

**PULSE DIAGNOSIS MATHEMATICAL MODEL USING  
MACHINE LEARNING**

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**IN**

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**SUBMITTED BY**

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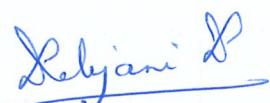
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## **CERTIFICATE**

This is to certify that **Ms. Jain Abhilasha Kailash Kumar Usha Devi, and Birwadkar Natalie Dayan Judith** B. Tech Biomedical Engineering, (VIII Semester) of the School of Biotechnology and Bioinformatics, carried out the Dissertation entitled, "**PULSE DIAGNOSIS MATHEMATICAL MODEL USING MACHINE LEARNING**" for the partial fulfillment of Bachelor of Technology in Biomedical Engineering. The dissertation has not formed the basis for the award of any degree, diploma, associate-ship or fellowship. The dissertation represents independent work carried out by the candidates.

Place: Navi Mumbai

Date: 21<sup>st</sup> May, 2019



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## CERTIFICATE

We certify that the research work presented in this thesis titled "**Pulse Diagnosis Mathematical Model Using Machine Learning**" has been carried out by **Ms. Abhilasha Jain**, Roll No. **BBE – 15005** under my supervision and this is her bonafide work. The research work is original and has not been submitted for any other degree of this or any other University. Further, they were regular students and has worked under my guidance as full time students at **D.Y.Patil Deemed to be University** until the submission of the thesis to the D.Y.Patil Deemed to be University.

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## **DECLARATION BY THE CANDIDATE**

This is to state that the work embodied in this thesis titled "**Pulse Diagnosis Mathematical Model using Machine Learning**" forms our own contribution to the research work carried out under guidance of **Asst. Prof. Divya Subramanian** at **D.Y.Patil deemed to be University**. This work has not been submitted for any degree for this University or any other University. Whenever references have been made to previous work of others, it has been clearly indicated as such and included in the Bibliography.

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*Abhilasha Jain*

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## **ABBREVIATIONS**

CAM	:	Complementary & Alternative Medicine
AAM	:	Ancient Ayurvedic Medicine
PWV	:	Pulse Wave Velocity
BMI	:	Body Mass Index
TSH	:	Thyroid Stimulating Hormone
LEDs	:	Light Emitting Diodes
VLEDs	:	Visible Light Emitting Diodes
UV	:	Ultra-violet
IR	:	Infra - red
NIR	:	Near Infra - red
OEICs	:	Opto-Electronic Integrated Circuits
PPG	:	Photo-plethysmograph
Op-Amp	:	Operational Amplifiers
HPF	:	High Pass Filter
LPF	:	Low Pass Filter
BPM	:	Beats Per Minute
ADC	:	Analog to Digital Converter
ML	:	Machine Learning
GSCV	:	Grid Search Cross Validation
PCA	:	Principle Component Analysis
MLP	:	Multi-layer Perceptron
CART	:	Classification & Regression Tree
DT	:	Decision Tree
GBT	:	Gradient Boosted Tree
SVM	:	Support Vector Machines
ANN	:	Artificial Neural Network
GI	:	Gini Index
IG	:	Information Gain

# **ABSTRACT**

The work embodied in this project is aimed at quantifying an Ayurvedic practice of diagnosing medical conditions from pulse readout of the human body. This quantification essentially involves the investigation of the existence of a mathematical model that would take as input the features of a pulse wave and would be able to with some reliability return a binary value as to the presence of disease or ailment.

The process of obtaining such quantification entailed the collection of pulse wave data from a site of known importance and also information regarding the medical condition of such subjects. The pulse waves were then analysed firstly using existing signal processing parameters and eventually using machine learning techniques. The initial analysis served as a feature filter for the subsequent machine learning process. The project was performed as a within subjects analysis by first collecting their wave samples for analysis and then collecting information regarding their medical conditions based on their medical history.

The mathematical model was eventually developed using an artificial neural network as a classifier. The success of that algorithm in learning a function for performing such a classification points towards the validity of the Ayurvedic practice and the existence of such a model.

# **1. INTRODUCTION**

Ayurveda is a truly holistic health system which supports you from the cradle to the end of your life. The Ayurvedic mode of living aims to maximise your lifespan by optimising your health through interventions that care for your body, mind, spirit and environment. Ayurveda places a great emphasis on the prevention of disease and on health promotion, as well as on a comprehensive approach to treatment.

Unlike some other systems of medicine, Ayurveda is not just concerned with the absence of disease. As Sushruta, a physician in the sixth century BC informs us, you are only considered healthy when your appetite is strong, your tissues (dhatus) are functioning normally, your humours (the doshas: vata, pitta and kapha) are in balance, bodily wastes are eliminated well, and your mind and senses experience joy.

Ayurveda places great emphasis on the effects of the different seasons and your diet on the equilibrium of the body. Different doshas, or attributes, are prevalent at different times of the day, and during the seasons these cause physiological changes in your body. Ayurveda understands that moving with the times and climate is a mainstay of good health because you are a microcosm of what's going on in your environment

Within the practice of Ayurveda are specialities – just like in Western systems

8 Primary Ayurvedic Specialisations are: -

1. Toxicology (agada tantra)
2. Childhood diseases or paediatrics (bala tantra)
3. General surgery (shalya tantra)
4. Internal medicine (kaya chikitsa)
5. Psychiatry and mental disorders (bhuta vidya)
6. Management of diseases of the head and the neck (salakya tantra)
7. Fertility treatment (vajikarana)
8. Rejuvenation and the treatment of geriatrics (rasayana)

The forte of the approach of mainstream medicine is in diagnosis and acute medical conditions such as trauma. However, in the management of deep-seated chronic ailments, mainstream medicine sometimes lacks the sophistication of Ayurveda, which

always takes the underlying causes of pathology into consideration. Ayurvedic interventions can deeply purify your body and eliminate toxins from your system. Iatrogenic diseases – those that are unintentionally caused by medical treatment – are on the increase and were estimated as being the third-largest cause of death in a study by Starfield in 2000 in the United States. Ayurveda's more subtle and individualised approach to treatment shows no such ill effects.

In the past 20 years, Ayurveda has undergone a resurgence. It's now practised all over the world and often works in harmony with a more modern approach. Qualified Ayurvedic physicians are medical practitioners, and many hospitals treat patients using solely Ayurvedic tenets, without causing any of the adverse reactions of modern treatment.

Pulse diagnosis is one of the eight diagnostic technique used in Ayurveda, traditional Chinese medicine, traditional Mongolian medicine, Siddha medicine, traditional Tibetan medicine. As the health of the organs can be felt in the different pulses, it provides a clear window into the pulsating waves of the body. Pulse diagnosis is subtle and complex. It receives information through kinaesthetic, visual, and intuitive channels, which is then evaluated using the knowledge of physiology, energetics and the information received from the patient.

Mathematical modelling is the art of translating problems from an application area into tractable mathematical formulations whose theoretical and numerical analysis provide insight, answers and guidance useful for the originating application. Mathematical modelling is indispensable and successful in many applications. It gives precision and direction for problem solution and enables a thorough understanding of the system modelled. It prepares the way for better design or control of a system and allows the efficient use of modern computing capabilities.

## **2. LITERATURE REVIEW**

Alternate and traditional medicine (known as complementary and alternative medicine or CAM globally) has attained a lot of importance in recent years since approximately 70 % of the population prefer to use traditional medicine compared to modern medicine for treatment purposes. Ayurveda is one of the oldest forms of medicine and has been prevalent for over 5000 years. The verbal knowledge of Ayurveda passed on from generation to generation before the written texts could be available. Ayurveda uses three measurement techniques to gather information namely darshana (observation), sparshana (touch) and prashna (questioning). In sparshana (touch) technique, the pulse on wrist (generally known as 'nadi' in Ayurveda) discloses enormous information depending on its rate, rhythm, movement, force, tension and volume, consistency of the vessel wall and temperature. Ayurveda considers three fundamental principles manifested from the panchamahaboota called as the tridoshas. Wrist pulse-based diagnosis, known as Nadi-Pariksha in Ayurveda is one of the oldest forms/techniques for diagnosis. It considers any imbalance in the tridoshas as an indication for the onset of the detected through Nadi-Pariksha.

Prakruti Nidana , the basis of diagnosis and treatment under Ayurveda, describes one's natural constitution (prakruti) in terms of three basic principles vata, pitta, and kapha, collectively called the tridosha. Ether (space), Air, Fire, Water and Earth, are the five basic elements in human body, the combination of which manifest tridosha . From the Ether and Air elements, the bodily air principle called Vata is manifested. The Fire and Water elements exist together as the fire principle called Pitta. The Earth and Water elements exhibit as the water principle, Kapha. In the physical body, Vata is the subtle energy of movement; Pitta is the energy of digestion and metabolism, whereas Kapha is the energy that forms structure of the body. These three doshas determine individual's constitution and govern functions of the body in normal conditions and when out of balance, they contribute to the disease process.

Diagnosis according to Ayurveda, is to find the root cause of a disease. Out of the eight different kinds of examinations Nadi-Pariksha (pulse examination) is very important. Nadi-pariksha is done at the root of the thumb by examining the radial artery using three fingers. The radial pulse is usually chosen as the site to read the Nadi (pulse) because it is more convenient to read and is more readily available than other pulse sites. Ayurveda uses the pulse pressure signals which are observed over radial artery,

at the wrist, for identification of health status of the human being. The features associated with the pulse pressure signals are important from diagnostic point of view. Ancient Ayurveda identifies the health status by observing the wrist pulses in terms of 'Vata', 'Pitta' and 'Kapha' as the basic elements of human body and in their combinations. They are further substantiated by their gati, bal, taal etc. Pulse is also classified as fast or slow, tense or tender, floating or sinking, large or small, empty or full, etc., with each term reflecting a personal constituent or condition of the body.

These pulses are felt at specific positions on the wrist of the patient: vata on the index finger, pitta on the middle finger and kapha on the ring finger placed distally, medially and proximally to the heart . It helps in the identification of the constitution at birth (prakruti) of the person, which forms the basis of the healing process. Knowledge of the current situation (vikruti) enables to identify the illness, considering the difference between prakruti and vikruti. It also tracks the psychosomatic or conflicting nature between the mind and body and helps in the analysis of the tridoshas. The Nadi Vidwans feel them by placing their hand in a specific orientation on the patients wrist, also, it is said that analysis of hollow organs and semi-solid organs is done by feeling the nature of pulse at the deep and superficial layers of the wrist radial artery by applying proper external pressure. One of the major drawbacks in the pulse-based diagnosis is that it is subjective and depends on the Ayurvedic doctor (vaidya) examining the patient and it requires a long experience in pulse examination and a high level of skill and knowledge and can vary from person to person. One third of the population in developing countries lack access to essential medicines. Thus, combining traditional medicine with conventional modern medicine could help provide better and safer facilities. The recent trend follows to replicate this system in terms of a device which will be smart enough to diagnose diseases by capturing the signals from wrist using various types of sensor, depending on the disease to be diagnosed. Thus it is advisable to develop a device which is objective and can be used in Indian Medical system for disease diagnosis. Present thesis is an attempt in the same direction.

## 2.1. The Radial pulse: Ayurvedic View

Nadi Pariksha (Pulse examination) is done by feeling the pulse at three points on the radial artery by using three fingers. The three points on the wrist indicating the positions of three doshas are shown in Fig.1.1.

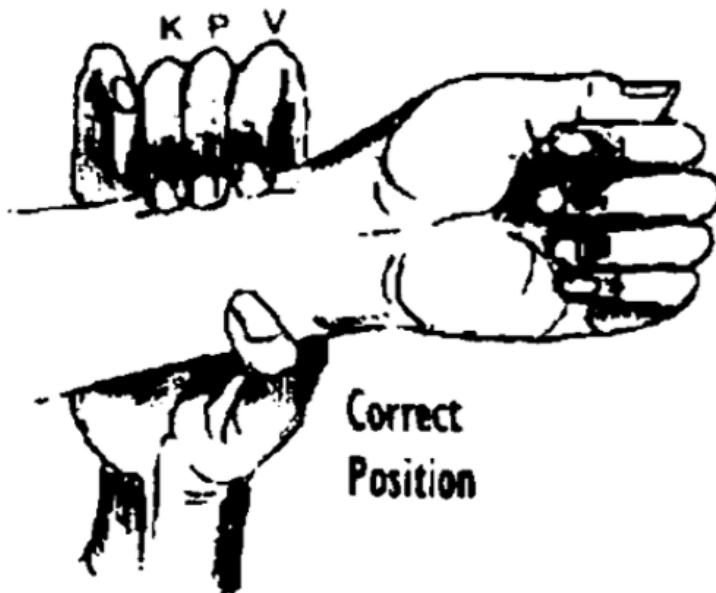


Figure 2.1.1. Correct Position of Vata, pitta & Kapha

In AAM (Ancient Ayurvedic Medicine) diagnosis is done with the help of the information obtained from the three pressure points on either left wrist (in case of men) or on right wrist (in case of women). Vata pulse is best felt under the index finger. Vata pulse is superficial, cold, light, thin, feeble and empty. With more pressure, it disappears. It moves fast and may become irregular. With keen observation one can feel a little leech or a little cobra moving under the finger. Vata pulse is cold to the touch.

Pitta pulse is best felt under the middle finger. Pitta pulse is full with a strong throb. It is hot and abrupt, with high amplitude, good volume and considerable force. It moves like a leaping frog. It is hot to the touch. Kapha pulse is felt at proximal finger. It is deep, slow, watery, wavy and cool to the touch. It moves like a swimming swan.

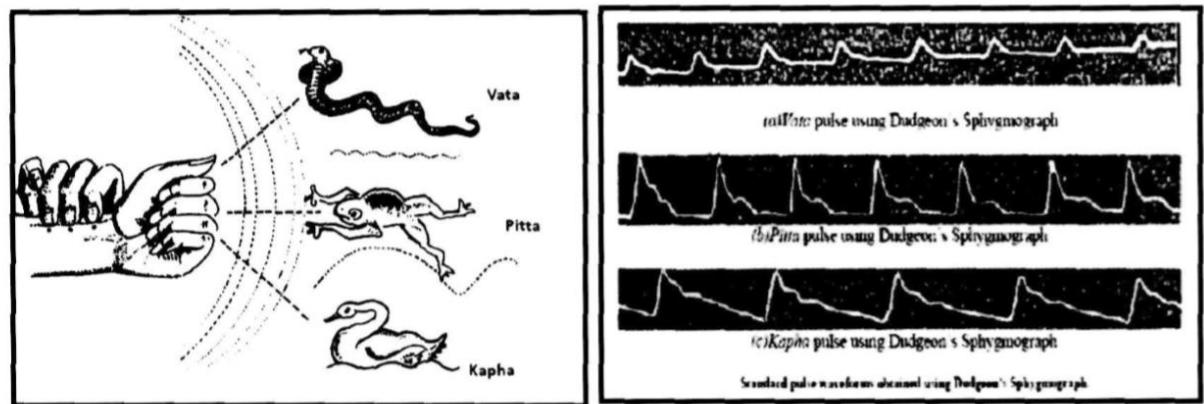


Figure 2.1.2. Type of Pulse wave at Vata, Pitta & Kapha

Table 2.1.1. Characteristics of Pulse

	VATA	PITTA	KAPHA
<b>Gati</b> (Movement)	Sarpa (Cobra)	Manduka (Frog)	Hansa (Swan)
<b>Vega</b> (Rate)	80 - 95	70 - 80	50 – 60
<b>Tala</b> (Rhythm)	irregular	regular	regular
<b>Bala</b> (Force)	Low	High	Moderate
<b>Akruti</b> (Tension & Volume)	Low	High	Moderate
<b>Tapamana</b> (Temperature)	cold	Hot	Warm to cool

## **2.2. The Radial pulse: Modern View**

Radial pulse is defined as the rhythmic expansion of arterial wall due to the transmission of pressure waves along the wall of arteries that are produced during each systole of the heart (3). The radial pulse is periodic fluctuation that is caused by the heart and occurs at the same frequency as the heart beat . The radial pulse perceived by a clinician is the pressure pulse in a large, accessible artery.

Generally, there are two main components of a pressure wave: forward moving wave and a reflected wave.The forward wave is generated when the heart (ventricles) contracts during systole. The wave before dicrotic notch reflects the heart systole; the wave after the notch reflects the diastole. Peak 1 and peak2 are the percussion wave and dicrotic wave of pulse respectively. The parameters H1, H2 and H3 are the heights of peak 1, valley and peak2 in pulse respectively. The parameters t1, t2 and t3 are their corresponding time values. W1 and W2 are their widths at the heights 0.9 times of H1 and H2 respectively.

Analysis of the pulse can be done in Frequency domain, time domain or mixed domain. Time-domain parameters of pulse signal used by scientists during analysis are shown in figure 2.2.1. In frequency domain the harmonic components of the radial pulse are calculated and their ratios are used for analysis. Below is the schematic figure of Pulse Parameters.

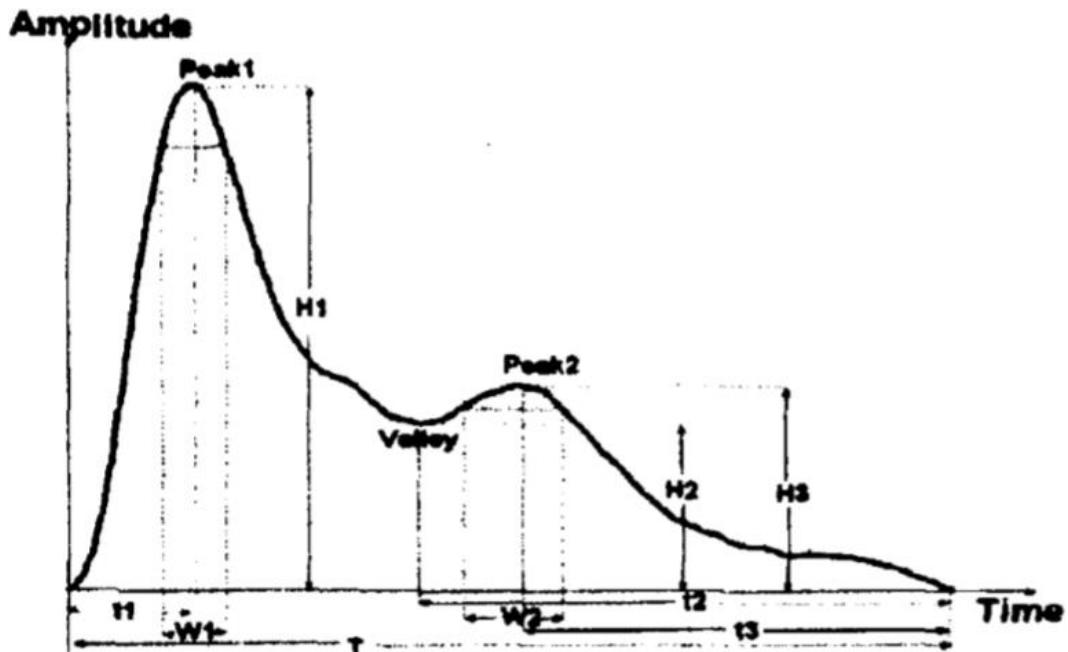


Figure 2.2.1. Radial Pulse Wave

Pulse assessment has its importance even in modern medicine. It is used as a primary diagnostic tool for examination of a person's heart rate and blood pressure parameters. The pulse by definition is the rhythmic beating of the arteries, caused by the recurrent contractions of the heart. Variations in pulse is considered as key diagnosis in heart conditions such as tachycardia, bradycardia, arrhythmia's etc.

The arterial pulse is formed due to swelling (distension) of the arteries and the contraction which results due to the elasticity of arterial wall. The contraction of the heart determines the frequency and rhythm of the pulse. The tension between the arteries and duration of the pulse depends on the elasticity and peripheral resistance . A typical pulse waveform consisting of three beats is shown in Figure (b). The arterial pulse waveform typically consists of four areas namely the percussion wave (P), tidal

wave (T), dicrotic notch (V) and dicrotic wave (D).

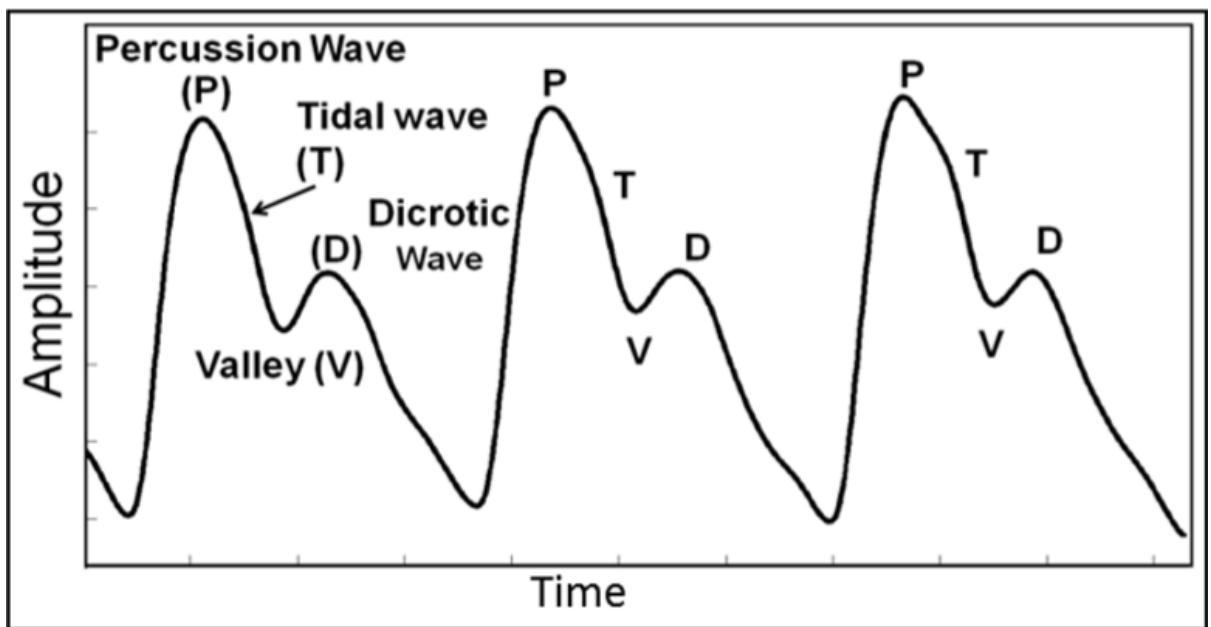


Figure 2.2.2. Different Parts of Radial Pulse

Percussion wave is the ascending portion of the graph formed during the systolic phase of the cardiac cycle. This P wave is caused from left ventricular ejection; followed by the tidal wave, which is a reflected wave. The dicrotic notch is a small downward deflection in the pulse contour occurring because of the closure of the semilunar valves, detecting the end of the systolic phase in the cardiac cycle in some instances. The wave trailing behind the notch is the dicrotic wave (recoil wave), formed because of the reflected impulse of closure of the aortic valves. General features which typically preside over the arterial pulse waveform are stoke volume, cardiac output, peripheral resistance, mean arterial pressure and arterial stiffness.

Different diseases or conditions cause variations in the typically obtained P-T-V-D waveform which can be analysed by appropriate sensing, feature extraction, pattern recognition i.e. proper instrumentation.

### **2.3. Pulse Waveform in Diabetes Patient:-**

T2DM mellitus is a group of metabolic diseases characterized by hyper-glycaemia resulting from defects in insulin secretion, insulin action, or both. It is the most prevalent form of the disease and is often asymptomatic in its early stages and can remain undiagnosed for many years. The prevalence of diabetes for all age-groups worldwide was estimated to be 2.8% in 2000 and 4.4% in 2030. The total number of people with diabetes is projected to rise from 171 million in 2000 to 366 million in 2030. The urban population in developing countries is projected to double between 2000 and 2030. The world prevalence of diabetes among adults (aged 20–79 years) will be 6.4%, affecting 285 million adults, in 2010, and will increase to 7.7% and 439 million adults by 2030. Between 2010 and 2030, there will be a 69% increase in numbers of adults with diabetes in developing countries and a 20% increase in developed countries. Chronic diseases such as heart disease, stroke and diabetes are leading causes of death in the US .It affects more than 21 million Americans , and the death rate from diabetes has increased 45% since 1987 . From 1980 to 2005, prevalence of diabetes among the US population rose from 5.8 million to 14.7 million. Approximately 9.6% of Americans aged 20 years or older (a total of 20.6 million people) have diabetes. India has the largest diabetic population in the world. Changes in eating habits, increasing weight and decreased physical activity are major factors leading to increased incidence of type 2 diabetes With India having the highest number of diabetic patients in the world, the sugar disease is posing an enormous health problem in the country. Calling India the diabetes capital of the world, the International Journal of Diabetes in Developing Countries says that there is alarming rise in prevalence of diabetes, which has gone beyond epidemic form to a pandemic one. The International Diabetes Federation estimates that the number of diabetic patients in India more than doubled from 19 million in 1995 to 40.9 million in 2007. It is projected to increase to 69.9 million by 2025. Currently, up to 11 per cent of India's urban population and 3 per cent of rural population above the age of 15 has diabetes. Diabetes affects all people in the society, not just those who live with it. The World Health Organization estimates that mortality from diabetes and heart disease cost India about \$210 billion every year and is expected to increase to \$335 billion in the next ten years.

These estimates are based on lost productivity, resulting primarily from premature death.

The present methods that are adopted for diabetes detection are invasive. These methods involve collecting blood sample from patient followed by some chemical analysis. For pulse acquisition, ayurvedic doctor uses three fingers starting from index finger, middle finger and ring finger. In ancient literatures, be it Ayurveda, Chinese, Unani, or Greek, pulse based diagnosis has its own unparalleled importance. The organ under distress is zeroed down by feeling the palpation from the three fingers placed on the radial artery. These pulsations dictate the Physiological status of the entire human body. Each person is born with one of the seven prakritis, Vaat, Pitta, kapha, Vaat-Pitta, Vaat-Kapha, Pitta-Kapha or Sama prakriti. Ayurveda does not comply with the ‘general line of treatment approach’ of modern medicine, as it is a complete health treatise which restores the balance of doshas in the body thereby ridding the body of the disease. According to ayurveda, an individual suffering from Diabetes Mellitus Type-II shows aggravated kaphadosha and vaatdosha. Diabetes Mellitus is known to Indians from Vedic period onwards by the name Asrava (Prameha).

The parameters of the pulse like shape, rhythm, amplitude, frequency and the pulse rate are focused for extraction of Nadi features. The features extracted from the signals are used to train the neural network. The neural network is trained. The training data set which includes time domain features extracted from waveforms is created. This data set is used to train the network. While training the network, the number of hidden layer neurons is adjusted by trial and error way so as to get minimum error. The data samples are randomly divided into three kinds training, validation and testing. Training multiple times generated different results due to different initial conditions and sampling. Pulse rate is calculated by detecting the peaks in each pulse signal. From various literature, the pulse rate of the normal person is given as, for vaat 80-95, pitta 70-80 and kapha=50-60. The variations in these extracted features are observed and prakriti of subject is determined. For more precise prakriti determination, questionnaire is given to the subject.

### 2.3.1. Observations:

The patient suffering from diabetes shows excess pulse rate of kapha signal and also peak amplitude value is found to be lowered. T2DM mellitus is a group of metabolic diseases characterized by hyperglycaemia resulting from defects in insulin secretion, insulin action, or both. It is the most prevalent form of the disease and is often asymptomatic in its early stages and can remain undiagnosed for many years. The vata wave forms were broad showing a regular shape, size , pattern, amplitude, frequency, rhythm and pitta dosha wave forms are sharp and shorter in breadth when compared to vata and they resemble in their shape , size , pattern, amplitude, frequency, rhythm to some extent . Kapha waveform shows short irregular and haphazard waves which vary in breadth when compared to vata and kapha waveforms. The pulse signals vary in rhythm, amplitude, frequency, slopes and so on. A pulse signal from healthy subject shows a typical waveform with regular rhythm, stable amplitude, and balanced shape. A disorder will cause alterations in the physiological processes and thus in the acquired pulse signals, leading to different patterns.

The vata predominance in the collected data and good classification numbers indicate the possibility of detection of diabetes using modern data acquisition and analysis methods. Each of the signals show variations in the parameters Amplitudes, Frequency, Rhythm, and therefore carry different patterns with different information.

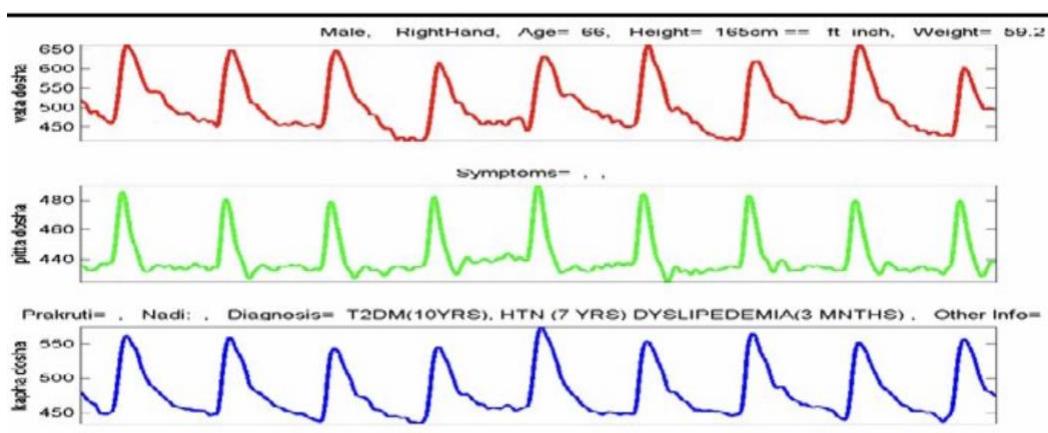


Figure 1.3.1. Example of Pulse Waveform of T2DM Subject

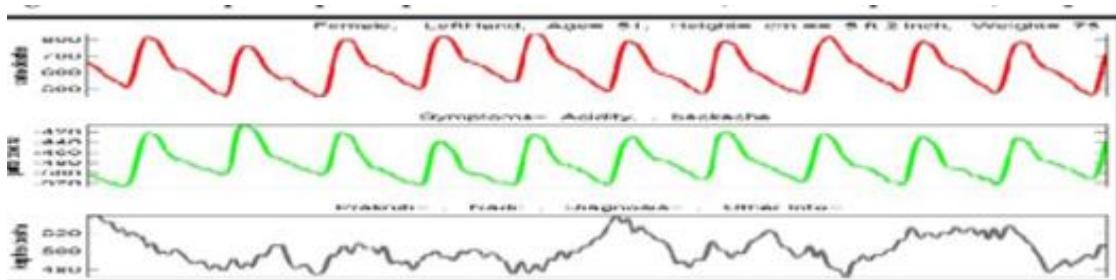


Figure 2.2.2. Example of Pulse Pattern in Non TDM Subject

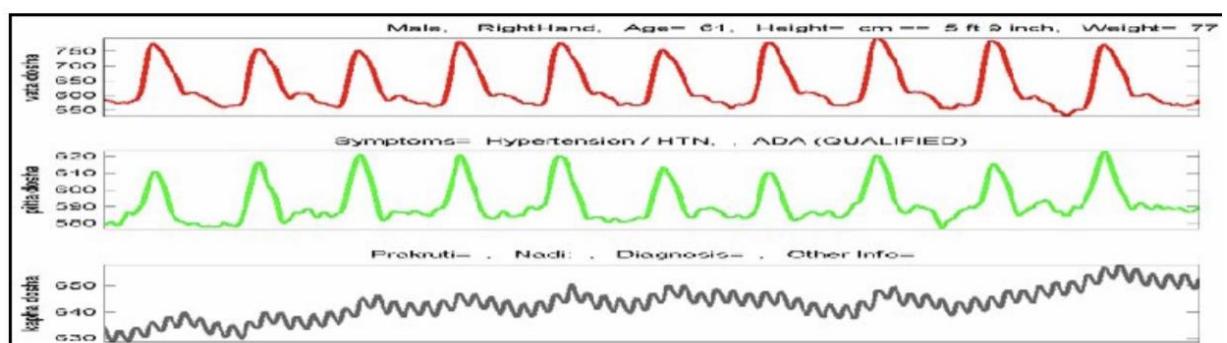


Figure 2.3.3. Example of Pulse Pattern in Pre DM Subject

Table 1.3.1. Mean Peak Values of Vata, Pitta & Kapha in normal & diabetic patient

Mean Values	$A_p E_n$		
	vata	pitha	Kapha
Normal Patients	0.2651	0.2517	0.2849
Diabetic Patients	0.1771	0.1731	0.1751

According to the study , PWV(Pulse Wave Velocity) and pulse pressure in diabetic patients was considerably higher than the non-diabetic patients. The increase in

augmentation index (associated with several cardiovascular disorders), inferred that arterial stiffness was high in patients having type-2 diabetes compared to non-diabetic. Diabetes is demonstrated by the kukkuta (cock) gati and the prominent dosha for DM is generally kapha. The patient suffering from diabetes shows excess pulse rate of kapha signal and also peak amplitude value is found to be lowered.

