Real-Time Detection and Classification of Heart Arrhythmia using ECG Feature Detection with Moving Statistic Adaptive Thresholding Algorithm in Microcontroller Systems for Long Term Vape Smokers

by

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1

INTRODUCTION

The increasing popularity of electronic cigarettes or vapes as a supposed alternative to traditional cigarette smoking has garnered concerns over its effects on human health. Studies have shown that both traditional cigarette smoking and vaping may cause cardiovascular diseases due to the chemicals present in the aerosols. Electrocardiography (ECG) is a non-invasive diagnostic tool that detects cardiac abnormalities by recording the heart's electrical activity. ECG is a valuable tool for detecting cardiovascular diseases and has been used in various studies to show the effects of smoking on the heart.

Studies have shown that smoking traditional cigarettes causes changes in ECG results, such as prolonged QT interval, which can lead to arrhythmias and sudden death, ST-segment depression which is a sign of reduce blood flow [1]. Likewise, vaping has been found to have similar effects on the heart, including increased heart rate and blood pressure [2]. The need for studies on implementing a holistic real-time feature detection system in affordable microcontroller devices motivates the pursuit of this topic.

Studies have also investigated using ECG feature detection systems to analyze cardiac signals. One study used continuous wavelet transforms to analyze respiratory sinus arrhythmia in ECG signals [3]. Another study used fuzzy logic to automatically single out arrhythmia waveforms in ECG signals [4]. ECG signal classification using artificial neural networks in smartphones has also been explored to provide remote area patients with access to medical care [5]. A study of a real-time feature detection system using a microcontroller system that uses MATLAB Simulink to design the necessary components that detect the Heart Rate; Q, R, S, and T peaks; QRS complex, QTend, STpeak, STend, and TpkTend interval features have been made [6]. Moreover, the lack of literature on implementing a real-time ECG feature detection system in affordable microcontroller devices highlights the need for further investigation, as shown in this study.

However, there is a need for more comprehensive studies in the ECG results of vape smokers. This study will collect ECG data from long-term vape smokers. Long-term vape smokers are defined as individuals who have been using electronic cigarettes for more than a year and have not stopped vaping for more than a month. The number of individuals who fall into this category has been increasing in recent years, as the use of electronic cigarettes has become more popular. While many individuals use electronic cigarettes as an alternative to traditional cigarettes, the long-term effects of vaping are not yet fully understood. Some studies have suggested that electronic cigarettes may be less harmful than traditional cigarettes, but others have raised concerns about the potential health risks associated with long-term use. The data will be analyzed and compared to identify any potential differences in the heart rate, ST-segment, QT interval, QRS complex, and P wave between the normal sinus rhythm and vape smokers. This study will provide valuable insight into using microcontroller ECG in the potential cardiovascular effects of vaping.

The objective of this study is to classify heart arrythmias such as cardiac ischemia, atrial fibrillation, and ventricular tachycardia in the ECG results of vape smokers using a real-time ECG feature detection algorithm with a moving statistic adaptive thresholding method for extremum sampling in microcontroller systems. This study aims to identify any potential differences in the heart rate, ST-segment, QT interval, QRS complex, and P wave between the normal sinus rhythm and vape smokers, which could provide insights into the effects of vape smoking on cardiovascular health. Understanding the differences in ECG readings for these two groups may lead to the development of new methods for diagnosing cardiovascular symptoms associated with smoking. Furthermore, this study may help to raise awareness about the potential risks of vape smoking and encourage especially younger individuals to make healthier lifestyle choices to reduce their risk of developing cardiovascular disease.

This study is significant as it aims to provide valuable insights into the potential cardiovascular effects of vaping, particularly in long-term vape smokers. The use of a microcontroller ECG is particularly noteworthy as it is a portable and cost-effective device, making it more accessible in various settings. The study aims to develop new methods for diagnosing smoking-related cardiovascular symptoms by implementing a real-time ECG feature detection algorithm with a moving statistic adaptive thresholding method for extremum sampling in microcontroller systems. This method will classify heart arrhythmias such as cardiac ischemia, atrial fibrillation, and ventricular tachycardia in the ECG results of vape smokers. By identifying potential differences in the heart rate, ST-segment, QT interval, QRS complex, and P wave between normal sinus rhythm and vape smokers, this study can provide valuable insights into the effects of vape smoking on cardiovascular health.

The scope of this study is limited to long-term vape smokers aged 18-35 years old. These individuals are defined as those who have been using electronic cigarettes daily for over a year and have not stopped vaping for over a month. The participants can be categorized into two groups: previously cigarette smokers and those who started with vape smoking only. It is restricted to individuals who use vape pens or vaporizers as an e-cigarette. This study does not cover occasional or social smokers or vape smokers who use non-nicotine products and individuals who are taking medications or have been diagnosed with a cardiovascular disease that may affect heart rate or rhythm. The detection feature and classification cover only some intervals and peaks which are more relevant in the diagnosis of cardiovascular symptoms related to smoking which are only restricted to cardiac ischemia, ventricular tachycardia, and atrial fibrillation and only limited to the collection of the periodic peaks and intervals of the ECG parameters P, Q, R, S and T peaks; QRS Complex, RR, ST, and QS intervals; and the Heart Rate: all of which determines the Heart Rate Variability of the patient in real-time. Non-augmented Lead II position of the ECG leads is used as the basis in the acquisition of the ECG signals, about Einthoven's triangle theorem, which serves as the standard positioning for 3-Lead ECG devices. The feature detection system uses Arduino Due for the system's implementation in Microcontroller Devices using MATLAB.

