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Pulse Diagnosis Using Signal Processing and Machine Learning Techniques

CAPSTONE PROJECT

B.Sc. Electrical and Electronics Engineering

Charlotte Maxine Dawson-Amoah

2021

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CAPSTONE PROJECT

Capstone Project submitted to the Department of Engineering, Ashesi University College in partial fulfilment of the requirements for the award of Bachelor of Science degree in Electrical and Electronics Engineering.

Charlotte Maxine Dawson-Amoah

2021

DECLARATION

I hereby declare that this capstone is the result of my own original work and that no part of it has been presented for another degree in this university or elsewhere.

Candidate’s Signature: C.D.A

Candidate’s Name:

Charlotte Maxine Dawson-Amoah

Date:

26th April 2021

I hereby declare that preparation and presentation of this capstone were supervised in accordance with the guidelines on supervision of capstone laid down by Ashesi University College.

Supervisor’s Signature:

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Supervisor’s Name:

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Date: ……………………………………………………………………………………………

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To my supervisor, Dr Siby Samuel, whose encouragement and academic advice helped me undertake this project. To my loving parents, whose endless love and financial support have made me the person I am today, and to the Almighty God, who has been my strength and support during tumultuous times.

Abstract

For many centuries, pulse diagnosis has been a technique studied and applied in determining the state of health of the human body. However, its subjective nature puts it at a disadvantage in presenting an accurate diagnosis of the human body. In this project, practical research is done to standardize pulse diagnosis by acquiring body signals and applying signal processing and machine learning techniques for analysis. A prototype acquisition system is designed to obtain the body signals such as the pressure pulse waves from arteries and ECG signals. The system's efficiency was verified using cross-correlation analysis between the data acquired from the system and the standard data from Lei Zhang’s database and MIT physio net database. For the diagnostic system for the signal analysis, the time domain, frequency domain, and time-frequency domain of the signal processing techniques are adopted to extract features such as the power spectral density to be further used for classification and distinction between different signal groups. Applying the different techniques showed a distinction between the different groups of signals that aided the Support Vector Machine and K-Nearest Neighbour classification models to achieve above 90% and 80% accuracy. The experimental process and results provided insight into ways pulse diagnosis could be standardized for healthcare services.

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Chapter 1: Background

From the Ancient Egyptians, Indians to Chinese and even in modern times, physicians used traditional medical techniques passed from generation to generation by memory and oral traditions to heal and provide medical service. A typical medical technique identified and used in different cultures throughout generations is pulse diagnosis. The principle behind pulse diagnosis is using the features and characteristics felt when blood travels with different patterns. Pulses can be palpated on any part of the body, whereby the artery can be felt near the body's surface. There are many types of arteries, such as the carotid artery located in the neck, the wrist's radial artery, femoral artery at the groin, popliteal artery behind the knee, posterior tibial artery near the ankle joint and the dorsal pedis artery on foot[16]. Patterns and characteristics of pulse wave assessed allows the determination of the condition of health of the body. Knowledgeable and experienced physicians assess pulse. However, the assessment techniques and diagnostic characteristics are sometimes tricky due to their subjective nature. To efficiently diagnose a patient's health status, one must have in-depth knowledge and practice to confirm their diagnosis. However, this is not enough because of ambiguity and a high erroneous probability from the subjective assessment.

The subjective manner of diagnosis is still controversial due to ambiguity and probability of error with which it affects the reliability of the process. However, a solution to this is to find ways for greater standardization of the methods and understanding of techniques to improve and accurately verify the diagnostic methods. In this paper, the research project aims to achieve this goal using signal processing and machine learning techniques to better assess the characteristics of pulses to aid in accurately depicting the state of the body and prove its efficiency in diagnosing the health of the human body.

1.1 Definition and History of Traditional Pulse Diagnosis

Traditional pulse diagnosis is mainly linked to Traditional Chinese Medicine (TCM). It is one of the major four clinical diagnostic methods in TCM with the others being inspection, interrogation, auscultation, and olfaction (listening and smelling)[19]. The technique involves a TCM doctor palpitating six locations. Three positions on the left and right hands near the wrist. These three points are known as "cun", "guan", and "chi" in Figure 1[19]. Comparing the pulses on both the left and the right wrist, the three points can aid in determining the health status of the human body. Quantifying pulse diagnosis provides a scientific base to the pulse diagnosis, especially TCM pulse diagnosis, to substantiate its clinical value [19]. The pulse is objective, but the condition is subjective because the quality of the pulse felt by the physician is represented by the subjective judgement of the physician [20]. In medical texts, around twenty-four to thirty pulse conditions are documented in Chinese medical texts such as large, small, rugged and soft[19]. Some other features such as pulse rate, pulse volume, pulse height, and strength can also be determined. The need to standardize the pulse diagnosis is due to reasons such as lack of concise and precise standards to guide doctors in diagnosis and their assessment based on their perception.

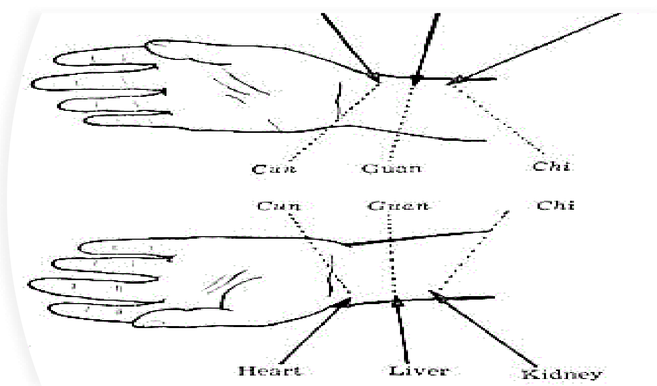


Figure 1:Points of Palpitation on the Arm

1.2 Research objectives of the project

For the overall project in the nascent stages, the aim was to develop a non-invasive health diagnosis system using the principle of pulse diagnosis. However, during research and evaluation, the project was broken down into two sub-projects. These sub-projects are developing a pulse acquisition system and the diagnostic system, which entails assessing signal quality and characteristics. Focusing on the signal quality and pulse characteristics assessment, the paper proposes some signal processing and machine learning techniques to assess and analyze the signal. It would aid in developing a non-invasive health diagnosis system and provide a foundation in proving the efficiency of pulse diagnosis through pulse pattern and characteristics gathered from a pulse system and database. The objectives are:

- Adoption of the signal processing techniques for evaluating and standardizing pulse waveform
- Adopting machine learning for the classification of different pulses and abnormalities detected.
- Creating a prototype pulse acquisition system to gather data to test the techniques

1.3 Motivation and Significance of Study

- To develop a practical, non-invasive health diagnosis system
- To be able to provide an objective analysis of the pulse using cost-efficient materials and techniques
- To be able to prove the efficiency of pulse analysis for diagnosis and treatment of ailments
- Explore and learn different processing and machine learning techniques to improve the acquisition of signals measured for interpretation.

1.4 Proposed Scope of the work

The scope of work is founded on principles of diagnosis based on the signal character with the aid of information found in Traditional Chinese Pulse diagnosis and other recent developments of techniques in other pulse diagnosis processes. It provides insight into the different attributes, methods and concepts of pulse diagnosis, which would aid in the processes of the project. Signal processing techniques such as power spectral density in conjunction with different filters would be used to analyze the characteristics and patterns of primary datasets gathered from a database. These datasets are from Lei Zhang's homepage and MIT physio net database. It would aid in evaluating the most efficient technique to maintain the characteristics of the pulse wave for further analysis and machine training. In future scope of the work, it includes creating a pulse acquisition system whereby real-time data can be acquire. A trained system would be used through machine learning, and the real-time data would be classified based on its characteristics. This process would contribute to affirming the efficiency of pulse diagnosis and aid in acquiring the health state patients with a lower probability of errors.

Rough Diagram of the Initial Proposed Project System

Even though the paper's focus is on the signal quality and pulse characteristics assessment of the data, steps were taken in the development of a prototype pulse acquisition system to assess the dynamics of gathering pulse signals from the body. For the prototype, the proposed design was to use sensors, oscilloscope and KL25Z. The sensors acquire the pulse signal from the patient's body, which is then stored on the computer via Bluetooth module. The analog to digital converter of the KL25Z can be adopted to convert the analog signal to digital format before it is stored, as seen in Figure 2. A backup plan was also to use the oscilloscope to gather data which would then be plotted and compared to the database set signals and pulse data read by the KL25Z. The proposed system design uses the TCM theory whereby the forefinger, middle finger and ring finger are used in pulse assessment. However, only the forefinger was used in this case. The sensor is placed on the tip of the forefinger to take pulse values.

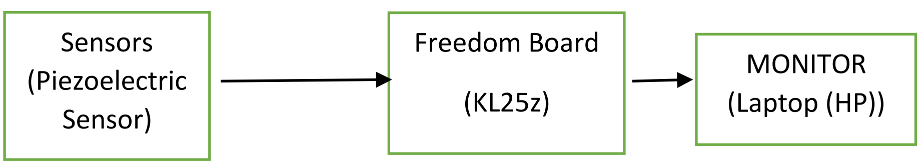


Figure 2: Block Diagram of Acquisition System Design

Rough Description of Proposed Scope of Work

Datasets from the different database are used in the analysis of signal qualities and pulse characteristics. Pre-processing techniques will be used to remove noise and baseline drift to make the pulse more accurate for analysis. For characteristic assessment, the time domain analysis, frequency domain analysis and time-frequency analysis will be used. It is to assess distinctions of pulses measured which are capable of aiding in identifying diseased and healthy pulses. In pulse characteristic assessment, it enables the extraction of features for easy classification. Classifiers such as linear, nonlinear, or quadratic pulse classifiers provide statistical techniques for quantifying pulse conditions. In this scope of work, electrocardiogram (ECG) signals would be assessed because these signals can provide both cardiac and noncardiac activities of the body. Figure 3 outlines the quick steps that would be taken in the course of the project.

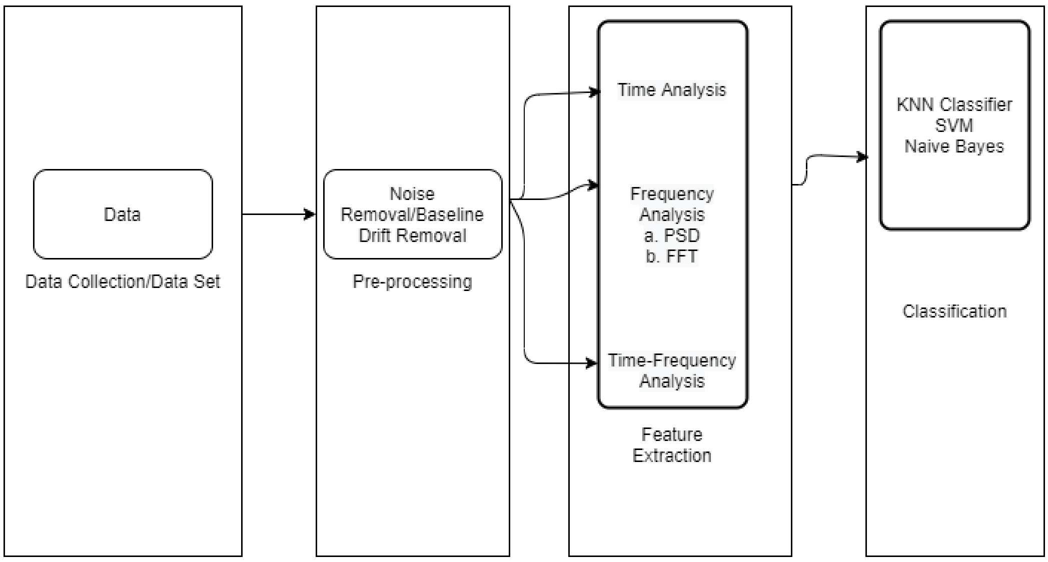


Figure 3: Block Diagram of Diagnostic System Design

1.4.1 Anticipated Outcomes of the Project

- Distinct visibility of the different signal frequencies and signal characteristics for feature extraction
- Analysis of signal characteristics to determine the pathological conditions of the patient
- Classification pulses with the aid of machine learning tools

1.4.2 Research Methodology Used

- Literature Review

1.4.3 Requirements

Some requirements of the project are:

Tools	Reasoning/Justification
Freedom Board KL25Z	This tool provides ADC capabilities without the need of building the converter . The tool was also readily available.
Piezoelectric Sensor (Piezo ceramic element)	High sensitivity tool for measuring pressure changes. It is also portable and cheap.
1M, 100k,470000, 4700, 1M ohm Resistors	Used in the construction of the instrumentational amplifier, the large

	resistance values provide potential for a larger and easily controllable gain
Rechargeable Battery (AA+)	Used as a power source for the system to aid in the development of a portable system
1uF, 100nF capacitors	These values aided in generating a desired gain of 50 for the instrumentational amplifier during calculation
Oscilloscope	To backup data gathered during measurement and visualize the data read to evaluate the efficiency of the system
LM358 operational amplifier	As compared to the commercial amplifier, it is much cheaper which aids in achieving the goal of building an affordable system
MATLAB	To carry out the signal processing capabilities of the project easily with in-built tools providing guidance for a beginner analyzer

Chapter 2: Literature Review

From [2], pulse diagnosis is an essential method in diagnosing an individual's health status. The traditional method is using fingertips and applying pressure to the skin where the arteries can be felt. This article describes a portable, low-cost system for pulse-type estimation using a smartphone connected to two sensors, including one photoplethysmography (PPG) sensor and one galvanic skin response (GSR) sensor. A five-minute PPG pulse information and skin impedance on twenty-four acupoints from 80 subjects. A fully connected neural network (FCN) provided high prediction accuracy for patients with a traditional Chinese medicine wiry pulse. The design architecture was divided into three parts, namely the sensing system, smartphone and cloud server. The sensor platform collects signals from the subject, where it uses an android platform to display a user interface where it allows the user to view signals obtained in real-time. Measured data is stored in the phone and transmitted to a cloud server. PMAF method used to remove motion artefacts and noise. However, the deep neural network models could not be adopted for the study due to a lack of a sufficient dataset. Further analysis would be done once more data is acquired in the future.