## **2.4. Pulse Waveform in Hypertension Patients:-**

Cardiovascular refers to the Cardio (heart) and vascular (blood vessels). The system has two major functional parts: central circulation system and systemic circulation system. Central circulation includes the pulmonary circulation and the heart from where the pulse wave is generated. Systemic circulation is the path that the blood goes from and to the heart. Pulse wave is detected at arteries which include elastic arteries, medium muscular arteries, small arteries and arterioles. The typical muscular artery has three layers: tunica intima as inner layer, tunica media as middle layer, and tunica adventitia for the outer layer. The material properties of arteries are highly nonlinear. It depends on the contents of arterial wall: how collagen, elastin and protein are located in the arteries. Functional and structural changes in the arterial wall can be used as early marker for the hypertensive and cardiac diseases.

Blood flow is the key to monitor the cardiovascular health condition since it is generated and restrict within such system. Currently the most widely used method for haemodynamic parameters detecting is invasive thermo-dilution method. Impedance-cardiography is the most commonly used non-invasive method nowadays; however, it is too complex for clinical routine check. Pulse wave analysis is an innovative method in the market to do fast and no burden testing.

Pulse is one of the most critical signals of human life. It comes directly from heart to the blood vessel system. As pulse transmitted, reflections will occur at different level of blood vessels. Other conditions such as resistance of blood flow, elastic of vessel wall, and blood viscosity have clear influence on pulse. Pathological changes affect pulse in different ways: the strength, reflection, and frequency. So pulse provides abundant and reliable information about cardiovascular system. Pulse can be recorded as a set of time series data and represented as a diagram which is called pulse

waveform or pulse wave for short. The cardiac output calculated by pulse wave factors is accurate even when heart rate, blood pressure, and total peripheral resistance change.

Early Detection of cardiovascular diseases is one of the most important usages for pulse wave monitoring. The convenience non-invasive technique makes it extremely suitable for widely use at community levels. Factors derived from pulse wave analysis have been used to detect hypertension, coronary artery diseases. Pulse wave is suggested to be early marker for those diseases and guide for health care professions during the therapy.

Hypertension is a clinical syndrome whose principal characteristic is an increase in systemic arterial pressure and it is the one of the most common cardiovascular diseases in the world. According to 2017 Indian guidelines for the management of hypertension the prevalence of hypertension has been increasing in India for decades, reaching 23.2%, which has greatly affected the health status of people. In addition, hypertension and other cardiovascular diseases, whose prevention cannot be ignored, possess the characteristics of high incidence, high mortality, and heavy medical burden. At present, the data on the classification and prediction of hypertension mainly come from inpatient electronic medical records, environmental and genetic factors, and gene expression data. pulse diagnosis has always played an important role in clinical diagnosis and treatment and subhealth recuperation. The pulse wave reflects the shape of the pulse beats and pulse graph is used as the objective image for recording the pulse wave.

The software outputs the information parameters of pulse for subsequent analysis. Time domain features of the pulse wave [10, 22, 23] including 6 duration features ( $t$ ,  $t_1$ ,  $t_2$ ,  $t_3$ ,  $t_4$ , and  $t_5$ ), 5 amplitude features ( $h_1$ ,  $h_2$ ,  $h_3$ ,  $h_4$ ,  $h_5$ ,  $h_1/t_1$ ,  $h_3/h_1$ , and  $h_4/h_1$ ), 4 width features ( $w_1$ ,  $w_2$ ,  $w_1/t$ , and  $w_2/t$ ), and 2 area features ( $A_s$ ,  $A_d$ ) were extracted by Shannon energy envelope and Hilbert transform.

Table 2.4.1. Meanings of Features extracted from pulse waveform in hypertension patient

No.	Features	Meaning
1.	h1	Main wave amplitude. It reflects the compliance of the aorta and the cardiac ejection fuction of the left ventricular
2.	h2	Main isthmus wave amplitude. Same physiological significance as h3.
3.	h3	Heavy wave front wave amplitude. It reflects the elasticity of arterial vessels and its peripheral resistance.
4.	h4	Dichrotic notch amplitude. It reflects the peripheral resistance of arterial vessels and the closure of aortic valve.
5.	h5	Gravity wave amplitude. It reflects the compliance of the aorta and the function of aortic valve.
6.	t1	Left ventricular rapid ejection period. The time value from the start point to the crest point of the main wave on the pulse graph.
7.	t2	The duration of the beginning of the tidal wave.
8.	t3	The duration of the crest of the tidal wave.
9.	t4	Left ventricular systolic duration. The time value from the start point to the dichrotic notch on the pulse graph.
10.	t5	Left ventricular diastolic duration. The time value from the dichrotic notch to the end point on the pulse graph.
11.	t	Includes left ventricular systolic and diastolic duration. The time value from he start point to the end point on the pulse graph.

12.	w1	Main wave 1/5 height. The duration of maintaining high intravascular pressure.
13.	w2	Main wave 1/5 height. The duration of maintaining high intravascular pressure.
14.	w1/t	The ratio of the width of the main wave at its 1/3 height to the entire pulse cycle. It reflects the proportion of the duration time of continuous high pressure in the aorta in the entire pulse cycle.
15.	w2/t	The proportion of the duration time of continuous high pressure in the aorta in the entire pulse cycle.
16.	h1/t1	Cardiovascular function
17.	As	Systolic area. The area on the pulse graph is related to cardiac output.
18.	Ad	Diastolic area

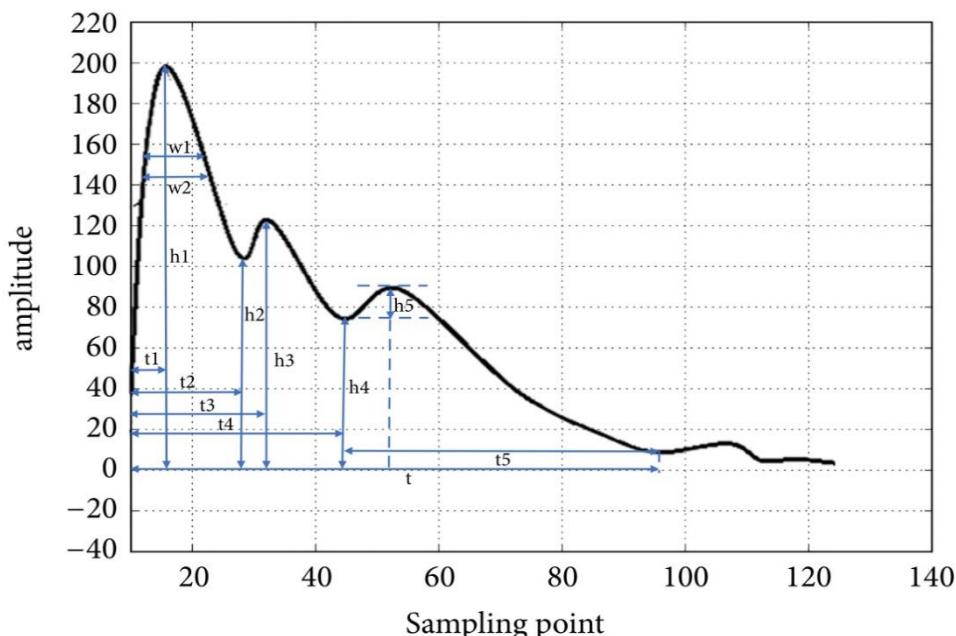


Figure 2.4.1. Features of pulse wave for hypertension patient

Table 2.4.2. Comparison of the Variables between Hypertension group and Healthy Group

<b>Feature</b>	<b>Healthy group</b>	<b>Hypertension group</b>	<b>p value</b>
Age	$44.44 \pm 9.204$	$44.7 \pm 8.706$	0.37
BMI	$23.91 \pm 2.961$	$25.55 \pm 3.306$	0.0 **
w1	$0.18 \pm 0.035$	$0.18 \pm 0.033$	0.55
w2	$0.13 \pm 0.034$	$0.14 \pm 0.034$	0.05
As	$0.22 \pm 0.029$	$0.22 \pm 0.028$	1
Ad	$0.11 \pm 0.035$	$0.1 \pm 0.036$	0.0 **
h1	$116.0 \pm 35.992$	$126.11 \pm 44.893$	0.0 **
h2	$84.98 \pm 32.215$	$93.18 \pm 40.319$	0.02 **
h3	$78.02 \pm 29.356$	$85.73 \pm 36.019$	0.01 **
h4	$44.78 \pm 15.047$	$47.55 \pm 18.016$	0.09
h5	$12.8 \pm 4.455$	$12.16 \pm 4.056$	0.04 **
t1	$0.14 \pm 0.021$	$0.14 \pm 0.022$	0.31
t2	$0.24 \pm 0.037$	$0.24 \pm 0.041$	0.0 **
t3	$0.27 \pm 0.033$	$0.27 \pm 0.038$	0.08
t4	$0.36 \pm 0.03$	$0.36 \pm 0.034$	0.23
t5	$0.41 \pm 0.023$	$0.41 \pm 0.028$	0.0 **
t	$0.85 \pm 0.119$	$0.83 \pm 0.128$	0.01 **

h1/t1	$838.82 \pm 276.686$	$919.03 \pm 355.812$	0.0 **
h3/h1	$0.67 \pm 0.128$	$0.68 \pm 0.133$	0.36
h4/h1	$0.39 \pm 0.082$	$0.38 \pm 0.082$	0.11
w1/t	$0.21 \pm 0.036$	$0.22 \pm 0.033$	0.0 **
w2/t	$0.16 \pm 0.036$	$0.16 \pm 0.035$	0.0 **
HR	$77.08 \pm 9.613$	$80.4 \pm 11.839$	0.0 **
H20 score	$85.74 \pm 4.868$	$76.38 \pm 10.331$	0.0 **

Compared with healthy group P <0.05, \*\* P <0.01

Compared with the healthy group, the hypertension group has higher BMI, h1, h2, h3, t2, t5, h1/t1, w1/t, and HR and lower h5, t, w2/t, H20 score, and Ad (P<0.05).

Previous studies showed that hypertension and pulse waves had a strong correlation, and statistical description of this study also confirmed this phenomenon. The comparative results of the pulse wave characteristics showed that the values such as h1/t1, h1, h3, and w1/t were higher than those in the healthy group. Therefore, the differences of characteristics in pulse wave between hypertensive and healthy group made it possible to further classify them using machine learning. Different sample clustering had found a certain degree of regularity. Pulse waves with higher heat values were grouped together (typical hypertension pulse wave); pulse waves within middle-ranged heat values were collected together (mixed part of hypertension pulse wave and healthy pulse wave); pulse waves with low heat values were gathered together. Further observation revealed that the pulse wave with a lower heat value was mixed with more noise. This part of the noise was in line with the pulse wave neither in hypertensive group nor in healthy group. This noise primarily derives from respiration and muscle tension. On the one hand, the respiration can lead to abnormalities in the pulse wave. On the other hand, subjects who have the high muscle tension are likely to cause tremor of the pulse wave. Therefore, the elimination of such pulse wave is necessary. . The

results of traditional analysis and machine learning imply that the variables of h1/t1, h5, t, Ad, BMI, and t2 are likely to connect with hypertension.

## 2.5. Pulse Waveform of Patients with Thyroid

The thyroid gland is an endocrine gland located in the neck below the thyroid cartilage. The main function of the thyroid gland is producing thyroid hormones, the principal ones being triiodothyronine (T3) and thyroxine (T4). T3 and T4 are synthesized from both iodine and tyrosine. The thyroid also produces calcitonin, which plays a role in calcium homeostasis. The two conditions resulting from impairment of the thyroid glands are hypothyroidism and hyperthyroidism, of which hypothyroidism is more common.

Hypothyroidism is a major condition affecting many people. Most are unaware they have thyroid disease as the clinical signs are not visible externally. Only when they take the blood test will they know. In hypothyroidism, the thyroid gland does not produce a sufficient amount of the thyroid hormones thyroxine (T4) and triiodothyronine (T3).

Thyroid problems are among the most common endocrine disorders presently seen worldwide. Hypothyroidism results when the thyroid gland fails to produce enough of the thyroid hormone, due to structural or functional impairment that significantly impairs its output of hormones, this leads to the hypo metabolic state of hypothyroidism. It is estimated to affect between 3.8-4.6% of the general population. The prevalence of primary hypothyroidism is 1:100, but increases to 5:100. The female-male ratio is approximately 6:1. There is no direct reference of thyroid in Ayurvedic classics, but Galganda and Gandmala have been frequently used in these classics. According to Charaka presentation of multiple Granthi around the neck is called Gandmala and single swelling on the Parshava of the neck is Galganda. So Galganda and Gandmala can be co-related with hypothyroidism. The incidence of hypothyroidism is increasing day by day, and there is increasing demand to treat the disease through the Ayurvedic system of medicine, as it is completely natural and safe. The root cause of hypothyroidism is disequilibrium of tridosha. In this article effort is

made to review some Ayurvedic herbs for correction of imbalance in tridosha and flawed function of the thyroid gland.

One cause of thyroid disease is autoimmune disorder. Antibodies present in the body itself attack the thyroid glands resulting in a condition named autoimmune thyroiditis which eventually destroys the thyroid gland.

Another reason is physical and mental stress. Physical stress can be defined as stress on the physical body where it is not able to accommodate a lifestyle such as fast food, disturbed sleep patterns and environmental risk factors. Mental stress can arise from work pressure, emotional weakness, grief or family disputes. All of these factors result in the secretion of cortisol, the hormone which acts as a protective mechanism to stress. Originally developed as a response to physical threat, when the duration of stress increases too much cortisol causes the tissues to no longer respond to the thyroid hormone signal. This is known as thyroid resistance. It can cause thyroid stimulating hormone (TSH) levels to be elevated while T4 and T3 are within the normal range

The main causes of thyroid disease are diet and lifestyle factors that imbalance the digestive fire or *agni* and metabolism. Stress and overwork also play an important part as this causes imbalanced agni and vitiation of the dosha. In thyroid disorders *kapha dosha* is vitiated which can cause a depletion of *ojas*. Once the ojas is affected then the immune system begins to act improperly, attacking the thyroid gland and resulting in depletion of thyroid functions and body metabolism.

Kapha dosha has the property of *guru* which means heaviness. It also has the property of *manda* or dullness. Treatment should focus on reducing *manda* guna of Kapha dosha. Ayurvedic herbal formulas for thyroid include Vaisvanara curnam for Agni Dipana, Varunadi Kasayam, Punarnavadi kasayam and Kancanara guggulu. The practice of nasya is also beneficial.

There are several classification system for the pulse wave. The notch can be used as the indicator to classify pulse wave into four categories as follows:- Figure is shown below

- Class I: A distinct incisura is inscribed on the downward slope of the pulse wave
  - Class II: No incisura develops but the line of descent becomes horizontal
  - Class III: No notch is present but a well-defined change in the angle of descent is observed
  - Class IV: No evidence of a notch is seen
- 

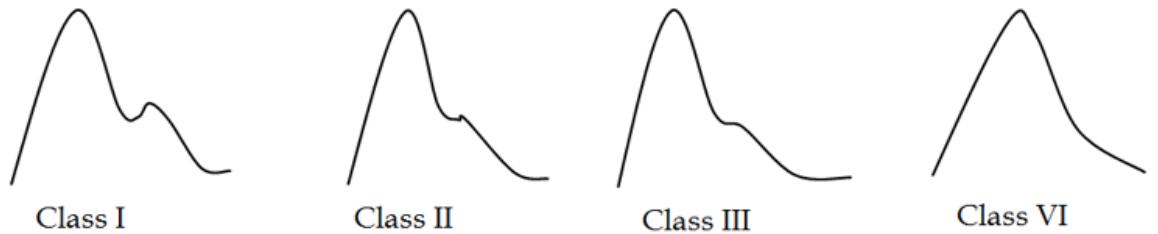


Figure 2.5.1. Pulse Wave Classification using Notch as feature.

This classification focus on the notch of the wave form which is considered as the indicator of arterial stiffness. This evaluation also continues wave forms to include other possible diseases. This is given in the table below:-

Table 2.5.1. Possible disease & Physiological cause of different pulse types

Pulse type	Physiological cause	Possible disease
Small & weak	Decreased stroke volume	Heart failure, hypovolemia, severe aortic stenosis
	Increased peripheral resistance	
Large & bounding	Increased stroke volume	Fever, anaemia, hyperthyroidism, aortic regurgitation, bradycardia, heart block, atherosclerosis
	Decreased peripheral resistance	
	Decreased compliance	
bisferiens	Increased arterial pulse with double systolic peak	Aortic regurgitation, aortic stenosis and regurgitation, hypertrophic cardiomyopathy
Pulsus alternans	Pulse amplitude varies from peak to peak, rhythm basically regular	Left ventricular failure

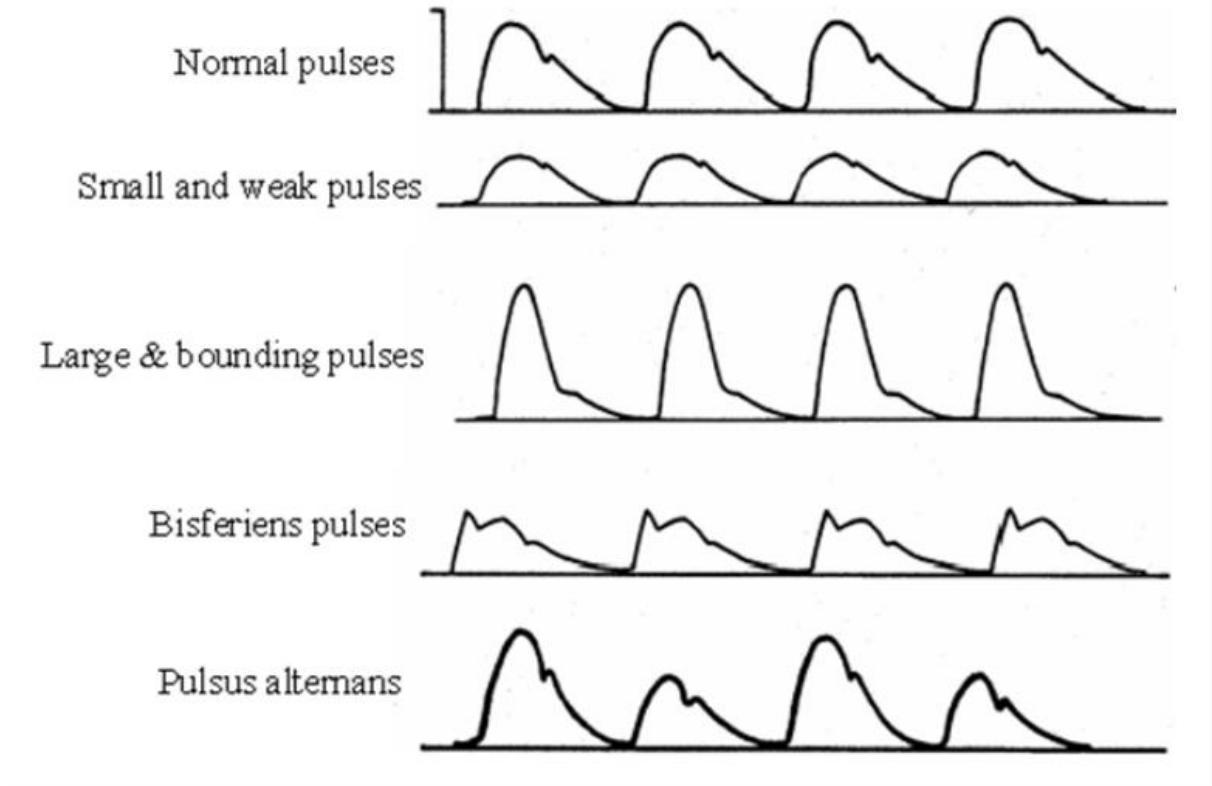


Figure 2.5.2. Pulse Wave Types

In order to get more precise information from the wave form, researchers have taken the traditional pulse diagnosis as the reference and have mapped the characters of pulse diagnosis with the pattern of wave form. It can also be used to detect certain cardiovascular risk as well as the classification. For example, acute anterior myocardial infarction will have a sharp systolic component and very small diastolic component which suggests poor blood supply.

**Rate:** □ Pulse rate is accurate measure of heart rate. Pulse rate increases during the conditions like exercise, emotional conditions, fever, anaemia, pregnancy and hyperthyroidism. Pulse rate decreases during the conditions of sleep, hypothermia, and hypothyroidism

### **3. Materials & Methods**

## 3.1. Materials

### 3.1.1 LEDs (Light Emitting Diodes)

Light Emitting Diodes (LEDs) are the real unsung heroes in the electronics world. They have various applications and are found in many devices. The first visible-light LEDs were of low intensity, and limited to red colour. Modern LEDs are available across the visible, ultraviolet, and infrared wavelengths, with very high brightness. Among other things, they form numbers on digital clocks, transmit information from remote controls, light up watches and tell you when your appliances are turned on.

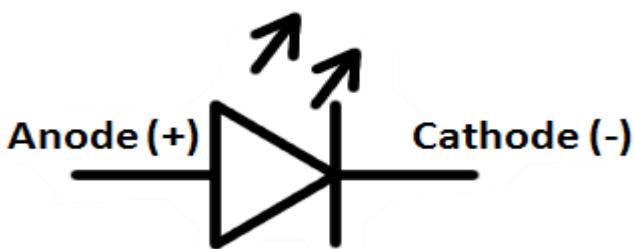


Figure 3.1.1. LED Symbol

Basically, LEDs are just tiny light bulbs that fit easily into an electrical circuit. But unlike ordinary incandescent bulbs, they don't have a filament that will burn out, and they don't get especially hot. They are illuminated solely by the movement of electrons in a semiconductor material, and they last just as long as a standard transistor. The lifespan of a LED surpasses the short life of an incandescent bulb by thousands of hours. Tiny LEDs are already replacing tubes that light up LCD HDTVs to make dramatically thinner televisions.

A light-emitting diode (LED) is a two semi-conductor light source. It is a PN-junction diode, which emits light when activated. When a suitable voltage is applied to the leads, electrons are able to recombine with electron holes within the device, releasing energy in the form of photons. This effect is called electroluminescence, and the colour of the light (corresponding to the energy of the photon) is determined by the energy band gap of the semiconductor.

Light is a form of energy that can be released by an atom. It is made up of many small particle-like packets that have energy and momentum but no mass. These particles, called photons, are the most basic units of light. Photons are released as a result of moving electrons. In an atom, electrons move in orbitals around the nucleus. Electrons in different orbitals have different amounts of energy.

For an electron to jump from a lower orbital to a higher orbital, something has to boost its energy level. Conversely, an electron releases energy when it drops from a higher orbital to a lower one. This energy is released in the form of a photon. A greater energy drop releases a higher-energy photon, which is characterized by a higher frequency. This involves a drop from the conduction band to a lower orbital, so the electrons release energy in the form of photons. This happens in any diode, but you can only see the photons when the diode is composed of certain material. For example, the atoms in a standard silicon diode are arranged in such a way that the electron drops a relatively short distance. As a result, the photon's frequency is so low that it is invisible to the human eye, i.e. it is in the infrared portion of the light spectrum. This isn't necessarily a bad thing, of course: Infrared LEDs are ideal for remote controls, among other things.

Visible light-emitting diodes (VLEDs), such as the ones that light up numbers in a digital clock, are made of materials characterized by a wider gap between the conduction band and the lower orbitals. The size of the gap determines the frequency of the photon, in other words, it determines the colour of the light.

While LEDs are used in everything from remote controls to the digital displays on electronics, visible LEDs are being widely used and growing popularity, thanks to their long lifetimes and miniature size. Depending on the materials used in LEDs, they can be built to shine in infrared, ultraviolet and all the colours of the visible spectrum.

The human eyes are detectors which are designed to detect visible light waves (or visible radiation). Visible light is one of the few types of radiation that can penetrate our atmosphere and be detected on the Earth's surface. Since the discovery of infrared spectrum, there are forms of light (or radiation) which we cannot see. Actually we can only see a very small part of the entire range of radiation called the electromagnetic

spectrum. The figure 6 indicates the wide range of electromagnetic spectrum along with gamma rays, X-rays, UV, infrared, etc. The only difference between these different types of radiation is their wavelength or frequency. The wavelength increases (and the frequency decreases) as we move from gamma rays to radio waves. All of these forms of radiation travel at the speed of light.

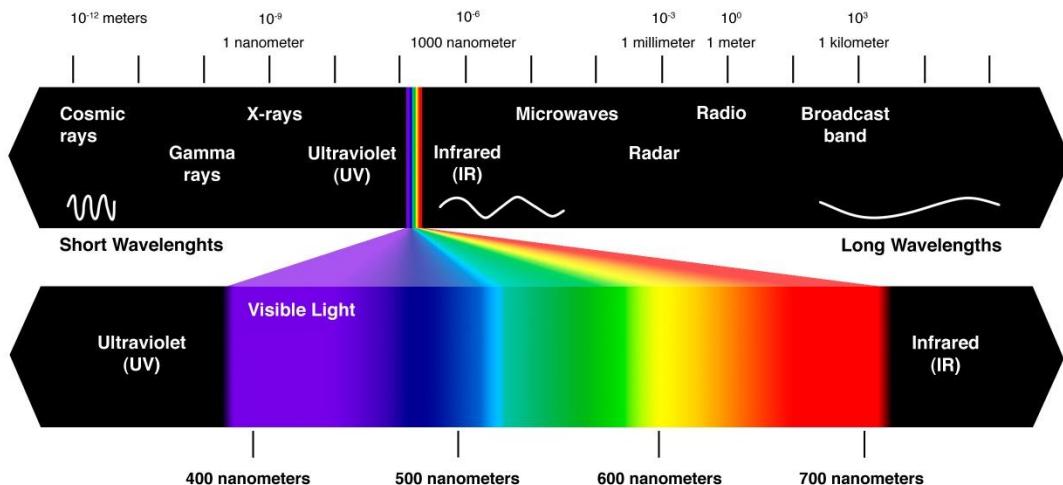


Figure 3.1.2. Electromagnetic Spectrum

### 3.1.1.1. LED selection:

As discussed above, there are various types of LEDs owing to the broad range of electromagnetic spectrum. It is found that the full spectra of purple-to-IR light can be used to assess heart rate in a wearable device near the skin. However, some wavelengths work better than others, depending on the use case.

Each wavelength of light has a benefit depending on what biometric one is trying to measure, how one's trying to measure it, the use case in which it is measured, and the measurement accuracy requirements.

*Infrared (IR) LED:* Infrared radiation lies between the visible and microwave portions of the electromagnetic spectrum. Infrared waves have wavelengths longer than visible and shorter than microwaves, and have frequencies which are lower than visible and higher than microwaves. Infrared is invisible radiant energy, extending from the

nominal red edge of the visible spectrum at 700 nanometres to somewhat 1mm. Infrared is further classified into three categories: near, mid and far-infrared. Near infrared (NIR) refers to the part of the infrared spectrum that is closest to visible light and far-infrared refers to the part that is closer to the microwave region. Mid – infrared region is between the above two mentioned. Infrared LEDs, commonly used in remote controls for televisions and a wide variety of sensing and data communications applications, reach wavelengths of 940 nm and higher.

What our eyes perceive as colour is created by light's frequency (the number of light waves that pass a point in a certain time). Red is the lowest frequency of light that humans normally can see, and infrared's frequency below that level. Current medical devices often use the “near-infrared”, which is just beyond what the eye can see. This frequency is not blocked by water, so it can be used in the body, which is largely made up of water.

*Green LED:* Green light PPG sensors are used in the majority of optical heart rate monitor (OHRM) products for a few reasons: there is a vast amount of existing knowledge of the technology because of its common use. The body absorbs green really well, it's great for reducing signal distortion, but it doesn't penetrate deep. A lot of it is absorbed by body so one doesn't get anything deeper than pulse signal. It is also lesser affected by ambient light owing to the lesser scattering of green component of ambient light.

Furthermore, since green light is not majorly absorbed by blood compounds such as carboxy-haemoglobin as is the case with infrared radiation, one does not observe a large DC shift in the pulse signal, and can get a closer representation of the pressure wave electronically.

### **3.1.2. Photo- detectors:**

Photodetector is one of key component in optoelectronic integrated circuits (OEICs). Photodetectors are extensively used in optical communication systems, optical interconnections, and biomedical imaging and they typically operate from visible to near – infrared wavelength. Photo detectors are used primarily as an optical receiver, which operates by converting light signals that hit the junction to a voltage or current. The junction uses an illumination window with an anti-reflect coating to absorb the light photons. The result of the absorption of photons is the creation of electron-hole pairs in the depletion region. The principle that applies to photo detectors is the photoelectric effect, which is the effect on a circuit due to light. Most common examples of photo detectors are photodiodes and phototransistors. Other optical devices which are similar to photo detectors are solar cells, which absorbs light and convert it into electricity. LED is also similar to photo detector but is inverse of photodiode, instead of converting light to a voltage or current, it converts a voltage or current to light.

#### **3.1.2.1. Photodiode:**

Photodiodes are unique among light detectors in that when illuminated, they generate an output which is proportional to light level. They are solid state light detector that consists of a shallow diffused P-N junction with connections provided to the outside world.

A **photodiode** is a semiconductor device that converts light into current. The current is generated when photons are absorbed in the photodiode. A small amount of current is also produced when no light is present. Photodiodes are similar to regular semiconductor diodes except that they may be either exposed (to detect vacuum UV or X-rays) or packaged with a window or optical fiber connection to allow light to reach the sensitive part of the device. A photodiode is designed to operate in reverse bias.

