School of Computing
FACULTY OF ENGINEERING AND PHYSICAL SCIENCE
UNIVERSITY OF LEEDS

Simulating Cardiac Arrhythmia for Neural Network Classification

Liam James Beckingham

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The candidate confirms that the following have been submitted.

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Final Report	PDF version	Via Minerva Submission Portal (10/05/21)
Source Code and Models	Project GitHub URL	Supervisor, Assessor (10/05/21)

Type of project: Exploratory Software

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.

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Abstract

Electrocardiogram (ECG) signals are used to help experts diagnose a wide range of cardiac arrhythmia, in recent years machine learning techniques have been tackling the problem of classifying these ECG signals however due to the relative rarity of these arrhythmia throughout the population the data sets used to teach these classifiers can often be relatively small and/or imbalanced, which can lead to potential issues with training and classification. Recent papers have shown the potential for using simulated data as a substitute in order to remove this imbalance, or to increase volume of data in which we have to train the classifiers with, thus increasing the accuracy of said models. Additionally it has also been shown that there are mathematical models which seem to replicate the range of arrhythmia we see in the real world by simulating these ECG signals, having the potential to be very useful in helping train classifiers which are more accurate than those previously proposed, which would be an invaluable asset in a real-world medical setting.

Acknowledgements

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Chapter 1

Introduction

1.1 Overview

Cardiac arrhythmia such as Atrial fibrillation or Atrial flutters refer to a group of conditions stemming from "abnormalities in the rate, rhythm, or both of the heartbeat" [35] in medicine the most common way to diagnose a patient with a condition is through using an electrocardiogram (ECG) to collect ECG signals which are then interpreted in order to identify any underlying issues a patient may have, traditionally this was and still is done by experts in the field but there has been in recent years a deeper understanding and acceptance of machine learning techniques to aid in this classification [10] which has allowed us to create better models in order to help experts interpret the mass of signals they can be presented with. Due to the nature of these signals being quite rare in context due to a small portion of the population suffer from these arrhythmia there is often a class imbalance in the data set which can lead to potential issues within classifiers learning from them [36]. It has been shown that there is potential to aid machine learning methods using simulated data to fill gaps we may have in existing data sets [43] and recently papers have been published showing ways in which we can replicate the abnormality's we see in ECG signals using mathematical equations meaning we can simulate cardiac arrhythmia [8]. The union of these aforementioned techniques leaves the potential for repairing the class imbalance we see in existing data sets and/or increasing the size of them leaving the potential for new classifiers to be built with these data sets to have a greater accuracy and therefore greater utility in a real-world medical setting.

1.2 Aims and Objectives

The aim of this project is to create a deep neural network and assess how the effectiveness of this network changed based on the introduction of simulated data into the training set. The objectives of this project are:

- Review cardiac arrhythmia's and ECG signals
- Review how mathematical models can replicate the ECG data
- Review deep neural networks and appropriate frameworks
- Build a deep neural network able to classify ECG signals

- Build a program which can create ECG signals from the mathematical models
- Try different ratios of real-world : simulated data in training models
- Analyse the accuracy of each model and assess the effectiveness of introducing this simulated data

1.3 Deliverables

The deliverables for the project are as follows:

- The final report containing background research, implementation details and evaluation
- GitHub repository (`https://github.com/Liambeck99/ECG_Classification`) containing source code to the following:
  - Neural network used for training
  - Program used to simulate ECG data

Chapter 2

Background research

2.1 Cardiac Arrhythmias

2.1.1 Definition

There are 5 main type of cardiac arrhythmia's being: atrial fibrillation (AF) , supra-ventricular tachycardia, bradycardia, heart block and ventricular fibrillation [28] each being a result of an abnormality in the electrical signals within the heart. The heart is made up of many specialised groups of cells one of which being the sinoatrial (SA) node which is considered the pacemaker of the heart [7], there are others such as the atrioventricular (AV) node and the His-Perjunke system (HP) all of which have established role in the function of the heart and any change in this activity can result in arrhythmia's [14, 19].

2.1.2 Prevalence

Atrial fibrillation is the most common of the arrhythmia's and has associations with increased risk in stroke [1], death and other heart diseases. It was estimated that in 2010 the number of men and women living with AF was 20.9 million and 12.6 million respectively [24] additionally people over the age of 55 have a one in five lifetime risk of developing AF [21]. Though most cases of AF often go unnoticed as there is no health repercussions most peoples first introduction to this underlying condition is when there is a catastrophic case of AF which can lead to heart failure or other major conditions. The same can be said for many of the other previously mention types of arrhythmia. More so than ever the topic of health is at the forefront of every ones minds in the age of COVID-19 and relations have been made between an increase in arrhythmia's in patients with COVID-19, though it has been argued that this is because of a systematic illness and not the actual virus [5, 11], it just proves the point that now more than ever accurate systems are needed in order to be able to quickly classify arrhythmia and a range of other issues to hasten the diagnosis period for patients.

2.2 ECG Signals

2.2.1 Collection of data

There is a wide range of techniques of collecting ECG data falling into three main categories: on-the-person, off-the-person and in-the-person, the majority of which falling into the on-the-person category [10] which is what we'll be using for this project. The techniques falling under this banner commonly require an electrode be attached to the person in various positions and there is a wide range of where and how many of these are attached. Commonly used configurations are 5/10/12 lead configurations where leads are placed across the chest, arms and legs in various positions in order to gain a unique insight into the electrical patterns in the patient. Electrodes placed on the chest are the best for arrhythmia classification, since they are located closest to the heart muscles thus picking up the signals the strongest.

2.2.2 Data structure and pre-processing

The wave segments we can extract from these leads highlight the unique features that is associated with the electrical activity of the heart, see Fig. 2.1. The most notable of which are the P, QRS, T waves. Each of which corresponding too "denominated atrial depolarization (P wave), ventral depolarization (QRS complex) and repolarization (T wave)" [10]. These are the main features used in diagnosis of a patient as any change in the behaviour of this wave structure be in frequency, strength, consistency etc. are all pointers which are used to diagnose arrhythmia's.

Though before we can extract this data into a useful format the raw data needs to be pre-processed in order to remove noise and distortion often found in ECG signal. There is a wide range of pre-processing techniques though most recently wavelet transforms have been used to reduce noise, examples would be FrFT, FrWT and IPCA each technique having its own benefit [18]. Luckily we have access to databases that are already pre-processed and available open-source for researchers to use allowing us to bypass any ethical issues associated with the collection of data as they are already anonymised and ready for use. The three of which, which will be considered for use in this project are: the MIT-BIH arr database [27], a 2020 study of 12-lead ECG database of more than 10,000 patients [42] and the data set provided by the PhysioNet computing in cardiology challenge 2017 [33], each having its own benefits and drawbacks.

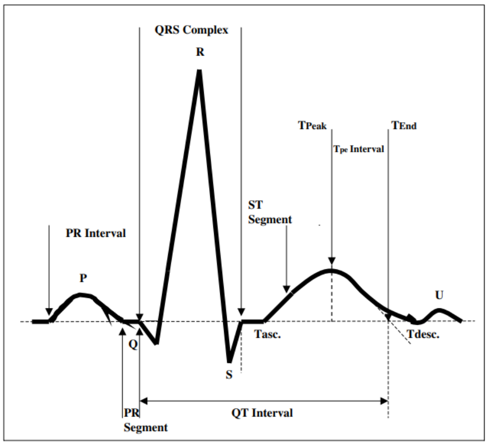


Figure 2.1: Key features and intervals associated with a wave segment

2.3 Simulating ECG signals

2.3.1 Delay-differential equations

Due to the nature of how the ECG signal is created in the real-world it is quite difficult to create a simple model in order to recreate it. Thus we are introduced to delay-differential equations, a delay differential equation is a unique type of differential equation, the major difference being that the solution to the derivative at any one point is dependant on the solution at previous times in the equation [39].

$$y'(t) = f(t, y(t), y(t - \tau_1), y(t - \tau_2), ..., y(t - \tau_k))$$

The simplest of which have the above form [37]. The time delays expressed in the form τ_k are positive constants. Though an expert understanding of these equations is not needed, an intuition of how the unique feature that they are dependant on the solution at previous times allows us to create more complex models and due to this time dependant feature we can create models that appear to repeat across time intervals which you can see would be useful in simulating an ECG signal.

2.3.2 Proposed mathematical model

The proposed model of Cheffer and Savi [8], based upon the earlier works of Gois and Savi [17] and Glass [16] uses a conceptual model of the heart, see Fig 2.2. It displays the previously mentioned key groups within the heart responsible for its function, sinoatrial (SA) node, atrioventricular (AV) node and the His-Perjunke system (HP). Each of which has some influence over one another and an incoming electrical value from the autonomic nervous system.

In this model they define each node as having its own time delay and own unique electrical pattern based upon their role and timing in the function of the heartbeat. In

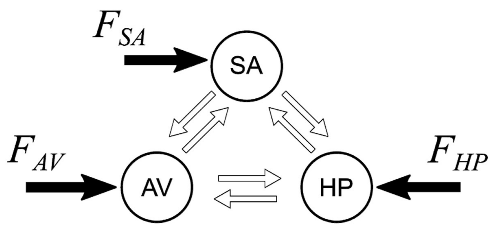


Figure 2.2: Conceptual model of heart functioning [8]

the conceptual model the SA oscillator triggers first followed by the AV oscillator and finally the HP oscillator. Each oscillator has its own delay differential equation which relates to its own behaviour and they're each associated with on another and this is shown through coupling among them in the equations. The combination of all of these oscillators allow us to replicate ECG rather accurately. Equation 2.1 is the proposed mathematical model by Cheffer and Savi [8] and see Fig 2.3 for the graphs of each oscillator and their summation into a recognisable ECG signal.

$$\begin{aligned}
\dot{x_1} =& x_2 \\
\dot{x_2} =& F_{SA}(t) - \alpha_{SA} x_2 (x_1 - v_{SA_1})(x_1 - v_{SA_2}) - \frac{x_1(x_1 + d_{SA})(x_1 + e_{SA})}{d_{SA} e_{SA}} - k_{AV-SA} x_1 \\
& + k^{\tau}_{AV-SA} x_3^{\tau_{AV-SA}} - k_{HP-SA} x_1 + k^{\tau}_{HP-SA} x_5^{\tau_{HP-SA}} \\
\dot{x_3} =& x_4 \\
\dot{x_4} =& F_{AV}(t) - \alpha_{AV} x_4 (x_3 - v_{AV_1})(x_3 - v_{AV_2}) - \frac{x_3(x_3 + d_{AV})(x_3 + e_{AV})}{d_{AV} e_{AV}} - k_{SA-AV} x_3 \\
& + k^{\tau}_{SA-AV} x_1^{\tau_{SA-AV}} - k_{HP-AV} x_3 + k^{\tau}_{HP-AV} x_5^{\tau_{HP-AV}} \\
\dot{x_5} =& x_6 \\
\dot{x_6} =& F_{HP}(t) - \alpha_{HP} x_6 (x_5 - v_{HP_1})(x_5 - v_{HP_2}) - \frac{x_5(x_5 + d_{HP})(x_5 + e_{HP})}{d_{HP} e_{HP}} - k_{SA-HP} x_5 \\
& + k^{\tau}_{SA-HP} x_1^{\tau_{SA-HP}} - k_{AV-HP} x_5 + k^{\tau}_{AV-HP} x_3^{\tau_{AV-HP}}
\end{aligned} \tag{2.1}$$

These equations can be quite unintuitive at first glance however you can see the clearly in Fig 2.3 how each equations x_1, x_3, x_5, previously denoted in terms of only their derivatives, correspond to each of the isolated oscillators they're trying to represent SA, AV or HP and from this you can visualise how the combination of all three of these could form the shown ECG signal. The exact summation to compute the ECG is given as follows:

$$X = ECG = \beta_0 + \beta_1 x_1 + \beta_2 x_3 + \beta_3 x_5 \tag{2.2}$$

where $\beta_0, \beta_1, \beta_2, \beta_3$ are constants, therefore

$$\dot{X} = \frac{\delta ECG}{\delta t} = \beta_1 x_2 + \beta_2 x_4 + \beta_3 x_6 \tag{2.3}$$

Cheffer and Savi [8] have shown through experimentation that many arrhythmia can be replicated using this model and have provided a table of values for constants found in equations 2.1 in order to replicate these arrhythmia's. The replicated arrhythmia's shown by Cheffer and Savi [8] can be seen in Fig 2.4. Therefore all we need to do to create a bank of simulated ECG signals is to transform these models into code and then introduce a slight variation into the variables when producing the ECG therefore we can create a mass of simulated ECG which all differ slightly in order to replicate the uniqueness we see in the real world.

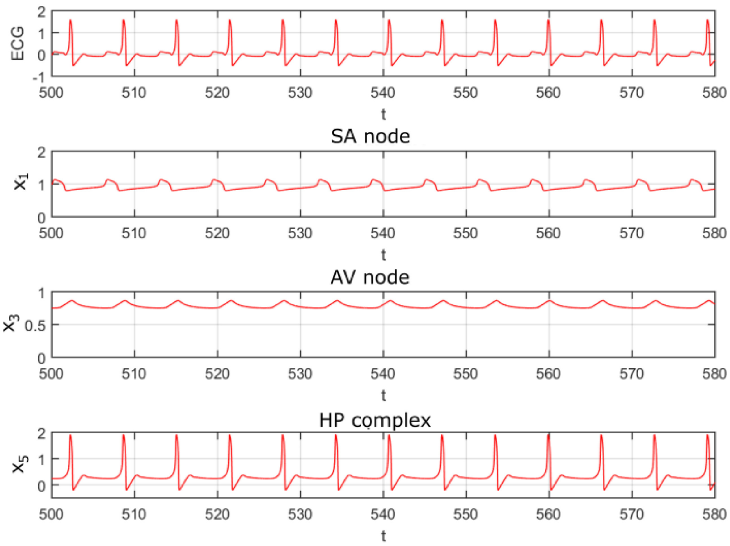


Figure 2.3: Normal ECG representation and isolated oscillators [8]

2.4 Deep Neural Networks

2.4.1 Classification

Classification in machine learning is the process of predicting and grouping sets of data into preset categories based upon inherent features in the data and how the 2 sets may differ. Classification is a type of supervised learning where the labels denoting which of the groups a data point belongs too is provided alongside the data being classified.

2.4.2 Convolutional neural networks

A convolutional neural network is a type of deep neural network that over the past decade has proven extremely powerful in image recognition and speech analysis [3]. It

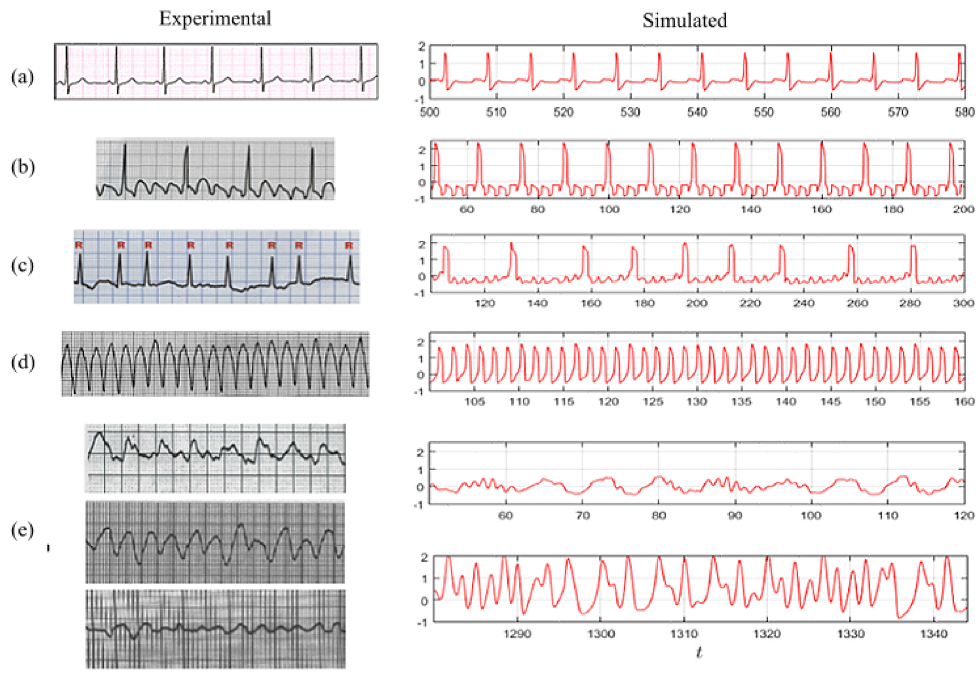


Figure 2.4: Experimental and Simulated ECG signals (a) normal, (b) atrial flutter, (c) atrial fibrillation, (d) ventricular flutter and (e) different types of ventricular fibrillation [8]

works through a technique called feature extraction. Feature extraction works by passing a filter across the entire image and using this filter it condenses the image into a new layer in which each point in this layer is equivalent to the filter applied to the image at the corresponding point in the image, see Fig 2.5. The filter would contain the feature we are seeking to extract. In image recognition this feature is often very basic edges so a vertical/horizontal/diagonal lines, and from there you would apply filter again to this new layer and so on and from this we extract a hierarchy of features and this is what we use to classify images. We could input an image of a number 0 and learn that a very specific combination of vertical/horizontal/diagonal lines in a very certain order define the number 0 and differentiate it from a number 7 and this is, at the most basic level, how convolutional neural networks work. They are excellent at pattern recognition making them the most suitable candidate for the work we are doing and have already been shown to be very good at doing so [22, 41].

