Masterarbeit

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Deep Learning of Cardiac Related Condition using a Non-Contact Multi-Sensor System

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Acknowledgments

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Abstract

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Inhaltsverzeichnis

Symbols

1 Abbreviations

AV	atrioventricular
ECG	electrocardiogram
RT	re-polarization time
SA	sino-atrial

Abkürzungen

H_2O	Wasser
RWTH Aachen	Rheinisch-Westfälische Technische Hochschule Aachen
DPO	Diplomprüfungsordnung

Physikalische Größen

v	Geschwindigkeit	$\frac{km}{h}$
t	Zeit	h

Mathematische Größen

M	mathematische Beispielgröße

Indizes

k	Anzahl der Prozeßschritte
$P_1...P_n$	Prozeßschritt P_1 bis P_n
V_{Ziel}	Zielvektor

Konstanten

π	3.141592653589

1 Introduction

1.1 Anatomy of Heart

The function of the heart is to pump the blood inside the body, which is stimulated by an electrical stimulus. The heart pumps blood thorugh the arteries, veins to the different parts of the body such as organs, muscles and tissues.

The heart is made up of 4 chambers, left and right atria, and left and right ventricles,as can be seen in Figure 1.1. The right atrium receives de-oxygenated blood from the whole body and pumps it into the right ventricle which then pumps the blood to the lungs for oxygenation. The left atrium receives oxygenated blood from the lungs and pumps it into the left ventricles which then pumps the oxygenated blood to the whole body. The aorta carries oxygenated blood to the different part of the body and the pulmonary arteries carry the de-oxygenated blood back to the lungs for oxygenation. The important point to note here is that, the blood flows to different organs via arteries and returns back to heart via veins.

The main components of the cardiac conduction system are:

1. Synoatrial (SA) Node
2. The Atrioventricular (AV) Node
3. Atrioventricular (AV) Bundle or Bundle of His
4. Right and Left Bundle Branches
5. Purkinje Fibers

The SA node, also known as sinus node, is a natural pacemaker of the heart which is located at the right atrium. It produces an electric stimulus at the rate of 60 to 100 signals per minute (under normal condition), which travels through the heart to make it pump the blood to the body. It initiates all heart beats and determine the heart rate. Electrical impulse from the SA node spread throughout the atrium which results in the contraction of the atrium. The AV node which is located on the other side of right atrium, near the AV valve. The purpose of this node is to serve as a gateway to the ventricles. It also delays the passage of electrical impulse to the ventricles. It is to ensure that, all the blood is ejected from the atria to the ventricles before the ventricles contract. The AV node then passes the signal to the atrioventricular (AV) bundle or bundle of His. The bundle is divided into two parts, right and left bundle branches to stimulate the right and left ventricles. The signal is then travels down to the Purkinje fibers where from the signal spreads upwards

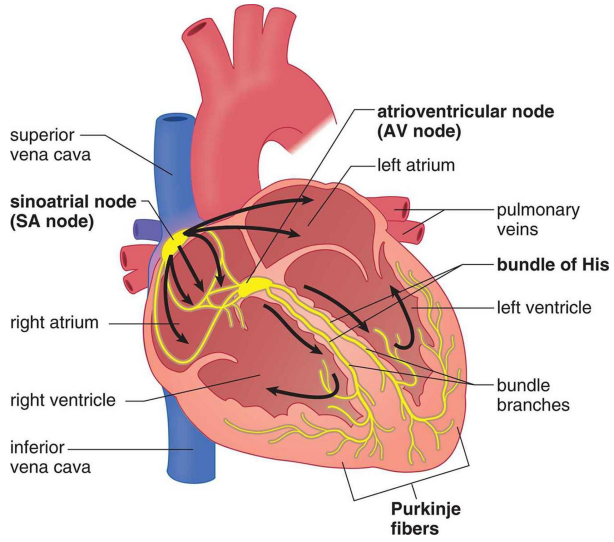


Figure. 1.1: The electrical activity of heart, taken from [Sch17].

throughout the ventricular myocardium. Each contraction of the ventricles represents one single heartbeat.

Each heartbeat is composed of two phases, known as systole and diastole. During **systole**, the heat muscles contract and the blood is pumped from ventricles to the different parts of the body. During **diastole**, the hearts muscles relax and the blood from atria flows into the ventricles. The pressure generated during systole from the ventricular contraction is high, whereas, during diastole, the muscle relaxation reduces this pressure.

The electrical activity of the heart can be detected in the form of Electrocardiogram by placing electrodes on the body surface. It is a powerful tool for diagnosing the status of patient's heart.

1.2 The Electrocardiogram

Electrocardiogram (ECG) is an essential tool for diagnosing the electrical activity of the heart. It is a simple, non-invasive procedure to measure the activity of the heart. Most of the tools available today to measure the ECG are based on the electrodes which are required to be attached to the body. The electrodes sense the electrical currents inside the body and transmit them to the ECG monitor. These currents are then transformed into appropriate waveforms which represent the heart's polarization and depolarization cycle. Different components of the wave represent activity of different parts of the heart.

In conventional 12-lead ECG, 10 electrodes or leads are attached to the patient's body and then the electrical activity of heart is viewed from 12 different perspectives. These

12 views of heart are captured by placing the electrodes on chest, wrists, and ankles. The main purpose of ECG is to identify any cardiac arrhythmia, ischemia, problems with heart rate or irregularities.

These 10 electrodes are divided into 2 groups.

1. 6 chest electrodes

2. 4 limb electrodes

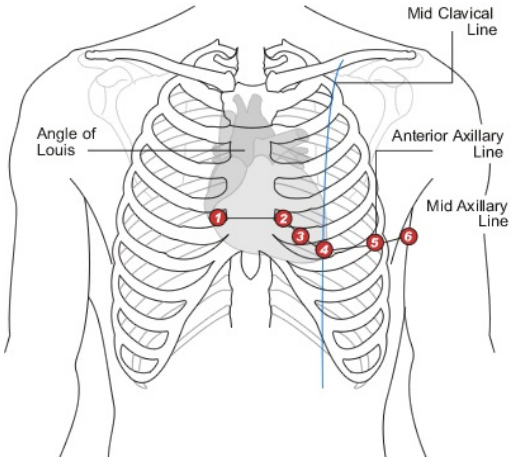


Figure. 1.2: The leads position on chest, taken from [The].

Chest Electrodes

The chest electrodes are denoted as "V" and they all are numbered from V1 to V6 as can be seen in Figure 1.2. The electrodes are positioned at the following locations on the chest:

- V1 - Fourth intercostal space (between ribs 4 and 5) on the right sternum
- V2 - Fourth intercostal space (between ribs 4 and 5) on the left sternum
- V3 - Placed in the middle of V2 and V4
- V4 - Fifth intercostal space (between ribs 5 and 6) at the mid-clavicular line
- V5 - Placed horizontally on anterior axillary line with V4
- V6 - Placed horizontally on Mid-axillary line with V4 and V5

The 3 different axillary lines **anterior axillary line**, **midaxillary line**, and **posterior axillary line** can be seen in Figure 1.3.

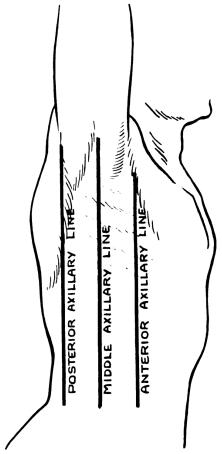


Figure. 1.3: The axillary lines on the right side of chest, taken from [Com17a].

Limb Electrodes

The 4 limb electrodes are denoted as RA, LA, LL, RL and there respective positions are:

- RA - Anywhere on right arm between shoulder and elbow, but avoiding thick muscles.
- LA - Symmetric to the RA position, but on left arm
- RL - Anywhere on right leg between the torso and the ankle
- LL - Symmetric to the RL position, but on left leg

The limb electrodes are shown in Figure 1.4

1.3 ECG Complex

ECG complex represents the electrical activity of heart during one cardiac cycle. A normal cardiac cycle consists of five waveforms labeled with P, Q, R, S and T as can be seen in Figure 1.5. The Q, R and S waves are referred to as one unit, the QRS complex. The ECG signal represents the conduction of electrical impulses from the atria to the ventricles. The important parameters in the ECG signal are:

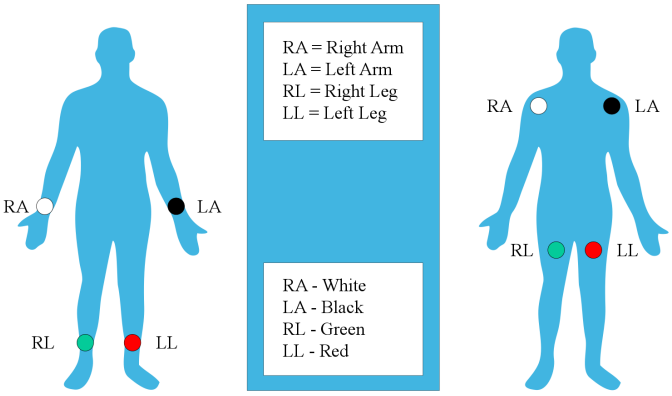


Figure. 1.4: The possible position of limb leads, taken from [Com17b].

1.3.1 P Wave

The P wave is the first component of the ECG signal. It occurs due to contraction of the both left and right atrium. This process also known as atrial depolarization. A normal P wave has following characteristics (in lead II):

- duration: 0.06 to 0.12 seconds
- amplitude: 2 to 3 mm high
- location: before the QRS complex

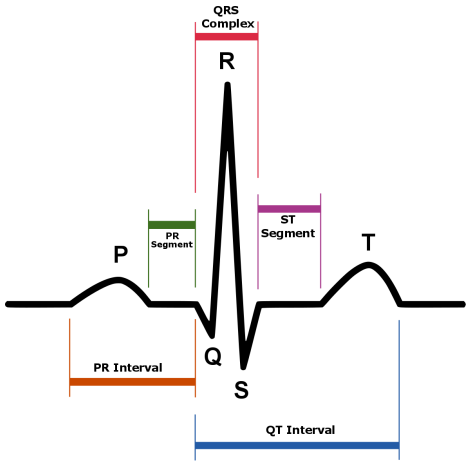


Figure. 1.5: The ECG signal, taken from [Com17c].

1.3.2 QRS Complex

The QRS complex follows the P wave and represents contraction of the both right and left ventricles. This contraction results in the blood ejection from the heart which eventually pumps into the arteries, creating a pulse. The Q and S waves are relatively very small whereas, R wave is comparatively very big. A normal QRS complex has following characteristics (in lead II):

- duration: 0.06 to 0.10 seconds
- amplitude: 5 to 30 mm high
- location: follows the P wave

1.3.3 T Wave

The T wave represents the ventricle re-polarization. It occurs during the last part of ventricle systole. The T wave has following characteristics (in lead II):

- duration: 0.10 to 0.25 seconds or greater
- amplitude: <5 mm high
- location: follows the QRS complex

1.3.4 PR Interval

The PR interval is the time interval between the end of contraction of the atrium and beginning the contraction of the ventricles. A normal PR interval has following characteristics:

- duration: 0.12 to 0.20 seconds
- location: From the beginning of P wave to the beginning of the QRS complex

1.3.5 ST Segment

The ST segment represents the end of ventricular depolarization and the beginning of the ventricles relaxation. The Point between the end of QRS complex and the beginning of ST segment is called as the J point. A normal ST segment has following characteristics:

- duration: 0.08 to 0.12 seconds
- location: From the end of QRS complex to the beginning of T wave

1.3.6 QT Interval

The QT interval is the time interval between the ventricular depolarization and repolarization. The QT duration varies according to the heart rate. Faster heart rate results in smaller QT interval whereas, slower heart rate may results in bigger QT interval. The bigger QT interval may results in irregular heart beat. A normal QT interval has following characteristics:

- duration: 0.36 to 0.44 seconds
- location: From the beginning of QRS complex to the end of T wave

1.4 Disadvantages of Attached Electrodes

While it is easy to monitor the electrical heart activity by placing the electrodes directly on the body but it has several disadvantages as well.

