degrees) and produces an ECG output voltage such that it can be easily read by the ADC and thus the users. This schematic can be used for layout design. The preamplifier and ADCs can be designed using 0.18μm CMOS technology. The improved parameters from both the technologies can be optimized using soft computing algorithms such as fuzzy logic, neural network, BFO, genetic algorithm etc.

**3. R.Sandhiya, M.Thenmozhi, Dr.S.Mary Praveena Department of Electronics and Communication Engineering Sri Ramakrishna Institute of Technology "Design and Development Virtual ECG Machine with Problem Identification Using Labview" Volume 3 , Issue 3, Pages 08-11 ,2014 [6]**

The electrocardiogram (ECG) is a recording of the electrical activity of the heart which serves in diagnostic application. The ECG records the electrical activity that results when the heart muscle cells in the atria and ventricles contract. The ECG waveform is analyzed by the cardiologist in diagnosis various disease and condition associated with the heart. The purpose of this project is to develop a virtual ECG machine through Lab VIEW. The function of this system is to identify the various heart diseases with respect to change in QRS complex, P wave, and T wave of the patient. Three electrodes a signal from ECG amplifier is then interfaced with Lab VIEW software for the purpose of display and enabling for further signal processing. Signal is analyzed through Lab VIEW, the output of the system re connected to the human body, one on the right arm, left arm and other on the right leg as reference or ground to extract ECG signal from human body. The electrical signal appeared at the ECG input is typically less than 1mV and it is essential to amplify. An Amplifier circuit is designed to acquire and process the signal. The output of the circuit is recorded on a PC using Lab VIEW (DAQ card) interface card. Normally, the problem of amplification is signal has a lot of noise interference which appears at the input from ac power line, arrangement of component and other source. These interferences should be overcome.

The simulation of ECG signal using Lab VIEW and Hardware implementation of Virtual ECG Machine was obtained. From this machine the problem is identified by comparing both reference and test signal and it displays the type of the problem present in the patient.

4. **Abdul Qayoom Bhat, Vineet Kumar and Sunil Kumar Department of ECE LPU, Punjab, India "Design of ECG Data Acquisition System" Volume 3, Issue 4, April 2013 [7]**

ECG, electrocardiogram plays a vital role in the diagnosis of heart related problems. Good quality ECG is used by the doctors for identification of physiological and pathological phenomena. ECG is very sensitive in nature and even if small amount of noise interferes with it, the characteristics of the signal change. The main objective of the processing of ECG signal is to provide us the accurate, fast and reliable information of clinically important parameters like duration of QRS complex, the R-R interval, occurrence, amplitude and duration of P,R and T waves. This demands that the pre processed waveform should be free from noises, which in turn depends on the method of recording the ECG from the patient's body. In this paper two important methods of ECG data acquisition are enlisted, the 3-lead and the 12-lead ECG data acquisition systems.

The study of the cardiac arrhythmias is one of the most important aspects in the biomedical engineering as cardiac disease is one of the major causes of deaths in the world. The importance of the electrocardiogram in the diagnosis of cardiac diseases, demands the advances in the medical technology to develop low cost acquisition systems with increased efficiency. With the development of information technology, microelectronics and the communication technology, low power microprocessors, more efficient signal processors and obviously an efficient software platform/tool to analyse the results should be developed.

5. **Chia-Cheng Chiang ,Journal of Information Technology and Applications "Construction and Application of an Electronic ECG Management System" Vol. 2, No. 3, pp. 135-140, 2007 [8]**

Electrocardiogram (ECG) is one of the most used non-invasive and low-cost diagnostic examinations in clinical practice. Most hospitals use plain paper for ECG recording and storage. In modern hospitals, medical data need to be digitized for efficient management. The primary objective of this study was to develop an electronic 12-lead ECG database management system for a local hospital. The system was developed by using PHP, MySQL, and Matlab for file transmission, format conversion, record storage, and signal analysis of SCP-ECG records. Computerized ECG data were collected in a local hospital since August 2003. Open-source formats (XML, SVG, PNG) were transformed for further application and representation of ECG.The established electronic ECG management system can provide effective ECG informatics services to aid diagnosis for clinical physicians and ECG signal processing for researchers. In the future, studies will be done on other medical signals such as holter ECG, exercise ECG, patient monitor, and phenocardiogram. The establishing of an inter-hospital medical signal database will also be investigated.

**Table 2.1: Comparison between Journals**

| JOURNAL | DISCUSSION |
|---|---|
| Indigenous Design of Electronic Circuit for Electrocardiograph | Explains several techniques of reducing noise and CMRR . |
| An Improved ECG Signal Acquisition System Through CMOS Technology | Gives an improved version of the output of ECG with less noise and improved phase margin. |
| Design and Development Virtual ECG Machine with Problem Identification Using Lab view | The problem is identified by comparing both reference and test signal and displays the type of the problem present in the patient. |
| Design of ECG Data Acquisition System | Data acquisition for 3 lead and 12 lead systems. It was observed that low power microprocessors, more efficient signal processors and an efficient software platform/tool to analyze the results should be developed. |
| Construction and Application of an Electronic ECG Management System | A disease-specific database was established that physicians and researchers can review and analyze from ECG |

## 2.2 CAD SYSTEM REVIEW

**1. Mrs. M.D. Ingole, Mr. S.V. Alaspure , Dr. D.T. Ingole "Electrocardiogram (ECG) Signals Feature Extraction and Classification using Various Signal Analysis Techniques" January, 2014**

This paper presents the method to analyze ECG signal extract features and classification according to different arrhythmias. Cardiac arrhythmias which are found are Normal Sinus, Supraventricular Tachycardia, Right Bundle Branch Block, Left Bundle Branch Block, Ventricular Tachycardia. A dataset was obtained from a records set which were manually classified using MIT-BIH Arrhythmia Database Directory then features are extracted using DWT (Discrete wavelet transform) and classification is done according using various methods ANN (Artificial neural network), ANFIS (adaptive neuro-fuzzy inference system), SVM (State vector machine), & Statistical classifier.ECG pattern varies in many factors from person to person. These factors may be height of peaks, width of QRS complex, presence or absence of peaks, heart rate etc. It is found that the system is very robust and can identify and predict features even from highly abnormal ECG. The algorithm implemented for feature extraction selects affective features to distinguish each arrhythmia properly. Classification techniques applied and according to overall performance SVM has best results but having limitation of classifying output into two categories it cannot be used in practical system. Taking into account the overall performance of the system ANN is the best classification techniques in terms of accuracy, sensitivity and predictivity. In terms computation speed time required to give the output is negligible. Due to short processing time and relatively high accuracy of the proposed method, it can be used as a real-time arrhythmia classification system. High accuracy of the system makes it highly reliable and efficient.