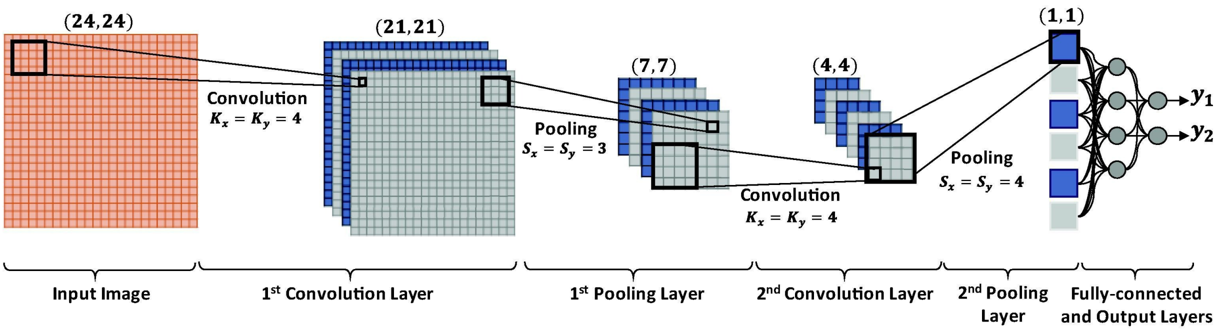


Figure 2.5: Example of convolutional neural network [22]

2.4.3 (Max) Pooling

Pooling is a layer found in CNNs and is used to down sample an image in order to focus on higher level features within the layer. Pooling refers to the reduction of a layer into a new pooled layer through the use of a filter, it passes the filter across the image using a stride equal to the size of the filter so not to overlap the filter with itself and reduces the size of the image by the size of the filter, in Fig 2.5 the convolution layer is 21x21 and the pooling layer uses a 3x3 filter meaning you can fit 7 horizontal 3x3 filters side by side across the 21 wide image and equally can fit 7 vertical filters going down the image meaning that the corresponding pooled layer is 7x7. The filter can reflect a particular operation we want to apply to the image most commonly we use a filter which selects the highest value within the filter and which is why it is referred to as the max pooling layer.

$$\begin{bmatrix} 14 & 7 & 21 & 11 \\ 8 & 3 & 6 & 9 \\ 5 & 12 & 5 & 8 \\ 18 & 1 & 1 & 7 \end{bmatrix} \xrightarrow{\text{2x2 Max Pool}} \begin{bmatrix} 14 & 21 \\ 18 & 8 \end{bmatrix}$$

2.4.4 Dying ReLU problem

The rectified linear unit (ReLU) is one of the most widely used activation functions in deep learning [23] it works by ensuring that the convolution layer is still a positive image.

$$ReLU = X_i = \begin{cases} xi & \text{if } x_i \geq 0 \\ 0 & \text{if } x_i < 0 \end{cases} \tag{2.4}$$

However one of the downsides to using this activation function in deep neural networks is due to the dying ReLU problem, also known as the exploding/vanishing gradient problem [12, 25] which occurs when the network becomes so large that it is unable to propagate the gradient information backwards from the output layers back to the input layers so it is extremely difficult to update and train the initial layers. To resolve this issue in deep neural networks there is other activation functions that have been proposed and shown to work better in training models such as the leaky rectified linear unit (LReLU) equation 2.5 or exponential linear unit (ELU) equation 2.6 [30, 40] and do so by instead of setting the negative values to 0 they apply a function to them to help stop the gradient vanishing.

$$LReLU = X_i = \begin{cases} x_i & \text{if } x_i \geq 0 \\ \frac{x_i}{\alpha_i} & \text{if } x_i < 0 \end{cases} \tag{2.5}$$

$$ELU = X_i = \begin{cases} \alpha_i(exp(x_i) - 1) & \text{if } x_i \geq 0 \\ x_i & \text{if } x_i < 0 \end{cases} \tag{2.6}$$

Chapter 3

Project Planning and Management

3.1 Initial plan

The project will be divided into 5 key sections:

- Report writing: an in depth report containing an introduction to the project, an explanation of the work done and a final evaluation of the projects final results.
- Creating a Neural Network: able to classify a real world data set
- Simulating ECG: re-implementation of functions able to replicate ECG signals
- Training models: using a range of different ratios of real:simulated data
- Analysing the models: using the appropriate metrics to assess the effectiveness of the models and the utility of the simulated data

3.2 Timeline

The timeline for project has been presented in Figure 3.1, it was created in order to aid in the projects work flow. The bulk of the time will be spent will be in creating the neural network able to classify ECG and creating a program able to convert the mathematical models into usable ECG signals that can use with the existing network to train it, as each stage is heavily dependant on the previous thus there has been left a lot of room for overlap as there could be unforeseen circumstances when creating these systems.

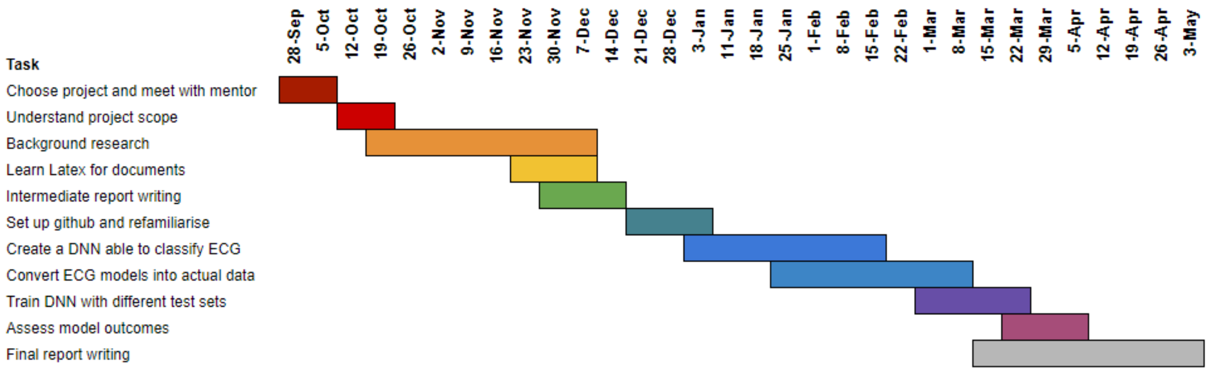


Figure 3.1: A Gantt chart showing timescale for the project

3.3 Methodology

As mentioned in the previous section there are parts of this project where the progression to the next stage is dependant on the previous stage being completed because of this a waterfall based approach was taken [4]. This fixed method is based upon taking predefined steps leading up to the completion of the final product and because of this is perfect for this project. The waterfall approach consists of a few key stages those being; analysis, design, coding, testing, implementation. The first 2 stages analysis and design are done in the first 3 chapters of this report. The rest of the stages will be done throughout the workflow of this project to ensure each part of the plan is finished when it is supposed to be to ensuring the overall project is complete on time.

3.4 Version control

Throughout this project a remote repository will be used in order to manage and save the workflow of this project. Commits will be used whenever major updates to the project have been done. Doing so not only provides a backup location in which the project is being stored in case anything was to happen locally but it also provides a history of changes to the project in case at any point a reversion to a previous state was necessary. This will be done using GitHub and the repository link can be found here `https://github.com/Liambeck99/ECG_Classification`

3.5 Risk mitigation

As the project is entirely based upon the final networks output there is no risk from external factors and all ways risk can be mitigated will come from inside the scope of the project, this could be achieved by doing or or all of the following :

- Simplify the deep neural network being created
- Focus on fewer types of cardiac arrhythmia for classification
- Use a smaller data set for training, validation and testing
- Test fewer ratios of real : simulated data for analysis

Chapter 4

Implementation

4.1 Language and Library Choices

For the creation of the classifier the Python programming language will be used. Other languages were considered such as Java or C however they were deemed unsuitable. This is because Python is a language that offers less complexity and more readability than other languages such as C or Java. In addition to this Python has many frameworks and libraries which simplify the implementation of complex models designed specifically for machine learning and data analysis. Keras [9] was chosen as the framework to create the classification model. It is a deep learning framework which offers a user friendly API with low level functionality allowing the creation of highly customisable models which are intuitive. Alongside this NumPy [20], SciPy [38] and Pandas [29] will be used as they offer a fast and efficient way to handle large data sets and have a range of utilities for data manipulation and data-analysis. Additionally Scikit-learn [31] will also be used as it is another machine learning library which offers additional functions which will be useful in the creation of the classifier.

For the simulation of arrhythmia, Python was considered alongside C as they also offer a range of libraries designed for the creation of delay differential equations. On the other hand Mat-lab [26] is a high-performance language designed for a range of tasks one of them being technical computing in math and computation. Mat-lab has a designated library for delay-differential equations to accompany this it has an in depth documentation with examples of how to implement and utilise each function. For this reason Mat-Lab was chosen as the most appropriate language for the re-implementation of the models presented in Cheffer and Savi.

4.2 Simulating ECG

4.2.1 Re-implementation of models

The function used in Mat-lab was the dde23 function. It is part of the delay differential equation library, this function is specifically designed to be used for equations in which there is a constant time delay which is what is needed for this model. The dde23 function takes 4 inputs those being the delay differential equation to be solved, the system lags, history or the starting value of the system and the time frame in which it is to be solved. The solution to dde23 is defined as:

```
sol = dde23 ( ddefun , lags , histopry , tspan )
```

The following conditions that define the history are applied for all simulations [17]:

$$x_0 = \begin{bmatrix} -0.1 & 0.025 & -0.6 & 0.1 & -3.3 & \frac{2}{3} \end{bmatrix}^T \tag{4.1}$$

Time delays in the model which are passed into the into the dde23 function as system lags, again for all simulations, are the following [8]:

$$\text{lags} = \begin{bmatrix} \tau_{SA-AV} & \tau_{AV-HP} \end{bmatrix} = \begin{bmatrix} 0.8 & 0.1 \end{bmatrix} \tag{4.2}$$

The time frame is simply a vector defining the start and ending time for the solution space in which we want to solve this equation. So if we wanted the solution space for the first 100 seconds tspan would be defined as follows:

$$\text{tspan} = \begin{bmatrix} ts & tf \end{bmatrix} = \begin{bmatrix} 0 & 100 \end{bmatrix} \tag{4.3}$$

The delay differential equation is the most complex argument passed into the dde23 as it itself is also a function defined as ddefun. The function ddefun takes in multiple arguments then outputs a single column vector with the solution to each of the 6 corresponding equations from Equation 2.1. The solution to ddefun is defined as:

```
xp = ddefun ( t , y , Z , p , i )
```

Where t corresponds to the current time at which the solution is being taken, y is a column vector that approximates the solution $y(t)$. Z is a 2x6 vector in which each column holds the values for the lagged version of the equations, so $Z(:,1)$ (the first column) approximates the solution at $y(t-0.8)$ at the latter $Z(:,2)$ approximates the solution at $y(t-0.1)$. The Argument p is a struct which passes all of the variables needed for the equations, which can be seen in Table 4.1 and Table 4.2. Finnaly i is an index which is used in conjunction to the struct p to access certain sets of values within the struct.

It was decided that the addition of the further 2 arguments p and i was necessary though they are not by needed in order for ddefun to work correctly. By including these arguments to be passed to the function it removes the need for all of the parameters to be initialised inside the function every time ddefun is called, not only saving running time but also it means that it reduces the size of the ddefun function meaning that is is more readable. In addition to this it means that the values for the parameters are not hardcoded within the function equations, which allows 2 things. Firstly that by changing the index from 1-6 we can select between each of the arrhythmia quickly and efficiently, as it will select a new column from the parameters Table 4.2. Secondly it allows the manipulation of these parameters before they are passed into the function which becomes useful later when randomness needs to be introduced into the system.

Table 4.1: Cardiac system parameters for normal rhythm

SA oscillator		HP Oscillator	
a_{SA}	3	a_{HP}	7
v_{SA_1}	1	v_{HP_1}	1.65
v_{SA_2}	-1.9	v_{HP_2}	-2
d_{SA}	1.9	d_{HP}	7
e_{SA}	0.55	e_{HP}	0.67
AV oscillator		Couplings	
a_{AV}	3	k_{SA-AV}	3
v_{AV_1}	0.5	k_{AV-HP}	55
v_{AV_2}	-0.5	k^{τ}_{SA-AV}	3
d_{AV}	4	$k^t au_{AV-HP}$	55
e_{AV}	0.67	Time Delays	
		τ_{SA-AV}	0.8
		τ_{SA-AV}	0.1

Table 4.2: Parameters that differ from normal rhythm to describe arrhythmia

	Atrial flutter	Atrial fibrillation	Ventricular flutter	Ventricular fibrillation with stimulus	Ventricular fibrillation without stimulus
SA oscillator					
v_{SA_1}	1.65	1	1	1	1
v_{SA_2}	-4.2	-1.9	-1.9	-1.9	-1.9
AV oscillator					
a_{AV}	7	7	3	3	3
HP oscillator					
a_{HP}	7	7	7	0.5	0.5
External Stimuli					
ρ_{SA}	0	8	0	0	0
ρ_{HP}	0	0	0	30	0
ω_{SA}	0	2.1	0	0	0
ω_{HP}	0	0	0	0.8	0
Couplings					
k_{SA-AV}	0.66	0.66	3	3	3
k_{AV-HP}	14	14	45	30	14
k^{τ}_{SA-AV}	0.02	0.09	3	3	0.4
k^{τ}_{AV-HP}	0.66	38	20	30	38
Time Delays					
τ_{SA-AV}	0.66	0.8	0.8	0.8	0.8

Using these parameters suggested in Cheffer and Savi [8] alongside the of the set of equations also provided in this paper, the program created was able to re-implement the models. The results can be seen in Figure 4.1. The created program is able to simulated not only a normal rhythm but 5 different arrhythmia seen in real world data sets. The main focus to be taken from this is the ability to simulate both a normal rhythm and atrial fibrillation as they will be the 2 classes used for classification in the classifier. Though it cannot be certified that the re-implementation is exact without access to the models used by Cheffer and Savi, one of the main characteristics which defines atrial fibrillation can be seen in the models created. That is the irregularity of QRS complexes [32], while in the normal model there appears to be a clear and consistent p wave, qrs complex followed by a t wave.

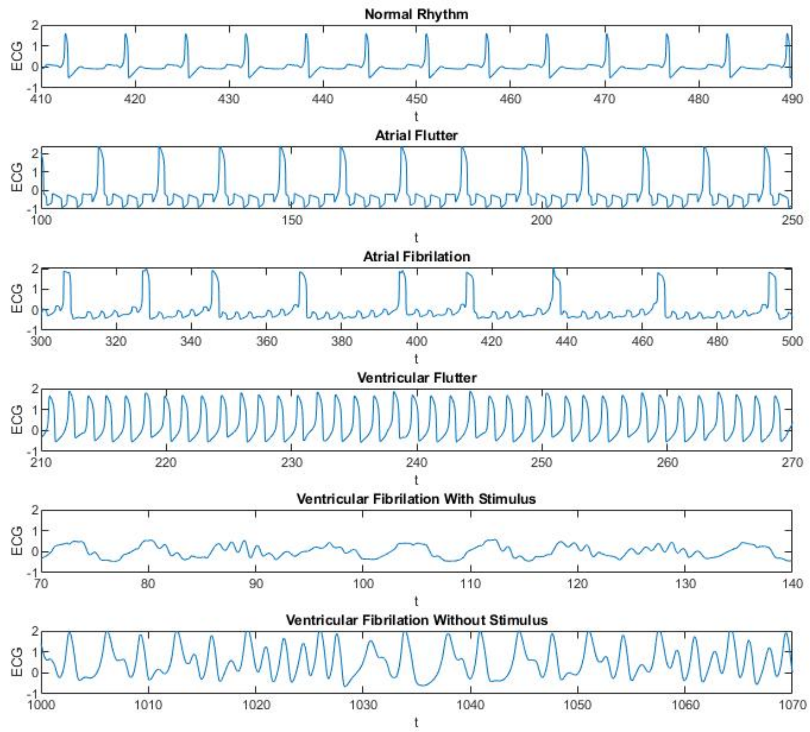


Figure 4.1: Simulated ECG of both normal rhythm and different arrhythmia

4.2.2 Merging simulated data with real data

When merging the simulated data with the real data set it is not sufficient to simply add one to the other. There are other considerations which must be done first to ensure the merging of the 2 will prove useful when trying to train the classifier. The classifier will learn features within the data and from there will learn a boundary to distinguish between the 2 classes based upon the difference in the features. Any differences between the real and simulated data can be detrimental to the ability to classify data points.

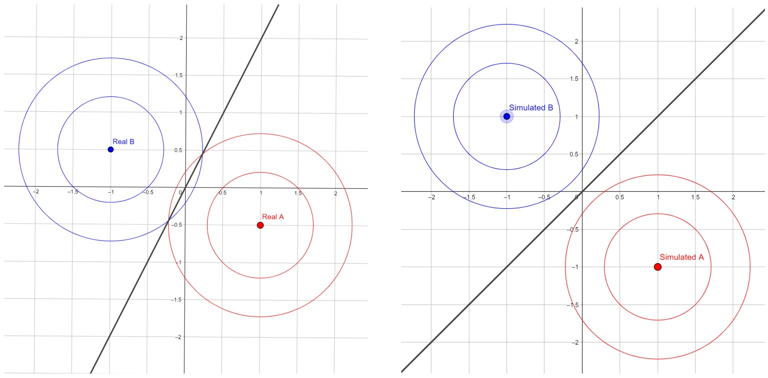


Figure 4.2: Example of classification boundary's in a 'real' (left) and 'simulated' (right) data set

Figure 4.2 highlights this, the figure displays the mean as the centre point and standard deviation as rings associated with each class for both the real and simulated data sets. The line dividing the two is the classification boundary that is learned by the model, though only a small difference in the mean and standard deviation there has been a noticeable impact on the boundary. If the simulated data was to be added in its current state this would have a knock on effect where the classification boundary for the merged data set would become a hybrid of the 2 and reflect the middle point of these 2 boundary's. Since the model is being used classify real data, if the addition of simulated data is going to be useful it is desirable to amend the simulated data better reflect the real data to maximise its effectiveness.