- It limits the patient's mobility.
- Discomfort for the patient as electrodes are directly attached to the body.
- Loss of cardiac monitoring in case if patient moves.
- Long contact of the electrodes may irritate the skin.

1.5 Noise in ECG Signal

Most of the time, the ECG signal is corrupted by the different types of noises and artifacts which changes the characteristics of the ECG signal [LD]. Hence, it becomes very difficult to extract the useful information from the signal. Following are the major noises which are present in the ECG signal.

1.5.1 Power Line Interference

Power line interference is a 60 Hz noise which is present in ECG signal because of improper grounding of the ECG equipment or interference from the nearby equipment. In order to remove this type of noise, a proper use of filter is required. A 60 Hz notch filter can be used to remove the power line interference. Figure 1.6 illustrates the 60 Hz power line interference in ECG signal.

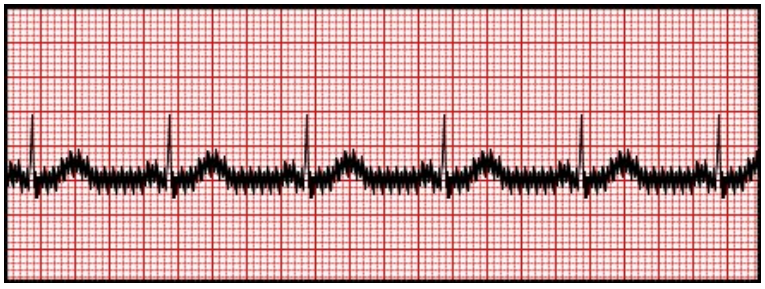


Figure. 1.6: 60 Hz AC Interference, taken from [mau17].

1.5.2 Baseline wander

Baseline wander is a low frequency components which corrupt the ECG signal because of breathing, body movements, dirty or loose electrodes , electrode impedance, etc. Generally they have frequency greater than 1 Hz. A high pass filter can be used to remove the baseline wander. The baseline wandering in ECG signal can be seen in Figure 1.7.

1.5.3 Muscle Noise

This type of noise is caused by muscle contractions besides heart which results in the change of heart electric potential [MG13]. When the other muscles near the electrodes depolarized and re-polarized, they also generate waves which is then picked up by the ECG. They generally occur in short time burst and have higher amplitude values than the

Figure. 1.7: Baseline wandering in ECG signal, taken from [mau17].

ECG signal. It can be removed using wavelet transform [MPS+11]. An example of ECG signal effected by muscle contractions can be seen in figure 1.8.

Figure. 1.8: ECG signal combined with muscle noise , taken from [mau17].

1.6 Arrhythmias

Irregularity in the heartbeat is known as arrhythmia (also called dysrhythmia) [med17]. During arrhythmia, a heart is out of normal rhythm and may feel like the heart is skipped a beat or beat with an irregular pattern. A normal heart rate lies between 60 to 100 beats per miutes and arrhythmia can occur with normal heart rate, slow heart rate (called bradycardia) in which heart rate is less than 60 beats per minute or with rapid heart rate (called tachycardia) in which heart beats faster than 100 beats per minute.

1.6.1 Causes of an Arrhythmia

Arrhytmia can be caused by one of the following reasons:

- Heart disease
- Electrolyte imbalance

- Changes in heart muscle
- After surgery effects

1.6.2 Types of Arrhythmias

The most common types of arrhythmias are:

Premature Ventricular Contraction

It is a type of arrhythmia in which the heart beat is initiated by the ventricles rather than the SA node. It is is generally refers as ßkipped beats". This is the most common type of arrhythmia which occurs with or without any heart disease. It could be the result of too much stress, usage of too much cocaine or restless. But sometimes it can also be caused by heart disease. Most of the time PVC are considered as harmless and rarely need a treatment.

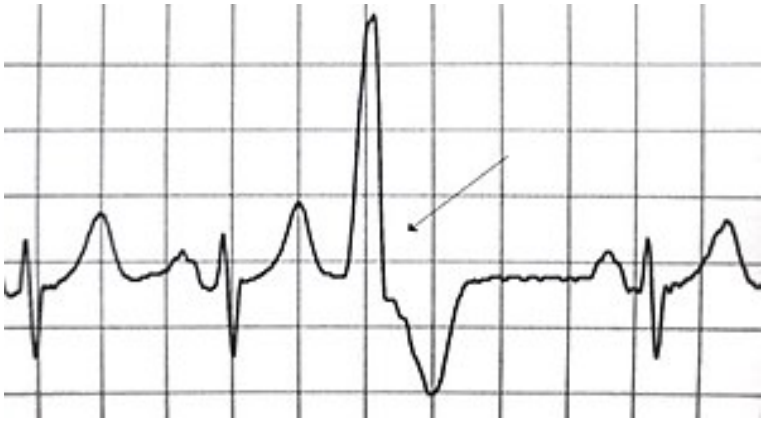


Figure. 1.9: Premature Ventricular Contraction, taken from [con17b].

Atrial Fibrillation

This type of arrhythmia caused by the abnormal contraction of the upper chamber of heart. During atrial fibrillation, the atria beats irregularly without any coordination with the ventricles. This could results in heart palpation, shortness of breath and weakness.

Atrial Flutter

This type of arrhythmia caused by problems in the heart's electrical system. It is similar to atrial fibrillation but rhythm in atria is more organized than the atrial fibrillation. The risk factors and causes of atrial flutter are similar to those of atrial fibrillation.

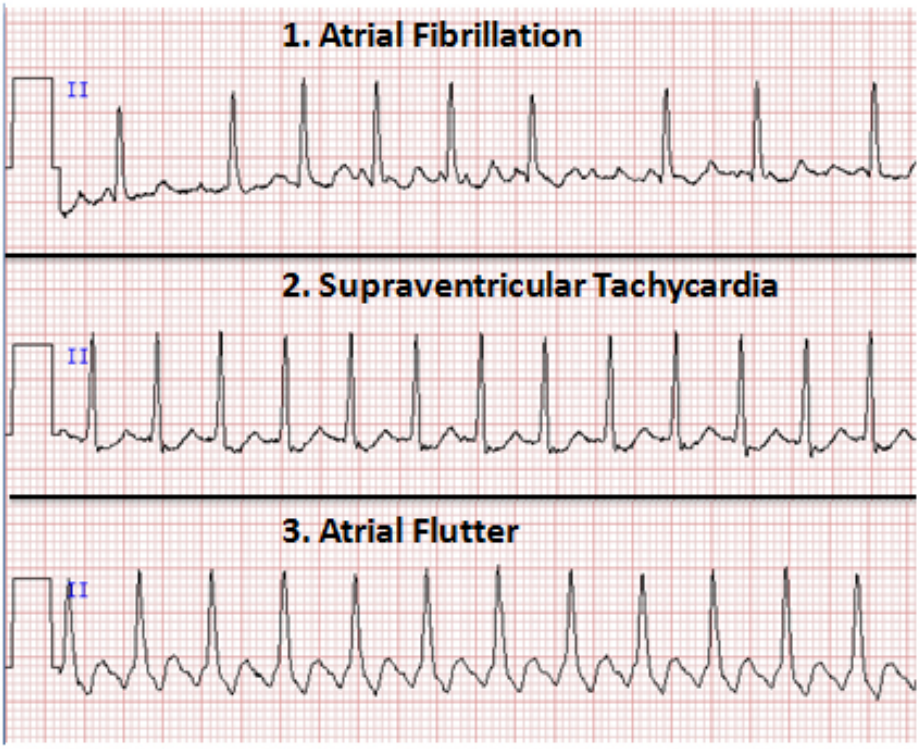


Figure. 1.10: Atrial Fibrillation vs Atrial Flutter vs Tachycardia , taken from [sum17].

Bradycardia

In this type of arrhythmia, the heart beats slower than the normal pace, usually less than 60 beats per minute. This could be because of the disease in electrical heart system.

Tachycardia

In this type of arrhythmia, the heart beats faster than the normal pace, usually, more than 100 beats per minute. when the heart beats too fast, it may not pump blood effectively to the body parts, which could result in shortness of breath.

Heart Block

In this type of arrhythmia, the heart beats slowly because of the delay or complete block of the electrical signal between the upper chambers and the lower chambers of the heart. It is also called atrial ventricular block (AV block).

Bundle Branch Block

Bundle branch block can be of two types, left bundle branch block (LBBB) and right bundle branch block (RBBB). In a normal heart, both bundles depolarized simultaneously and contract at the same time. In this type of arrhythmia, the affected bundle depolarized slowly whereas the un-affected bundle depolarized normally which results in a broader QRS complex, generally longer than 120 milliseconds duration. LBBB and RBBB can be seen in figure 1.11.

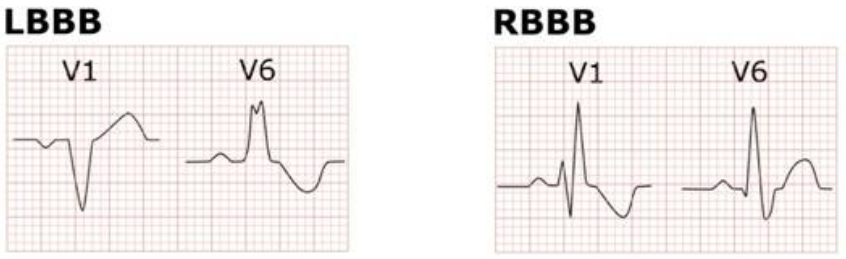


Figure. 1.11: LBBB vs RBBB , taken from [bil17].

2 ECG Signal and Data Processing

2.1 Devices

Wireless sensor devices and contact-less sensor devices are the current trends in the health informatics. The recent improvements in the sensor devices made it possible for the people to bring this idea into reality. When medical sensor devices are combined with cloud computing, it can be thought of as a complete solution for a health care system which not only can be used in hospitals but also can be utilized out of the hospital when the doctor is unreachable regardless of the patients location. Doctors will still be able to monitor his patient condition and according to the patient situation they can instruct the device, that is, attached to the patient, to take appropriate actions. One example can be thought of as a person running somewhere and during that he/she feels some heart pain. Sensors assess the patient's condition and immediately send some notification to the doctor. After looking at the conditions, he sends back a response to the devices, which then acts according to the instruction such as, injects some medicine into the patient body. It can also be used to keep track of the patient location so, in the case of emergency, an ambulance can be instructed to go there. Many of the sensors can be installed in the patient's surrounding, whereas, several sensors can be wearable. These sensors can monitor body temperature, respiration, heart rate, blood pressure, ECG, EEG, etc. Along with sensors, it might be possible that there are several actuators attached to the patient body which is activated by certain events such as, the rise of sugar level in blood.

