Media Engineering and Technology Faculty
German University in Cairo

Bio-assisted Self Driving Cars

Bachelor Thesis

Author:	Omar Mohamed Galal Elhanafy
Supervisor:	Dr. Yasser Shoukry
Submission Date:	3 July, 2022

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This is to certify that:

(i) the thesis comprises only my original work toward the Bachelor Degree

(ii) due acknowledgement has been made in the text to all other material used

Omar Mohamed Galal Elhanafy
3 July, 2022

Acknowledgments

I would like to write this chapter to thank everyone, who without them this thesis wouldn't have been made and completed

To Dr.Yasser Shoukry, whom I worked under his supervision, at the University Of Irvine, without your guidance and willingness to allow me to perform this thesis, this wouldn't have been possible.

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Abstract

Heart attack is one of the leading causes of human death worldwide. Many fatal car accidents happen due to the heart attack of drivers that leads to the loss of control of the vehicle, therefore, real-time detection and early warning of heart attacks in drivers can be enormously helpful in reducing road accidents. The electrocardiogram (ECG) has always been an important biomedical test to diagnose cardiovascular diseases. In addition, detection of atrial fibrillation (AF) from ECG recordings is one of the prevailing challenges in the field of cardiac computing. Current approaches for single lead ECG monitoring opposed to 12 lead ECG monitoring have yielded lower accuracies. The aim of this thesis is to propose most accurate models to detect AF from single lead ECG , in order to further improve wearable devices to detect AF in real time and alert the driver of early signs of irregular heart rhythms. I refer to the PTB-XL dataset which is to distinguish the AF rhythms from non-AF rhythms using a short single lead ECG recording. In this study, I propose multiple machine learning models and deep learning models to discriminate two classes normal sinus rhythm, or AF. I designed a pipeline for AF detection from ECGs. First, was to process to extract R-peaks. Second, the sequence of heartbeat codes is passed to proposed models to combine a signal-level representation capturing heart rhythm. Third, the signal representations are passed to the different models for detecting AF. Results I processed and trained the multiple models on the structured training data set and used a ten-fold cross validation classification. On the test data set, we obtained an accuracy ranging from 80% to above 90% for NSR, AF. Results suggest that with the proposed models it is possible to classify cardiac abnormalities from a single lead ECG even when the recordings are of short duration.

Contents

Chapter 1

Introduction

1.1 Overview

Cardiac Arrhythmias characterise a group of various heart conditions where heart rhythms do not follow a normal healthy sinus pattern. Atrial fibrillation (AF) arises among the most common arrhythmias occurring in 1–2% of the general population [37]. In order to detect such type of arrhythmia, a person's electrocardiogram (ECG) signal, which is a simple and noninvasive procedure to assess the electrical activity of the heart. This condition can affect drivers while driving, so this thesis to present different classification models in real time detection of arrhythmias produced by medical sensor, which can be integrated with autonomous vehicles to make a safer environment for the driver.

1.2 Motivation

Fatal road accidents have become an alarming issue all over the globe. A driver with a medical condition such as Cardiac Arrhythmias is much more vulnerable to being hit and much more likely to cause a crash, leading to the injury and death of not only his own life but the life of others. For the driver to be able to detect such conditions early while driving can help drastically in saving their lives. As autonomous vehicles are increasing, they can be integrated with modules that can detect continously the driver's heart rhythm and alert him early on by connecting to medical sensors.

1.3 Related Works

In this section, we review some of the state-of-the-art approaches for AF detection for ECG signals. The related work can be divided into two categories: traditional approaches (Section 1.3.1), including machine learning solutions, and deep learning models (Section 1.3.2).

1.3.1 Traditional Methods

Traditional approaches for atrial fibrillation detection usually includes signal preprocessing for the removal of noises and to clean the data. Next is feature extraction, where two main characteristics of AF ECG signals are the absence of P-waves and irregularity of R-R intervals(RRIs). The absence of a P-wave and other features proved to be unreliable for preprocessing of the ECG data in the presence of noise, since these methods depend heavily on QRS-complex extraction.

Asgari et al. [2] proposed to apply a wavelet representation to extract peak-to-average power ratio and log energy entropy to substitute the detection of P-wave and R peak.

Islam et al. [15] proposed a normalization procedure to discard the effect of ectopic heartbeats of the AF signals, before computing normalized entropy as a measure of irregularity of heartbeat duration in a fixed-length window.

1.3.2 Deep Learning Methods

Deep learning (DL) methods, on the other hand, learn task-specific features from available data contrary to traditional methods that depend on the manually crafted features. DL methods act like a mixture of both Machine Learning (ML) algorithms, which are Supervised learning and Unsupervised. DL models recieve its data as features, which act as inputs to the system, and their labels, but unlike ML it can recieve raw data without preprocessing and iteratively train and learn on the data to find a pattern that connects the input data with its corresponding label. DL algorithms therefore can be applied to both RRI tachograms and raw ECG signals.