Doing this on an ECG data set more considerations have to be made as it is not a single value that can be taken and amended. Ideally all of the features of the simulated arrhythmia data set should have the same mean and standard distribution as the real data set. However within the scope of this project it is not feasible to do so thus the most optimal features should be amended. There a range of features to be considered, highlighted in Figure 4.3. One of the key features associated with atrial fibrillation is the in frequent period between the R waves in ECG signals [2]. Due to this the R wave will be used as the key feature to best reflect the real data set. Three main characteristics regarding the R wave that will be used are the RR interval, total R waves per ECG and R wave amplitude.

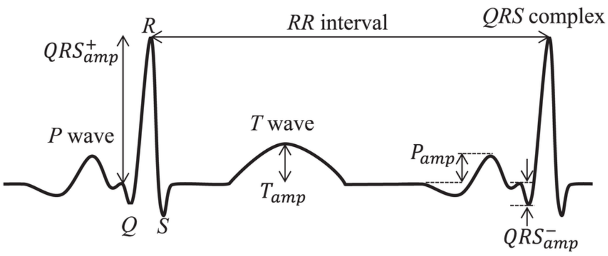
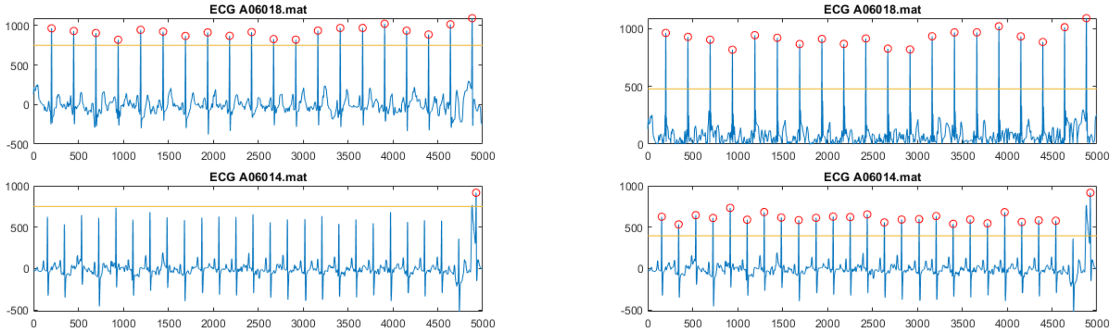


Figure 4.3: Features of an ECG signal [34]



(a) (b)

Figure 4.4: R wave detection with MinPeakHeight (a)= 750, (b)= avg+3*stdDev

4.2.3 'Real' data analysis

Matlab has a function named findpeaks() which is designed for the purpose of finding local maxima in a provided input vector. Using this function a new program was written which takes the entire ECG dataset as an input. It then outputs the average value and the standard deviation in the dataset for each of the following; RR interval, R wave amplitude and total R waves.

Findpeaks takes multiple inputs as well as the input vector, the minimum peak height and the minimum peak distance. The minimum peak height cannot be set to a fixed arbitrary value and used for all ECGs as there is a fluctuation the amplitude of peaks between different ECGs. A value that is satisfactory for one ECG may return that another ECG has very little or no R peaks shown in Figure 4.4. To combat this a unique value has to be calculated for each ECG. To do this as each ECG is a fixed vector of 1x5000, where each value in the array contains the amplitude of the ECG at that point. It is simple to calculate the average value for each ECG and the standard deviation. Using this information we can set the minimum peak threshold to be at approximately the 99th percentile using the empirical rule. By setting the minimum peak height for each ECG equal to $averageValue + 3 * standardDeviation$ the function will find a unique threshold for each ECG. The improvement is highlighted in Figure 4.4.

Present in the dataset are other anomalous ECGs that affect the final result in a non-desirable way. The first one being that the ECG can be inverted, this is caused when the device used to record the ECG has been oriented in the incorrect way. When this occurs the findpeaks function returns that there are no R waves as it is looking for peaks above a threshold. A simple way to correct for this is to take the absolute value for each value in the array before passing the array to the findpeaks function, Figure 4.5. Secondly noise within the data can also skew the calculation of the threshold so that it returns that there are fewer or no R waves, Figure 4.6. Since there are so few of these cases within the dataset, suitable averages can be found which describe the entire dataset without the inclusion of these outlying cases. Through experimentation with

		Normal Rhythm	Atrial Fibrillation
RR interval	μ	307	272
	σ	148	147
Num. R waves	μ	16	20
	σ	6	8
R wave amp	μ	899	828
	σ	504	428

Table 4.3: 'Real' data statistics with removed anomalies

different values it was decided that if an ECG had 3 of fewer peaks it would be excluded from the calculation of the average. Using 3 as the boundary removes the most extreme cases while leaving a large enough portion of the data-set to get an accurate measure for the entire dataset. After dealing with aforementioned issues, the R wave statistics can be calculated, see Table 4.3.

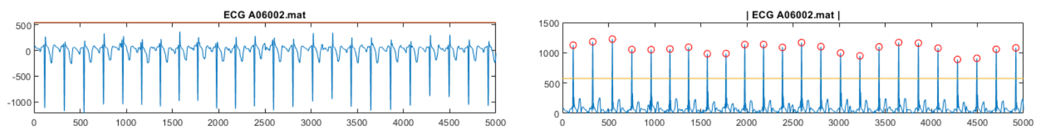


Figure 4.5: Correcting for inverted ECG by taking the absolute value

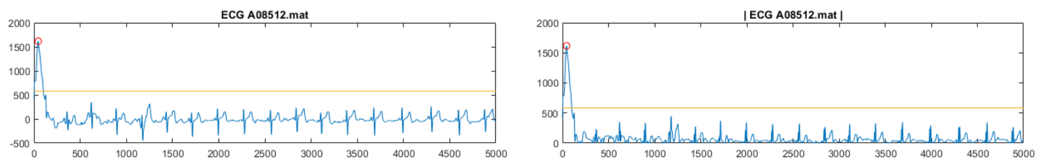


Figure 4.6: Example of noise in data leading to incorrect R wave detection

4.2.4 Generating large dataset

To generate a large dataset randomness has to be introduced into the model so that each simulated ECG added is not the same as the previous. While doing so the R wave statistics of the simulated dataset need to match as close as possible to those in Table 4.3. Cheffer and Savi [8] pointed to the fact that by treating the couplings as random variables we can get nondeterministic effects. By modeling the coupling parameter as a normal distribution around the value the parameter is initialised to with standard deviations we can get the random effects we desire. Using this knowledge the coupling parameters can be written as,

$$k_i \sim N(\overline{k_i}, \sigma_k^2) \tag{4.4}$$

This was implemented in Matlab through the introduction of a simple function which takes in the value for kbar alongside the standard deviation and returns the random value chosen from this normal distribution.
An update to the original code used to generate the ECG was needed in order to begin to generate the dataset. Firstly introducing code which creates a repository to store the data set and the accompanying code which saves the ECG into the repository in the correct format. By placing the function call which generates the solution space for the the ECG inside of a for loop the code now can continuously generate the desired amount of ECG signals. Also inside this loop before solving the set of equations, a call is made to the previously described randomness function to randomise the chosen parameters. Those being coupling and also the time frame in which the recording is taken.
While introducing randomness, though the coupling alone does introduce some variance to the number of R waves in the ECG it alone does not produce the desired distribution in the total number of R waves in the dataset. The randomness of the coupling mainly controls the general formation of the ECG and where peaks occur meaning it has a much greater effect on the RR interval. Because of this the time frame was also chosen to be randomised as there is a clear trend in that increasing the time span in which the ECG is taken results in more R waves being detected in this time span, Figrue 4.7. Using the plot, estimations of the time span needed in order to get the desired total R waves can be inferred. For a normal rhythm the mean number of R waves is 16 and for atrial fibrillation it is 20, the time spans needed in order to achieve these are approximately 386 and 479 respectively.

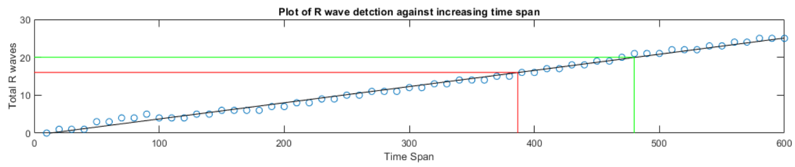


Figure 4.7: Estimation of mean time span needed for desired total R waves

Now by initialising the value of the time span to this value for each respective rhythm and altering the coupling parameters. New graphs can be plot which shows how the change in the coupling affects the R wave interval. Firstly altering the SA-AV coupling alone, indicates that there is a correlation between increasing the value of SA-AV and the average RR interval, Figure 4.8. From the initial plot it indicates that a value of the coupling lower than the initial value of 0.66 will increase the average RR interval to achieve the desired value. Through experimentation values below 0.65 frequently cause a run time error in the program where the program runs but does not reach an end point therefore any values below this have been disregarded. Further inspection of the SA-AV value from 0.65 to 0.654, Figure 4.9, shows how sensitive the system of equations is to this parameter change, using the line of best fit on this graph its indicates that a value for the SA-AV coupling at 0.651. Furthermore changing the coupling parameter representing the AV-HP node shows no clear trend in how it affects the RR interval Figure 4.10. However what can be inferred from this is that changing this value as well can also be useful in introducing additional randomness into the system. This method was then repeated to get the parameters for the normal rhythm as well.

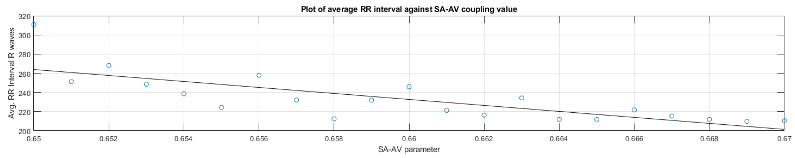


Figure 4.8: Average RR interval change from SA-AV: 0.65 - 0.67

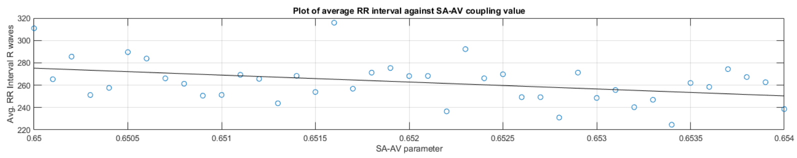


Figure 4.9: Average RR interval change from SA-AV: 0.65 - 0.654

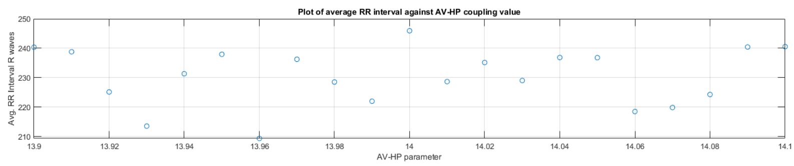


Figure 4.10: Average RR interval change from AV-HP: 13.9 - 14.1

Using this knowledge we can set the values to be randomised by the created function. For the normal rhythm the mean values for the time span, SA-AV and AV-HP coupling parameter are . Then for atrial Fibrillation the mean values are 480, 0.651, 14.0 respectively. Due to how sensitive the equations are and how a slight update to the parameter can lead to big change in the output. Multiple datasets were created until reaching the final dataset which best represented the the real data based upon these two measures of RR interval and total R waves.

After this the final stat to match was the average R height. This value was adjusted after the data was generated, it was done by calculating the average height and standard deviation across the generated dataset. From there the difference in this average was calculated and then the simulated dataset was multiplied by this value. Doing this meant that the final measure had now been adjusted to represent the real data. The final statistics can be seen in Table 4.4

		Real		Simulated	
		Normal	Atrial	Normal	Atrial
RR interval	μ	307	272	315	279
	σ	148	147	137	112
Num. R waves	μ	16	20	17	19
	σ	6	8	7	5
R wave amp	μ	899	828	911	827
	σ	504	428	508	428

Table 4.4: Simulated data statistics

4.3 Creating a Classifier

4.3.1 Data preparation

Before building the classifier, the data needs to be prepared in order to get it into the correct format to be used when training the model. Originally the Physionet2017 dataset was a folder of 8528 individual ECGs in the form of .mat files each of varying lengths. Each file had an accompanying .hea file of the same name, which contained information about that ECG such as the time and date at which it was taken. Within this 8528 files there was 4 classes; normal rhythm, atrial fibrillation, other rhythm and noisy data. Accompanying these files was a single .csv file which contained an array of the corresponding labels for each file.

The classes labeled as other and noisy are not useful in the context of this project as they are too vague. The ECG model that has built is able to simulate both a normal rhythm and atrial fibrillation so for this reason these 2 classes need seperated from the rest of dataset. While doing this the file containing the labels needs to be updated to reflect this change. After doing this the dataset is reduced from 8528 to 5925 ECGs, 5154 and 771 of which, being normal rhythm and atrial fibrillation respectively.

An additional issue with the original dataset is that the ECGs are of varying length. Each .mat file contains an array of numbers, ranging in the length from 2714 to 18286. Due to the decisions made for the choice of classifier, this would cause issues as each entry is required to be the same length. To resolve this issue each file has to be trimmed to the same length. There is potential that by uniquely choosing the section to keep for each ECG, bias may be introduced. For example by simply looking for sections with an irregular RR interval and choosing those sections, the dataset used for learning will greatly reflect this. Unfortunately this is not the lone feature which describes atrial fibrillation. Because of this the model trained may appear extremely good at classifying atrial fibrillation in this specific dataset, however may not generalise well to other data. In an attempt not to introduce any bias into the dataset the first X elements of the array were taken for each ECG hopefully removing this affect.

When deciding how many long of each ECG recording to take a trade-off has to be considered. The trade-off being between maximising the number of ECGs passed through the model and maximising the length of each individual ECG. We want to pass as many unique ECGs through the model as possible so the model sees a wide range of each class so it can generalise to a larger dataset. Furthermore it is also important that each ECG is sufficiently long so that through convolution the model can extract higher level features from the each ECG. One consideration was to trim each ECGs array of values to match that of the minimum (2714). By doing so the throughput is maximised however the length of each individual ECG is minimal. It was decided in the end to trim each ECGs array of values to be of length 5000 and if it was any shorter to discard it. By doing this the length of each individual ECG has almost doubled from 2714 to 5000 meaning that each ECG has double the amount of values and thus features for the model to interpret. By doing so the total size of the dataset is reduced from 5925 to 5549. 93.7% of the original dataset has been retained leaving a large enough portion of the data to sufficiently train the model.

After doing these 2 steps, instead of having a unique file for each ECG they all are required to be in a single .csv file thus all need concatenated and saved into a single file. All of this was done in a Matlab script the pseudo code of which can be seen in Algorithm 1.

Algorithm 1 Prepare Data

```
Load ECG_Files, Labels
for i = 0 to length(ECG_Files) do
    if ECG label == Other or Noisy then
        Continue
    else if Length of ECG < 5000 then
        Continue
    else
        Add first 5000 values to next row in updatedData
        Add label to next row in updatedLabels
    end if
end for
Save updatedData and updatedLabels to CSV file
```

After doing so the next step was to join the 2 databases of the real and simulated data. After completing the domain alignment described in subsection 4.2.4. Merging the two datasets can be done by concatenating the simulated dataset to the real dataset and noting how many simulated values were added as this information will be needed when training. Initially 622 instances of simulated arrhythmia were added to the dataset to double the amount of atrial fibrillation instances in the dataset.

4.3.2 Building the neural network

The model was built on and trained on google colab [6], a Jupyter notebook environment used often for machine learning models. Upon creating the environment firstly all of the libraries and relevant functions need imported ready for use.

Once the environment is ready for use the data needs to be imported. This can be done in numerous ways, one option would be to upload the file to the environment manually. An issue with this is that each time that the web page is closed all data saved or uploaded to it is lost. Meaning that the data will have to be re-uploaded again the next time a model needs to be trained. Also any models trained will have to be manually downloaded before closing the browser and risk being lost if this is not done before closing. Another option is to use google drive as a repository. Google colab has utilities which allows google drive to be mounted to the environment and be treated as repository meaning that not only can the data be uploaded once to google drive and imported when needed. But all of the trained models can be saved to this drive and this removes the risk of accidentally losing any models by forgetting to download them at the end of a session.

As there are 2 classes present in the dataset, normal rhythm and atrial fibrillation it can be viewed as a binary dataset. Using an encoding function imported from the sklearn library the original labels 'N' and 'A' were transformed to be represented by 0 and 1. Doing this meant that the final output layer in the model can be converted to output a single value of either 0 or 1 representing a normal rhythm or an instance of atrial fibrillation.