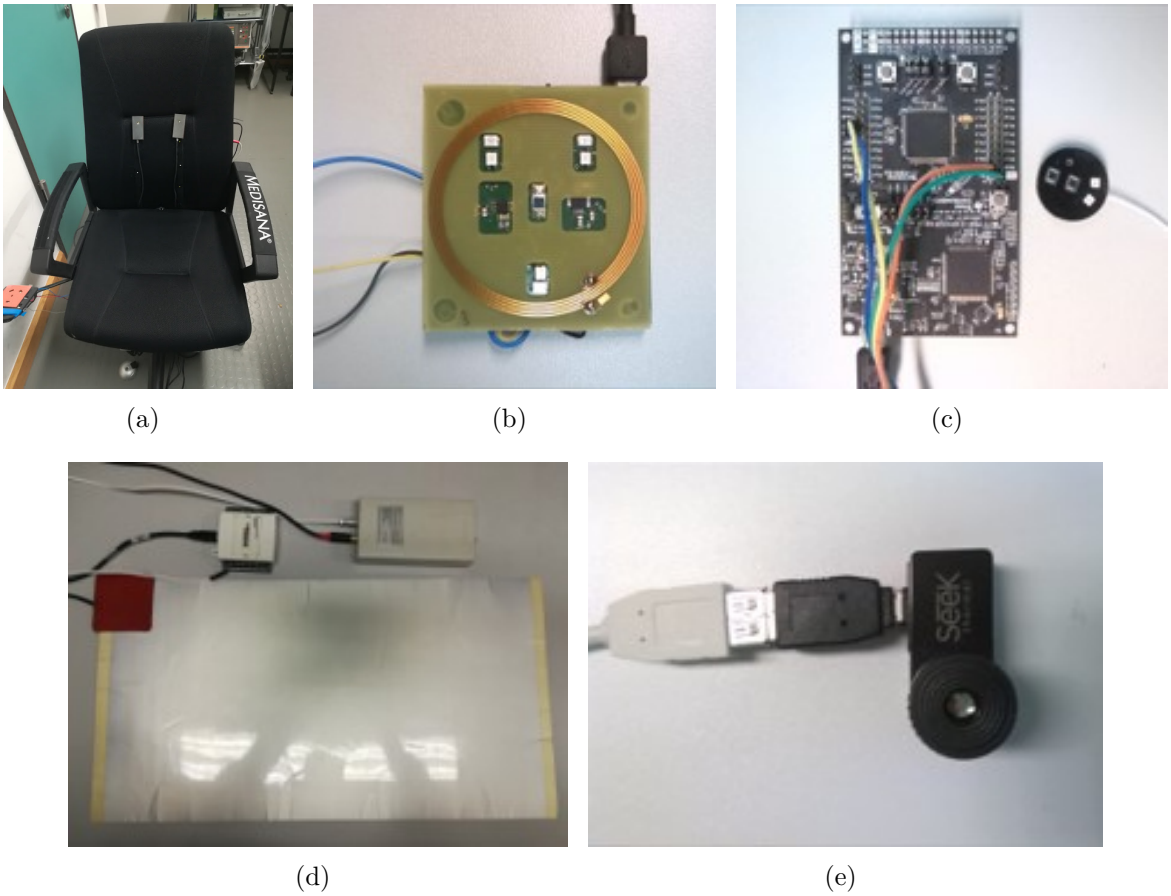
Multiple contact-less sensor devices are used to implement a system for the thesis, which collect data of the user and process that in real-time. The following devices are used in the implementation:

2.1.1 Magnetic Impedance Sensor

The magnetic impedance (MI) sensor measures the small changes in electrical resistance of the chest or different regions of the body. It uses a special electrodes which emit very low voltage electric current into the body. As the voltage level is very low, therefore, it does not interfere with the heart's electrical system. The MI sensor measures the resistance to the flow of current as it passes through the body via blood, as blood is a good conductor.

During systole, as the blood volume increases, impedance decreases. Similarly, during diastole, the blood volume decreases and the impedance increases.

The MI sensor provides 42 bytes of data packet, which splits into the attributes shown in table 2.1. The byte identifier of the sensor can be seen in the table 2.2.



(a) (b) (c)

(d) (e)

Figure. 2.1: A set of sensor devices: (a) an ECG sensor; (b) a MI sensor; (c) a PPG sensor; (d) a BCG sensor; and, (e) a thermal camera.

Tab. 2.1: Attributes of MI s ensor.

Attributes	**Size (Bytes)**
MI_RAW	4
MI	4
RED_RAW	4
ECG_RAW	4
IR_RAW	4
RED_AVG	4
ECG_AVG	4
IR_AVG	4
ACC_X	2
ACC_Z	2
ECG_REF	2
RESP_REF	2
BATTERY	2

There is an exception in the data packet when it contains *0x8101* or *0x8102*. In this case, the size of the data packet may vary according to the no. of count of the corresponding bytes. Moreover, the data packet should be examined and if it contains the corresponding bytes, the data packet should be modified and the bytes *0x8101* should be replaced with *0x81* and *0x8102* should be replaced with *0x82*. This modification has been done in order to differentiate it with the header and data packet identifier as they have the same value.

Tab. 2.2: Byte identifiers for the MI sensor.

2-Byte Identifier	Description
0x81	Header
0x82	Data Packet

2.1.2 Photoplethysmogram Sensor

The Photoplethysmogram (PPG) sensor is used to measures the variations in blood flow in the body which each heart beat. A PPG sensor uses a light source to illuminate the blood and a photo-detector to measures the variations in the light intensity associated with changes in the blood volume. The decrease in light intensity indicates the increase in blood volume and increase in light intensity indicates the decrease in blood volume.

The sensor provides the PPG signal with 4 different channels, a temperature, which is measured in Celsius and accelerometer coordinates. The size of the data changes according to the attributes which can be seen in the table 2.3. The frequency of the data packets changes according to the attributes. The temperature value is sent every one second, whereas, the frequency rate of PPG channels is 100 samples per second. Similarly, for the accelerometer coordinates, the data rate is 50 samples per second.

2.1.3 ECG Sensor

As described in section 1.2, the ECG signal is usually collected by placing electrodes directly on the body but it has several disadvantages as well, which is described in section 1.4. Therefore, non-contact capacitive electrodes has been used to collect the ECG signals of the person. Unlike traditional electrodes, which rely on galvanic contact, the capacitive electrodes are insulated from skin using dielectric material, such as, air gap, clothes, etc. The ECG signal propagates via skin to the dielectric material and then to the electrodes through a capacitive coupling. The major drawback of this approach is that it is very sensitive to body motion.

2.1.4 Ballistocardiogram Sensor

The ballistocardiogram (BCG) sensor measures the ballistic forces associated with cardiac contraction and ejection of blood. These ballistic forces are mainly measures by the electro-

Tab. 2.3: Attributes of PPG Sensor.

2-Byte Identifier	Attributes	Size (Bytes)	Data
0x0050	ppg (8 Bytes)	2	Channel 1
		2	Channel 2
		2	Channel 3
		2	Channel 4
0x0054	Temperature (2 Bytes)	2	Temperature
0x0041	Accelerometer coordinates (6 Bytes)	2	X Coordinate
		2	Y Coordinate
		2	Z Coordinate

mechanical film (EMFi) sensor which converts the mechanical energy into the electrical signal and vice versa. Most of the time, the EMFi sensing device is placed on a chair or bed, which measures the pressure associated with the cardiac activity.

2.1.5 Thermal Camera

A thermal camera is also used to measures the temperature of the person. A thermal seek camera is used for the implementation which captures the thermo temperature images, from which then the temperature is calculated.

2.2 ECG Signal Processing

QRS complex detection is the basis for processing ECG signal. Regardless of what application is required, the accurate detection of QRS complex is a pre-requisite for feature extraction. In order to detect the QRS complex accurately, it is necessary to detect the R-peak position correctly. Once the QRS complex is identified, further examination of the signal can be performed such as heart rate, arrhythmias, classification of ECG signal, ST segment etc. Moreover, P and T waves can be identified correctly.

The "QRS Complexïs the combination of Q, R and S waves and it represents the contraction of the ventricles. It plays a significant role in the detection of cardiac arrhythmias.

Many methods have already been proposed for the detection of QRS complex. These methods fall into 3 categories [PZZ10].

1. Filter Method
2. Artificial Intelligence Method
3. Wavelet transform Method

2.2.1 Filter Method

The filter method use bandpass filter to filter the ECG signal [PT85][RSN97]. In this method, QRS complex is intensify by suppressing the P and T wave. This method is generally very quick and take less time to implement. But the major drawback of this method is that the frequency band of QRS complex and of noise overlapping, affect its performance.

2.2.2 Artificial Intelligence Method

The detection of QRS complex using this method is fast, accurate and more robust. But in reality, it is very time consuming and difficult to implement [XHT92][Pie91][CSCB90]. Therefore, this method is not very popular and not widely used as compared to the other methods.

2.2.3 Wavelet Transform Method

Wavelet transform method becomes very popular in detecting the QRS complex. It is based on time-frequency analysis. It is very efficient and takes less to implement. Many people have already used wavelet transform for detecting the QRS complex. Yazhu Qiu [QDFM06] used Mexican-hat wavelet to detect ECG signal. In the proposed method, although the processing was fast, but it sometimes didn't detect the onset and offset of QRS complex accurately. Nevertheless, it is considered as simple, faster and easier to implement comparatively.

2.3 Wavelet Transform

Transformation is applied to signal in order to get further information about the signal which is not easily available in the raw signal. Most of the time, signals are generally represented in time domain, but in many cases, the important information is hidden in the frequency domain of the signal. Fourier transform is a tool which allows to view the frequency components of the signal. But the major drawback of this transformation is that, a signal can not be viewed in both time and frequency domain at once. Thus, it makes hard to distinguish which frequency components exist at any instance of time. Therefore, a tool was required which helps to view signal in both domain.

Wavelet transform is a very useful tool for analyzing the signal simultaneously in both time and frequency domain [Add17]. It uses a little wavelike functions known as ***wavelets***. Wavelets are used to transform a signal into another representation where signal information can be viewed in a more useful form and this process is known as *wavelet transform*.

Generally there are two operations involved with wavelet. Either they can be stretched or squeezed or can be translated to other locations on the signal and if the wavelet matches the shape of the signal at specific location or scale, it produces a large transform value. And similarly, if the signal and the wavelet do not correlate, it produces a low transformed value. There is a single function called "mother wavelet"which is stretched or translated to produce a family of basis functions known as "daughter wavelets". It is defined as:

$$\Psi_{a,b}(t) = \frac{1}{\sqrt{|a|}}\Psi\left(\frac{t-b}{a}\right), \quad a, b \in \mathbb{R}, a \neq 0 \tag{2.1}$$

where a is the scaling parameter which measures the degree of scale, and b is the translation parameter which measures the time location of the wavelet. If $|a| < 1$, then it mainly corresponds to higher frequencies. And on the other hand, if $|a| > 1$, it corresponds to lower frequencies. It is important to note here that the variation in time and frequency scale of wavelet is supervised by the Heisenberg uncertainty principle. At large scale, the time domain is not very clear, whereas, frequency domain is much finer. As the scale decreases, the frequency domain becomes worse, whereas, time domain becomes finer.

