School of Computing
FACULTY OF ENGINEERING AND PHYSICAL SCIENCE

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Final Report

Arrhythmia Diagnosis from ECG by Phase Space Analysis and Convolutional Neural Networks

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The candidate confirms that the following have been submitted*:*

Items	**Format**	**Recipient(s) and Date**
Online Report	*PDF*	*SSO(10/05/21)*
Software Source Code	*GitLab Repository*	*Supervisor, assessor(10/05/21)*

Type of Project: Exploratory Software(ESw)

The candidate confirms that the work submitted is their own and the appropriate credit has been given where reference has been made to the work of others.

I understand that failure to attribute material which is obtained from another source may be considered as plagiarism.

(signature of student) Xiaohan Mei

Summary

Currently, there is no research in medical science and computer science to diagnose arrhythmias by phase space reconstruction from ECG and convolutional neural network model. This paper is the first to research on this problem and try to figure out the possibility of how this approach can be used to assist diagnosis of arrhythmias. The following article will discuss the whole process of conducting the research including background research, analysis and design, development and implementation, evaluation and results, discussion and conclusion and ethics.

Acknowledgements

I have received a great deal of support and help in the process of conducting this project.

First, I really appreciate my supervisor, Dr Toni Lassila. He has always been patient and energetic to answer my question, guide me how to solve the problem, which contributes a lot to the completeness of my project. Also, I want to thank my assessor, Dr Mehmet Dogar for his valuable feedback on my intermediate report, and advice on how to conduct the final report.

Secondly, I would like to thank my friend who is a medical student. He taught me a lot of knowledge on medical science and also gave me valuable advice.

Lastly, I would like to thank my parents for their support in the process of conducting the project.

Content

Chapter 1 Introduction

1.1 Introduction

An arrhythmia is a problem with the rate or rhythm of the heartbeat. Arrhythmia has two types which are ventricular fibrillation(VF) and atrial fibrillation(AF). The project mainly focuses on the diagnosis of atrial fibrillation(AF). In clinical practice, ECG is used to diagnose the arrhythmia.[1] According to the World Stroke Organization, atrial fibrillation is the most frequent cardiac arrhythmia. After analyzing the data of atrial fibrillation in 195 countries and regions in the world, China, Israel and Canada found that there were 37.57 million patients with atrial fibrillation, 3.05 million new cases of atrial fibrillation and 287000 deaths due to atrial fibrillation in 2017. 65~69 years old is the highest incidence rate of atrial fibrillation, 85~89 years old is the highest mortality rate of atrial fibrillation. After adjusting for gender, age, height, weight, systolic and diastolic blood pressure, heart failure, myocardial infarction, diabetes, antihypertensive drugs, current smokers and income groups, the prevalence of atrial fibrillation in China and Southeast Asia was the highest in the world. In general, the number of new cases of atrial fibrillation in men was more than that in women, but the number of deaths due to atrial fibrillation in women was more than that in men. [2] Fortunately, stroke can be prevented by the cardiac pacemaker, operation and defibrillation. Therefore, the correctness of diagnosis of atrial fibrillation will make a huge difference.

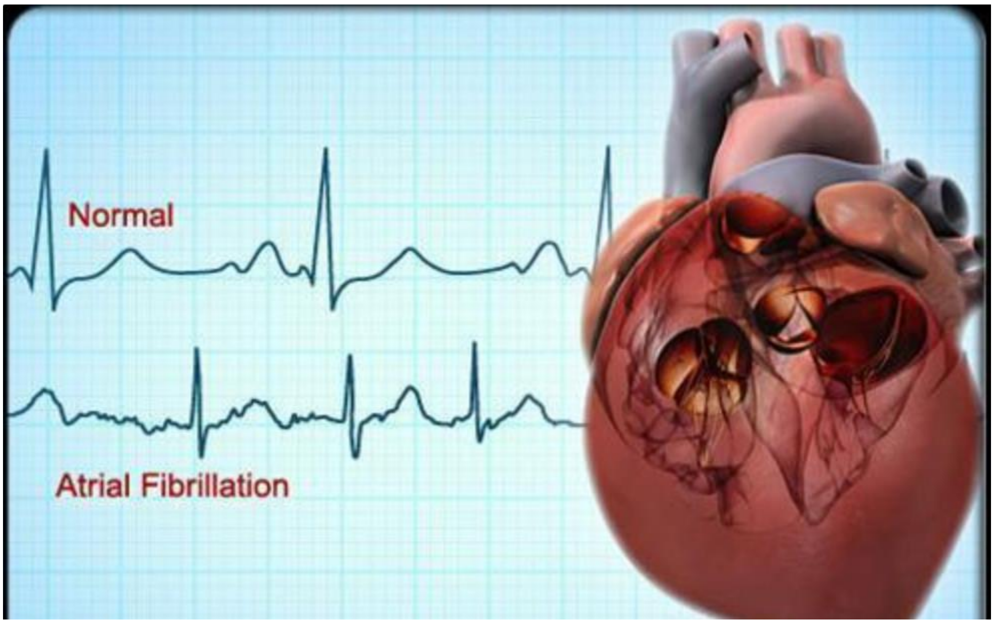


Figure 1.1 ECG comparison between normal rhythm and atrial fibrillation

Atrial fibrillation is classified into four subtypes: new-onset AF, paroxysmal AF(terminate spontaneously), persistent AF(not terminate spontaneously) and permanent AF(sinus rhythm or normal rhythm cannot be maintained). Research shows that it is highly likely that paroxysmal AF may evolve into permanent AF. Furthermore, in clinical practice, if patients do not have apparent symptoms of AF, AF may be largely neglected. Therefore, an automatic detection system will help monitor AF and improve the timely diagnosis and treatment of AF.

A lot of researches have investigated how the neural networks could improve the diagnosis of arrhythmia. Fang et al.[3] proposed that these researches found it arduous to observe the features in ECG since ECG is a random nonlinear dynamic system. In situations of noise, the features are even harder to be extracted. Due to the features of CNN, a fully automated diagnosis system can be built to solve this problem. Therefore phase space analysis of ECG will be implemented together with convolutional neural networks to see if we can improve the diagnosis of arrhythmia.

1.2 Aim

This project will use the dataset of ECG and explore an appropriate method of phase-space reconstruction of the dataset. Also, This project will be investigating how the new development of fully automated software using the Machine Learning branch of convolutional neural networks could assist the arrhythmia diagnosis from the reconstructed phase space(RPS) of ECG.

1.3 Objective

The objectives for the project are as follows:

- Review the papers of diagnosis of arrhythmia.
- Implement an appropriate method of phase-space analysis of ECG.
- Design and implement a convolutional neural network model that could be used on training.
- Evaluate the performance of this model according to several measures.

1.4 Deliverables

- Source code for the exploratory software.
- A report explaining the research, planning and the implementation of the software.
- Instructions explaining the usage and operation of the software.

1.5 Gantt Chart

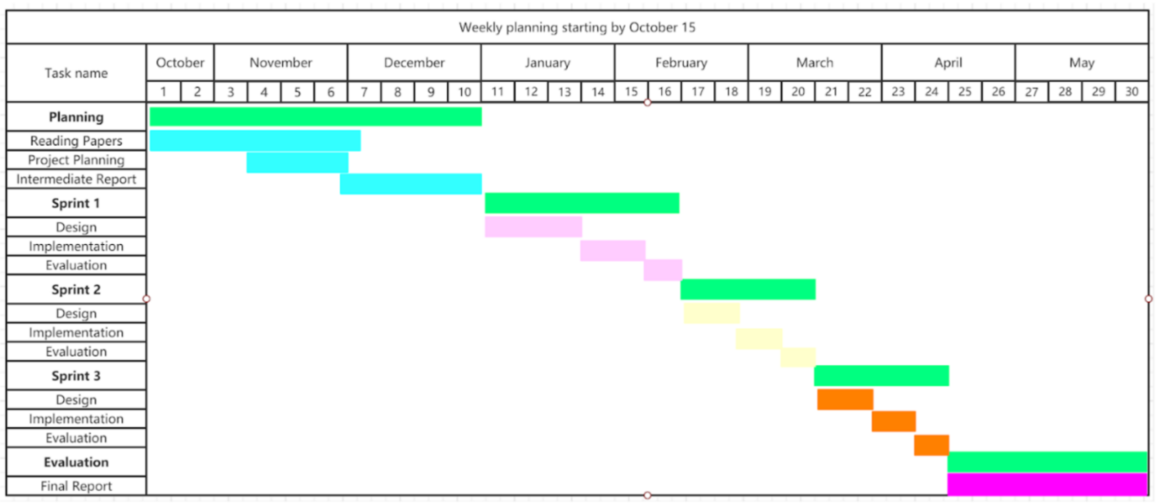


Figure 1.2 (a) Initial plan

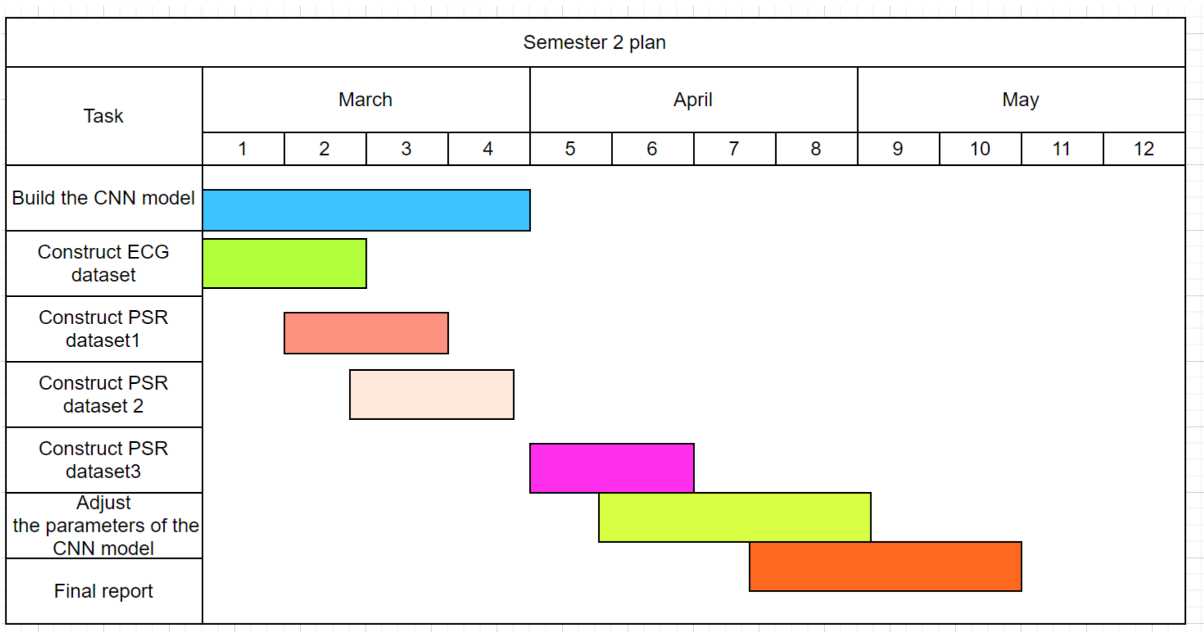


Figure 1.2(b) Semester 2 plan

1.6 Project Methodology

Considering that this is an individual project and time length is limited, Agile method will perfectly meet our needs. Agile project management will be applied in the development of the software. Compared with the Waterfall Model, Agile allows us to deliver the most valuable software early. Also, since the model is expected to be revised and redesigned to reach a better accuracy, Agile processes welcome changes in our design.