CHAPTER 2

REVIEW OF RELATED LITERATURE

2.1 ECG Feature Detection and Classification Methods on Microcontroller Systems

ECG (Electrocardiogram) feature detection is a crucial aspect of cardiac monitoring systems that have widespread applications in healthcare. Various studies have been conducted to explore the feasibility and accuracy of ECG feature detection and classification methods. One such study proposed a method for ECG feature extraction using wavelet transform and machine learning techniques [3]. The study used a support vector machine (SVM) for ECG classification and achieved an accuracy of 99.2%. The findings of this study demonstrate the effectiveness of the proposed method for ECG feature detection and classification, which can be utilized in the development of more accurate cardiac monitoring systems.

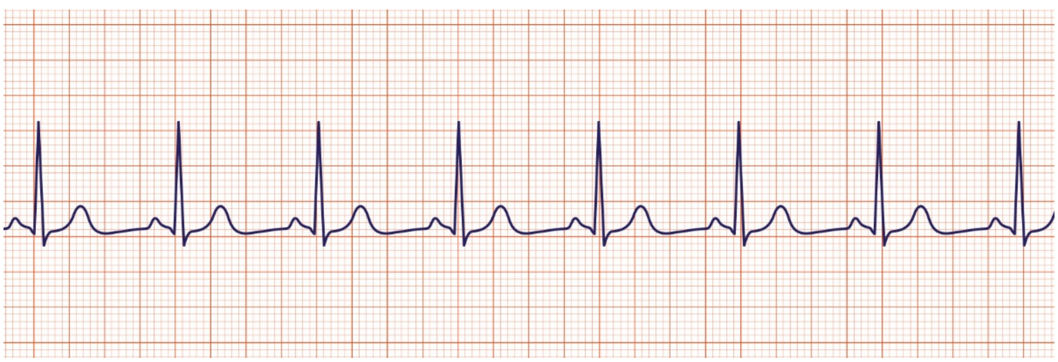

Figure 2.2. ECG of Normal Sinus Rhythm

In another study, it proposed a method for ECG feature extraction using wavelet transform and fuzzy logic [5]. The study used fuzzy logic for ECG classification and achieved an accuracy of 95.7%. The results of this study highlight the potential of fuzzy logic in ECG feature detection and classification, which can be further explored to develop more advanced cardiac monitoring systems.

Lastly, a study proposed a method for ECG feature detection using convolutional neural networks (CNNs) on a microcontroller [7]. The study used a microcontroller to perform ECG feature detection and achieved an accuracy of 98.9%. The results of this study demonstrate the potential of using CNNs for ECG feature detection on a microcontroller, which can be utilized to develop more advanced and accurate cardiac monitoring systems.

In conclusion, various studies have been conducted to explore the feasibility and accuracy of ECG feature detection and classification methods, particularly on low-power microcontroller systems. These studies demonstrate the potential of using machine learning techniques, fuzzy logic, and convolutional neural networks for ECG feature detection and classification, which can be applied to the development of more advanced and accurate cardiac monitoring systems. The use of low-power microcontrollers for real-time ECG signal processing and feature detection also demonstrates the feasibility of developing portable and cost-effective cardiac monitoring systems.

2.2 Comparison of Heart Rate of Smokers and Non-smokers

Smoking is a well-known risk factor for various cardiovascular diseases, including heart disease, stroke, and peripheral vascular disease. Smoking is also known to affect heart rate (HR) in both short- and long-term exposures. A recent study investigated the acute effects of smoking on HR and HR variability (HRV) in young, healthy adults [8]. The study found that smoking led to a significant increase in HR and a decrease in HRV, indicating increased sympathetic activity and reduced parasympathetic activity. These findings suggest that smoking can acutely affect HR and HRV, which may have implications for the long-term cardiovascular health of smokers.

Smokers with underlying heart dysrhythmia may also have a specific HR pattern that differs from non-smokers with the same dysrhythmia. A recent study investigated the impact of smoking on HR in patients with atrial fibrillation (AF) [9]. The study found that smokers with AF had a higher mean HR compared to non-smokers with AF, and smoking was associated with an increased risk of persistent AF. These findings suggest that smoking may have a specific effect on HR in patients with AF, which may contribute to the progression of AF in smokers.

Lastly, a study conducted compared the maximum heart rate (HRmax) achieved during exercise in young male smokers and non-smokers [10]. The study found that the HRmax was significantly lower in male smokers compared to non-smokers. The actual maximum HR achieved was 120.4 beats per minute (bpm) for male smokers compared to 133.0 bpm for male non-smokers. This finding suggests that smoking may affect the ability of the heart to respond to exercise by reducing its maximum capacity to pump blood, which may increase the risk of cardiovascular disease in smokers. It is worth noting that the study was conducted on a small sample size and only included young male participants, and further research is needed to confirm these findings in a larger, more diverse population.