The wavelet transform is defined as:

$$X_W(a,b) = \frac{1}{\sqrt{|a|}}\int_{-\infty}^{\infty} h * \left(\frac{t-b}{a}\right)x(t)\mathrm{d}x \tag{2.2}$$

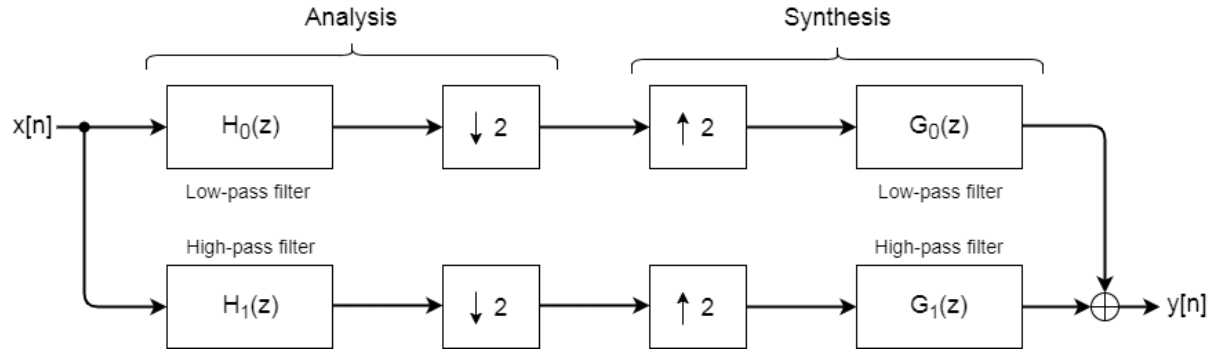


Figure. 2.2: Two-channel filter bank

2.3.1 Continuous Wavelet Transform

2.3.2 Discrete Wavelet Transform

In this thesis, Biorthogonal Spline wavelet is used for detecting the ECG signal. This approach is based on the modulus maxima of zero point to detect the singular point.

For multi-resolution decomposition of signals, a dyadic DWT (discrete wavelet transform) is used where all bandpass filters have different frequency resolution. This is done by first using low-pass and high-pass filters to split the signal into low and high frequency components.

2.4 Biorthogonal Wavelet Transform

2.5 Biorthogonal Spline Wavelet Filter Construction

Let say, $H_0(z)$ and $H_1(z)$ are low-pass filters in the analysis filter bank (decomposition) and $G_0(z)$, $G_1(z)$ are high-pass filters in the synthesis filter bank (reconstruction), as can be seen in the figure 2.2. After passing the input signal $X[n]$ from the filters, the resulting signal is first down-sampled by 2 and then up-sampled by 2 respectively, producing the final output signal $Y[n]$. It is worth to note here that $Y[n]$ is the reconstructed signal.

The idea is to determine H_0, H_1, G_0 and G_1 such that, $Y[n]$ is just a delayed version of input signal $X[n]$. This is called as perfect reconstruction filter bank. A perfect reconstruction filter bank is also known as “biorthogonal“ and the associated filters as biorthogonal filters.

After passing the input signal from the channel 1, it will produce:

$$Y_0(z) = \frac{1}{2}G_0(z)[H_0(z)X(z) + H_0(-z)X(-z)] \tag{2.3}$$

Similarly, for the 2nd channel, it will produce:

$$Y_1(z) = \frac{1}{2}G_1(z)[H_1(z)X(z) + H_1(-z)X(-z)] \tag{2.4}$$

Adding the output of these 2 channels will produce the final output.

$$\begin{aligned} Y(z) &= Y_0(z) + Y_1(z) \\ &= \frac{1}{2}G_0(z)[H_0(z)X(z) + H_0(-z)X(-z)] + \frac{1}{2}G_1(z)[H_1(z)X(z) + H_1(-z)X(-z)] \end{aligned} \tag{2.5}$$

Arranging $Y(z)$ in such a way so that, one part should depends on $X(z)$ and the other part on $X(-z)$. We get,

$$Y(z) = \frac{1}{2}[G_0(z)H_0(z) + G_1(z)H_1(z)]X(z) + \frac{1}{2}[G_0(z)H_0(-z) + G_1(z)H_1(-z)]X(-z) \tag{2.6}$$

The important thing to note here is that, $X(-z)$ is the aliasing part, and $X(z)$ is the distortion part.

2.5.1 Design of Biorthogonal Spline Wavelet Filter

The perfect reconstruction for filter bank can be achieved if the following two conditions are satisfied.

1. No aliasing:
$$G_0(z)H_0(-z) + G_1(z)H_1(-z)]X(-z) = 0 \tag{2.7}$$

2. No distortion:
$$G_0(z)H_0(z) + G_1(z)H_1(z) = mz^{-k} \tag{2.8}$$

where m is constant and k is a time delay.

In order to satisfy condition 1 i.e., to get rid of aliasing, one can do:

$$\begin{aligned} G_0(z) &= H_1(-z), \\ G_1(z) &= -H_0(-z) \end{aligned} \tag{2.9}$$

So now, we only need to find two filters values instead of four. Lets assume that,

$$P_0(z) = G_0(z)H_0(z) \tag{2.10}$$

From equation 2.9 and 2.10, we can deduce:

$$G_1(z)H_1(z) = -H_0(-z)G_0(-z) = -P_0(-z) \tag{2.11}$$

After getting these values, the condition 2 (no distortion) can be re-written as:

$$P_0(z) - P_0(-z) = mz^{-k} \tag{2.12}$$

In the above equation, only one filter value is required i.e., $P_0(z)$ (also called half band filter). The perfect reconstruction conditions naturally implies that the both analysis and the synthesis filters are biorthogonal to each other, i.e., a biorthogonal filter bank makes sure that synthesis filter bank is the inverse of analysis filter bank.

2.5.2 Steps for Designing FIR Filter Bank

The steps for designing FIR filter bank can be summarized as:

1. Design a low-pass filter for $P_0(z)$ which satisfy the equation 2.13. One option is to use Daubechies function to find the value for $P_0(z)$:

$$P_0(z) = (1 + z^{-1})^{2p}Q(z) \tag{2.13}$$

   where p can be any integer and $Q(z)$ be a polynomial of degree $(2p - 2)$.

2. Factorize $P_0(z)$ to get the values for $G_0(z)$ and $H_0(z)$.

3. Find the filter coefficients for high-pass filters using the equations 2.9.

Lets assume that, $P = 2$ and and $Q(z)$ be a quadratic polynomial $(a + bz^{-1} + cz^{-2})$. Substituting these values in equation 2.13 will produce a polynomial of degree z:

$$P_0(z) = (1 + z^{-1})^4(a + bz^{-1} + cz^{-2}) \tag{2.14}$$

Substituting $a = c = -\frac{1}{16}, b = 4$, we get:

$$P_0(z) = \frac{(1 + z^{-1})^4(-1 + 4z^{-1} + z^{-2})}{16} \tag{2.15}$$

Factorizing $P_0(z)$ to get $H_0(z)$ and $G_0(z)$. Lets say we get:

$$\begin{aligned} H_0(z) &= \frac{(1 + z^{-1})^3}{4} \\ &= \frac{(1 + 3z^{-1} + 3z^{-2} + z^{-3})}{4} \end{aligned} \tag{2.16}$$

and

$$\begin{aligned} G_0(z) &= \frac{(1 + z^{-1})(-1 + 4z^{-1} + z^{-2})}{4} \\ &= \frac{(-1 + 3z^{-1} + 3z^{-2} - z^{-3})}{4} \end{aligned} \tag{2.17}$$

Then by equation 2.13, we have:

$$\begin{aligned} H_1(z) &= G_0(-z) \\ &= \frac{(-1 - 3z^{-1} + 3z^{-2} + z^{-3})}{4} \end{aligned} \tag{2.18}$$

and

$$G_1(z) = -H_0(-z) \\ = \frac{(-1 + 3z_3^{-1}z^{-2} + z^{-3})}{4} \tag{2.19}$$

Therefore, the filter coefficients are:

$$\begin{aligned} h_0(0) &= \frac{1}{4} & h_0(1) &= \frac{3}{4} \\ h_0(2) &= \frac{3}{4} & h_0(3) &= \frac{1}{4} \\ h_1(0) &= \frac{-1}{4} & h_1(1) &= \frac{-3}{4} \\ h_1(2) &= \frac{3}{4} & h_1(3) &= \frac{1}{4} \\ g_0(0) &= \frac{-1}{4} & g_0(1) &= \frac{3}{4} \\ g_0(2) &= \frac{3}{4} & g_0(3) &= \frac{-1}{4} \\ g_1(0) &= \frac{-1}{4} & g_1(1) &= \frac{3}{4} \\ g_1(2) &= \frac{-3}{4} & g_1(3) &= \frac{1}{4} \end{aligned} \tag{2.20}$$

2.6 Mallat's Algorithm

The binary wavelet transform or dyadic wavelet transform of a signal $f(n)$ can be calculated by using Mallat algorithm [MH92] as follows:

$$s_{2^j} f(n) = \sum h_k s_{2^{j-1}} f(n - 2^{j-1}k), \tag{2.21}$$

$$w_{2^j} f(n) = \sum g_k s_{2^{j-1}} f(n - 2^{j-1}k). \tag{2.22}$$

where, $s_{2^0} f(n)$ is the original signal to be processed. In our case, it is ECG signal. $w_{2^j} f(n)$ is the wavelet coefficient i.e., the dyadic wavelet transform of the signal and $s_{2^j} f(n)$ is the approximation coefficient for the scale j. h_k and g_k are the coefficients of low-pass filter and high-pass filter respectively which are defined in the equation 2.20. The signal is

decomposed into several frequency bands at certain scale j and then the frequency bands which have noises, are set to zero. And by using the synthesis filters, the de-noised signal can be reconstructed.

2.7 Using Wavelet Transform to Identify Singular Point of QRS Complex

2.7.1 Feature Extraction Using Wavelets

Most of the time, the important information of signal resides on the irregularities and singularities of the signal and wavelets can be used to extract those information. When the filter bank and wavelets are chosen appropriately, the wavelets are able to capture the irregularities and singularities of the signal. Mathematically, the local singularity of a signal is measured using Lipschitz exponent, the inflection points of signal $f(n)$ appear as extrema at $\frac{df(t)}{dt}$ and as zero crossing points at $\frac{d^2f(t)}{dt}$. Therefore, Mallat has suggested to use a wavelets which is the first derivative of a scaling function.

2.7.2 Lipschitz Exponent

The functions which are infinitely differentiable are described as smooth or with no singularity [XCWX13]. If at some point, the function has non continuous derivative, then the point is known as singular point. The Lipschitz exponent is a good application to measure the singularity of the point.

2.7.3 Relationship between Lipschitz Exponent and Modulus Maximum

Mallat has shown in his paper [MH92] that, all signals and noise in their may be completely represented by their singularities and singularities are generally referred in terms of Lipschitz exponents. If a signal is n times differentiable at time t_0, then its nth derivative is singular and it will be described as Lipschitz α where $\alpha > n$. If a signal is continuously differentiable at time t_0, then it is non-singular and has Lipschitz exponent 1.

Signals can have negative Lipschitz exponent as well. For example, many signals have singularities with positive Lipschitz exponents whereas, noise has negative Lipschitz exponent. Therefore, having this mind, it makes it possible to separate a signal from noise if the singularities of noise can be detected and separated.

Tab. 2.4: Wavelet Transform ECG Signal Frequency Range

Transform Scale	Frequency Range (Hz)
2^1	90.0~180.0
2^2	29.92~84.24
2^3	1.52~38.88
2^4	5.76~19.44

Generally, it is known that the singularity of a signal is directly proportional to the Lipschitz exponent. Therefore, as the transform scale increases, the wavelet transform modulus maxima will also get increases (Lipschitz exponent > 0) and similarly it will decreases when Lipschitz exponent < 0. It can be seen that R wave in the original ECG signal appears as a pair of positive and negative extreme in the waveform which resulted after the decomposition of wavelet transform.

2.8 Dataset

The MIT-BIH Arrhythmia dataset is used for the implementation of the system. It contains 48 hours of recording of 47 subjects. Each record contains 2 signals, namely MLII and V5, with a recording of 30 minutes duration. The sample rate for the recording is 360 samples per second per channel with 11 bit resolution over a 10mV range. Each record consists of 3 files:

- Header file (.hea): It contains information such as number of samples, sampling frequency, ECG signal format, number of ECG leads and their types, patient‘s history and the detailed clinical information.
- ECG signals (.dat): It contains the original signal values of both MLII and V5 leads. The signals from MLII lead are considered only for the analysis.
- Attribute file (.atr): It contains the annotation information of the ECG signal, annotated by the doctors.