GitLab will be used to ensure version management and changing management. Branches will be utilised to encourage modularity in the development. The GitLab repository is available at https://gitlab.com/Leomxh/individual-project.

1.7 Risk Management Strategy

Risk	Strategy
The time required to develop the software is underestimated.	Since we use Agile project management, the most valuable software will be ensured first and then improve our software which has higher accuracy.
Loss of work	Gitlab will be used to have version management, change management. Therefore, loss of work can be possibly avoided.

Chapter 2 Background Research

2.1 Arrhythmia

2.1.1 Definition of Arrhythmia

An arrhythmia is an uneven heartbeat. It means your heart is out of its usual rhythm.

2.1.2 Types of Arrhythmias

Arrhythmias are divided up by where they happen. If they start in the ventricles, or lower chambers of your heart, they’re called ventricular. When they begin in the atria, or upper chambers, they’re called supraventricular.[4] Doctors also group them by how they affect your resting heart rate. Bradycardia is a heart rate of fewer than 60 beats per minute. Tachycardia is more than 100 beats per minute.

2.1.3 Electrocardiograph(ECG)

In a heartbeat cycle, the heart will contract regularly and produce electrical stimulation after external stimulation, and then relax after the stimulation disappears. In this process, a large number of myocardial cells will produce regular potential changes. The potential change curve can be recorded through the electrode(the same meaning as lead), and the curve is amplified, which is the clinical ECG, That is ECG. ECG is a kind of weak bioelectrical signal with the following characteristics:

(1) Weak: the amplitude of ECG signal is in the range of 10uv-5mv, which is a low amplitude signal.

(2) Instability: ECG signal is constantly changing and easily contaminated by the noise or interference in the environment, resulting in a lot of valuable information of ECG signal is submerged, it is difficult to detect, and different individuals have different ECG at different times, even if the same individual has different waveform in different physiological states.

(3) Low frequency: the frequency range of ECG signal is mainly in 0.05-100hz, and the main energy is concentrated in 0.5-40hz.

The cardiac cycle can be divided into several features. The main features are the P wave, PR interval, QRS complex, Q wave, ST segment, and T wave. Each of these components represents the electrical activity in the heart during a portion of the heartbeat [5]. The P wave represents the depolarization of the atria. Therefore, in the project, this feature is mainly focused on.

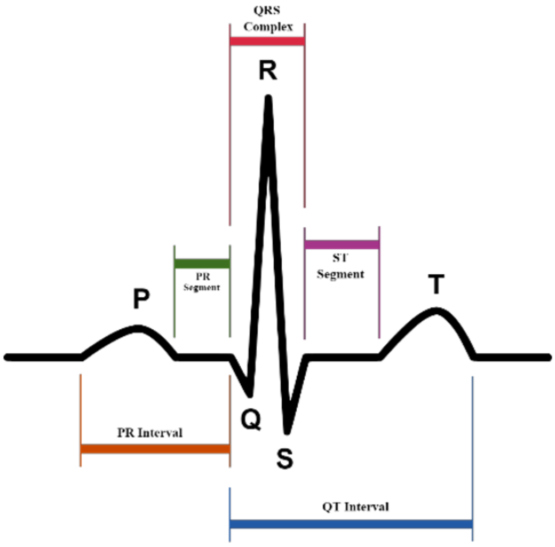


Figure 2.1 A normal heartbeat cycle of ECG

2.2 Phase Space Analysis

2.2.1 Chaos Theory

Chaos in a scientific sense is not a simple disorder or chaos, but a state of order with rich inner layers without obvious period and symmetry. Prigogine, the Nobel Laureate in physics, pointed out that chaos and order coexist. In a chaotic system, order spontaneously emerges from disorder and chaos through a self-organizing process. Chaotic systems have nonlinear characteristics, but they are not the same. The linear process is periodic, while the nonlinear system is an incomplete linear process, which contains linear, random (completely irregular) and chaos. Chaos is a dynamic transition state between linear and random, which is the main behavior mode of a nonlinear system. Like complexity, chaos also has irregularity, and the two kinds of irregularity often occur at the same time, but they have completely different concepts. Complexity usually refers to the irregularity of space form, while chaos means the irregularity of time rhythm. Chaos is shown in the dynamic change of time series.

According to modern research, the human body is a large number of linear and nonlinear relations, and the heart is one of the most complex nonlinear dynamic systems. The anatomical fractal like structure is the physiological basis of the nonlinear rhythm characteristics of a healthy heart. Coronary artery and vein, chordae tendineae connecting mitral valve and tricuspid valve with myocardium, and Schipper system all have fractal like structures. Many experimental observations show that the physiological rhythm of the heart is not only different from periodic oscillation, but also not completely random. It has chaotic characteristics and appears to be random in the deterministic system. The human physiological rhythm represented by the long-time surface ECG signal shows the self similar characteristics of fractal structure in different time scales. The phase space diagram shows that its dynamic characteristics are close to the strange attractor, and the change pattern of heart rate conforms to the chaotic dynamic process.

2.2.2 Attractor

Strange attractor. The behavior characteristics of chaotic systems can also be expressed in geometric form, which is called "strange attractor" or "chaotic attractor". The strange behavior of chaotic attractors was first discovered by Japanese scholar Yoshisuki Ueda in 1961. Strange attractor is a kind of attractor with fractal structure and phase space structure. Its dimension is related to the complexity of the system, which is commonly used to quantitatively characterize the geometry of attractors. Another quantitative characterization of strange attractors is Lyapunov exponent (Lyapunov exponent). The dimension of strange attractors can be obtained from Lyapunov exponent. Some scholars summarize that chaos reflects the dynamic characteristics of the system, and strange attractor represents the geometry of the attractor. The attractor of chaotic systems has singular geometric properties, which is different from the periodic attractor of periodic systems. Mathematicians call its dimension fractal dimension. Lyapunov exponent and dimension are two measures for quantitative evaluation of dynamic systems, which measure the regularity degree and geometric structure of dynamic behavior respectively. They are widely used to evaluate chaotic characteristics.

2.2.3 Phase Space Reconstruction

ECG is a class of nonlinear signals and its unpredictable, stochastic time behavior and it is chaos. PSR[6] theory is the base for chaotic time series. Two key points were mentioned in Book Analysis of Observed Chaotic Data[17]: Chaos is irregular in time and slightly predictable and Chaos has structure in phase space. Therefore, PSR is expected to provide an approach to extract some features, rules in ECG. Point in the phase space represents the state in chaos and trajectory represent the times change.

The most famous theory for PSR is Takens' time-delay embedding theorem. Suppose we have a dynamical system x(n). Then the delayed vector y(n) can be constructed in a multidimensional phase space as follows: $\mathbf{y(n)=[x(n),x(n+\tau),x(n+2\tau),\ldots,x(n+(d-1)\tau)]]}$, where d is the embedding dimension and $\boldsymbol{\tau}$ is the embedding delay. The central issues in

Takens' theorem is to find what time delay τ to use and what dimension d to use.

2.2.4 Two-dimensional Method

Many science fields such as weather, physics have applied phase space reconstruction and convolutional neural networks together to solve a problem and the results have proved the method to be effective. Usually a two-dimensional reconstructed phase space will be used since it is easier for image processing.

George Koulaouzidis et al.[7] conducted a study to develop a statistical index based on the PSR of the ECG for the accurate and timely diagnosis of ventricular arrhythmia. They also pointed out that a closed trajectory can be observed in healthy people(figure 2.2). Also, the PSR technique is sensitive to detect arrhythmia and discern certain morphological changes in ECG. In the proposed method, a 20ms delay was selected and time segment is defined as a window of 10 ECG, image standard was a high resolution gray-scale image of pixel size 1024 × 1024.

Figure 2.2 Space phase reconstruction of 10 heart beats form a sinus rhythm ECG

2.2.5 Three-dimensional Method

Yanjun Li et al. proposed a novel approach to phase space reconstruction of single lead ECG for QRS complex detection.[8] The value of τ is very difficult to select because there is little theory of how τ can be derived. So a three dimensional approach is created in this paper. From (x, y, t), the first two coordinates (x, y) were situated in the x-y coordinate system, where x represents the amplitude of the ECG and y presents the first order difference of x. Usually the QRS complex is the most obvious waveform due to its highest amplitude, and therefore, the largest semi-circle in the RPS is usually derived from the QRS complex. The location of the QRS complex in the original ECG is determined by the time coordinate t that corresponds to the largest semi-circle in the x-y coordinate system. The paper also summarized three advantages over the delay coordinate mapping, namely, two-dimensional method.