After the data had been imported and converted to the correct format the model could now be built. The model was based upon the model presented by Yildrim et al. [41]. The model used in this paper was used to achieve an overall accuracy of 92.24 when classifying 7 classes. But when classes were grouped into 4 new classes based upon similar medical treatments it was then able to achieve an accuracy of 96.13%. Knowing that the model is reported to reliably be able to classify ECG is an excellent foundation to use to investigate the utility of adding simulated ECG to datasets. The model presented in Yildrim et al. [41] needs amended to reflect the dataset being used to train it. The key difference being that the new dataset being used only has 2 classes insetad of 4 or 7. This update was done by converting the final dense layer from having 4/7 units and having a softmax activation function used to predict the most likely class. To a final dense layer with just 1 unit with a sigmoid activation function which predicts a class of either 0 or 1. For the same reason the loss function used to describe the model also needed changing, this was done by converting from a loss modeled by categorical cross entropy to binary cross entropy.

The same adam optimiser was used to adjust the weights of the model as in the presented in model in Yildrim [41]. However the learning rate stated of 0.002 often led

Layer Type	Layer Parameters	Output Shape	Total Parameters
Conv1D	Filters=64, Size=21, Strides=11	453×64	1408
MaxPooling1D	PoolSize=2	226×64	0
BatchNorm	-	226×64	256
LeakyReLU	Alpha=0.1	226×64	0
Dropout	Rate=0.3	226×64	0
Conv1D	Filters=64, Size=7, Strides=1	220×64	28736
MaxPooling1D	PoolSize=2	110×64	0
BatchNorm	-	110×64	256
Conv1D	Filters=128, Size=5, Strides=1	106×128	41088
MaxPooling1D	Pool Size=2	53×128	0
Conv1D	Filters=256, Size=13, Strides=1	41×256	426240
Conv1D	Filters=512, Size=7, Strides=1	35×512	918016
Dropout	$Rate = 0.3$	35×512	0
Conv1D	Filters=256, Size=9, Strides=1	27×256	1179904
LSTM	Unit=128, Return Sequences=True	13×256	0
MaxPooling1D	PoolSize=2	13×128	197120
Flatten	-	1664	0
Dense	Unit=64, Activation=ReLU	64	106560
Dense	Unit=1, Activation=Softmax	1	65

Table 4.5: Model summary of DNN

to erratic behaviour in the training model, with models tending too classify every ECG as a normal rhythm and not improve beyond that. 0.002 was likely ideal for training with multiple classes however upon the conversion to a binary classifier became less effective. It was found that a learning rate a factor of 10 smaller than that suggested, of 0.0002 was much more effective.
After re-implementing the model and updating it to fit the purpose of the new dataset the final model summary can be seen in Figure 4.5. The final model has 2,899,649 parameters if which 2,899,393 of those are trainable.

4.4 Training Models

4.4.1 Train-test split

As the dataset is relatively small it is much more appropriate to use k-fold cross validation to evaluate the model rather than the traditional train-test-validation split. K-fold cross validation spilts the entire dataset into equal size sections each of which takes a turn being the test data while the remaining are all used to train the model. Evaluating the model using this method is much more appropriate as the 'real' dataset only contains 5549 ECGs, which can be considered relatively small.
5 K folds will be used for each instance trained used meaning that the 'real' dataset will be split into 2 subsets in ratios of 80:20 of training and test data. A further consideration

when splitting the data is that they cannot be split completely randomly. If they were, a situation may arise where the test set has no instances of one class. Due to this when evaluating the performance of this model the metrics will be skewed as it may appear to not be able to classify this missing class when in actuality there are no instances in the test set to classify. Because of this while the training and test sets must be randomised they must each contain the same ratios of each class. The sklearn toolkit [31] has a function which does exactly this, StatifiedKFold provides indices to split the data into the training and test sets while preserving the precerntage samples for each class.
When introducing simulated data into the model, steps must be taken in order so that the models metrics are reflective of the actual performance of the model. If the simulated data was included when the dataset was being split into each K fold this means that the simulated data may appear in each of the test sets. In a real word application of this classifier it would be exclusively used to classify real data. Though steps have been taken to reduce the differences between the real and simulated data, it cannot be said that the simulated data perfectly represents the real data. Because of this the test set must contain exclusively real data. The simulated data may be added to the training data as it is being used to assist the model learn key features. This way the metrics gathered by the model are reflective of a real world application it may finds its self in. And using this inferences can be made about the effectiveness of introducing the simulated data into the training set.
This was done by first using the StratifiedKfold function to return the indices for the each K split, but only passing it the real data initially. Then the indices for all the simulated data can be then added to the training set index afterwards, ensuring the test set is all real data.

4.4.2 Callbacks

A callback is an object passed to the training function which performs various actions during the training process. Using the test sets loss value and callbacks within the keras library optimisations can be added to the training method. Using the test sets loss value is important as if over-fitting is occurring the training sets loss will continue to drop while the test sets will not. Knowing that it has stopped improving the training method will respond accordingly.
The first of which being to to call the ReduceLROnPlateau() callback. If the loss value is has plateaued and is no longer improving one reason may be that the learning rate is too large. As it approaches the local optimum it is if the learning rate is too large it will behave erratically and stop converging. A solution to this is to lower the learning rate as it begins to do this. ReduceLROnPlateau() monitors this value and if after 5 epochs the learning rate is then decreased by a factor of 5.
The second useful callback is EarlyStopping(). This is introduced to stop the model

when it is no longer improving. If the model after 10 epochs, meaning even after the learning rate has been lowered it still does not show any improvement it will stop training that model and move noto the next K fold if available.
The final callback is ModelCheckpoint() and is used to save the models. Every model was saved during the training phase for each model trained on the varying data-sets throughout this process.

4.4.3 Ratio of real to simulated data

When training the models various ratios of real:simulated data were investigated. Naturally the model was trained with entirely real data as a control to compare all other results to. As the dataset being used only has 2 classes, normal rhythm and atrial fibrillation, from the simulated models only simulated atrial fibrillation will be used. This is because the original dataset is already imbalanced therefore introducing any more normal rhythms will further increase this imbalance.
To investigate the efficacy of the simulated data direct comparisons will be made against the entirely real model. The dataset used has 622 instances of atrial fibrillation. After the K folds have been created there is on average 122.4 instances in the test set, leaving 497.6 in the training set. As a comparison varying ratios of real:simulated will be used in this training set making sure they all sum up to the total 498. Doing so leaves the main variable being changed between models is the varying ratios of real:simulated data. 5 models will be trained including the real control model to investigate this case. Those being the following ratios of real:simulated; 100:0, 75:25, 50:50, 25:75 and 0:100 in each case the total of real to simulated data will be equal to 498.
The next set of models will be trained to address the class imbalance across the entire dataset. When doing so there is a further scenario that needs to be considered besides that of normal rhythm to atrial imbalance. That is the ratio of real to simulated data may also affect the ability to classify. Using this further models will be trained much in the similar way to previously described however in this instance there will be no limitation in that the sum of the real and simulated data must equal 498. For reference in the original dataset atrial fibrillation cases make up approximately 10% of the entire dataset. Using the introduction of the simulated atrial fibrillation instances to correct for this. Models will be trained in which the total cases of atrial fibrillation is increased using the introduction of simulated arrhythmia.

Chapter 5

Evaluation

For the following chapter the normal rhythm will be referred as the positive class and atrial fibrillation will be referred to as the negative class. Further acronym's, shown below, will be used when describing the models performance when classifying each arrhythmia.

TP (True positive)	Normal rhythm correctly classified
FP (False positive)	Atrial fibrillation incorrectly classified
TP (True negative)	Atrial fibrillation correctly classified
FP (False negative)	Normal rhythm incorrectly classified

5.1 Choice of Metric

When evaluating the models the choice of metric used to quantify the performance is extremely important. As the dataset used for training is imbalanced having a 5549:622 classes of normal:atrial fibrillation. Because of this the typical metric of accuracy can result in misleading conclusions on how well the classifier is performing. As an example if a dataset was to contain 100 values, 90 of them being of class A and 10 of them as class B. If a trained model was to classify every class as A the model would appear to be 90% accurate. This model that appears 90% accurate has no utility, it appears to be fairly accurate however it cannot be said to be accurate at distinguishing the 2 classes as it simply classifies everything as 1 class. Due to this there are more appropriate metrics to be considered when working with imbalanced datasets [13]. Furthermore when deciding upon a metric the nature and the purpose of the classifier has to be considered as the best metric will reflect the intended purpose of the classifier. The classifier is being used to detect cardiac arrhythmia ECG signals in real patient data. An application of this classifier could be for real time detection of arrhythmia from a patient in a medical setting in which the classifier notifies a medical practitioner if atrial fibrillation has been detected.
The diagnostic odds ratio (DOR) is often used in medical testing with binary classification. The DOR is a measure of the effectiveness of a diagnostic test [15]. In this case the diagnosis being between a normal heart rhythm and atrial fibrillation. Its mathematical definition can be seen in equation 5.1. The advantage of using this metric is that it provides a single value as an indicator, this value can range from 0 to infinity. Useful tests have a value of greater than one and the higher the value of DOR the better the performance of the test. While a useful indicator for overall classification

performance, it alone does not suffice as the lone metric to judge the performance of the classifier. This is due to the nature of arrhythmia classification, DOR is an good measure of the overall performance however it does not take into account the implications for each incorrect classification. In a real world application missing an instance of atrial fibrillation may have more severe implications than incorrectly. DOR can be useful in gaining a general intuition as to how well the model is performing but more nuanced metrics must be used to evaluate each model in more detail.

$$\text{Diagnostic odds ratio, DOR} = \frac{TP/FN}{FP/TN} \tag{5.1}$$

In a real world situation it would be imperative to detect every possible instance of arrhythmia. Meaning that for the classifier, the optimal number of atrial fibrillation cases incorrectly classified would be 0. The positive predictive value (PPV) will be used to measure the models performance for this. The PPV, defined in equation 5.2, measures what proportion of the positive predictions were correct. By comparing the models based upon this metric the model with the highest PPV will correctly identify more cases of atrial fibrillation. Hence if the sole measure of how well the model has performed is to detect all cases of this then it will be the best model.

$$\text{Positive predictive value, PPV} = \frac{TP}{TP + FP} \tag{5.2}$$

In conjunction to this attention must also be paid to the total number of false negatives. As a classifier may appear to correctly identify all instances of atrial fibrillation but through doing so has also falsely classified a large portion of normal rhythms as this as well. Which is also not ideal in a classifier.

For the evaluation of the models the positive predictive value will be used to identify the best performing models over each dataset. The first evaluation will be done based upon the model with the highest PPV score a as it is model with the correctly identifies the most instances of atrial fibrillation. Additionally another consideration will be made to consider how many instances of false negatives the model has. An initial threshold of a PPV value of 95% will be used and all model which surpass this threshold will be considered. From there the models will be distinguished based upon the minimum number of false negatives in order to derive the overall best performing model.

5.2 Training With Entirely Real Data

Firstly the classifier was trained using an entirely real data set. The best performing model and evaluation of this model will be used as a control to compare all other results too. Plotting the diagnostics odds ratio, see figure 5.1, for both the training and validation datasets indicates that the classifier is indeed learning to distinguish between the two classes. As previously mentioned a classifier a classifier that has no use and is equally likely to predict each class has a score of 1, the models trained are able to reach well above that. When comparing the training and validation plot on each graph it is clear for each k fold that it reaches a point in which the training DOR continues to grow where as the validation DOR stagnates. This is likely due to the overfitting of the model on the training datatset this claim is further supported by plotting the training and validation loss for each fold shown in figure 5.2. By plotting the loss it is clear to see when overfitting has began to occur as the loss value for the validation set has plateaued or started increasing where as the training loss has continued to drop. By comparing these 2 graphs for each K fold an estimate can be made for when the model has began to overfit. At this point any model after this point should be disregarded as it will not generalise well to a different dataset. This point is most apparent on K fold 4, that at around the 11th epoch the model begins to overfit the training data and has stopped improving on how well it can classify the validation data. For each Kfold 1 through 5 the point at which the model has began to overfit are 35, 12, 21, 11 and 22 respectively. The models after each of these cases will not be considered as they lose the ability to generalise well.

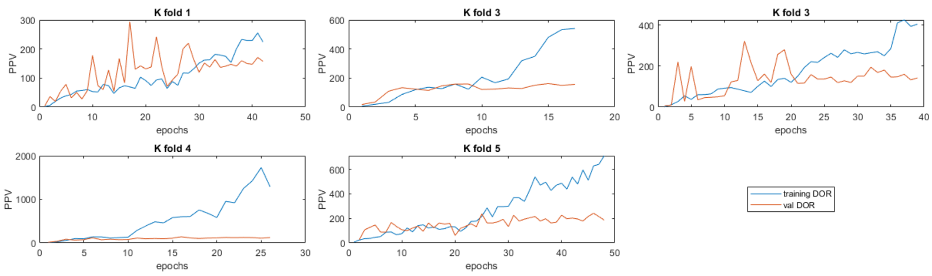


Figure 5.1: Training and validation diagnostic odds ratio plot for each k fold of real data

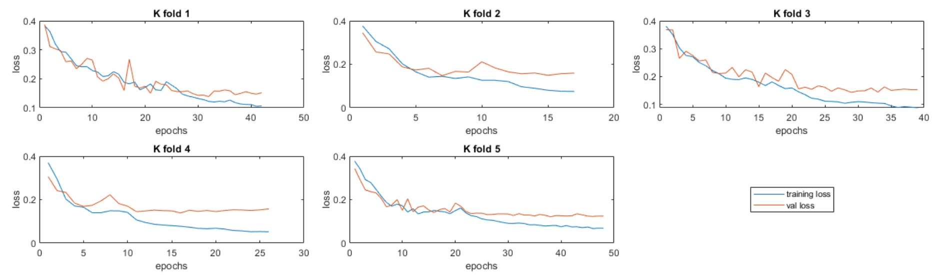


Figure 5.2: Training and validation loss values plotted for each k fold of real data

Plotting the positive predictive values for each of the folds shown in figure 5.3 shows how the models performed as they were trained. Disregarding the models that were overfit the model the statistics for each fold can be seen in Table 5.1 .The model which performed the best came in the 5th fold of data. This model achieved the highest PPV of 0.9711 or 97.11%, only incorrectly predicting 28 atrial fibrillation instances as normal out of the total 970 predicted as normal. Furthermore the first K fold had the lowest amount of false negatives given the threshold of PPV $>$ 95% with only 9 false negatives.

	PPV Max (%)	Total PPV > 95%	Lowest FN
Kfold 1	96.08	13	9
Kfold 2	96.17	4	11
Kfold 3	95.31	2	16
Kfold 4	96.86	3	20
Kfold 5	97.11	12	11
Average	96.30	4.4	13.4

Table 5.1: Real Model statistics

The confusion matrix for both pf these can be seen in Figure 5.4. Taking an average across each of the folds gives a true reflection of how each classifier performed as a whole across the entire data set. Calculating the average indicates that when trained on purely real data the classifier has an average PPV of 96.30% and an average lowest false negative score of 13.4.

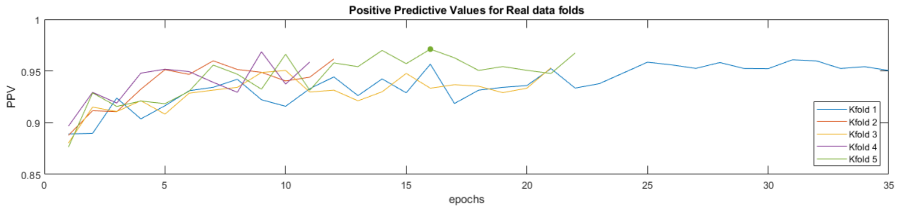


Figure 5.3: Positive predictive value of models for each fold

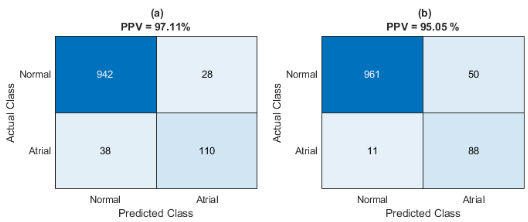


Figure 5.4: Confusion matrix of model with: (a) Max PPV, (b) Min FN

5.3 Introducing Simulated Data into the Training Set

5.3.1 Keeping the training set size constant

To get a true understanding of how the well the simulated data performs at replicating atrial fibrillation models were trained in which the total amount of atrial fibrillation in the training set was constant.

Figure 5.5 and Figure 5.6 show the DOR plot and loss plot for each fold when only simulated data was used for training. When comparing this model to the model trained on entirely real data a clear difference in the in maximal values the DOR reached in the model trained on entirely simulated data is significantly higher. This indicates that using the model, when classifying the training data has a much better performance. This is likely due to the fact that an entire class in the training data is simulated, therefore the model is learning to distinguish between real and simulated data. However it must be said that when used to classify the validation data the model still does appear to perform reasonably well, reaching a highest DOR value in k fold 3 of 380. Using the loss plot as for guidance, figure 5.6, overfitting began across the 5 folds at 12, 22, 15, 17 and 16 respectively. This process was repeated to eliminate all over fitted models for each of the datasets used and the final PPV plots for each dataset can be seen in Figure 5.8.