In article[1], a design of a pulse diagnosis sensor is a non-invasive method for the measurement of health in Ayurveda. Ayurveda is known as Nadi Parikshan. An examination of the pulse at the wrist signifies life's presence. An Ayurvedic physician uses the pulse to determine heart rate and vibration patterns, representing the status of the body and mind in a period. The article presents the design and development of pulse diagnosis in which an MPXM2053D sensor from FREESCALE. Signal conditioning circuit designed using an instrumentation amplifier and real-time monitoring is done using myRIO DAQ card in LabView with filtering performed in Matlab. Frequency domain analysis was conducted using power spectrum with the extraction of features. Further analysis required the interpretation of features to distinguish between a healthy and unhealthy individual. Classifiers were obtained to classify the health status of individuals, and the outcome of the results showed high accuracy, sensitivity and specificity.

In western medicine, they are using devices such as MRI, which looks inside the human body. Even with western medicine, pulse information only contains information on rate, rhythm, and the pulse wave volume based on the state of the heart and blood vessels. However, oriental medicine using wrist pulse diagnosis can effectively diagnose the body's health as any western medicine or western device with even more signal pulse characteristics to classify. These characteristics denote various types of pulses, and in the case of Traditional Chinese Medicine, there are twenty-four to twenty-seven different types. Park and Lee [18] developed a diagnosing system that detects signal using a piezoelectric sensor and using the signal to detect possible liver illness and heart disorder.

This paper [21] gives an overview of different reseach works done in relation to electromyograhic signals (EMG). The classifcation was mainly based on Support Vector Machines (SVM) however, other techniques such as the K-Nearest Neighbors (KNN) and Artifical Neural Network (ANN) were referenced. The mean absolute value, zero crossing, slope sign changes and waveform length were features that were extracted based on time domain frequency domain, time-frequency domain and spatial domain analysis. They achieved more than ninety-five percent effectiveness without feature selection using SVM. Two different kernels were also applied namely Gaussian and Radial Basis Function which were used to classify five different leg movements through four myoelectric signal channels with the combination of previously extracted features. Multile Kernel Learning SVM obtained more than ninety percent accuracy. In the end, knowledge on pattern classification was adopted based on the needs and chracteristics of a system. SVM was seen to offer high classification accuracy since it allowed the combination with other methods to reach a high accuracy percentage.

Monitoring of vital signals using doppler radar has been an emerging research topic in current years. In this article [12], vital signal is measured using radar and de-noising technique based on sample entropy and wavelet threshold is proposed. The noisy radar signal is first decomposed into a series of intrinsic mode functions. Each intrinsic mode function was analyzed using sample entropy to find the functions with noise. The functions with noise were then de-noised using wavelet threshold. To extract accurate vital signals, spectrum analysis and KullbackLeible divergence calculations were performed on all the functions with a few selected to reconstruct respiration and heartbeat signals. The effectiveness of the algorithm was assessed and verified using experimentation. The results showed that the algorithm could reduce noise effectively and was beneficial in extracting accurate vital signals.

Chapter 3: Project Description

3.1 Overall Background

In pulse diagnosis, pulse readings require different finger pressure strengths on artery vessels to gain accurate pulses and information. The physician palpates the pulse and judges the patient's health. Pulse taking can be done from different body locations such as the neck, behind the knees, foot and other parts of the body. In this research, the inch opening of TCM was one of the techniques used in pulse-taking. Inch opening is located around the radial artery in the wrist area[23]. This pulse location consists of three positions: the 'cun', 'guan' and 'chi', with the 'guan' position being the focus. Judging the health conditions of the entire body with inch opening is relatively easy since it constitutes the meeting point of the blood vessels.

However, the project aims to expand its scope in gaining pulses from other body areas to compensate for amputees and other patients with issues taking pulse measurements from the wrist.

3.1.1 ECG and Pulse Readings

Pulse waveforms contain information on the state of the human body based on the strength, shape, width and variation of rhythms. Through the sequence of the pulse wave, a physician can detect whether the pulse is fast or slow, floating or sinking. Clinically, there are between twenty-four to thirty pulse patterns in Traditional Chinese pulse diagnosis, and they are classified based on shapes, rhythm and other characteristics. From Table 1, each position of wrist pulse detection is related to different organs of the human body based on TCM. From Table 2 it shows the pulse patterns used to describe a signal based on the properties "felt" or observed.

Left Hand	Cun (Inch)	Heart
	Guan (Bar)	Liver
	Chi (Cubit)	Kidney
Right Hand	Cun (Inch)	Lung
	Guan (Bar)	Spleen
	Chi (Cubit)	Kidney

Table 1: Shows the relationship of different positions to the human organs

Property	Pulse Pattern
Position	Floating, deep, hidden
Strength	Faint, weak
Trend	Feeble, forceful
Tense Ability	Tight, taut, tympanic, firm, hollow, soggy
Shape	Slippery, smooth, bouncing
Width	Surge, thready
Rhythm	Running, knotted, intermittent, scattered
Pulse Rate	Slow, rapid, moderate
Length	Long, short

Table 2: The Patterns of Twenty-Seven and their Properties

As stated before, pulse diagnosis was practised with different cultures, and Ayurvedic pulse diagnosis was adopted in India. Unlike the Cun, Guan and Chi, in Ayurveda, there are Vata Dosha, Pitta Dosha and Kapha Dosha [2], but the principle and meanings are relatively the same. Even though this project does not directly use Cun, Guan and Chi in its analysis, or directly using length, smoothness or rigidity of the signal to identify it, other characteristics such as the energy in the signal, the frequency in the signal can be used in the characterization of the signal for identification based on signal processing.

The electrocardiogram (ECG) signal is slightly different from the pulse. The pulse is a pulse pressure wave that indicates the diastolic and systolic pressures in the arteries, usually measured using pressurizing the measurement point. The ECG signals are more of electrical signals that represent the heart's cardiac activities, which provides information on the heart rate rhythm, dynamics, and morphology[22]. For a normal ECG signal, it consists of P-waves with a QRS complex and T-waves. For the analysis of ECG signals, QRS complex and R-peaks play an essential role, especially in detecting the beats per minute and heart rate variability. The ECG signal is essential in assessing the state of the body since heart is a very important organ of the body. Information from the ECG signal can aid in the identification of abnormalities in areas of the heart and even in other parts of the body.

3.1.2 Data Set description

Data gathered from different databases was used to conduct the signal processing and machine learning techniques. The wrist pulse waveform dataset was taken from Lei Zhang's homepage[10], which is publicly available. The data set has 100 samples of a normal pulse, 54 samples of pulse with pancreatitis, 77 samples with Duodenal Ulcer (DBU), 35 samples of Appendicitis and 54 samples of Acute Appendicitis. ECG signal dataset used is derived from a different database. ECG signals are used to assess the heart and other cardiac activities. ECG Data set was gathered from MIT physio net. The database contains 310 ECG recordings obtained from 90 people. Signals are digitized at 500Hz with a 12bit resolution.

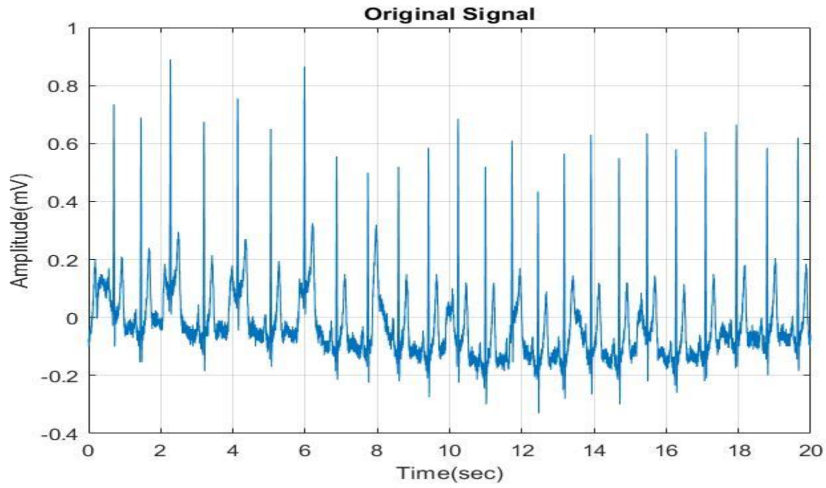


Figure 4 Graph of Original ECG Signal

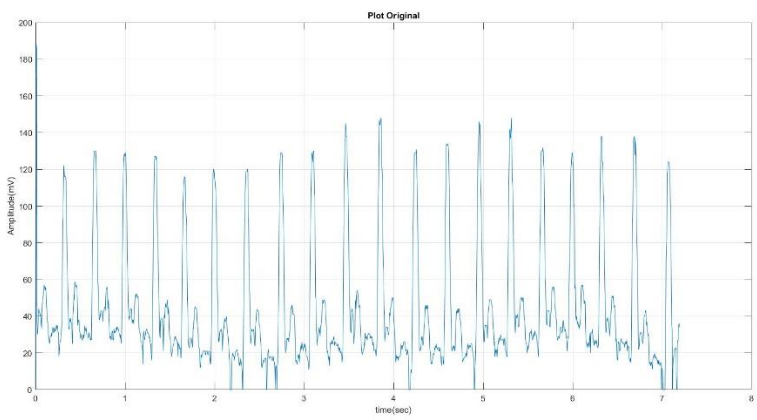


Figure 5 Original signal of Normal Wrist Pulse Signal

3.2 Pulse Acquisition System

For this scope of the project, a prototype system was designed. The system consists of a sensor, amplifier, and a computer to visualize the signal. Different sensors can acquire pulse waveforms, such as piezoelectricity sensors, infrared sensors, Doppler ultrasonic and many more. Using a Pugh chart, assessments were made for three sensors based on cost-effectiveness, accuracy and portability. The sensors were infrared, doppler radar, piezoelectric and polymer-based pressure sensors. The radar sensor is based on the doppler effect, which can detect vital signal through the difference between transmitted and received electromagnetic waves[25] . It is advantageous in remote monitoring without direct contact with the person, and it is not affected by environmental conditions such as temperature. Radar waves have a strong penetrating ability, which helps in long-term physiological monitoring. In this project, however, the contactless attribute of the radar sensor is undesirable due to the application of different pressure strengths on the pulse. The infrared sensor represented as a reflection-type pulse sensor that emits red or green light towards the body and measures the amount of light reflected using a photodiode [13]. The amount of light absorbed varies based on the changes in the blood vessel volume, which gives the waveform. The same as the doppler radar, it is contactless, making it difficult to apply pressure. Both the piezoelectric and polymer-based pressure sensor is similar. The pressure has been developed for non-invasive monitoring with the polymer being used as a dielectric material with high deforming properties. Some of these pressure sensors use capacitance to sense a change in pressure with applied forces, whilst others use piezoelectricity. In modern creations, nanoscience is used in its creation which requires skill to increase accuracy and sensitivity without being affected by environmental conditions. The piezoelectric ceramic sensor provides reliability, flexible and sensitivity to applied forces and pressures. It is highly portable, providing a convenient way to be applied to the skin non-invasively.