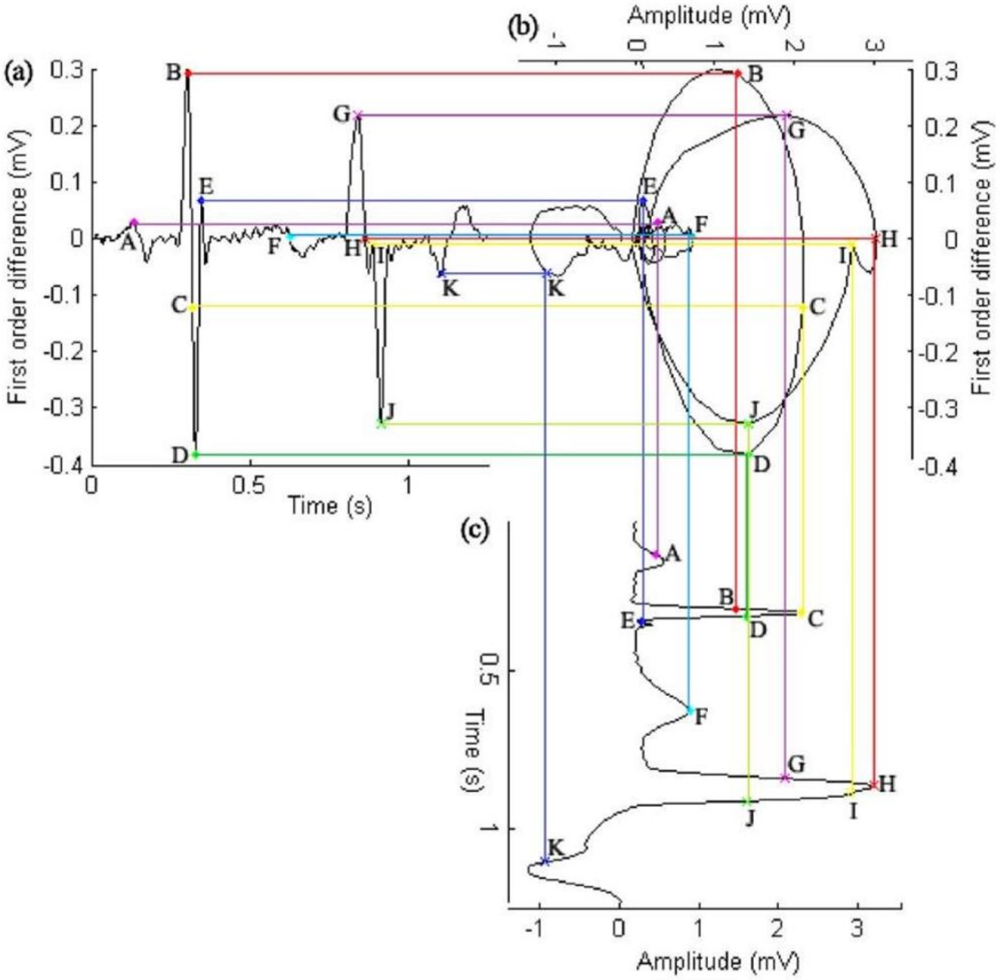


Figure 2.3. ECG phase space reconstruction with the two-dimensional coordinate system, (a) the first order difference y, (b) the x-y phase coordinate system, (c) the amplitude x.

2.3 Machine Learning

2.3.1 Convolutional Neural Network

In deep learning, a convolutional neural network has a better ability on image classification and most commonly applied to analyzing visual imagery. There are not many researches based on 2D-CNN regarding arrhythmia diagnosis since ECG itself is one dimensional signals and this research is of great value. Tae Joon Jun et al. proposed a 2-D convolutional neural network for ECG arrhythmia classification.[9] By transforming one-dimensional ECG signals into two-dimensional ECG images, noise filtering and feature extraction are no longer required. In addition, training data can be enlarged by augmenting the ECG images which result in higher classification accuracy.

They also pointed out one advantage of using CNN. So far ECG arrhythmia detection system are vulnerable to noise signals because ECG is one-dimensional signal and therefore the dimension degree is equal to degree of the classification. However, when the ECG signal is treated as the two-dimensional image, the proposed CNN model can automatically ignore the noise data while extracting the relevant feature map throughout the convolution and pooling layer. According to their results, they have reached 99.05% accuracy, which outperforms many other methods like SVM, RNN, 1D CNN.

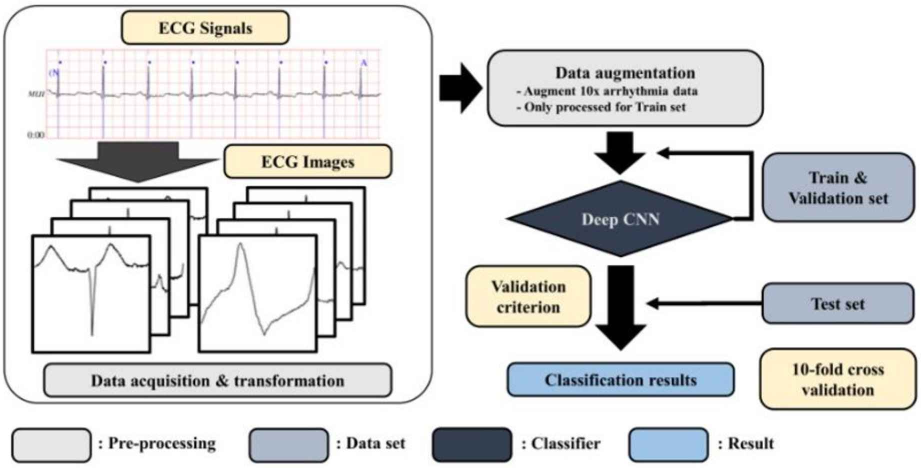


Figure 2.4 Overall procedures processed in ECG arrhythmia classification

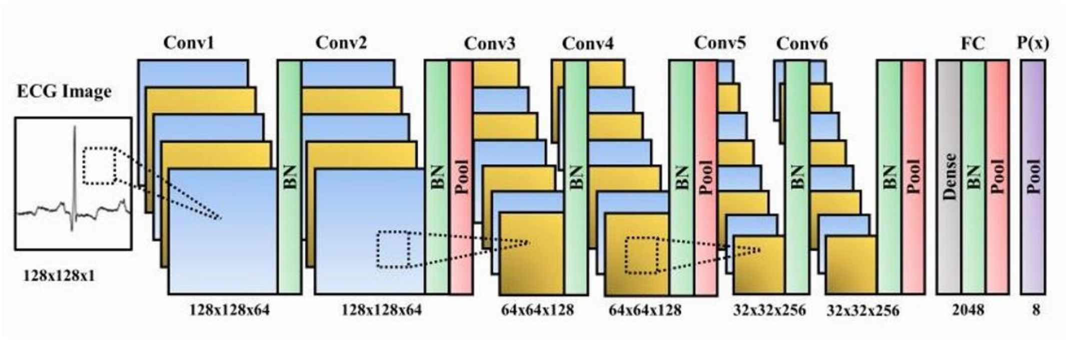


Figure 2.5 The architecture of proposed CNN model

Shu Lih Oh et al. proposed an approach of 1D CNN.[10] They propose an automated system using a combination of convolutional neural network (CNN) and long short-term memory (LSTM) for diagnosis of five arrhythmia types on ECG signals. The novelty of this work is that we used ECG segments of variable length from the MIT-BIT arrhythmia physiobank database. The proposed system achieves a high accuracy of 98.10%.

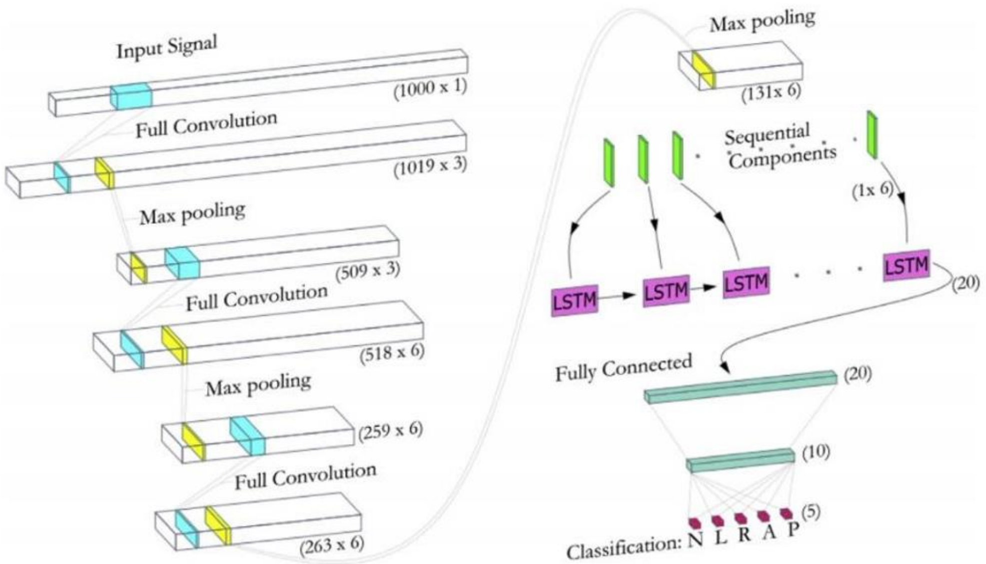


Figure 2.6 An illustration of the proposed CNN-LSTM architecture

2.3.2 Other methods

Usha Desai et al. proposed an approach to diagnosis of ECG for arrhythmia classification.[11] The approach has three central parts. The first part is Discrete Wavelet Transform which is effective for nonlinear feature extraction. Second part is independent Component Correlation Algorithm, which has been used in signal processing very often.

The third part is SVM which achieves a result of 98.49% accuracy.

Akin et al. present a resampling strategy based Random Forests (RF) ensemble classifier to improve diagnosis of cardiac arrhythmia.[12] There are two central procedures: (i) developing a feature selection algorithm for arrhythmia dataset (ii) applying random forest method to classify the types of arrhythmias and evaluate the results. The best accuracy they reached is 90.0%.