Convolutional neural networks (CNN) have shown convincing capability in feature extraction for computer vision tasks; therefore, many researchers adapted CNNs to solve AF detection task. For example, Fan et al. [11] explore multiscale fusion of deep CNN networks (MS-CNN) to detect AF signals based on single-lead ECG recordings from the Physionet Challenge database. In addition, Hannun et al. [13] developed a CNN algorithm to achieve state-of-the-art performance in classifying ECG beats into fourteen different classes. However, they used a large amount of privately collected data for training their model.

1.4 Thesis Structure

This thesis is composed of an abstract followed by 5 chapters. Beginning with the Introduction chapter which contains 4 sections, the Overview that gives the reader a general idea of the thesis and its outcome, Motivation stating the problem addressed and aim, Related Works to show other researches that was reviewed and inspired, Second, is the Background chapter where it gives detailed overview of each aspects, concepts, and methodologies in the thesis. Following this is the Implementation chapter, containing two detailed sections of the offline implementation of preprocessing Single Lead ECG Signal and training different models, and the online implementation of Single Lead ECG Signal reading and classification. Leading to the fourth chapter which is the Results, showing to comparisons of the classification models and which model is best suited during Real-Time classification. Ending with the Conclusion and Future Work to state whether the aim is achieved and how this thesis can help in which other works

Chapter 2

Background

2.1 Physiological Signals and Electrocardiogram

The electrocardiogram (ECG) signal contains the electrical activity that occurs in the human heart. If there is a disturbance in the heart, an abnormality in the ECG signal will be identified [36]. It is the most common noninvasive tool to study the functionality of the heart and diagnose several abnormal atrial fibrillation (AF), a condition in which the heart beats with an irregular or abnormal rhythm, is made up of sequences of three or four distinct waves including the P-wave, QRS complex, T-wave and U-wave. By reading ECG information, a physician can diagnose a variety of arrhythmia heartbeats. Physicians make judgments based on the interval and morphological information of an ECG signal, such as the shape of these three original waves and the heartbeat's rhythm [21].

A normal ECG trace (Figure 2.1) consists of components that indicate electrical events during one heartbeat. P wave is the first short upward movement of the ECG tracing, which indicates that the atria are contracting and pumping blood into the ventricles. The QRS complex normally begins with a downward deflection, Q, a larger upwards deflection, a peak (R), and then a downwards S wave. The QRS complex represents atrial repolarization and ventricular depolarization and contraction. The PR interval indicates the transit time for the electrical signal to travel from the sinus node to the ventricles. T wave is normally a modest upwards waveform representing ventricular repolarization.

2.2 A Review of 12 Lead ECG

In a conventional 12-lead ECG, ten electrodes are placed on the patient's limbs and on the surface of the chest. The overall magnitude of the heart's electrical potential is then measured from twelve different angles ("leads") and is recorded over a period of time (usually ten seconds). In this way, the overall magnitude and direction of the heart's electrical depolarization is captured at each moment throughout the cardiac cycle[20].

The first three lead which are I, II and III are called the limb leads. These electrodes that produce the signals are located on the limbs, where there is one on each arm and one on the left leg. The limb leads form the points of what is known as Einthoven's triangle [17]. Lead I is the voltage difference between the left arm electrode and right arm electrode, Lead II is the voltage difference between the (positive) left leg electrode and the right arm electrode, and Lead III is the voltage difference between the (positive) left leg electrode and the left arm electrode.

Leads aVR, aVL, and aVF are the augmented limb leads. They are derived from the same three electrodes as leads I, II, and III, but they use Goldberger's central terminal as their negative pole. Goldberger's central terminal is a combination of inputs from two limb electrodes, with a different combination for each augmented lead. It is referred to immediately below as "the negative pole" [39].

Together with leads I, II, and III, augmented limb leads aVR, aVL, and aVF form the basis of the hexaxial reference system, which is used to calculate the heart's electrical axis in the frontal plane [10].

The precordial leads lie perpendicular to the other six leads. The six precordial electrodes act as the positive poles for the six corresponding precordial leads: (V1, V2, V3, V4, V5, and V6) [23].

2.3 Single Lead ECG Monitoring

Recently, wearable physical activity monitoring devices (such as heart-rate monitoring system, accelerometers, pedometers, and multiple-sensor devices) have become very popular among athletes for training optimization. In particular, cardiac monitoring devices are typically used for training optimization in terms of intensity, volume, duration and frequency. They usually measure instantaneous HR and sometimes record HRS [27].

Most prominent wearable devices capture only one of leads of the ECG, whether it is like the apple smart watch, which is worn on the wrist, or athletic devices that are worn across chest. What enhances these devices is that they are capable of connecting to other devices through Bluetooth, where the user is able to read their ECG and detect,for example, their heart rate or any signs of arrhythmia without the continuous need of using complex devices and assistance of a doctor.