For constant pressure, different pressure strengths were applied with the sensor at the measuring point of the radial artery to obtain the pulse waveform. The Kl25z was adopted to provide analog to digital converter (ADC) capabilities in converting the analog signals detected into digital data to be assessed. In the design of the acquisition system, before the ADC conversion, an instrumentational amplifier is applied. Commercial instrumentational amplifiers are relatively expensive. Thus, one was created using three LM358 general purpose operational amplifiers. In designing the instrumentational amplifier, most resistors had the same value, which was 1M ohm, whilst one resistor is known as the gain resistor (R_g), had a value of 1k ohm. Thus, in this design, R_g controls the gain of the amplifier, which is a gain of 50. The ADC design of the system uses the 16-bit analog-to digital converter of the KL25Z freedom board. From the ADC module, one of the twenty-four ended inputs of the module.

		Sensors			
Selection Criteria	Weight	Infrared	Doppler radar	Piezoelectric	Polymer-based Pressure
Availability	2	2	-	2	0
Low Cost	1	2	-	1	0
Accuracy	2	1	-	1	2
Sensitivity	2	1	-	2	2
Size	2	1	-	2	2
Portability	2	2	-	2	2
Physical Contact	2	0	0	2	2
Total	13	9	-	12	10

Figure 6 Pugh Chart Analysis of Sensors

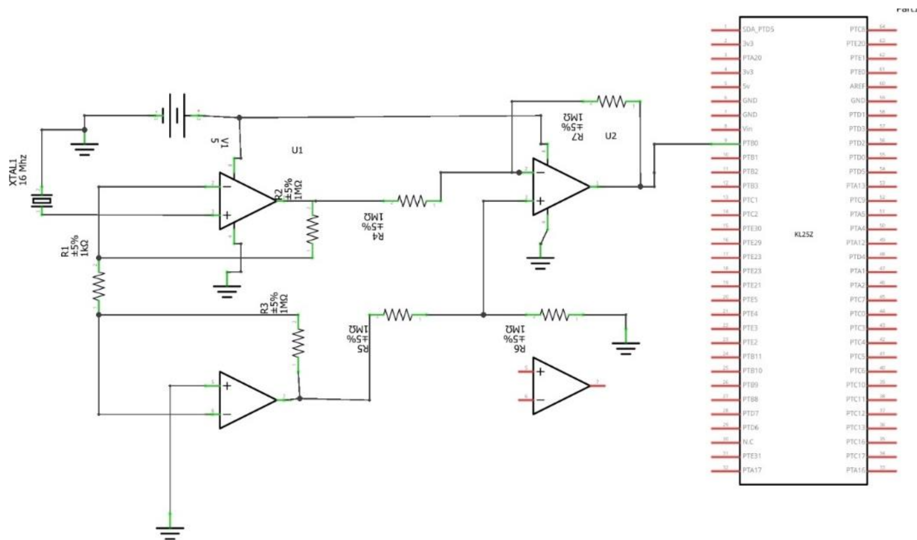


Figure 7 Instrumentational Amplifier using LM358

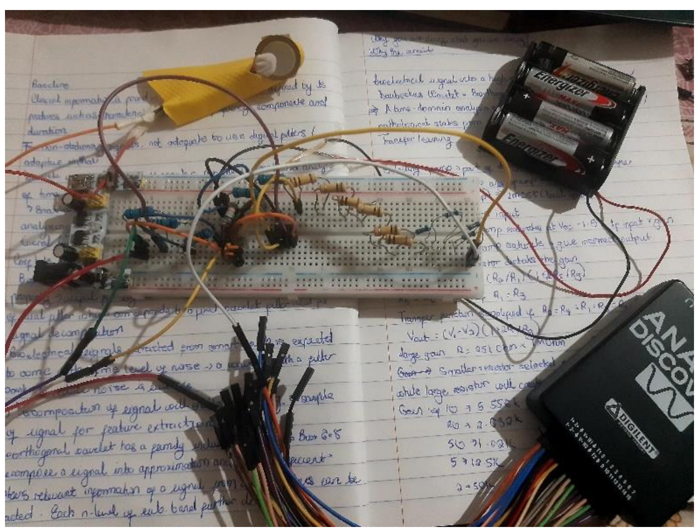


Figure 8: Prototype of Pulse Acquisition System

Chapter 4: Methodology

4.1 Hypothesis in Pulse Diagnosis

As stated before, pulse diagnosis is very subjective based on oral knowledge and experience. The human body is made up of organs that receive blood from the heart through the arteries. Blood flows through the arteries to the branches from the heart producing waves during the process in the arteries. Transmitted and reflected waves are generated at boundaries between the arteries and branches. The body organs produce oscillations in the reflected waves, which affects the frequency spectrum of reflected waves[24]. The state of the organ affects the frequency of the reflected waves. The information gained from arteries felt on the skin's surface is generally carried by the oscillated waves. In the research, a hypothesis is developed based on the radial pulses to brachial pulses. The oscillated waves generated in the arteries hold information that can be used to evaluate frequencies, the strength of the signal and duration to assess the physiological status of the body with respect to the pulse wave pressures.

4.2 Pre-processing of Pulse Waveform

Just like the electrocardiogram, the pulse wrist signal can be affected by interference. In recording the pulse waveform, transducers are used. The main types of noise that affect the signal are baseline drift, powerline interference and transducer motion noise.

4.2.1 Baseline Removal

For the baseline drift, the x-axis of the signal drifts rather than moving in a straight direction, causing a shift in the entire signal. In most cases, the baseline drift is caused by the impedance in transducers, movement of the person and respiration. The frequency of baseline drift is around 0.5Hz however, increased movement of the body can cause the baseline frequency to increase. Since the signal is of low frequency, a possible filter considered was the high pass filter. However, this was not the only consideration since powerline interference was also present. This interference is characterized by a 50 or 60Hz frequency accompanied by harmonics. The transducer motion noise is caused when the impedance of the skin changes around the transducer. Their frequency range is around 1 to 10Hz. In designing these filters using signal processing methods; efficiency and simplicity were critical to extracting the detrended signal.

4.2.2 Normalization

The signal is also normalized. Normalization is scaling signals in identical levels; normalizing power gives all the signals the same power. Normalization aims to make every datapoint have the same scale, thus making each feature important. Normalization is useful for classification algorithms such as nearest-neighbour classification and clustering. Min-max normalization is one of the common ways of normalizing data. For features, minimum values get transformed into 0 whilst the maximum value was transformed into 1 with other values transformed into decimals. However, it has issues in handling outliers. The formula is below:

$$\frac{\text{value-min. value}}{\text{max. value-min. value}}$$

Equation 1: Min-Max Normalization

Z-score normalization, however, avoids outlier issues whereby the normalization formula is

$$\frac{\text{value-}\mu}{\sigma}$$

Equation 2:Z-score Normalization

where μ is the mean value of the feature and σ is the standard deviation of the feature. If a value is equal to the mean of all the values of the feature, it is normalized to 0. In this project, min-max normalization guarantees that the features have the same scale even though it does not handle outliers compared to the z-score. However, the z-score does not produce normalized data with the exact scale.

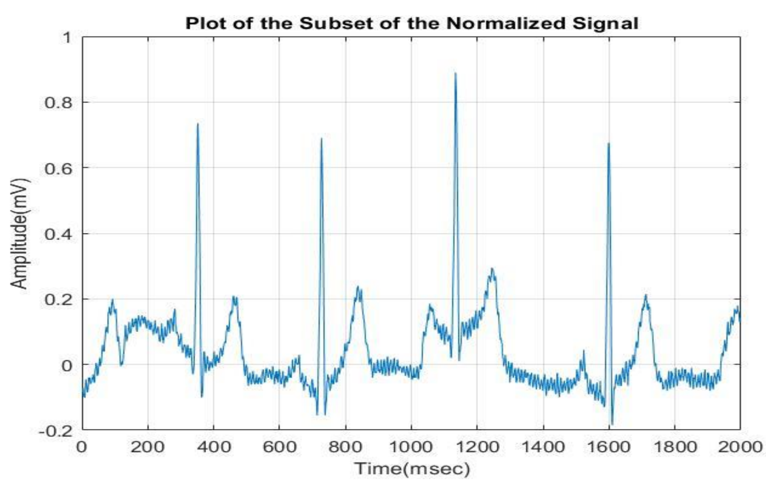


Figure 9:Subset of Normal ECG Signal

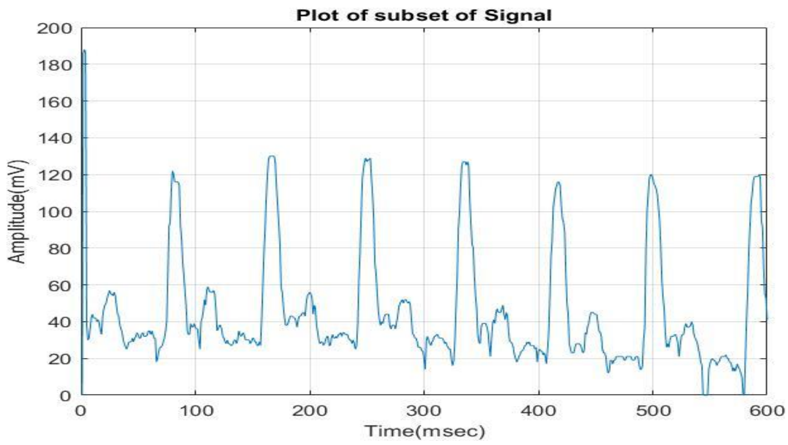


Figure 10:Subset of Normalized Normal Sinus Wrist Pulse Signal

4.2.3 Savitzky-Golay Filter

Another method applied in detrending the signal or for baseline drift removal is using a Savitzky-Golay smoothing filter. Similar to 'polyfit' and 'polyval', this data smoothing method shows the fitting of a low degree polynomial by the method of linear least squares. The purpose of the filter is to smoothen the data and increase its precision without distorting the signal. A moving average filter generally averages several points on the input signal. The output signal contains each point averaged.

$$y[i] = \frac{1}{M}\sum_{-(m-1)/2}^{(M-1)/2} x[i+j]$$

Equation 3:Output of Moving Average Filter

where M is the number of points used in the moving average. In selecting the window size for the signal, the baseline wander spectrum must be considered, and, in this case, it is less than 0.6Hz as is in most bio-medical signals such as the photoplethysmogram (PPG) and ECG. Thus, the window length is time domain dependent. It does not affect the method if the baseline wander were to deviate from 0.6Hz slightly. The baseline wander is obtained by applying the moving average filter on the data. The length of the moving average filter is normally around 5% of the data length to preserve the shape. The moving average filtering process is repeated several times to avoid unwanted peaks at the edges of the window. The process does not affect the high-frequency components of the original signal.

In Matlab's implementation, the Savitzky-Golay filter is represented by a function called sgolayfilt found in the Signal Processing toolbox. This function requires the data vector input, the polynomial order and the frame length, which is usually an odd value. For the moving average filter, output points y[i] obtained is from the moving average on the input points around x[i]. Input points from j=-(M-1)/2 to (M-1)/2 are added and then averaged by M. To gain the corrected signal, the baseline wander subtracted from the original signal. It is easier to accomplish if both signals have the same length and sampling frequency. The subtraction process can cause minor distortions at the ends of the window.

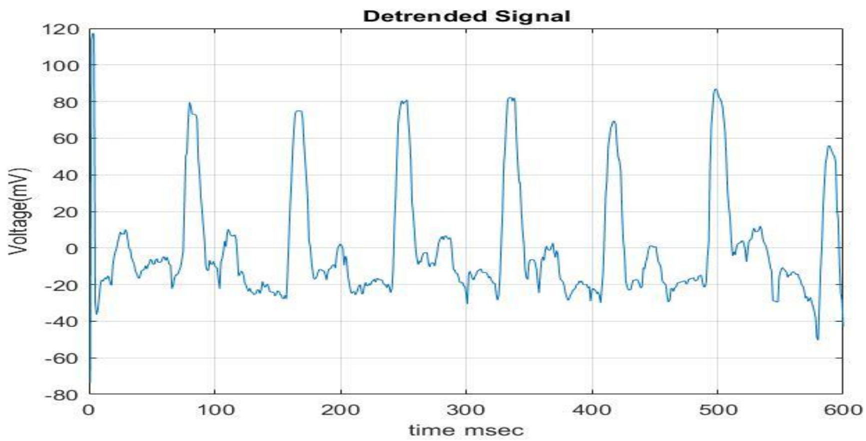


Figure 11: Detrended Normal Wrist Pulse

<u>4.2.4 Pan-Tompkins Algorithm</u>

This algorithm is used under the pre-processing stage. This process includes noise removal, signal smoothing and highlighting of the QRS complex. For the decision stage, thresholds are used to eliminate the noise peaks yet preserve the signal peaks with information. The design begins with a low pass filter and a high pass filter to create a bandpass filter. The sampling rate for this algorithm was 100Hz. Figure 12 showcases the order of the algorithm.