**2.Muhammad Fahad Shinwari, Naveed Ahmed, Hassan Humayun, Ihsan ul Haq, Sajjad Haider and Atiq ul Anam "Classification Algorithm for Feature Extraction using Linear Discriminant Analysis and Cross-correlation on ECG Signals" International Journal of Advanced Science and Technology Vol. 48, November, 2012**

This paper develops a novel framework for feature extraction based on a combination of Linear Discriminant Analysis and cross-correlation. Multiple Electrocardiogram (ECG)

signals, acquired from the human heart in different states such as in fear, during exercise, etc. are used for simulations. The ECG signals are composed of P, Q, R, S and T waves.A novel framework is achieved and an algorithm based system is designed. It involved feature extraction techniques like Linear Discriminant Analysis and Cross- correlation. The doctors can now quickly extract the information from ECG signal from the heart patient with less reading errors. It would also reduce the doctors work load. So a precise and convenient

**3. Mansi Varshney, Chinmay Chandrakar , Dr.(Mrs)Monisha Sharma "A Survey on Feature Extraction and Classification of ECG Signal" International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering Vol. 3, Issue 1, January 2014**

This paper discusses various techniques earlier proposed in literature for extracting feature from an ECG signal. In addition this paper show the comparative study of method which is used to check the accuracy of overall system. The proposed schemes were mostly based on Artificial Neural Networks (ANN), Support Vector Machines (SVM), Multi layer perceptron (MLP) and Morphological descriptor time-frequency distribution (MD-TFD) and other Signal Analysis techniques. All these techniques and algorithms have their advantages and limitations. The above methods are used to extract features of ECG signal. The diagnosis of arrhythmia diseases is been done. All methods find the parameters of ECG signals. MLP method is best among the rest because it determines the hearts bundle branch which is widely used in the diagnosis.

**4. S.Karpagachelvi, Dr.M.Arthanari, Prof. & Head, M.Sivakumar "ECG Feature Extraction Techniques - A Survey Approach" (IJCSIS) International Journal of Computer Science and Information Security, Vol. 8, No. 1, April 2010**

ECG Feature Extraction plays a significant role in diagnosing most of the cardiac diseases. One cardiac cycle in an ECG signal consists of the P-QRS-T waves. This feature extraction scheme determines the amplitudes and intervals in the ECG signal for subsequent analysis. The amplitudes and intervals value of P-QRS-T segment determines the functioning of heart of every human. Recently, numerous research and techniques have been developed for analyzing the ECG signal. The proposed schemes were mostly based on Fuzzy Logic Methods, Artificial Neural Networks (ANN), Genetic Algorithm (GA), Support Vector Machines (SVM), and other Signal Analysis techniques. All these techniques and algorithms

have their advantages and limitations. This proposed paper discusses various techniques and transformations proposed earlier in literature for extracting feature from an ECG signal. In addition this paper also provides a comparative study of various methods proposed by researchers in extracting the feature from ECG signal. The examination of the ECG has been comprehensively used for diagnosing many cardiac diseases. Various techniques and transformations have been proposed earlier in literature for extracting feature from ECG. This proposed paper provides an over view of various ECG feature extraction techniques and algorithms proposed in literature. The feature extraction technique or algorithm developed for ECG must be highly accurate and should ensure fast extraction of features from the ECG signal. This proposed paper also revealed a comparative table evaluating the performance of different algorithms that were proposed earlier for ECG signal feature extraction. The future work mainly concentrates on developing an algorithm for accurate and fast feature extraction. Moreover additional statistical data will be utilized for evaluating the performance of an algorithm in ECG signal feature detection. Improving the accuracy of diagnosing the cardiac disease at the earliest is necessary in the case of patient monitoring system. Therefore our future work also has an eye on improvement in diagnosing the cardiac disease.

**Table 2.2: Comparison between Journals**

| JOURNAL | DISCUSSION |
| --- | --- |
| Electrocardiogram (ECG) Signals Feature Extraction and Classification using Various Signal Analysis Techniques | Presents the method to analyze ECG signal extract features and classification according to different arrhythmias |
| Classification Algorithm for Feature Extraction using Linear Discriminant Analysis and Cross-correlation on ECG Signals | This paper develops a novel framework for feature extraction based on a combination of Linear Discriminant Analysis and cross-correlation |
| A Survey on Feature Extraction and Classification of ECG Signal | This paper discusses various techniques of classification and shows the comparative study of method which is used to check the accuracy of overall system |
| ECG Feature Extraction Techniques - A Survey Approach | This proposed paper discusses various techniques and transformations proposed earlier in literature for extracting feature from an ECG signal. |

# CHAPTER 3

# HARDWARE OPTIMIZATION

The electrocardiogram, or ECG / EKG is a surface measurement of the electrical potential generated by electrical activity in cardiac tissue. Current flow, in the form of ions, signals contraction of cardiac muscle fibres leading to the heart's pumping action. Applications of an ECG range from monitoring heart rate, heartbeat, heart rhythm to the diagnosis of specific heart conditions. The basics of ECG measurement are the same for all applications, but there can be variation in the methods and representation of the circuit.

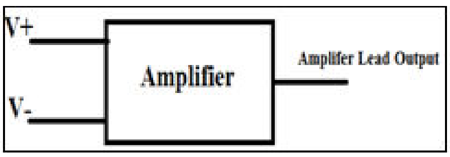
## 3. 1 CHALLENGES IN ECG MEASUREMENTS

1. Raw ECG signals are low in amplitude

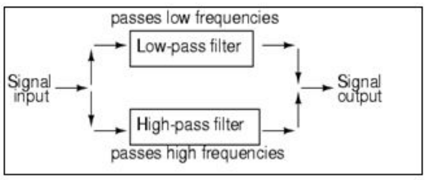
   **Amplitude:**
   P-wave — 0.25 mV
   R-wave — 1.60 mV
   Q-wave — 25% R wave
   T-wave — 0.1 to 0.5 mV

2. Problem with having poor signal quality: Hard to obtain physiological insight because
   - Noise due to muscle contractions,
   - common voltage,
   - DC offset value and
   - RF interference from an ECG circuit.