### **3.1.2.2. Phototransistor:**

Phototransistors are solid state light detectors that possess internal gain. This makes them much more sensitive than photodiodes of comparably sized area. These devices can be used to provide either an analog or digital output signal. The phototransistor can be viewed as a photodiode whose output photocurrent is fed into the base of a conventional small signal transistor. While not required for operation of the device as a photodetector, a base connection is often provided allowing the designer the option of using base current to bias the transistor. A **photo transistor** is about one hundred times more sensitive than a photo diode.

### **3.1.2.3 Matched Detector Emitter Pairs**

The sensor used initially in this project is TCRT5000, which is a reflective optical sensor with both the infrared light emitter and phototransistor placed side by side and are enclosed inside a leaded package so that there is minimum effect of surrounding visible light.

Dimension of this leaded package is very small to make it feasible for a small portable device, 10.2 mm x 5.8 mm x 7 mm. Its operating range is within >20% relative collector current is 0.2 mm to 15 mm, which gives a typical output current of 1 mA when tested. It has daylight blocking filter, which reduces the interference of ambient light. Emitter of phototransistor detects the signal up to 950 nm wavelength, since IR wavelength is 940 nm, the duo works perfectly. The circuit diagram below shows the external biasing circuit for the TCRT5000 sensor. A fingertip placed over the sensor will act as a reflector of the incident light. The amount of light reflected back from the fingertip is monitored by the phototransistor.



Figure 3.1.3. TCRT5000

### 3.1.2.4 Integrated Diode Transimpedance Amplifiers:

One of the barriers to using a photodiode as an effective detector is the fabrication of the current to voltage, or transimpedance amplifier. This is a rather involved procedure that requires precision in the selection of component values owing to many variables affecting the performance such as even the photodiode dark current.

Component selection is further complicated by the commercial availability of only certain tolerance bands. However, there exist integrated photodiode and transimpedance amplifier based sensors that mitigate these issues. One such sensor would be the Texas Instruments OPT101. However, the Avago APDS-9008 proved to be a nifty little sensor, given its form factor and operational range.

The APDS-9008 came with a responsivity close to that of the human eye, and a light sensitivity with a fairly linear voltage to-intensity curve. Finally it is packaged with a focussing lens that helps concentrate the incident radiation on to the sensor better

### 3.1.3. Operational Amplifiers

An Op-Amp is basically a multi-stage amplifier that uses a number of amplifier stages interconnected to each other for DC amplifications. Therefore, it is used extensively in signal conditioning, filtering or to perform mathematical operations such as integration, addition, differentiation, etc.

Op-amps are voltage-amplifying devices that are used with external feedback components such as resistors and capacitors. These feedback components determine the operation of the amplifier by the different configurations of these feedback components.

An Operational Amplifier consists of two high impedance inputs and an output port. The two input ports are called inverting input (with a negative sign) and non-inverting input (with a positive sign).

In linear amplifiers, the output signal is the value of input signal multiplied by amplifier gain.

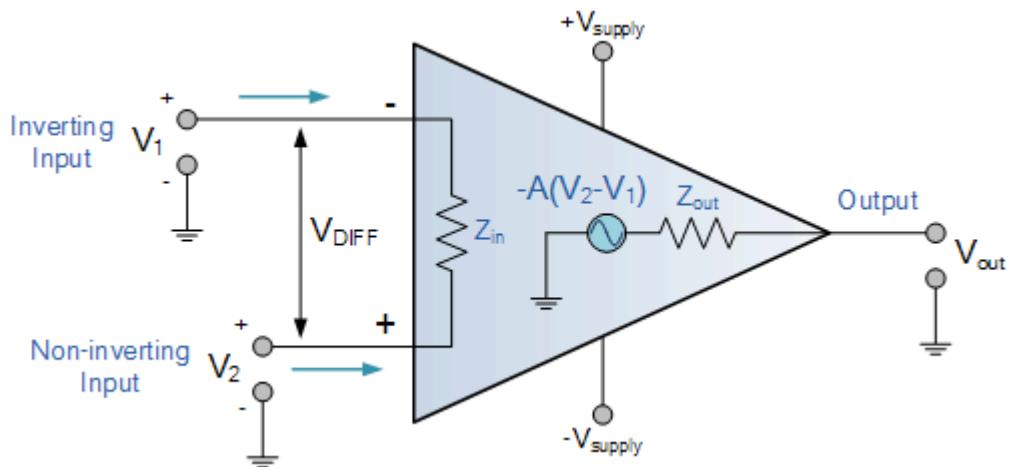


Figure 3.1.4. Ideal Op-Amp

Ideal Operational Amplifier Features:

- Infinite open-loop gain  $G = v_{out} / v_{in}$

- Infinite input impedance  $R_{in}$ , and so zero input current
- Zero input offset voltage
- Infinite output voltage range
- Infinite bandwidth with zero phase shift and infinite slew rate
- Zero output impedance  $R_{out}$
- Zero noise
- Infinite common-mode rejection ratio (CMRR)
- Infinite power supply rejection ratio.

The operational amplifiers used in the instrumentation circuit described above are from the MCP604 IC, which has got four general purpose Op-Amps offering rail-to-rail input and output over the 2.7 to 6V operating range.

### **3.1.3.1. MCP604 Operational Amplifier IC**

MCP604 is a low cost, high accuracy, resistor programmable, linear operational amplifier. Varying a single external resistor can vary the MCP604's gain. MCP604 quad operational amplifier (op amp) has a gain bandwidth product of 2.8 MHz with low typical operating current of 230uA. MCP604 uses Microchip's advanced CMOS technology, which provides low bias current, high-speed operation, high open-loop gain and rail-to-rail output swing.

MCP604 operates with a single supply voltage that can be as low as 2.7V, while drawing less than 325 of quiescent current per amplifier. This amplifier is ideal for industrial process control, low-power battery-operated devices, portable equipment, data acquisition equipment, test equipment and low-end audio applications.

Additional Features:

- Low Input Bias Current:1 pA (typ.)
- Gain-Bandwidth Product: 2.8 MHz
- Low Quiescent Current: 230  $\mu$ A/amplifier (typical)

- Low Input Offset Voltage: 2 mV (max.)
- Unity Gain Stable
- Rail to Rail Output
- Extended Temperature Range

## **3.2. Methods**

### **3.2.1 Photo-plethysmography (PPG)**

This project is based on the principle of photo-plethysmography (PPG) which is a non-invasive method of measuring the variation in blood volume in tissues using a light source and a detector. Since the change in blood volume is synchronous to the heart beat, this technique can be used to calculate the heart rate. Transmittance and reflectance are two basic types of photo-plethysmography. For the transmittance PPG, a light source is emitted in to the tissue and a light detector is placed in the opposite side of the tissue to measure the resultant light. Because of the limited penetration depth of the light through organ tissue, the transmittance PPG is applicable to a restricted body part, such as the finger or the ear lobe. However, in the reflectance PPG, the light source and the light detector are both placed on the same side of a body part. The light is emitted into the tissue and the reflected light is measured by the detector. As the light doesn't have to penetrate the body, the reflectance PPG can be applied to any parts of human body. In either case, the detected light reflected from or transmitted through the body part will fluctuate according to the pulsatile blood flow caused by the beating of the heart.

The following picture shows a basic reflectance PPG probe to extract the pulse signal from the fingertip. A subject's finger is illuminated by an infrared light-emitting diode. More or less light is absorbed, depending on the tissue blood volume. Consequently, the reflected light intensity varies with the pulsing of the blood with heart beat. A plot for this variation against time is referred to be a photo-plethysmographic or PPG signal.

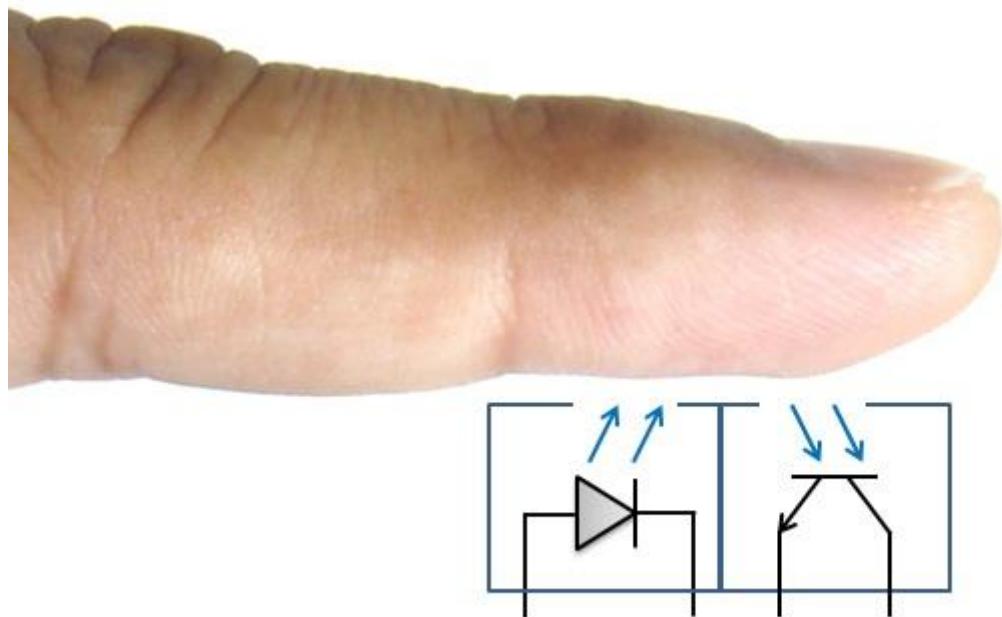


Figure 3.2.1. Finger photo-plethysmography (reflectance approach)

The PPG signal has two components, frequently referred to as AC and DC. The AC component is mainly caused by pulsatile changes in arterial blood volume, which is synchronous with the heartbeat. So, the AC component can be used as a source of heart rate information. This AC component is superimposed onto a large DC component that relates to the tissues and to the average blood volume. The DC component must be removed to measure the AC waveform with a high signal-to-noise ratio. Since the useful AC signal is only a very small portion of the whole signal, an effective amplification circuit is also required to extract desired information from it.

### 3.2.2. Collection of data

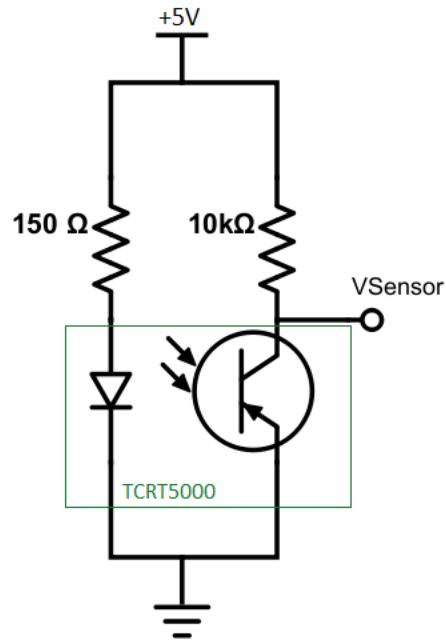


Figure 3.2.2. Biasing of TCRT5000

The output ( $V_{SENSOR}$ ) from the sensor is a periodic physiological waveform attributed to small variations in the reflected IR light which is caused by the pulsatile tissue blood volume inside the finger. The waveform is, therefore, synchronous with the heart beat. The following circuit diagram describes the first stage of the signal conditioning which will suppress the large DC component and boost the weak pulsatile AC component, which carries the required information.

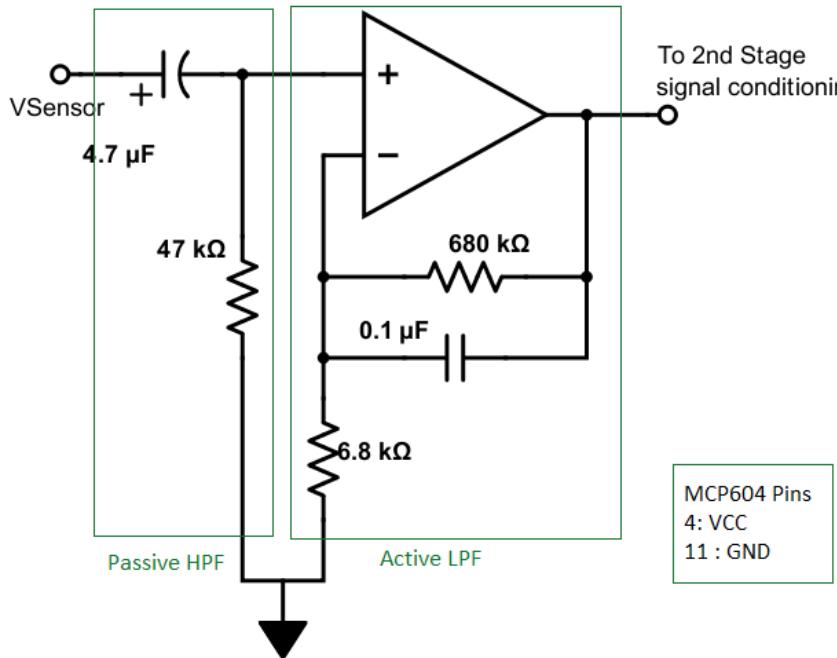


Figure 3.2.3. First stage of signal conditioning

In the circuit shown above, the sensor output is first passed through a RC high-pass filter (HPF) to get rid of the DC component. The cut-off frequency of the HPF is set to 0.7 Hz. Next stage is an active low-pass filter (LPF) that is made of an Op-Amp circuit. The gain and the cut-off frequency of the LPF are set to 101 and 2.34 Hz, respectively. Thus the combination of the HPF and LPF helps to remove unwanted DC signal and high frequency noise including 60 Hz (50 Hz in some countries) mains interference, while amplifying the low amplitude pulse signal (AC component) 101 times.

The output from the first signal conditioning stage goes to a similar HPF/LPF combination for further filtering and amplification (shown below). So, the total voltage gain achieved from the two cascaded stages is  $101 \times 11 = 1111$ . The two stages of filtering and amplification converts the input PPG signals to near TTL pulses and they are synchronous with the heartbeat. The frequency ( $f$ ) of these pulses is related to the heart rate (BPM) as,

$$\text{Beats per minute (BPM)} = 60 \times f$$

The final stage of the instrumentation constitutes a simple non-inverting buffer to lower the output impedance. This is helpful if an ADC channel of a microcontroller is used to read the amplified PPG signal.

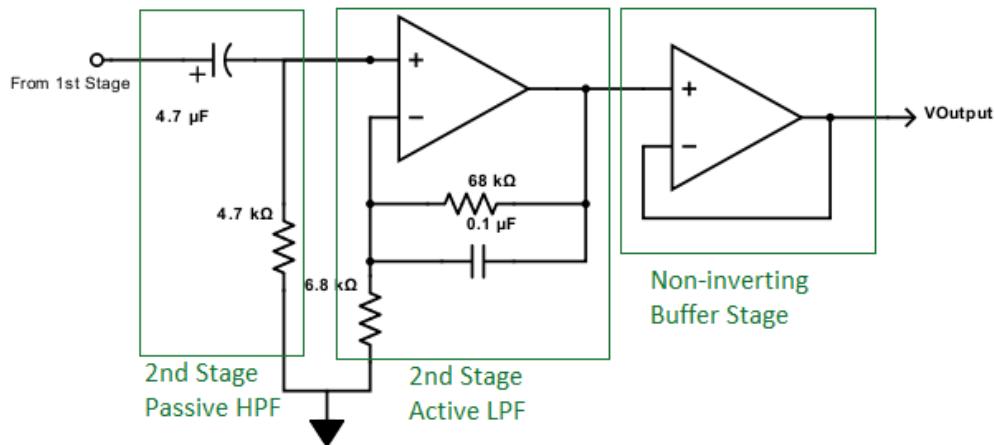


Figure 3.2.4. Second stage of signal conditioning

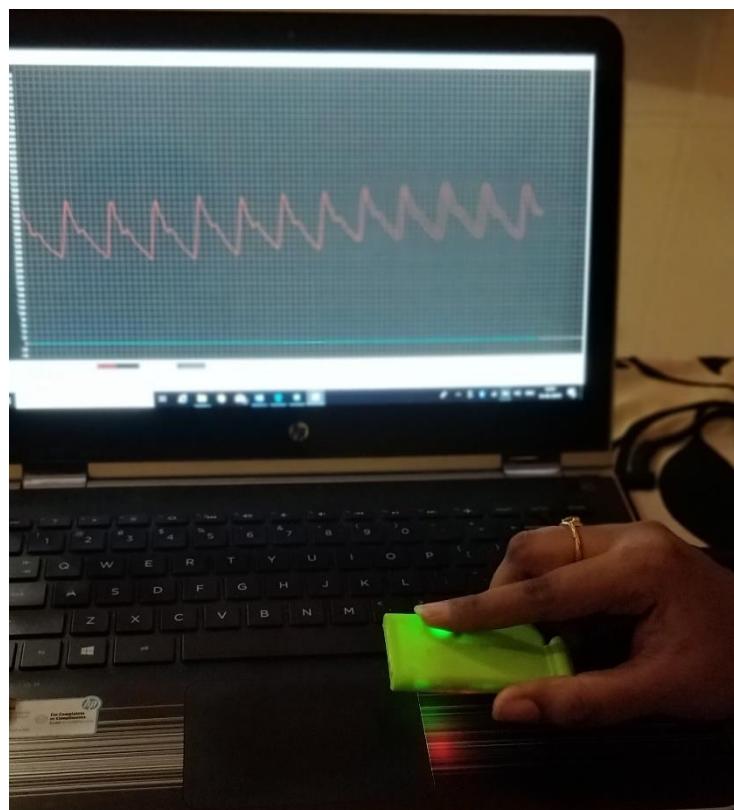


Figure 3.2.5. Final Hardware to collect the data

The signal collected using the custom sensor was saved into a text file. This file was then read using Python and the signal values were converted into a Python list containing the ADC values read at each given time period. Here on, a recursive Butterworth bandpass filter was applied to the signal. Essentially, this filter acts on the signal in the forward and backward direction, thus ensuring that the noise is minimal. Post filtering, the signal was subjected to a custom peaks detection algorithm, so as to find the fiducial points of the signal. This resulted in finding the amplitudes and positions of the peaks of the waves, and the same for the dichrotic notch. These extracted features were now used to determine the average, median, maximum and minimum amplitude values for the peak and dichrotic notch for each signal. These obtained values were then used as signal features to be fed into the ML classifier. It is further intended to obtain the principle frequencies and a couple of dominant harmonics from each signal to provide as features.

These features were then passed on to a multilayer perceptron neural network. This is an acyclic feedforward neural network, in that it facilitates only a unidirectional flow of information. This particular architecture was chosen in order to avoid complexity in the network. The neural network size and the hyper-parameters were decided with a mix of experimentation and a process called Grid Search Cross Validation. GSCV essentially searches through the hyper-parameter space and returns the best possible combination of the hyper-parameters that result in optimal performance of the classifier. The classifier shall be retrained as newer data arrives, and shall finally be tested and validated in order to judge its performance on some withheld data points.

In order to avoid the curse of dimensionality which prescribes an exponentially growing number of samples with each increasing feature, a feature selection routine is to be undertaken. Preferably a wrapping method shall be used where the feature search evaluates every possible combination of features and returns one that maximizes classifier accuracy. Further a feature analysis might be undertaken in order to determine the dominant and important features for the classifier. This shall be done using Principle Component Analysis or PCA.

### **3.2.3. Machine Learning**

Broader notion about building artefacts, computational artefacts typically, that learn over time based on experience. And then in particular it's not just the act of building these artefacts that matter, it's the math, science, engineering and computing behind it, that matters. It's everything that goes into building intelligent artefacts that almost by necessity have to learn over learn.

Essentially it is when a system learns a function over time not through explicit programming, but through iteratively performing an action and being bettered through feedback. Regardless of whether it is supervised feedback on betterment from a human agent, or unsupervised feedback from internal iterative function convergence.

#### **3.2.3.1. Neural Network**

A neural network is a learning structure designed to mimic the function of a web of biological neurons. The most basic (artificial) neural network is one that consists of just a single neuron, called a perceptron. The perceptron is a learning algorithm for a binary classifier, which classifies an input based on the return value of the activation function, which is typically assigned as one for a class, and zero for other classes. A number of layers of such perceptrons, appropriately weighted, may be concurrently used, and are eventually simplified into two layer input-output systems by linear algebra simplification. The multilayer perceptron is a feedforward neural network; it has no cycling between two layers resulting in a unidirectional movement of information. A multilayer perceptron however, in addition to the linear activation function of a perceptron, also contains neurons with non-linear activation functions such as sigmoid function or hyperbolic tangent function neurons. A typical multilayer perceptron consists of three or more layers, indicating one or more hidden layers in addition to the input and output layers. Since a multilayer perceptron is a fully connected feedforward network, each connection is a weighted one. These weighted connections are adjusted through a back-propagation in order to perform supervised learning. Typically the change in the weights at each learning iteration is found using a gradient descent algorithm in order to minimize the error between the prediction and the target variable.

Let us take a look at the parameters for this particular algorithm

*Hidden Layer Size:* This specifies the number of neurons and the number of hidden layers as a tuple. In effect this parameter defines function approximation via the number of weighted neurons and the layers of such neurons.

*Activation Function:* The activation function for the hidden layers was a rectified linear unit function, which acts as a ramp function, analogous to finding the maximum among the input of the neuron and zero, along with a unit addition to the neuron input. Other popular functions include the hyperbolic tangent ( $\tanh$ ) and the sigmoid activation function.

Choosing an appropriate level of model complexity is a key balancing act in machine learning. If the model is too complex, it will fit the data used to construct the model very well but generalise poorly to unseen data (overfitting); if the complexity is too low the model won't capture all the information in the data (under-fitting).

In machine learning, model performance depends heavily on the hyper-parameter values selected. The goal of hyper-parameter exploration is to search across various hyper-parameter configurations to find a configuration that results in the best performance. Typically, the hyper-parameter exploration process is painstakingly manual, given that the search space is vast and evaluation of each configuration can be expensive.

## *The Process of Learning Parameters*

It is a 4 step process:

- Input data is taken
- A generalised function is obtained
- Predicting values
- Parameter learning

The model parameters tell how to transform input data into desired output whereas, the hyper-parameters are used to determine the structure of the model in use.

Most common learning algorithms feature a set of hyper-parameters that must be determined before training commences.

The hyper-parameters change for different training algorithms and few don't even need one like ordinary least squares.

A hyper-parameter can change the outcome of a model for good with regards to the time taken to train it. So, the choice of hyper-parameters plays a crucial role. Having hyper-parameters is half part of the solution, the second part is knowing what kind of hyper-parameters suits the need.

*GridSearchCV*: Essentially, it searches a vector in the hyper-parameter space. Say, there's an n-dimensional space defined by n – parameters, then in that space, there exists some vector that optimizes the performance of the classifier. This vector is a specific solution, or even the only optimal solution. Gridsearch CV essentially searches this n-D space for such a vector that delivers this optimal performance. There's also a randomsearch CV, that essentially samples vectors from this space based on some distribution, but that usually results in suboptimal solutions. Also, Gridsearch returns a combination that can at times over fit the training data, in such instances we repeat the GridsearchCV and select the suboptimal solution and not the

most optimal solution because we don't want our hyper-parameter combination overfitting the training data. Gridsearch over the entire space is time consuming and cumbersome, so we usually just use a tiny portion of the space based on prior experience. So Gridsearch in many ways is a partially deterministic function since it uses heuristics to define the search boundary to ease the complexity of the operation.

The datasets chosen is biological datasets, more particularly datasets containing symptoms that eventually needed classification into categories of affected or non-affected. However, a major bottle neck towards working these wonders remains the gathering of data. The implementations of all the algorithms in this work were done using the scikit-learn (sklearn) library in Python. Other auxiliary libraries such as Numpy and Matplotlib were used. The hyper-parameters in the implementation for the dataset was achieved by using a GridSearch algorithm which essentially weighed the merits of several combinations of hyper-parameters and returned one with the greatest score. The parameter space was user defined in this implementation. However, the non-GridSearch version contains parameters tuned by hand using a good old trial and error method aiming to maximize test and validation set accuracy. The parameter values listed therefore for the dataset are from the GridSearch implementation. An extensive list of parameter values can be found as a comment at the bottom of each individual Python file for each algorithm. Finally the implementation for the artificial neural network does not contain a GridSearch version for tuning the hyper-parameters. This was owing to the lengthy run times due to the many parameters that needed tuning.

### 3.2.3.2. Decision Trees

Decision trees are a method for approximating discrete valued target functions. Each node in the tree tests some specific attribute of the instance in question. The implementation for this algorithm contains the pruned approach. The method of choice for pruning was pre-pruning, in that an early stoppage criterion was chosen in order to prevent the tree from growing too large and overfitting the data. The algorithm implemented is the CART (Classification and Regression Tree). A CART is a binary tree where each node represents a single input variable and a split on that variable. Let's now examine a few parameters that are important in the implementation of these

trees. The first of these is the splitting criterion; there are a couple of popular approaches: information gain and the Gini score. Let us consider each in turn.

*Information Gain:* Entropy measures the homogeneity of the samples and information gain measures the expected reduction in this entropy. Information gain is thus used in the selection of the best attribute to split on at each step of growing the tree.

*Gini Score:* The Gini score provides an intuition of how good a split is by showing how mixed the classes are in the sub groups created by that split. Typically splits with a lower Gini score are preferred.

The remaining parameters are largely concerned with regularization of the algorithm and to avoid overfitting it to the training data. Methods for avoiding overfitting are often called pruning techniques. There are two popular methods to perform this pruning, one is to implement some early stoppage criteria to prevent the tree from growing to become too complex and fit only the training data perfectly. The other would be to grow the tree as it normally would, then perform reduced error pruning on it to remove nodes that do not increase the overall error on the test data. A few parameters that help in the former of these pruning methods are as follows:

*Maximum Depth:* This prevents a tree from growing beyond a certain depth and is used as a parameter to prevent overfitting. This ensures that a tree does not grow overly complex and fit only the training data well.

*Minimum Samples to Split:* This is the minimum number of samples to consider when evaluating a split. This ensures that the efficiency of a split is measured against at least this minimum number of samples in order that the decision node generalizes well.

*Maximum Features:* This is the maximum number of features to consider when evaluating the merits of a split. This is to ensure that redundant features do not affect the merits of a split. This ensures that relevant features do not get suppressed when evaluating a split owing to the presence of other features.

*Minimum Impurity Decrease:* This ensures that the tree is grown only when the impurity in the data decreases by at least a set fraction. In turn this prevents redundant complexity in trees.

### 3.2.3.3. Gradient Boosting

This family of algorithms produces a prediction model as an ensemble of weak learners such as decision trees. This effectively results in a number of such weak learners coming together to create a strong learner. The algorithm used here is called GBT (Gradient Boosted Tree). The regularization techniques used here are largely to prevent the model from overfitting. A natural and intuitive parameter to control would be the number of weak learners, in this instance the number of decision trees. A very high number of trees may eventually lead to the model overfitting the training data, a very small number might lead to poor generalization. An optimal number has to be found that minimizes error on the test and validation sets. The learning rate is a parameter that tries to avoid overfitting via shrinkage. Typically it is observed that a small learning rate leads to better generalization although this might not be valid in all cases. Finally, each tree can be regularized by controlling the maximum depth to which it grows and the maximum leaf nodes each possesses much like the standalone CART algorithm. The implementation in this work primarily uses the number of weak-learners parameters and the parameters for pruning trees to regularize the model.

### 3.2.3.4. Support Vector Machines

This algorithm essentially views data points as d-dimensional vectors which could be potentially separated by a (d-1)-dimensional hyperplane. A hyperplane is chosen by virtue of its margins. Reasonably a hyperplane that has maximum distance to data points on either of its sides is typically chosen. This distance is often known as the decision margin. The SVM algorithms also possess an important parameter called the kernel function. The kernel function takes a data point as an input and transforms it to a desired output form. Essentially the kernel function returns the inner product between pairs of input data vectors. The hyperplanes are essentially a set of vectors whose dot products with other vectors in that space are constants. The sum or the products of such a hyperplane vector and a test data point mapped via a kernel function is a

measure of the closeness of the test point to points on either side of the hyperplane. This measure can ultimately be used to classify the test point into one or the other group.

**Kernel Functions:** Let us look at a couple of popular kernel functions used in conjunction with this algorithm:

*Polynomial Function:* This essentially returns a dot product of the pair of input data points summed to a constant variable exponentiated to the degree  $d$  of the chosen polynomial.

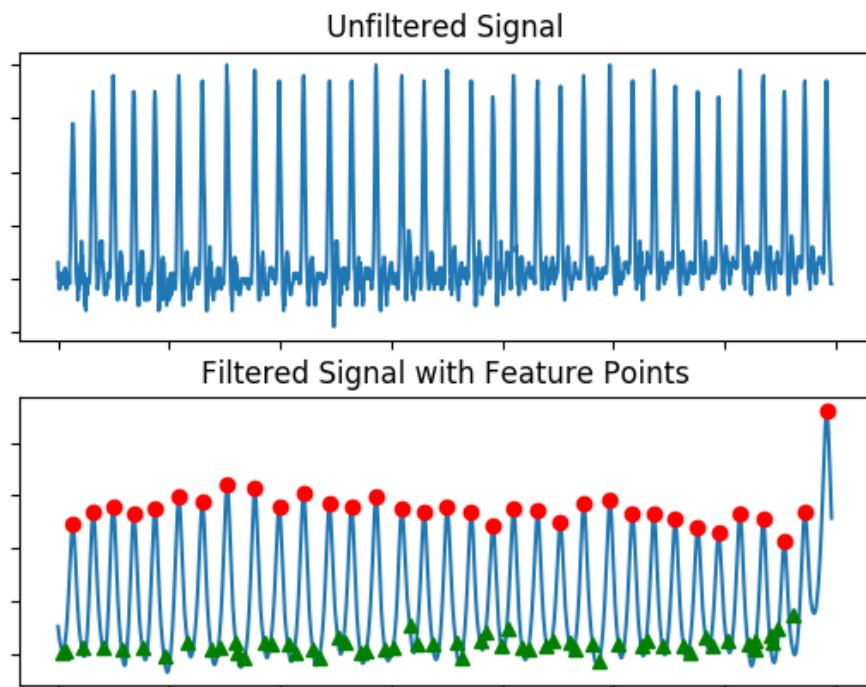
*Radial Bias Function:* This essentially returns an exponent of the squared distance norm multiplied by the negative of the gamma parameter.

*Gamma Parameter:* This parameter is the kernel coefficient. The value of gamma essentially decides the influence of a support vector on the ultimate classification of the test data point.

*C Parameter:* This is often known as the penalty parameter. It specifies the error margin of the classifying hyperplane. The penalty value is inversely proportional to the width of the margin.

## **4. Plethysmograph Signals from various subjects**

## Subject 1



Part of the unfiltered signal to facilitate better viewing of the signal.