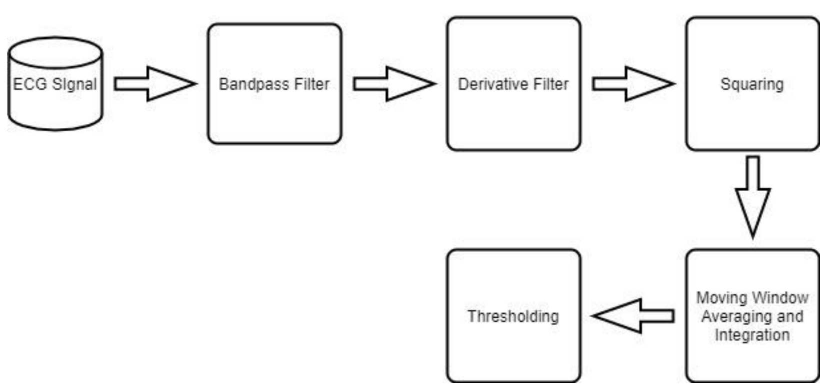


Figure 12: Block Diagram of the Pan Tompkins Algorithm Process

The digital bandpass reduces the noise that affects the ECG signal. The low pass filter and high pass filter was designed using the z-domain and transfer function. The Low pass filter removes high-frequency noise such as the powerline interference, whilst the high pass filter removes low frequency such as the baseline wander. Direct current (DC) components are removed and normalized. The Derivative filter differentiates the ECG signal to determine the QRS complex slope information by suppressing the low-frequency P and T waves. The squaring function enables the signal data to be displayed as positive values. It aids in the reduction of false detection in the signal and emphasizes on significant differences of the QRS complex. The moving window integration aids in acquiring information from the signal with the window size matching the QRS complex. The algorithm helps detect high amplitudes of the R-wave slope; however, there is a possibility of false detection of R-waves.

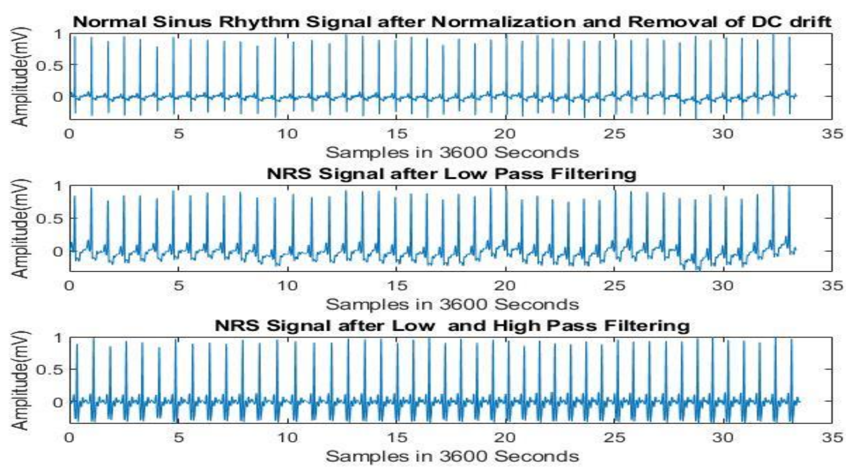


Figure 13: Application of Pan-Tompkins Algorithm

Both the Savitzky-Golay Filter and Pan-Tompkins Algorithm can be used for either the ECG Signal or the pulse waveform. However, the Pan-Tompkins Algorithm seems more efficient in the pre-processing of the ECG signal as compared to the Savitzky-Golay Filter.

4.3 Signal Comparison and Similarity

For the acquisition system of the pulse, verification needs to be done on the pulse measured. Identifying that the pulse measured is accurate or at least similar to standard pulses already in databases can verify the potential of the prototype for data collection. Cross-correlation technique can be used to assess the accuracy of the measured signal as compared to a standard pulse. Cross-correlation quantifies similarities between two signals as a function of delay of one relative to the other. Cross-correlation can be performed with signals of different lengths. However, the same sampling frequency must be the same and, in this project, it is 500Hz. This method is applied between the Normal Sinus Rhythm Pulse waveform, and the pulse waveform gathered from the dorsal artery gathered in the foot. The MATLAB function xcorr is used to determine if the signal is the same or at least similar to the database signal. This method provides the basis of pulse analysis to verify that the pulse measured by the system is the same as the current pulse in the database, assuming all pulses gathered from different arteries are the same and neglecting the use of different sensors and systems for gathering the pulse data.

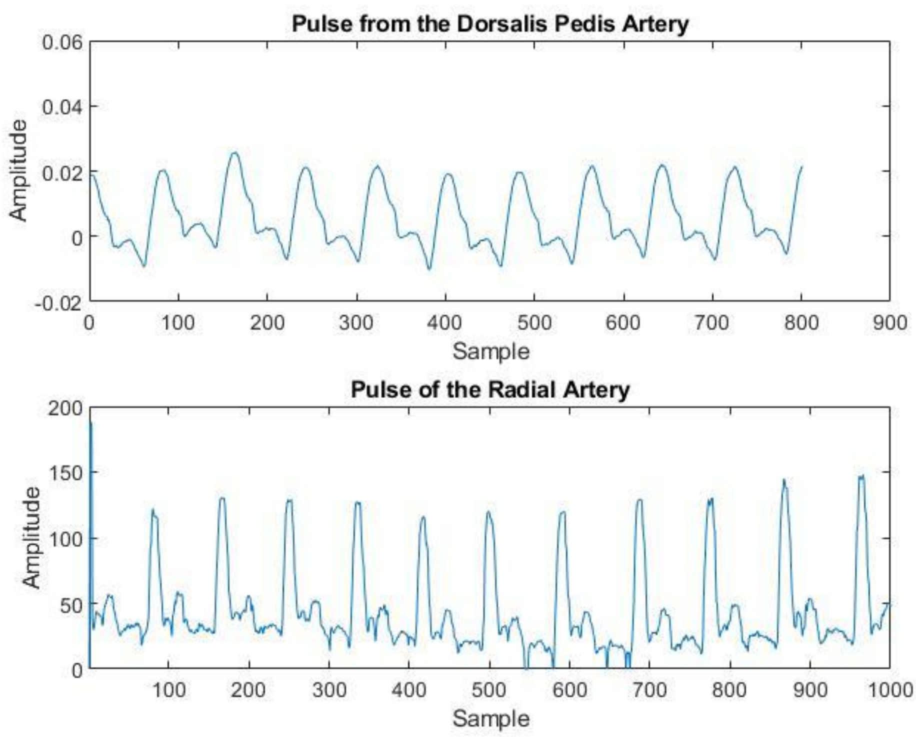


Figure 14:Graphs of Pulses from the Dorsal Artery and Radial Artery

4.4 Time Domain Analysis of Pulse Pressure Wave and ECG Signal

In TCM, features as stated before such as the strength, smoothness and length describe the pulse for diagnosis. However, looking at the formation and movement of the pulses, other quantifiable characteristics can be used to describe pulses. A pulse is produced by the workings of the heart, blood vessel and microcirculation. A pulse wave is composed mainly of the primary wave, tidal waves, and wave components. From the research process, eighteen features of the pulse were observed whereby eight features are of time-domain and ten features of frequency-domain[19]

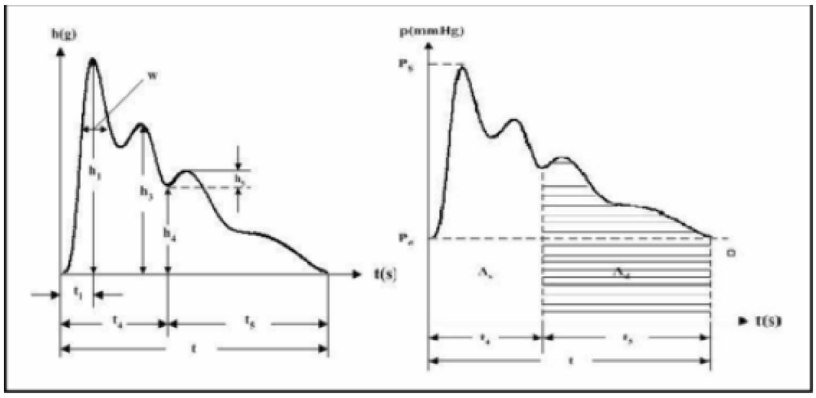


Figure 15: Standard Pulse Waveform

Figure 15 is used as a template for the pulse- wave time-domain analysis. Features from the pulse wave for analysis are the pulse wave amplitude (PWA), dicrotic notch, pulse wave diastolic peak, pulse wave duration, rise time and the inter-beat interval. The pulse parameters on the time domain are the peak (h1) amplitude, which reflects the left ventricular and arterial compliance. The amplitude of the tidal wave is represented by (h3). The amplitude of the dicrotic wave(h_5) and h1 reflect the function of the aortic valve. Since analysis is done in the time domain, the duration of activities or characteristics of the signal must be noted. The duration between the beginning of the pulse and the peak is represented by t1. t_4 corresponds to the systole period, whilst t_5 also corresponds to the diastole period. The pulse wave duration is measured as t, with being the width of the main peak. w/t reflects the vasoactivity and the peripheral resistance of the artery. The area of the systole period is A_s, and A_d is the area of the diastole period.

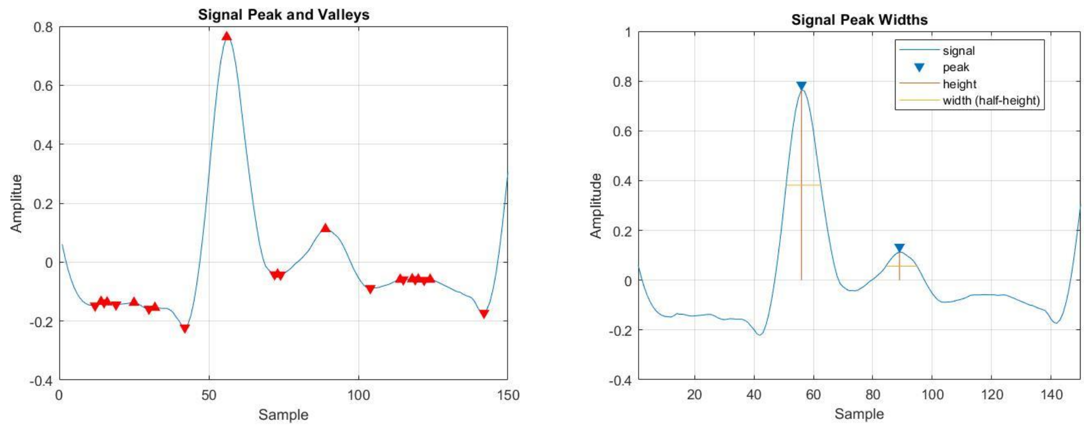


Figure 16:a &b

Figure 16 displays the application of findpeaks in the Signal Processing Toolbox of Matlab, the peaks and height were identified.

For ECG signals, time-domain analysis uses dynamic features such as the R-R interval, heart rate and heart variability (HRV). It includes the identification of peaks, segments, intervals and points. In classifying ECG signals such as the arrythmia (ARR), congestive heart failure (CHF) and Normal sinus rhythm signal used in the project, their characteristics concerning time must be identified. In evaluating the signals using the R-R interval, the following are the reasons why:

a. R has the largest amplitude compared to the PQST waves that may be identified in the signal.

b. It is easier to calculate the heart rate, which indicates the heartbeat per minute, by calculating the interval between two R peaks.