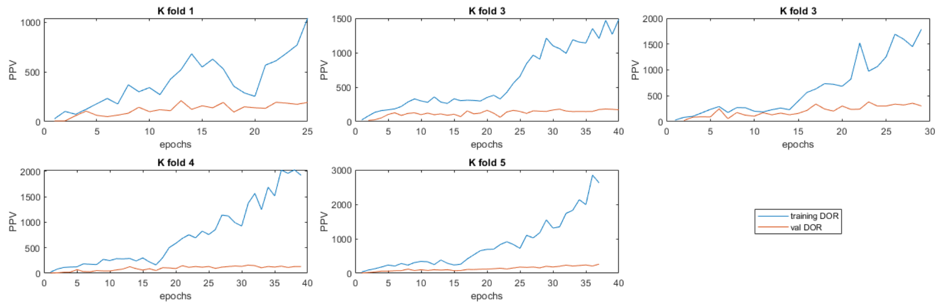


Figure 5.5: Training and validation DOR plot for each k fold of using only simulated data to train

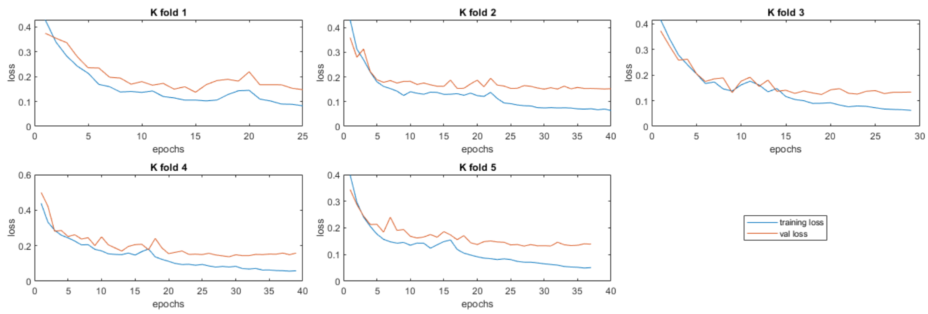


Figure 5.6: Training and validation loss plot for each k fold of using only simulated data to train

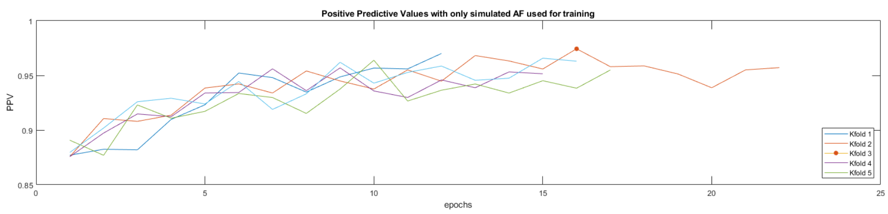


Figure 5.7: Positive predictive value of validation set predictions

Figure 5.8 shows that the introduction of simulated data into the training set does not hinder the ability to classify the entirely real validation set. Table 5.2 shows the best performing models across all of the trained models in which the total real and simulated data in the training set was 498. All models in which simulated data was introduced

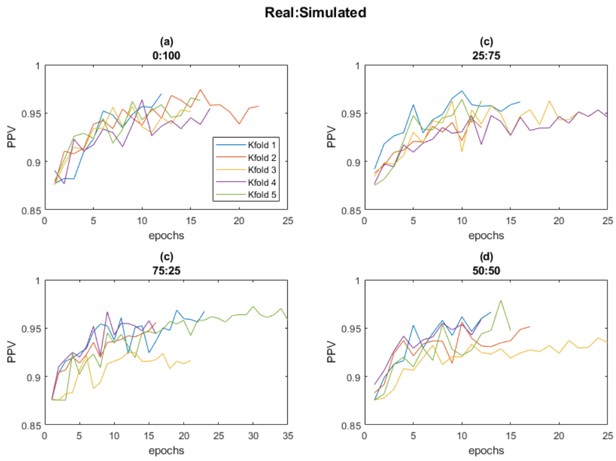
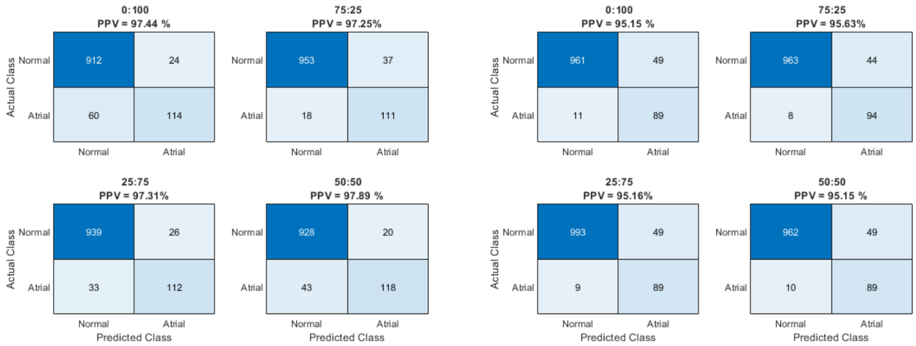


Figure 5.8: Positive predictive value of models for each fold



(a) Maximum PPV (b) Lowest FN

Figure 5.9: Confusion Matrix of best performing models

had a model which out performed the original model which was trained exclusively on real data, when looking at the PPV. When taking the average PPV across all of the folds for each classifier all of the models performed approximately the same as the original model. Surprisingly the model which was trained exclusively with simulated atrial fibrillation data seemed to outperform the initial model on this PPV metric alone.

Comparing the model with the lowest FN value, given the threshold of PPV being above 95%, shows that for each classifier the best performing model had a similar value to that of the original model. The worst of which only falsely classified 3 more ECGs. A few of the classifiers when trained had at least 1 fold in which there was no models which passed this threshold. The most noticeable difference came when taking the average lowest false negative score across each of the folds. Only 1 model out performed the initial model and only slightly. However this was a model in which one of the folds had 0 above the threshold so the average was taken across the remaining 4. The rest of the classifiers performed noticeably worse under this measure, the worst of which being the entirely simulated set incorrectly classifying 7 more ECGs.

Across each of the classifiers trained the average PPV value remained approximately the

	Ratio of Real:Simulated atrial fibrillation in training set				
	100:0	75:25	50:50	25:75	0:100
PPV Max (%)	97.11	97.25	97.89	97.31	97.44
Average	96.30	95.78	96.02	95.95	96.62
Lowest FN	9	8	10	9	11
Average	13.4	17.75*	18.75*	13.25*	20.4

Table 5.2: Statistics across all models as real:simulated data is varied
(* 1 fold didn't achieve any above threshold so average is across 4 folds)

same. Indicating that whether real or simulated data used for training of final classifier, it had no significant effect on the classifiers ability to detect every instance of atrial fibrillation. However the average lowest false negative value appears to increase with the increasing ratio of simulated data. From this it can be suggested that the simulated atrial fibrillation is performing well at imitating the real instances. But by introducing it, the classifier then performs worse in the sense that it is incorrectly predicts more of the normal rhythm as atrial fibrillation. Therefore the need for real data in the training set is indeed important.

5.3.2 Increasing the size of the training set

Next, models were trained in which the total instances of atrial fibrillation in the training set was increased using the simulated cases. As highlighted in the previous section the real data is important in the models overall ability to make the correct predictions in the validation set. Thus excessive simulated data will hurt the classifiers overall performance. Using this, models were trained so that in the training set, the ratio of real:stimulated atrial fibrillation favoured the real instances. 3 models were trained varying the total amount of atrial fibrillation instances. Initially the dataset had 622 instances of atrial fibrillation, the 3 models trained increased this to 1224, 887 and 777. Through doing so the ratio of real:simulated data in each model was 50:50, 70:30, and 80:20 respectively.

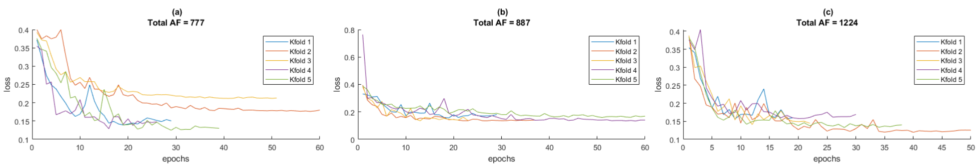


Figure 5.10: Validation loss of models with increased AF in training set

Looking at the DOR across the validation sets for each model, Figure 5.11 indicates that the classifier is indeed learning to correctly classify normal and atrial rhythms. The first graph representing the total atrial fibrillation in training did have spike to a DOR value in excess of 400 for 2 earlier models. However on average the plots on graph (a) and graph (b), while fluctuating tended not to exceed a DOR value of 200. The final plot

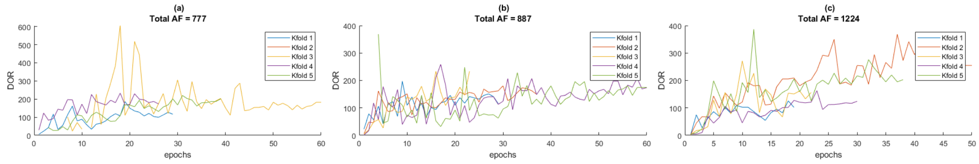


Figure 5.11: Validation DOR of models with increased AF in training set

showing the classifier trained with double the amount of AF classes did consistently exceed a DOR value of 200 indicating that it potentially was outperforming the others more consistently.

Removing the overfitted models and plotting the PPV values across the models yields the graphs shown in Figure 5.12. From this graph it can be seen that for each dataset used the models trained are able to achieve a PPV value of approximately 95%. In addition to this it can be seen that the best performing model came from the dataset in which double the number of AF were used in training.

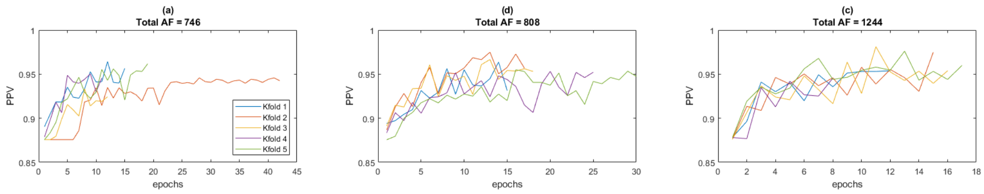


Figure 5.12: Validation PPV of models with increased AF in training set

Table 5.3 shows the statistics of all these models and the original model as reference. The first model in which only 155 simulated arrhythmia were added performed worse than the original model across all stats. The second model where the ratio of real to simulated was 70:30 totaling 887 atrial fibrillation on the training set performed similarly to the original model. It had an average PPV value within 0.03% of the original model and while its lowest false negative score was lower than the original model the average across all folds was slightly higher.

The best performing model was the model in which the number of atrial fibrillation in the training set was doubled using the simulated arrhythmia. This model had the highest PPV value out of all models trained. In conjunction to this had a higher average than the original model meaning it correctly identified more of the atrial fibrillation instances in the validation set. The best model trained from this dataset also had a lower false negative value score than the original model. It also had a lower average across all of the folds indicating that it was able to better predict instances of normal rhythm and not incorrectly classify them.

The fact that only the model with all of the simulated arrhythmia out performed the original model may be due to how the instances for the other models were chosen. The average values of the total R waves, average RR interval and R wave height were averaged across the entire 622 simulated atrial fibrillation instances. For the classifiers

trained with less than the total 622, which arrhythmia was used was chosen at by taking the first X from the entire set. When doing so it may have been the case that the statistics across this subset regarding the R wave no longer reflected the original atrial fibrillation statistics. Hence the classifier did not perform as well as expected.
When all of the data was used the R wave statistics were as expected and matched the real atrial fibrillation data as closely as possible. Doing so and doubling the total instances of atrial fibrillation in the training set improved the classifiers ability to recognise more cases of atrial fibrillation. In addition to this the classifier also correctly identified more cases of a normal rhythm. Both of these being true indicates that the use of simulated data while training did have some benefit.

	Total AF instances in training set			
	622	777	887	1244
Total simulated AF added	0	155	265	622
PPV Max (%)	97.11	96.42	97.49	98.11
Average	96.30	95.10	96.27	96.628
Lowest FN	9	15	8	5
Average	13.4	17.6**	16.6	10*

Table 5.3: Statistics across all total AF in training set is varied
(* 1 fold didn't achieve any above threshold so average is across 4 folds)
(** 2 folds didn't achieve any above threshold so average is across 3 folds)

Chapter 6

Conclusion

6.1 Summary

This section will review the objectives that were set in section 1.2.
Objectives 1, 2 and 3 were to review cardiac arrhythmia's and ECG signals, to review how mathematical models can replicate ECG data and to review deep neural networks. This objective was achieved in Chapter 2 where research was conducted into each of these areas. An understanding of the structure of ECGs signals was gained and how this structure differs when a patient has been diagnosed with having an arrhythmia. Research was done into how mathematical models can replicate such arrhythmia's. And finally researching deep neural networks a number of techniques and frameworks were discovered which were used throughout the project.
Objective 4 was to create a deep neural network able to classify ECG signals. This objective was met in section 5.2, where the classifier created was trained entirely on real data and able to achieve an average PPV score across all of the folds of 96.3%. Indicating that it was able to distinguish between the 2 classes quite well.
Objective 5 was to create a program able to create ECG signals from mathematical models. Re-implementing the models presented in Cheffer and Savi [8] in section 4.2.1 achieved this objective. The re-implemenation of this program was able to create ECG signals for 6 different rhythms though only 1 was used for training models.
Objective 6 and 7 were to try differing ratios of real:simulated data when training models and analyse how effective the introduction of simulated data was. This objective was met in section 5.3 where varying models were trained with a differing amounts of simulated data. An evaluation and conclusions were drawn for each of these models.
Overall, I believe that the aims of the project were all met. The models trained showed how the introduction of simulated data affects the utility of the final classifier. It has been shown that, providing the simulated arrhythmia introduced in training are representative of the real arrhythmia. That the resulting classifier can indeed benefit from this increase of data and yield a better classifier compared to one trained on an smaller entirely but entirely real dataset.

6.2 Future Work

To further investigate the utility of simulating arrhythmia to improve classification there are 2 approaches that may be taken.

The first of which being to improve how well the simulated ECG represents the real arrhythmia. In this project only the R wave was considered but for further research more variables could be used. For example also considering the entire QRS complex as well as the P wave and additional intervals regarding these 2 additional features. Ensuring these values are also as close to the real arrhythmia as possible may yield better results. Secondly this project only looked at one simulated arrhythmia. There already exists classifiers which can classify multiple arrhythmia. The models presented in Cheffer and Savi [8] provides models able to simulate 6 rhythms. Instead of creating a binary classifier used to distinguish between normal and atrial fibrillation. A model could be created which utilises more of these simulated arrhythmia in order to create a multi class classifier.

6.3 Ethical, Legal, Social, Professional issues

6.3.1 Ethical issues

One issue that has to be considered is the use of patient data. However the dataset used was publicly available and was pre-anonymised therefore there are no ethical issues in using or potentially leaking the patient data in this dataset.

6.3.2 Legal issues

One legal issue to consider is the use of intellectually property. However this project has cited all resources that have been used throughout this project. The re-implementation of the models presented in Cheffer and Savi [8] and classifier presented in Yildrim et al. [41] have been well cited throughout.
The use of third party data may also be of concern however as the dataset used is publicly available and pre-anonymised this is not of concern.

6.3.3 Social issues

There are no social issues to consider with this project. It may be said that working with machine learning can have risks attached if used in an incorrect or malicious way. However the model created was done so for a specific reason and does not pose and serious risks.

6.3.4 Professional issues

Professional issues such as misrepresenting skills and resources did not arise during this project. The aim and objectives was set at the beginning of project were all met indicating that it was completed within my level of competence. Additionally skills and resources that were beyond my scope such as creating mathematical models to replicate arrhythmia were well cited as to where they originated from.

6.4 Self Assessment

Being the largest project I had undertaken to this date I had little experience in how to manage, research and complete a project of this scale. Working on this project I have gained a great appreciation of how important doing thorough background research before attacking such a project. Having spent very little time in the past reading scientific literature my ability's to do so has improved 10 fold over the course of the project. Not only my ability to read and analyse academic material but also my ability to actually search for useful material and learning quickly as to whether it is useful or applicable to my work. I had never encountered delay differential equations before and only had a vague understanding of what an ECG was. Through my research I feel I now have a much deeper understanding and appreciation for these two areas.
Coming into the project with knowledge of machine learning but having only previously worked on a very simple network in my own time and then coursework in my module last year. Working on a neural network of this scale has given me a much greater appreciation of the field. Learning to utilise the available frameworks such as Keras to implement a deep neural network of this scale has and will be an invaluable asset going forwards. In addition to this it has been eye opening to see how machine learning can be used in fields that I previously hadn't even considered machine learning to be relevant. Seeing how applicable and beneficial it can be to whole range of situations is extremely exciting to see. Having previously been interested in the field I can confirm that it is something I will definitely seek to continue with in the future.
Reflecting on the project as a whole I'm extremely happy with the re implemenation of the ECG models. As previously mentioned, I had never heard of delay differential equations before starting this project and also never used Matlab so to come up with what I feel was an accurate re implementation is very rewarding. I'm happy with the classifier built however I wish I had the chance to train and evaluate more models. Training a classifier so that all 5 K folds are complete could take a few hours to complete. Pairing this with the fact that initially I had not been saving the model history so all of the initial models trained I had no proof. Because of this days of work was lost however I did not let that hold me back and continued training and feel I trained enough to properly justify the results the project.