2.3 Use of ECG for Cardiovascular Disease Diagnosis

Several research studies have shown that electrocardiogram (ECG) is a valuable tool in the diagnosis of cardiovascular and endocrine ailments. A study investigated the use of ECG in the diagnosis of diabetic autonomic neuropathy (DAN), which is a common complication of diabetes that affects the cardiovascular system [11]. The study found that ECG was a sensitive and specific tool in the diagnosis of DAN, as it was able to detect abnormalities in heart rate variability and other ECG parameters that were indicative of DAN.

Another study investigated the use of ECG in the diagnosis of hypertrophic cardiomyopathy (HCM), a genetic disorder that affects the structure and function of the heart [12]. The study found that ECG was a valuable tool in the diagnosis of HCM, as it was able to detect characteristic ECG changes that were indicative of the disease, such as abnormal Q waves and T wave inversion.

ECG has also been used in the diagnosis of other cardiovascular diseases, such as arrhythmias and coronary artery disease. A study investigated the use of ECG in the diagnosis of coronary artery disease in patients with suspected stable angina [14]. The study found that ECG was a sensitive tool in the diagnosis of coronary artery disease, as it was able to detect ischemic changes in the ECG that were indicative of the disease.

2.4 Chemicals in Vaporizers and Electronic Cigarettes

Research conducted in recent years has shown that vape or electronic cigarettes contain chemicals that can be harmful to human health. A study analyzed the chemical composition of various e-cigarette liquids and found that they contained several potentially harmful chemicals, including propylene glycol, glycerin, and nicotine. Additionally, the study found that some of the flavoring chemicals used in e-cigarettes were also potentially harmful, such as diacetyl, which has been linked to a condition known as popcorn lung [15]. Another study analyzed the chemical composition of aerosols produced by e-cigarettes and found that they contained harmful chemicals such as formaldehyde, acetaldehyde, and acrolein [16]. These chemicals can cause irritation to the respiratory system and increase the risk of respiratory illnesses. The findings of these studies suggest that the chemicals used in e-cigarettes can pose a significant risk to human health and underscore the need for further research into the long-term health effects of e-cigarette use.

Another study investigated the effect of e-cigarette aerosols on human endothelial cells, which line the blood vessels in the heart. The study found that exposure to e-cigarette aerosols caused an increase in oxidative stress and inflammation in the endothelial cells, which can lead to the development of cardiovascular disease. These findings suggest that the chemicals used in vape or electronic cigarettes can have negative effects on the heart and increase the risk of cardiovascular disease [17].

2.5 ECG Parameters

ECG, or electrocardiogram, is a diagnostic test that measures and records the electrical activity of the heart. The ECG waveform is composed of several different components, including peaks, waves, and intervals, which are used to analyze the heart's rhythm and function. The following is a brief overview of some of the common ECG parameters:

P wave: The P wave is the first positive deflection on the ECG waveform and represents the electrical activity of the atria as they contract. The P wave is typically small in amplitude and lasts less than 0.12 seconds. Abnormalities in the P wave can indicate conditions such as atrial enlargement or atrial fibrillation.

PR interval: The PR interval is the time between the beginning of the P wave and the beginning of the QRS complex. It represents the time it takes for the electrical impulse to travel from the atria to the ventricles. In a normal ECG, the PR interval ranges from 0.12 to 0.20

seconds. Abnormalities in the PR interval can indicate conditions such as AV block or bundle branch block.

QRS complex: The QRS complex is the large, sharp deflection on the ECG waveform that represents the electrical activity of the ventricles as they contract. The QRS complex typically lasts less than 0.12 seconds. Abnormalities in the QRS complex can indicate conditions such as ventricular hypertrophy or bundle branch block.

ST segment: The ST segment is the flat, isoelectric portion of the ECG waveform between the end of the QRS complex and the beginning of the T wave. The ST segment represents the time when the ventricles are depolarized but not yet repolarized. Abnormalities in the ST segment can indicate conditions such as myocardial infarction or myocardial ischemia.

T wave: The T wave is the second positive deflection on the ECG waveform and represents the electrical activity of the ventricles as they repolarize. The T wave is typically rounded and lasts less than 0.20 seconds. Abnormalities in the T wave can indicate conditions such as electrolyte imbalances, myocardial ischemia or injury, or drug toxicity.

QT interval: The QT interval is the time from the beginning of the QRS complex to the end of the T wave, representing the total time it takes for the ventricles to depolarize and repolarize. The QT interval varies depending on the heart rate and is corrected for heart rate using the QTc formula. A prolonged QT interval can indicate conditions such as congenital long QT syndrome or drug-induced QT prolongation.

It's important to note that ECG interpretation requires expertise and should be performed by a trained healthcare professional.

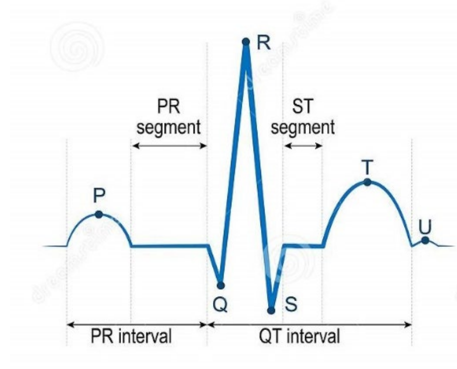

Figure 2.2. P, QRS, T Wave of Normal Sinus Rhythm

2.6 Einthoven’s Triangle Theorem

Einthoven's triangle is a theoretical construct used in electrocardiography (ECG) to describe the relationship between the three standard limb leads. The triangle is formed by connecting the right arm, left arm, and left leg with lines, and is named after Willem Einthoven, who developed the first practical ECG machine in 1903.