Number of Heart Beats per minute =BPM

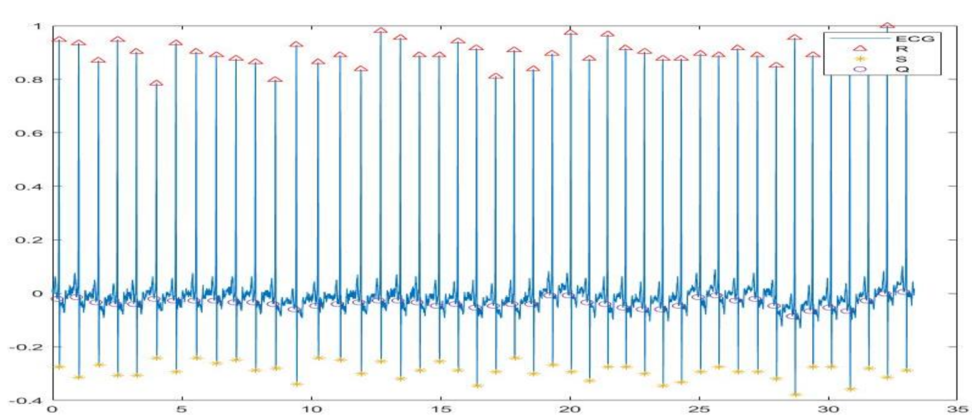


Figure 17: Identification of the QRS complex of the Normal Sinus Rhythm ECG signal

4.5 Frequency Domain Analysis

This type of analysis represents the frequency components of the signal. The analysis is done through the power spectral density (PSD) and other frequency parameters to provide a different perspective from the time-domain analysis. Using Fourier analysis, the signal can be converted into the frequency domain. The signal must have linearity and periodicity to be able to apply Fourier transform to interpret the signal correctly.

The signal's power spectral density is the magnitude square of the Fourier transform of the real-time signal. In other words, it describes the power in the signal as a function of frequency. It shows the different strengths of the frequency variations in the signal. The Fast Fourier Transform is applied in gaining the spectrum density of the signal.

4.6 Time-Frequency Analysis

In the frequency domain analysis, the application of the Fourier transform assumes that the signal has periodicity due to the finite time duration; however, signals such as the ECG or the pulse waveform are non-stationary signals. It means that the signal varies in both time and frequency, limiting the Fourier transform's ability in cases where the frequency begins to change. In situations like this, the short-time Fourier transform and time wavelets can be applied. Analysis would be done using the short Fourier transform and wavelet methods. Even though with Fourier transforms, the issue is in choosing the time window for a short time. The signal can be divided into windows before Fourier transform is applied to each window separately. The problem with choosing the time window is that the low frequencies require a significant time window whilst the high frequencies use short time windows.

Due to the limitations of the Short-Time Fourier transform, the smoothed Pseudo Wigner-Ville Distribution was used in the time-frequency analysis of the signals. In applying Wigner-Ville distribution in Matlab, the energy density correlates the signal with time and frequency. The frequency component of the signal is examined as a function of time, and the energy intensity of the frequency components can be determined at different points in time.

However, due to interference terms in the wigner-ville distribution, interpretation of the results can lead to errors. Thus, the smoothed Pseudo Wigner-Ville Distribution is applied to decrease the effects of the terms of interference.

4.7 Machine Learning

Machine learning is the adaptation of artificial intelligence in algorithms to learn from data and apply the data to make decisions. Machine learning in healthcare is undeniably practical, especially in disease identification, automation of medical bills, and the development of decision support systems[6]. In this area of pulse diagnosis, the pulses and ECG signal classification are evaluated based on energy density, RR intervals, and diastolic and systolic attributes. In this project, two techniques are applied namely, the Support Vector Machine and Kernel Neural Network for the evaluation and classification of signals.

Most biomedical signals such as electroencephalogram (EEG) and ECG are linked to nonlinear dynamical systems. Dynamical systems change over time, and these are the basis of nonlinear methods for the analysis of signals. Dynamical systems can be categorized as linear or nonlinear systems. Natural biological systems on one hand are known to have nonlinear qualities because linear equations cannot describe most biological entities. Physiological and Biological systems such as ECG signals have a level of complexity, especially with noise interference from the environment.

4.7.1 Support Vector Machine

The Support Vector Machines (SVM) technique identifies a number of dimensional hyperplanes to separate a set of input feature points into different classes. It is a supervised learning method used for classification and regression. For cases where the categories can be separated linearly, it uses hyperplanes with maximum margin to separate the categories. For nonlinear data, the kernel function maps the data to a larger dimensional space to be separated linearly. There are many forms of kernel functions such as gaussian, radial basis function and polynomials. For the classification using SVM, polynomials namely the linear and quadratic functions are adopted.

Cross-validation is used for assessing the predicting model results that will generalize to an independent data set. Cross-validation aims to test the model's ability to predict new data not used in constructing the model. In beginning of the cross-validation process, the data is split randomly into subsets, with one subset used as the training set; the other used as the testing or validation set. The dataset labels include the name of the individuals, date and the disease type (Duodenal Ulcer, Pancreatitis, Acute Appendicitis, Appendicitis and Normal Pulse Pressure Wave) in a tabular form. Features such as the PSD, energy density and mean frequency of the data set aided in improving the performance of SVM. SVM is advantageous where the data is unknown be it semi-structured or unstructured. It also generally doesn't suffer from overfitting and performs well when there is clear distinction between classes. The limitation however, is that, SVM works well with binary classification as compared to multi-class classification and it also doesn't bode well with large datasets.

4.7.2 KNN Model for Classification

The K-Nearest Neighbours is known as one of the simple classification methods. For this form of classification, success is dependent on the k value. By default, in the Matlab Classification Learner App, the k value is 5. There is a possibility of misclassification if the k value is an even number because the algorithm uses majority voting. There would be a case whereby two labels or classes would have equal votes. Using Euclidean distance to measure similarity, data with the same class label are close to each other based on distance measured. The advantage of using the KNN model is in the area of multiclass classification. Thus, if the dataset has more than two labels or categories, KNN provides a suitable algorithm to do so. The limitation with this form of classification is the time taken to calculate the distance between data points. However, time for classification was not affected in this case since the sample data was below 10,000.

Using the classification learner app to evaluate the SVM model and KNN model makes it easier to split the data using holdout or kfold into a training dataset and validation dataset. The accuracy reflected is based on the validation dataset.

Chapter 5: Result

5.1 Observation from the Prototype Acquisition System

For the pulse acquisition system, the output using the freedom board were undesirable. Figure 19 displays the results of the measured radial pulse. The interpretation of radial pulse from the kl25z was unfortunately inaccurate for deeper analysis. The oscilloscope showed stable results in the MATLAB software by highlighting the diastole and systole components of the pulse pressure wave that can be assessed.

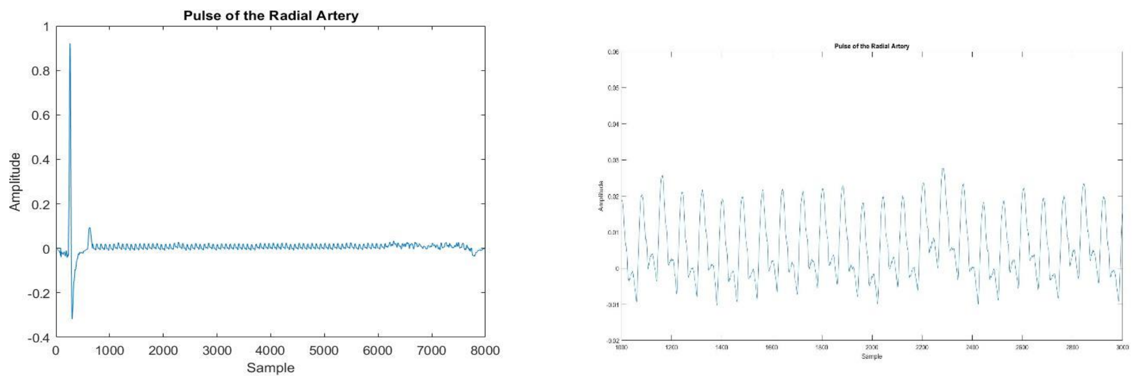


Figure 18: Result of the Wrist Pulse Acquisition System on Oscilloscope

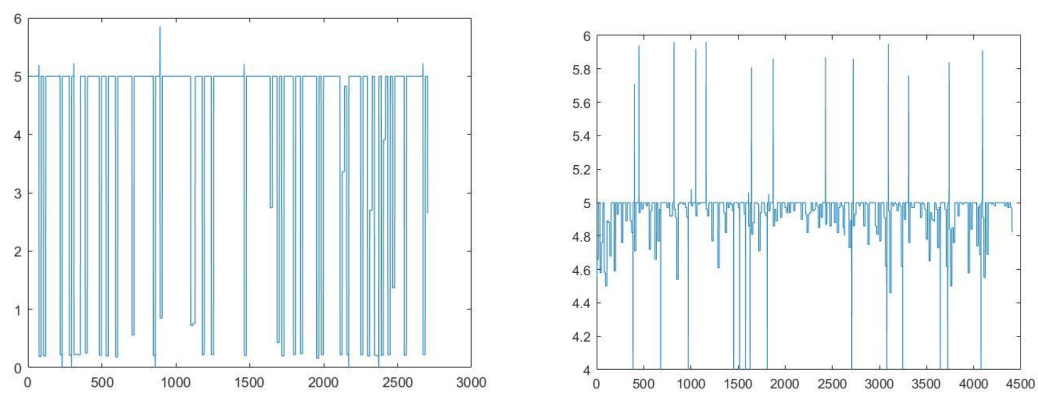


Figure 19: Wrist Pulse Result of the Pulse Acquisition System using KL25Z

Analyzing the results from the acquisition system compared with the Normal Sinus Rhythm pulse gathered from the database. Cross-correlation provided insight into proving that both signals despite being measured from different body locations could be similar and even the same. It helped prove that the system had potential in being efficient in the aspect of pulse acquisition. This is further proven within Figure 20. Whereby the power spectrum of both signals have correlated components around 2.8Hz, 5.8Hz and 8.05Hz. In Figure 21, the first graph indicates that the database signal and the measured signal are loosely correlated.

Meaning that there isn't any similarity between the two signals. However, in adjusting the lag position or time delay of the measured signal, the result in the second graph indicates similarity between the two signals.

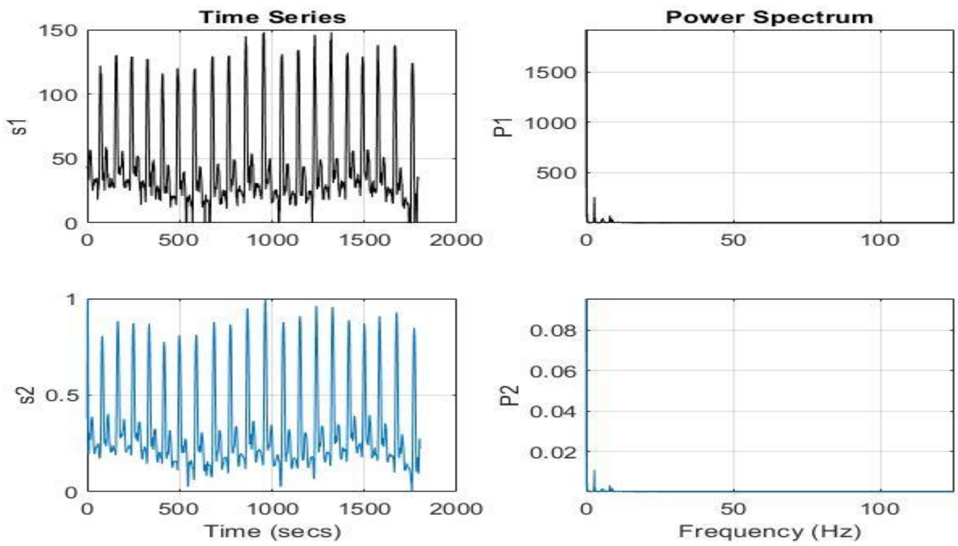


Figure 20:Diagram representation of the Frequency Content of both Signal for Comparison