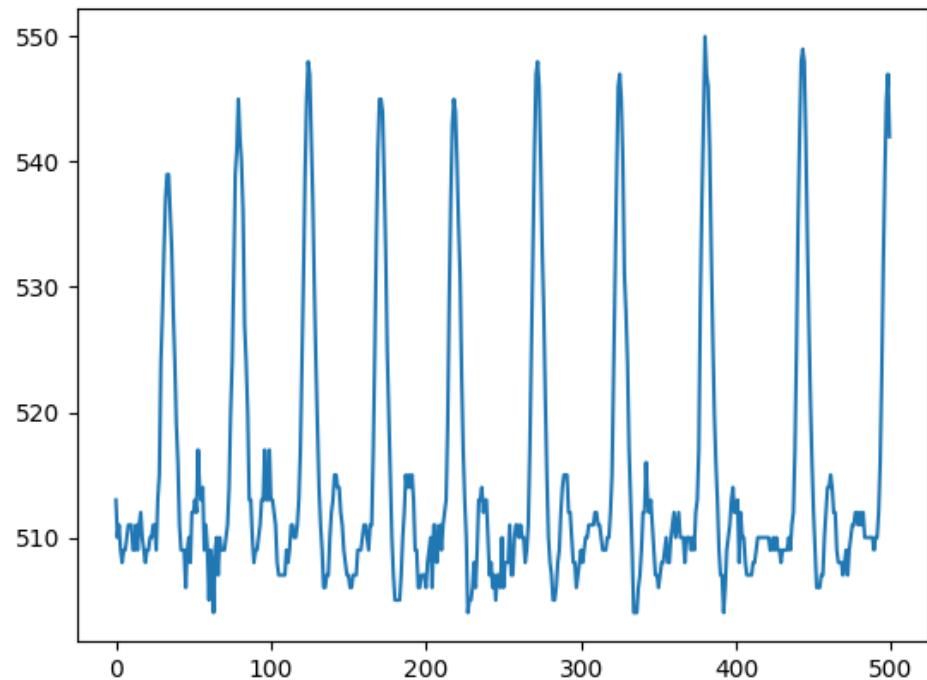
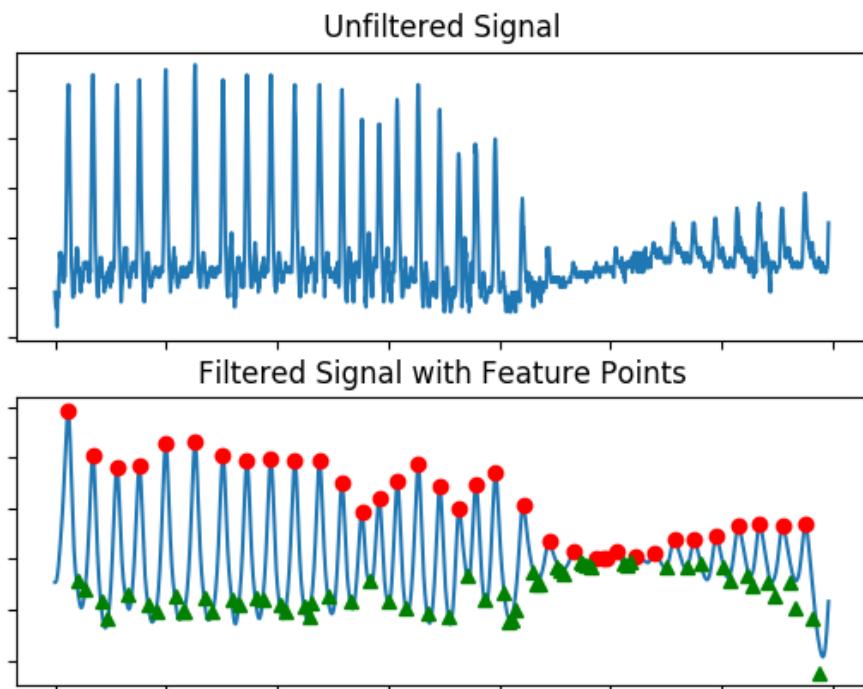


Figure 4.1. Unfiltered & Filtered Signal with Feature Points

## Subject 2



Part of the unfiltered signal to facilitate better viewing of the signal

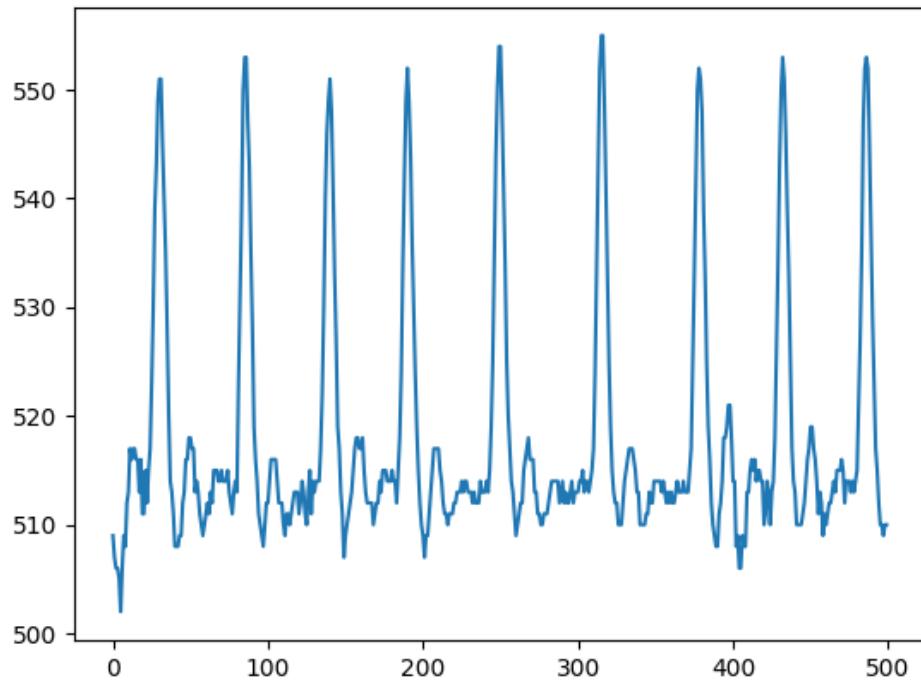
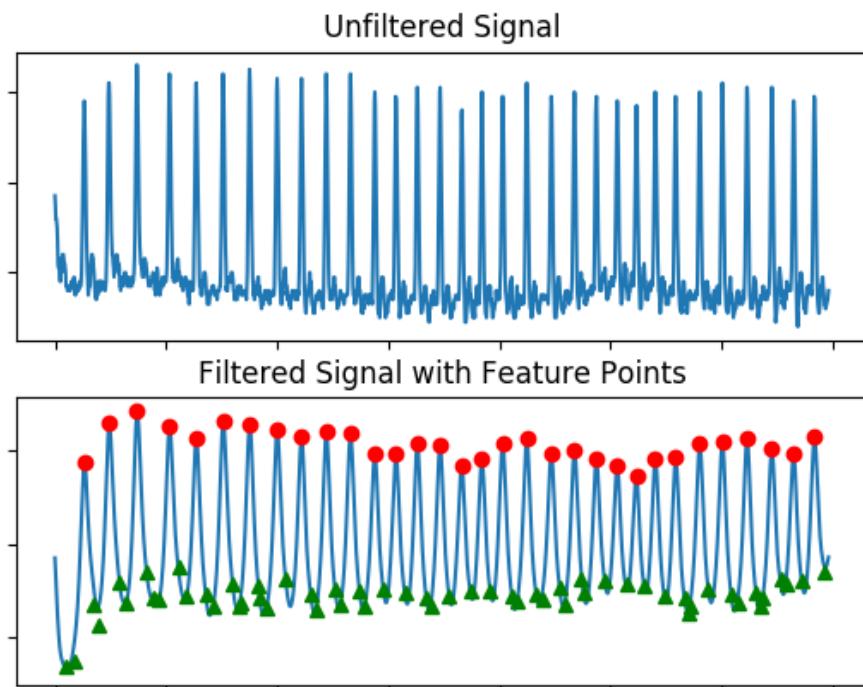


Figure 4.2. Unfiltered & Filtered Signal with Feature Points

### Subject 3



Part of the unfiltered signal to facilitate better viewing of the signal

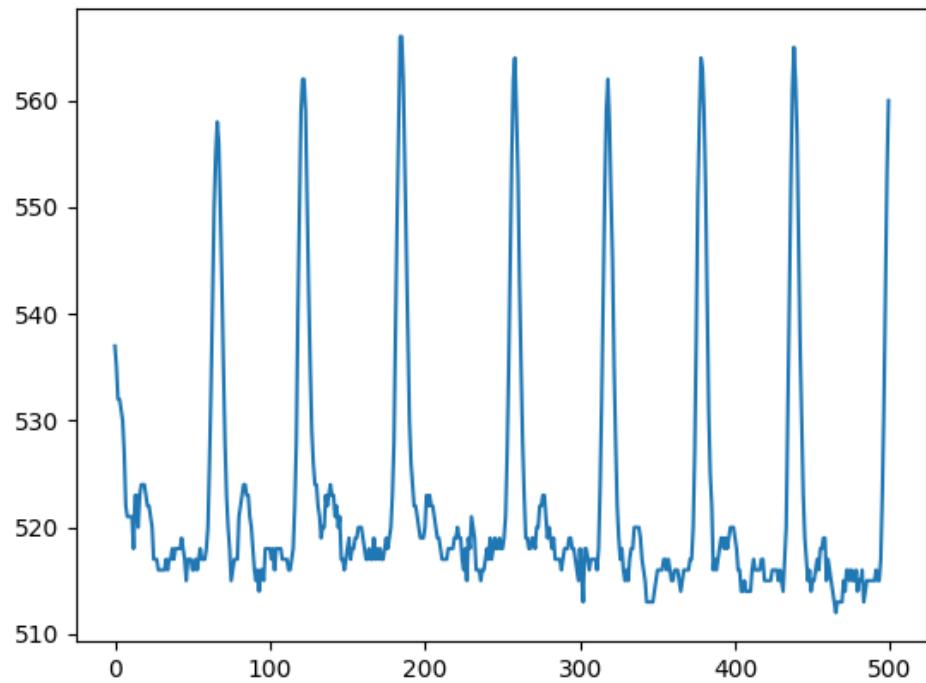
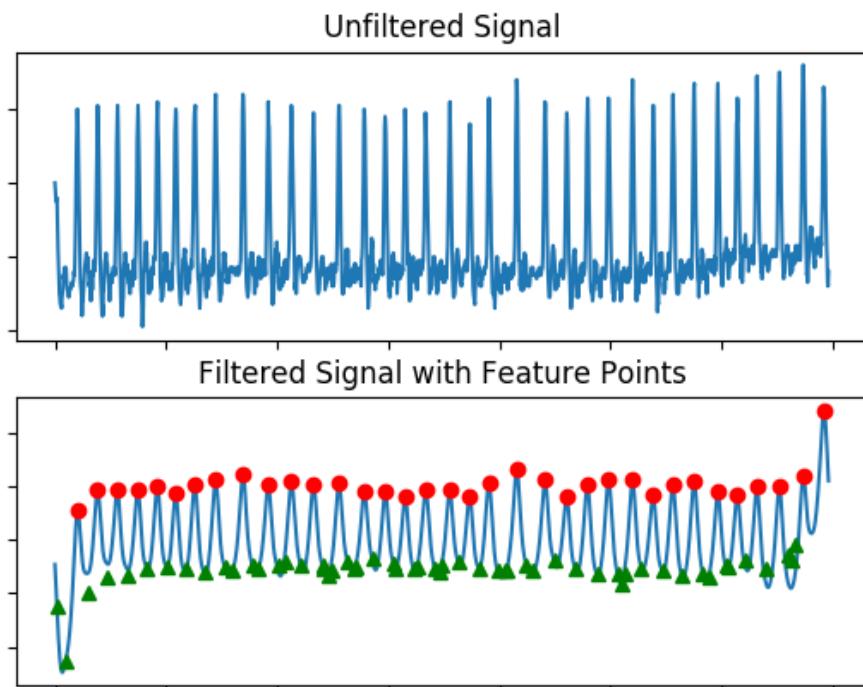


Figure 4.3. Unfiltered & Filtered Signal with Feature Points

## Subject 4



Part of the unfiltered signal to facilitate better viewing of the signal

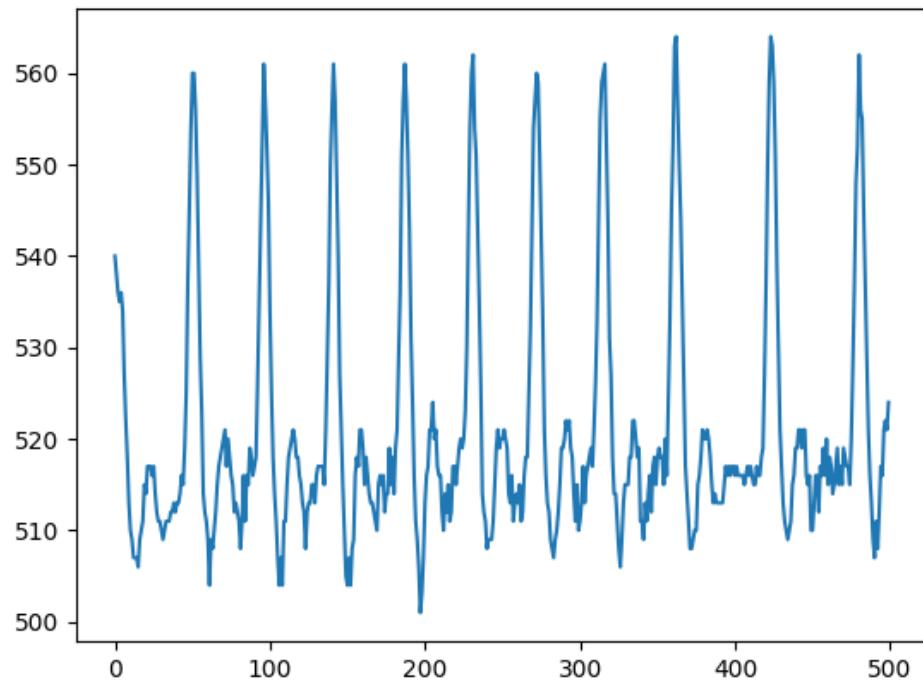
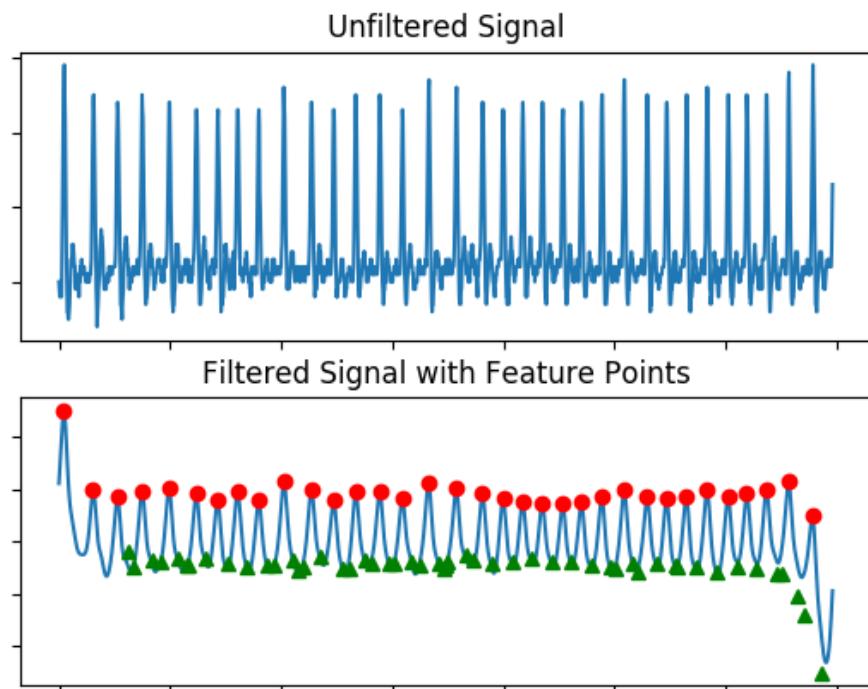


Figure 4.4. Unfiltered & Filtered Signal with Feature Points

## Subject 5



Part of the unfiltered signal to facilitate better viewing of the signal

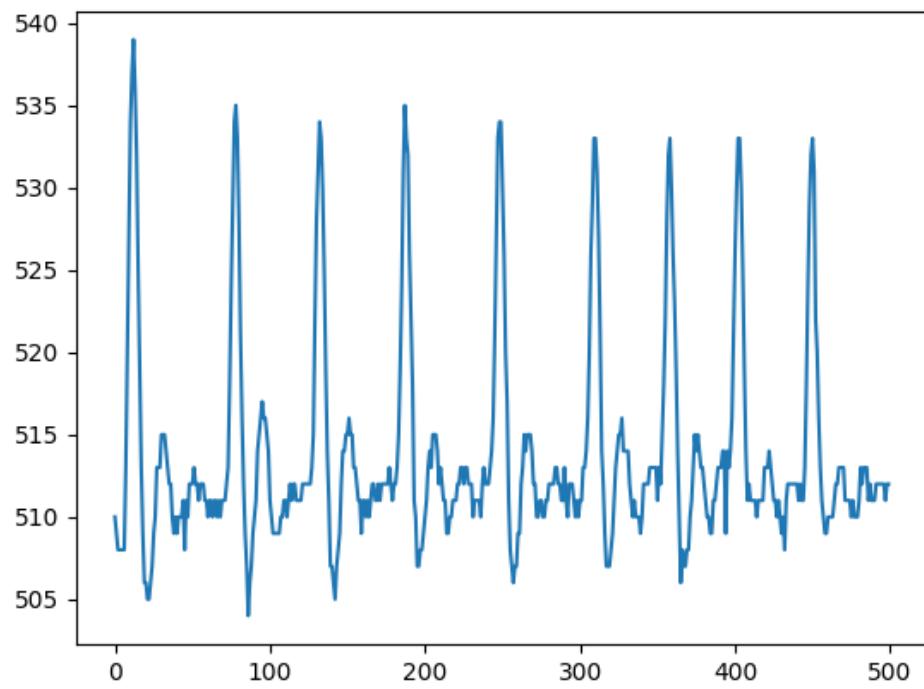
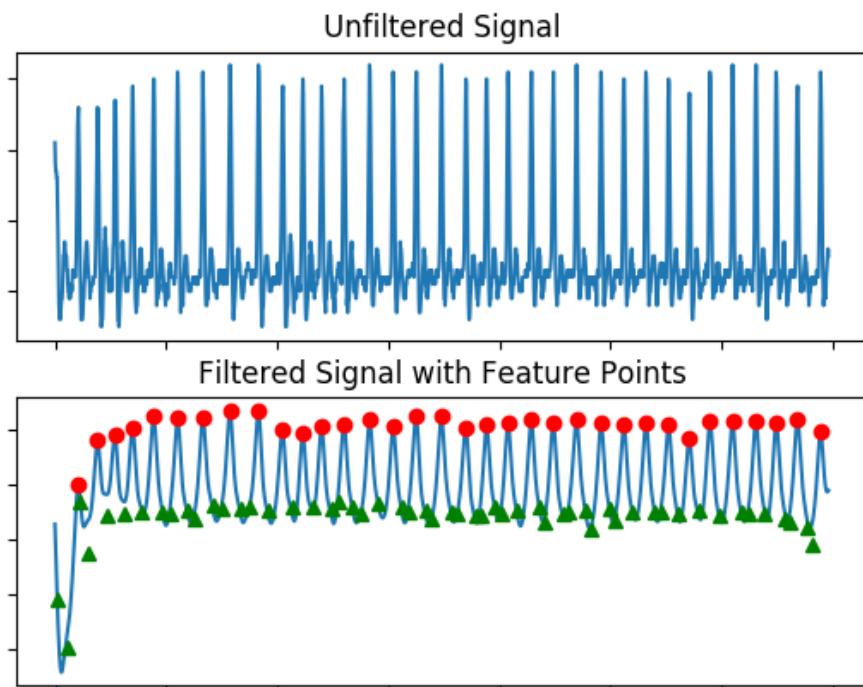


Figure 4.5. Unfiltered & Filtered Signal with Feature Points

## Subject 6



Part of the unfiltered signal to facilitate better viewing of the signal

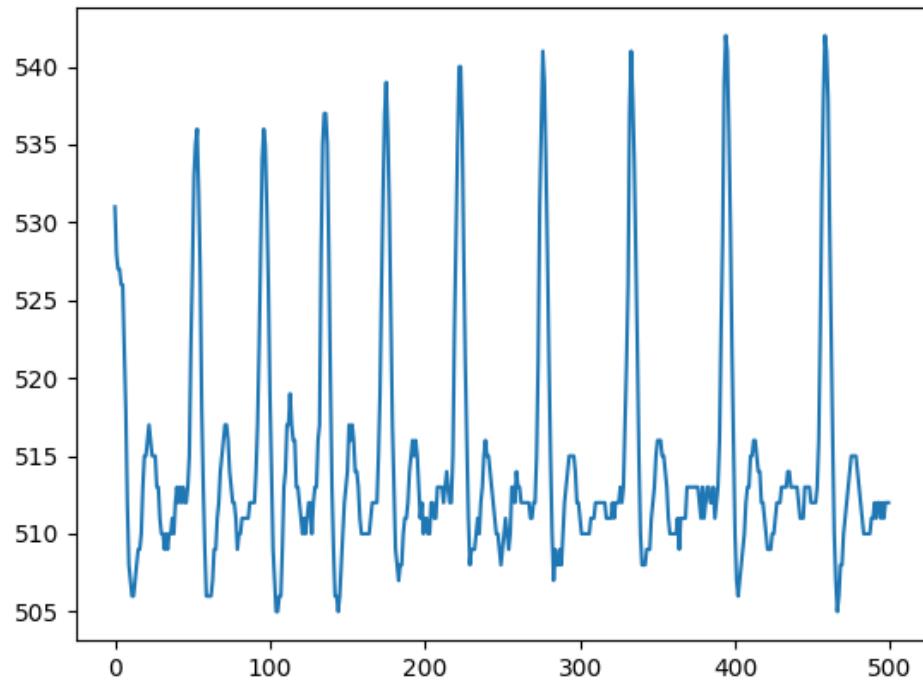
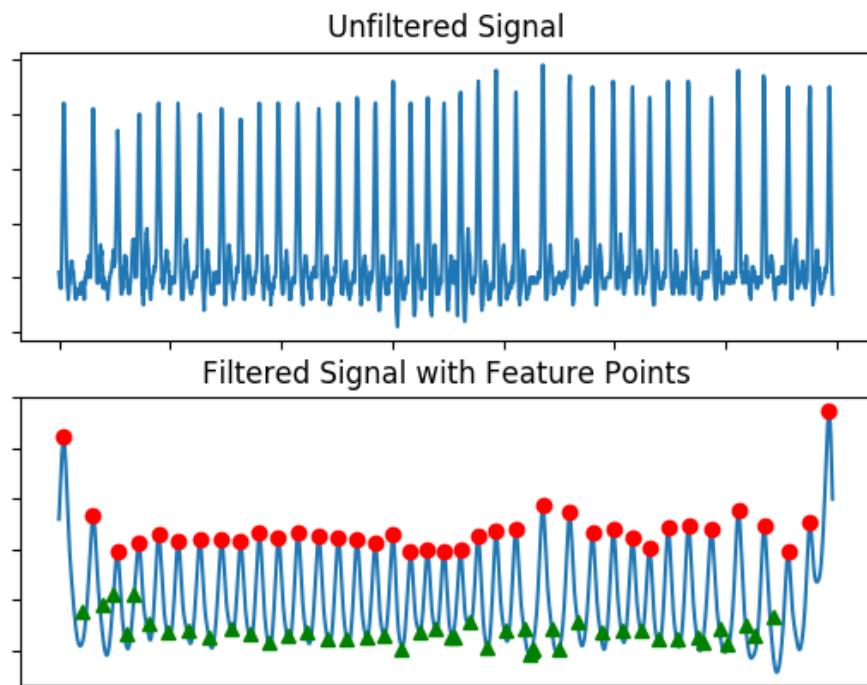


Figure 4.6. Unfiltered & Filtered Signal with Feature Points

## Subject 7



Part of the unfiltered signal to facilitate better viewing of the signal

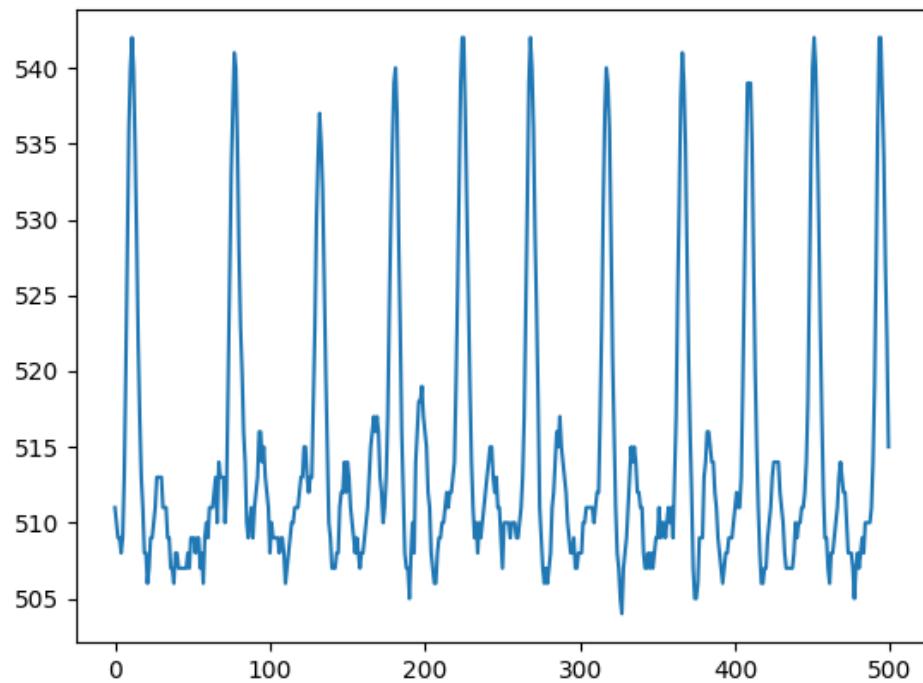
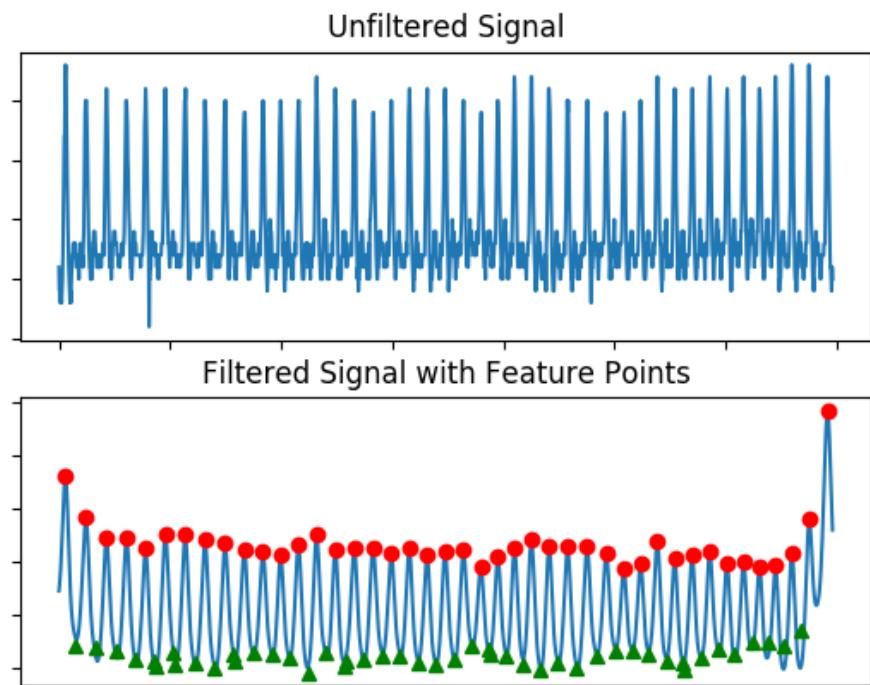


Figure 4.7. Unfiltered & Filtered Signal with Feature Points

## Subject 8



Part of the unfiltered signal to facilitate better viewing of the signal

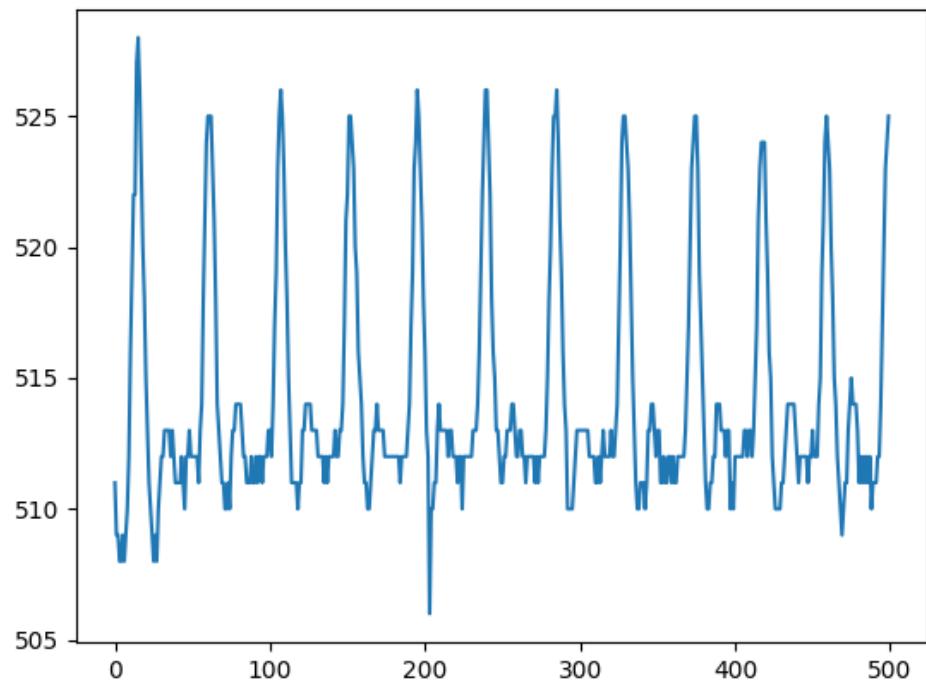
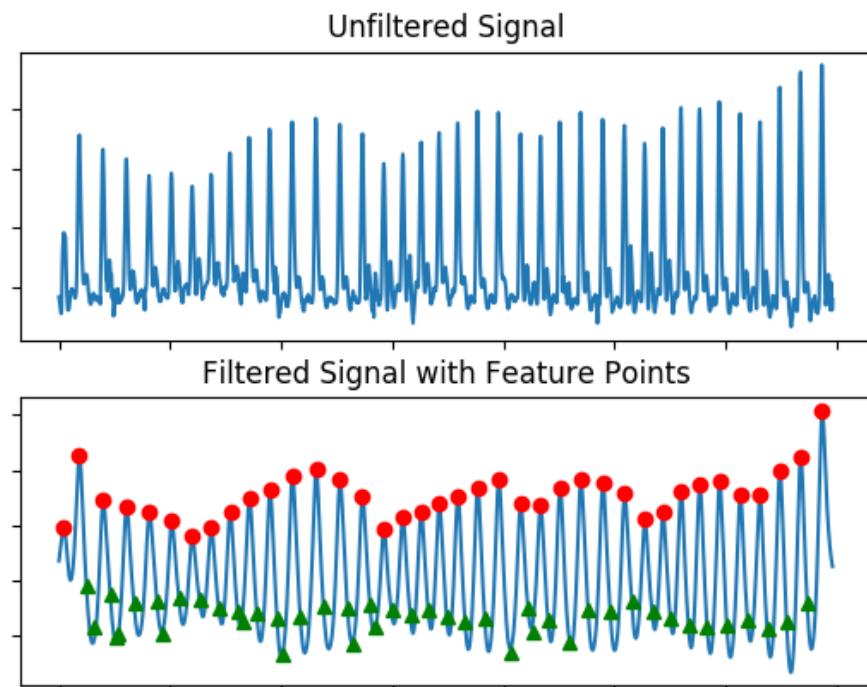