   General Solution:




(a)




(b)

**Fig 3.1: General Solution : a) for amplification of low voltage signal, b) for removal of noise, common voltage, DC offset value**

## 3.2 FUNCTIONAL BLOCK DIAGRAM

The existing functional blocks of ECG are shown in fig. 3.2 –

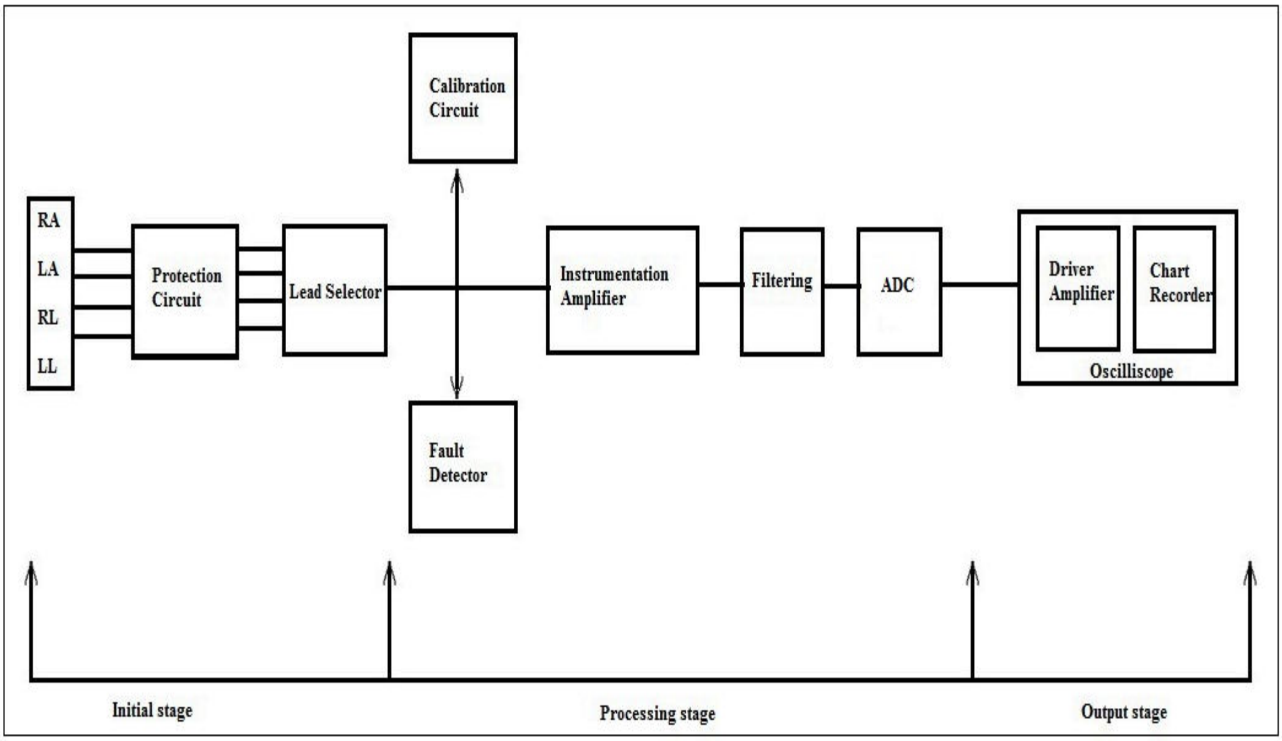



**Fig.3.2:Block diagram of ECG**

**3.2.1 PROTECTION CIRCUIT**: This circuit includes protection devices so that the high voltages that may appear across the input to the electrocardiograph under certain conditions do not damage it. The protection circuit includes a first switch that selectively connects a buffered monitoring point of the lead to the input of the telemetry circuit whenever a telemetry mode of operation is desired. A second switch switchably connects the buffered monitoring point to ground in the presence of any high level signals appearing on the lead, thereby preventing such high level signals from being applied to the telemetry circuit [4].

**3.2.2 LEAD SELECTOR**: Each electrode connected to the patient is attached to the lead selector of the electrocardiograph. The function of this block is to determine which electrodes are necessary for a particular lead and to connect them to the remainder of the circuit. It selects one or more leads to be recorded.

**3.2.3 CALIBRATION SIGNAL:** A 1 mV calibration signal is momentarily introduced into the electrocardiograph for each channel that is recorded.

**3.2.4 FAULT DETECTOR:** Another common non-heart signal is called lead-off. As the name suggests, it represents a fault situation. To detect lead-off, the ECG monitors the impedance between each of the differential-sensing electrodes and the lead-off electrode. Sometimes, this impedance measurement provides an input for measurements of respiration rate. This is detected by changes in thoracic impedance as the chest rises and falls [4].

**3.2.5 INSTRUMENTATION AMPLIFIER**: It is sometimes desired to amplify the difference of two signals. The difference amplifier may not meet circuit design criteria due to its low input resistance. Here, two non-inverting amplifiers may be combined with a difference amplifier in order to create an instrumentation amplifier as shown in fig.3.3 and its output voltage is given as (eq. 1).

$$V_{out} = \left(1 + \frac{2R_2}{R_1}\right)\left(\frac{R_4}{R_3}\right)(V_2 - V_1) \qquad (1)$$

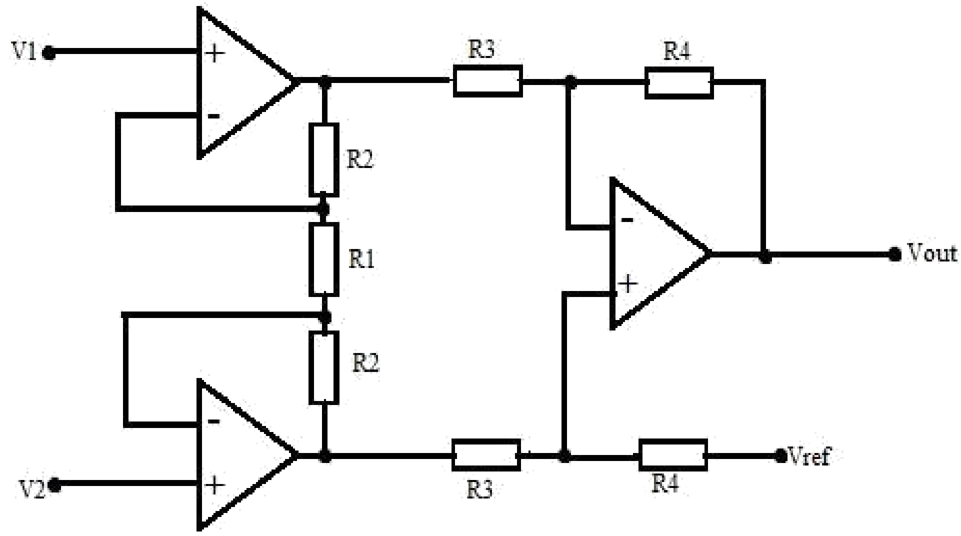



**Fig.3.3: Instrumentation amplifier**

**3.2.6 FILTERS**: Filters are used to remove unwanted noise. Especially in ECG work, the signal levels are very small (around 1mV), so it is necessary to use filtering to remove a wide range of noise. This noise may come from an unstable dc offset from electrode/body interface, muscle noise, mains hum (50/60Hz), electrical noise from equipment in the environment and from within the ECG equipment itself, such as from internal dc/dc converters.