There is a specific python package available, wfdb-python for reading the data from the MIT-BIH dataset. The ECG signals of one of the patients can be seen in Figure 2.3. It contains 2 signals, namely, MLII and V5.

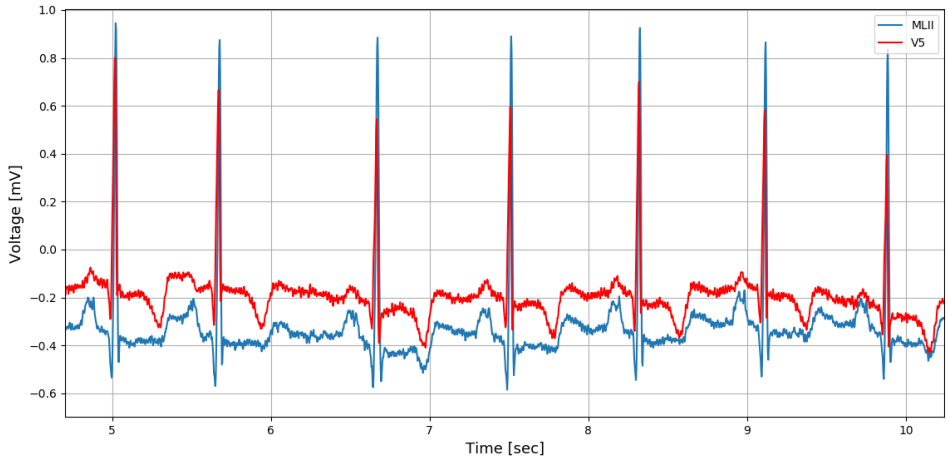


Figure. 2.3: The ECG signals from MIT-BIH dataset.

The signals are in a raw form and need to be processed before they can be used. Most of the time, the signals are also contaminated with noise, baseline drift, etc. and they are required to be cleaned to get the correct values.

2.9 Preprocessing

The ECG signal is required to be processes before it is analyzed, as it contains several noises and artifacts. The most common noises are the baseline wander and 60Hz power interference. Baseline wander generally appears because of the subject respiration or the body movements. It has a frequency range of 0Hz to 0.5Hz. The power interference affects the signals because of the electrical appliances in the surrounding.

Two different methods has been used to remove the noise and artifacts from the signal in the system implementation.

1. Wavelet Transform Method

2. Band-pass Filter Method

2.9.1 Wavelet Transform Method

The wavelet transform is a very interesting technique for analyzing the signal in the time-frequency domain. It distributes the signal in such a way that the resulting block is well

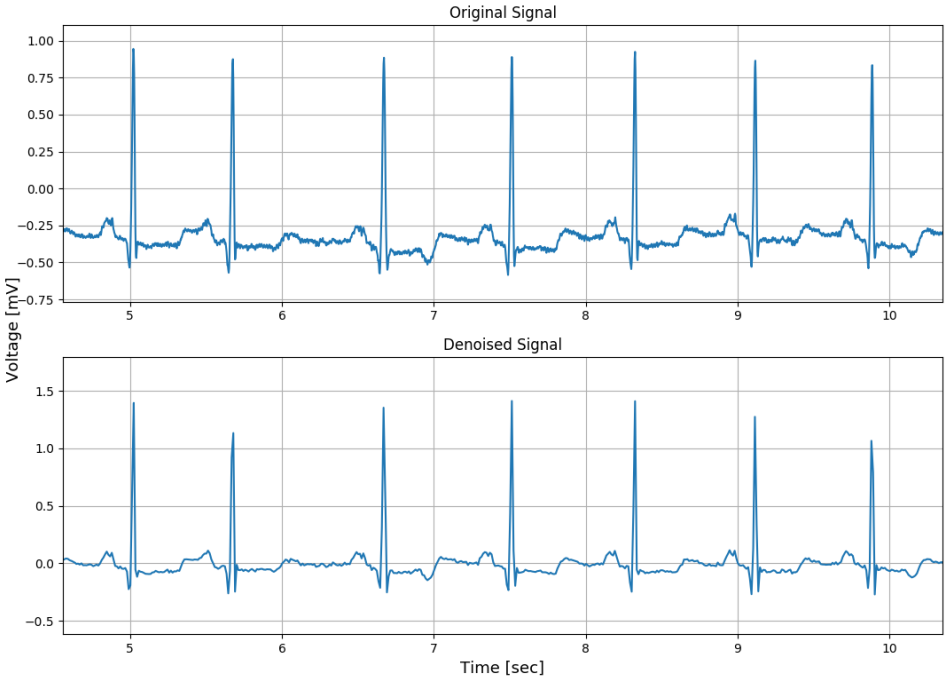


Figure. 2.4: The filtered ECG signal using wavelet.

localized in both time and frequency. Decomposition of the signal into different frequency bands is obtained by passing the signal through high-pass and low-pass filter respectively, which results in 2 sets of coefficients namely, approximation coefficients and detail coefficients. The approximation coefficients contain the low-pass filter output and the detail coefficients contain the high-pass filter output. The next step split the approximation coefficients again into 2 parts using the same process and so on.

The original signal contains the high-frequency noise and the baseline drift. The wavelet transform can be used to remove the corresponding noises and the baseline drift. The process starts by decomposing the original signal into 8 layers using wavelet type bior2.6, which results in the corresponding detail and approximation coefficients. Mostly, the layers 1 and 2 of the detail coefficients contain the high-frequency noise and the layer 8 of the approximation coefficients contain the baseline drift. Therefore, the layers 1 and 2 of the detail coefficients and layer 8 of the approximation coefficients are set to 0; which then results in the de-noised signal with no baseline drift. The resulting ECG signal can be seen in the Figure 2.4.

2.9.2 Band-pass Filter Method

A band-pass filter is a type of filter which passes only frequencies in a certain range or spread without disturbing the input signal. The range of frequencies, let say, f1 and f2, are called the frequency passband.

Band-pass filter can be used to reduce the baseline drift, motion artifacts and high-frequency noise from the ECG signal. A passband of 3 Hz to 45 Hz has been used. After passing the ECG signal through the band-pass filter, the resulting signal produced is the de-noised signal with no high-frequency and baseline drift. The de-noised signal can be seen in the Figure 2.5.

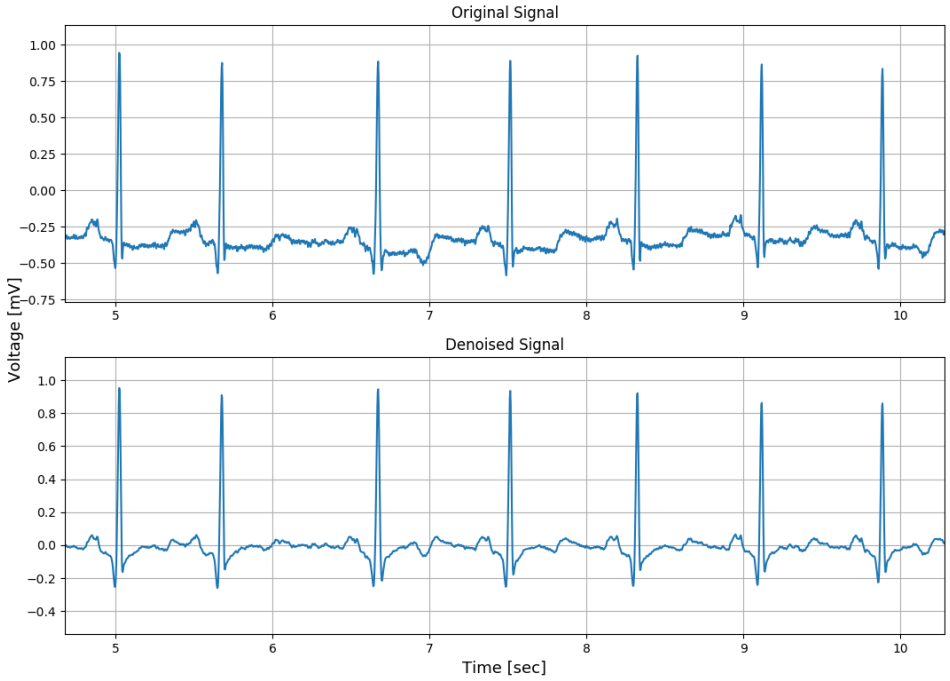


Figure. 2.5: The filtered ECG signal using bandpass filter.

2.10 QRS Detection

QRS detection is the basis for processing the ECG signal. Regardless of what application is required, the accurate detection of QRS is a pre-requisite for feature extraction. A good wavelet base can help detect the features of ECG signal more appropriately with speed and accuracy. Therefore, Biorthogonal spline wavelet is used to detect QRS wave. Biorthogonal

spline wavelet transform of ECG signal is calculated using the Mallat algorithm. Figure 2.6 shows the Biorthogonal spline wavelet transform of ECG signal at 4 different scales.

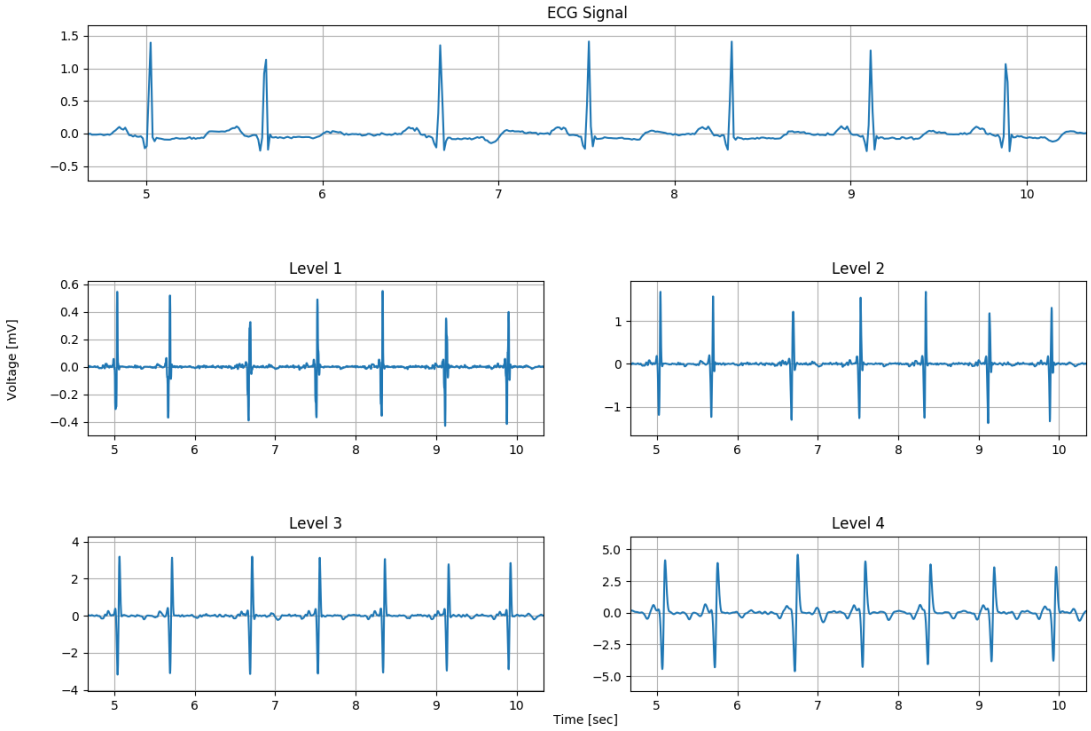


Figure. 2.6: ECG signal and its decomposition at different scales.