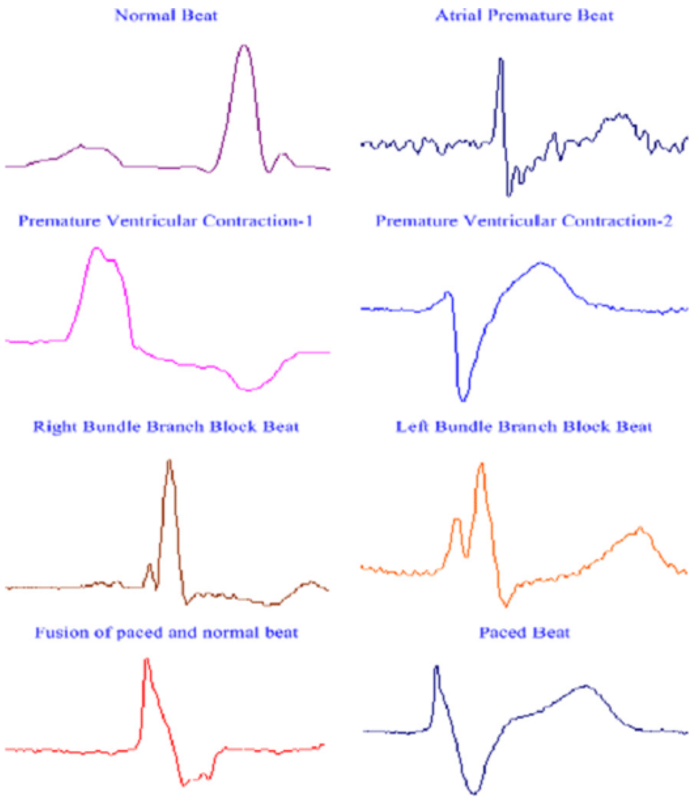

FIGURE 2.1: Typical-arrhythmia-heartbeats-in-time-domain-Lead-II-signal

The problems that arises when classifying single lead ECG signals, is that they provide less information than the 12 lead ECG as it is only one lead, and is more sensitive to noise which results in less readable data for the classifier to be able to detect an AF in the signal.

2.4 Single Lead ECG Signal Processing Techniques

The signal processing module is one of the most important parts to clean an ECG signal. In this module single lead ECG signals are processed in order for real time classification. In this section, the main techniques and methods used to process Single Lead ECG Signals will be presented.

2.4.1 ECG Signal Processing

The preprocessing stage of the ECG signal is crucial as it allows to process raw data into more cleaner data for our classification Machine Learning and Neural Net-

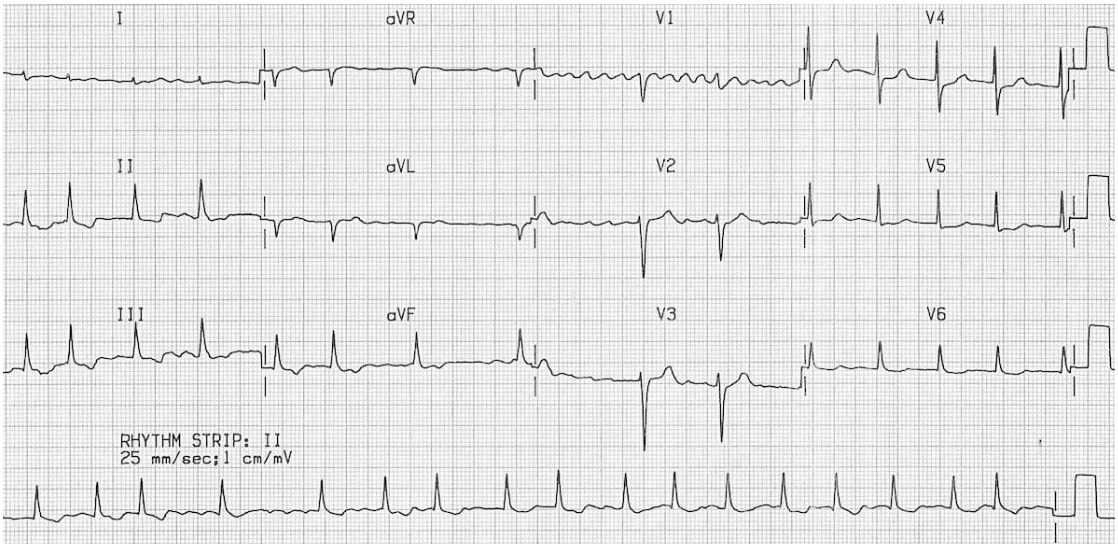

FIGURE 2.2: Atrial Fibrillation (12 Lead signal).

works models. This stage include removing the base line wander, motion artifacts and other interruptions of original recorded signal [32]. In this thesis, these techniques will be used in order to preprocess the Single Lead Ecg signal. Due to wireless transmission, the ECG signal is prone to noise due to its low frequency-band, where it ranges from 0.5-150 Hz, and to improper channel. Additional preprocessing steps include weighted averaging filter and independent component analysis. The filtering and smoothing techniques are applied in preprocessing stage to attenuate P and T waves as well as noise [22].

2.4.1.1 Baseline Wander Removal

Baseline wander (BW) is a low-frequency artifact in electrocardiogram (ECG) signal recordings of a subject [3], which is caused by movement and respiration of the patient. BW removal is a necessary step as it makes the interpretation of ECG recordings difficult. This artefact can be observed where the base axis (x-axis) of a signal appears to 'wander' or move up and down rather than be straight. Since the baseline signal is a low frequency signal, a high-pass filter like Finite Impulse Response (FIR) filtering with a cut-off frequency of 0.5 Hz can be used to estimate and remove the BW [16].