**3.2.7 MEMORY SYSTEM:** Many modern electrocardiographs store electrocardiograms in memory as well as printing them out on a recorder. The signal is first digitized by an analog-to-digital converter (ADC), and then samples from each lead are stored in memory. Patient information entered via the keyboard is also stored. The microcomputer controls this storage activity.

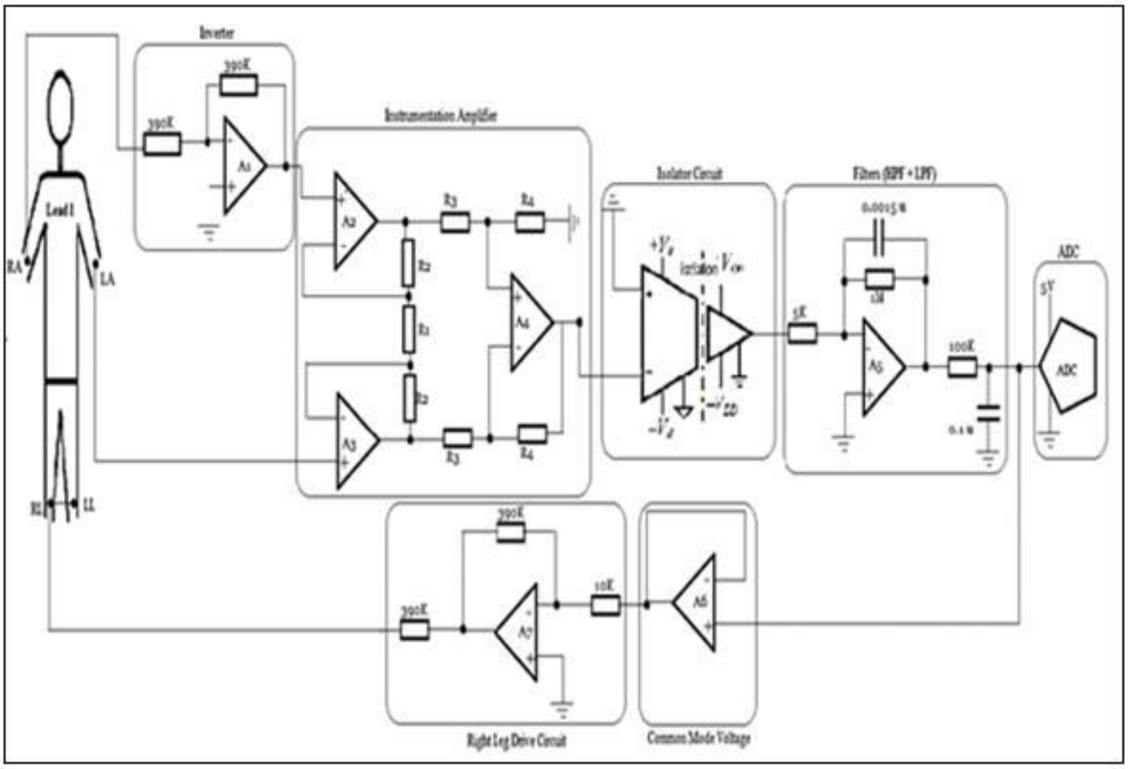


**Fig. 3.4: Existing Circuit diagram of an ECG [4]**

## 3.3 PROPOSED HARDWARE DESIGN

**3.3.1 REMOVAL OF INVERTER:** As for lead I, RA (right arm) is at negative terminal and LA (left arm) is at positive terminal so, instead of using inverter after RA we put this point at the negative terminal of instrumentation amplifier.

**3.3.2 FILTERS :** ECGs are subject to different kinds of noise internally and externally ,this noise may come from an unstable dc offset from electrode/body interface, muscle noise, mains hum (50/60Hz), electrical noise from equipment in the environment and from within the ECG equipment itself. As we know in ECG work, the signal levels are very small (around 1mV), so it is necessary to use filtering to remove a wide range of noise. We have included Filtering in the front end of the instrumentation amplifier because separate filters at the end are making circuit complex. The inclusion of filters at front end not only simplifies the circuit
but also produces a cleaner result because the input to instrumentation amplifier is now a filtered input with lesser effect of noise and interference.

**3.3.3 REMOVAL OF DC OFFSET :** At the output of difference amplifier we have cascaded a high pass filter to suppress the dc level present at the output. This circuit acts as high pass filter and used to eliminate DC level. Hence when feedback is applied, the DC component is eliminated at output voltage and whole stage thus behaves as a HPF with gain G.