Most of the QRS complex energy lies in the 3rd scale, therefore, we can use the maximal minimal method in the 3rd layer of the detail coefficient to find the R waves. The process starts by taking the first derivative of the 3rd layer to find the maximum and minimum points and then the 2nd derivative to locate the actual maximum and minimum values. The resulting waves are shown in Figure 2.7. As it can be seen that, there are other peaks available as well, therefore, to get the maximum and minimum pair only, a threshold needs to be set. And all the values that do not fulfill the threshold should be discarded. For finding the threshold, the result of the 2nd derivative is divided into 4 parts and from each part, the maximum value is located. After getting the values, the average is calculated for these values and that average is then divided by 3. The resultant value is a new threshold. The pair can be seen in Figure 2.8.

The value of R wave lies at the zero-crossing point (with a little delay) which is between the maximum and the minimum value pair. For compensating the delay, a maximum value can be searched in the window of 20 points to the zero-crossing point. The detected R-peaks can be seen in Figure 2.9. The flow chart for finding the R peaks is shown in Figure 2.10.

After getting the R-peaks, Q and S peaks have to be detected. Q and S wave generally

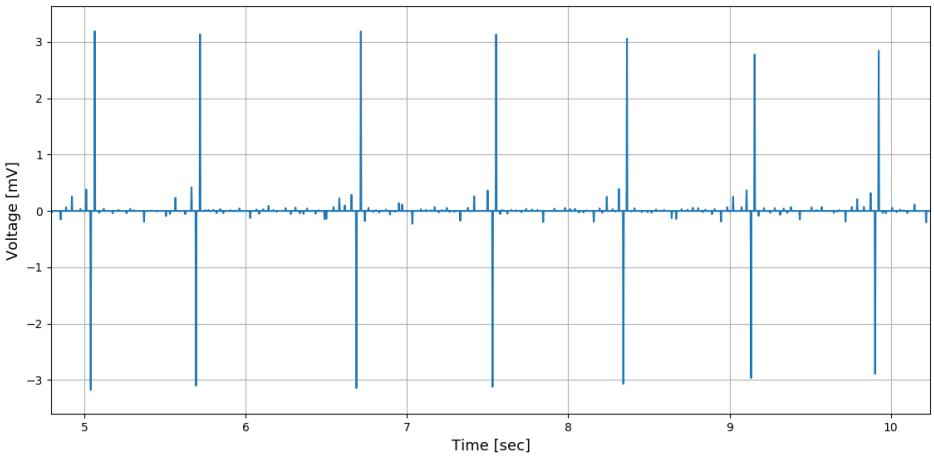


Figure. 2.7: Maximum and minimum values on scale 3.

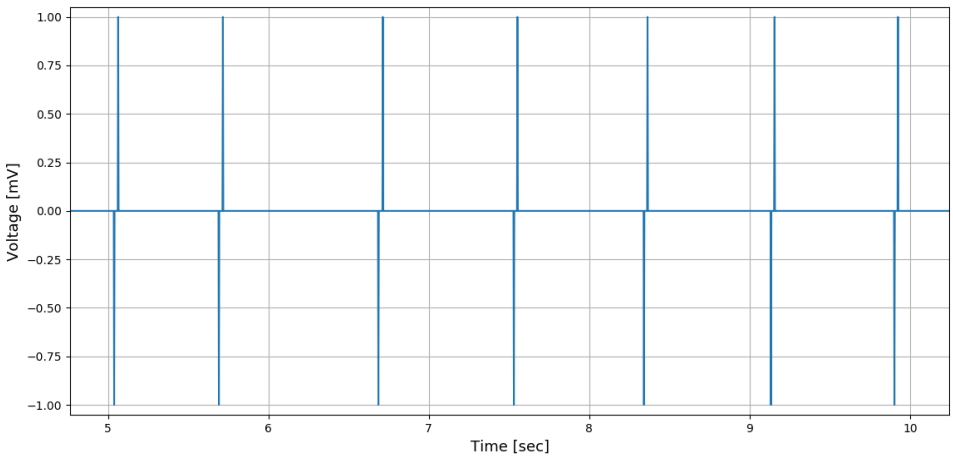


Figure. 2.8: Maximum and minimum values pair for finding the R peaks.

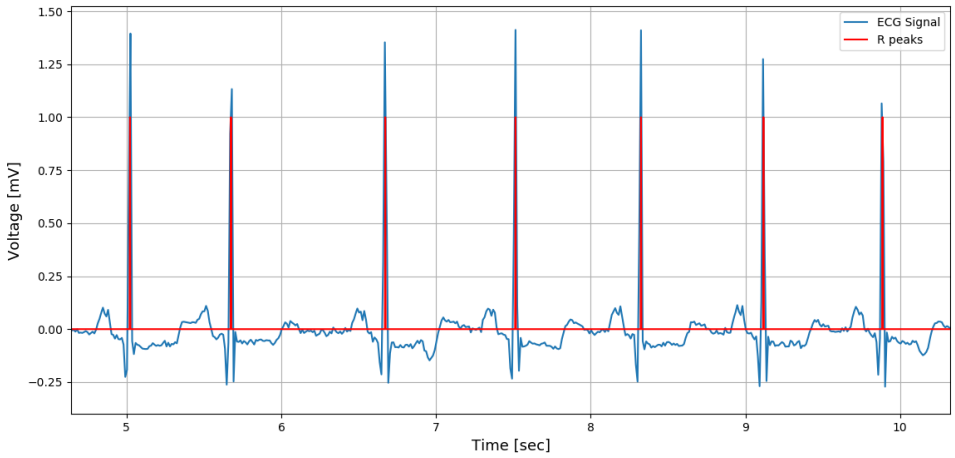


Figure. 2.9: Detected R peaks.

are of high frequency; therefore, their energies are mainly on the 1st scale. For finding the Q wave, the algorithm starts by looking on the left side of the R wave and finds the first non-zero value i.e. the Q wave. And because of the delay, the minimum value is searched in the window of 10 points to the detected Q wave. The same process is executed for the S wave, but in this case, the direction was on the right side of the R wave. The detected QRS complex can be seen in Figure 2.11.

After detecting the QRS complex, P and T waves are required to be detected as they also have very important significance to identify the arrhythmia. P wave generally occurred before the QRS complex and T wave after the QRS complex, therefore, they can be detected based on QRS location.

2.11 P and T Wave Detection

Most of the P and T waves energy lies on the scale 4 and the QRS complex energy lies on the scale 3 of detail coefficient. If QRS complex (that was detected on scale 3) is used, it sometimes misses the P wave or identifies the wrong position. Therefore, it is first required to detect QRS complex on scale 4 and then find P and T waves. The same algorithm is used to detect the QRS complex on scale 4 that is used to detect on scale 3, as described in section 2.10.

After getting the QRS on scale 4, a window size of 100 is used for detecting the P wave. The starting point of the window is one sample less than from Q wave position and if the window size is added to this position, we get the beginning of the window. RR interval is also calculated between the 2 consecutive R peaks. 1/3 of the RR interval is used for

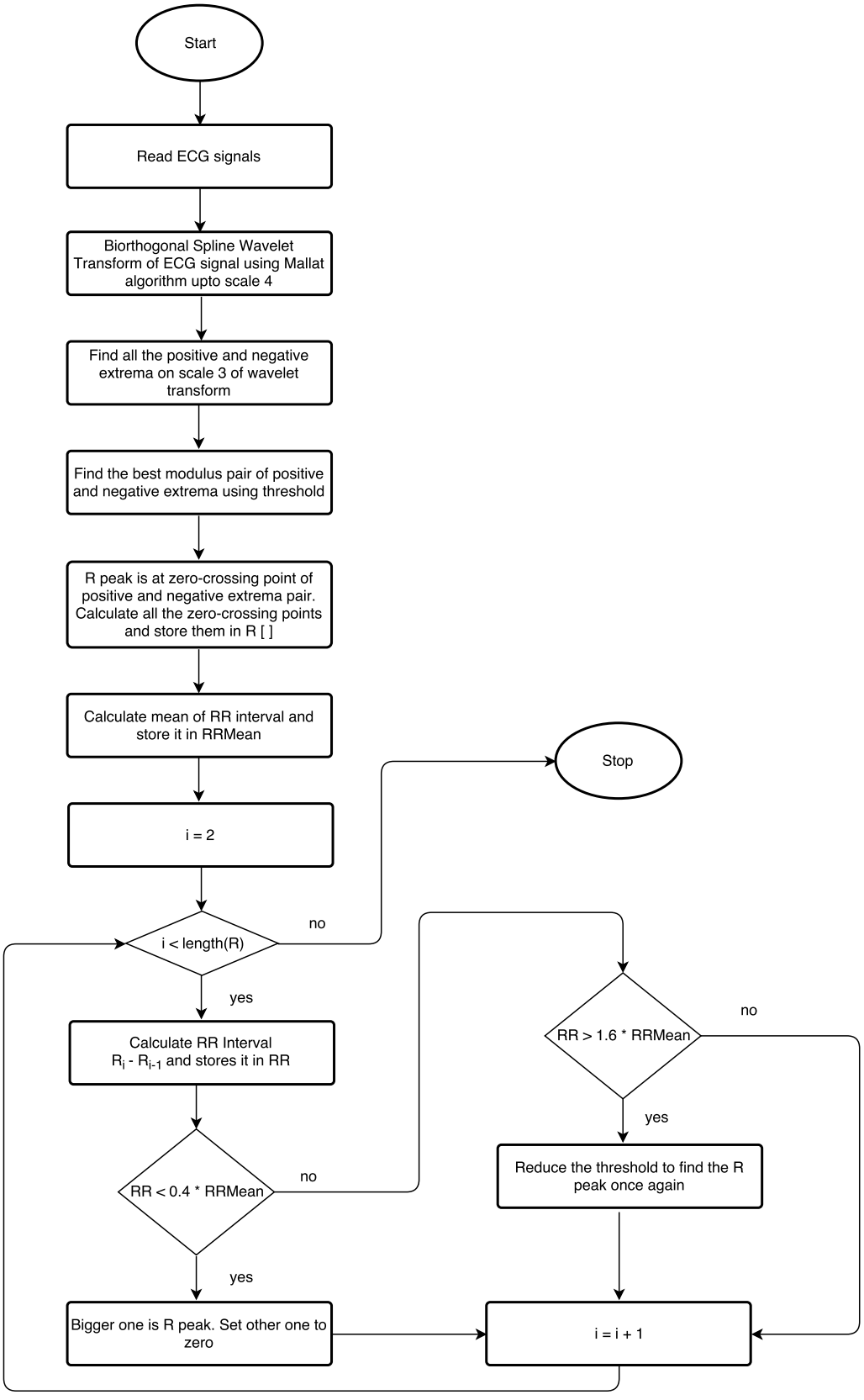


Figure. 2.10: R peak flow chart.

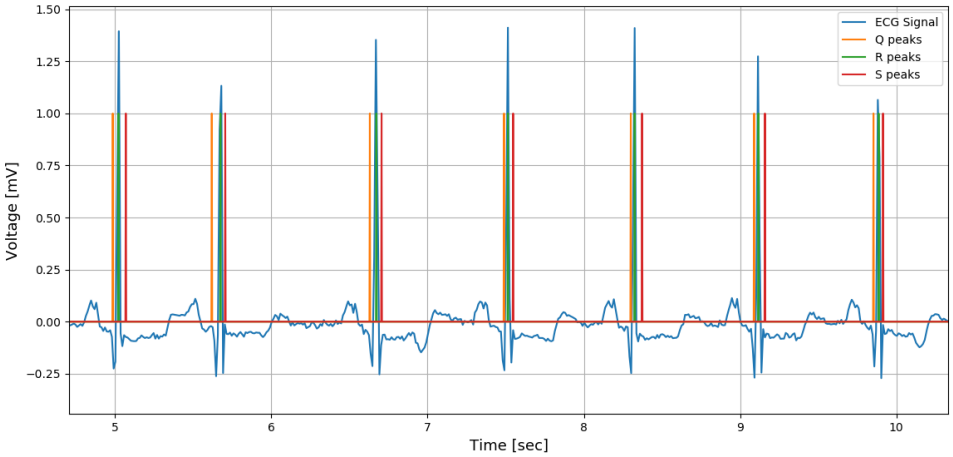


Figure. 2.11: Detected Q, R and S peaks.