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Appendices

Appendix A

Tables of Trained Models

A.1 Total Atrial Fibrillation = 622 , 100:0 (Real:Sim)

K fold = 1											
Training						Validation					
Loss	Accuracy	TP	FP	TN	FN	Loss	Accuracy	TP	FP	TN	FN
0.383	0.870	3854	546	6	32	0.388	0.845	914	114	24	58
0.363	0.875	3866	534	18	20	0.311	0.888	968	120	18	4
0.321	0.891	3830	429	123	56	0.304	0.896	934	77	61	38
0.294	0.903	3828	374	178	58	0.298	0.902	966	103	35	6
0.292	0.905	3839	374	178	47	0.259	0.914	965	88	50	7
0.269	0.912	3829	335	217	57	0.262	0.911	943	70	68	29
0.245	0.917	3835	318	234	51	0.235	0.922	952	67	71	20
0.242	0.918	3834	311	241	52	0.250	0.906	925	57	81	47
0.242	0.922	3828	288	264	58	0.271	0.916	960	81	57	12
0.229	0.921	3819	285	267	67	0.265	0.917	969	89	49	3
0.223	0.920	3817	284	268	69	0.206	0.926	959	69	69	13
0.208	0.928	3834	268	284	52	0.192	0.929	949	56	82	23
0.210	0.929	3824	251	301	62	0.200	0.925	966	77	61	6
0.224	0.920	3805	276	276	81	0.217	0.926	948	58	80	24
0.216	0.928	3818	253	299	68	0.203	0.929	967	74	64	5
0.188	0.931	3817	237	315	69	0.160	0.939	947	43	95	25
0.183	0.932	3799	213	339	87	0.268	0.921	970	86	52	2
0.189	0.928	3812	245	307	74	0.175	0.930	965	71	67	7
0.162	0.941	3816	191	361	70	0.168	0.932	965	68	70	7
0.170	0.938	3813	201	351	73	0.174	0.933	964	66	72	8
0.182	0.934	3804	212	340	82	0.150	0.945	959	48	90	13
0.162	0.940	3809	191	361	77	0.191	0.934	968	69	69	4
0.160	0.940	3814	195	357	72	0.181	0.935	964	64	74	8
0.190	0.927	3818	257	295	68	0.179	0.933	950	52	86	22
0.178	0.938	3807	195	357	79	0.160	0.941	948	41	97	24
0.166	0.934	3803	209	343	83	0.156	0.944	954	44	94	18
0.147	0.944	3821	184	368	65	0.156	0.949	963	48	90	9
0.141	0.945	3815	174	378	71	0.158	0.953	962	42	96	10
0.137	0.949	3808	149	403	78	0.148	0.947	961	48	90	11
0.132	0.950	3824	160	392	62	0.143	0.943	957	48	90	15
0.128	0.952	3825	154	398	61	0.144	0.950	956	39	99	16
0.122	0.953	3815	137	415	71	0.139	0.949	955	40	98	17
0.120	0.955	3821	135	417	65	0.158	0.947	961	48	90	11
0.122	0.954	3822	138	414	64	0.157	0.946	958	46	92	14
0.121	0.954	3821	139	413	65	0.161	0.944	960	50	88	12
0.126	0.951	3820	151	401	66	0.159	0.947	959	46	92	13
0.118	0.957	3822	127	425	64	0.145	0.948	957	43	95	15
0.113	0.959	3831	127	425	55	0.150	0.948	960	46	92	12
0.111	0.959	3829	125	427	57	0.156	0.946	960	48	90	12
0.111	0.959	3829	125	427	57	0.150	0.947	959	46	92	13
0.105	0.961	3829	115	437	57	0.147	0.950	960	44	94	12
0.106	0.959	3822	116	436	64	0.152	0.949	959	44	94	13

K fold = 2											
Training						Validation					
Loss	**Accuracy**	**TP**	**FP**	**TN**	**FN**	**Loss**	**Accuracy**	**TP**	**FP**	**TN**	**FN**
0.376	0.876	3885	551	1	1	0.345	0.884	965	122	16	7
0.306	0.890	3835	437	115	51	0.257	0.905	959	93	45	13
0.271	0.905	3823	359	193	63	0.248	0.911	968	95	43	4
0.202	0.931	3835	256	296	51	0.188	0.931	965	70	68	7
0.166	0.942	3830	201	351	56	0.174	0.943	958	49	89	14
0.141	0.948	3820	164	388	66	0.182	0.940	959	54	84	13
0.145	0.948	3810	156	396	76	0.148	0.950	956	40	98	16
0.135	0.952	3820	147	405	66	0.167	0.946	961	49	89	11
0.142	0.947	3809	158	394	77	0.164	0.944	962	52	86	10
0.126	0.958	3822	124	428	64	0.211	0.936	962	61	77	10
0.126	0.954	3813	131	421	73	0.184	0.939	961	57	81	11
0.121	0.957	3820	127	425	66	0.165	0.949	953	38	100	19
0.097	0.966	3829	96	456	57	0.157	0.949	951	36	102	21
0.090	0.967	3826	85	467	60	0.160	0.950	957	41	97	15
0.081	0.972	3836	76	476	50	0.149	0.953	954	34	104	18
0.076	0.973	3838	72	480	48	0.157	0.951	954	36	102	18
0.075	0.973	3832	64	488	54	0.159	0.950	958	42	96	14

K fold = 3											
Training						Validation					
Loss	**Accuracy**	**TP**	**FP**	**TN**	**FN**	**Loss**	**Accuracy**	**TP**	**FP**	**TN**	**FN**
0.381	0.871	3859	547	5	27	0.368	0.875	964	131	7	8
0.350	0.879	3862	514	38	24	0.367	0.873	916	85	53	56
0.303	0.898	3832	400	152	54	0.265	0.913	970	95	43	2
0.276	0.911	3848	358	194	38	0.291	0.905	948	81	57	24
0.271	0.908	3828	351	201	58	0.276	0.910	970	98	40	2
0.251	0.918	3839	317	235	47	0.256	0.913	948	73	65	24
0.239	0.920	3835	305	247	51	0.260	0.919	952	70	68	20
0.222	0.922	3834	294	258	52	0.215	0.921	951	67	71	21
0.210	0.930	3837	260	292	49	0.211	0.925	940	51	87	32
0.194	0.934	3832	240	312	54	0.212	0.928	941	49	89	31
0.190	0.934	3834	241	311	52	0.233	0.928	965	73	65	7
0.189	0.933	3829	240	312	57	0.199	0.930	965	71	67	7
0.195	0.933	3819	231	321	67	0.224	0.923	970	83	55	2
0.190	0.932	3810	227	325	76	0.216	0.931	968	73	65	4
0.180	0.936	3833	230	322	53	0.164	0.941	960	53	85	12
0.167	0.943	3834	203	349	52	0.213	0.932	966	69	69	6
0.181	0.938	3827	217	335	59	0.196	0.933	963	65	73	9
0.168	0.943	3837	203	349	49	0.183	0.936	968	67	71	4
0.157	0.945	3834	190	362	52	0.225	0.931	969	74	64	3
0.159	0.943	3827	193	359	59	0.208	0.932	966	69	69	6
0.145	0.947	3835	184	368	51	0.156	0.943	956	47	91	16
0.135	0.953	3836	157	395	50	0.162	0.939	960	56	82	12
0.122	0.957	3835	140	412	51	0.154	0.946	961	49	89	11
0.119	0.956	3837	146	406	49	0.167	0.943	960	51	87	12
0.111	0.959	3835	131	421	51	0.161	0.946	958	46	92	14
0.111	0.960	3837	127	425	49	0.147	0.950	956	40	98	16
0.109	0.960	3832	125	427	54	0.159	0.944	956	46	92	16
0.104	0.962	3836	119	433	50	0.152	0.941	960	53	85	12
0.108	0.961	3835	124	428	51	0.143	0.945	955	44	94	17
0.110	0.962	3832	116	436	54	0.148	0.950	957	41	97	15
0.109	0.961	3831	117	435	55	0.149	0.950	957	41	97	15
0.106	0.962	3831	115	437	55	0.159	0.948	963	49	89	9
0.105	0.962	3832	115	437	54	0.144	0.950	959	42	96	13
0.104	0.960	3832	122	430	54	0.163	0.948	962	48	90	10
0.095	0.962	3837	119	433	49	0.150	0.948	958	44	94	14
0.089	0.969	3838	90	462	48	0.153	0.947	959	46	92	13
0.092	0.969	3843	96	456	43	0.155	0.948	960	46	92	12
0.090	0.968	3839	95	457	47	0.153	0.945	958	47	91	14
0.088	0.968	3843	100	452	43	0.153	0.946	959	47	91	13

K fold = 4											
Training						Validation					
Loss	**Accuracy**	**TP**	**FP**	**TN**	**FN**	**Loss**	**Accuracy**	**TP**	**FP**	**TN**	**FN**
0.370	0.876	3879	542	10	8	0.306	0.886	955	110	28	16
0.296	0.897	3832	403	149	55	0.242	0.914	948	72	66	23
0.203	0.925	3814	261	291	73	0.233	0.917	964	85	53	7
0.171	0.940	3820	201	351	67	0.184	0.931	947	52	86	24
0.165	0.941	3809	186	366	78	0.169	0.935	947	48	90	24
0.140	0.950	3817	154	398	70	0.174	0.941	957	51	87	14
0.140	0.948	3823	166	386	64	0.194	0.930	955	62	76	16
0.149	0.945	3800	155	397	87	0.223	0.925	961	73	65	10
0.148	0.947	3810	160	392	77	0.182	0.932	926	30	108	45
0.141	0.948	3816	160	392	71	0.170	0.930	957	64	74	14
0.107	0.963	3837	116	436	50	0.145	0.945	951	41	97	20
0.095	0.968	3839	94	458	48	0.148	0.942	942	35	103	29
0.087	0.971	3844	86	466	43	0.152	0.943	949	41	97	22
0.083	0.970	3843	88	464	44	0.149	0.942	946	39	99	25
0.080	0.973	3850	84	468	37	0.148	0.945	949	39	99	22
0.077	0.974	3847	76	476	40	0.139	0.951	946	29	109	25
0.073	0.974	3849	79	473	38	0.151	0.946	950	39	99	21
0.068	0.976	3852	70	482	35	0.146	0.944	946	37	101	25
0.066	0.976	3846	67	485	41	0.150	0.946	948	37	101	23
0.068	0.974	3841	69	483	46	0.145	0.947	945	33	105	26
0.064	0.978	3860	72	480	27	0.150	0.949	947	33	105	24
0.058	0.979	3850	56	496	37	0.153	0.947	951	39	99	20
0.056	0.982	3856	50	502	31	0.152	0.948	951	38	100	20
0.052	0.982	3862	54	498	25	0.150	0.948	949	36	102	22
0.053	0.984	3863	47	505	24	0.153	0.945	949	39	99	22
0.052	0.981	3861	57	495	26	0.157	0.947	952	40	98	19

K fold = 5											
Training						Validation					
Loss	Accuracy	TP	FP	TN	FN	Loss	Accuracy	TP	FP	TN	FN
0.377	0.876	3882	548	4	4	0.343	0.877	972	137	1	0
0.342	0.886	3861	479	73	25	0.292	0.906	940	72	66	32
0.292	0.902	3839	387	165	47	0.245	0.915	967	89	49	5
0.279	0.907	3829	355	197	57	0.237	0.921	967	83	55	5
0.248	0.914	3828	325	227	58	0.231	0.919	968	86	52	4
0.216	0.921	3816	282	270	70	0.206	0.926	962	72	66	10
0.187	0.934	3827	235	317	59	0.167	0.940	949	44	94	23
0.170	0.937	3818	213	339	68	0.175	0.943	963	54	84	9
0.179	0.930	3807	231	321	79	0.200	0.931	965	70	68	7
0.172	0.935	3800	203	349	86	0.151	0.945	944	33	105	28
0.143	0.946	3816	170	382	70	0.204	0.928	963	71	67	9
0.158	0.939	3808	194	358	78	0.144	0.946	954	42	96	18
0.135	0.950	3816	154	398	70	0.166	0.946	958	46	92	14
0.143	0.950	3819	154	398	67	0.172	0.941	935	29	109	37
0.144	0.946	3813	166	386	73	0.152	0.950	959	43	95	13
0.150	0.947	3819	168	384	67	0.141	0.948	942	28	110	30
0.146	0.945	3806	166	386	80	0.154	0.952	956	37	101	16
0.144	0.945	3809	165	387	77	0.160	0.945	961	50	88	11
0.135	0.949	3812	154	398	74	0.143	0.948	960	46	92	12
0.149	0.948	3815	160	392	71	0.184	0.931	944	49	89	28
0.162	0.940	3806	186	366	80	0.170	0.941	959	53	85	13
0.139	0.947	3807	155	397	79	0.146	0.950	949	32	106	23
0.127	0.954	3820	137	415	66	0.136	0.953	951	31	107	21
0.122	0.954	3821	137	415	65	0.138	0.950	949	33	105	23
0.112	0.959	3823	121	431	63	0.138	0.961	952	23	115	20
0.107	0.964	3824	98	454	62	0.131	0.954	951	30	108	21
0.105	0.959	3817	114	438	69	0.132	0.954	950	29	109	22
0.100	0.964	3827	99	453	59	0.134	0.954	955	34	104	17
0.095	0.964	3829	102	450	57	0.135	0.955	958	36	102	14
0.091	0.965	3826	97	455	60	0.134	0.950	951	35	103	21
0.091	0.968	3832	89	463	54	0.127	0.960	952	24	114	20
0.092	0.968	3834	92	460	52	0.136	0.955	955	33	105	17
0.090	0.967	3828	90	462	58	0.129	0.957	955	31	107	17
0.084	0.970	3839	88	464	47	0.129	0.959	952	26	112	20
0.084	0.973	3842	77	475	44	0.125	0.959	953	26	112	19
0.082	0.971	3835	76	476	51	0.132	0.953	939	19	119	33
0.079	0.972	3839	78	474	47	0.128	0.957	956	32	106	16
0.081	0.970	3834	81	471	52	0.121	0.954	951	30	108	21
0.081	0.971	3835	76	476	51	0.127	0.954	954	33	105	18
0.075	0.971	3842	84	468	44	0.126	0.960	953	25	113	19
0.081	0.971	3826	70	482	60	0.125	0.958	953	28	110	19
0.074	0.973	3836	69	483	50	0.126	0.957	957	33	105	15
0.075	0.972	3836	76	476	50	0.135	0.956	957	34	104	15
0.071	0.974	3843	72	480	43	0.130	0.955	955	33	105	17
0.074	0.972	3839	76	476	47	0.124	0.959	953	26	112	19
0.067	0.975	3841	66	486	45	0.123	0.961	955	26	112	17
0.069	0.975	3836	59	493	50	0.124	0.959	952	25	113	20
0.068	0.977	3840	58	494	46	0.124	0.957	951	27	111	21

A.2 Total Atrial Fibrillation = 622 , 75:25 (Real:Sim)

K fold = 1											
Training						Validation					
Loss	**Accuracy**	**TP**	**FP**	**TN**	**FN**	**Loss**	**Accuracy**	**TP**	**FP**	**TN**	**FN**
0.428	0.850	3741	654	3	6	0.381	0.876	972	138	0	0
0.357	0.872	3694	512	145	53	0.301	0.895	957	102	36	15
0.294	0.902	3691	376	281	56	0.263	0.908	958	88	50	14
0.255	0.913	3690	326	331	57	0.226	0.918	966	85	53	6
0.227	0.917	3677	294	363	70	0.202	0.923	966	79	59	6
0.196	0.930	3666	228	429	81	0.184	0.930	968	74	64	4
0.183	0.931	3676	231	426	71	0.162	0.937	956	54	84	16
0.173	0.934	3666	210	447	81	0.159	0.947	959	46	92	13
0.162	0.939	3664	187	470	83	0.155	0.943	957	48	90	15
0.166	0.937	3656	187	470	91	0.170	0.935	964	64	74	8
0.157	0.943	3682	188	469	65	0.147	0.949	954	39	99	18
0.174	0.933	3657	206	451	90	0.193	0.923	967	80	58	5
0.156	0.942	3664	174	483	83	0.139	0.946	962	50	88	10
0.136	0.949	3683	161	496	64	0.140	0.949	963	48	90	9
0.157	0.945	3667	164	493	80	0.194	0.925	968	79	59	4
0.151	0.944	3674	174	483	73	0.193	0.931	960	65	73	12
0.146	0.944	3661	160	497	86	0.144	0.939	954	50	88	18
0.156	0.943	3658	164	493	89	0.154	0.942	961	53	85	11
0.138	0.948	3671	151	506	76	0.124	0.958	956	31	107	16
0.132	0.951	3667	134	523	80	0.134	0.949	955	40	98	17
0.121	0.955	3677	128	529	70	0.125	0.951	959	41	97	13
0.119	0.957	3679	121	536	68	0.129	0.951	962	44	94	10
0.114	0.957	3678	122	535	69	0.120	0.956	955	32	106	17
0.109	0.959	3683	117	540	64	0.135	0.950	959	42	96	13
0.109	0.961	3687	113	544	60	0.128	0.952	961	42	96	11
0.108	0.960	3678	109	548	69	0.131	0.950	959	43	95	13
0.103	0.963	3688	104	553	59	0.122	0.950	956	39	99	16
0.109	0.960	3680	111	546	67	0.124	0.956	958	35	103	14
0.099	0.966	3691	94	563	56	0.126	0.957	961	37	101	11
0.096	0.966	3694	96	561	53	0.128	0.953	960	40	98	12
0.100	0.963	3688	102	555	59	0.124	0.954	961	40	98	11
0.093	0.967	3691	89	568	56	0.130	0.952	962	43	95	10
0.098	0.964	3691	103	554	56	0.138	0.949	961	46	92	11