Figure 4.8. Unfiltered & Filtered Signal with Feature Points

## Subject 9



Part of the unfiltered signal to facilitate better viewing of the signal

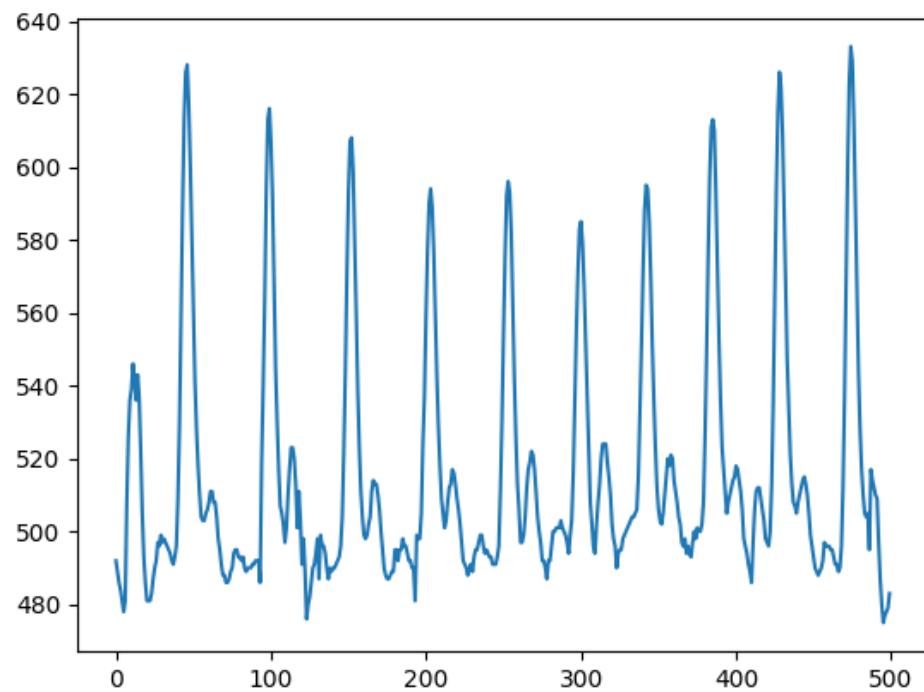
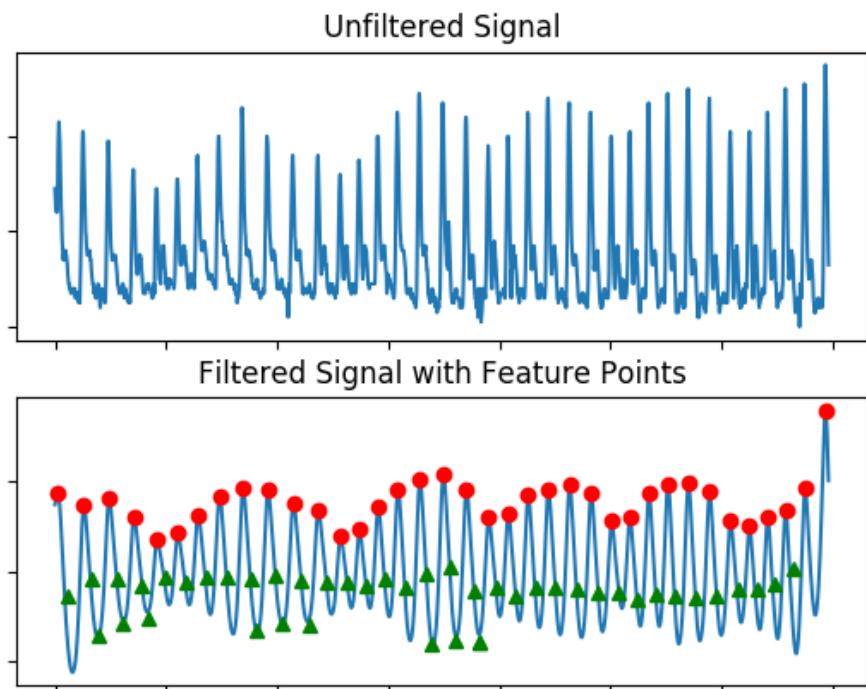


Figure 4.9. Unfiltered & Filtered Signal with Feature Points

## Subject 10



Part of the unfiltered signal to facilitate better viewing of the signal

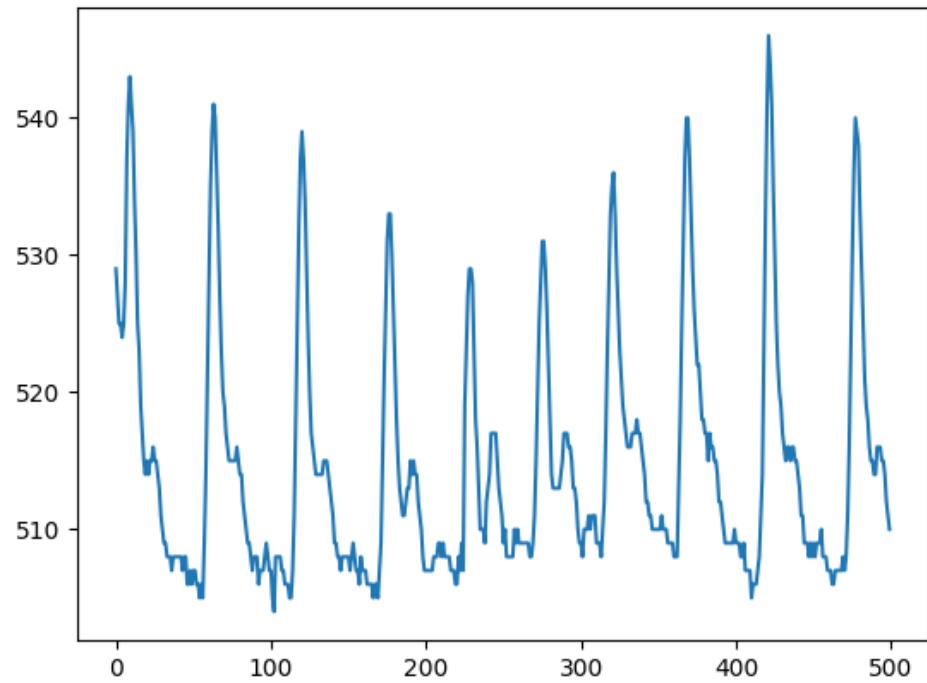
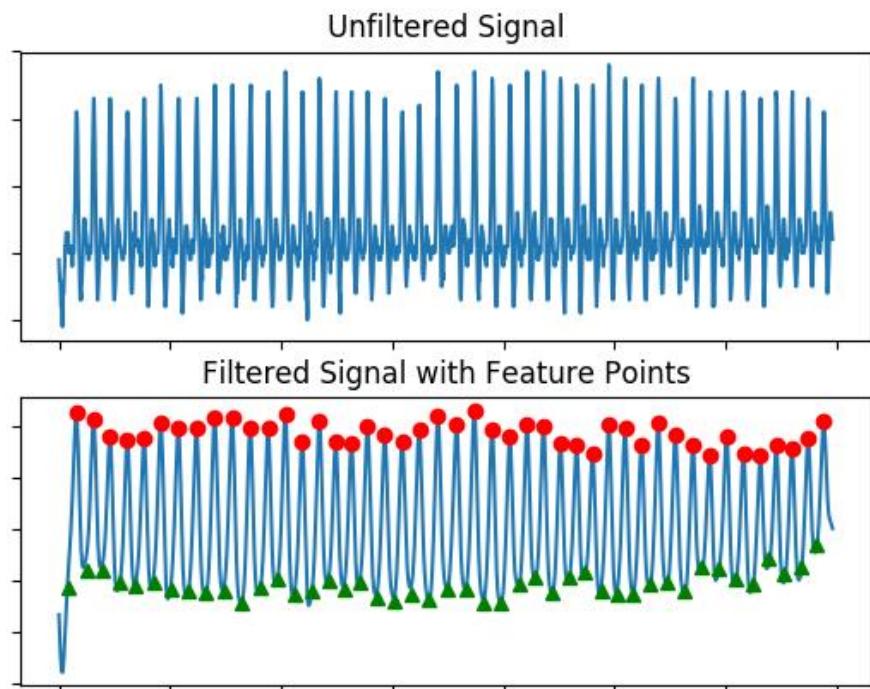


Figure 4.10. Unfiltered & Filtered Signal with Feature Points

## Subject 11



Part of the unfiltered signal to facilitate better viewing of the signal

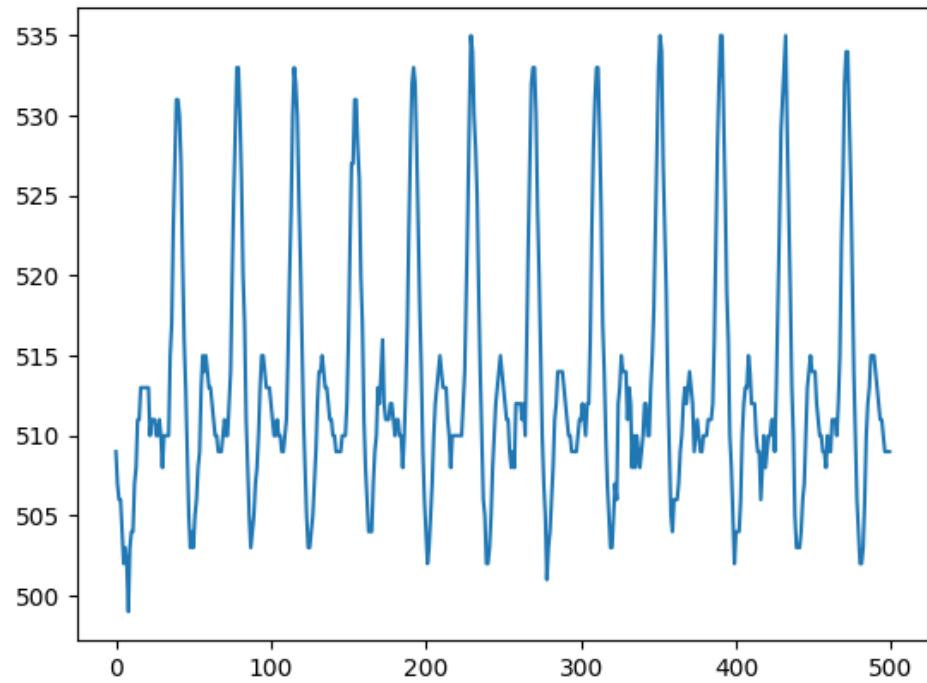
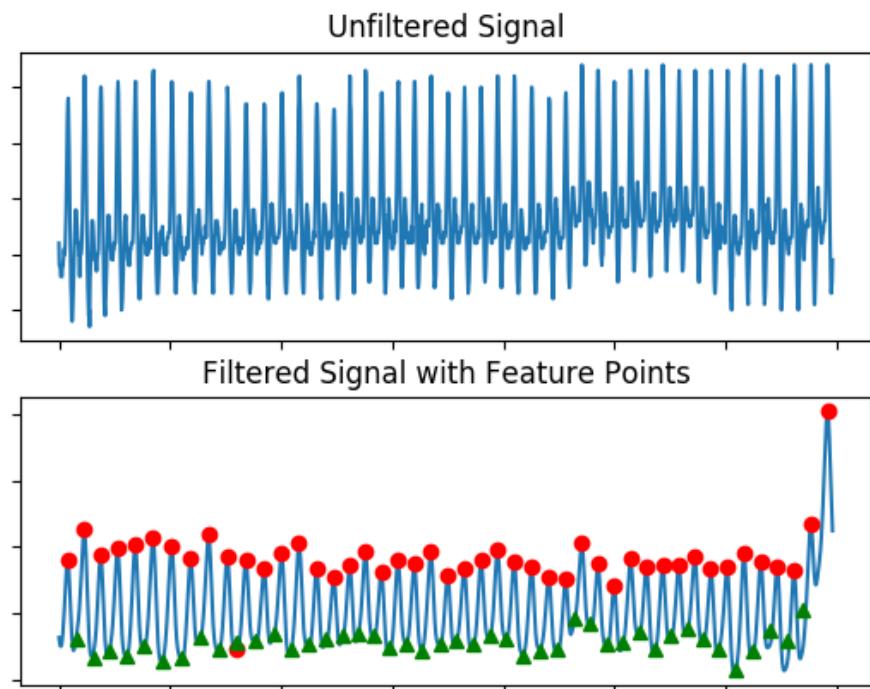


Figure 4.11. Unfiltered & Filtered Signal with Feature Points

## Subject 12



Part of the unfiltered signal to facilitate better viewing of the signal

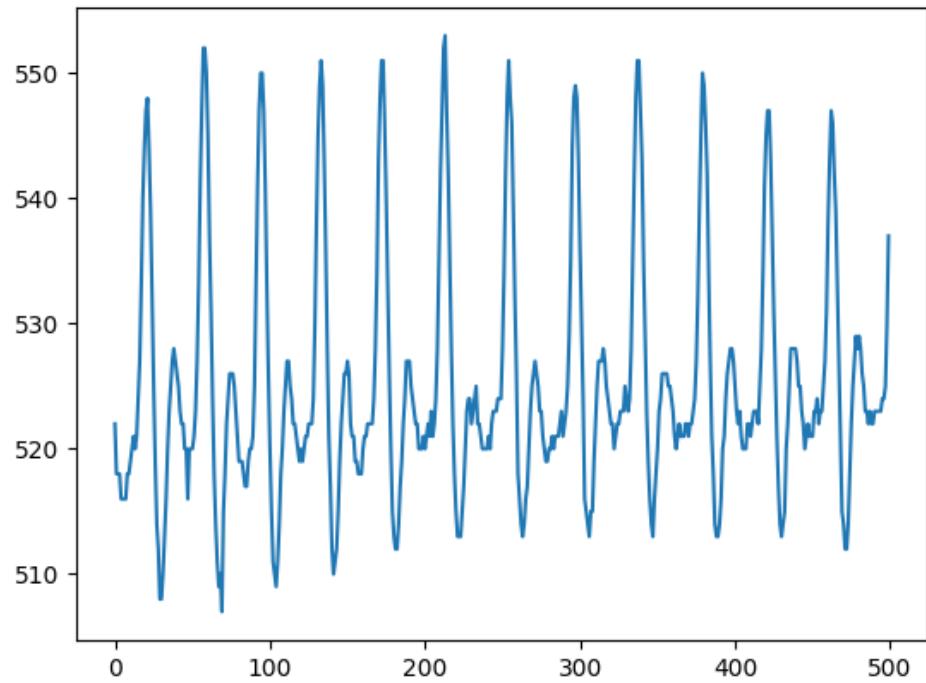
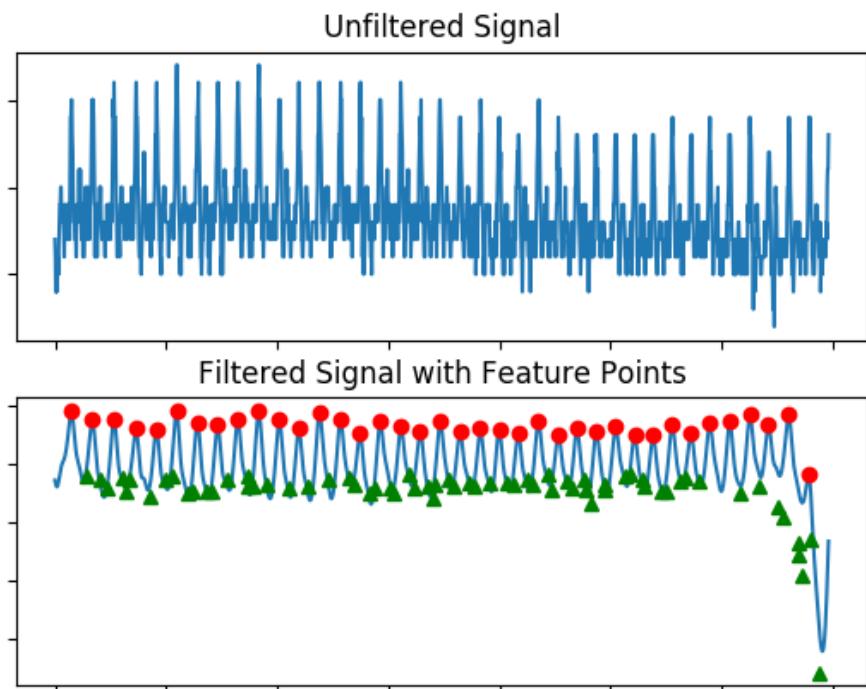


Figure 4.12. Unfiltered & Filtered Signal with Feature Points

## Subject 13



Part of the unfiltered signal to facilitate better viewing of the signal

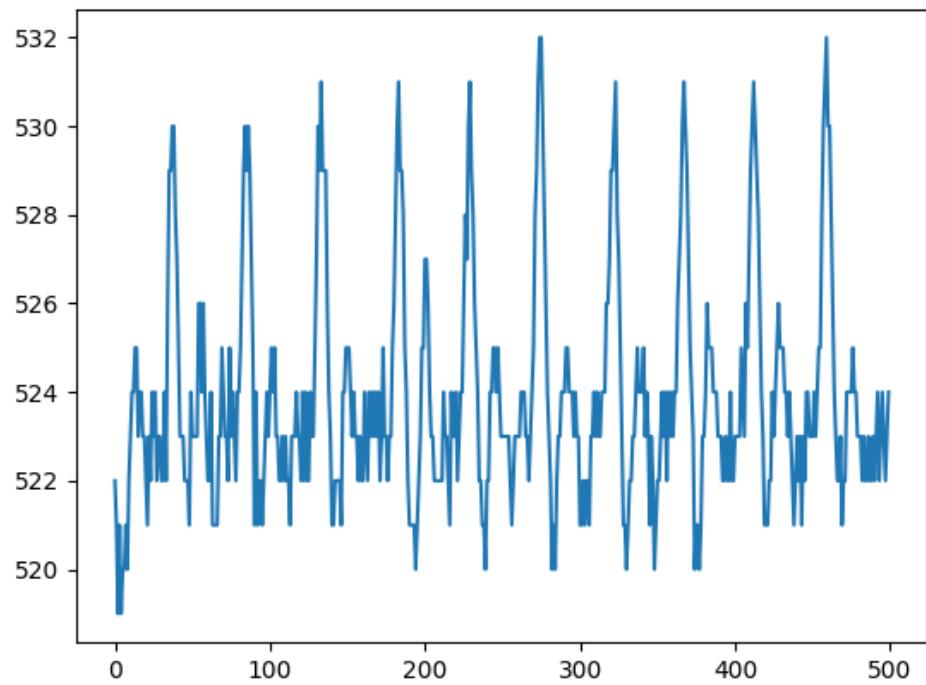
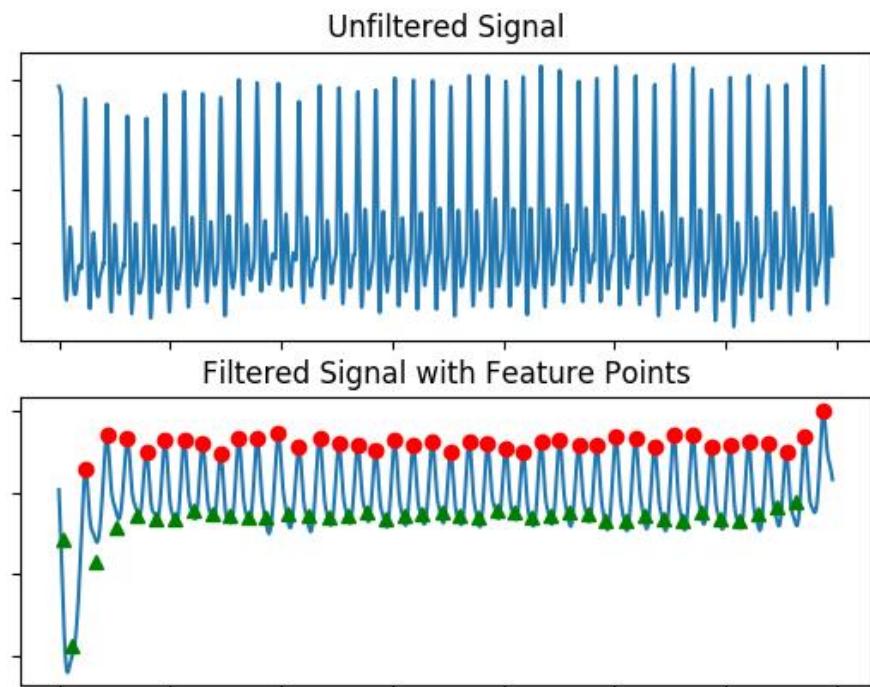


Figure 4.13. Unfiltered & Filtered Signal with Feature Points

## Subject 14



Part of the unfiltered signal to facilitate better viewing of the signal

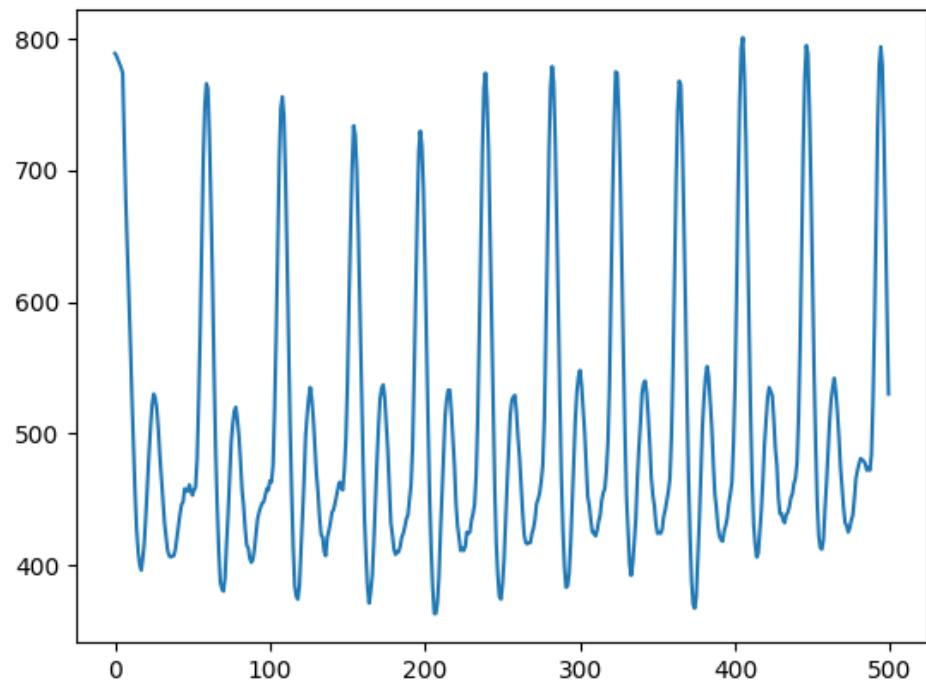
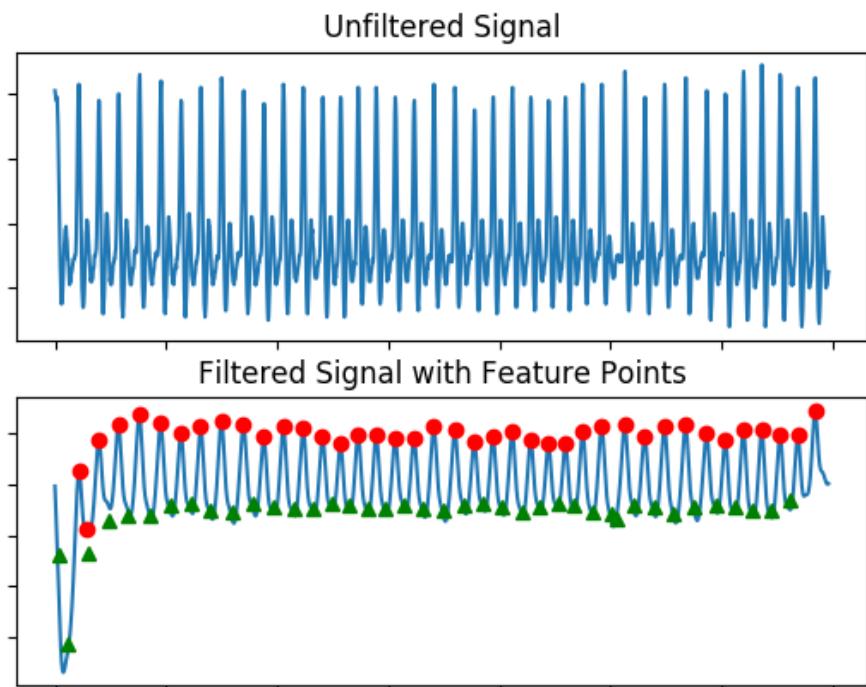


Figure 4.14. Unfiltered & Filtered Signal with Feature Points

## Subject 15



Part of the unfiltered signal to facilitate better viewing of the signal

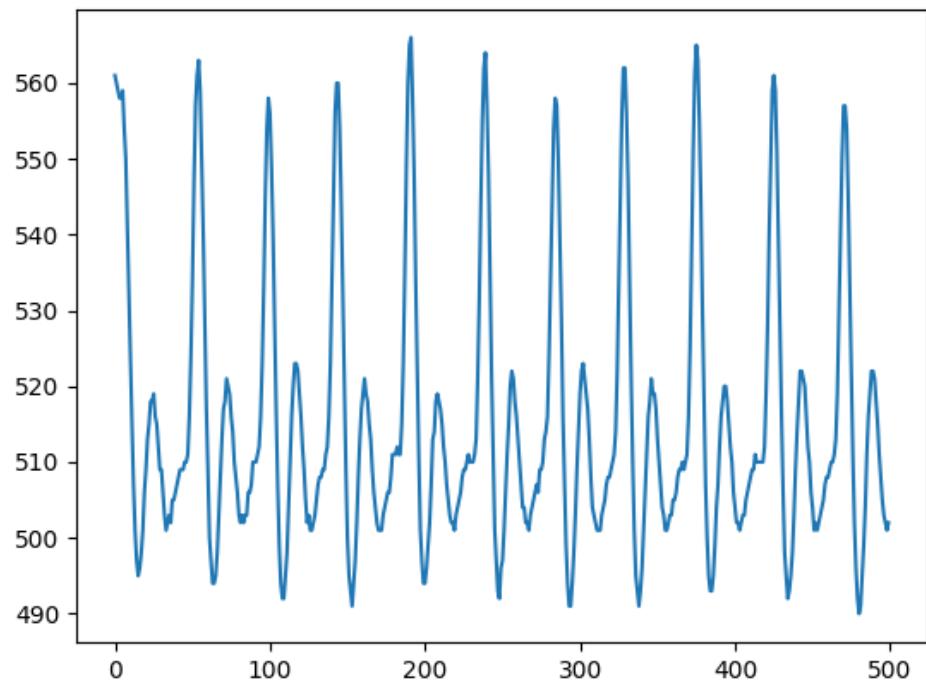
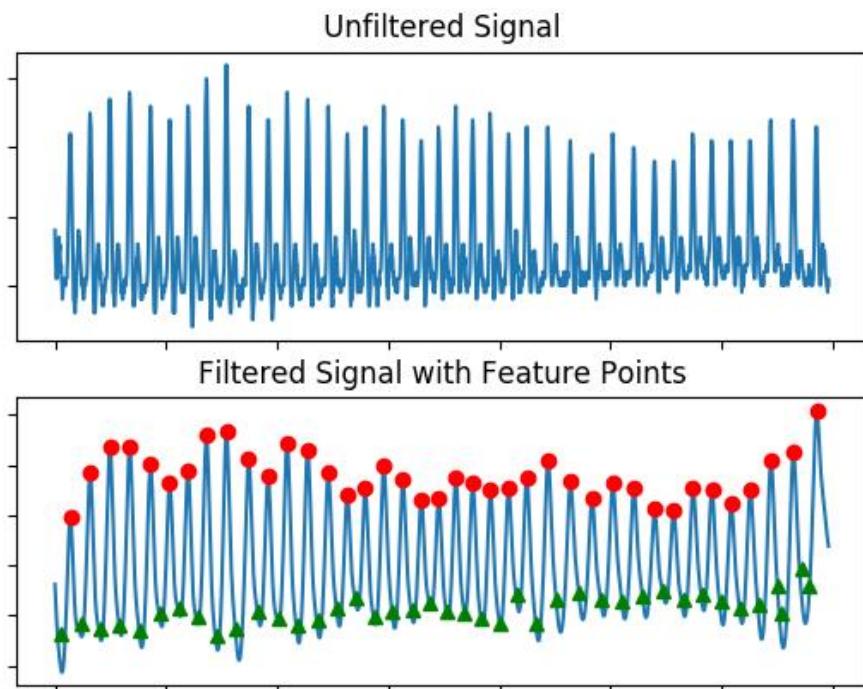