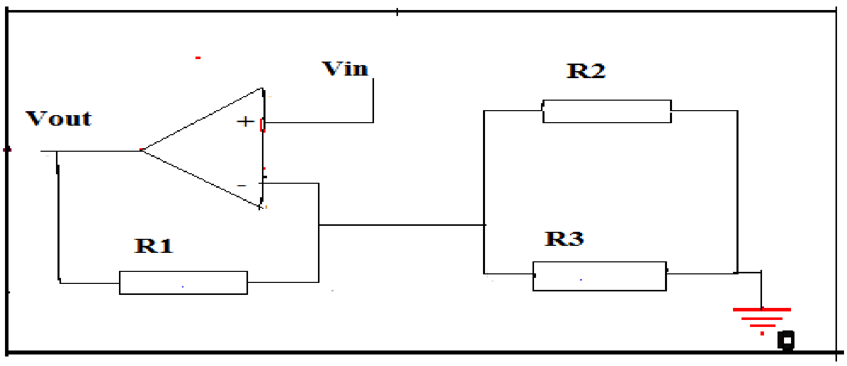



**Fig 3.5: DC offset remover circuit**

**3.3.4 RIGHT LEG DRIVEN CIRCUIT :** An important step in the ECG circuit designing is to plan right leg driven circuit. The motivation of the right leg drive circuit is to reduce interference from the amplifier. It is possible to amplify an ECG signal and create a DC common mode bias electrically off the inputs of the differential amplifier. However, when this is done there is extreme susceptibility to common mode interference which is where the need for the right leg drive comes in. The right leg drive inverts and amplifies the average common mode signal back into the patient's right leg . This action cancels 60 Hz noise from AC power and creates a cleaner ECG output signal. The more gain that can be used in the feedback loop also improves the common mode rejection ratio. Cancelling noise in this way relaxes the attenuation needed from the common mode rejection of the instrumentation amplifier. The right leg driven circuit also acts as a protection circuit. If an abnormally high voltage should appear between the patient and ground due to electrical leakage or other means, the auxiliary op−amp in the right leg circuit saturates. This effectively ungrounds the patient since the amplifier can no longer drive the right leg. The resistance R0 between the patient and ground is usually several MΩ and is therefore large enough to protect the patient. With a 5 MΩ resistor, for examples, and a supply voltage of 10 V, the amplifier will saturate at a current of approximately 2 µA. Since higher the gain of the op-amp of the right leg driven circuit, cleaner is the result so we have to increase the gain of the op amp. There can be two methods through which the gain of the op amp can be increased, either with the cascading of op-amp that is, hooked up one after another or increasing the value of feedback resistance. While implementing the former method for increasing gain what we observed was that there is a limit to the amplification that can be attained this way. When amplifiers were cascaded, the later circuits received noise at their inputs along with the signals. This noise had caused distortion. So we opted the later method for increasing the gain of the right leg driven circuit.

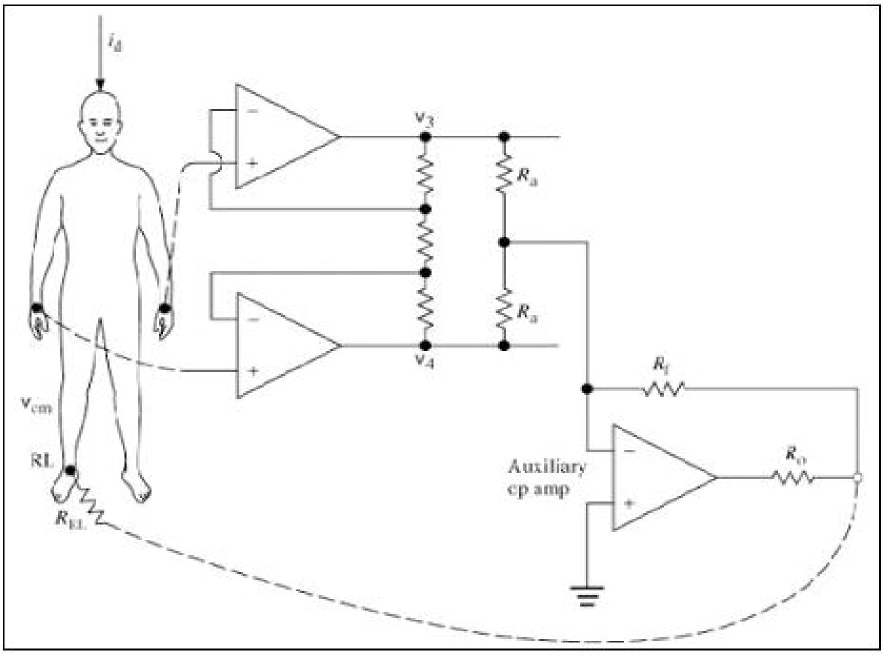



**Fig. 3.6: Right Leg Driven Circuit**

**3.3.5 PROPOSED CIRCUIT DIAGRAM :** Based on our understanding, we have come with the following circuit diagram-

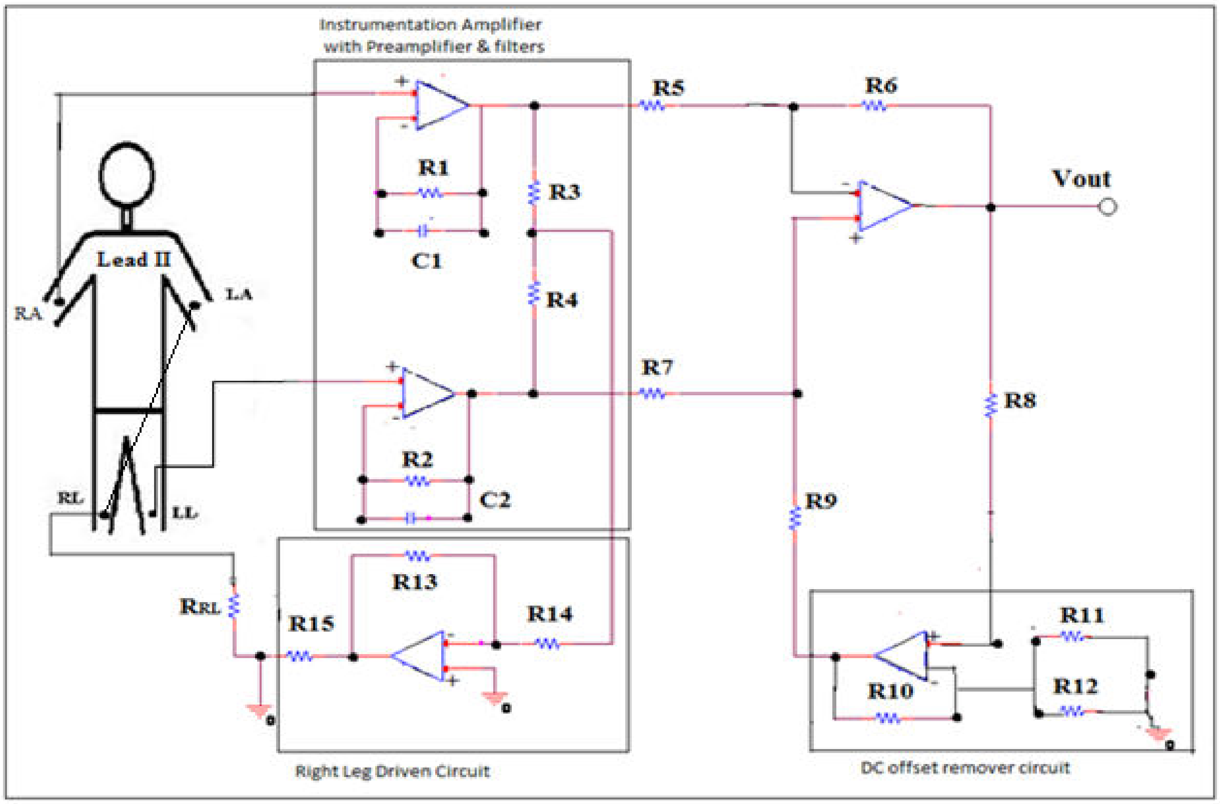



**Fig. 3.7: Proposed Circuit Diagram of an ECG**

### 3.4 OUTPUT

On applying a sinusoidal signal at the input terminals of the instrumentation amplifier the output obtained at the terminal Vout :