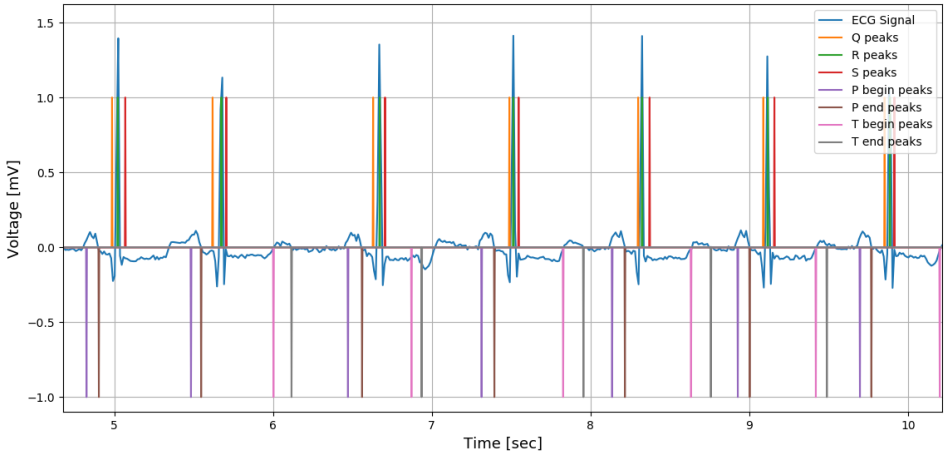


Figure. 2.12: Detected P,Q,R,S and T waves.

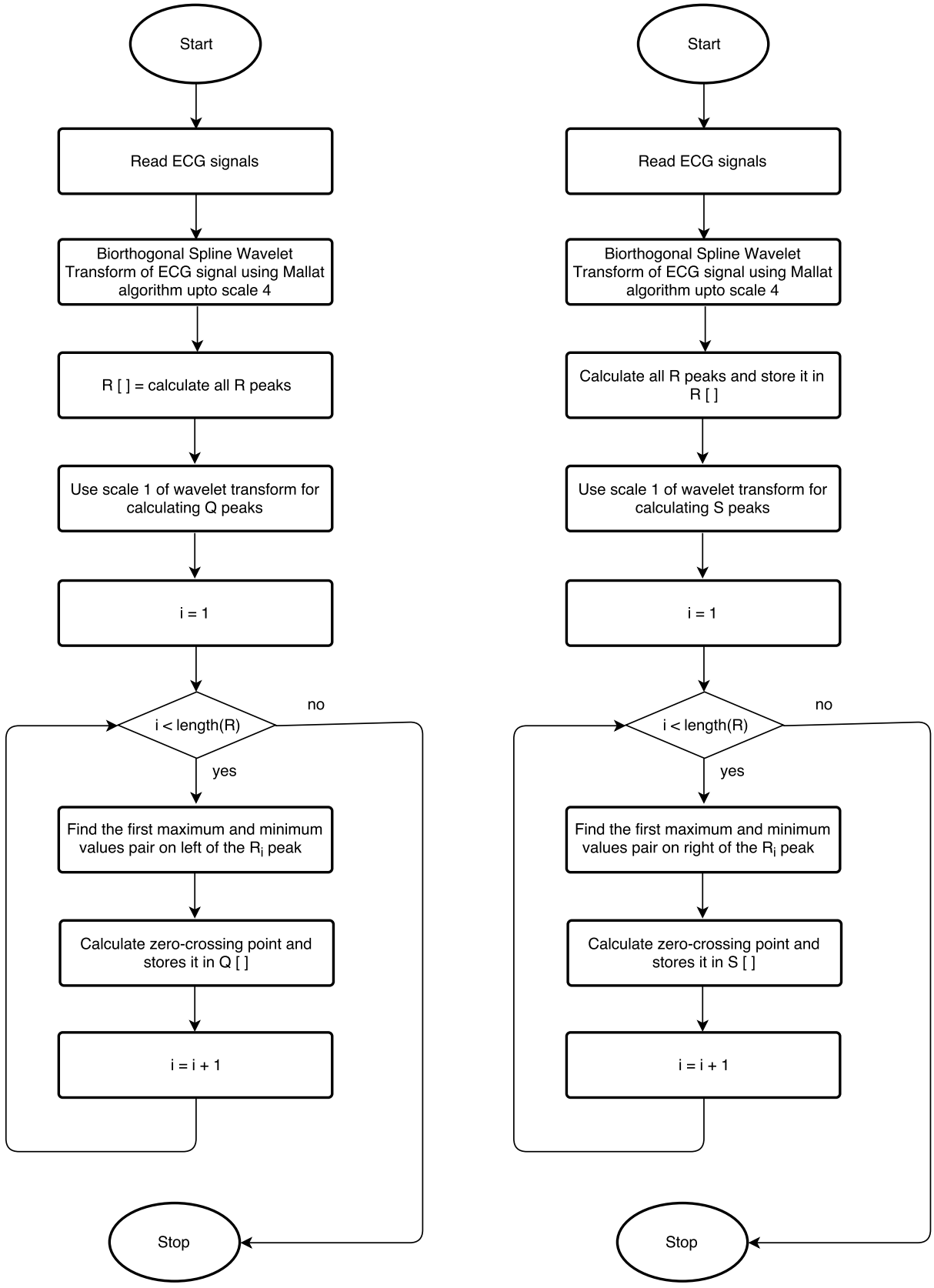


Figure. 2.13: Q and S peak flow chart.

detecting the P wave and 2/3 of the RR interval is used for detecting the T wave. Once the window is identified on the scale 4, the max and min values are identified in that window as P wave lies on the zero-crossing point of min and max pair. The average is taken to calculate the P wave position of scale 4. Once the P wave position is calculated, the P wave is identified relatively on the original signal. One point to note here is that the scale 4 data is shifted because of filtering, therefore, it is required to shift the detected position few samples back to get the appropriate value.

The same approach is used for detecting the T wave, but instead of looking the window before the QRS complex, here the window is searched after the QRS complex for detecting the T wave.

All detected waves can be seen in the figure 2.12. The flow chart for finding the P wave and T wave is shown in Figure 2.14 and 2.15 respectively.

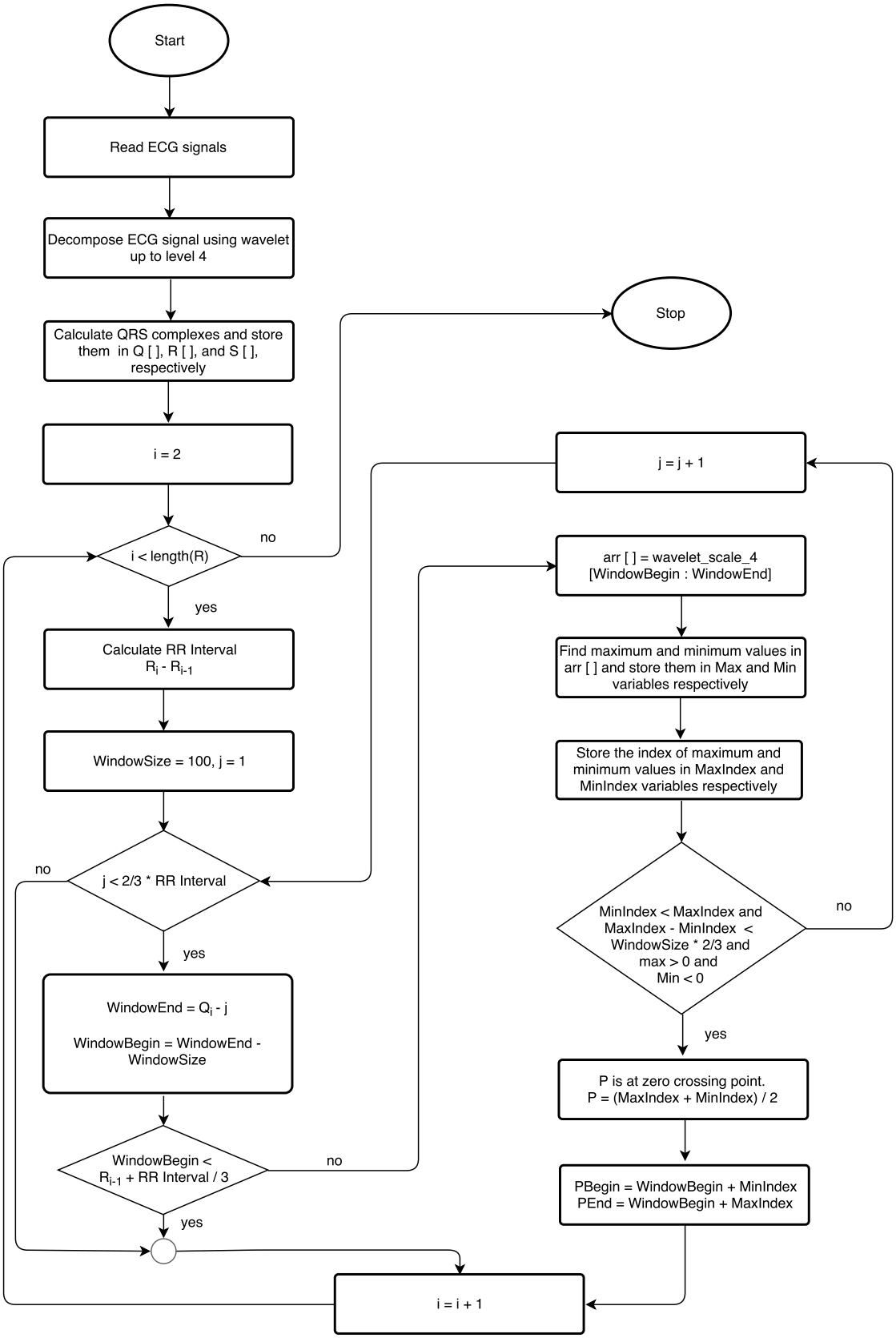


Figure. 2.14: P wave flow chart.