2.4.1.2 Power line Interference Removal

Power line Interference occurs when the patient is not properly grounded obscuring completely the ECG waveform, also another cause is loose contact with the electrodes. Usually this interference is recognizable, because it is characterized by 50 or 60 Hz sinusoidal interference, possibly accompanied by a number of harmonics, which results in poor quality tracings [18]. This can be solved using digital notch filters, which suppress the PLI in ECG signals. Notch filters are usually used to remove a single frequency, where it can be assist to remove the 50 or 60 Hz interference.

2.4.2 ECG Signal Feature Extraction

For ML models, the direct insertion of the observations in the pattern recognition system is not recommended, because this procedure can frequently result in a model with low accuracy and high computational cost, due to the phenomenon know as curse of dimensionality. This phenomenon states that the amount of data needed to properly describe the different output classes increases exponentially with the dimensionality of the feature vector. In the case of a time series like a raw ECG signal, each instant of time that the signal was recorded is taken as a feature. Hence, the dimensionality of the feature vector increases proportionally as the time and sampling frequency of the signal increases.

2.4.2.1 Fast Fourier Transforms

FFT is the simplest way of analyse a signal with the help of Discrete Fourier Transform (DFT) [6]. It is used to convert the ECG signal,in time domain, to an ECG signal in the frequency domain for a more accurate representation of peak values. The QRS complex can be represented by the mathematical summation of a series of sine waves of various frequencies and amplitudes.

2.4.3 ECG Signal Classification Models

Machine Learning (ML) a subset of Artificial Intelligence (AI) field, which revolves around the central idea for computers able to perform tasks without being previously explicitly programmed. This idea is achieved through the development of systems, processes and algorithms [25]. ML algorithms are able to predict the result of future observations after a training period learning from the data features. Data features are common and measurable characteristics for every instance (observation) in the data set, that contain useful information about the discriminatory characteristics of the data [4].

Deep learning refers to a more optimized class of ML techniques, where many layers of information processing stages in hierarchical architectures are exploited for unsupervised feature learning and for pattern classification [24]. Deep Learning networks mimics the human brain, where there are multiple nodes that represent the neurons in out brain. The structure of neural networks (NN) is that they contain multiple layers that are connected to each other, there are three sections of the layers the input layer, the hidden layers, and the output layer. These networks use supervised and/or unsupervised strategies to automatically learn hierarchical representations in deep architectures for classification, there are some weights that need to be considered where NN don't need the same preprocessing pipeline as ML models, as they detect patterns in the data, but at the same time requires large data in order to learn.

In this thesis, we compare 7 models, they are ML, ML, ML, ML, DNN, CNN models, respectively, to predict whether the single lead ECG is an arrhythmia signal.

2.4.3.1 Standard Vector Machine

Support Vector Machine (SVM) was introduced by Vapnik [7], and is used for binary classification. The basic idea is to find a hyperplane which separates the d-dimensional data perfectly into its two classes [9]. SVM is a supervised classification method. The hyperplane that maximizes the geometric distance to the closest data points is needed. This is accomplished by minimizing (subject to the distance constraints) [9].

There functions that are used for pattern analysis called Kernels or kernel methods (also called Kernel functions) and they are used to solve a non-linear problem by using a linear classifier. Three types kernels I will use are linear, polynomial and radial basis function (RBF).

Also there are parameters that are used in order to improve the model, which are C and Gamma coefficients. C is a hyper meter in SVM to control error, where the lower the C means lower error acceptance in separating the data and if we have a larger C means larger error acceptance. Gamma decides that how much curvature we want in a decision boundary. Higher Gamma values mean more curvature, while lower Gamma values mean less curvature, Gamma is usually used with the RBF kernel.

2.4.3.2 Random Forest Classifier

Random Forest algorithm was presented firstly by Breiman [5]. Since then, it has been known as one of the most accurate machine learning algorithms. This supervised learning procedure, influenced by the early work of [1], operates according to the simple but effective "divide and conquer" principle. The Random Forest algorithm is based on decision trees, that are models able to map complex input spaces into simpler, discrete or continuous input spaces, splitting an original problem in several simpler and smaller ones [12].

2.4.3.3 Logistic Regression

Regression techniques are versatile in their application to medical research because they can measure associations, predict outcomes, and control for confounding variable effects [33]. One such method is logistic regression, which measures the individual contribution of each independent variable to the overall influence of a set of independent variables on a binary result. Logistic regression iteratively determines the strongest linear combination of variables with the highest likelihood of identifying the observed outcome using elements of linear regression indicated in the logit scale.