Figure 4.15. Unfiltered & Filtered Signal with Feature Points

## Subject 16



Part of the unfiltered signal to facilitate better viewing of the signal

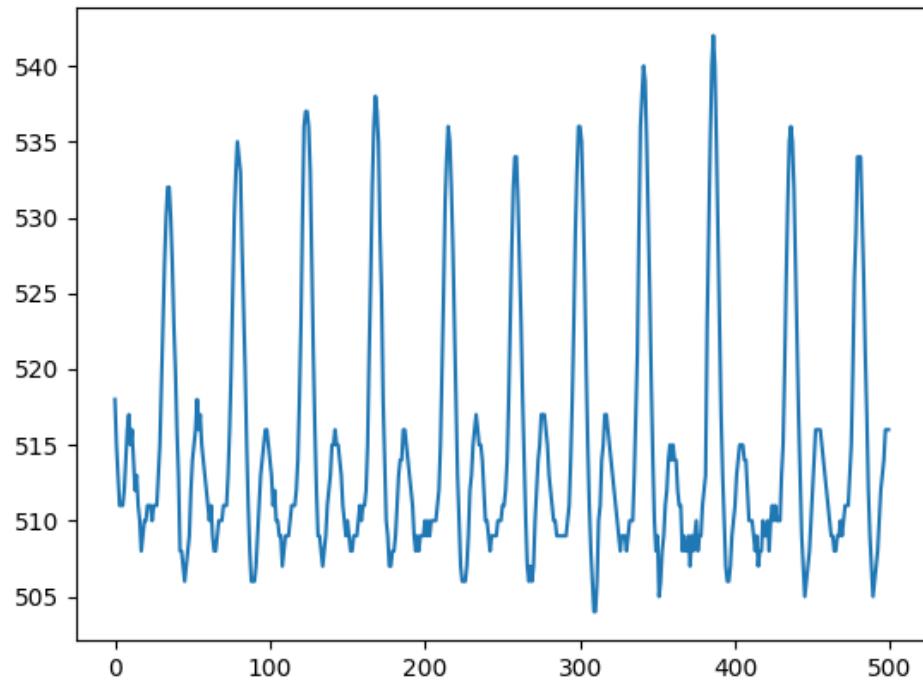
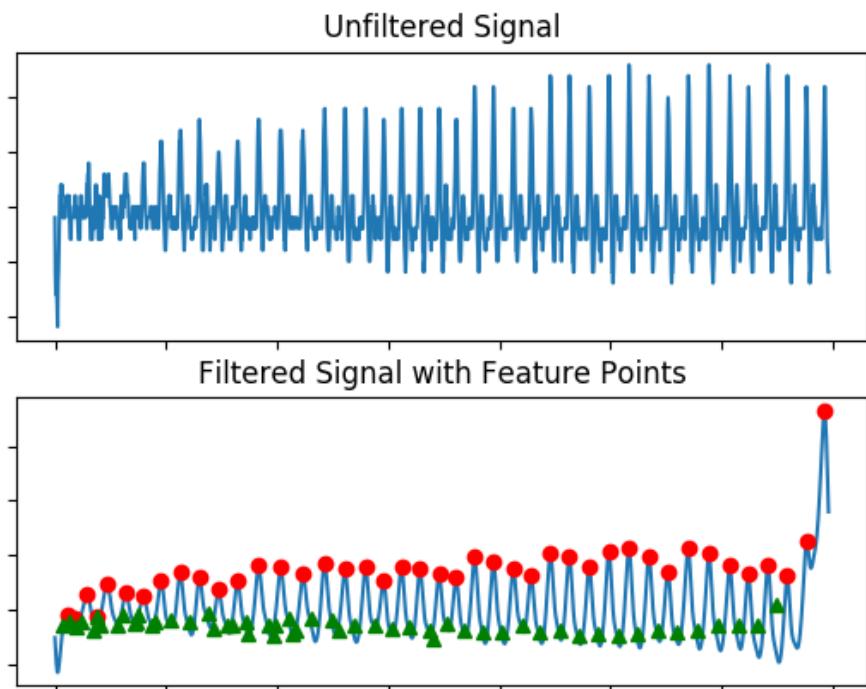


Figure 4.16. Unfiltered & Filtered Signal with Feature Points

## Subject 17



Part of the unfiltered signal to facilitate better viewing of the signal

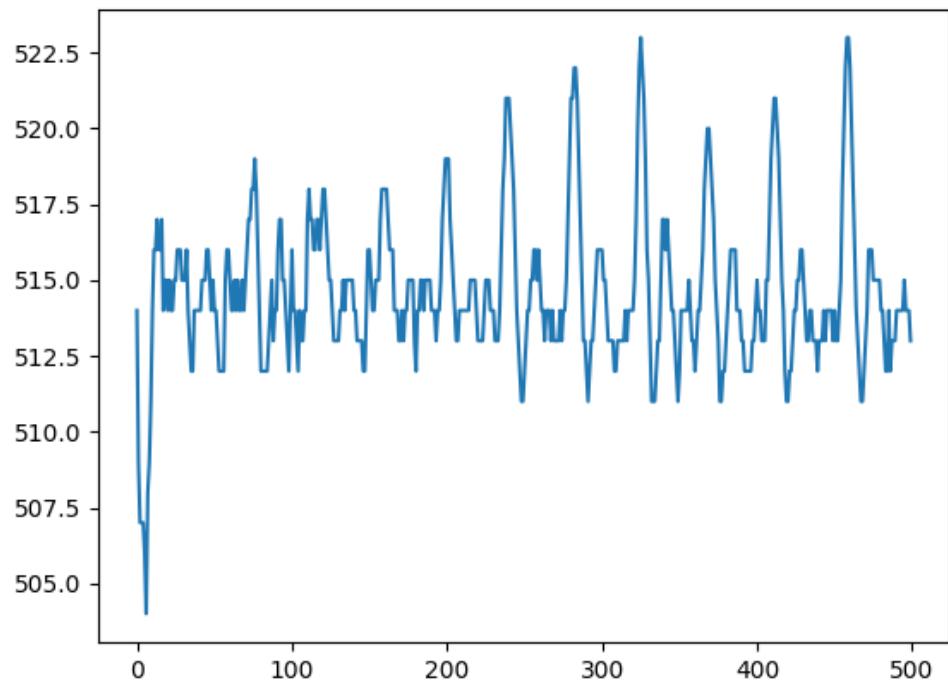
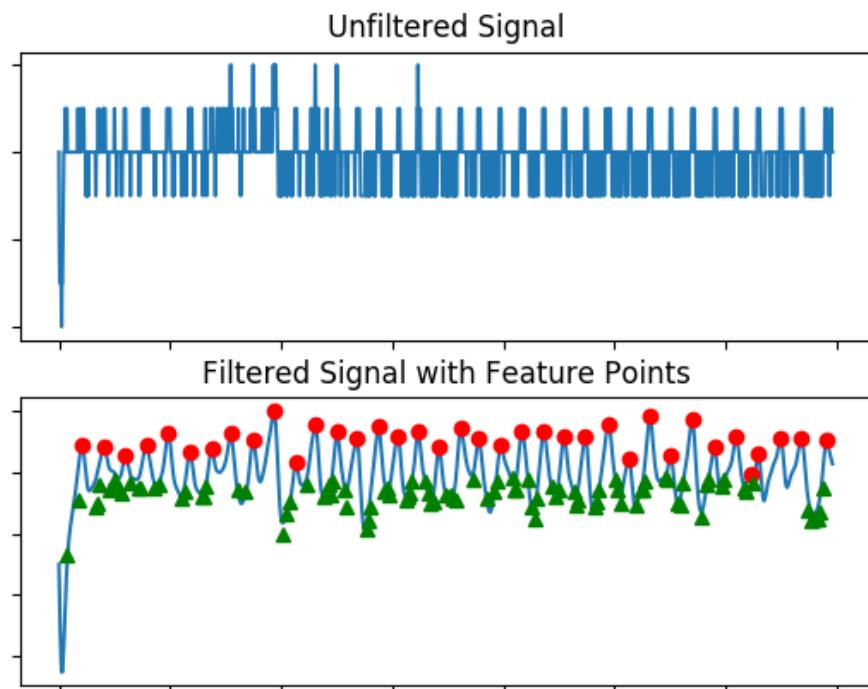


Figure 4.17. Unfiltered & Filtered Signal with Feature Points

## Subject 18



Part of the unfiltered signal to facilitate better viewing of the signal

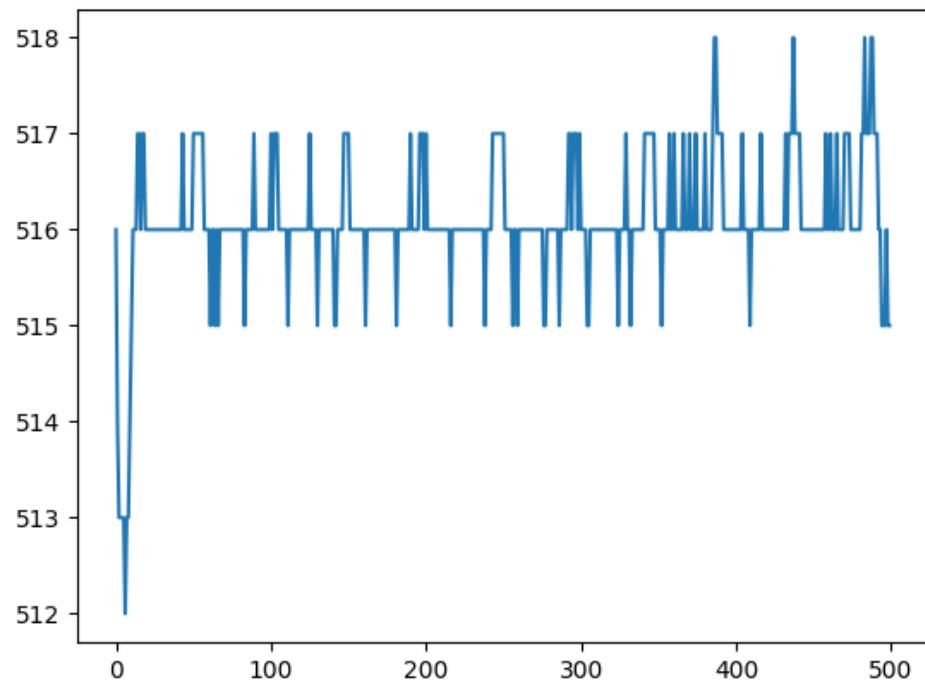
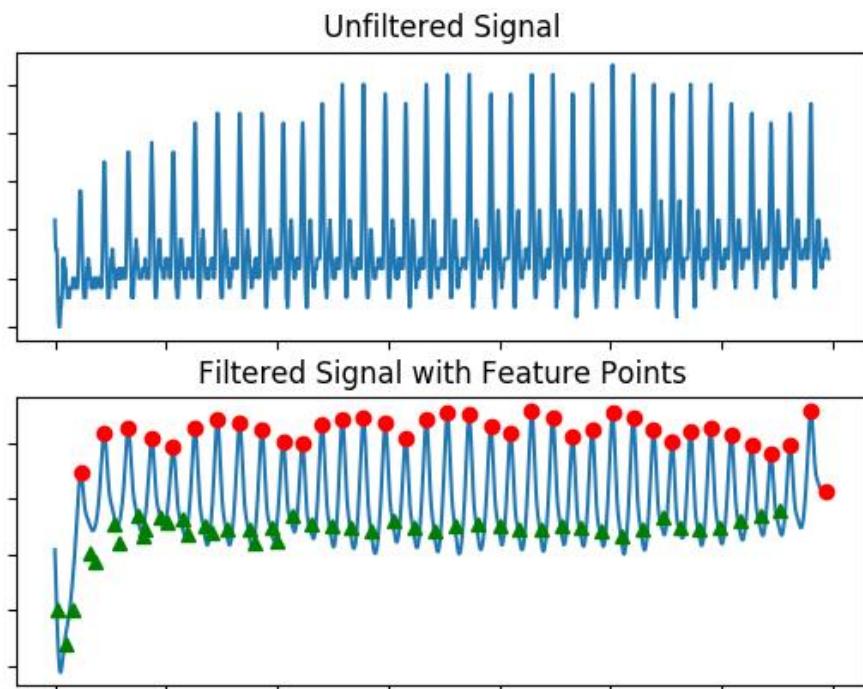


Figure 4.18. Unfiltered & Filtered Signal with Feature Points

## Subject 19



Part of the unfiltered signal to facilitate better viewing of the signal

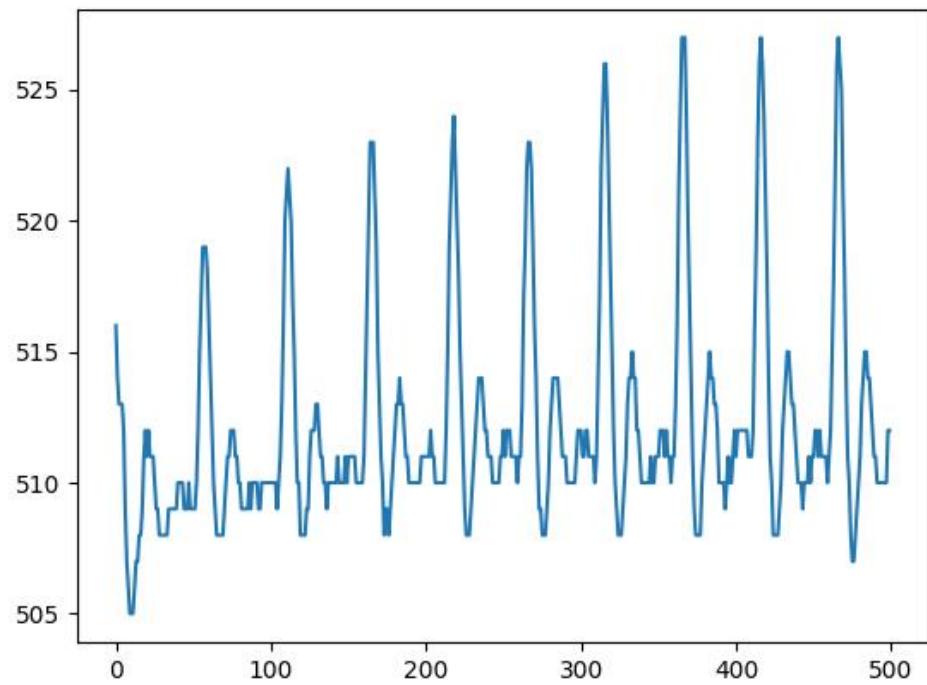
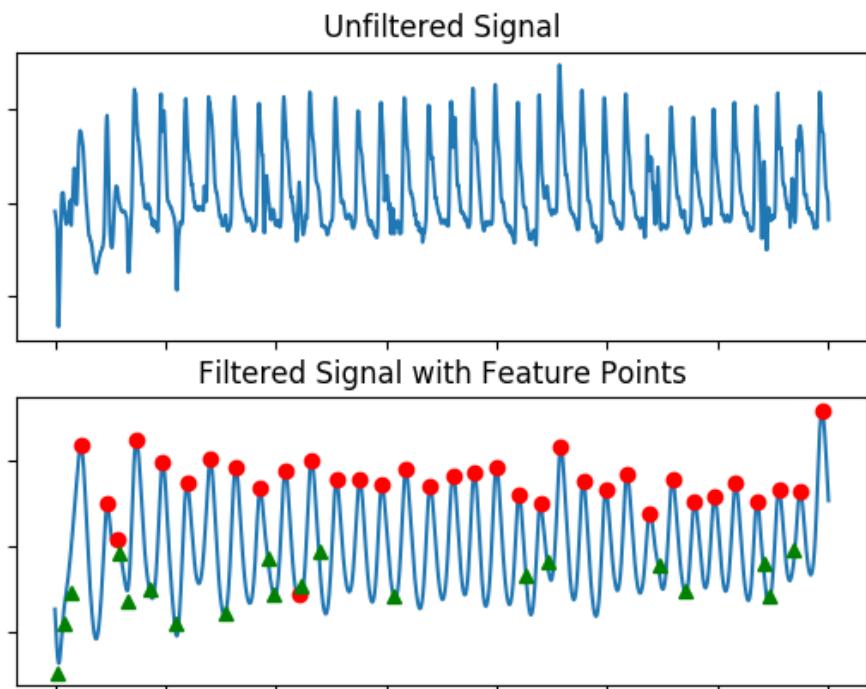


Figure 4.19. Unfiltered & Filtered Signal with Feature Points

## Subject 20



Part of the unfiltered signal to facilitate better viewing of the signal

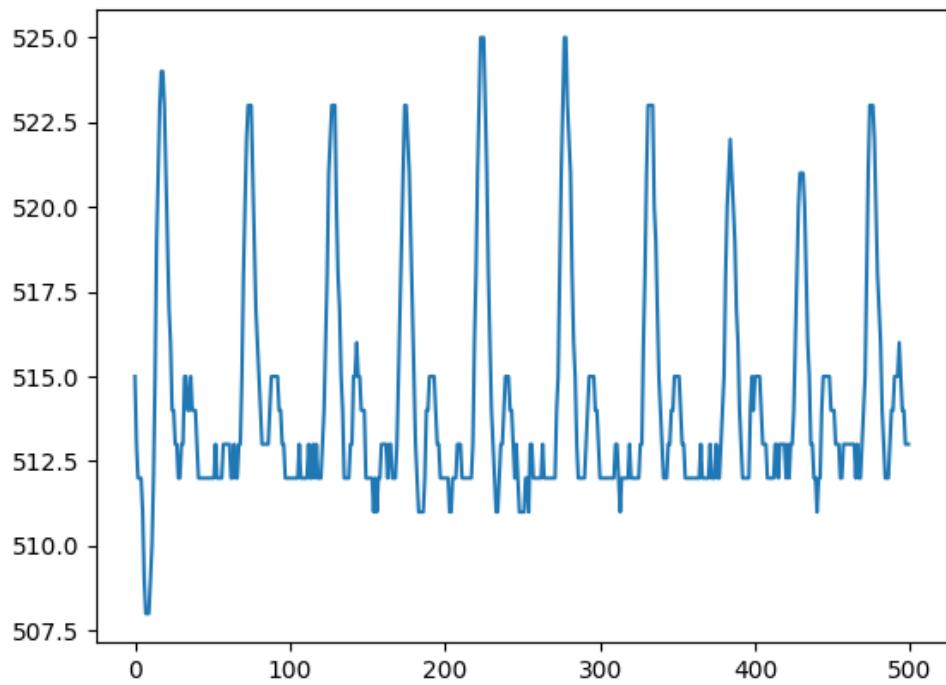
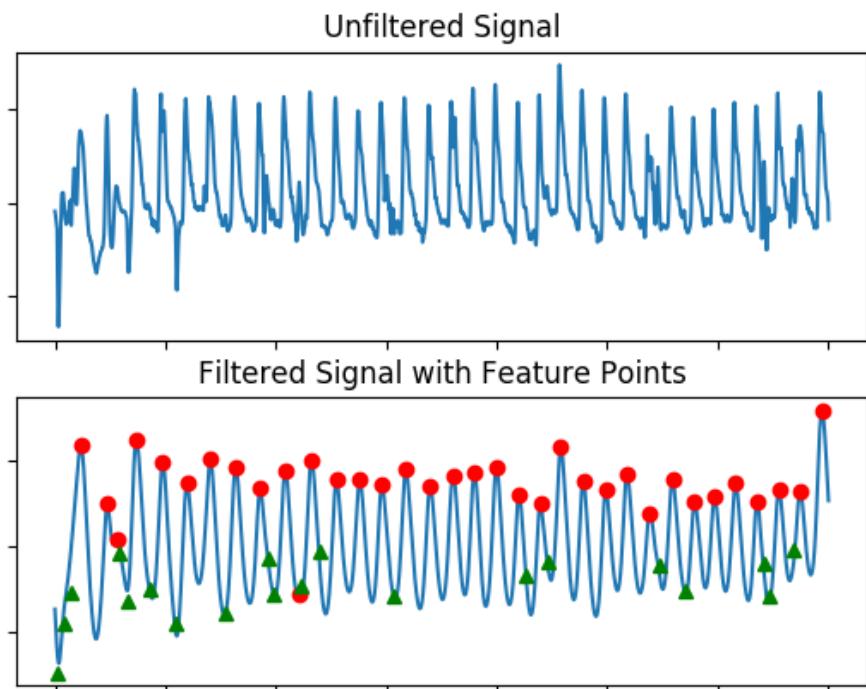


Figure 4.20. Unfiltered & Filtered Signal with Feature Points

## Subject 21



Part of the unfiltered signal to facilitate better viewing of the signal

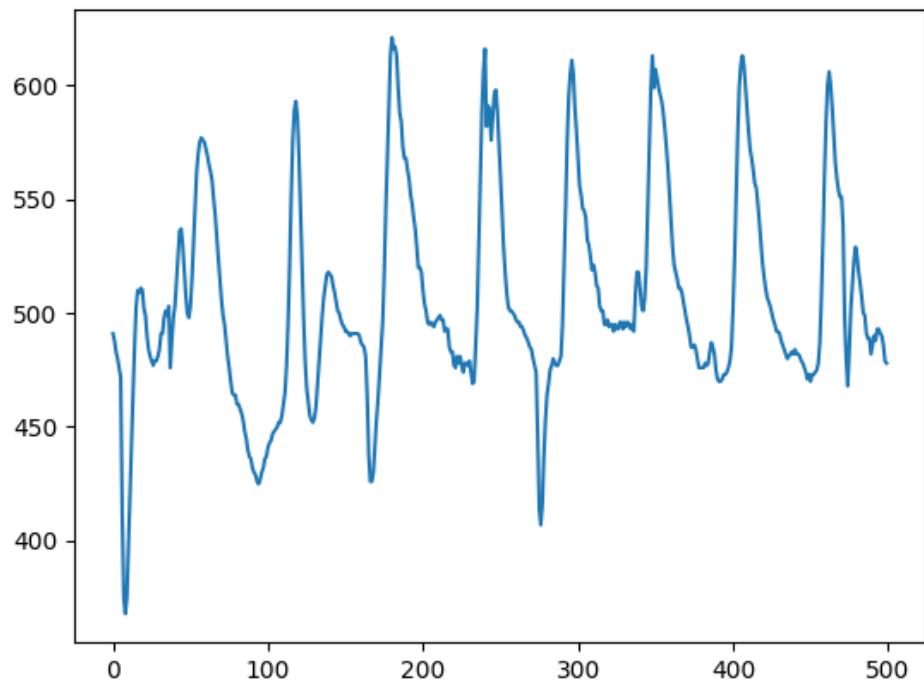
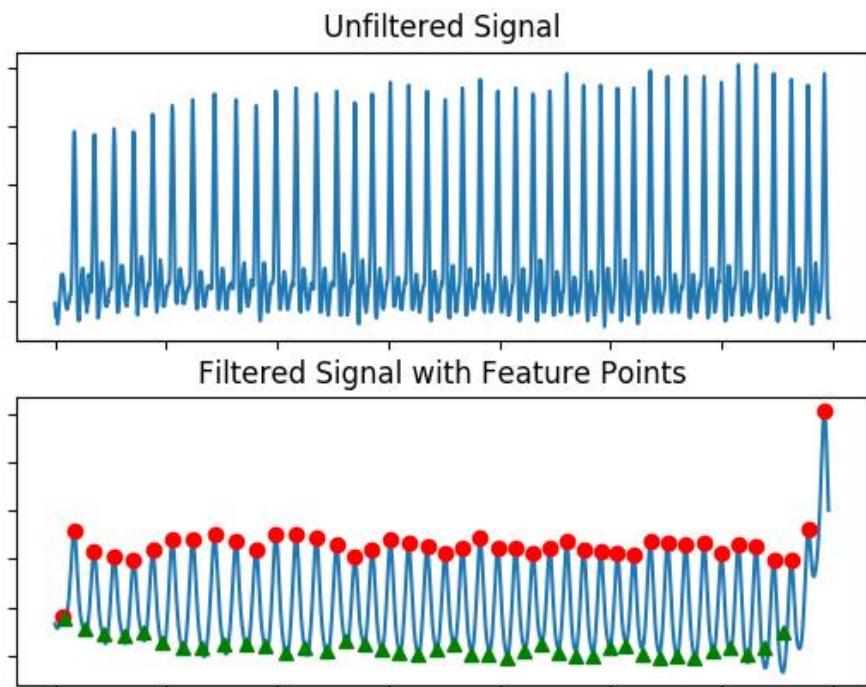


Figure 4.21. Unfiltered & Filtered Signal with Feature Points

## Subject 22



Part of the unfiltered signal to facilitate better viewing of the signal

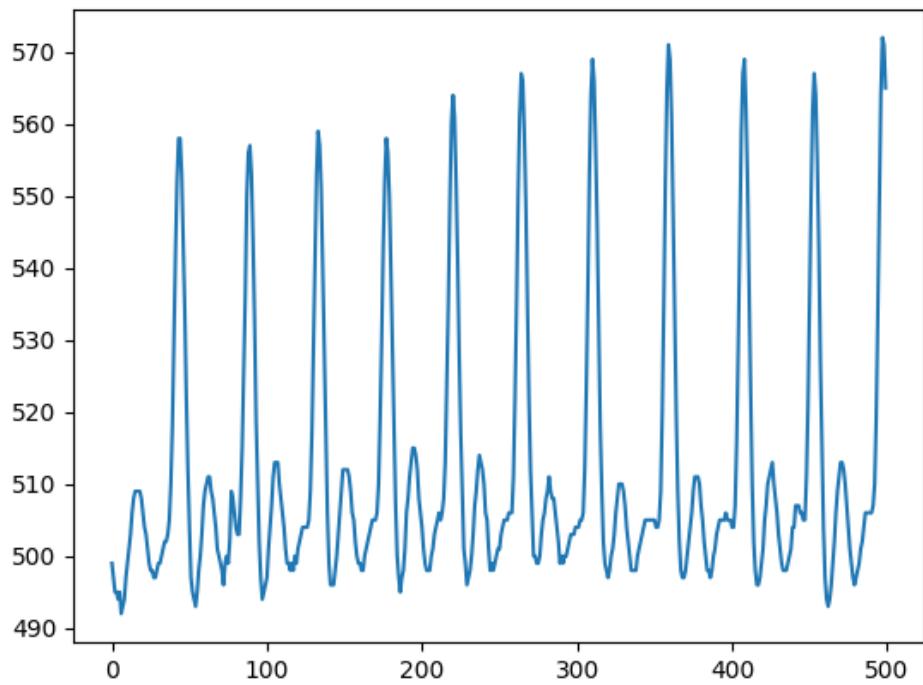
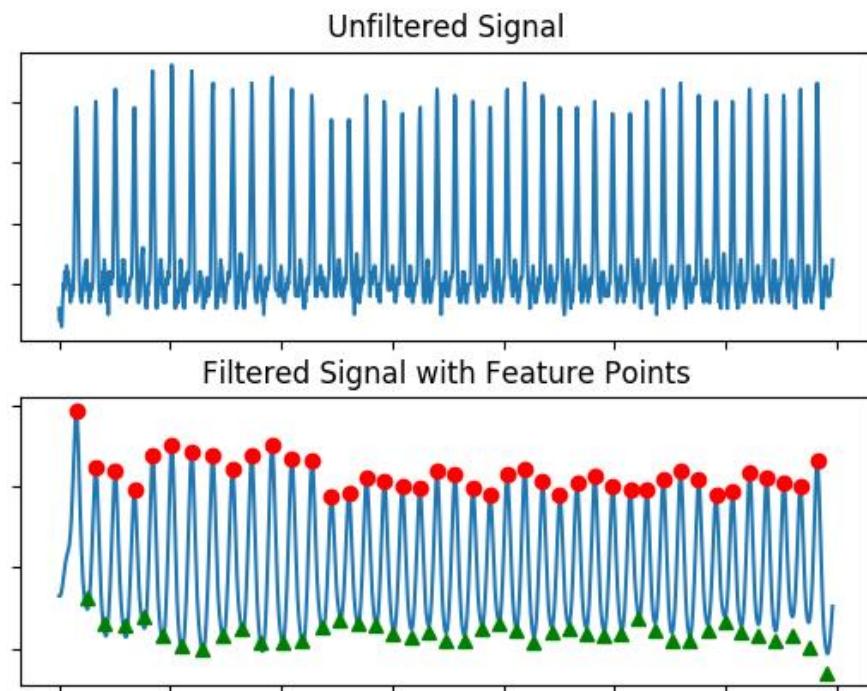


Figure 4.22. Unfiltered & Filtered Signal with Feature Points

Subject 23



Part of the unfiltered signal to facilitate better viewing of the signal

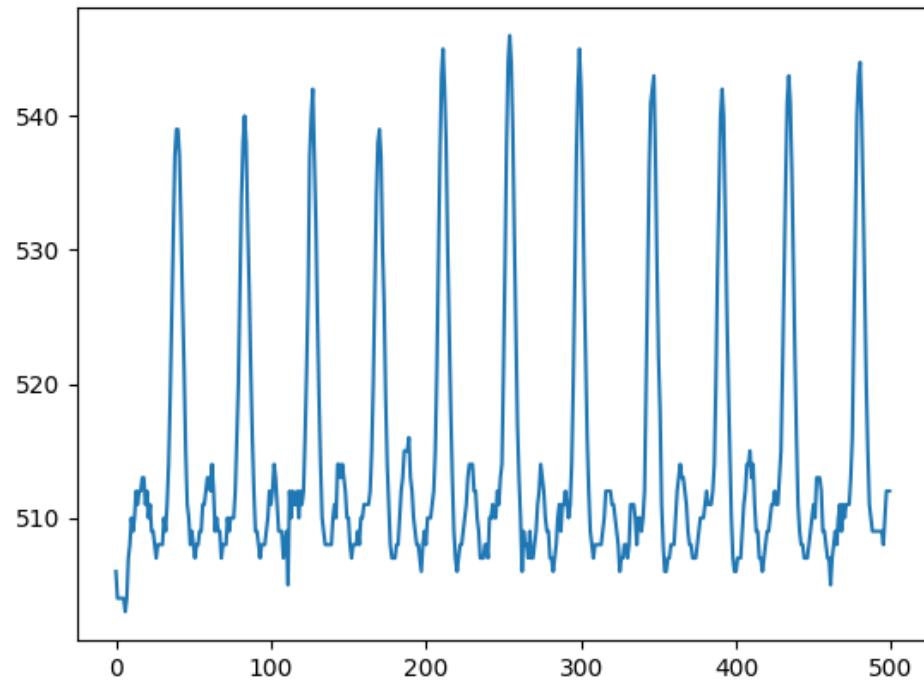
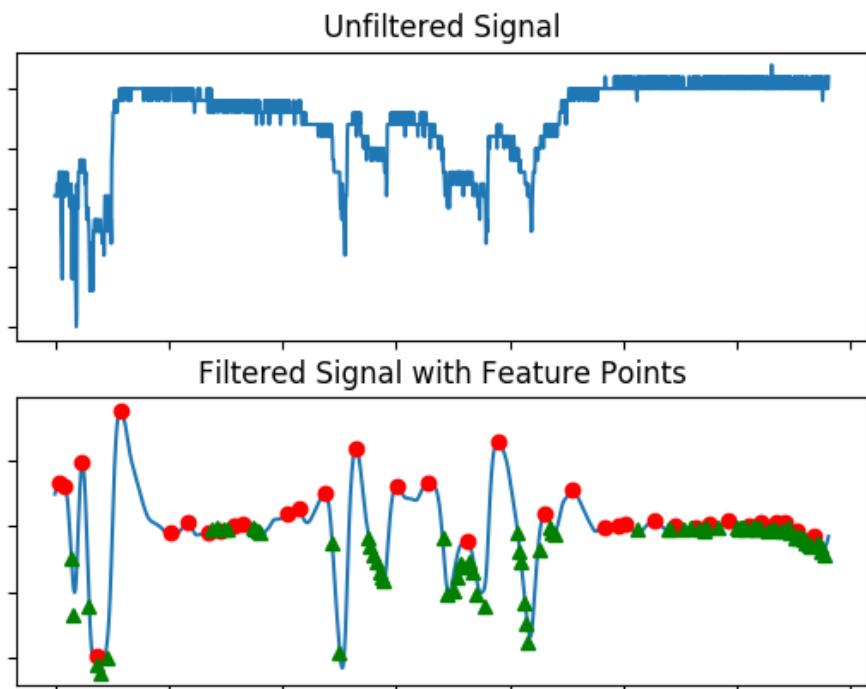