2.4 Dataset

2.4.1 MIT-BIH

At present, there are four internationally recognized standard databases: MIT-BIH (Massachusetts Institute of technology Beth Israel Hospital Database), AHA (American Heart Association) and CSE (common standards for quantitative electrocardiography), CSE database, European ST-T database.

At present, the most widely used and widely recognized database is MIT-BIH arrhythmia database. This database contains all kinds of ECG signals and is rich in quantity(figure 2.8), which provides experimental data for the automatic classification of ECG signals in this paper. The database is described in detail below.

MIT-BIH arrhythmia database 48 ECG records, and the duration of each record is 30 minutes. The records came from 25 men and 22 women. For each record, there are two channels of signals. The first channel is usually MLⅡ lead(record 102 and 104 is V5 lead); The second channel is usually V1 lead(some are V2 lead or V5 lead, among which record 124 is V4 lead). In order to keep the consistency of lead, MLⅡ lead is often used in research.

<table>
<tr><td>0</td><td></td><td>No TQRS</td></tr>
<tr><td>1</td><td>N</td><td>Normal beat</td></tr>
<tr><td>2</td><td>L</td><td>Left bundle branch block beat</td></tr>
<tr><td>3</td><td>R</td><td>Right bundle branch block beat</td></tr>
<tr><td>4</td><td>a</td><td>Aberrated atrial premature beat</td></tr>
<tr><td>5</td><td>V</td><td>Premature ventricular contraction</td></tr>
<tr><td>6</td><td>F</td><td>Fusion of ventricular and normal beat</td></tr>
<tr><td>7</td><td>J</td><td>Nodal (junctional) premature beat</td></tr>
<tr><td>8</td><td>A</td><td>Atrial premature beat</td></tr>
<tr><td>9</td><td>S</td><td>Premature or ectopic supraventricular beat</td></tr>
<tr><td>10</td><td>E</td><td>Ventricular escape beat</td></tr>
<tr><td>11</td><td>j</td><td>Nodal (junctional) escape beat</td></tr>
<tr><td>12</td><td>/</td><td>Paced beat</td></tr>
<tr><td>13</td><td>Q</td><td>Unclassifiable beat</td></tr>
<tr><td>14</td><td>~</td><td>Signal quality change</td></tr>
<tr><td>15</td><td></td><td>Not specified</td></tr>
<tr><td>16</td><td>|</td><td>Isolated QRS-like artifact</td></tr>
<tr><td>17</td><td></td><td>Not specified</td></tr>
<tr><td>18</td><td>s</td><td>ST change</td></tr>
<tr><td>19</td><td>T</td><td>T-wave change</td></tr>
<tr><td>20</td><td>*</td><td>Systole</td></tr>
<tr><td>21</td><td>D</td><td>Diastole</td></tr>
<tr><td>22</td><td>"</td><td>Comment annotation</td></tr>
<tr><td>23</td><td>=</td><td>Measurement annotation</td></tr>
<tr><td>24</td><td>p</td><td>P-wave peak</td></tr>
<tr><td>25</td><td>B</td><td>Left or right bundle branch block</td></tr>
<tr><td>26</td><td>^</td><td>Non-conducted pacer spike</td></tr>
</table>

Figure 2.8 Annotations in MIT-BIH database

2.4.2 The 2017 PhysioNET/CinC Challenge

The 2017 PhysioNet/CinC Challenge is raised by PhysioNet in order to diagnose arrhythmias by analysing the single short ECG lead recording (between 30 s and 60 s in length). The dataset contains four types normal rhythm, atrial fibrillation, noise and others.[14]

ECG recordings, collected using the AliveCor device, were generously donated for this Challenge by AliveCor. The training set contains 8,528 single lead ECG recordings lasting from 9s to just over 60s (see Table 2) and the test set contains 3,658 ECG recordings of similar lengths. The test set is unavailable to the public and will remain private for the purpose of scoring for the duration of the Challenge and for some period afterwards.

Table 2: Data profile for the training set.

Type	# recording	Time length (s)				
		Mean	SD	Max	Median	Min
Normal	5154	31.9	10.0	61.0	30	9.0
AF	771	31.6	12.5	60	30	10.0
Other rhythm	2557	34.1	11.8	60.9	30	9.1
Noisy	46	27.1	9.0	60	30	10.2
Total	**8528**	**32.5**	**10.9**	**61.0**	**30**	**9.0**

Figure 2.7 Overall information of database provided by The 2017 PhysioNet/CinC Challenge

Chapter 3 Analysis & Design

3.1 Introduction

In this chapter, the requirements will be discussed as well as the specific implementation method will be determined. Also, the original dataset and the input dataset will be discussed.

3.2 Requirements

In the project, three requirements are designed to be satisfied. First, an appropriate phase space analysis should be constructed. Second, the diagnosis of atrial fibrillation should be fully automatic. Third, the software can reach a high accuracy of diagnosis since this project is related to medical science, accuracy makes a huge difference.

3.3 Methods

In general, phase space analysis has many methods. Saman Parvaneh er al.[16] researched on Poincare section and Poincare hyperplane to predict the termination of atrial fibrillation. Trained SVM supported this method to achieve a good result. As stated in the Background research, an novel index based on the PSR of the ECG for the accurate and timely diagnosis of ventricular arrhythmia was found by George Koulaouzidis et al.[7]. All of these methods can serve as a tool for us to pre-processing and construct our input dataset for CNN models. In the project, the most common way of phase space analysis—phase space reconstruction—will be implemented because this method has already been proved effective to reflect the information contained in ECG signals. Furthermore, since the CNN model has the advantage of image recognition, it is convenient to produce a 2-dimensional image dataset by phase space reconstruction. One thing also needs to point out is that the embedding dimension which was chosen equal to two is also proved to be able to produce the ECG attractor(As stated in chapter 2, attractor is a key part of Chaos Theory).

Last, classification of data will be done by constructing a Convolutional Neural Network model. Whatever is traditional machine learning or deep learning, classification is all based on the different features contained in data of different labels. Therefore, feature extraction is required to do the classification. However, the methods of extraction between traditional machine learning and CNN are different. For traditional machine learning, feature extraction is done manually and requires professionals or developers to have a deep knowledge of the professional knowledge while for CNN, it can automatically extract the features contained in each type of the data. Since the project is related to medical science, CNN is suitable for the project. The central part of feature extraction in CNN is the convolution. Usually, the features extracted by convolution will have redundancy and multiple convolution will make the network have too many parameters which is not good for the training process. So pooling layers will be implemented after convolutional layers. After being trained by several convolutional layers and pooling layers, features will evolve from low-level to high-level and the network will use the feature to do the classification.

CNN can be used to classify the types of ECG signals and PSR images because CNN has characteristics of locally connection and weight sharing. Locally connection enables features in different types of image to exist in the local area of the whole image. Therefore, convolutional kernels can be trained on these small areas and a kernel whose size is the whole image(fully connected) is unnecessary. In this case, the features can be extracted more effectively and the number of parameters in the network is reduced. Figure 3.1(a) shows a fully connected neural network and figure 3.1(b) shows the locally connected neural network. Weight sharing can ensure feature extraction is not affected by the position of features in each picture and also reduce the number of parameters in the network. For one type of image, they have the same features but the position of features in each image may have differences. For example, the zebra crossing on the road in each image can hardly be overlapped. Therefore, in convolutional layers, multiple kernels are applied to extract the features and each kernel weight will be maintained when it moves on the image. Since ECG signals and PSR images satisfy the conditions of locally connection and weight sharing, CNN can be implemented.

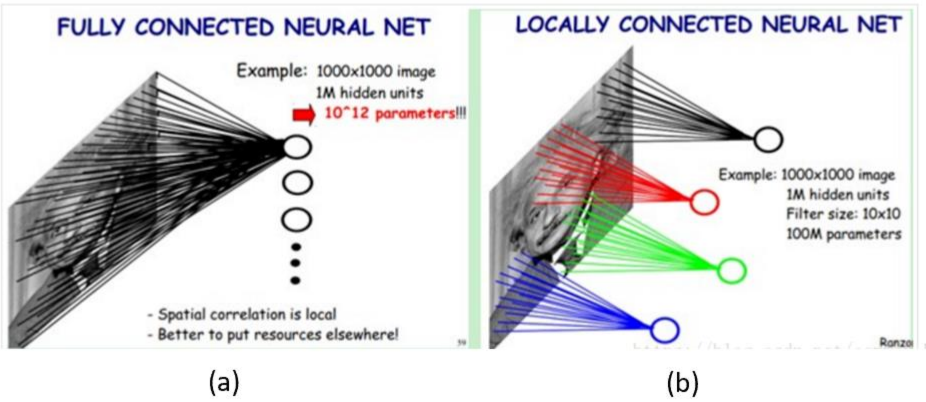


Figure 3.1 (a)Fully connected neural network (b)locally connected neural network

The following figure 3.2 shows the flow chart of building the software.

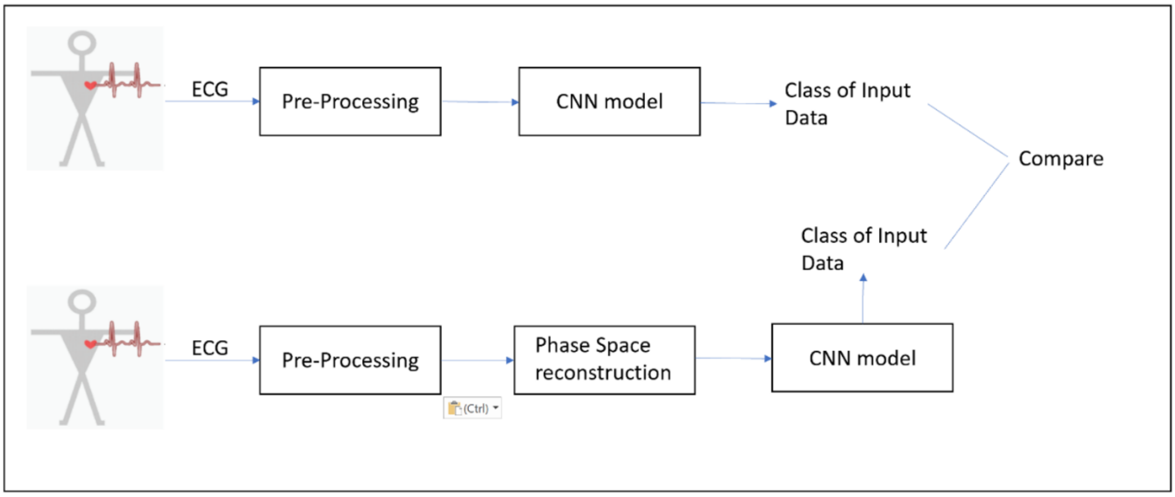
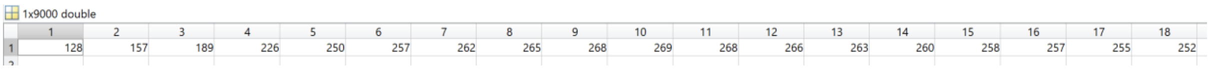


Figure 3.2 Block diagram of procedures of software

3.4 Input Data

From the view of the whole software, the input data is ECG signals which is stored as MATLAB V4 WFDB-compliant form. The figure 3.3 shows the visualization of part of data A00002 in Matlab.