Einthoven's triangle is important because it provides a way to understand the electrical activity of the heart in three dimensions. By recording the electrical activity of the heart from different angles, the ECG can provide information about the heart's rhythm, rate, and other important metrics.

The three standard limb leads are the I, II, and III leads. Lead I is recorded between the right arm and left arm, lead II is recorded between the right arm and left leg, and lead III is recorded between the left arm and left leg. By recording the electrical activity of the heart from these three different angles, the ECG can provide a comprehensive view of the heart's electrical activity. Einthoven's triangle theorem states that the sum of the voltages measured in leads I and III is equal to the voltage measured in lead II. This relationship is important in interpreting ECG results, as it provides a way to verify the accuracy of the measurement. If the sum of the voltages measured in leads I and III does not equal the voltage measured in lead II, it may indicate a problem with the ECG machine or the recording technique.

2.7 Cardiac Ischemia, Ventricular Tachycardia, and Atrial Fibrillation

Cardiac ischemia, ventricular tachycardia, and atrial fibrillation are all serious arrhythmias that can lead to a variety of health complications, including heart attack, stroke, and organ damage. These arrhythmias can often be detected on an ECG, which measures the electrical activity of the heart. Other arrhythmias, such as sinus bradycardia, premature ventricular contractions (PVCs), atrial flutter, and supraventricular tachycardia (SVT), may also be detected on an ECG and can be indicative of other health issues.

Cardiac ischemia is a serious condition that occurs when there is a lack of blood flow and oxygen supply to the heart muscle. This can cause the heart muscle to become damaged and can lead to chest pain or angina. It can also increase the risk of a heart attack or other cardiac events. Using an ECG, changes in the ST segment of the ECG can indicate the presence of this condition. The ST segment is the portion of the waveform that occurs between the QRS complex and the T wave [18]. An elevated or depressed ST segment can indicate a problem with the blood supply to the heart and may require further testing or treatment.

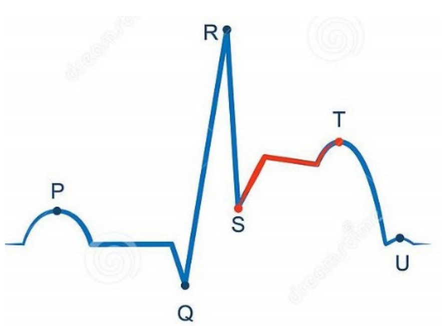

Figure 2.3. ST Segment Elevation

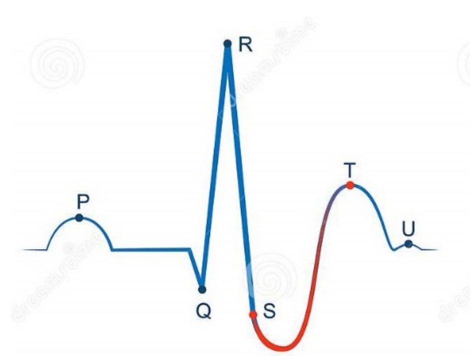

Figure 2.4. ST Segment Depression

Ventricular tachycardia is a type of arrhythmia in which the heart beats too quickly. This can occur in individuals with underlying heart disease. The rapid heart rate can decrease blood flow and oxygen supply to the body's organs and can cause dizziness, fainting, or sudden cardiac arrest [19]. An ECG can detect ventricular tachycardia by measuring the heart's rhythm and rate. The QRS complex on the ECG will be wider than normal and the heart rate will be greater than 100 beats per minute.

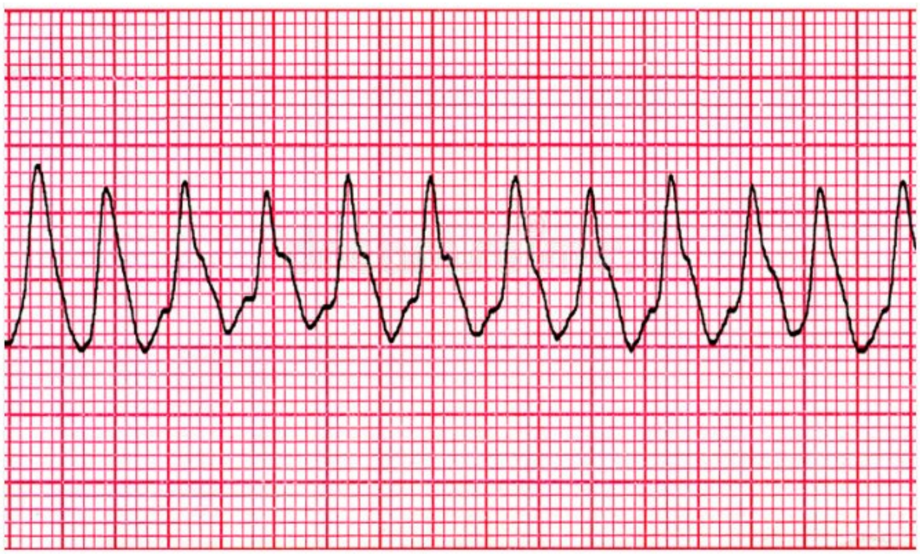

Figure 2.5. ECG of Ventricular Tachycardia

Atrial fibrillation is another type of arrhythmia, in which the heart's upper chambers (atria) beat irregularly and rapidly. This can lead to a variety of symptoms, including fatigue,