2.4.3.4 K Nearest Neighbor

One of the potential statistical classifiers is the KNN, which is used to categorise objects based on the nearby training examples in the feature space. It is a lazy learning approach where all calculations are postponed until classification and the KNN function is locally approximated. Although a training dataset is necessary, it is only used to fill a sample of the search space with cases whose class is known. For this reason, this technique is also known as a lazy learning algorithm. No actual model or learning is conducted during the training phase.It implies that the training data points are not used to make any generalisations and that the testing phase will require the entire training set. When a case whose class is unknown is offered for evaluation, the algorithm computes its K nearest neighbours, and the class is determined by voting among those neighbours. The training part of the KNN algorithm is highly quick, but the testing phase is expensive in terms of both time and memory [34].

2.4.3.5 Feedforward Neural Networks

In order to build neural networks (NNs), the neurons need to be connected with each other. The simplest architecture of a (NN) is a feedforward structure. The practical learning of the parameters of this network can be accomplished with the backpropagation algorithm. For computational efficiency when learning the Stochastic Gradient Descent is used, which calculates a gradient for a set of randomly chosen training samples (batch) and updates the parameters for this batch sequentially, resulting in a faster learning.

2.4.3.6 Convolutional Neural Network

CNN is another neural network type that can receive raw ECG signals as input. One advantage of CNNs is that they are in-variant to time-domain translation. Typically, in traditional artificial neural networks, each neuron in a layer is connected to all neurons in the next layer, whereas each connection is a parameter in the network. Instead of using fully connected layers, a CNN uses a local connectivity between neurons, a neuron is only connected to nearby neurons in the next layer. This can significantly reduce the total number of parameters in the network.

2.5 Zephyr BioHarness 3.0 (BH3)

BH3 is a physiological monitoring telemetry device developed by Zephyr designed for training optimization of professional athletes.It is a wireless chest-based wearable device, capable of real-time and long-distance recording of various physiological parameters, including heart rate, respiratory rate, core temperature, activity levels and posture [26]. The module is an adjustable belt, which is chest strap that contains a skin conductive electrodes to capture the heart rate, ECG and respiratory signals through the recording of cardiac electric impulses, and produces an output in beats per minute.

Chapter 3

Implementation

In this chapter are presented the experimental procedure used to develop an Real Time Atrial Fibrillation detector. Here is introduced the tools used to develop the signal processing steps, as well as to train the reliability of the evaluated models.

3.1 Laptop Specification

The laptop used for implementation is an Asus Vivobook X512FA-X512FA, its processor is Intel Core i7-8565U with CPU at 1.80GHz and RAM of 12.0 GB. System type 64-bit operating system, x64-based processor.

3.2 Data Processing Tools

There are a number tools that were used in this work: the array management module Numpy, the data manipulation and analysis module Pandas, the data visualization module MatPlotlib, the scientific tools module Scipy, the deep learning framework Keras, the machine learning framework Scikit-learn, the GUI toolkit PYQT5 and a package to tune the neural networks, KerasTuner.

3.2.1 Numpy Module

Numpy is an array management module that provides sophisticated functions to perform operations with multidimensional arrays. Besides that, Numpy scripts are internally performed in C language, so the use of Numpy arrays gives a faster code than using standard Python objects [14] .

3.2.2 Pandas Module

Pandas is a module that provide high-performance and easy-to-use data structures. It is built on top of numpy, which provies easier visualization of Numpy arrays, data manipulation and analysis [29].

3.2.3 Matplotlib Module

Matplotlib is a mature and popular plotting package that provides publication-quality 2D and 3D plotting [29].

3.2.4 Scipy Module

Scipy is a Python-based ecosystem for open-source software for mathematics, science and engineering, it is a collection of numerical algorithms and domain-specific toolboxes, including signal processing, optimization and statistics [38].

3.2.5 Scikit-Learn Module

Scikit-learn is a powerful module with functions that are used for data mining, data analysis and machine learning. It has several regression, classification and clustering algorithms, and it is most used for its easy building of machine learning models [30].

3.2.6 Keras Module

Keras is a high-level, deep learning API developed by Google for implementing neural networks. It is written in Python and is used for to make the implementation of neural networks simpler. It is built on top of Tensorflow, which a low level deep learning library, but is more complex to use for building neural networks. Due to being a high level API, Keras is slower than other deep learning frameworks, but extremely beginner-friendly. [8].

3.2.7 KerasTuner Module

KerasTuner is an easy-to-use, scalable hyperparameter optimization framework that solves the pain points of hyperparameter search[28]. This module is used in order to tune the parameters of the implemented neural networks, where after configuring the range of neurons for each layer the tuner searches for the optimized model using various search algorithms.

3.2.8 HeartPy Module

HeartPy was developed to help analyse noisy heart rate data collected in driving settings (both simulated and on-road), and designed to be resistant to typical noise patterns [35]

3.3 Data Streaming And GUI Tools

In order to create a Graphical User Interface (GUI) and the connection between the Zephyr BioHarness sensor and the laptop used for implementation, a few tools were used: the Lab Streaming Layer (LSL) module and its python API PYLSL for near real time data streaming, and PYQT5 module for building the GUI.