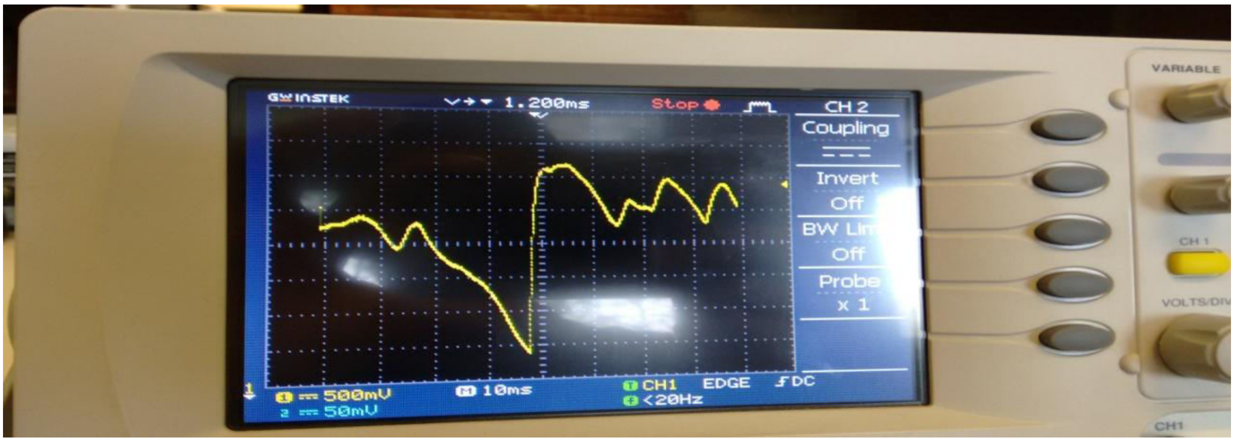



**Fig.3.8: Waveform received at the terminal Vout**

# CHAPTER 4
# THE CAD SYSTEM

## 4.1 PROPOSED CAD SYSTEM DESIGNS FOR CLASSIFICATION OF ECG WAVES

In the present work, a CAD system design has been proposed to classify the different ECG waves. For the design of this CAD system, a dataset of 83 ECG samples was taken. The CAD system consists of (*a*) feature selection module (*b*) feature extraction module (*c*) classification module. In the feature extraction module, for extracting the features two methods are employed (*1*) Morphological Features (*2*) Texture based features [14].We have employed the morphological method for the purpose of extraction.

Each feature set is normalized by using min-max normalization. The normalized feature set is then bifurcated into training and testing datasets. In the classification module, performance of four different classifiers namely k-NN, SVM and smooth support vector machine (SSVM) is evaluated to obtain the class of the unknown testing instances**.**

### 4.1.1 FEATURE SELECTION

In the selection process, dataset of ECG samples of patients are collected and the required lead's waveforms of the 12 lead system are selected.

### 4.1.2 FEATURE EXTRACTION

The feature extraction is the process used to transform the visually extractable and non-extractable features into mathematical descriptors. These descriptors are shape-based (morphological features) and the intensity distribution based (textural features).

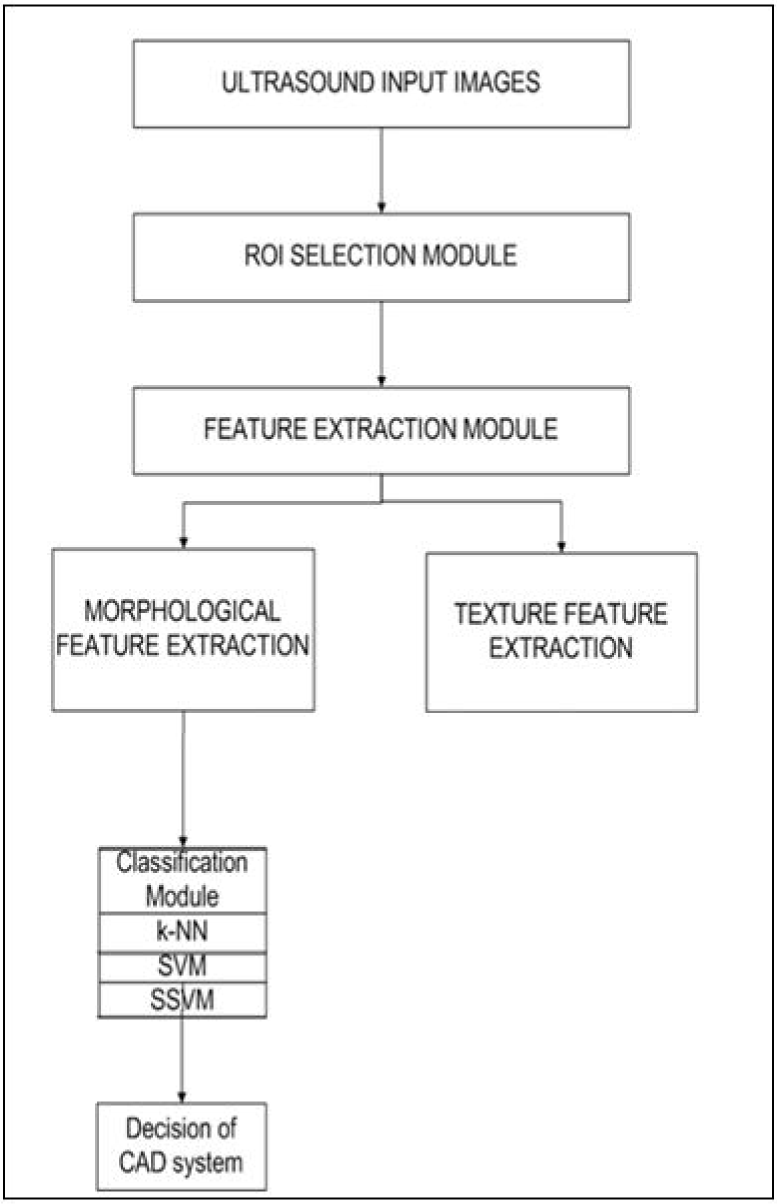



**Fig. 4.1: General framework of the proposed CAD system design**

#### 4.1.2.1 TEXTURAL FEATURES

*(a)* Statistical Methods

The statistical methods are used to extract the texture features from an image based on the gray level intensities of the pixels of that image. Based on the number of pixels used to compute the texture features, statistical methods can be classified into first-order statistics, second-order statistics and higher-order statistics.

(*b*) Signal Processing Based Methods

In these methods small convolution masks are used as filters and ROIs are convolved with these special filters so that the underlying texture characteristics are enhanced.