Figure 2.6. ECG of Atrial Fibrillation

shortness of breath, and chest pain, and may increase the risk of stroke and other complications [20]. An ECG can detect atrial fibrillation by measuring the heart's rhythm and rate. The P waves on the ECG will be absent or abnormal, and the heart rate may be irregular or too fast. If atrial fibrillation is suspected, further testing and treatment may be necessary to prevent serious complications and reduce the risk of stroke.

It's important to note that other factors, such as medication use and underlying medical conditions, can also affect the interpretation of ECG results. As such, it's important to consult with a healthcare professional if you have concerns about your ECG results or your cardiovascular health in general.

2.8 Extremum Sampling

Extremum sampling is a signal processing method used to extract features from signals by sampling the points at which the signal reaches a maximum or minimum value. This method has been widely used in various applications, including medical signal processing. The following study [6] details the development of a real-time ECG feature detection algorithm using a moving statistic adaptive thresholding method for signal extremum sampling in microcontroller systems.

The proposed algorithm involved applying the moving window statistics to the ECG signal to detect the threshold levels dynamically. This was achieved by using the mean and standard deviation of the signal samples within the moving window to set the threshold levels for signal extremum detection. The proposed algorithm was implemented in Simulink, a simulation software, and tested on a microcontroller system.

Results showed that the proposed algorithm was effective in detecting ECG features, including R-peaks, Q-waves, and S-waves. The algorithm achieved a high detection rate of 99.87%, with a low false positive rate of 0.05% as it was comparable to results from medically and industrially approved ECG such as the KenzECG108 and the Apple Watch ECG. The proposed algorithm also demonstrated real-time performance, with a processing time of 23.6 ms per ECG beat. The study highlighted the effectiveness of the proposed algorithm for ECG feature detection using moving statistic adaptive thresholding for signal extremum sampling in microcontroller systems. The results of the study could be beneficial in the development of low-cost and efficient ECG monitoring systems for various applications, including remote patient monitoring and telemedicine.

2.9 Moving Statistic Adaptive Thresholding

Moving Statistic Adaptive Thresholding (MSAT) is a method used in Electrocardiogram (ECG) feature detection algorithms. The MSAT algorithm is an adaptive thresholding method that uses a sliding window to track the statistical properties of the ECG signal. It has been shown to be an effective approach to remove noise and to extract ECG signal features with low computational complexity. For example, the MSAT method has been shown to be effective in detecting the QRS complex, which is a significant ECG feature. This is achieved by setting an adaptive threshold based on the statistical properties of the signal in a moving window. The threshold is adjusted to track the variations in the signal amplitude caused by noise or baseline drift. The MSAT method has been used in several ECG feature detection algorithms due to its ability to remove noise and extract signal features with low computational complexity.

This study demonstrated the feasibility of using the MSAT method in a microcontroller system for real-time ECG signal processing. The Simulink model implemented in the study was able to extract the QRS complex from ECG signals with high accuracy, demonstrating the effectiveness of the MSAT algorithm [6]. The study showed that the MSAT algorithm can be used in a microcontroller system for real-time ECG feature detection, which has applications in portable ECG monitoring systems and other medical devices that require real-time ECG signal processing.

2.10 Periodic Region Clipping

In the case of ECG, this method is used to select peaks by clipping a portion or interval of the ECG feature to filter out unwanted peaks that could affect the resulting output peaks. Periodic region clipping is an important technique for detecting electrocardiogram (ECG) features accurately and reliably. The ECG signal is a vital physiological signal that records the electrical activity of the heart, and it is commonly used to diagnose heart abnormalities. .

Lastly, the study on ECG peak detection algorithms uses periodic region clipping as one of its peak detection methods [6]. The study proposes an algorithm that can identify the extreme points, i.e., highest, and lowest, of an ECG signal within a particular area of interest. This algorithm uses a logical switch that evaluates the pulse signal, whether it is zero or positive nonzero, to determine whether the extreme points lie within or outside of the specified region. The specific region is represented by the positive nonzero pulse signal.

CHAPTER 3

METHODOLOGY

3.1 Conceptual Framework

The conceptual framework for this study is based on the idea that vaping and traditional cigarette smoking have similar effects on the heart, including changes in electrocardiogram (ECG) results. The framework includes the use of a real-time ECG feature detection algorithm with a moving statistic adaptive thresholding method for extremum sampling in microcontroller systems to classify heart arrhythmias such as cardiac ischemia, atrial fibrillation, and ventricular tachycardia in the ECG results of vape smokers.