3.3.1 Lab Streaming Layer Module

The lab streaming layer (LSL) is a system for the unified collection of measurement time series in research experiments that handles both the networking, time-synchronization, near real-time access as well as optionally the centralized collection, viewing and disk recording of the data. The reason it is used is because its real-time exchange of time series between applications. In addition, it has different language APIs and support multiple devices including the Zephyr Bioharness Sensor.[19].

3.3.2 PYQT5 Module

PyQt is a set of Python binding for the Qt Framework from C++ that can be used to create Desktop Graphical User Interfaces, which gives you all the complex functionalities of C++ Qt while providing the simple development in Python. It is used for creating large-scale GUI-based programs, in addition, provides the freedom to create GUIs while also providing a lot of good pre-built designs. [31].

3.4 PTB-XL - Atrial Fibrillation Detection

In the thesis, a subset of the PTB-XL Dataset is used as the offline data to evaluate the proposed model. This dataset is the to-date largest freely accessible clinical 12-lead ECG-waveform dataset comprising 21837 records from 18885 patients of 10 seconds length [40]. The normal sinus rhythms (labeled as SR), Atrial Fibrillation (labeled as AF) and all other VARIOUS Arrhythmias summed up into one class only (labeled as VA). The V1 lead was extracted in order to become suitable with the lead that the Zephyr Bioharness Wearable detect, as the V1 lead is the chest lead.

3.5 Offline Training Phase

In this phase, the PTB-XL data set is restructured, and where preprocessing along with feature extraction techniques are used to train the various models. Their accuracies are compared on the dataset, and the used neural networks was tuned even further.

3.5.0.1 Data Set Structuring

In order to train our models on the same lead as the Zephyr Bio-harness Sensor, the V1 lead, as this is one of the chest leads, was extracted from the dataset. The information csv file was used to know the classification of each subject and their 12 lead ECG, then the V1 lead was extracted from them and gathered along with their labels: 0 for normal sinus rhythms and 1 for Atrial Fibrillation rhythms.

3.5.0.2 Preprocessing

As a person's movement can the basewander effect on their ECG signals, the removal of the baseline is used to adjust the signal along the x-axis. This enables more accurate detection of the peaks, and whether there is any distortions in the waves.

3.5.0.3 Feature Extraction

Due to the time samples being the features, each ECG signal was 5000 time samples. To perform dimensional reduction, Fast Fourier Transform was used, where the time samples were reduced to 2500 and instead of being in the time domain, the signal was converted to the frequency domain for better detection of the peaks.