1x9000 double

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1	128	157	189	226	250	257	262	265	268	269	268	266	263	260	258	257	255	252

Figure 3.3 Part of data A00002.mat shown in Matlab

From the view of machine learning, the input data has two parts. Since the project makes a comparison between how CNN performs on the ECG and phase space reconstruction images, two input data are images of ECG and PSR produced by Python Matplot library.

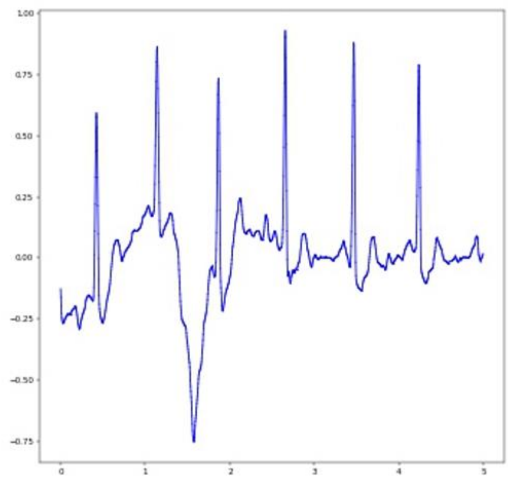


Figure 3.4 ECG drawn by Matplot(Unit: Time(s) in X-axis and Amplitude(mv) in Y-axis)

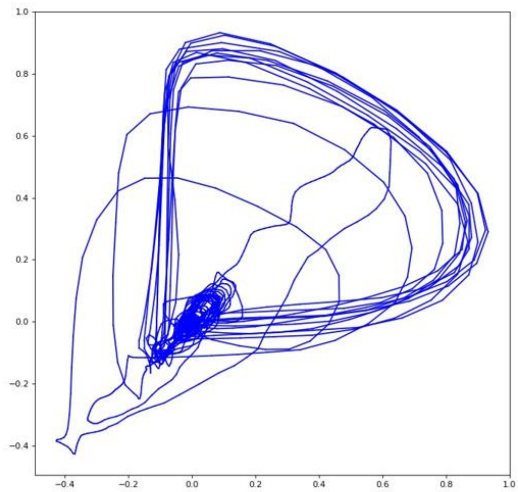


Figure 3.5 PSR image drawn by Matplot(Unit: Amplitude(mV) in X-axis and Amplitude(mV) in Y-axis)

3.5 Output Data

The output data will be a binary classification result of normal rhythm and atrial fibrillation.

3.6 Dataset

The dataset of The 2017 PhysioNet/CinC Challenge was chosen as the original dataset. The advantages over The MIT-BIH Arrhythmia Database is that this dataset is recorded from more patients while the MIT-BIH database from 48 patients. Also, MIT-BIH dataset contains some noise in its ECG data and the chosen dataset has already labelled the noise one and others are clean enough. So MIT-BIH requires Wavelet Transform, WT to free the noise which will not be suitable for the project. However, there are some problems in our chosen dataset. Compared with the normal rhythm, the number of samples of atrial fibrillation is small which means the data is very unbalanced. Therefore, data expansion is required after pre-processing.

The standards of the dataset will be explained below. ECG recordings were sampled as 300 Hz and they have been bandpass filtered by the AliveCor device. In other words, 1 seconds contains 300 samples. All data is provided in MATLAB V4 WFDB-compliant form.

Chapter 4 Development & Implementation

4.1 Introduction

In the previous chapter, the method of phase space analysis is selected, namely, phase space reconstruction. This chapter will discuss in detail each part of our design in order to give a clear point of view of how atrial fibrillation will be diagnosed.

4.2 Software Libraries, Tools and Programming Languages

4.2.1 WFDB Package

WFDB(WaveForm DataBase) Software Package is a library providing tools for reading, writing, and processing signals and waves in WFDB format.[17] WFDB library itself supports plotting the ECG signal. However, images of ECG were still plotted by Matplot and WFDB library was only used for reading and processing the original data in the project because of some issues in constructing the input dataset. In short, the WFDB package will be used to read the ECG data and then plot the ECG images and phase space reconstruction images as our input data.

4.2.2 Keras

Keras gives priority to the experience of developers. Keras is an API designed for humans, not machines. Keras follows the best practice of reducing cognitive difficulties: it provides a consistent and simple API, minimizes the number of user actions required for common use cases, and provides clear and actionable feedback when users make mistakes. This makes Keras easy to learn and use. This ease of use doesn't come at the cost of reduced flexibility: because keras is integrated with the underlying deep learning languages (especially TensorFlow), it allows you to implement anything you can write in the underlying language. In particular, TF. Keras can be seamlessly integrated with TensorFlow workflow as Keras API.

4.2.3 Python

Python is chosen as the main programming language. Since the WFDB package supports Python language and TensorFlow is also based on Python, Python is suitable for the project. The version of Python that the project based on is Python 3.7.9 [MSC v.1900 64 bit (AMD64)] on win32.

4.2.4 Pycharm & Jupyter Notebook

Pycharm IDE is good for using the chosen machine learning API Keras since the environment has already been configured. Pycharm provides a built-in Jupyter Notebook which is also easier for programming.

4.3 Procedures

4.3.1 Introduction

The implementation of our design is divided into two main stages:

1. Constructing the input dataset
2. Construct a convolutional neural network model

4.3.2 Construct the Input Dataset

All of our dataset has a standard image size which is 400X400 pixels. Other standards of data will be mentioned below.

The first dataset is ECG images. As shown in chapter 3, the time length of ECG data ranged from 9s to 61s. So if a standard size of image is chosen, the features in ECG data may be eliminated, which is shown in the following figure. In the software, the size of the image is chosen as 400X400 pixels. Figure 4.1(a) is the ECG image of data A00001 and 4.1(b) is the image of data A00005. Data A00001 has 9000 samples which is 30s and Data A00005 has 180000 samples which is 60s. Atrial fibrillation in ECG has features of P wave absence and P wave is replaced with irregular size, shape and time lengthy wave. Therefore, the features of atrial fibrillation can be hardly observed in figure and a good time segment should be chosen.

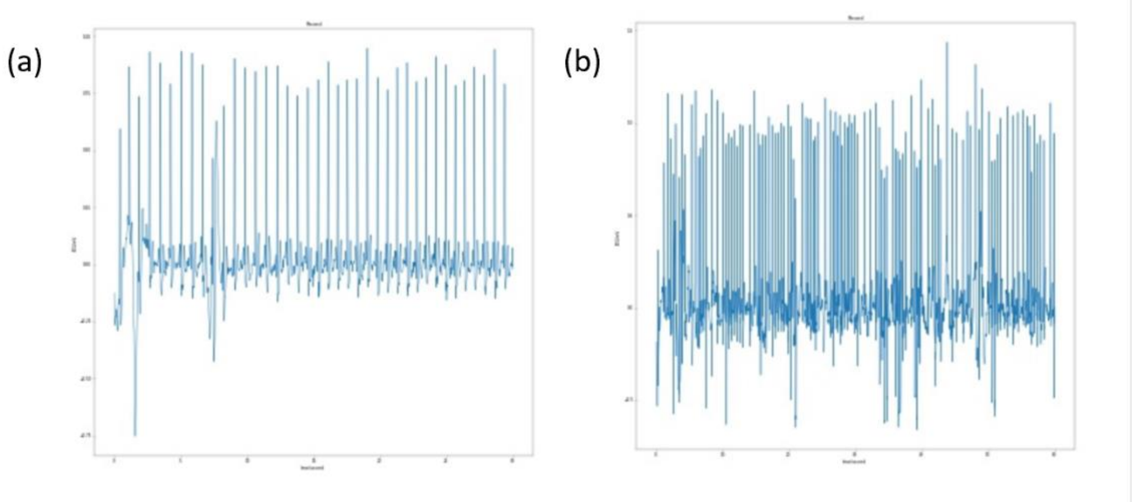


Figure 4.1 (a) ECG image of data A00001 with its original time segment (b) ECG image of data A00005 with its original time segment

By consulting some of the students in medical school, 5s time segment of ECG can roughly distinguish the normal rhythm from the atrial fibrillation. The figure 4.2(a) and figure 4.2(b) are the ECG images of the first 5s and they show the same data as above which is A00001 and A00005. Therefore, the features of atrial fibrillation can be clearly maintained.