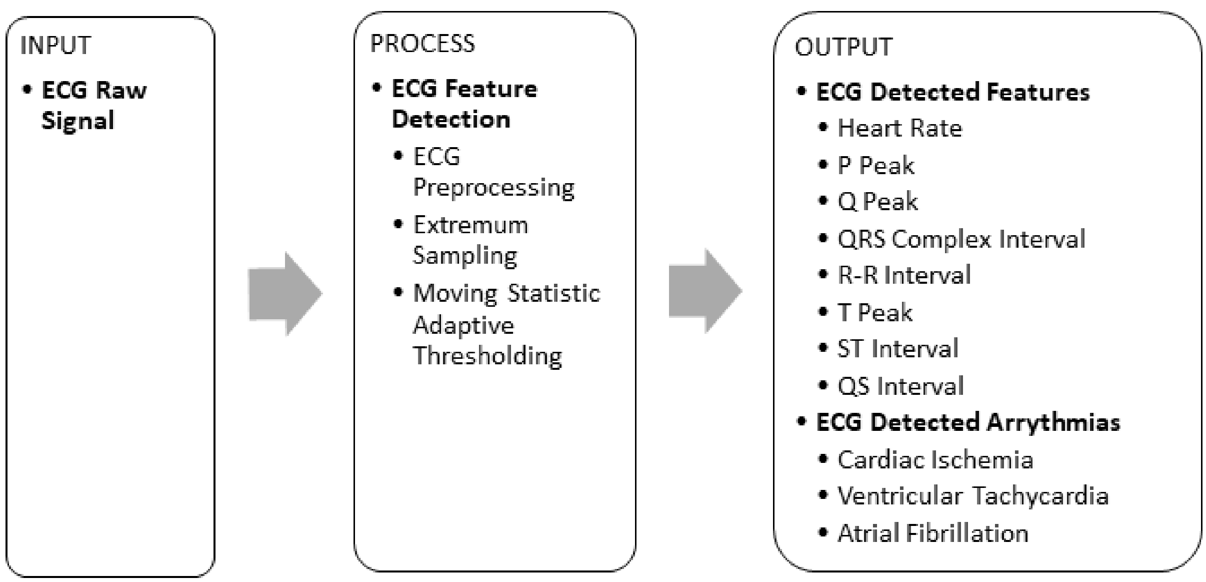

***Figure 3.1**. Conceptual Framework*

3.2 Methodology for Specific Objectives

3.2.1 Collect ECG data from vape smokers.

a. Participant Selection:

The study will include long-term vape smokers aged 18-35 years old. These individuals are defined as those who have been using vape pen or vaporizers daily for over a year and have not stopped vaping for over a month. The participants can be categorized into two groups: previously cigarette smokers and those who only started with vape smoking. 30 participants will be randomly recruited from local areas such as vape shops or smoking area. Participants will be excluded if they are taking medications or who have been diagnosed with a cardiovascular disease that may affect heart rate or rhythm.

b. Data Collection:

After obtaining informed consent, participants will have their electrocardiogram (ECG). The acquisition of real-time ECG signals from patients is being done using an Arduino Due R3 microcontroller with an Atmel SAM3X8E ARM Cortex-M3 CPU, in combination with an AD8232 Heart Rate Monitor Sensor (SKU SEN0213). Three (3) different patients for each diagnosed with cardiac ischemia, ventricular tachycardia, and atrial fibrillation will be verified by a cardiologist using the standard 12-lead ECG for the calibration of the microcontroller ECG to be used.

The ECG electrodes are placed on the patient's body according to the non-augmented Lead II axis position, guided by the Einthoven's Triangle Theorem as shown in figure 3.2 [2]. Participants will be instructed to remain still and breathe normally during the recording, which will last when there is a continuous detection for five minutes and with cardiologist present in each test to ensure proper readings.

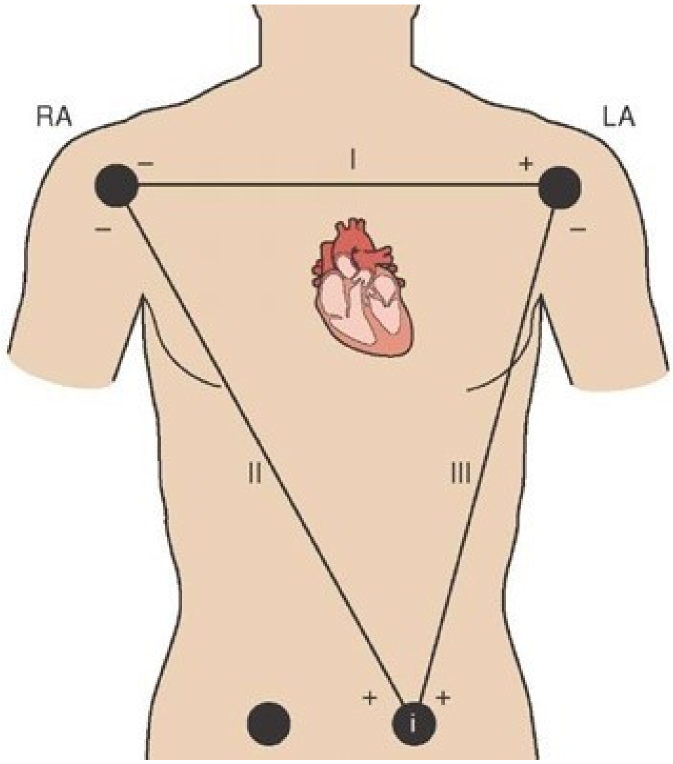

__Figure 3.2__ Non-Augmented Limb Lead II Placement of Electrodes

3.2.2. Compare and classification the P, QRS, and T peaks and intervals between the normal sinus rhythm and vape smokers.