These filters determine the properties of the texture by performing averaging, edge detection, spot detection, wave detection and ripple detection

(*c*) Transform domain Methods

Feature extraction can also be done in the transform domain over various scales by using different multi resolution schemes like wavelet packet transform (WPT) and Gabor Wavelet transform (GWT). It is logical to compute texture features in the transform domain as human visual system processes images in a multi scale way and scale is considered to be an important aspect for analysis of texture [14-15].

#### 4.1.2.2 MORPHOLOGICAL FEATURES

Morphological methods include the shape based properties which includes Area, Perimeter, Convexity, Eccentricity, Extent, Hole Area Ratio (HAR) and Solidity are calculated over the entire class of normal and abnormal.

a) *Area*: It calculates the area of the curve.

b) *Perimeter*: It calculates the perimeter of the lesion.

c) *Convexity:* It is the ratio of the perimeter of the convex hull to the overall contour.

d) *Eccentricity:* It is the ratio of the minor axis to the major axis. Its value always lies between the 0 and 1.

e) *Extent*: It is the ratio of the pixels in the bounding box that are also in the region.

$$\text{Extent} = \text{Area}/\text{Bounding Area} \qquad (2)$$

f) Hole Area Ratio (HAR): It is the ratio of the area of the holes in a shape to the area of the whole shape.

$$\text{HAR} = \text{Area of holes in shape} / \text{Area of the shape} \qquad (3)$$

g) Solidity: It gives the extent to which the given shape is convex or concave.

$$\text{Solidity} = \text{Area} / \text{Convex Area} \qquad (4)$$

### 4.1.3 FEATURE CLASSIFICATION

Classification is a machine learning technique used to predict the class membership of unknown data instances based on the training set of data containing instances whose class membership is known. In this module different classifiers like

- k-NN
- SVM
- SSVM

are employed to classify the unknown testing instances of mammographic images different classes based on the training instances. To avoid any bias caused by unbalanced feature values the extracted features are normalized in the range [0, 1] by using min-max normalization procedure [19-27].

### 4.1.3.1 *K*-NEAREST NEIGHBOR (*K*-NN) CLASSIFIER

The *k*-NN classifier is based on the idea of estimating the class of an unknown instance from its neighbors. It tries to cluster the instances of feature vector into disjoint classes with an assumption that instances of feature vector lying close to each other in feature space represent instances belonging to the same class. The class of an unknown instance in testing dataset is selected to be the class of majority of instances among its *k*-nearest neighbors in the training dataset. The advantage of *k*-NN is its ability to deal with multiple class problems and is robust to noisy data as it averages the *k*- nearest neighbors .Euclidean distance is used as a distance metric. The classification performance of *k*-NN classifier depends on the value of *k*. In the present work, the optimal value of *k* and number of counts to be retained is determined by performing repeated experiments for the values of *k*. If same accuracy is obtained for more than one value of *k*, smallest value of *k* is used to obtain the result. The example depicting the classification of an unknown instance is shown in Fig.4.2. In the example the test sample (×) should be either classified to the class of cross (+) or to the class of dash (-). When $k = 3$, the algorithm looks for three nearest neighbors. In the considered example, the test sample is assigned to the class of cross (+) because there are two cross and only one dash inside the circle [14-15].

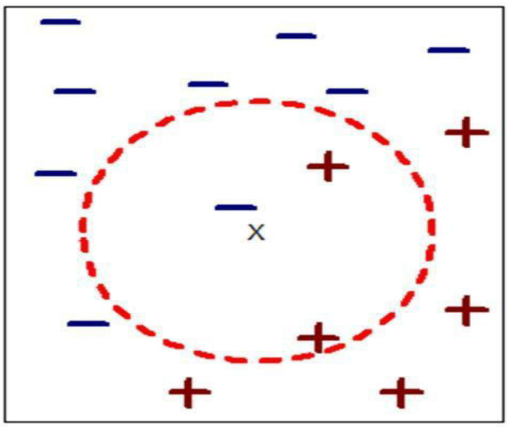


**Fig. 4.2: Example of k-NN classification for *k* = 3.**

**Note:** ×: unknown instance, +: Instance of class 1, –: Instance of class 2.

### 4.1.3.2 SUPPORT VECTOR MACHINE (SVM) CLASSIFIER

The SVM classifier belongs to a class of supervised machine learning algorithms. It is based on the concept of decision planes that define the decision boundary. In SVM, kernel functions are used to map the non-linear training data from input space to a high dimensionality feature space. Some common kernels are polynomial, Gaussian radial basis function and sigmoid. In the present work SVM classifier is implemented using LibSVM library and the performance of the Gaussian Radial Basis Function kernel is investigated. The critical step for obtaining a good generalization performance is the correct choice of regularization parameter C and kernel parameter . The regularization parameter C tries to maximize the margin while keeping the training error low. In the present work, ten-fold cross validation is carried out on the training data, for each combination of (C, ) such that, This grid search procedure in parameter space gives the optimum values of C and for which training accuracy is maximum [25-27].

### 4.1.3.3 SMOOTH SUPPORT VECTOR MACHINE (SSVM) CLASSIFIER

To solve important mathematical problems related to programming, smoothing methods are extensively used. SSVM works on the idea of smooth unconstrained optimization reformulation based on the traditional quadratic program which is associated with SVM .For implementing SSVM classifier, the SSVM toolbox developed by Laboratory of Data Science and Machine Intelligence, Taiwan was used. Similar to SVM implementation in case of SSVM also, ten- fold cross validation is carried out on training data for each combination. This grid search procedure in parameter space gives the optimum values of C and for which training accuracy is maximum.

## 4.2 PROPOSED CAD SYSTEM DESIGN

The block diagram of the proposed CAD system design for two-class ECG waves classification using morphological features is shown in Fig. 4.3.