Figure 4.23. Unfiltered & Filtered Signal with Feature Points

## Subject 24



Part of the unfiltered signal to facilitate better viewing of the signal

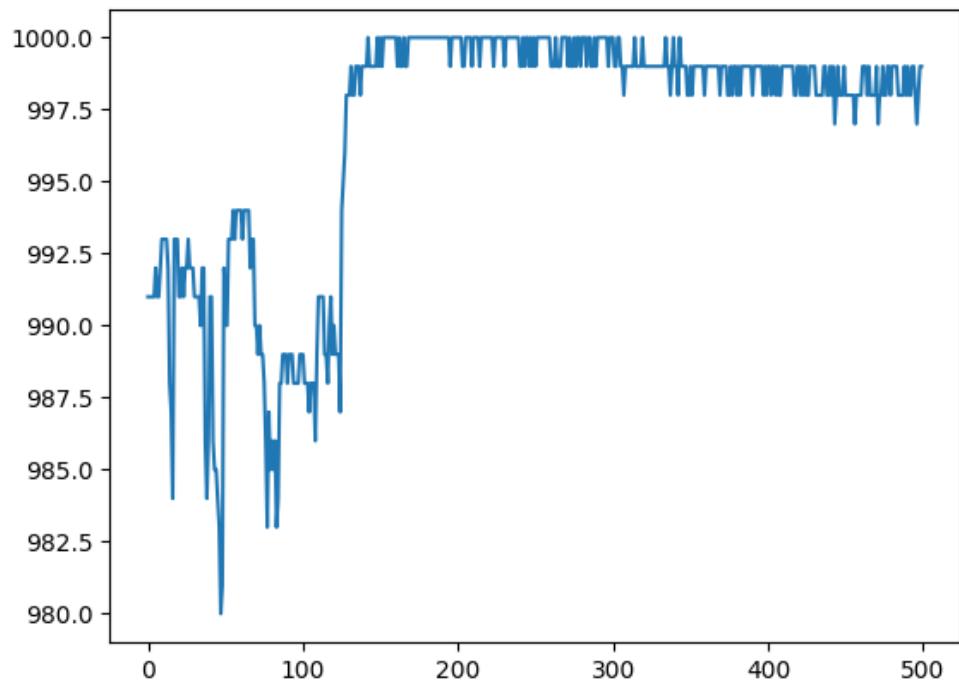
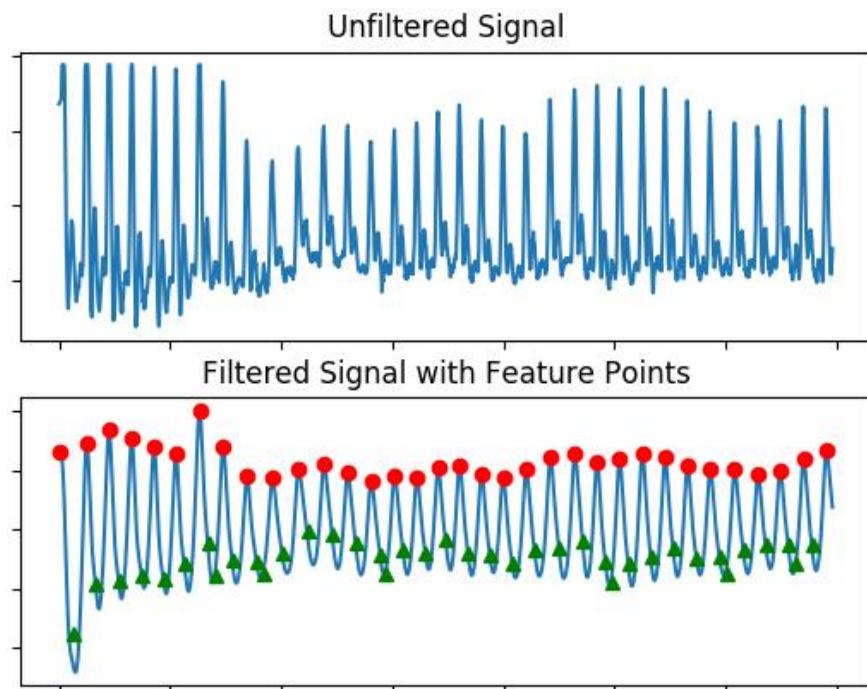


Figure 4.24. Unfiltered & Filtered Signal with Feature Points

Subject 25



Part of the unfiltered signal to facilitate better viewing of the signal

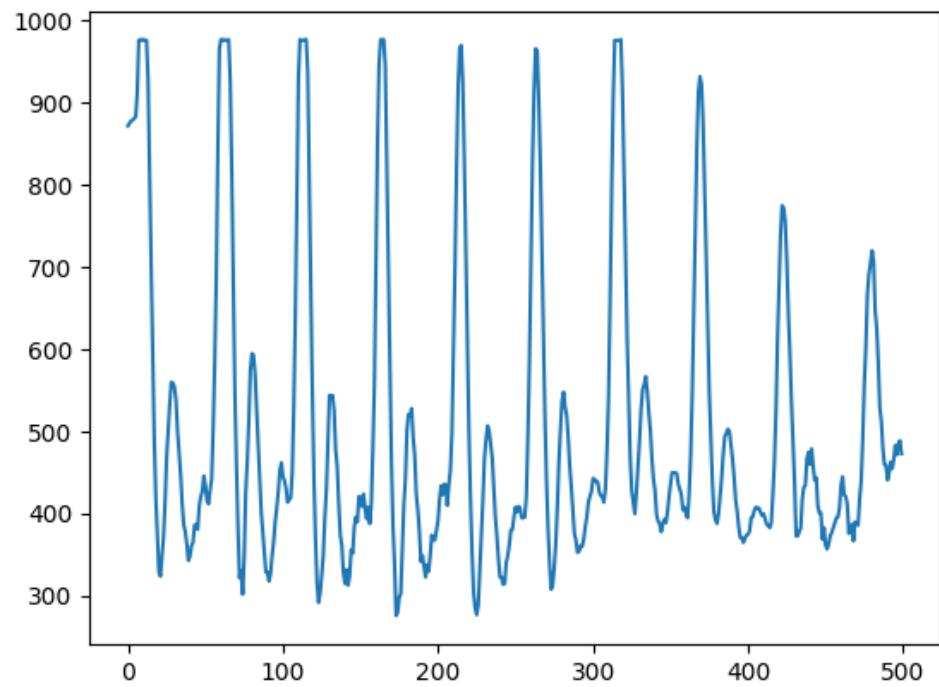
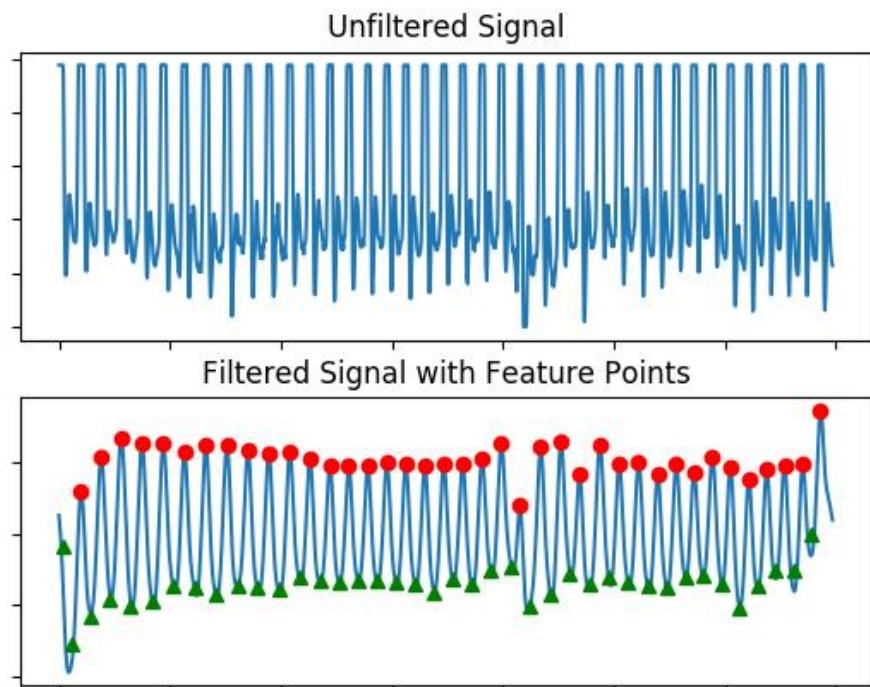


Figure 4.25. Unfiltered & Filtered Signal with Feature Points

## Subject 26



Part of the unfiltered signal to facilitate better viewing of the signal

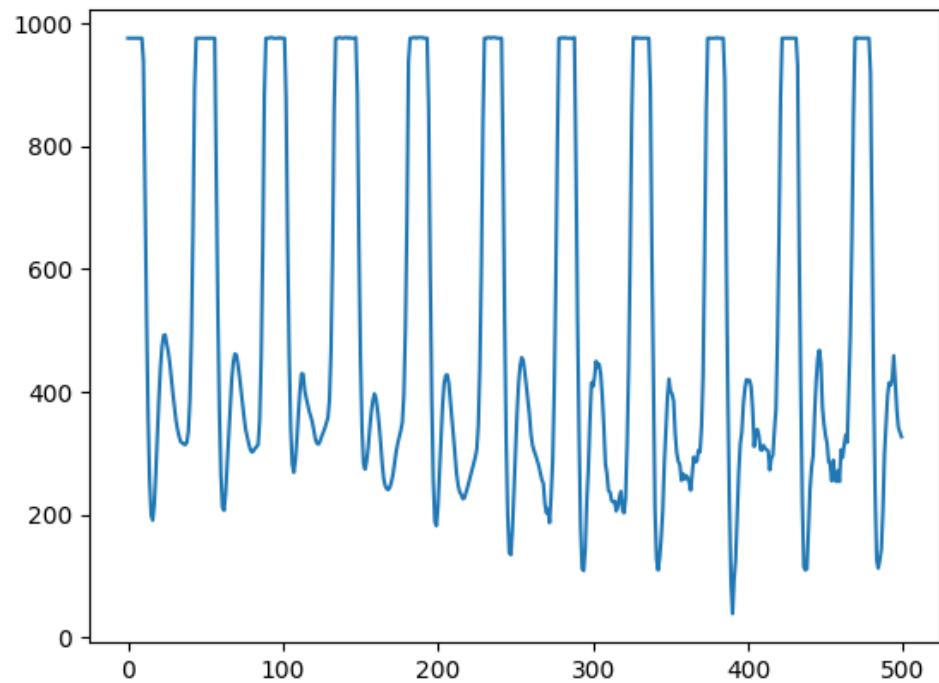
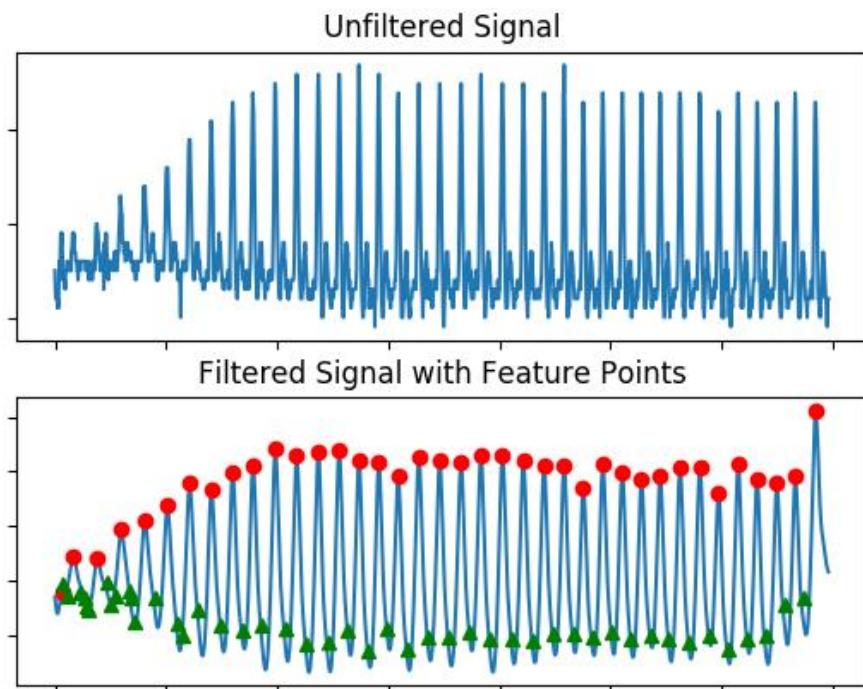


Figure 4.26. Unfiltered & Filtered Signal with Feature Points

Subject 27



Part of the unfiltered signal to facilitate better viewing of the signal

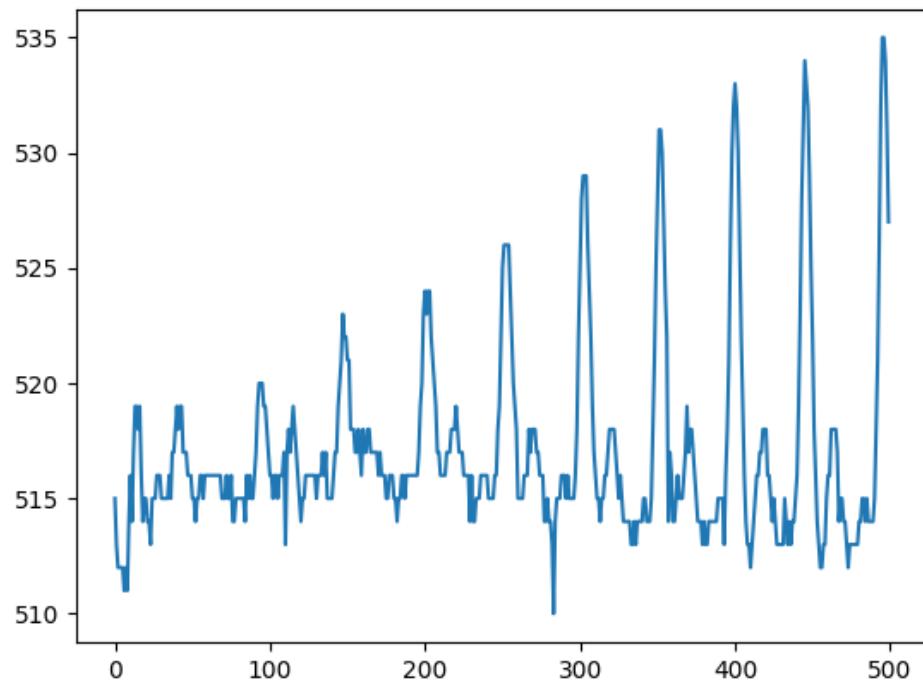
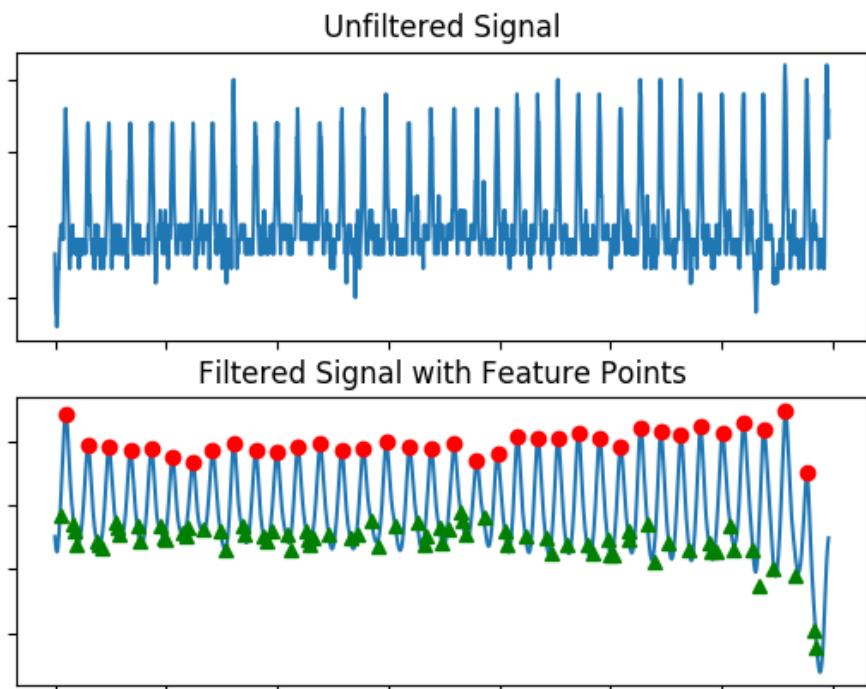


Figure 4.27. Unfiltered & Filtered Signal with Feature Points

## Subject 28



Part of the unfiltered signal to facilitate better viewing of the signal

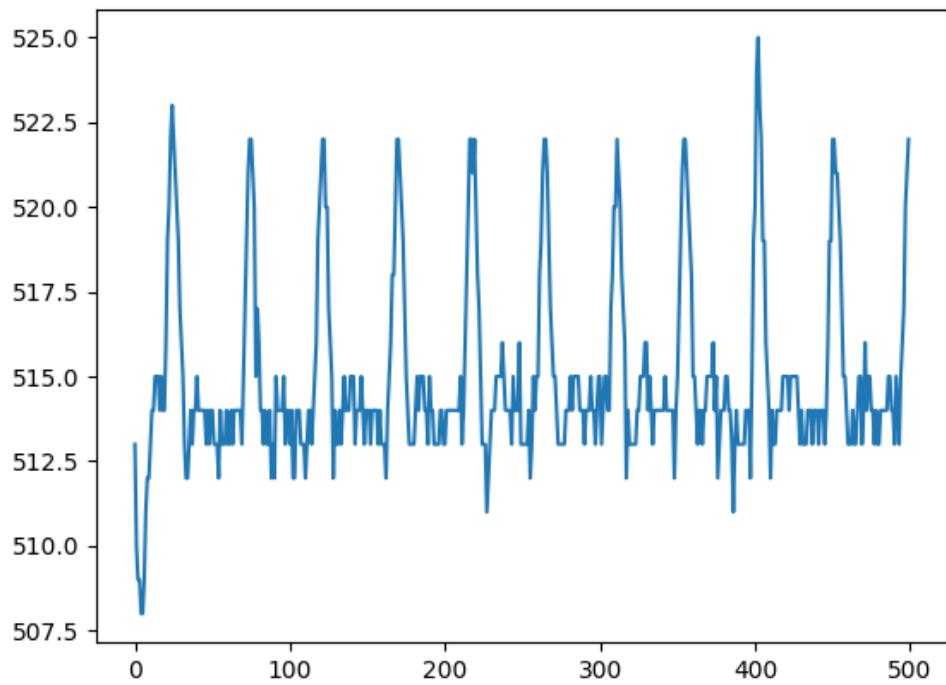
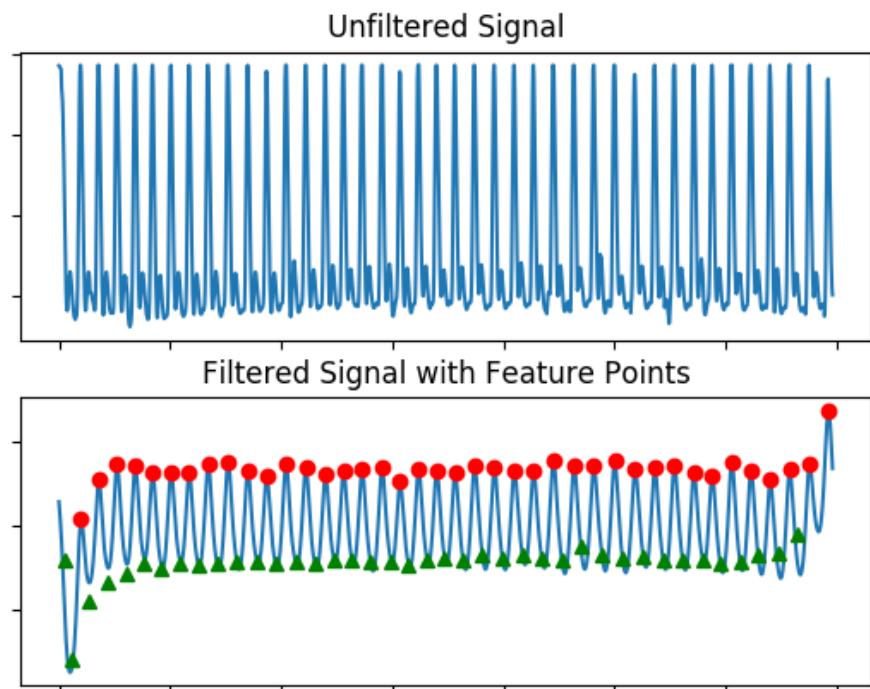


Figure 4.28. Unfiltered & Filtered Signal with Feature Points

## Subject 29



Part of the unfiltered signal to facilitate better viewing of the signal

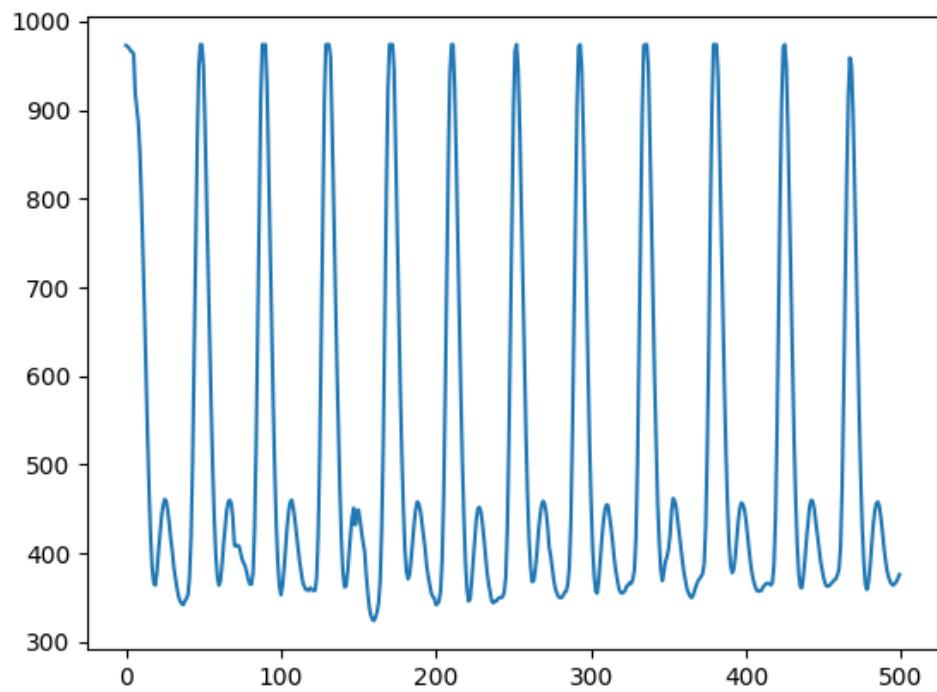
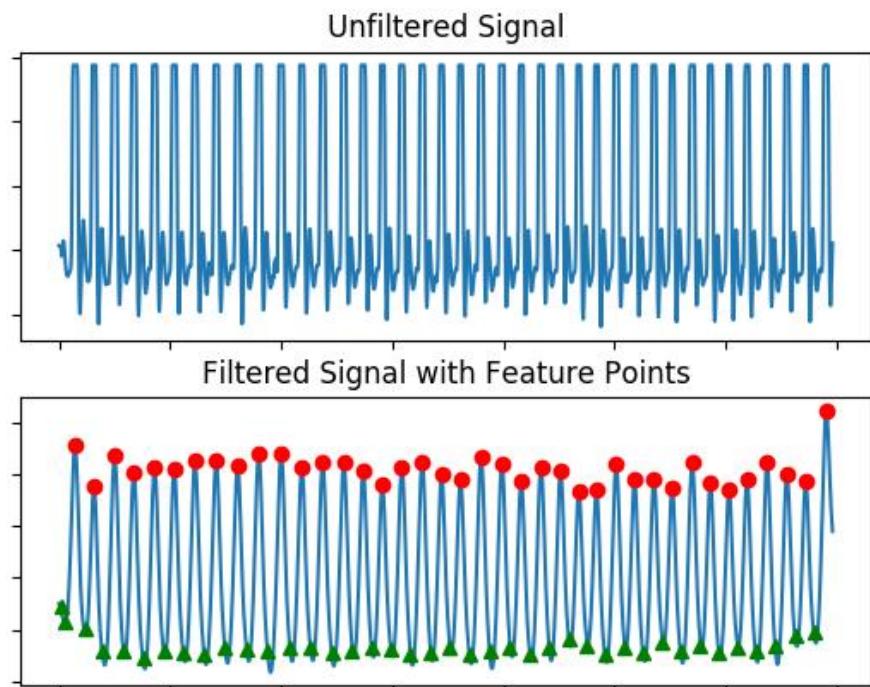


Figure 4.29. Unfiltered & Filtered Signal with Feature Points

## Subject 30



Part of the unfiltered signal to facilitate better viewing of the signal

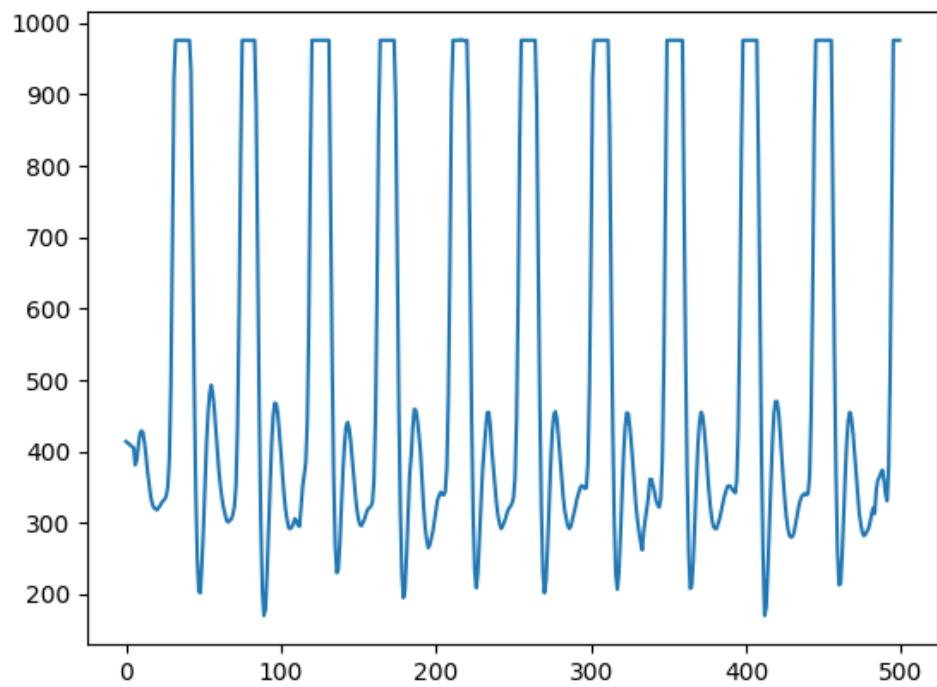


Figure 4.30. Unfiltered & Filtered Signal with Feature Points

Table 4.0.1. Features Extracted from Signal

SNo.	Mean Ap	Median Ap	Max Ap	Min Ap	Mean An	Median An	Max An	Min An	Gender
1	8.871575238	8.639023589	18.0873359	5.6471297	4.186611567	4.285944824	1.37421631	-5.762854	M
2	5.783351267	5.63386651	14.6263632	0.0622789	3.267899991	3.68889057	0.20513032	-11.15305	M
3	10.69454272	10.73896255	14.3359916	7.3047801	5.687659058	5.542798829	2.49561832	-13.20135	M
4	10.33955547	9.972606389	24.2245808	5.6228529	5.751770632	5.363108585	0.79131996	-22.61108	M
5	4.736173441	4.587344573	12.5128576	2.5379754	2.539635898	2.248129863	0.94989063	-12.52685	M
6	5.336714952	5.524716641	6.6643909	0.0268191	3.032002555	2.557547857	1.58789874	-14.82236	M
7	6.97742151	6.397981121	18.6678751	4.6961159	3.208098563	3.292311933	0.56930808	-5.444304	M
8	2.661600647	2.476766862	7.67827782	1.7326888	1.584924605	1.56409458	0.56983771	-2.177511	F
9	30.95275729	30.59876829	61.641264	15.802056	13.666728311	13.29038129	2.29340821	-27.20938	M
10	7.814599516	8.136927052	17.9362593	3.6193013	2.706031615	1.921823511	0.47659441	-8.091035	M
11	3.721895781	3.821483582	4.58375971	2.8240633	2.166146733	2.243181556	0.63245367	-2.859188	M
12	4.197846147	3.976826736	15.2554744	-2.682106	2.168725365	2.215728831	0.33046291	-4.212784	M
13	1.34904205	1.363084293	1.85708975	-0.341363	0.961166152	0.729698891	0.30373552	-7.144016	M
14	60.79851565	60.77591929	100.151192	29.39457	34.04840271	28.11893222	10.8086992	-188.4251	M
15	9.490489882	9.795646366	14.2514359	-8.890287	5.877139663	4.7778734946	3.02627523	-31.10855	M
16	4.488459246	4.257710198	7.71195081	2.3810253	2.189245853	2.279894508	0.11688883	-3.457934	M
17	1.881967076	1.887795027	9.12318444	-0.404154	0.737213342	0.718060484	0.26280566	-1.363009	M
18	0.26461993	0.273371545	0.49952538	-0.022398	0.193791255	0.165273744	0.04676598	-0.67482	M
19	3.006275839	3.133766449	3.95637668	0.3542692	1.596940612	1.300314386	0.55444246	-6.52329	M
20	2.271859632	2.309834924	3.38533886	0.7366002	1.273684274	1.050260994	0.44193827	-3.539352	M
21	37.75867492	38.62527362	79.7395305	-27.34682	24.07746019	25.32380202	2.17243053	-73.57305	F
22	12.98181495	12.47897988	40.7447703	-1.87641	8.2225390664	8.489717995	2.3569706	-10.32587	F
23	5.760025823	5.559840076	9.69313861	4.414048	4.051907528	4.065212083	1.86729044	-6.467732	F
24	0.424346485	0.110796994	3.53492396	-3.950834	0.819569968	0.332133984	0.0198647	-4.461291	M
25	116.6503881	110.1482622	201.768172	83.040368	50.33162678	45.46387967	2.25838059	-176.1985	M
26	210.2813281	200.7386782	347.62121	79.375283	142.8860349	140.0591448	0.6186627	-309.4283	M
27	3.755461371	4.151725491	6.23053098	-0.409578	1.547782045	1.820738362	0.04296978	-2.540586	M
28	2.01001569	1.922927979	3.00596382	1.0644483	1.104722851	1.005963645	0.20689485	-4.46514	M
29	133.4815872	133.4057031	271.722775	15.597106	89.55639895	82.56790781	18.4045461	-316.262	M
30	211.2026355	212.9942778	324.633049	169.10008	133.1827644	136.619076	56.5448387	-154.883	M

## **5. Results & Discussion**

The results of this work delve into a few important aspects. These aspects are namely the effect of the wavelength of light chosen on the signals obtained, the filtering applied on the signal, the features extracted and used and finally, the machine learning parts and its implications.

The wavelength chosen initially was 940nm infrared radiation. This was done so owing to the ready availability of matched pairs of emitters and detectors. Owing to the existence of such matched pairs, it was easy to construct accurate sensing devices. However, the increased sensitivity of these detectors meant that it was that much more susceptible to noise than a photodiode based detector. The initial issue with constructing a diode based detector was to do with two main setbacks. These were namely the form factor of the solution and the construction of the trans- impedance amplifier. The form factor of this solution became rather bulky to handle owing to the presence of the trans-impedance amplifier, hence became uncomfortable for the subjects to use. Secondly the construction of such an amplifier required rather precise component values, as mentioned earlier. These two combined to deter the construction of such a solution.