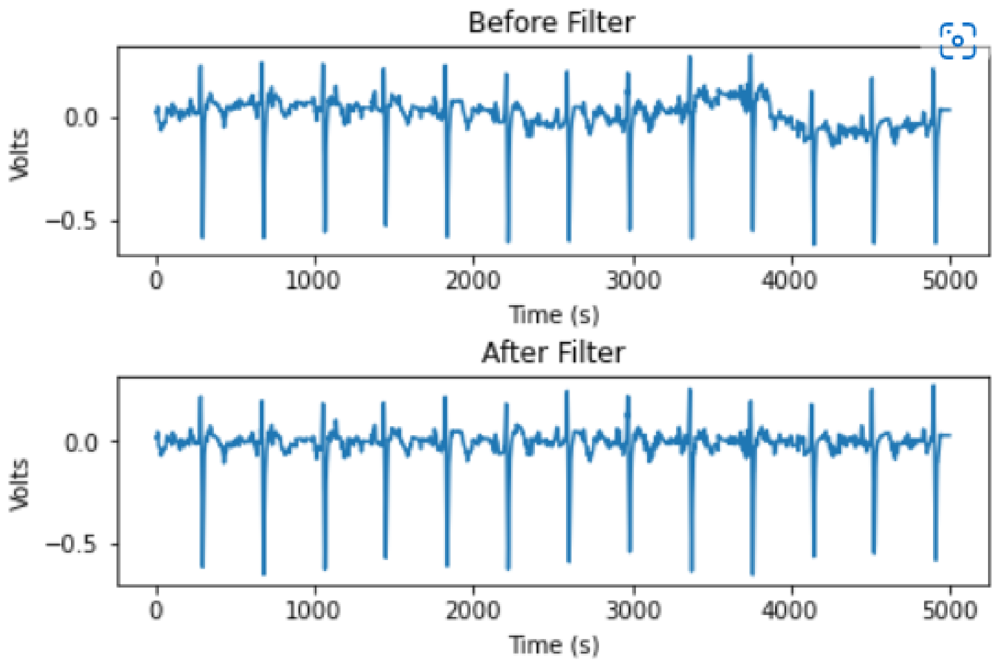

FIGURE 3.1: Filtering

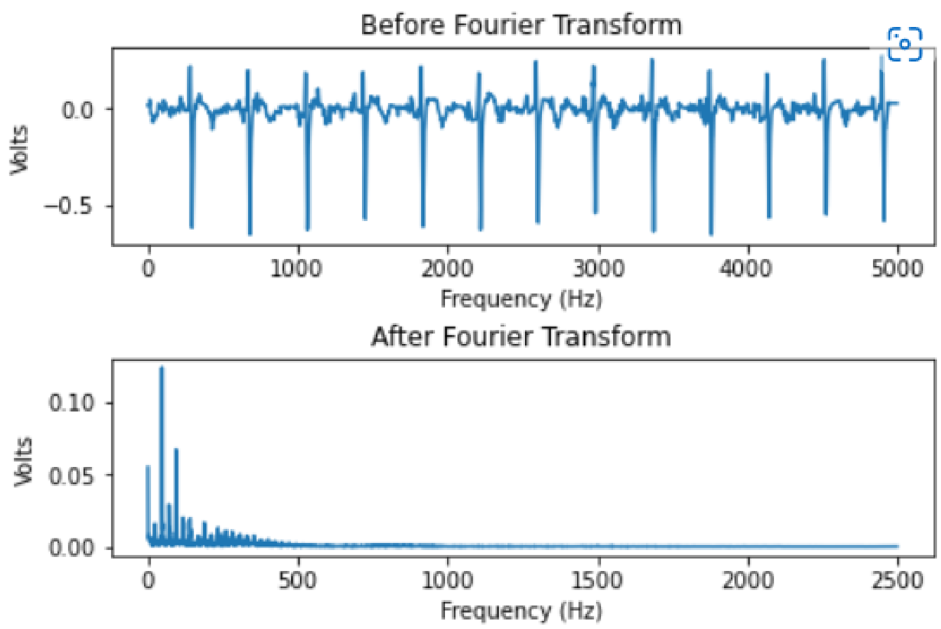

FIGURE 3.2: Feature Extraction

3.5.1 Machine Learning Approach

3.5.1.1 Classification

As the output is a binary output, where a normal sinus rhythm would be 0 and an Atrial Fibrillation would be 1 and each signal has its label, the models chosen where supervised models. The models used were SVM with Linear Kernel and C=4.5 and gamma=0.015, SVM with Polynomial Kernel and C=4.5 and gamma=0.015,SVM with RBF Kernel and C=4.5 andgamma=0.015, Random Forest Classifier, Logistic Regression, K Nearest Neighbor. The K Nearest Neighbor performed the best of them.

3.5.2 Deep Learning Approach

3.5.2.1 Classification

In order to evaluate all models, Deep Learning was used to see whether it evaluate better than the machine learning models or not. Neural Networks used were Feed Forward Neural Network, Feed Forward Neural Network with Keras Tuner, Convolutional Neural Network with 5x5 filters, Convolutional Neural Network with Keras Tuner. With the Feed Forward Neural Network with Keras Tuner performing best in accuracy as well as training time.

3.6 Online Testing Phase

During the online phase, the sensor is connected to the laptop in order to display real time plotting, as well as near real time classification. Also this phase is used to compare the trained models, and find which would result in a false positive reading, where a model would classify the signal incorrectly.

3.6.1 Single Lead ECG Sensor

To be able to record the single lead ECG signal, the Zephyr BioHarness 3.0 (BH3) wearable was connected to the laptop using Lab Streaming Layer(LSL), to initialize the data stream for near real-time access. Also the python interface for LSL is used in order to be compatible with using the models.