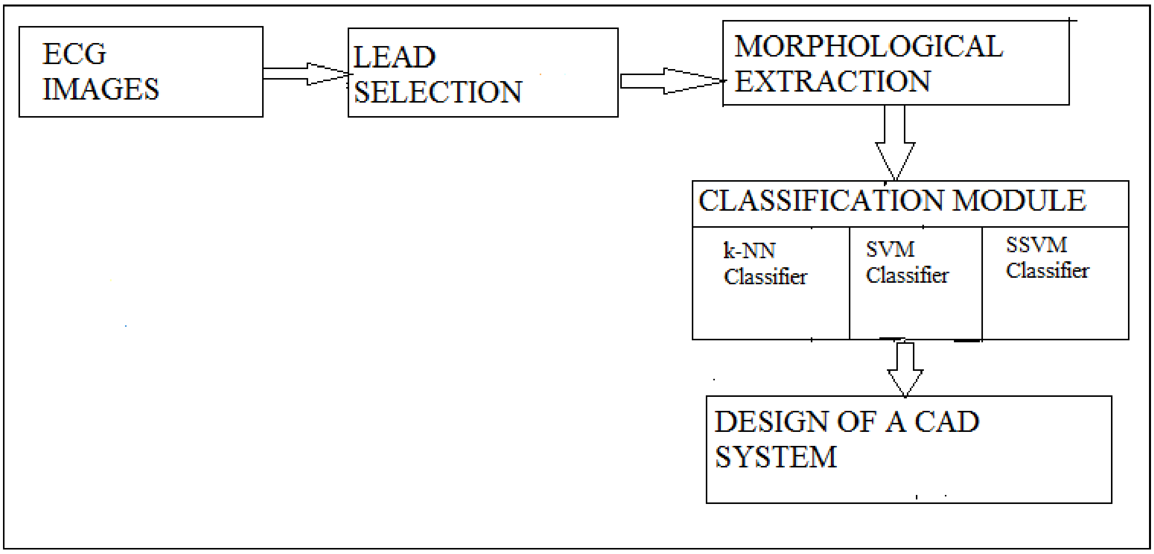



**Fig.4.3: Proposed CAD system design using morphological features**

The approach is implemented on the 83 samples collected from doctors. The samples of lead 2 were selected. Training and testing data was calculated using different morphological features are calculated like Area, Perimeter, Solidity, Convexity, Extent etc. Different classifiers like *k*-NN, SVM and SSVM were used on 48 training images (20 normal and 28 abnormal) and 35 testing images (15 normal and 20 abnormal) and confusion matrix was made.

The confusion matrix is a 2x2 matrix containing four components. These are:-

| **Confusion Matrix** | | Predicted | |
|---|---|---|---|
| | | Normal | Abnormal |
| Actual | Normal | ***p*** | ***Q*** |
| | Abnormal | ***r*** | ***S*** |

- *p* which gives the number of **correct** predictions that an instance is **normal**,
- *q* which gives the number of **incorrect** predictions that an instance is **abnormal**,
- *r* which gives the number of **incorrect** of predictions that an instance **normal**, and

- $s$ which gives the number of **correct** predictions that an instance is **abnormal**

Several standard terms are defined in this 2 class matrix:

- The ***accuracy*** **(*AC*)** is the ratio of the total number of predictions that were correct upon total number of predictions. It is given by the equation:

$$AC=(p+s)/(p+q+r+s) \tag{5}$$

- The ***Specificity*** **or *true abnormal rate*** **(*TAN*)** is the proportion of abnormal cases that were correctly identified, as calculated using the equation:

$$TAN = s/(r+s) \tag{6}$$

- The ***false abnormal rate*** **(*FAN*)** is the proportion of normal cases that were incorrectly classified as abnormal, as calculated by the equation:

$$FAN = q/(p+q) \tag{7}$$

- The ***Sensitivity*** **or *true normal rate*** **(*TN*)** is defined as the proportion of normal cases that were classified correctly, as calculated by the equation:

$$TN = p/(p+q) \tag{8}$$

- The ***false normal rate (FN)*** is the proportion of abnormal cases that were incorrectly classified as normal, as calculated by the equation:

$$FN = r/(r+s) \tag{9}$$

- Finally, ***precision*** **(*P*)** is the proportion of the predicted abnormal cases that were correct, as calculated using the equation:

$$P = s/(q+s) \tag{10}$$

The calculations of these features help us to classify the collected waveforms as normal or abnormal. The table 4.1 show us how we try to get the result of testing and training set by using different classifiers. The main idea is to divide them into four different categories using confusion matrix which gives us different results accordingly.

We define two categories which are Normal and Abnormal. Normal gives us the waveform results which are familiar to the normal ECG results obtained. The abnormal gives us the waveforms which are varied than the normal ECG due to some disorders caused by various reasons.

**Table 4.1: Classification performance of morphological features using *k*-NN, SVM and SSVM classifiers**

| Classifier | CM | | | OCA (%) | $ICA_N$(%) | $ICA_{AN}$ (%) |
|---|---|---|---|---|---|---|
| | | N | AN | | | |
| *k*-NN | N | 11 | 4 | 54.29 | 73.33 | 40 |
| | AN | 12 | 8 | | | |
| SVM | N | 9 | 6 | 68.57 | 60 | 75 |
| | AN | 5 | 15 | | | |
| SSVM | N | 5 | 10 | 71.43 | 33.33 | 100 |
| | AN | 0 | 20 | | | |

**Note**: CM: Confusion matrix, OCA: Overall classification accuracy; $ICA_N$: Individual class accuracy for normal class. $ICA_{AN}$: Individual class accuracy for abnormal class.

Then 83 samples of 12 lead systems were collected from various doctors out of whom lead 2 samples of the ECG waveforms are used to accurately classify and differentiate normal and abnormal waveforms using a CAD system. The CAD system produces a confusion matrix which shows that the highest OCA of 71.43 % is obtained from SSVM classifier. The highest individual class accuracy obtained for normal class is 73.33% from k-NN classifier and for abnormal class is 100% from SSVM classifier.
We can see that we get the various values in percentage of different terms for k-NN,SVM and SSVM classifiers. We find that the precision level for the result of k-NN is 66%, for SVM is 71% and for SSVM, the precision is 66%. Therefore, we get the best results from SVM classifier.

# CHAPTER 5
# CONCLUSION & FUTURE SCOPE

This work indicates the electronic implementation of ECG circuit by using instrumentation amplifier as bio-potential amplifier. This paper also explains the several techniques to reduce noise and to increase CMRR by using driven right leg circuit. With the help of high pass filter with gain G, we can reduce DC offset. RF interference can be reduced by filtering. At the end we have combined all the parts and made the existing circuit compact in size. Then 83 samples of 12 lead systems were collected from various doctors out of whom lead 2 samples of the ECG waveforms are used to accurately classify and differentiate normal and abnormal waveforms using a CAD system. The CAD system produces a confusion matrix which shows that the highest OCA of 71.43 % is obtained from SSVM classifier.

In this project, we have used lead II to perform all the operations, similarly other leads can also be evaluated using the same  proposed hardware. Here we have used the morphological feature extraction module. Other software extraction modules like the textural feature extraction can also be implemented to perform similar operations.

# LIST OF PUBLICATION

Akanksha Dhiman, Ambesh Singh, Shwetanjali Dubey, Shruti Jain, *"*Design of Lead II ECG Waveform and Classification Performance for Morphological features using Different Classifiers on Lead II *", Research Journal of Pharmaceutical, Biological and Chemical Sciences (RJPBCS)*,7(4): July-Aug 2016.

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