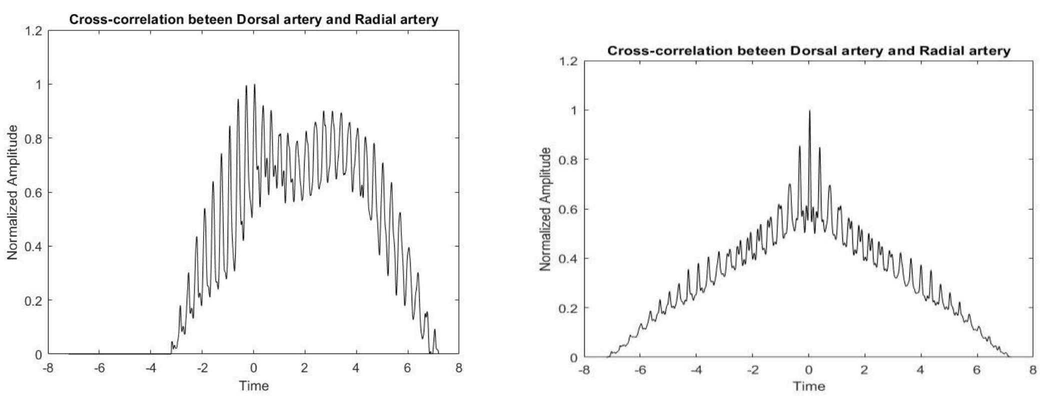


Figure 21: Graphs of the Cross-correlation results

5.2 Time Domain Analysis of Pulse Waveform and ECG signal

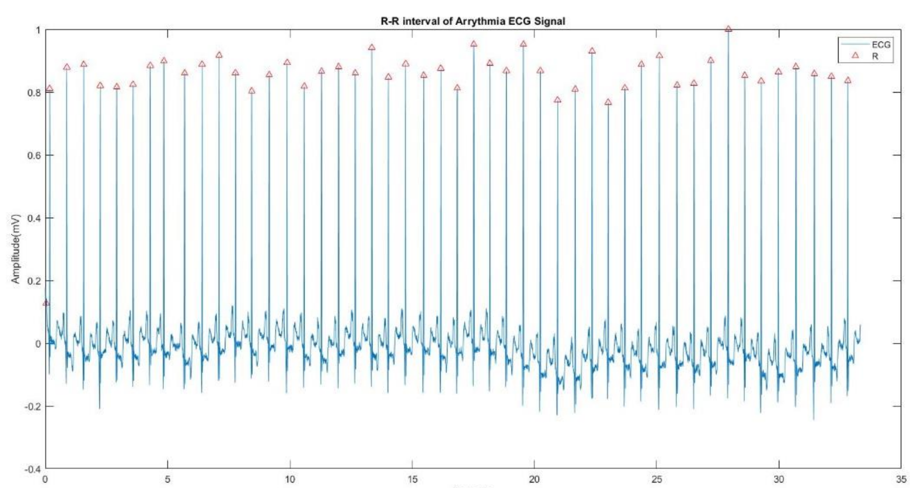


Figure 22:R-R Interval of Arrhythmic Signal

The heart rate calculated using the R-R interval of the Arrhythmic signal in Figure 22 was averagely 87.9 beats per minute with the duration of a beat lasting 0.7 seconds.

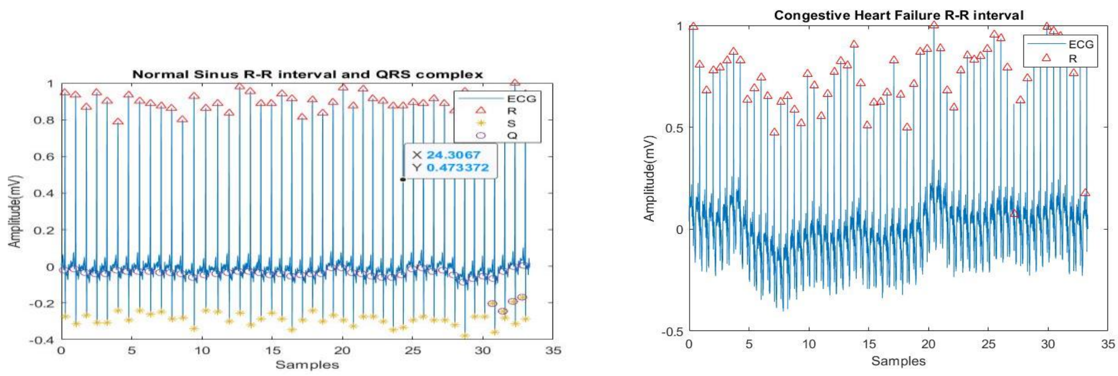
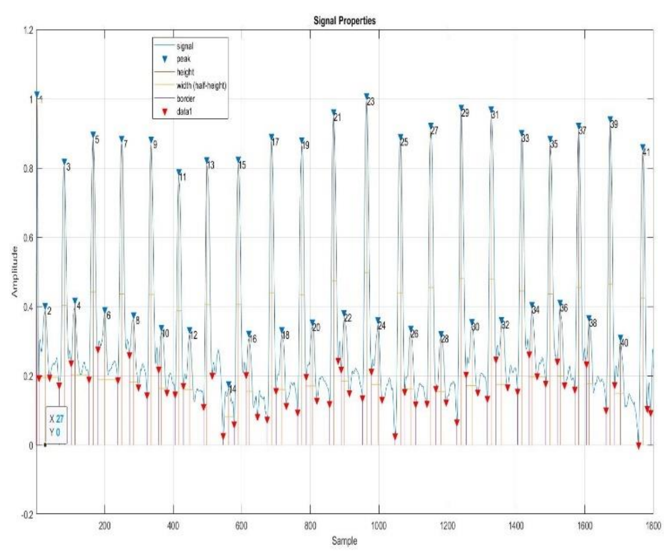


Figure 23:R-R interval of both Normal Sinus Signal and Congestive Heart Failure

The heart rate calculated using the R-R interval of the Normal Sinus signal was averagely 80.8 beats per minute with the duration of a beat lasting 0.7 seconds. For the ECG signal representing the congestive heart failure, the heart rate was detected to be 108.1 beats per minute with a beat occurring averagely every 0.6 seconds.



Location	PeakHeight	Width	Location	PeakDepth
3	1	4.9017	9	0.8059
27	0.38885	56.241	40	0.80418
83	0.80594	14.956	68	0.82733
114	0.40403	50.217	103	0.76331
167	0.88399	15.758	155	0.81002
201	0.3767	57.333	181	0.72337
250	0.87168	15.025	239	0.81204
285	0.36182	23.965	273	0.73978
336	0.86909	15.108	299	0.8329
366	0.32566	21.63	324	0.85537
417	0.77552	14.715	358	0.78118
448	0.3193	27.973	382	0.84831
498	0.81013	15.244	406	0.85304
562	0.16282	27.944	430	0.82868
590	0.81182	14.87	489	0.88924
621	0.3085	18.085	514	0.79897
687	0.87735	14.623	546	0.97289
717	0.31923	27.05	578	0.93959
775	0.86751	15.018	613	0.79722
806	0.34109	27.922	646	0.91807
868	0.94873	15.376	674	0.92554
898	0.36811	20.83	700	0.84298
964	0.995	15.163	730	0.88638
997	0.34769	27.59	763	0.90531
1063	0.87692	15.579	788	0.80239

Figure 24: Time Analysis of Pulse Waveform

For Figure 24, the peak amplitudes, peak depths which are associated with h1 and h3 of time domain analysis with the width indicating the duration at which each feature lasted. For example, the first instance of the peak height occurred at 0.03 seconds and the second peak occurring at 0.27 seconds . The combination of these two peaks roughly constitutes to the systole of a pulse indication that its duration last for approximately 0.3seconds.

5.3 Frequency Analysis of The Pulse Pressure Wave and ECG signal

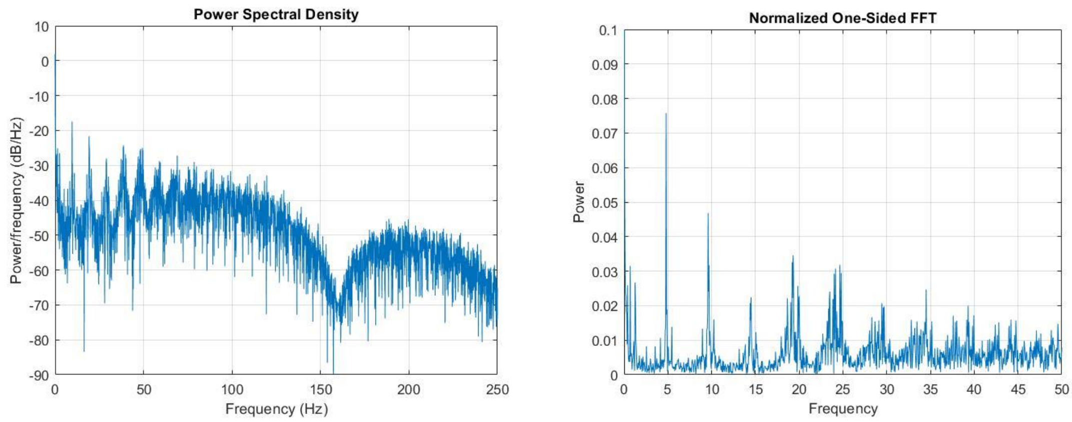


Figure 25: Power Spectral Density of ECG Arrhythmia Signal

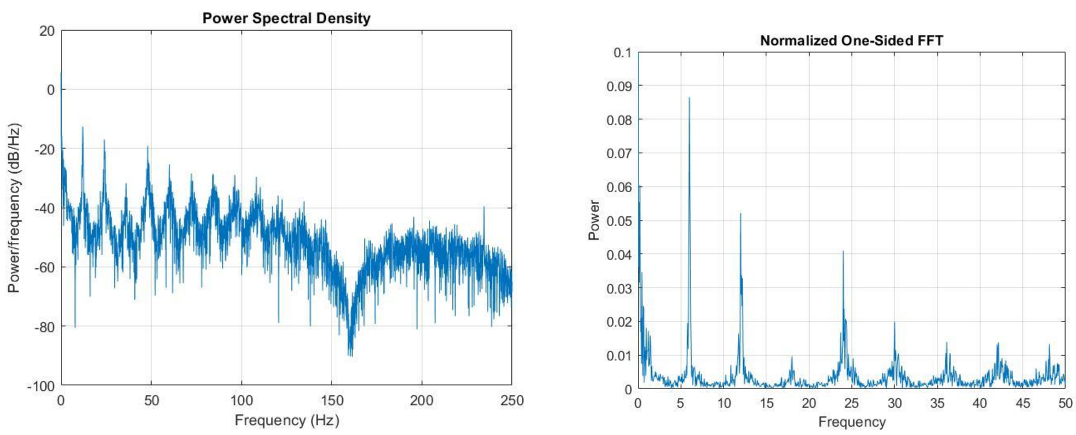


Figure 26: Power Spectral Density of ECG Congestive Heart Failure Signal

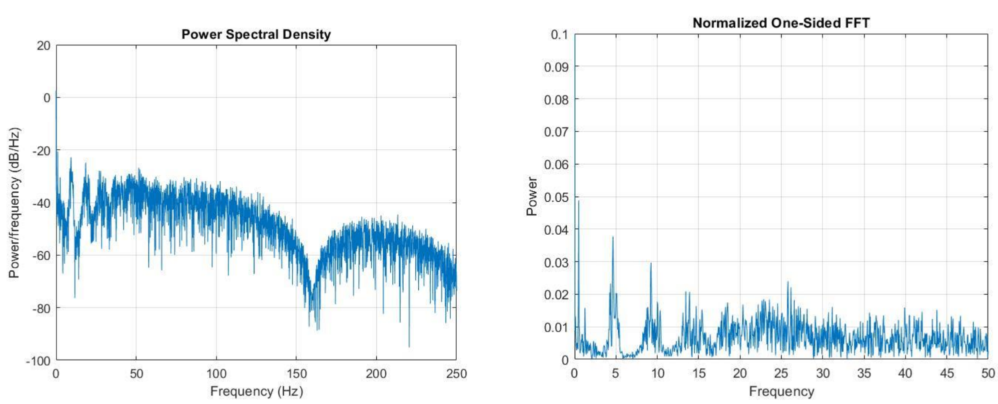


Figure 27: Power Spectral Density of Normal Sinus Rhythm ECG Signal

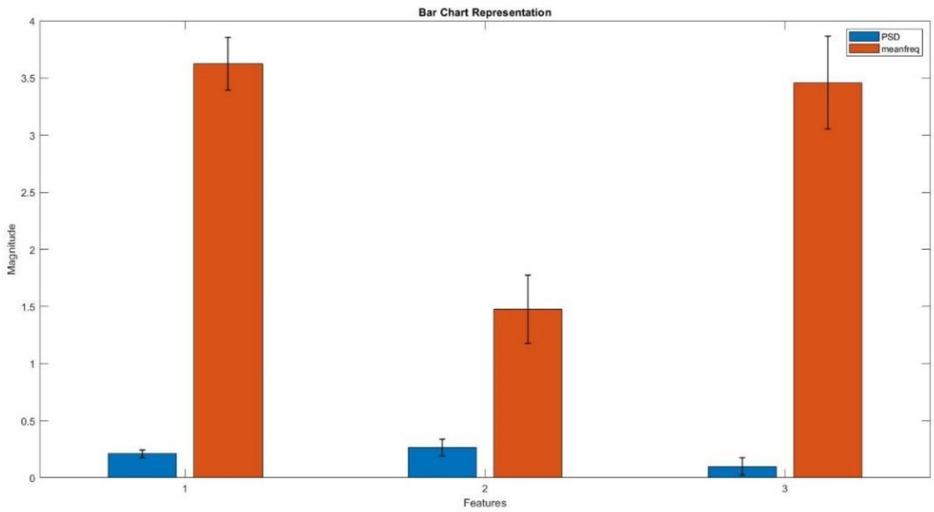
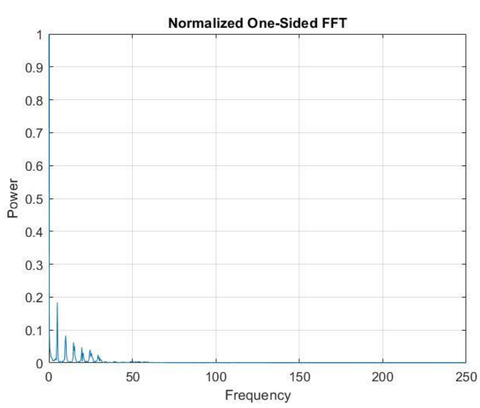


Figure 28: Comparison of the power spectral density and mean frequency of the different ECG signals using a bar chart.