K fold = 2											
Training						Validation					
Loss	**Accuracy**	**TP**	**FP**	**TN**	**FN**	**Loss**	**Accuracy**	**TP**	**FP**	**TN**	**FN**
0.425	0.851	3736	649	10	9	0.367	0.876	972	138	0	0
0.382	0.859	3705	581	78	40	0.307	0.900	963	102	36	9
0.322	0.886	3689	444	215	56	0.313	0.904	964	99	39	8
0.281	0.902	3677	364	295	68	0.275	0.903	946	82	56	26
0.275	0.908	3685	344	315	60	0.260	0.914	967	91	47	5
0.245	0.915	3680	308	351	65	0.255	0.914	957	80	58	15
0.237	0.921	3699	304	355	46	0.219	0.923	953	66	72	19
0.208	0.927	3666	243	416	79	0.255	0.915	962	84	54	10
0.181	0.937	3684	216	443	61	0.219	0.923	952	66	72	20
0.182	0.931	3661	219	440	84	0.196	0.926	955	65	73	17
0.160	0.941	3667	180	479	78	0.187	0.932	959	63	75	13
0.182	0.933	3658	206	453	87	0.190	0.934	958	59	79	14
0.157	0.944	3658	159	500	87	0.195	0.920	942	59	79	30
0.162	0.942	3668	180	479	77	0.196	0.925	945	56	82	27
0.144	0.946	3665	156	503	80	0.194	0.938	956	53	85	16
0.164	0.940	3658	179	480	87	0.190	0.925	932	43	95	40
0.123	0.955	3674	127	532	71	0.169	0.936	945	44	94	27
0.113	0.959	3677	113	546	68	0.173	0.937	952	50	88	20
0.107	0.959	3683	119	540	62	0.162	0.938	940	37	101	32
0.098	0.965	3688	99	560	57	0.171	0.941	954	48	90	18
0.097	0.965	3693	104	555	52	0.165	0.939	946	42	96	26
0.090	0.968	3688	84	575	57	0.164	0.943	951	42	96	21
0.087	0.967	3685	86	573	60	0.169	0.943	951	42	96	21
0.084	0.970	3692	79	580	53	0.165	0.943	954	45	93	18
0.080	0.972	3703	83	576	42	0.160	0.945	954	43	95	18
0.075	0.973	3695	69	590	50	0.160	0.946	952	40	98	20
0.079	0.969	3698	88	571	47	0.159	0.947	952	39	99	20
0.073	0.972	3694	71	588	51	0.161	0.944	951	41	97	21
0.073	0.975	3701	65	594	44	0.157	0.942	948	40	98	24
0.075	0.972	3698	78	581	47	0.158	0.944	950	40	98	22
0.075	0.972	3701	80	579	44	0.159	0.945	948	37	101	24
0.071	0.975	3702	66	593	43	0.156	0.945	947	36	102	25
0.073	0.974	3698	69	590	47	0.162	0.941	948	41	97	24
0.068	0.975	3703	69	590	42	0.158	0.945	947	36	102	25
0.070	0.975	3696	61	598	49	0.157	0.947	951	38	100	21
0.067	0.974	3701	69	590	44	0.155	0.947	950	37	101	22
0.067	0.976	3708	70	589	37	0.159	0.949	951	36	102	21
0.064	0.977	3706	61	598	39	0.158	0.945	948	37	101	24
0.065	0.976	3703	63	596	42	0.163	0.946	950	38	100	22
0.064	0.978	3711	62	597	34	0.165	0.944	950	40	98	22
0.064	0.978	3709	63	596	36	0.158	0.946	947	35	103	25
0.063	0.978	3706	57	602	39	0.159	0.946	949	37	101	23
0.061	0.977	3706	62	597	39	0.164	0.949	954	39	99	18
0.063	0.977	3707	64	595	38	0.158	0.947	949	36	102	23
0.064	0.977	3704	62	597	41	0.165	0.946	953	41	97	19
0.061	0.976	3702	62	597	43	0.161	0.947	950	37	101	22

K fold = 3											
Training						Validation					
Loss	**Accuracy**	**TP**	**FP**	**TN**	**FN**	**Loss**	**Accuracy**	**TP**	**FP**	**TN**	**FN**
0.428	0.849	3733	649	5	17	0.394	0.876	972	138	0	0
0.414	0.851	3750	654	0	0	0.360	0.876	972	138	0	0
0.405	0.854	3712	607	47	38	0.381	0.854	935	125	13	37
0.362	0.869	3687	512	142	63	0.336	0.884	971	128	10	1
0.303	0.896	3686	394	260	64	0.311	0.903	963	99	39	9
0.303	0.895	3653	367	287	97	0.296	0.890	929	79	59	43
0.324	0.891	3689	421	233	61	0.354	0.888	971	123	15	1
0.298	0.895	3665	376	278	85	0.331	0.895	970	115	23	2
0.274	0.911	3706	350	304	44	0.276	0.912	966	92	46	6
0.269	0.912	3706	345	309	44	0.285	0.908	958	88	50	14
0.281	0.910	3700	346	308	50	0.265	0.913	960	85	53	12
0.256	0.913	3681	314	340	69	0.303	0.910	949	77	61	23
0.260	0.911	3700	344	310	50	0.268	0.906	945	77	61	27
0.262	0.910	3665	312	342	85	0.298	0.914	966	89	49	6
0.266	0.903	3661	336	318	89	0.269	0.915	967	89	49	5
0.254	0.913	3700	332	322	50	0.251	0.915	965	87	51	7
0.252	0.915	3694	319	335	56	0.260	0.905	945	78	60	27
0.277	0.909	3707	357	297	43	0.290	0.908	968	98	40	4
0.255	0.916	3716	336	318	34	0.275	0.915	967	89	49	5
0.247	0.918	3705	315	339	45	0.265	0.914	969	92	46	3
0.264	0.911	3682	324	330	68	0.263	0.915	966	88	50	6
0.236	0.921	3720	317	337	30	0.258	0.917	961	81	57	11
0.226	0.923	3701	291	363	49	0.259	0.920	954	71	67	18
0.220	0.926	3714	289	365	36	0.253	0.917	965	85	53	7
0.224	0.923	3707	294	360	43	0.255	0.921	962	78	60	10
0.220	0.924	3695	279	375	55	0.248	0.921	964	80	58	8
0.220	0.924	3699	283	371	51	0.249	0.923	955	68	70	17
0.220	0.925	3701	283	371	49	0.246	0.923	963	77	61	9
0.220	0.926	3713	289	365	37	0.246	0.926	958	68	70	14
0.216	0.925	3709	291	363	41	0.252	0.919	964	82	56	8
0.217	0.923	3700	290	364	50	0.242	0.923	959	73	65	13
0.218	0.924	3692	275	379	58	0.246	0.927	965	74	64	7
0.215	0.927	3715	286	368	35	0.253	0.921	966	82	56	6
0.213	0.926	3680	254	400	70	0.241	0.923	953	66	72	19
0.210	0.927	3703	273	381	47	0.238	0.926	960	70	68	12
0.213	0.926	3707	283	371	43	0.237	0.926	960	70	68	12
0.204	0.929	3698	260	394	52	0.237	0.925	962	73	65	10
0.209	0.927	3700	270	384	50	0.244	0.925	961	72	66	11
0.204	0.930	3706	265	389	44	0.233	0.923	961	74	64	11
0.203	0.930	3700	260	394	50	0.236	0.920	966	83	55	6
0.201	0.929	3703	264	390	47	0.245	0.925	965	76	62	7
0.201	0.929	3703	264	390	47	0.239	0.923	952	65	73	20
0.196	0.929	3709	270	384	41	0.231	0.925	962	73	65	10
0.197	0.932	3718	268	386	32	0.241	0.923	964	78	60	8
0.201	0.928	3706	272	382	44	0.226	0.928	962	70	68	10
0.193	0.933	3709	256	398	41	0.234	0.925	959	70	68	13
0.198	0.930	3698	257	397	52	0.227	0.926	962	72	66	10
0.196	0.929	3695	257	397	55	0.231	0.925	960	71	67	12
0.193	0.930	3696	254	400	54	0.233	0.923	952	66	72	20
0.198	0.931	3706	259	395	44	0.235	0.925	960	71	67	12
0.188	0.933	3706	249	405	44	0.230	0.927	961	70	68	11
0.186	0.935	3712	249	405	38	0.231	0.924	957	69	69	15
0.184	0.933	3697	244	410	53	0.229	0.928	963	71	67	9
0.188	0.931	3699	254	400	51	0.227	0.925	961	72	66	11
0.184	0.935	3714	251	403	36	0.225	0.923	960	73	65	12
0.187	0.933	3704	250	404	46	0.233	0.923	964	77	61	8
0.186	0.934	3701	242	412	49	0.228	0.927	963	72	66	9
0.180	0.936	3706	238	416	44	0.227	0.926	960	70	68	12
0.184	0.938	3713	236	418	37	0.223	0.928	957	65	73	15
0.183	0.933	3697	241	413	53	0.227	0.928	962	70	68	10

K fold = 4											
Training						Validation					
Loss	Accuracy	TP	FP	TN	FN	Loss	Accuracy	TP	FP	TN	FN
0.427	0.849	3738	651	4	12	0.377	0.876	971	137	1	0
0.396	0.855	3727	617	38	23	0.341	0.867	913	90	48	58
0.305	0.892	3679	404	251	71	0.276	0.905	951	85	53	20
0.266	0.907	3671	331	324	79	0.241	0.911	949	77	61	22
0.224	0.919	3680	288	367	70	0.216	0.920	966	84	54	5
0.193	0.927	3669	239	416	81	0.201	0.924	958	71	67	13
0.162	0.940	3670	184	471	80	0.179	0.937	949	48	90	22
0.170	0.940	3662	178	477	88	0.242	0.922	966	82	56	5
0.160	0.942	3669	176	479	81	0.163	0.941	938	32	106	33
0.152	0.945	3667	158	497	83	0.178	0.935	957	58	80	14
0.136	0.953	3682	137	518	68	0.153	0.944	954	45	93	17
0.152	0.948	3677	155	500	73	0.149	0.940	950	45	93	21
0.135	0.954	3685	137	518	65	0.165	0.944	957	48	90	14
0.142	0.947	3668	150	505	82	0.174	0.935	952	53	85	19
0.134	0.947	3656	138	517	94	0.152	0.944	951	42	96	20
0.143	0.948	3674	154	501	76	0.164	0.939	960	57	81	11
0.140	0.947	3660	145	510	90	0.145	0.948	951	38	100	20
0.130	0.954	3675	129	526	75	0.244	0.922	967	82	56	4
0.150	0.943	3667	168	487	83	0.196	0.939	960	57	81	11
0.148	0.945	3671	164	491	79	0.204	0.922	911	26	112	60
0.164	0.939	3654	172	483	96	0.257	0.890	883	34	104	88
0.166	0.937	3658	184	471	92	0.179	0.930	949	56	82	22
0.145	0.949	3680	154	501	70	0.166	0.941	955	49	89	16
0.125	0.954	3667	121	534	83	0.160	0.944	950	41	97	21
0.124	0.951	3673	138	517	77	0.170	0.943	954	46	92	17
0.120	0.953	3664	123	532	86	0.162	0.938	946	44	94	25
0.117	0.954	3673	126	529	77	0.169	0.939	955	52	86	16

K fold = 5											
Training						Validation					
Loss	**Accuracy**	**TP**	**FP**	**TN**	**FN**	**Loss**	**Accuracy**	**TP**	**FP**	**TN**	**FN**
0.434	0.844	3711	654	5	35	0.384	0.876	971	137	1	0
0.425	0.850	3746	659	0	0	0.379	0.876	971	138	0	0
0.418	0.850	3746	659	0	0	0.348	0.876	971	138	0	0
0.377	0.860	3716	587	72	30	0.300	0.899	936	77	61	35
0.319	0.891	3694	430	229	52	0.272	0.905	971	105	33	0
0.288	0.901	3686	375	284	60	0.258	0.912	961	88	50	10
0.283	0.901	3697	385	274	49	0.227	0.920	962	80	58	9
0.263	0.912	3684	326	333	62	0.236	0.913	971	97	41	0
0.246	0.916	3681	307	352	65	0.241	0.915	931	54	84	40
0.244	0.917	3699	317	342	47	0.206	0.925	955	67	71	16
0.225	0.920	3674	280	379	72	0.176	0.932	953	57	81	18
0.226	0.926	3683	264	395	63	0.190	0.931	966	71	67	5
0.231	0.919	3686	296	363	60	0.237	0.922	970	85	53	1
0.217	0.924	3677	264	395	69	0.186	0.931	949	55	83	22
0.214	0.927	3673	248	411	73	0.274	0.889	899	51	87	72
0.238	0.923	3674	266	393	72	0.180	0.937	957	56	82	14
0.185	0.932	3668	223	436	78	0.165	0.947	964	52	86	7
0.176	0.937	3671	201	458	75	0.150	0.949	957	43	95	14
0.167	0.941	3698	210	449	48	0.151	0.950	961	46	92	10
0.149	0.944	3679	180	479	67	0.140	0.950	958	42	96	13
0.148	0.946	3683	176	483	63	0.182	0.941	965	59	79	6
0.151	0.947	3692	178	481	54	0.138	0.953	961	42	96	10
0.144	0.948	3684	166	493	62	0.136	0.954	962	42	96	9
0.138	0.951	3686	158	501	60	0.128	0.956	960	38	100	11
0.131	0.955	3696	149	510	50	0.136	0.955	961	40	98	10
0.134	0.953	3674	133	526	72	0.126	0.953	963	44	94	8
0.130	0.953	3679	140	519	67	0.122	0.959	962	37	101	9
0.122	0.957	3687	130	529	59	0.126	0.958	960	36	102	11
0.118	0.959	3684	120	539	62	0.121	0.957	959	36	102	12
0.128	0.953	3674	133	526	72	0.117	0.959	953	27	111	18
0.114	0.960	3685	114	545	61	0.124	0.959	962	36	102	9
0.119	0.960	3682	114	545	64	0.122	0.956	961	39	99	10
0.116	0.958	3678	116	543	68	0.118	0.956	958	36	102	13
0.115	0.958	3686	126	533	60	0.134	0.952	947	29	109	24
0.113	0.961	3690	115	544	56	0.122	0.952	960	42	96	11
0.103	0.963	3690	109	550	56	0.122	0.956	960	38	100	11
0.100	0.963	3690	106	553	56	0.119	0.958	960	36	102	11
0.101	0.965	3688	98	561	58	0.116	0.959	959	34	104	12
0.101	0.967	3685	84	575	61	0.119	0.957	959	36	102	12
0.098	0.966	3696	100	559	50	0.125	0.952	960	42	96	11
0.097	0.966	3701	105	554	45	0.118	0.958	958	34	104	13
0.096	0.966	3699	101	558	47	0.119	0.954	958	38	100	13
0.095	0.965	3700	106	553	46	0.125	0.955	959	38	100	12
0.095	0.967	3689	88	571	57	0.122	0.954	956	36	102	15
0.096	0.966	3695	97	562	51	0.117	0.952	952	34	104	19
0.093	0.967	3692	91	568	54	0.128	0.954	959	39	99	12
0.091	0.969	3695	86	573	51	0.134	0.954	961	41	97	10
0.090	0.967	3690	91	568	56	0.123	0.953	959	40	98	12

A.3 Total Atrial Fibrillation = 622 , 50:50 (Real:Sim)

K fold = 1											
Training						Validation					
Loss	Accuracy	TP	FP	TN	FN	Loss	Accuracy	TP	FP	TN	FN
0.440	0.835	3590	678	87	49	0.346	0.874	970	138	0	2
0.325	0.883	3579	456	309	60	0.295	0.897	967	109	29	5
0.271	0.909	3589	351	414	50	0.277	0.907	961	92	46	11
0.232	0.919	3581	300	465	58	0.247	0.914	965	88	50	7
0.186	0.935	3580	228	537	59	0.210	0.924	934	46	92	38
0.181	0.932	3554	216	549	85	0.184	0.928	965	73	65	7
0.157	0.943	3560	174	591	79	0.163	0.937	958	56	82	14
0.148	0.945	3559	162	603	80	0.134	0.951	960	42	96	12
0.138	0.949	3567	153	612	72	0.162	0.941	965	59	79	7
0.149	0.948	3564	155	610	75	0.142	0.951	956	38	100	16
0.139	0.950	3566	149	616	73	0.159	0.938	957	54	84	15
0.125	0.953	3566	136	629	73	0.151	0.952	959	40	98	13
0.126	0.954	3572	134	631	67	0.145	0.955	955	33	105	17
0.100	0.964	3585	103	662	54	0.130	0.957	955	31	107	17
0.090	0.969	3589	86	679	50	0.123	0.959	956	29	109	16
0.086	0.968	3587	88	677	52	0.123	0.961	958	29	109	14
0.077	0.974	3589	66	699	50	0.129	0.959	960	34	104	12
0.081	0.972	3592	77	688	47	0.115	0.962	956	26	112	16
0.072	0.974	3593	69	696	46	0.129	0.962	961	31	107	11
0.068	0.977	3602	65	700	37	0.119	0.961	957	28	110	15
0.063	0.977	3600	61	704	39	0.129	0.963	961	30	108	11
0.061	0.980	3608	58	707	31	0.127	0.962	957	27	111	15
0.057	0.981	3606	49	716	33	0.120	0.959	953	27	111	19
0.052	0.984	3611	44	721	28	0.122	0.961	956	27	111	16
0.050	0.983	3614	49	716	25	0.127	0.959	956	29	109	16
0.051	0.982	3608	47	718	31	0.125	0.959	955	29	109	17
0.048	0.986	3617	39	726	22	0.126	0.959	953	26	112	19
0.048	0.984	3609	39	726	30	0.128	0.960	959	31	107	13