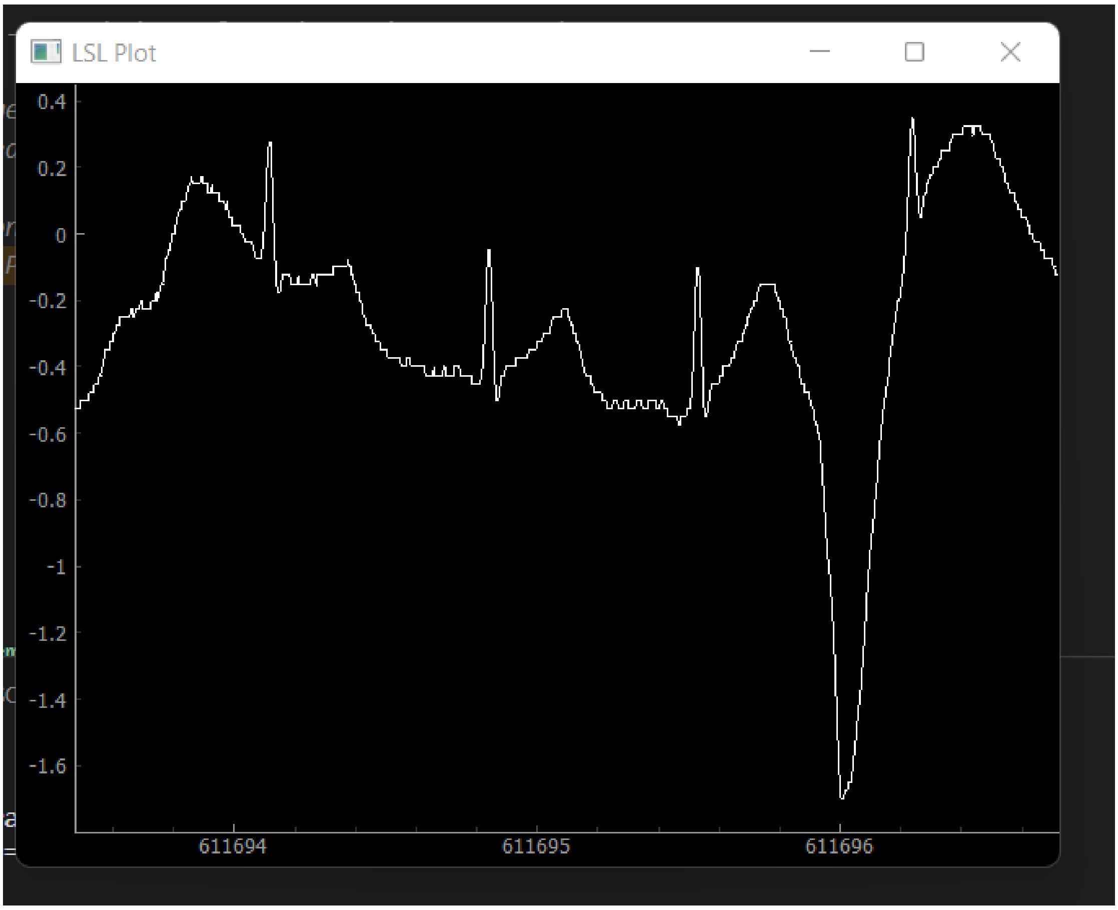

FIGURE 3.3: Real Time Plotting

3.6.2 Real Time Plotting

The GUI was built using PYQT5 in order to display the real time plotting of a person's ECG signal, seen the figure below.

3.6.3 Real Time Prediction

In order for the real time data to be similar to the data in the dataset used during the offline phase, a simple buffer was implemented to gather the a signal within an array of length 5000. Afterwards, the data is preprocessed asynchronously by removing the baseline wander then applying the Fast Fourier Transform, To compare the models, all 6 models are used to predict to the signal.

Chapter 4

Results

4.1 Result Accuracies

This chapter displays the comparisons between the models during offline phase, and which models performed best during the real time. From tables 4.1, the K Nearest Neighbor performed best out of all the Machine Learning model. The Convolutional Neural Network performed poorly and trained the longest time, while the Feed Forward Neural Network performed better than Convolutional Neural Network in terms of accuracy and training speed, in addition it outperformed the K Nearest Neighbor.

TABLE 4.1: Machine Learning Model Accuracies on the PTB-XL Dataset

Model	Accuracy
SVM, Linear Kernel,C=4.5,gamma=0.015	71.3%
SVM, Polynomial Kernel,C=4.5,gamma=0.015	66.9%
SVM, RBF Kernel,C=4.5,gamma=0.015	67%
Random Forest Classifier	66.95%
Logistic Regression	67.1%
K Nearest Neighbor	81.1%

TABLE 4.2: Deep Learning Model Accuracies on the PTB-XL Dataset

Model	Accuracy
Feed Forward Neural Network	79%
Feed Forward Neural Network with Keras Tuner	88.48%
Convolutional Neural Network with 5x5 filters	66.95%
Convolutional Neural Network with Keras Tuner	70%

Chapter 5

Conclusion and Limitations

The work presented here shows, in details, the study and implementation of the real time cardiac atrial fibrillation detection is possible. Studies and implementations about the main preprocessing, feature extraction and classification techniques were developed. Using the tools presented the software modules were developed in order to process and classify the Single Lead ECG signal from a wearable sensor. Functions to arrange data were generated, allowing the analysis of the ECG signal to become in a more flexible manner. Based on the results obtained after Baseline Wander Removal and Fourier Transform, it is possible to conclude that, in this case, that they are efficient but not the most optimal techniques in processing the ECG signal. In addition, the time spent by these methods to perform the tasks were far greater than the other approaches, where the obtained accuracies of 71.3%, 66.9%, 67%, 66.95%, 67.1% , 81.1% , 79% , 88.48%, 66.95% , 70% , using, respectively, SVM Linear Kernel, SVM, Polynomial Kernel, SVM, RBF Kernel, Random Forest Classifier, Logistic Regression, K Nearest Neighbor, Feed Forward Neural Network, Feed Forward Neural Network with Keras Tuner, Convolutional Neural Network with 5x5 filters , Convolutional Neural Network with Keras Tuner. It is important to note that thereis room for improvements in the developed system, since just some of the hyperparameters were tested in the neural network classifiers: number of neurons in hidden layer. In the same way, there is the possibility to perform other changes, such as trying to extract the QRS intervals, along the other intervals of the signal. In addition some limitation, where another more specific sensor can be used that can be for ECG signal recording.

Chapter 6

Future Work

Detecting cardiac problems such as Atrial Fibrillation is an important aspect for drivers, as it can prevent multiple accidents caused by these sudden problems. Future works can be approached like using mmwaves sensors in order for non contact Atrial Fibrillation, resulting in a more convenient way for the drivers instead of wearing a wearable device such as Zephyr Bioharness which was proposed in the in this study. Using mmwave sensors can be integrated with an autonomous vehicle for real time detection for the passengers within in, which provides a prominent way. But still there are only a number of researches in the field, which leads to more development in this area.

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