From the Frequency Domain Analysis, the power spectral density and the mean frequency differentiate amongst the signals. In the bar chart above, 1 represents the arrhythmia signal, 2 represents the Congestive Heart Failure, and 3 represents the Normal Sinus Rhythm signal. The error bars provide a graphical representation of variability and on the graphs shows the level of uncertainty in the measurement. For the arrhythmia signal the mean of the power spectral density was around 0.2098 and the mean of the mean frequency 3.6256 however, their standard deviation was 0.1010 and 0.7300 respectively using only 10 samples for analysis of the standard error. However, with increasing samples, the smaller the standard deviation becomes. For the congestive heart failure, the mean power spectral density was 0.2637 and for the mean frequency, 0.2376 and 0.9449, respectively. The mean power spectral density and mean frequency of the normal sinus rhythm signal are 0.0996 and 3.4589 respectively with a standard deviation of 0.2486 and 1.2882 associated with it for standard error calculation.



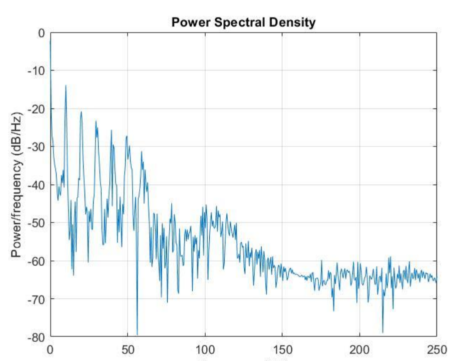


Figure (22) Power Spectral Density of Pulse of Appendicitis Signal

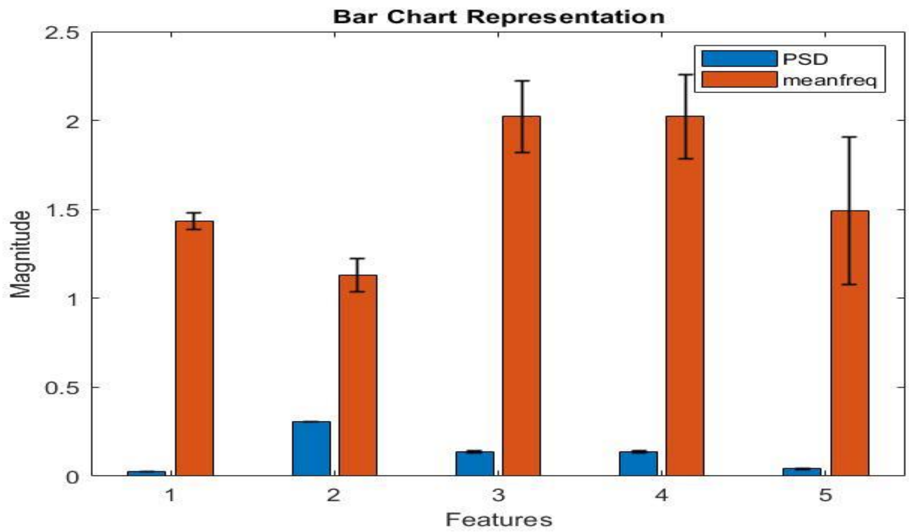


Figure (23) Comparison of the power spectral density and mean frequency of the different pulse waveform signals using a bar chart.

For the Pulse Waveform, five signals, the Appendicitis signal represented by 1. 2, represent the Normal signal, 3 three is for acute appendicitis, four is for the pancreatitis signal, and 5 is the signal for Ulcer Duodecenal Signal. There are distinctions between the signals based on the power spectral density and the mean frequency of the signal from the bar chart. However, based on these parameters, pancreatitis and acute appendicitis signals are similar in these aspects. For the calculation of the error bar, ten samples from each of the data set were used. The mean of the power spectral density of the appendicitis signal was 0.0250, that of the duodenal ulcer was 0.0409 and the pancreatitis signal was 0.1392. The acute appendicitis signal had a mean PSD of 0.1392 and for the normal sinus rhythm signal, 0.3091.

The mean of the mean frequencies of each signal are as follows:

Mean Frequencies	Signals
1.4916	Duodenal Ulcer
1.4338	Appendicitis
2.0212	Pancreatitis
2.0212	Acute Appendicitis
1.1310	Normal Sinus Rhythm

The Standard Deviation of the following features are as follows:

Signals	Standard Deviation of PSD	Standard Deviation of Mean Frequencies

Appendicitis	0.0017	0.1541
Normal Sinus Rhythm	1.85038×10^{-17}	0.094584
Acute Appendicitis	0.0170	0.6397
Pancreatitis	0.0166	0.7435
Duodenal Ulcer	0.0140	1.3096

5.4 Time-Frequency Analysis of The Pulse Pressure Wave and ECG signal

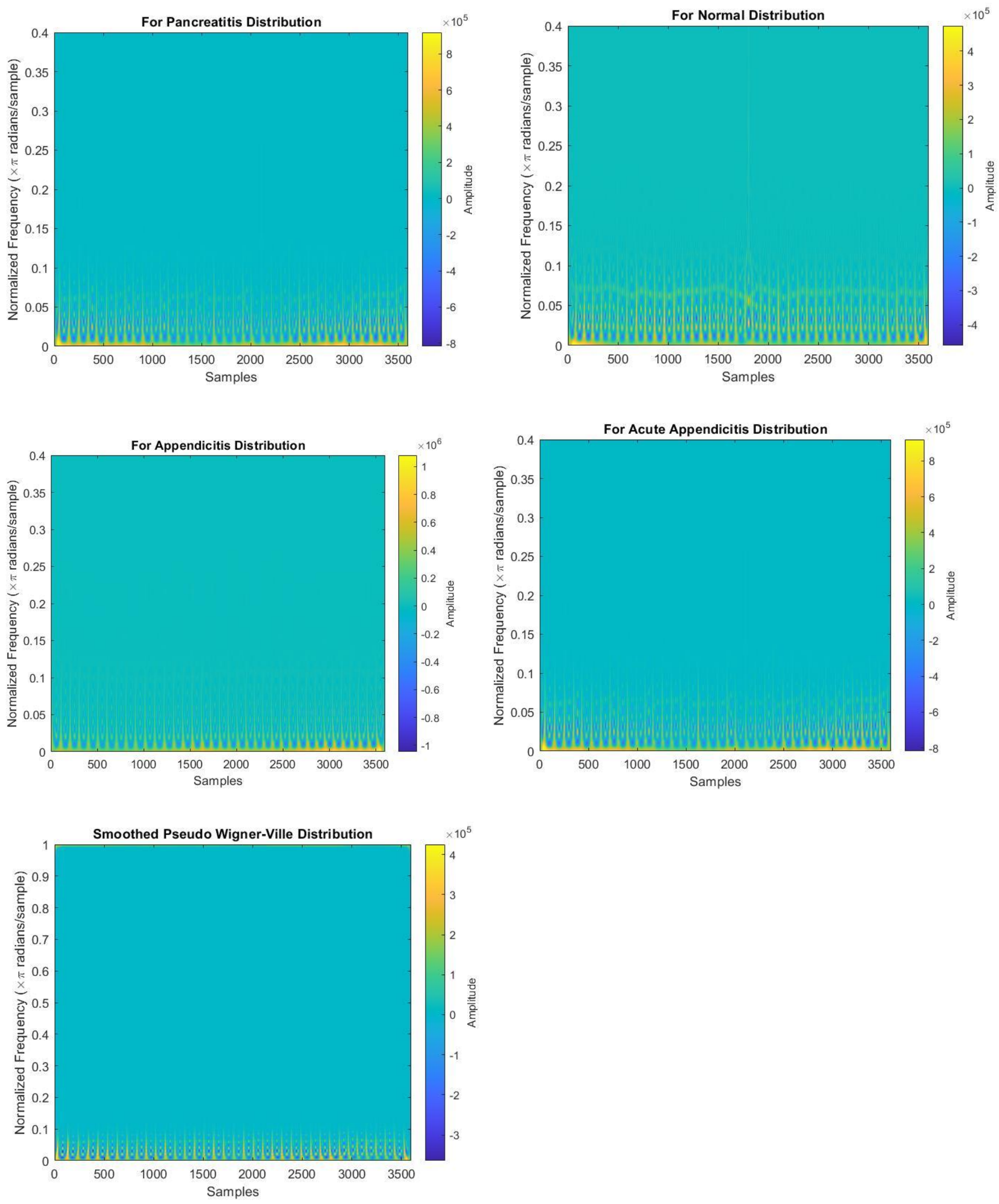


Figure 29: Results of the Energy Density within the Signals

The energy density of the signal is given both in time and frequency by the smoothed pseudo-Wigner-ville distribution. For the energy density of the normal pulse waveform, a value of 3.3723×10^{3} was recorded. The values recorded for the acute appendicitis pulse was 5.3552×10^{3}, appendicitis pulse was 5.0667×10^{3}. The pancreatitis pulse waveform was

5.3552×10^3, and the pulse waveform that depicts the characteristics of an ulcer patient has an energy density of 3.4009×10^3 .The unit for energy density is Joule-seconds per square meter.

5.5 Classification Results of ECG and Pulse Pressure Wave

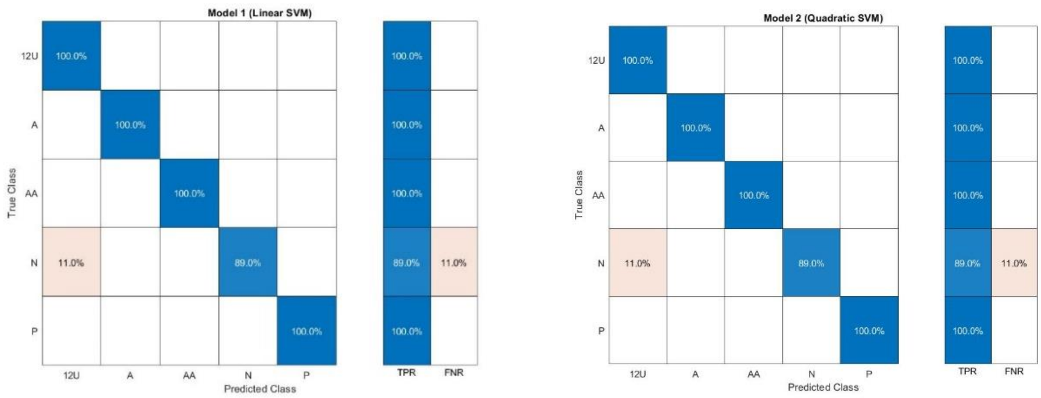


Figure 30: Classification based on Frequency Domain Features

The SVM classification based on the features of the name, PSD values and mean frequencies of the pulse waveform signal provided a good performance model. From both the linear and quadratic SVM model, the accuracy was 0.966 with a positive predictive value (PPV) of 0.975. The sensitivity of both models was 0.978.

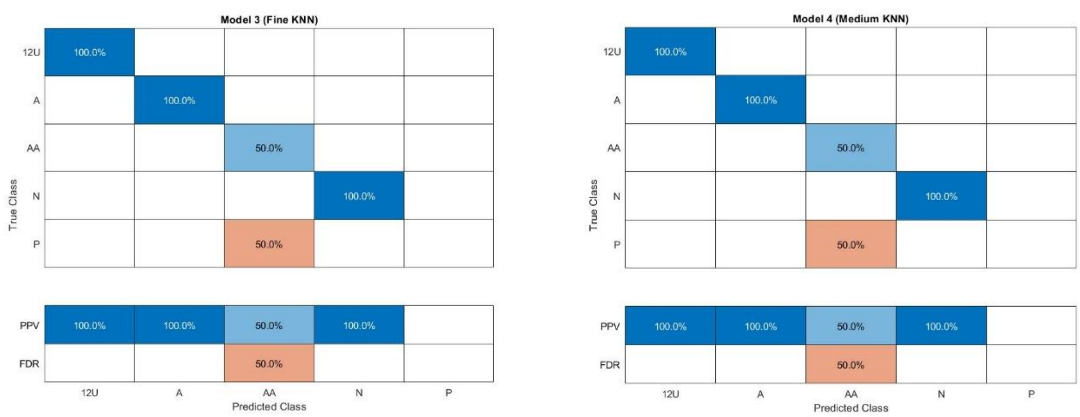


Figure 31: Classification using KNN model

The KNN model of classification was based on only one feature: the energy density from the time-frequency analysis. Based on the performance of the model, its accuracy was recorded at 83.1%. The PPV was 0.5 overall due to a significant confusion with acute appendicitis and pancreatitis results from the confusion matrix results.