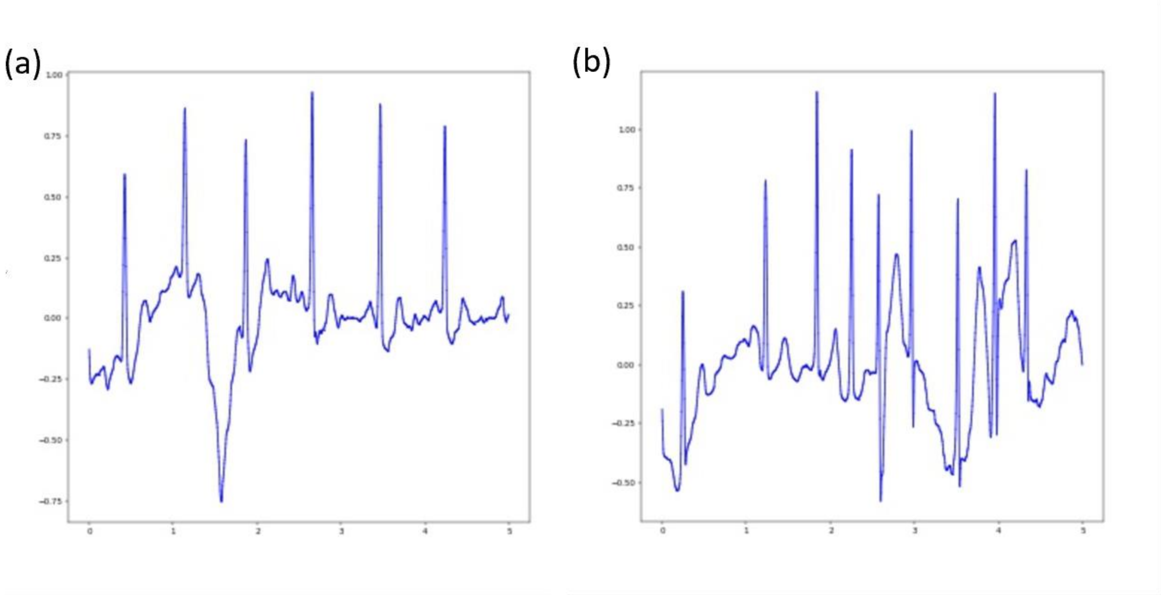


Figure 4.2 (a) ECG image of data A0001 with 5s time segment (b) ECG image of data A0005 with 5s time segment

The second dataset is phase space reconstruction of ECG. Since Takens' theory is applied, what time delay τ to use and what dimension to use are two problems of this reconstruction. Because the 2-dimensional image is more simple for the constructed CNN model in the project, dimension d is chosen as two. Then, time delay τ should be selected. In practice, there are two methods of choosing a time delay τ —either empirically choose a time delay τ or by applying the average mutual information function which was introduced by Henry Abarbanel[18]. Through background research, two time delays 10ms and 20ms were chosen. Last, time segments have a huge impact on the training process which is stated in chapter 3. Three time segments were tested in the project which were 4s, 8s, 10s. Samples of data A00001 are shown in figure 4.3.

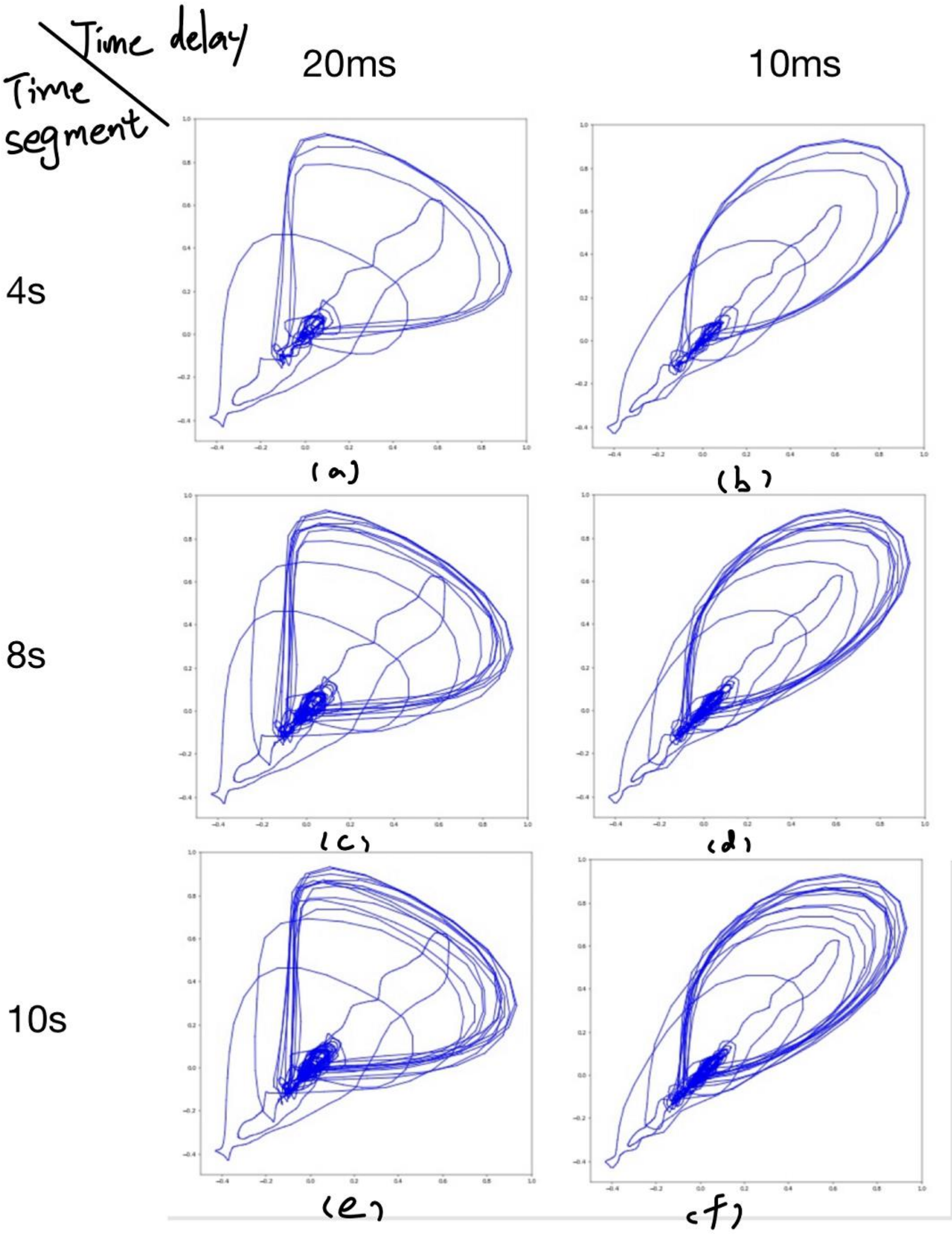


Figure 4.3 (a)PSR from 4s time segment ECG with 20ms time delay (b)PSR from 4s time segment ECG with 10ms time delay (c)PSR from 8s time segment ECG with 20ms time delay (d)PSR from 8s time segment ECG with 10ms time delay (e)PSR from 10s time segment ECG with 20ms time delay (f)PSR from 10s time segment ECG with 10ms time delay

In the process of constructing the above two datasets, a common problem is caused by the original data provided by the chosen dataset. The samples labelled with atrial fibrillation are far less than the samples labelled with normal rhythm which implies the input is largely unbalanced. Therefore, two methods are applied to expand the data samples which are labelled with atrial fibrillation so that the problem can be mitigated. First method is to split the AF data with the same time length which means several images are produced in one AF data. Second method is to mirror the image of AF. Sample of the first method is shown in figure 4.4. Sample of the second method is shown in figure 4.5.

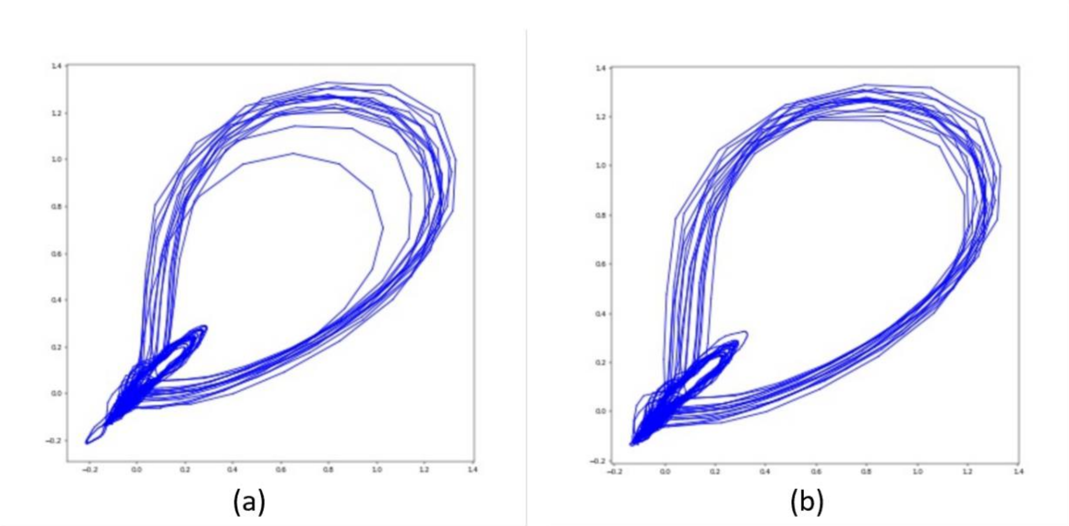


Figure 4.4 (a)PSR image of data A0004 which starts from sample 0 to 2400(8s) (b)PSR image of data A0004 which starts from sample 2700 to 5100(8s)

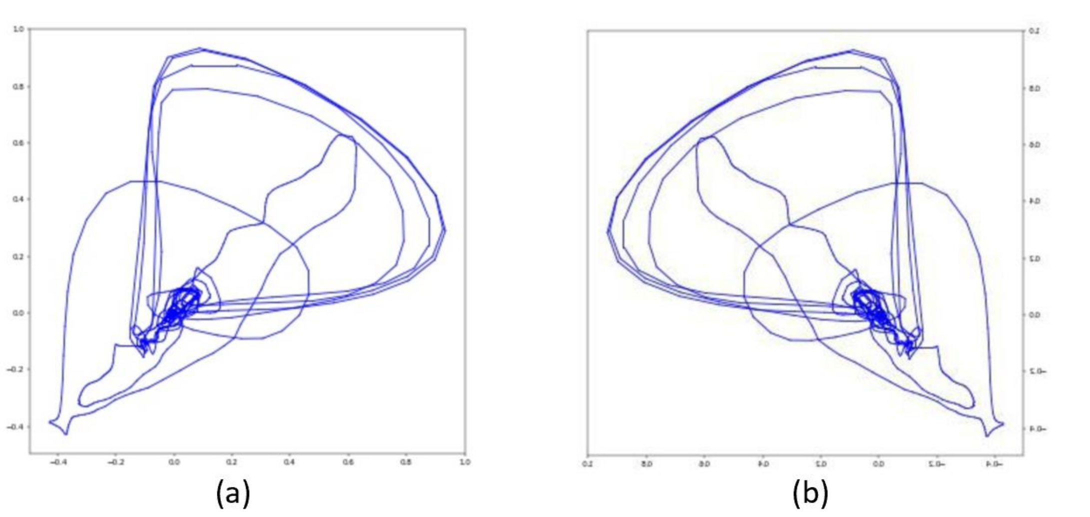


Figure 4.5 (a) original PSR image of data A0001 (b)PSR image after mirroring from (a)