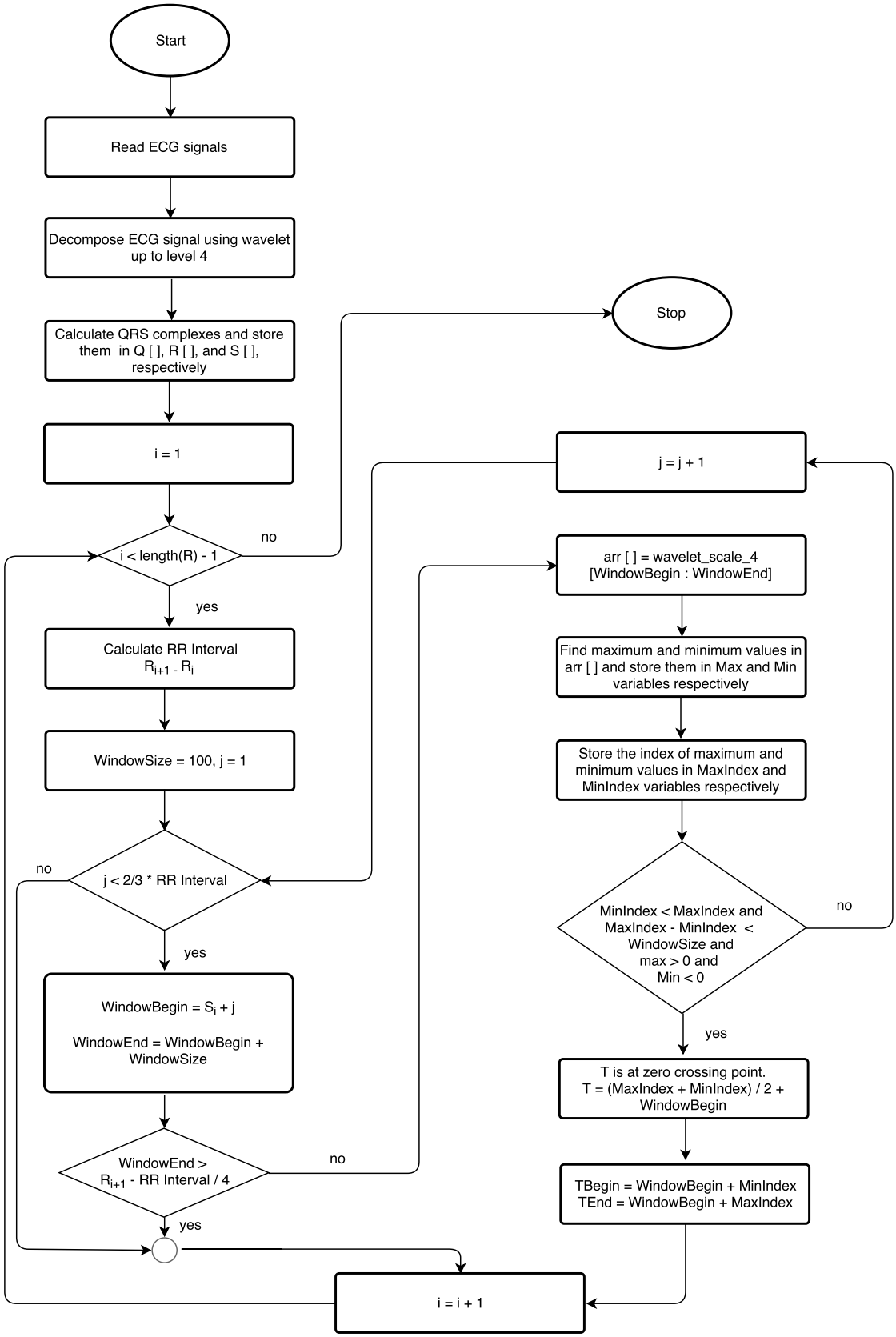


Figure. 2.15: T wave flow chart.

3 Deep Learning

Deep learning is a subfield of machine learning which in fact, is a subfield of Artificial Intelligence (AI). Deep learning has emerged as one of the most exciting field of computer science, and it is keep expanding its scope. It has been used in many technologies such as, in medical to identify the diseases, automatic game playing, self-driving cars, image recognition, natural language processing and many more. The reason why deep learning is successful in many different domain is its ability to understand multiple levels of representation of data. Its mean that, it not only has ability to classify and predict, but also has ability to learn different level of complexity. Before diving into deep learning, it is necessary to understand a broader field "machine learning".

3.1 Machine Learning

Machine Learning [1] is a data analysis method. It gives the computer the ability to learn from data without being explicitly instructed. By using different machine learning algorithms, it helps to find hidden insights of data and allow us to build models to make predictions. It can be classified into 2 categories.

1. Supervised Learning

2. Unsupervised Learning

3.1.1 Supervised Learning

In supervised learning, the labeled data is used to train the models. Here, labeled data represents that we know the input and output variables in advance. Thus, we know what we are looking for and then we use an algorithm to come up with a mapping function which maps the input variables to the output variables. Learning is supposed to be stopped when the level of performance reaches to the desired result. Supervised learning is generally divided into regression and classification.

- **Regression**: A problem in which the output variable is a category.

- **Classification**: A problem in which the output variable is the real value.

3.1.2 Unsupervised Learning

In unsupervised learning, we only have input data and no corresponding output variables. Thus, there are no labels given and it is expected to find the structure in the data itself, i.e. finding hidden patterns to learn more about data. It is different from supervised learning in that we don't know what will be the correct value. Unsupervised learning is generally divided into clustering and association.

- **Clustering**: Group objects in such a way that the objects, which are similar to each other, placed in the same cluster.
- **Association**: Discover rules that define the large portions of the data such as people who buys product X may buy Y as well.

The objective of machine learning is to analyze the past and present data and predict or make a decision for the future data. In supervised learning, the basic work flow is to build a model, evaluate or tune a model and then deploy it in the production environment where it will do the predictions. The work flow can be seen in figure.

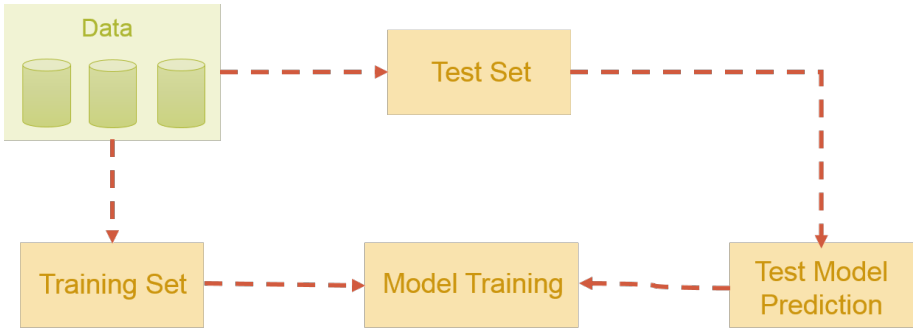


Figure. 3.1: Basic supervised machine learning workflow.

Machine learning is generally powered by a huge amount of data which is generally referred aa Big Data. It is generally defined as a too big or complex data which cannot be processed on a single machine. As the data is growing day by day, the new tools are also required to process that big data on multiple machines and extract the useful insights from the data.

One of the problem with the traditional machine learning model is the feature extraction challenge. The model designer or the programmer needs to specifically tells the model which features it should consider to make a correct decision. The model heavily relies on the programmer's understanding of data and this was a huge burden on the programmers. For a problems like object recognition, language translation, it was a huge problem.

Deep learning comes into play to solve the problem of feature extraction. They have the capability to focus only on the right features by themselves by understanding as much data

as possible, requiring very little input from the programmer. This feature of deep learning models makes it very powerful tool for the current machine learning era.

3.2 Artificial Neural Networks

Artificial neural networks (ANNs) are generally inspired by the biological neural networks that mimics brain functionality [con17a]. These systems generally learned by considering examples instead of specifically define rules for certain situations or cases. An ANN is a network of nodes called artificial neurons which are connected to other neurons using a link called synapse. Each neuron gets the input, process the input and pass the output to the next neuron. In most basic state, an ANN consists of 3 layers:

1. Input Layer
2. Hidden Layer
3. Output Layer

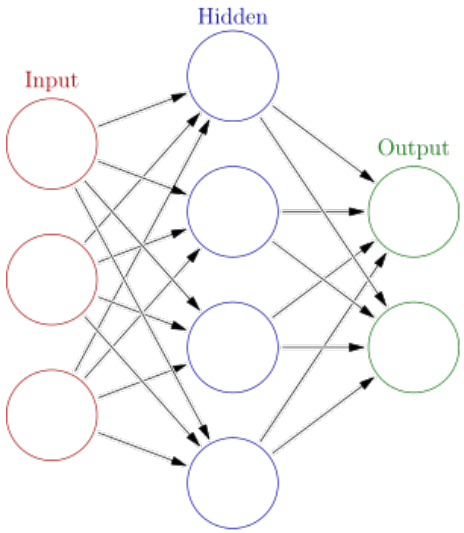


Figure. 3.2: An artificial neural network with its 3 basic layers, taken from [con17a].

3.2.1 Artificial Neuron

An artificial neuron is the most basic unit of ANN. It consist of inputs and produces an output. Generally, the inputs are multiplied by some weights to specify which inputs are more important. The higher the value of weights, the more important they are. The inputs

are shown as a, b and c and weights as w_1, w_2 and w_3 in figure 3.3. After then the products are summed together and passed to the activation function. An activation function is a function which takes an input an generates an output based on certain threshold. So, if the summed value is greater than the threshold value of that activation function, the output is produced or in other terms, the neuron fired else no output is produced and neuron does not fired.

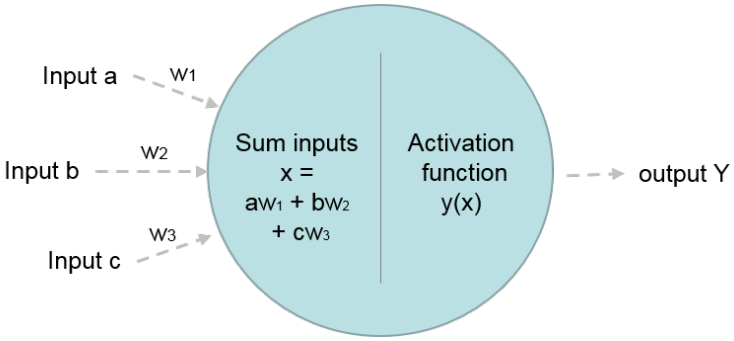


Figure. 3.3: A single artificial neuron.

Artificial neurons adjust the weights as the learning proceeds and the process of finding weights is known as learning. ANN considers many different examples and find the best possible combination of weights to provide the most accurate results. There are many other parameters involved as well to find a good combination of weights.

3.2.2 Activation Function

A function that takes an input and produce output based on threshold value is known as activation function [ujj17]. There are many step functions available. Few of them are:

Sigmoid

It takes a real value input and scale it to the range of 0 to 1. It is also known as logistic function. It is represented as:

$$y = \frac{1}{1+e^{-x}}$$

The another variation of sigmoid function is softmax function which is used for multiclass classification.

Tanh

It takes a real value input and scale it to the range of -1 to 1. It is also a sigmoidal function as it also takes s-shaped.

ReLU

It stands for Rectified Linear Unit. It is the most used activation function as it is the ideal choice to be used in convolutional neural networks. It takes the real value input and all negative values are mapped to zero. It is represented as:

$$f(x) = max(0, x)$$

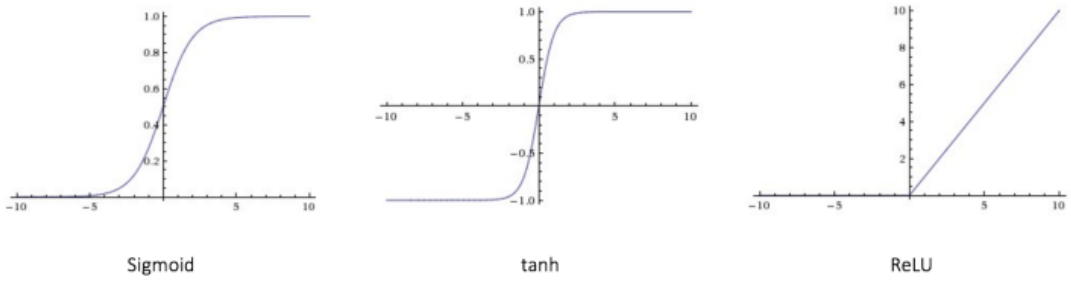


Figure. 3.4: Activation functions, taken from [ujj17].

The graph of all the activation functions defined above can be seen in figure 3.4.

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