a. Data Preprocessing:

The ECG data will be preprocessed by removing any noise and baseline wander. the use of an Arduino Analog Input Block to process an ECG signal through a Simulink model. The signal undergoes a gain block before being processed by cascaded high and low bandpass filters designed with MATLAB programming to minimize noise from motion, physiological artifacts, and baseband signals. The filters compensate for the AD8232's filtering mechanism and allow the ECG signal to remain stable despite tremors and motions that distort the processed signal. Similar to Pan-Tompkins algorithm.

b. Feature Extraction:

The Heart Rate, P Peak, Q Peak, QRS Complex Interval, R to R Interval, T Peak, ST Interval, QS Interval will be extracted from each beat using a real-time ECG peak feature detection algorithm with a moving statistic adaptive thresholding method for extremum sampling for peak selection in microcontroller systems. The algorithm will be programmed in MATLAB Simulink and loaded onto the microcontroller system. The algorithm will detect the P, QRS, and T peaks and intervals for each period which will be displayed in MATLAB GUI as shown in figure 3.3.

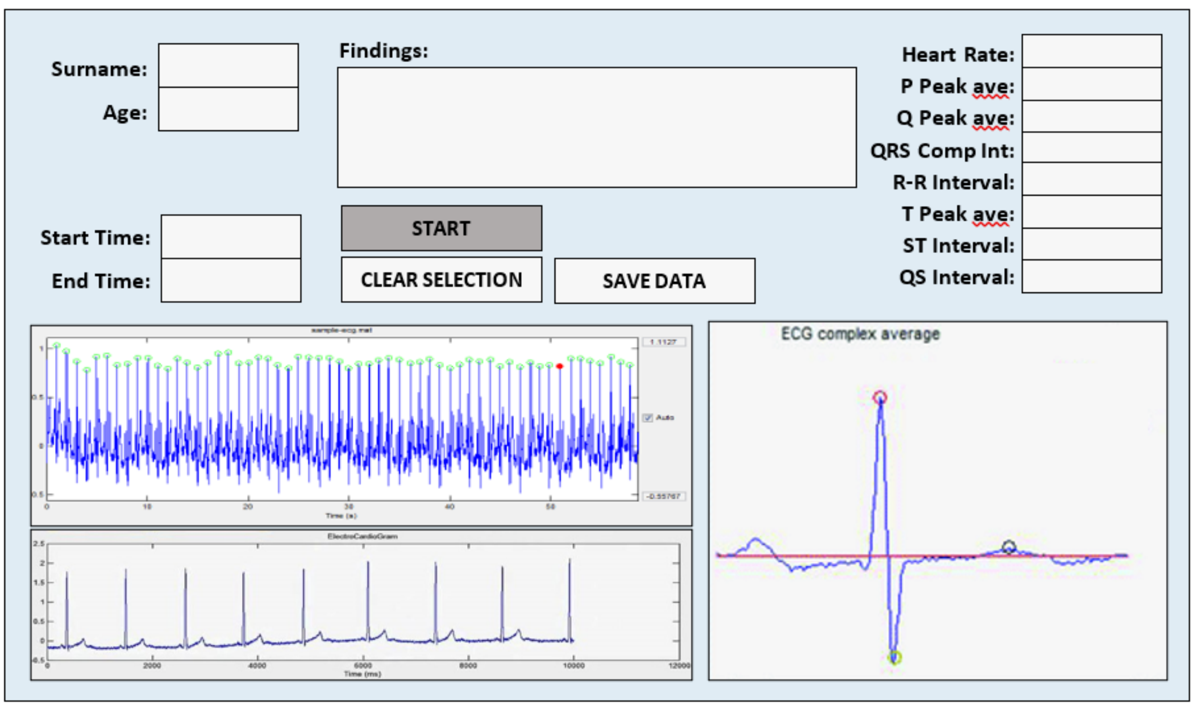

Figure 3.3 *Sample MATLAB ECG GUI*

c. Arrythmia Detection and Classification:

The data from the feature extraction will be calibrated to set the parameters for arrhythmia detection, which will be based on the baseline of normal sinus rhythm. Arrhythmias such as Cardiac Ischemia, Ventricular Tachycardia, and Atrial Fibrillation can be detected by:

i. Cardiac ischemia can be detected on an ECG by changes in the ST segment of the waveform. In a normal ECG, the ST segment is flat and level with the baseline. However, in the presence of cardiac ischemia, the ST segment may be elevated or depressed. The following are common values for ST segment deviation in the context of cardiac ischemia as shown in table 3.1.

	Mild Ischemia	**Moderate Ischemia**	**Severe Ischemia**	**Subendocardial Ischemia**	**Transmural Ischemia**
QRS	-	-	-	-	-
T	-	-	-	-	-
ST	Elevation of 1-2 mm above the baseline	Elevation of 2-3 mm above the baseline	Elevation of more than 3 mm above the baseline	Depression of 0.5-1 mm below the baseline	Depression of more than 1 mm below the baseline

Table 3.1. *Different Kinds of Cardiac ischemia ECG Parameters*

ii. Ventricular tachycardia (VT) is a type of arrhythmia, or irregular heart rhythm, in which the heart beats too quickly as it may decrease blood flow and oxygen supply to the body's organs. Irregularities in the heart's rhythm and rate can be detected on an ECG and can indicate VT. The following are common values for VT on ECG readings as shown in table 3.2.