4.3.3 Construct a CNN Model

Although there are already some existing architectures such as AlexNet, VGG16, Inception, all these architectures are not quite appropriate for the project. Because these architectures all have millions of parameters which is not efficient for training our dataset. Considering that the dataset is small and designed input data will be 2000 images, the whole training matrix size is 2000*400*400. The implemented convolutional neural network is shown in figure 4.6.

```
Model: "sequential_10"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
conv2d_20 (Conv2D)           (None, 400, 400, 10)      280       
_________________________________________________________________
conv2d_21 (Conv2D)           (None, 400, 400, 10)      910       
_________________________________________________________________
max_pooling2d_20 (MaxPooling (None, 200, 200, 10)      0         
_________________________________________________________________
conv2d_22 (Conv2D)           (None, 198, 198, 40)      3640      
_________________________________________________________________
conv2d_23 (Conv2D)           (None, 196, 196, 40)      14440     
_________________________________________________________________
max_pooling2d_21 (MaxPooling (None, 98, 98, 40)        0         
_________________________________________________________________
dropout_10 (Dropout)         (None, 98, 98, 40)        0         
_________________________________________________________________
flatten_10 (Flatten)         (None, 384160)            0         
_________________________________________________________________
dense_10 (Dense)             (None, 2)                 768322    
=================================================================
```

Figure 4.6 CNN model record

4.3.4 Training Process of CNN

Epochs, Batch size and learning rate are focused on and adjusted to improve the accuracy of classification. Every time the model is trained, the input dataset should be randomly shuffled.

```
for root, dirs, files in os.walk(ecg_route):
    random.shuffle(files)
```

Figure 4.8 Code snippet of shuffle the input data

Chapter 5 Evaluation & Results

5.1 Introduction

In this chapter, the software will be evaluated by several measurements which is accuracy, sensitivity and precision. Three measurements are calculated using formula 1: (TP+FP)/(TP+FP+TN+FN), formula 2:TP/(TP+FN) and formula 3:TP/(TP+FP) respectively. Then since the database is from The 2017 PhysioNet/CinC Challenge, the results provided by that Challenge will be compared with. Also, the results will be compared with the several papers' results though different database are used. Last, an evaluation will be done on the achievements or failures of the software.

5.2 Results

5.2.1 Confusion Matrix

All the confusion matrices in the table are of the best accuracy.

Table 1

<table>
<tr><th>No.</th><th>Input dataset</th><th>Confusion matrix</th></tr>
<tr><td>1</td><td>Type: ECG images
Time segments: 5s</td><td><table><tr><th></th><th>Normal</th><th>Atrial fibrillation</th></tr><tr><td>Normal</td><td>95</td><td>55</td></tr><tr><td>Atrial fibrillation</td><td>82</td><td>68</td></tr></table></td></tr>
<tr><td>2</td><td>Type: PSR images
Time segments: 4s
Time delay: 10ms</td><td><table><tr><th></th><th>Normal</th><th>Atrial fibrillation</th></tr><tr><td>Normal</td><td>102</td><td>48</td></tr><tr><td>Atrial fibrillation</td><td>50</td><td>100</td></tr></table></td></tr>
</table>

<table>
<tr><td>3</td><td>108Type: PSR images
Time segments: 4s
Time delay: 20ms</td><td><table><tr><th></th><th>Normal</th><th>Atrial fibrillation</th></tr><tr><td>Normal</td><td>118</td><td>32</td></tr><tr><td>Atrial fibrillation</td><td>46</td><td>104</td></tr></table></td></tr>
<tr><td>4</td><td>Type: PSR images
Time segments: 8s
Time delay: 10ms</td><td><table><tr><th></th><th>Normal</th><th>Atrial fibrillation</th></tr><tr><td>Normal</td><td>99</td><td>51</td></tr><tr><td>Atrial fibrillation</td><td>52</td><td>98</td></tr></table></td></tr>
<tr><td>5</td><td>Type: PSR images
Time segments: 8s
Time delay: 20ms</td><td><table><tr><th></th><th>Normal</th><th>Atrial fibrillation</th></tr><tr><td>Normal</td><td>106</td><td>44</td></tr><tr><td>Atrial fibrillation</td><td>52</td><td>98</td></tr></table></td></tr>
<tr><td>6</td><td>Type: PSR images
Time segments: 10s
Time delay: 10ms</td><td>The model cannot converge.</td></tr>
<tr><td>7</td><td>Type: PSR images
Time segments: 10s
Time delay: 20ms</td><td><table><tr><th></th><th>Normal</th><th>Atrial fibrillation</th></tr><tr><td>Normal</td><td>96</td><td>54</td></tr><tr><td>Atrial fibrillation</td><td>56</td><td>94</td></tr></table></td></tr>
</table>

All of the confusion matrix has shown above except the PSR images which have 10s time segments and 10ms time delay. Parameters have been adjusted many times and the model still cannot converge. Therefore, the confusion matrix is not provided here.

5.2.2 Accuracy, Sensitivity, Precision

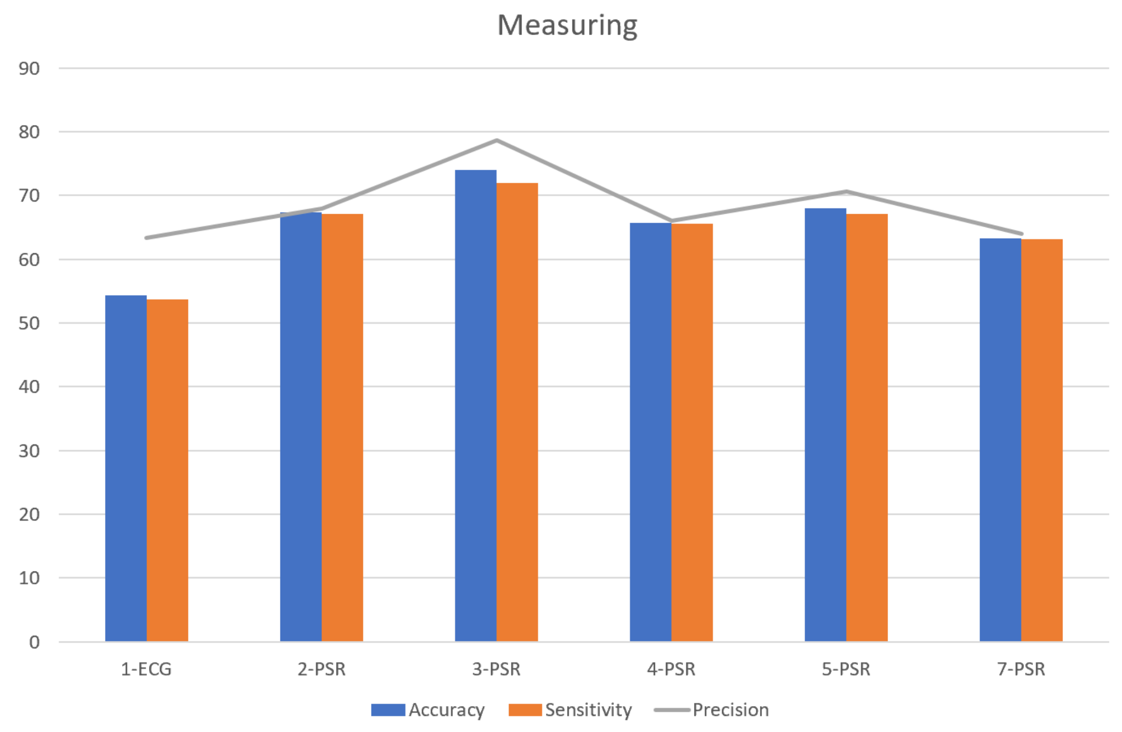


Figure 5.1 Histogram of three measurements

The number before PSR or ECG such as 2-PSR in figure 5.1 is corresponding to the No in Table 1. 2-PSR refers to No.2 in Table 1.

Figure 5.1 shows that by CNN model performs better on PSR images than ECG images. Second, best accuracy is achieved by PSR image of 4s time segment and 20ms time delay, with accuracy of 74%, sensitivity of 71.95% and precision of 78.67%. Thirdly, it also shows that PSR with 20ms time delay outperforms PSR with 10ms time delay. Therefore, the best method of phase space reconstruction will be a reconstruction using the embedding dimension d=2 and time delay =20ms from 4s time segment ECGs.

5.3 Comparisons

Table 2 Results on MIT-BIH Arrhythmia Database

Authors	Methods	Accuracy(%)
Yanjun Li et al.	Coordinate(x, y, t) mapping	99.81
Yazdani et al.	Adaptive mathematical morphology	99.78
Zidelmal et al.	S-Transform and Shannon energy	99.75

Cvikl et al.	Delay coordinate mapping	99.64
Lee et al.	Dealy coordinate mapping	99.57

Table 3 Results on the 2017 PhysioNet/CinC Challenge (67 authors)

Rank	Authors	Accuracy(%)
1	Tomás Teijeiro et al.	83
1	Shreyasi Datta	83
1	Morteza Zabihi	83
1	Shenda Hong	82
5	Mohammed Baydoun	82
44	Griet Goovaerts et al.	74

Table 2 and Table 3 shows some results of diagnosis arrhythmia. Compared with these results, the accuracy of proposed software still has a large room for improvement.