However, the availability of an integrated photodiode based solution changed this situation, since it solved both the form factor issue and the precision amplifier issue. These integrated solutions were in effect the perfect answer to the problem. This in turn meant lesser hardware side filtering was required as opposed to the transistor based approach which required a multi stage active filtering circuit. This design choice resulted in another pleasant change, from infrared to green radiation. This was initially made to match the sensitivity of the detector, but soon turned out to be a much better design altogether. It meant that there was little to no DC shift in the pulse wave, which ultimately meant that one could get a closer approximation electrically of the actual mechanical pressure wave.

This eventually led to a change in the filtering circuit which now required fewer stages, although the cut offs remained largely similar. Ultimately this led to a smaller silicon footprint on the circuit and reduced the form factor to a very manageable size when coupled with surface mounted components. Moving on to the filtering performed on the software end, this was done more as an effort to provide a steeper cut off than

anything else. This stage effectively rid the signal of unwanted jitter that might have crept in owing to the typical hardware filter roll off characteristics. The feature detection performed was a simple relative maximum finding among the signals that provided the peak and dicrotic notch positions. There were more involved algorithms present such as a maximum z-score based approach, which were avoided in favor of computational speed and efficiency.

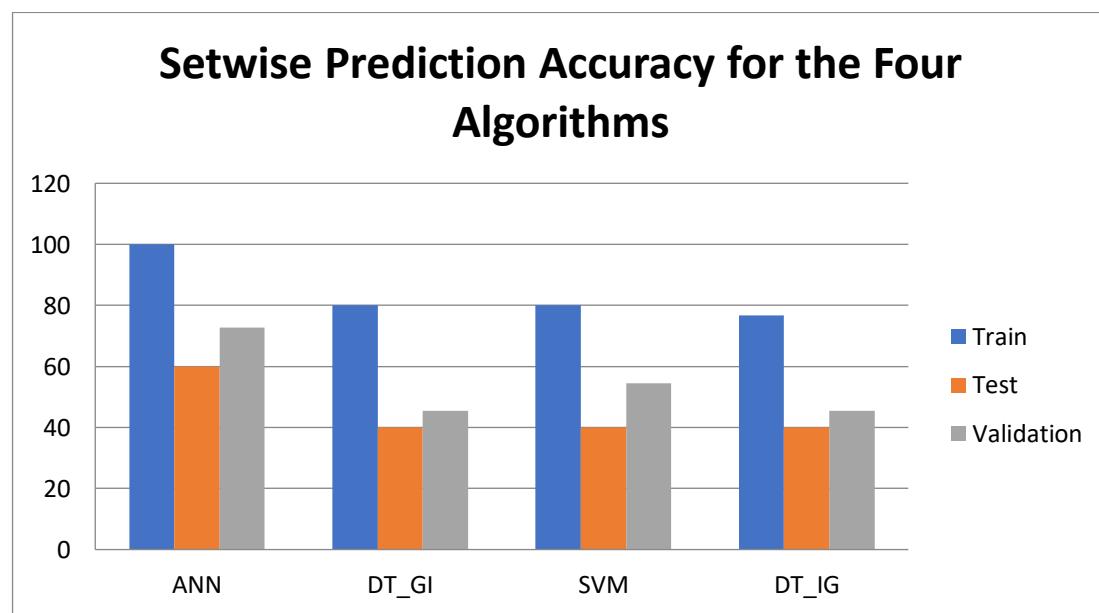
The features extracted were largely to do with the amplitude and their changes over time. It was also felt necessary to extract the central tendencies of these amplitudes in order to better capture more long term signal behavior. The number of features extracted was deliberately kept rather low in order to avoid the curse of dimensionality which effectively states that the number of samples needed to grow as a binary exponent of the number of features. Even so, one can observe that the work underwent a rather close shave from Occam's razor. The dataset was also put through a feature selection algorithm to find if there were any redundant features, so that the ultimate complexity of the work would be reduced.

Finally we come to the machine learning aspect of the work. This part of the work was taken up for reasons that do not entirely have the intentions of a classical machine learning exercise at heart. This part was performed in order to investigate if there could exist a mathematical relation that could provide insights about the presence of disease given features of the subject's pulse wave. Essentially, this was undertaken in order to accurately model the mathematics behind this relation, including all the real world fuzziness associated with it. As is common in this practice, a number of algorithms were tried, of which the most relevant ones were detailed earlier in this document. This was done in order to find the best approach to creating such a model as envisioned. Ultimately one does have to rely on some experimentation in formulating such approaches otherwise one shall end up throwing the most complex algorithm possible at every problem.

Moving away from the design discussion, let us now discuss the results from these algorithms. The results are graphically outlined in the following figure from which it becomes patently obvious that the artificial neural network trumps the other assortment of algorithms. This particular approach displays a hundred percent accuracy on the

training data set and also displays quite high accuracies for the test and validation sets. One might wonder if sixty and seventy two percent accuracies are good enough, but therein lies the catch. Accuracy for machine learning algorithms can be a rather slippery slope. At times high accuracy can belie a grossly overfitting algorithm. Thus the satisfactory accuracy in turn indicates a healthy algorithm which can only improve with a growing database. The learning curves too indicate this very observation. As opposed to the curves for the two decision tree methods, the neural network curves actually appear to converge which indicate a balanced belief in the dataset from the agent. The artificial neural network emerged as the most capable of capturing a non-linear relationship. Although support vector machines can do the same, they need very complex kernel functions to do so. Decision trees thrive on decisions based on independent features.

Ultimately these results indicate that there might be some underlying method to these diagnosis claims owing to the fact that these are significantly better than a random guess at arriving at a conclusion



*Figure 5.0.1. Setwise Prediction Accuracy for the Four Algorithm*

Table 5.0.1. Prediction Accuracy of four algorithms

	<b>Train</b>	<b>Test</b>	<b>Validation</b>
<b>ANN</b>	100	60	72.73
<b>DT_GI</b>	80	40	45.45
<b>SVM</b>	80	40	54.5454
<b>DT_IG</b>	76.67	40	45.45

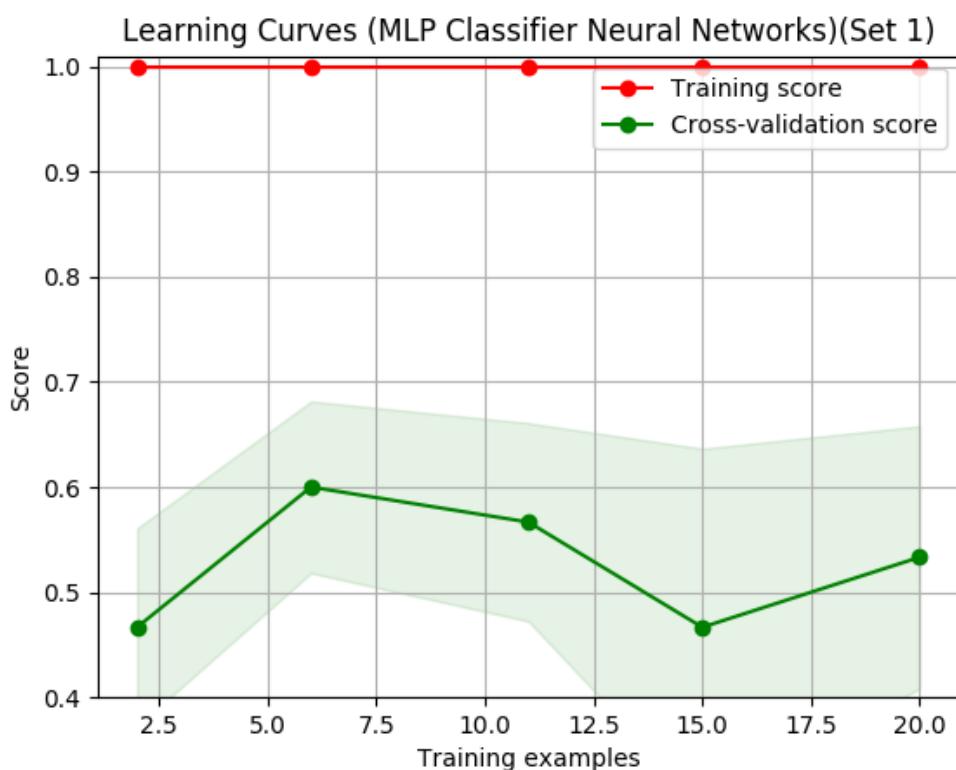


Figure 5.0.2. Learning Curve (MLP Classifier Neural Networks)

Figure 5.0.3. Learning Curve (Decision Trees Gini)

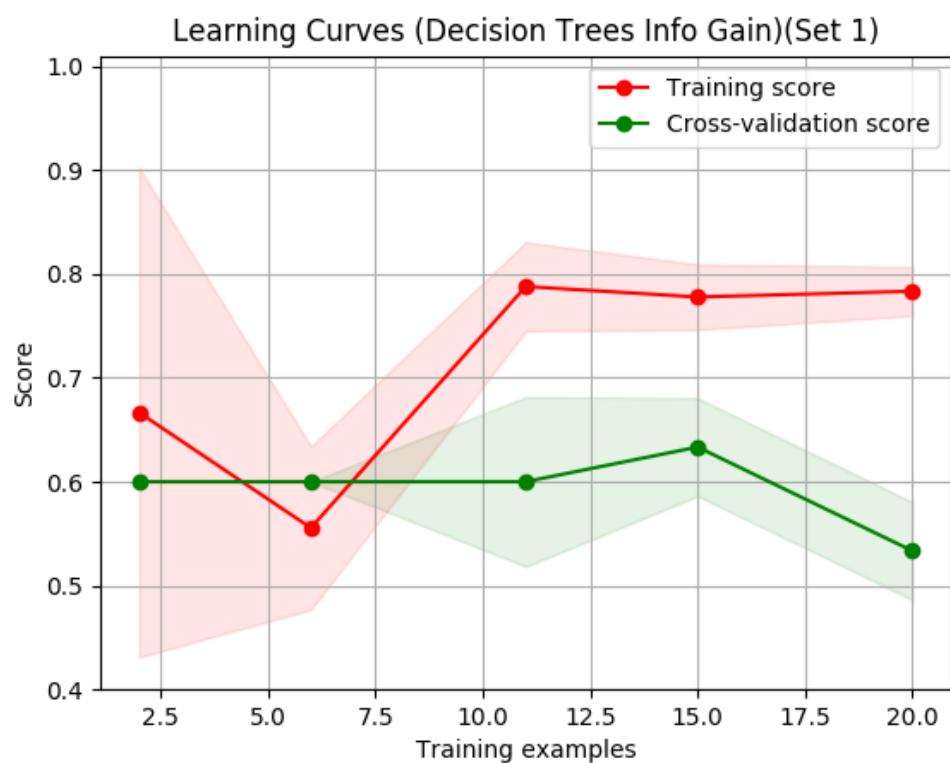
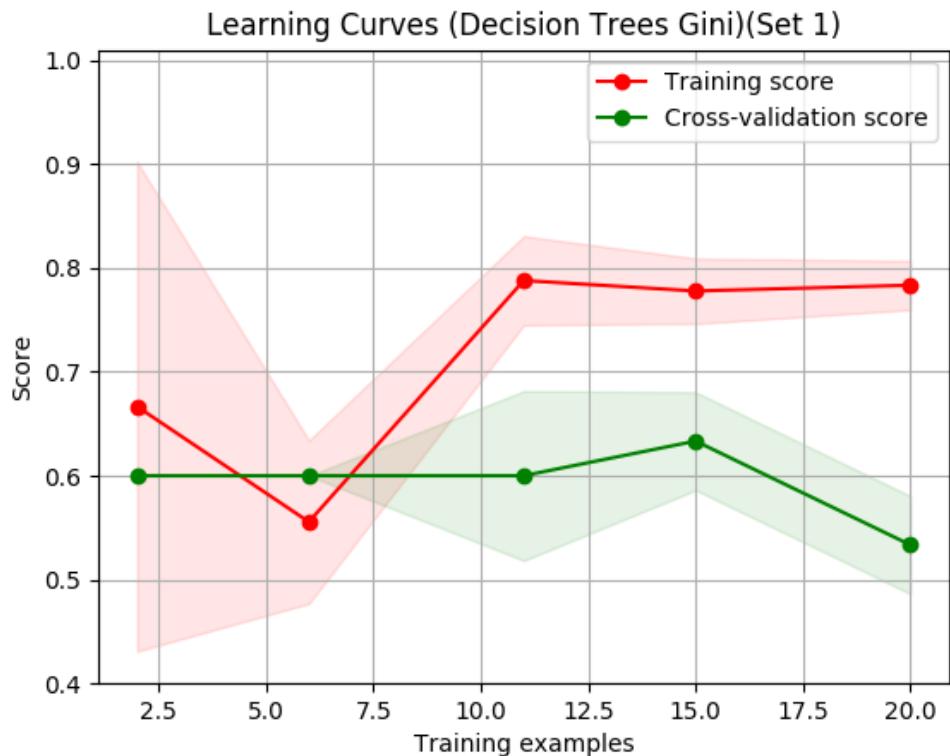


Figure 5.0.4. Learning Curve (Decision Trees Information Gain)

## **6. CONCLUSION**

From the work undertaken, one can safely make the assumption that there exists merit to the usage of pulse waves as a diagnostic tool. The specificity of such a diagnosis is yet undetermined, in that if it is enough to measure a distinction among different ailments. However, that is a study reserved for the future.

Moving on to the Ayurvedic model, the study undertaken indeed suggests that such a diagnostic method might not be entirely randomized guessing. The accuracy of the artificial neural network suggests that the method is definitely better than guessing at the presence of an ailment. To conclude that the accuracy is final would be a grave mistake, especially when there is ample potential for the database to grow, and for features to get added.

A noteworthy aspect of the study is that the model created by the artificial neural network might not match the one envisioned by the practitioners of the Ayurvedic technique. This however is an expected development since the same relation could potentially be modeled in various different ways.

In conclusion, as the study set out to investigate the merits of pulse diagnosis and find a mathematical and scientific grounding for the practice should any exist, one can conclude that such grounding does exist and can potentially be refined through more exploration and a stronger database. The investigation and its results point towards a strong possibility of the existence of a scientific relation between the pulse waveform and the presence of an ailment. With a larger database and potentially more significant features one can hope for a more solid quantification of the method than what has been investigated now.

## **7. FUTURE SCOPE**

The future scope for this study entails a few approaches. The first and foremost priority would be to grow the database of pulse signals to a significant number. This exercise would be of paramount importance since it would ultimately improve the quality of learning that an agent performs towards the classification goal. For this goal to be achieved there needs to be some improvements in the data collection methodology, which given some time can be made. Essentially the data collection system can be made to transmit the data wirelessly in the future over a Bluetooth connection so that the subjects can have ease of access to the system. The wireless nature can be extended to include applications on mobile operating systems for the data collection so that the device can be deployed to care centres to be used easily by the personnel there.

The second area for investigation would be to develop a learner that is independent of a feature selector, in this case the human who decides the features to be extracted from the signal. Think of this learner as a convolutional neural network that deals with single dimensional arrays as opposed to multi-dimensional image arrays. In this way, we free the learner of any inherent bias that the feature selector might introduce. This in turn provides the learner complete access to the signal itself and not merely the parts that the selector considers important.

There could be further scope for on policy learners that can be deployed readily to subjects. These on policy learners essentially learn as they interact with the subject and environment. Think of this as an agent which is capable of forming the activation function for ailment or not as it interacts with the patient and their pulse. In essence this is aimed at providing a more personalized approach to this problem. The initial training phase might be rather tedious however it would then essentially exist as a very personalized diagnostic tool for the given person.

Finally it would be well to centralize the database on a cloud server with the appropriate encryption standards for the instances of this device to access. This could ensure that the device can retrain itself and update its model as and when significant amounts of new data arrive.

## **8. REFERENCES**

1. Fan, Z., Zhang, G., & Liao, S. (2011). Pulse wave analysis. In Advanced Biomedical Engineering. IntechOpen.
2. Viswanth, S., Joshi, A., & Kulkarni, B. (2017). Exploring analytical patterns of the arterial pulse. *Journal of Ayurveda and Holistic Medicine (JAHM)*, 5(5), 25-44.
5. Bhat, S. (2018, February 02). How Ayurveda Can Help Hypothyroidism. Retrieved from <https://www.theayurvedaexperience.com/blog/ayurveda-can-help-hypothyroidism>
7. Kallurkar, P., Patil, K., Sharma, S., & Sharma, N. (2015). Nadi Diagnosis Techniques. *International Journal Of Public Mental Health And Neurosciences*, 2(1), 17-23.
8. Kulkarni, R. P., Kumbhar, S. M. Diagnosis of Diabetes Based on Nadi Pariksha Using Tridosha Analysis and ANN
9. Ranajan, Mridul. (2015). REVIEW ON AYURVEDIC MANAGEMENT OF HYPOTHYROIDISM WITH CRITICAL ANALYSIS. 10.13140/RG.2.1.4693.5767.
10. Pal, Madhabendranath. (1991). The tridosha theory. Ancient science of life. 10. 144-55.
11. Uiowa. (2015, March 19). Your finger's pulse holds the key to your heart's health. Retrieved from <https://now.uiowa.edu/2013/09/your-fingers-pulse-holds-key-your-hearts-health>
12. Yasuno, S., Ueshima, K., Oba, K., Fujimoto, A., Hirata, M., Ogihara, T., ... & Nakao, K. (2010). Is pulse pressure a predictor of new-onset diabetes in high-risk hypertensive patients?: a subanalysis of the Candesartan Antihypertensive Survival Evaluation in Japan (CASE-J) trial. *Diabetes care*, 33(5), 1122-1127.
13. Davies, J. I., & Struthers, A. D. (2005). Beyond blood pressure: pulse wave analysis—a better way of assessing cardiovascular risk?.
15. Korpas, D., Halek, J., & Doležal, L. (2009). Parameters describing the pulse wave. *Physiological research*, 58(4).
16. Goyal, K., & Agarwal, R. (2017). Pulse based sensor design for wrist pulse signal analysis and health diagnosis.
19. Xu, L., Meng, M. Q. H., Wang, K., Lu, W., & Li, N. (2009). Pulse images recognition using fuzzy neural network. *Expert systems with applications*, 36(2), 3805-3811.
20. Ohal, S. K., Vaidya, R.J., Arterial Blood Pressure Measurement and Pulse Wave Analysis. *IOSR Journal of Electronics and Communication Engineering (IOSR-JECE)*
21. Scarpello, J. H. B., Martin, T. R. P., & Ward, J. D. (1980). Ultrasound measurements of pulse-wave velocity in the peripheral arteries of diabetic subjects. *Clinical science*, 58(1), 53-57.

## **9. APPENDICES**

## **9.1. MCP604 IC**

### **2.7V to 6.0V Single Supply CMOS Op Amps**

#### **9.1.1. Description**

The Microchip Technology Inc. MCP601/1R/2/3/4 family of low-power operational amplifiers (op amps) are offered in single (MCP601), single with Chip Select (CS) (MCP603), dual (MCP602), and quad (MCP604) configurations. These op amps utilize an advanced CMOS technology that provides low bias current, highspeed operation, high open-loop gain, and rail-to-rail output swing. This product offering operates with a single supply voltage that can be as low as 2.7V, while drawing 230  $\mu$ A (typical) of quiescent current per amplifier. In addition, the common mode input voltage range goes 0.3V below ground, making these amplifiers ideal for single-supply operation. These devices are appropriate for low power, battery operated circuits due to the low quiescent current, for A/D convert driver amplifiers because of their wide bandwidth or for anti-aliasing filters by virtue of their low input bias current. The MCP601, MCP602, and MCP603 are available in standard 8-lead PDIP, SOIC, and TSSOP packages. The MCP601 and MCP601R are also available in a standard 5-lead SOT-23 package, while the MCP603 is available in a standard 6-lead SOT-23 package. The MCP604 is offered in standard 14-lead PDIP, SOIC, and TSSOP packages. The MCP601/1R/2/3/4 family is available in the Industrial and Extended temperature ranges and has a power supply range of 2.7V to 6.0V.

#### **9.1.2. Features**

- Single-Supply: 2.7V to 6.0V
- Rail-to-Rail Output
- Input Range Includes Ground
- Gain Bandwidth Product: 2.8 MHz (typical)
- Unity-Gain Stable
- Low Quiescent Current: 230  $\mu$ A/amplifier (typical)
- Chip Select (CS): MCP603 only

- Temperature Ranges: -
  - o Industrial: -40°C to +85°C
  - o Extended: -40°C to +125°C
- Available in Single, Dual, and Quad

### 9.1.3. Typical Applications

- Portable Equipment
- A/D Converter Driver
- Photo Diode Pre-amp
- Analog Filters
- Data Acquisition
- Notebooks and PDAs
- Sensor Interface

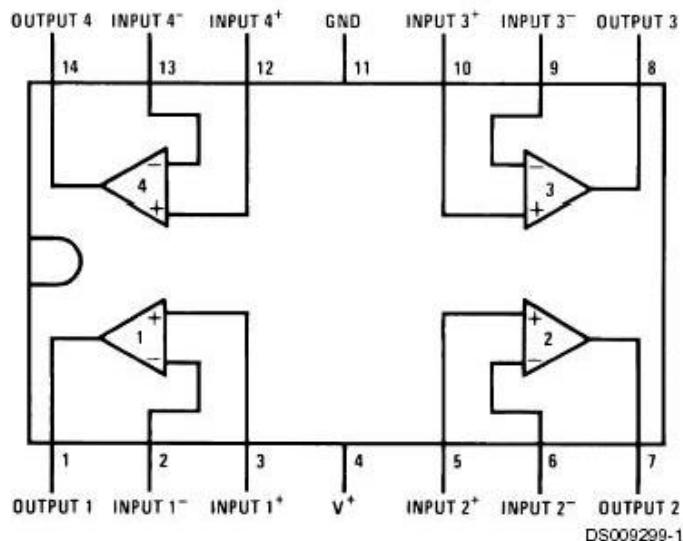


Figure 9.1.1. Top View of Quad-amp dual-in-line Package

MCP604 is available in standard 14-lead PDIP, SOIC and TSSOP packages. The packaging is smaller and offers lower power than other discrete designs. Hence, it is good fit for battery-powered, portable applications.

Table 9.1.1. Parametrics of MCP604

<b>Name</b>	<b>Value</b>
Temp. Range(°C)	-40 °C to +125 °C
Vos Max ( $\mu$ V)	2000
# per Package	4
Iq Typical ( $\mu$ A)	230
Iq Max ( $\mu$ A)	325
GBWP (kHz)	2800
Operating Voltage Range (V)	2.7 to 6.0
Device Description	Linear Op-Amps
Input Voltage Noise Density (nV/rt(Hz))	29
PSRR Min (dB)	80
CMRR Min (dB)	75
Vos/Ta ( $\mu$ V/°C)	2.5
Ib (pA)	1
Aol (dB)	110
PM (deg)	50
Isc (mA)	22
Rail-to-Rail	Out
Unity Gain Stable	Yes
Slew Rate (V/uS)	2.3

## **9.2 Arduino Nano**

The Arduino Nano is a small, complete, and breadboard-friendly board based on the ATmega328P (Arduino Nano 3.x). It has more or less the same functionality of the Arduino Duemilanove, but in a different package. It lacks only a DC power jack, and works with a Mini-B USB cable instead of a standard one.

### **9.2.1. Power**

The Arduino Nano can be powered via the Mini-B USB connection, 6-20V unregulated external power supply (pin 30), or 5V regulated external power supply (pin 27). The power source is automatically selected to the highest voltage source.

### **9.2.2. Memory**

The ATmega328 has 32 KB, (also with 2 KB used for the bootloader. The ATmega328 has 2 KB of SRAM and 1 KB of EEPROM.

### **9.2.3. Input and Output**

Each of the 14 digital pins on the Nano can be used as an input or output, using `pinMode()`, `digitalWrite()`, and `digitalRead()` functions. They operate at 5 volts. Each pin can provide or receive a maximum of 40 mA and has an internal pull-up resistor (disconnected by default) of 20-50 kOhms. In addition, some pins have specialized functions:

- Serial: 0 (RX) and 1 (TX). Used to receive (RX) and transmit (TX) TTL serial data. These pins are connected to the corresponding pins of the FTDI USB-to-TTL Serial chip.

- External Interrupts: 2 and 3. These pins can be configured to trigger an interrupt on a low value, a rising or falling edge, or a change in value. See the `attachInterrupt()` function for details.
- PWM: 3, 5, 6, 9, 10, and 11. Provide 8-bit PWM output with the `analogWrite()` function.
- SPI: 10 (SS), 11 (MOSI), 12 (MISO), 13 (SCK). These pins support SPI communication, which, although provided by the underlying hardware, is not currently included in the Arduino language.
- LED: 13. There is a built-in LED connected to digital pin 13. When the pin is HIGH value, the LED is on, when the pin is LOW, it's off.

The Nano has 8 analog inputs, each of which provide 10 bits of resolution (i.e. 1024 different values). By default they measure from ground to 5 volts, though it is possible to change the upper end of their range using the `analogReference()` function. Analog pins 6 and 7 cannot be used as digital pins. Additionally, some pins have specialized functionality:

- I2C: A4 (SDA) and A5 (SCL). Support I2C (TWI) communication using the `Wire` library (documentation on the [Wiring website](#)).

There are a couple of other pins on the board:

- AREF. Reference voltage for the analog inputs. Used with `analogReference()`.

- Reset. Bring this line LOW to reset the microcontroller. Typically used to add a reset button to shields which block the one on the board.

#### **9.2.4. Communication**

The Arduino Nano has a number of facilities for communicating with a computer, another Arduino, or other microcontrollers. The ATmega328 provide UART TTL (5V) serial communication, which is available on digital pins 0 (RX) and 1 (TX). An FTDI FT232RL on the board channels this serial communication over USB and the FTDI drivers (included with the Arduino software) provide a virtual com port to software on the computer. The Arduino software includes a serial monitor which allows simple textual data to be sent to and from the Arduino board. The RX and TX LEDs on the board will flash when data is being transmitted via the FTDI chip and USB connection to the computer (but not for serial communication on pins 0 and 1). A SoftwareSerial library allows for serial communication on any of the Nano's digital pins. The ATmega328 also support I2C (TWI) and SPI communication. The Arduino software includes a Wire library to simplify use of the I2C bus. To use the SPI communication, please see ATmega328 datasheet.

#### **9.2.5. Programming**

The Arduino Nano can be programmed with the Arduino software. Select "Arduino Duemilanove or Nano w/ ATmega328" from the Tools > Board menu (according to the microcontroller on your board). The ATmega328 on the Arduino Nano comes preburned with a bootloader that allows you to upload new code to it without the use of an external hardware programmer. It communicates using the original STK500 protocol. You can also bypass the bootloader and program the microcontroller through

the ICSP (In-Circuit Serial Programming) header using Arduino ISP or similar.

### **9.2.6. Automatic (Software) Reset**

Rather than requiring a physical press of the reset button before an upload, the Arduino Nano is designed in a way that allows it to be reset by software running on a connected computer. One of the hardware flow control lines (DTR) of the FT232RL is connected to the reset line of the ATmega328 via a 100 nanofarad capacitor. When this line is asserted (taken low), the reset line drops long enough to reset the chip. The Arduino software uses this capability to allow you to upload code by simply pressing the upload button in the Arduino environment. This means that the bootloader can have a shorter timeout, as the lowering of DTR can be well-coordinated with the start of the upload. This setup has other implications. When the Nano is connected to either a computer running Mac OS X or Linux, it resets each time a connection is made to it from software (via USB). For the following half-second or so, the bootloader is running on the Nano. While it is programmed to ignore malformed data (i.e. anything besides an upload of new code), it will intercept the first few bytes of data sent to the board after a connection is opened. If a sketch running on the board receives one-time configuration or other data when it first starts, make sure that the software with which it communicates waits a second after opening the connection and before sending this data.

Table 19.2.1 Technical Specification of Arduino Nano

Microcontroller	ATmega328
Architecture	AVR
Operating Voltage	5 V
Flash Memory	32 KB of which 2 KB used by bootloader
SRAM	2 KB
Clock Speed	16 MHz
Analog IN Pins	8
EEPROM	1 KB
DC Current per I/O Pins	40 mA (I/O Pins)
Input Voltage	7-12 V
Digital I/O Pins	22 (6 of which are PWM)
PWM Output	6
Power Consumption	19 mA
PCB Size	18 x 45 mm
Weight	7 g
Product Code	A000005

## **9.3. TCRT5000**

### **9.3.1. Description**

The TCRT5000 and TCRT5000L are reflective sensors which include an infrared emitter and phototransistor in a leaded package which blocks visible light. The package includes two mounting clips. TCRT5000L is the long lead version.

### **9.3.2. Features**

- Package type: leaded
- Detector type: phototransistor
- Dimensions (L x W x H in mm): 10.2 x 5.8 x 7
- Peak operating distance: 2.5 mm
- Operating range within > 20 % relative collector current: 0.2 mm to 15 mm
- Typical output current under test: IC = 1 mA
- Daylight blocking filter
- Emitter wavelength: 950 nm
- Lead (Pb)-free soldering released
- Compliant to RoHS directive 2002/95/EC and in accordance to WEEE 2002/96/EC

### **9.3.3. Applications**

- Position sensor for shaft encoder
- Detection of reflective material such as paper, IBM cards, magnetic tapes etc.
- Limit switch for mechanical motions in VCR
- General purpose - wherever the space is limited

## **9.4 APDS-9008**

### **Miniature Surface-Mount Ambient Light Photo Sensor**

#### **9.4.1. Description**

The APDS-9008 is a low cost analog-output ambient light photo sensor in miniature chipLED lead-free surface mount package. It consists of a spectrally suited photo sensor, which provides excellent responsivity that is close to the response of the human eyes, as shown in figure 2. The APDS-9008 is ideal for applications in which the measurement of ambient light is used to control display backlighting. Mobile appliances such as the mobile phones and PDAs that draw heavy current from display backlighting will benefit from incorporating these photo sensor products in their designs by reducing power consumption significantly. Application Support Information The Application Engineering Group is available to assist you with the application design associated with APDS9008 ambient light photo sensor module. You can contact them through your local sales representatives for additional details.

#### **9.4.2. Features**

- Excellent responsivity - Close responsivity to the human eye
- Miniature ChipLED Leadfree surface-mount package Height – 0.55 mm Width – 1.60 mm Depth – 1.50 mm
- Low sensitivity variation across various light sources
- Operating temperature : -40°C to 85°C
- Vcc supply 1.6 to 5.5V
- Lead-free package, RoHS compliance
- Output linearity across wide illumination range
- High output saturation voltage

### **9.4.3. Applications**

- Detection of ambient light to control display backlighting Mobile devices – Mobile phones, PDAs Computing devices – Notebooks, Webpads Consumer devices – TVs, Video Cameras, Digital Still Camera
- Automatic Residential and Commercial Lighting Management
- Electronic Signs and Signals