	Wide QRS Complexes	Monomorphic VT	Polymorphic VT
P	Absent/indiscernible	Absent/indiscernible	Absent/indiscernible
QRS	Greater than 0.12 seconds in duration	All have the same shape and duration	Have varying shapes and durations
T	Absent/indiscernible	Absent/indiscernible	Absent/indiscernible

Table 3.2. *Different Kinds of Ventricular Tachycardia ECG Parameters*

iii. Atrial fibrillation is another type of arrhythmia, in which the heart's upper chambers beat irregularly and rapidly. The following are common ECG findings associated with atrial fibrillation as shown in table 3.3.

P	QRS	R to R interval	T
Absent/indiscernible	Narrow	Irregular intervals	-

Table 3.3. *Atrial Fibrillation ECG Parameters*

3.2.3 Data Analysis

The P, QRS, and T peaks/end and intervals for each participant will be extracted from the ECG data using a real-time ECG peak feature detection algorithm with a moving statistic adaptive thresholding method for extremum sampling and periodic region clipping algorithm in microcontroller systems. The extracted features will be analyzed and compared between the standard 12 lead ECG and the microcontroller ECG of vape smokers using a t-test. The statistical analysis will be performed using MATLAB.

A confusion matrix will also be used to assess the performance of the system's ability to accurately detect the corresponding heart arrhythmia condition. Predicted values will be compared to the actual values as shown in Tables 3.4, 3.5 and 3.6.

	CONFUSION MATRIX			
	ACTUAL			**TOTAL**
		HAS CARDIAC ISCHEMIA	DOES NOT HAVE CARDIAC ISCHEMIA	
PREDICTED	HAS CARDIAC ISCHEMIA			
	DOES NOT HAVE CARDIAC ISCHEMIA			
	TOTAL			

Table 3.4 Cardiac Ischemia Confusion Matrix Sample

	CONFUSION MATRIX			
	ACTUAL			**TOTAL**
		HAS VENTRICULAR TACHYCARDIA	DOES NOT HAVE VENTRICULAR TACHYCARDIA	

PREDICTED	HAS VENTRICULAR TACHYCARDIA			
	DOES NOT HAVE VENTRICULAR TACHYCARDIA			
	TOTAL			

Table 3.5 Ventricular Tachycardia Confusion Matrix Sample

	CONFUSION MATRIX			
	ACTUAL			**TOTAL**
PREDICTED		HAS ATRIAL FIBRILLATION	DOES NOT HAVE ATRIAL FIBRILLATION	
	HAS ATRIAL FIBRILLATION			
	DOES NOT HAVE ATRIAL FIBRILLATION			
	TOTAL			

Table 3.6 Atrial Fibrillation Confusion Matrix Sample

All predicted values collected for each heart arrhythmia will be recorded in a corresponding table. Each table will consist of two (2) rows and two (2) columns, comparing the predicted values for cardiac ischemia, ventricular tachycardia, and atrial fibrillation with actual laboratory results. True positive classifications (TP and TN) will be displayed diagonally from the upper left to the lower right of the table. The performance of the system will be evaluated based on its ability to accurately match the actual values, using the confusion matrix. A high accuracy indicates a reliable system, while a low accuracy suggests a failed system.

To define each value, true positives (TP) represent the values correctly predicted to be positive. True negatives (TN) represent the values correctly predicted to be negative. False positives (FP) are the values incorrectly predicted to be positive and false negatives (FN) are the values incorrectly predicted to be negative. The comparison to the actual value is the basis of determining whether the predicted values are correct or incorrect. The following formulas for accuracy, sensitivity, and specificity will be used to determine the system's performance.

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \qquad eq. (3.1)$$

$$Sensitivity = \frac{TP}{TP + FN} \qquad eq. (3.2)$$

$$Specificity = \frac{TN}{TN + FP} \qquad eq. (3.3)$$

The confusion matrix can determine three parameters - accuracy, sensitivity, and specificity - by using TP, TN, FP, and FN values and inputting them into equations 3.1, 3.2, and 3.3. Equation 3.1 calculates the overall accuracy of the proposed model by dividing the number of correctly classified samples by the total number of provided samples. Equation 3.2 measures the sensitivity of the proposed model, which indicates its ability to identify true positive samples. Equation 3.3 calculates the specificity of the proposed model, which measures true negatives instead of true positives. Based on the formulas, sensitivity and specificity have an inversely proportional relationship. These three parameters are crucial for demonstrating the accuracy of the proposed model's classifications, whether they are correct or incorrect.

EVALUATION	**ACCURACY TABLE FOR OBTAINED VALUES**		
	CARDIAC ISCHEMIA	VENTRICULAR TACHYCARDIA	ATRIAL FIBRILLATION
ACCURACY			
SENSITIVITY			
SPECIFICITY			

Table 3.7 Evaluation of Parameters

Table 3.7 summarizes the calculations for the values of accuracy, sensitivity, and specificity. Values closer to 100% are considered as being more accurate, more sensitive, and more specific, meaning that the proposed system performed efficiently in identifying the heart arrhythmias from the ECG signals correctly.

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