Chapter 6: Discussion and Conclusion

In the beginning of this research project the objectives were aligned to creating a pulse acquisition system with a diagnostic system to perform real-time analysis of the data collected. These objectives were in adopting both signal processing techniques and machine learning tools for the analysis of the data. Generally, the aim of the project was achieved in terms of the application of the signal processing techniques whereby analysis was done in the time domain, frequency domain and time-frequency domain. In the time domain, the technique of associating features with their occurrence within a period of time helps in the classification of the signal in the identification of any abnormalities. For example, in the analysis of a normal sinus signal of Figure 24 in time domain, the approximate duration of the systole period was found to be around 0.3 seconds which the range of 0.3 to 0.4 seconds a systole period normally lasts[26].

The frequency domain analysis focused on two features namely the power spectral density and the mean frequency of the different signals. These features provided information on which frequencies dominated the different signals with respect to power. Distinctions were clearly made with the different signals except for the Acute Appendicitis signal and the Pancreatitis signal which had similar output values in terms of these features. The same was observed when the time-frequency analysis was applied in the calculation of the energy density between both signals. The time-frequency domain analysis helps to characterize the signal in both time and frequency domain simultaneously. In this case, the analysis displayed the energy distribution of signals with respect to both time and frequency. However, the Acute Appendicitis signal and the Pancreatitis signal had similar output values for this analysis also.

In adopting the machine learning techniques of SVM and KNN, both models depicted high accuracy results with the SVM having a greater advantage. Due to limited knowledge on the workings behind these models, the in-built classification learner app in MATLAB aided in the application of these models and the selection of domain analysis features to further increase the accuracy of the respective models. Overall, in the adoption of the signal processing techniques for the biological signals and machine learning for classification, the results were satisfactory with this level of studies. The satisfactory results show that there is potential in using features such as the power spectral density and the energy density of pulses to categorize whether they are healthy or unhealthy instead of using intuitive knowledge to diagnose.

6.1 Limitations

For the future design of the diagnostic system, the application of the signal processing techniques evaluated in the research seem satisfactory. However, there are limitations with them. A limitation for the project was in data collection whereby a limited amount of data set was used in the analysis of the project. A main cause of this limitation was the COVID-19 pandemic which inhibited the real-life collection of data from possible participants. Thus, a general conclusion cannot be formed without further experimentation and analysis from a wider group of people. The time domain analysis provided instances of where each pulse characteristic occurred however, confusion comes in the identification of which peak amplitude or peak depth is being referenced with respect to time as it is not specified in the table of data. For the frequency and time-frequency of the analysis, the limited features used is not substantial in the identification of distinction between the different groups of signals. As seen from the results the Acute Appendicitis signal and the Pancreatitis signal show similarities of output results in terms of these features.

The project also covered the design of the acquisition system. The overall system produced satisfactory results with the application of the oscilloscope. Hitches came about with the application of the KL25z ADC system capabilities with respect to resolution and approximation of output values. Also, during the process of measurement, issue arose with the constant pressure applied. How would you know the pressure applied is consistent and of the same magnitude throughout the process? How can the system be designed to measure pulses from different locations apart from the radial artery? These questions could not be answered during the course of the project.

6.2 Future Works

In the future progression of this project, the aim is in the development of a prototype embedded system for pulse diagnosis with features used in the project. To be able to develop the system for it, work must be done on the acquisition system whereby the adoption of non-robust, yet accurate tools would be used to control the contact pressure applied to the skin during measurement and also, the design would compensate for amputee individuals. For the diagnostic system of the prototype, future research would be conducted for the signal processing techniques which could be applied to evaluate the signals. More features to increase the accuracy of the time, frequency and time-frequency domain analysis of signals would be adopted. The development of an algorithm for the identification of different peaks in the time domain analysis would also aid in the evaluation of the data easily.

For the machine learning techniques for the design of the classification system further research will be conducted. The SVM model and KNN model worked efficiently in this project however, it dealt with small and structured set of data. In the cases where these properties are absent, other learning techniques such as the artificial neural network would be considered. Experimentations would also be carried out to develop a classification system with the combination of two or more existing classification models.

Annotated Bibliography

[1] A. Allataifeh and M. Al Ahmad, "Simultaneous piezoelectric non-invasive detection of multiple vital signs," *Sci. Rep.*, vol. 10, no. 1, pp. 1–13, 2020, DOI: 10.1038/s41598-019-57326-6.

This paper showcases the extraction of mechanical vibration using piezoelectric sensors. During breathing, the measured voltage signal is composed of cardiac cyclic activities modulated and respiratory cyclic activity. The proposed method utilizes piezoelectric and convolution techniques and Fourier Transformation to extract the corresponding signal of the cardiac cycle activities from a breathing signal measured in real-time. The main principle is extracting and monitoring multiple signals from a single piezoelectric material. A limitation of the algorithm is that the piezoelectric sheet should be placed on the chest and abdomen area. The algorithm can also handle small noises such as speaking and small movements and removed them by averaging the noises.

[2] A. M. Zafari and N. Ghasemzadeh, “A brief journey into the history of the arterial pulse,” *Cardiol. Res. Pract.*, vol. 1, no. 1, 2011, doi: 10.4061/2011/164832.

This paper illustrates the evolution of the knowledge on the arterial pulse from ancient times to the present. The techniques used to analyze arterial pulse and its characteristics have advanced from simple evaluation by touch to complex ultrasonography and plethysmography techniques. The basis of growth in the techniques and methodologies understood the observations and experiments of the ancient physician's perception of the arterial pulse. The paper highlights the different cultures that adopted the pulse diagnosis, ranging from Ancient Chinese to the Egyptians and even in Greece. The pulse wave analysis from the simplest of techniques to the most complex involved velocity, pressure, and volume. Current knowledge of the arterial pulse has culminated from the beliefs, observations, and interpretations throughout the history of medicine. The paper's purpose was to bring to light an understanding of the progression of the knowledge of the arterial pulse over the centuries and future developments related to it.

[3] A. E. Kalange and S. A. Gangal, “Piezoelectric sensor for human pulse detection,” *Def. Sci. J.*, vol. 57, no. 1, pp. 109–114, 2007, DOI: 10.14429/dsj.57.1737.

In this research paper, the outlook is given using piezoelectric sensors in human pulse detection. Pulse signals obtained processed through signal processing circuitry made of signal amplifier filters and noise-reduction circuit. A signal processing circuit is built and tested with pulse waveforms being analyzed. Compared to the strain gauge, the analysis was done based on noise and accuracy affected by the dc shift. With the help of a digital storage oscilloscope on three different people, observations were made on the feasibility of identifying the dominant pulse types of people.

[4] H. Chang, J. Chen, and Y. Liu, “Micro-piezoelectric pulse diagnoser and frequency domain analysis of human pulse signals,” *J. Tradit. Chinese Med. Sci.*, vol. 5, no. 1, pp. 35–42, 2018, doi: 10.1016/j.jtcms.2018.02.002.

Pulse diagnosis is to assess the physiological condition of the human body using the radial pulse. It is challenging to learn and requires one-to-one teaching. The paper highlights Traditional Chinese Medicine which uses four diagnostic techniques: inspection, auscultation-olfaction, interrogation and pulse. Pulse came up on top with the characteristics of being simple, applicable and precise. The experimentation in the paper carried out a homemade pulse diagnoser to measure human pulses for standardized comparison with studied pulses. The system consists of a piezoelectric transducer, differential amplifier, data acquisition instrument and Matlab Analysis program. Digitalized data is refined and analyzed by fast Fourier transform for frequency analysis. Frequency domain analysis avoids ambiguity in assessing the three

types of pulses compared to assessment in the time domain. Comparison with a published report and other simulation findings characterized the pulse types and the effects of various factors. Findings were applied to study the actual pulses in patients. Three pulse types detected, and in conclusion, the findings confirmed the different aspects of the analysis.

[5] I. Mahbub, H. Wang, S. K. Islam, S. A. Pullano, and A. S. Fiorillo, "A Low Power Wireless Breathing Monitoring System Using a Piezoelectric Transducer," *2016 IEEE Int. Symp. Med. Meas. Appl. MeMeA 2016 - Proc.*, no. June 2018, 2016, DOI: 10.1109/MeMeA.2016.7533756.

An overview of the operation of the proposed system is given from the measuring of breathing vibrations by the piezoelectric sensor to the transmission of digitized data to a central server using a radio wide-band with the complete electronic circuit created in an integrated circuit. Benefits of the piezoelectric sensor or the PVDF film are highlighted, and a brief perspective and function given for the different components of the proposed system. As a wearable device, a PVDF sensor effectively collects breathing rate whilst not inconveniencing the patient. The integrated circuit allows processing and wireless transmission of data using minimal resources.

[6] N. Ahmed, M. Ajmal, M. Hai, A. Khuzema, and M. Tariq, “Real-Time Monitoring of Human Body Vital Signs using Bluetooth and WLAN,” *Int. J. Adv. Comput. Sci. Appl.*, vol. 7, no. 10, pp. 210–216, 2016, DOI: 10.14569/ijacsa.2016.071028.

The paper provides a detailed outline of the different hardware components, such as the sensors and software used in monitoring body vital signs. In outlining the implementation process of the wireless body area network with the connection from the different sensors, it provides data to the transmission of the data through the radio frequency transmitter(Bluetooth) to the android device. The use of optical technologies was taken for the non-invasive monitoring of skin blood pulsation. The principle used was that oxygenated blood is bright red, whereas deoxygenated blood was dark red. A combination of red and near-infrared LEDs and photosensors were used to monitor the colour of blood. The system was reliable and straightforward in measuring body vitals and bringing change to medical telemetry.

[7] O. H. Jimmoh, S. Adedayo, O. S. Enemakwu, and I. N. Ajibola, “Microcontroller-Based Remote Temperature Monitoring System,” *IOSR J. Comput. Eng.*, vol. 18, no. 04, pp. 68–72, 2016, DOI: 10.9790/0661-1804056872.

The research aims to develop low cost intelligent remote monitoring intelligent system using mobile phones and the internet to aid doctors remotely monitor patients. The GSM network is used for the remote viewing of temperature readings measured. The proposed project presents a simplified way of alerting doctors or caretakers of abnormal temperature measurements through alarms and messaging using preset values from clinical decision support systems. Tests were conducted in a contained environment where results were confirmed with the expected results under average temperature.

[8] S. Misbahuddin, J. A. Zubairi, A. R. Alahdal, and M. A. Malik, “IoT-Based Ambulatory Vital Signs Data Transfer System,” *J. Comput. Networks Commun.*, vol. 2018, 2018, doi: 10.1155/2018/4071474.

A project initiative for live transmission of patient vital signs and other medical data or information to physicians in the hospital provides the ability to help and give instructions to

paramedics. It also helps physicians prepare for emergency cases in ample time. The method used in the project sends vital signs of multiple patients to the hospital's server. Received data can be recorded in a database for analysis. The server would also maintain records of on-duty doctors to allow patient vitals to be sent to the first available doctor's smartphone.

[9] S. Y. Park and J. J. Lee, "Self-diagnosis device using wrist pulse," *IECON Proc. (Industrial Electron. Conf.*, pp. 139–142, 2007, doi: 10.1109/IECON.2007.4460206.

In diagnosing a disease, western medicine looks into a patient's body using equipment such as MRI, but oriental and traditional medicine observes outside of the patient's body. Wrist pulse is a fundamental element for diagnosis in Traditional Chinese Medicine (TCM) which has many properties and features to diagnose disease. The paper brings to light a developed diagnosis system that detects a pulse signal using a piezoelectric film sensor and uses pulse to check possible liver illness and heart disorder. The document further highlights the pulse spectrum gained from an amplifier circuit via an analog to digital converter analyzed with DTFT. In discovering possible liver problems, the harmonic proportion of the pulse spectrum was computed. The arm and sensor are placed in a fixed position to avoid noise.

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