5.4 Evaluation

Firstly, the resolution of the input dataset is not high enough. Due to the limitations of the hardware and computing ability of computer, 400*400 pixel size is adopted in the software. However, if the cloud computing or other more powerful computers can support the software, a high resolution image like 1440*1440 pixel size of PSR images will definitely improve the accuracy.

Secondly, as stated in chapter 2, a central point in chaos theory as well as phase space reconstruction is the attractor. Figure 5.2 shows that the wave appears to be more stochastic, the more complex the structure of the attractor. Since ECG is a very complex nonlinear dynamic system, the structure of the attractor is really an important feature. Saman et al. also researched on using the Poincare section and Poincare hyperplane to explain the arrhythmia. The Poincare section and Poincare hyperplane is also derived from the phase space, which is shown in figure 5.3. Hence the clarity of trajectory is also of importance.

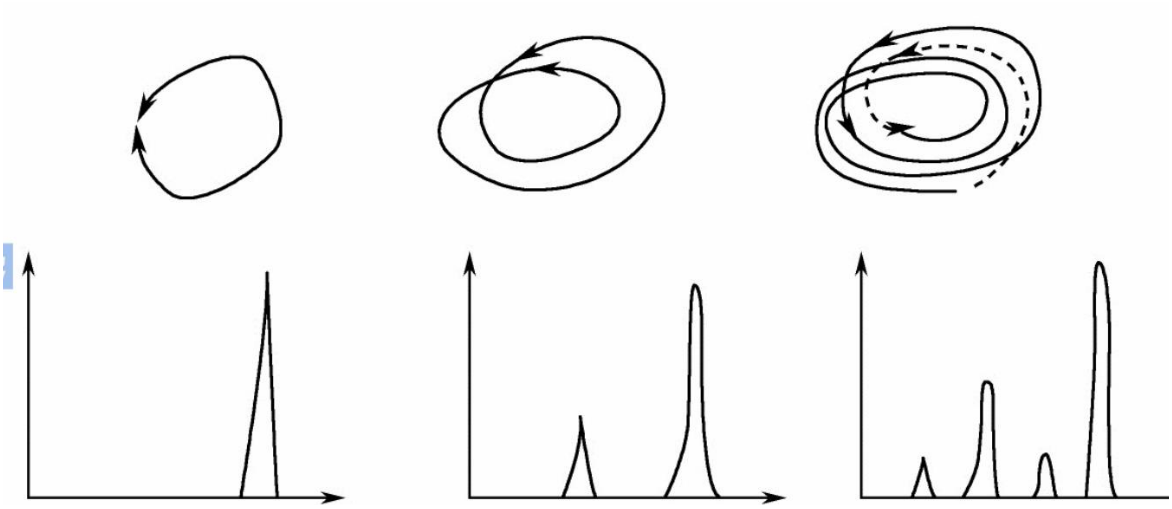


Figure 5.2 Three attractors from three waves.

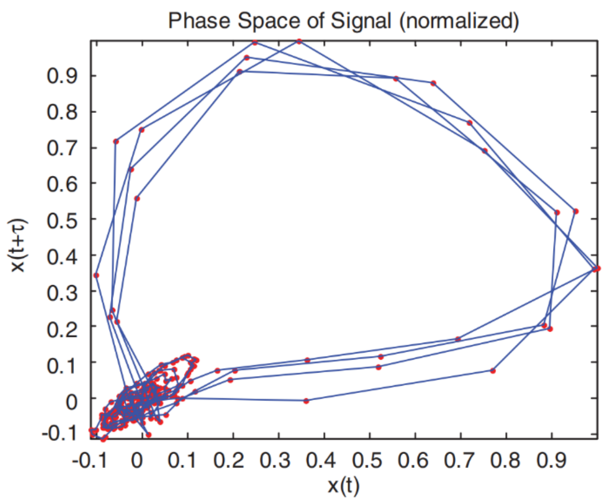


Figure 5.3 Poincare section and Poincare hyperplane in phase space

Thirdly, the method of choosing the dimension and time delay in Takens' time-delay embedding theory can be improved. Some research has proved the correctness of using False Nearest Neighbor Function to determine the embedding dimension and Average Mutual Information Function to determine the time delay. These two functions have been applied in some atmosphere research, however, ECG research rarely applied this method. Further improvements can research this method to determine a better dimension and time delay.

Chapter 6 Discussion & Conclusion

6.1 Introduction

In this chapter, the aims and objectives which set at section 1.2 will be reviewed and evaluated. Then, achievements, future improvements, limitations of the software will be discussed so that hopefully the software can be improved, even applied into clinical practice in future. At last, a personal reflection will be discussed.

6.2 Review of Aims and Objectives

The aim of this project is to explore an appropriate method of phase space analysis of ECG and investigate how the convolutional neural network model could assist the diagnosis of arrhythmia. The project aim was partly successful since arrhythmia has two types and only atrial fibrillation is what we explore. However, the software is still a fully automated system which is beneficial.

Regarding the project's objectives, the first objective is to explore the knowledge of arrhythmia in medical science. This was an important objective because the author's personal knowledge has nothing to do with arrhythmia. Therefore, knowledge of arrhythmia is important to the process of building this software. Through background research, basic knowledge of arrhythmias, ECG, and other cardiology knowledge were gained. Therefore, the objective is satisfied.

The second objective is to explore an appropriate method of phase space analysis of ECG. This part is the central part of this software. The phase space analysis should provide more features than ECG itself so that diagnosis of atrial fibrillation can be improved. The software shows the method of phase space reconstruction is successive and the time-delay embedding method is implemented. Therefore, the objective is satisfied.

The third objective is to construct a convolutional neural network model so that it could be used on training the dataset as well as part of the automated system. The model has illustrated in chapter 4 although the final result is not good enough. The model has shown some results which are useful to this project. In this case, this objective is partly satisfied.

The final objective is to evaluate the performance of this model according to several measures. This objective has been successfully conducted in chapter 5. The project itself has a comparison between the results between ECG images and phase space reconstruction images using the same CNN model. Then comparisons are also done with several papers and The 2017 PhysioNet/CinC Challenge results. Therefore, this objective is met.

6.3 Limitations

The software still has some limitations and deficiency. The first limitation is time efficiency. The software needs to read the ECG signals and then do the phase space reconstruction. This part requires a lot of time in reality. The second limitation is that the software is only based on one type of arrhythmia and therefore in the future another type of arrhythmia should also be researched. Another limitation is very hard to solve. By researching the existing database of arrhythmia, it is found that the number of samples in the arrhythmia dataset including both ventricular fibrillation and atrial fibrillation is far less than the normal rhythm. Furthermore, since the ECG signals are recorded by different standards, different dataset cannot be processed to integrate together. This will largely affect the performance of neural network models. Finally, the software needs to be more accurate and robust if applied in clinical practice.

6.4 Future Improvements

The biggest deficiency is the accuracy of the software. Fortunately, several improvements can be done to software and these improvements have a great possibility of success. Firstly, the most effective solution is to raise the resolution of images. So far, the images are 400*400 pixels which is not clear enough. However, if images are 1440*1440 pixels, definitely, the image will be clear enough but it also gives a burden on the hardware configuration and computing ability will make a huge difference. Secondly, the time delay $\boldsymbol{\tau}$ in the time-delay embedding method is chosen by researching previous papers. However, the average mutual information function which is shown in figure can be applied. This function has been proved effective on several nonlinear dynamic systems but has not been used on ECG signals yet. Therefore, in the future, this is a good point to research on. Thirdly, as stated in chapter 2 background research, a novel approach of 3-dimensional phase space reconstruction has an advantage of detecting arrhythmia on poor conditions of signals. Also, if the time-delay embedding method is still applied, a larger embedded dimension d can be tested and the value of d should be selected by research because a larger dimension will provide more information on original nonlinear dynamic systems and this may help improve the accuracy of software.

Last, this software can still be improved to diagnose all types of arrhythmias or even be applied to diagnosis of heart disease which can be observed from ECG signals. Though this requires a lot of work in the future, the completed software will have a good function in medical science and also has a large business market.

6.5 Personal Reflection

This project has a strong connection between computer science and medical science. The first time I researched this project, I knew it was quite demanding. Firstly, I have little knowledge of medical science. Therefore, I spent a lot of time learning the knowledge of arrhythmia. Hopefully, this knowledge has been useful in the later process of doing the project. Background research raises my interest in this project and also improves my research abilities. Reading and reviewing so many papers has let me gain a deeper learning of how machine learning in reality is applied to medical science, many state-of-art methods in both computer science and medical science.

Secondly, this project raised my awareness of time management. Through the whole process of conducting this project, some work was left behind schedule which made me very stressful. Therefore, in the future, if I have a chance to conduct a project whatever in a company or in a university, I can do better on my time management by the experience of this project.

To conclude, the experience of conducting this project not only let me have a further understanding how computer science can be applied to practice, especially the medical field, but also improve my professional abilities--researching skills, problem-solving skills, programming skills--and enhance my understanding of machine learning.

6.6 Conclusion

A fully automated software is proposed in this paper to diagnose atrial fibrillation. An appropriate phase space reconstruction method is proposed in this paper and a convolutional neural network model is constructed to classify atrial fibrillation. The results show CNN model has better performance to classify atrial fibrillation using phase space reconstruction method over using the original ECG images. Therefore, CNN model and phase space reconstruction can work together to assist the diagnosis of arrhythmia.

Chapter 7 Ethics

7.1 Ethics

There are many ethics taht should be noticed when related to the medical field. Firstly, the database is open access and therefore the dataset is credentialled. However, when the software is applied to clinical practice, privacy information of patients should be secured which requires the software to be more reliable and robust.

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Appendix A
External Materials

The external materials such as tutorials, software tools and libraries are listed below:

- Keras: https://keras.io/guides/
- WFDB package：https://archive.physionet.org/physiotools/wfdb.shtml
- Dataset：https://physionet.org/content/challenge-2017/1.0.0/
- Pycharm：https://www.jetbrains.com/pycharm/