K fold = 2											
Training						Validation					
Loss	Accuracy	TP	FP	TN	FN	Loss	Accuracy	TP	FP	TN	FN
0.446	0.834	3601	690	70	43	0.374	0.868	951	126	12	21
0.364	0.875	3606	514	246	38	0.315	0.894	972	118	20	0
0.296	0.899	3580	383	377	64	0.254	0.916	958	79	59	14
0.286	0.901	3573	364	396	71	0.256	0.902	925	62	76	47
0.266	0.913	3582	323	437	62	0.235	0.924	971	83	55	1
0.239	0.917	3567	290	470	77	0.222	0.927	959	68	70	13
0.228	0.925	3577	263	497	67	0.199	0.933	963	65	73	9
0.230	0.921	3580	282	478	64	0.215	0.929	958	65	73	14
0.233	0.917	3561	282	478	83	0.274	0.917	972	92	46	0
0.194	0.933	3576	227	533	68	0.186	0.932	940	43	95	32
0.193	0.932	3564	220	540	80	0.185	0.938	965	62	76	7
0.201	0.932	3577	233	527	67	0.216	0.931	966	71	67	6
0.201	0.929	3567	235	525	77	0.215	0.932	969	72	66	3
0.196	0.928	3558	232	528	86	0.194	0.930	961	67	71	11
0.196	0.930	3565	229	531	79	0.204	0.937	967	65	73	5
0.177	0.938	3586	214	546	58	0.200	0.943	961	52	86	11
0.162	0.943	3585	192	568	59	0.171	0.947	962	49	89	10
0.143	0.952	3590	159	601	54	0.169	0.947	965	52	86	7
0.132	0.955	3593	146	614	51	0.159	0.943	957	48	90	15
0.128	0.954	3584	142	618	60	0.171	0.948	964	50	88	8
0.129	0.953	3580	142	618	64	0.169	0.940	945	40	98	27
0.124	0.955	3580	133	627	64	0.160	0.950	961	45	93	11
0.118	0.960	3598	128	632	46	0.163	0.951	964	46	92	8
0.124	0.956	3586	136	624	58	0.183	0.947	968	55	83	4
0.112	0.959	3597	133	627	47	0.161	0.954	966	45	93	6
0.108	0.961	3594	120	640	50	0.162	0.951	963	45	93	9
0.107	0.962	3592	114	646	52	0.161	0.951	963	45	93	9
0.106	0.962	3595	120	640	49	0.166	0.954	966	45	93	6
0.101	0.964	3599	115	645	45	0.164	0.954	965	44	94	7

K fold = 3											
Training						Validation					
Loss	Accuracy	TP	FP	TN	FN	Loss	Accuracy	TP	FP	TN	FN
0.466	0.828	3639	749	8	8	0.377	0.876	972	138	0	0
0.435	0.838	3627	692	65	20	0.371	0.877	970	135	3	2
0.337	0.880	3586	467	290	61	0.386	0.887	971	124	14	1
0.322	0.893	3592	416	341	55	0.297	0.908	968	98	40	4
0.279	0.907	3586	350	407	61	0.300	0.907	969	100	38	3
0.267	0.908	3590	348	409	57	0.273	0.912	958	84	54	14
0.252	0.916	3598	322	435	49	0.283	0.906	936	68	70	36
0.242	0.916	3578	301	456	69	0.291	0.913	968	93	45	4
0.259	0.916	3591	315	442	56	0.254	0.917	963	83	55	9
0.226	0.924	3595	283	474	52	0.256	0.911	956	83	55	16
0.230	0.921	3604	307	450	43	0.243	0.920	951	68	70	21
0.247	0.915	3566	295	462	81	0.242	0.917	958	78	60	14
0.217	0.925	3590	272	485	57	0.230	0.918	961	80	58	11
0.230	0.920	3575	280	477	72	0.245	0.914	950	73	65	22
0.233	0.921	3578	277	480	69	0.238	0.919	967	85	53	5
0.216	0.924	3558	245	512	89	0.237	0.912	952	78	60	20
0.214	0.926	3575	256	501	72	0.223	0.922	960	75	63	12
0.214	0.925	3585	268	489	62	0.242	0.921	961	77	61	11
0.191	0.935	3594	232	525	53	0.215	0.925	959	70	68	13
0.228	0.919	3554	264	493	93	0.222	0.919	961	79	59	11
0.202	0.932	3572	225	532	75	0.215	0.927	955	64	74	17
0.200	0.928	3585	256	501	62	0.222	0.924	961	73	65	11
0.184	0.934	3582	225	532	65	0.249	0.923	958	72	66	14
0.230	0.918	3558	272	485	89	0.255	0.914	936	60	78	36
0.183	0.932	3546	199	558	101	0.223	0.921	950	66	72	22
0.176	0.939	3562	185	572	85	0.213	0.926	955	65	73	17
0.162	0.943	3591	193	564	56	0.212	0.927	954	63	75	18
0.158	0.943	3580	185	572	67	0.209	0.923	949	62	76	23
0.153	0.944	3578	177	580	69	0.217	0.928	955	63	75	17
0.147	0.949	3585	162	595	62	0.217	0.931	959	64	74	13
0.155	0.945	3570	167	590	77	0.212	0.930	958	64	74	14
0.147	0.945	3571	165	592	76	0.220	0.929	959	66	72	13
0.144	0.949	3592	168	589	55	0.201	0.932	959	62	76	13
0.141	0.951	3582	150	607	65	0.186	0.932	952	56	82	20
0.137	0.953	3597	158	599	50	0.204	0.936	960	59	79	12
0.149	0.950	3593	166	591	54	0.202	0.933	963	65	73	9
0.139	0.953	3583	145	612	64	0.192	0.933	956	58	80	16
0.138	0.951	3586	153	604	61	0.202	0.929	951	58	80	21
0.141	0.952	3592	156	601	55	0.190	0.933	948	50	88	24
0.134	0.957	3580	124	633	67	0.202	0.934	956	57	81	16
0.131	0.956	3594	141	616	53	0.198	0.934	957	58	80	15
0.130	0.956	3599	144	613	48	0.199	0.937	958	56	82	14
0.129	0.955	3590	139	618	57	0.195	0.935	953	53	85	19
0.129	0.957	3584	128	629	63	0.198	0.937	958	56	82	14

K fold = 4											
Training						Validation					
Loss	**Accuracy**	**TP**	**FP**	**TN**	**FN**	**Loss**	**Accuracy**	**TP**	**FP**	**TN**	**FN**
0.436	0.835	3595	674	85	51	0.354	0.873	945	115	23	26
0.306	0.892	3582	410	349	64	0.297	0.898	957	99	39	14
0.266	0.906	3589	355	404	57	0.300	0.896	930	74	64	41
0.236	0.914	3571	304	455	75	0.229	0.918	938	58	80	33
0.197	0.925	3574	258	501	72	0.230	0.922	957	73	65	14
0.167	0.938	3570	196	563	76	0.205	0.924	950	63	75	21
0.142	0.950	3578	152	607	68	0.177	0.931	954	60	78	17
0.161	0.941	3559	174	585	87	0.195	0.928	935	44	94	36
0.144	0.948	3567	148	611	79	0.193	0.937	953	52	86	18
0.143	0.948	3576	159	600	70	0.187	0.922	930	45	93	41
0.142	0.949	3570	150	609	76	0.181	0.936	958	58	80	13
0.161	0.938	3550	179	580	96	0.190	0.937	941	40	98	30
0.119	0.954	3584	142	617	62	0.165	0.946	955	44	94	16
0.101	0.965	3592	100	659	54	0.164	0.940	949	44	94	22
0.094	0.970	3600	87	672	46	0.170	0.941	952	46	92	19
0.093	0.970	3605	93	666	41	0.159	0.944	949	40	98	22
0.088	0.967	3588	86	673	58	0.167	0.941	953	47	91	18
0.085	0.970	3603	88	671	43	0.168	0.944	947	38	100	24
0.081	0.974	3602	72	687	44	0.165	0.944	952	43	95	19
0.083	0.973	3595	70	689	51	0.164	0.943	948	40	98	23
0.075	0.976	3613	71	688	33	0.156	0.950	948	32	106	23
0.070	0.975	3601	66	693	45	0.165	0.944	943	34	104	28
0.068	0.978	3616	68	691	30	0.173	0.944	951	42	96	20
0.069	0.976	3601	62	697	45	0.171	0.942	948	41	97	23
0.068	0.974	3601	68	691	45	0.178	0.944	955	46	92	16
0.060	0.979	3614	60	699	32	0.169	0.945	952	42	96	19
0.055	0.983	3613	42	717	33	0.173	0.946	953	42	96	18
0.054	0.982	3620	53	706	26	0.172	0.947	954	42	96	17
0.050	0.984	3615	41	718	31	0.173	0.948	956	43	95	15
0.054	0.981	3617	53	706	29	0.169	0.950	952	37	101	19
0.046	0.985	3620	41	718	26	0.176	0.946	953	42	96	18

K fold = 5											
Training						Validation					
Loss	**Accuracy**	**TP**	**FP**	**TN**	**FN**	**Loss**	**Accuracy**	**TP**	**FP**	**TN**	**FN**
0.465	0.823	3616	753	8	28	0.419	0.876	971	138	0	0
0.378	0.857	3585	571	190	59	0.351	0.872	957	128	10	14
0.315	0.889	3575	422	339	69	0.304	0.882	929	89	49	42
0.274	0.904	3575	355	406	69	0.298	0.893	933	81	57	38
0.262	0.909	3576	331	430	68	0.278	0.912	969	96	42	2
0.239	0.919	3587	298	463	57	0.218	0.927	963	73	65	8
0.218	0.926	3585	266	495	59	0.244	0.918	968	88	50	3
0.206	0.928	3570	242	519	74	0.175	0.938	948	46	92	23
0.178	0.932	3571	225	536	73	0.176	0.929	967	75	63	4
0.174	0.934	3552	200	561	92	0.210	0.922	967	82	56	4
0.164	0.941	3574	189	572	70	0.186	0.930	969	76	62	2
0.155	0.942	3572	182	579	72	0.171	0.939	960	57	81	11
0.147	0.949	3581	161	600	63	0.161	0.945	963	53	85	8
0.139	0.948	3566	149	612	78	0.161	0.943	928	20	118	43
0.135	0.950	3568	143	618	76	0.146	0.943	961	53	85	10
0.135	0.953	3579	141	620	65	0.143	0.945	959	49	89	12
0.147	0.949	3566	148	613	78	0.247	0.927	970	80	58	1
0.138	0.951	3572	146	615	72	0.227	0.936	970	70	68	1
0.134	0.953	3578	140	621	66	0.142	0.947	949	37	101	22
0.148	0.947	3553	142	619	91	0.152	0.945	960	50	88	11
0.132	0.953	3571	134	627	73	0.157	0.950	963	48	90	8
0.164	0.943	3566	175	586	78	0.162	0.937	947	46	92	24
0.169	0.937	3561	194	567	83	0.161	0.948	950	37	101	21
0.159	0.944	3569	170	591	75	0.172	0.940	963	58	80	8
0.132	0.951	3577	151	610	67	0.142	0.948	957	44	94	14
0.119	0.957	3589	135	626	55	0.137	0.948	950	37	101	21
0.121	0.957	3576	122	639	68	0.135	0.953	960	41	97	11
0.113	0.959	3582	120	641	62	0.136	0.950	960	45	93	11
0.108	0.963	3590	110	651	54	0.133	0.956	957	35	103	14
0.100	0.965	3592	101	660	52	0.133	0.955	961	40	98	10
0.103	0.962	3588	111	650	56	0.150	0.949	963	49	89	8
0.099	0.964	3585	100	661	59	0.128	0.953	956	37	101	15
0.094	0.968	3590	87	674	54	0.136	0.952	959	41	97	12
0.091	0.968	3594	89	672	50	0.127	0.958	961	37	101	10
0.093	0.965	3585	96	665	59	0.129	0.958	960	36	102	11
0.094	0.967	3591	94	667	53	0.126	0.952	954	36	102	17
0.085	0.970	3596	86	675	48	0.123	0.953	957	38	100	14
0.088	0.970	3598	88	673	46	0.124	0.953	956	37	101	15
0.081	0.973	3601	75	686	43	0.133	0.951	957	40	98	14
0.078	0.973	3603	77	684	41	0.138	0.952	956	38	100	15
0.081	0.972	3605	86	675	39	0.138	0.955	951	30	108	20
0.088	0.971	3599	84	677	45	0.136	0.951	954	37	101	17
0.081	0.972	3594	72	689	50	0.140	0.950	955	40	98	16
0.081	0.973	3602	77	684	42	0.142	0.950	956	41	97	15
0.079	0.975	3611	79	682	33	0.137	0.951	955	38	100	16
0.077	0.975	3603	70	691	41	0.137	0.950	956	41	97	15
0.073	0.974	3604	75	686	40	0.132	0.951	953	36	102	18

A.4 Total Atrial Fibrillation = 622 , 25:75 (Real:Sim)

K fold = 1											
		Training						Validation			
Loss	Accuracy	TP	FP	TN	FN	Loss	Accuracy	TP	FP	TN	FN
0.442	0.822	3454	708	167	75	0.353	0.887	964	117	21	8
0.299	0.892	3434	381	494	95	0.254	0.916	965	86	52	7
0.249	0.913	3455	309	566	74	0.244	0.917	956	76	62	16
0.186	0.934	3460	223	652	69	0.195	0.930	967	73	65	5
0.163	0.942	3462	188	687	67	0.160	0.948	955	41	97	17
0.159	0.940	3448	183	692	81	0.206	0.926	963	73	65	9
0.141	0.949	3453	147	728	76	0.179	0.940	963	58	80	9
0.128	0.953	3461	141	734	68	0.160	0.942	960	52	86	12
0.126	0.955	3464	132	743	65	0.157	0.942	942	34	104	30
0.114	0.960	3473	119	756	56	0.156	0.947	939	26	112	33
0.118	0.957	3461	121	754	68	0.140	0.945	952	41	97	20
0.113	0.962	3474	113	762	55	0.142	0.947	956	43	95	16
0.106	0.963	3473	106	769	56	0.133	0.943	951	42	96	21
0.103	0.963	3469	103	772	60	0.156	0.948	963	49	89	9
0.118	0.958	3466	122	753	63	0.169	0.944	951	41	97	21
0.136	0.949	3456	151	724	73	0.141	0.946	950	38	100	22
0.114	0.959	3464	117	758	65	0.151	0.947	957	44	94	15
0.120	0.957	3457	117	758	72	0.184	0.933	944	46	92	28
0.098	0.966	3479	98	777	50	0.143	0.950	954	37	101	18
0.079	0.973	3490	78	797	39	0.145	0.953	956	36	102	16
0.073	0.977	3492	65	810	37	0.151	0.951	959	41	97	13
0.071	0.977	3486	58	817	43	0.148	0.948	955	41	97	17
0.065	0.979	3494	59	816	35	0.144	0.950	950	33	105	22

K fold = 2											
		Training						Validation			
Loss	Accuracy	TP	FP	TN	FN	Loss	Accuracy	TP	FP	TN	FN
0.451	0.821	3464	720	150	70	0.381	0.874	952	120	18	20
0.338	0.881	3478	469	401	56	0.321	0.892	964	112	26	8
0.297	0.897	3477	397	473	57	0.291	0.897	953	95	43	19
0.277	0.908	3481	353	517	53	0.267	0.905	960	93	45	12
0.240	0.917	3468	299	571	66	0.237	0.918	964	83	55	8
0.224	0.924	3470	270	600	64	0.258	0.912	957	83	55	15
0.209	0.927	3478	265	605	56	0.204	0.927	956	65	73	16
0.178	0.944	3491	202	668	43	0.219	0.925	961	72	66	11
0.168	0.939	3465	198	672	69	0.184	0.935	961	61	77	11
0.159	0.947	3476	177	693	58	0.212	0.918	963	82	56	9
0.159	0.946	3466	171	699	68	0.181	0.932	953	56	82	19
0.153	0.949	3472	162	708	62	0.193	0.930	961	67	71	11
0.154	0.947	3474	174	696	60	0.159	0.944	947	37	101	25
0.139	0.948	3469	166	704	65	0.167	0.937	955	53	85	17
0.135	0.953	3476	148	722	58	0.159	0.938	961	58	80	11
0.122	0.955	3482	147	723	52	0.150	0.939	955	51	87	17
0.136	0.952	3459	136	734	75	0.169	0.940	952	47	91	20
0.130	0.953	3459	133	737	75	0.168	0.935	934	34	104	38
0.127	0.956	3471	130	740	63	0.164	0.938	962	59	79	10
0.131	0.956	3482	142	728	52	0.181	0.938	956	53	85	16
0.185	0.937	3449	194	676	85	0.181	0.928	934	42	96	38
0.124	0.956	3473	134	736	61	0.165	0.940	954	49	89	18
0.111	0.960	3475	115	755	59	0.151	0.939	950	46	92	22
0.101	0.963	3484	112	758	50	0.160	0.940	960	55	83	12
0.093	0.967	3483	94	776	51	0.151	0.936	953	52	86	19
0.092	0.965	3476	97	773	58	0.152	0.941	958	52	86	14

K fold = 3											
Training						Validation					
Loss	**Accuracy**	**TP**	**FP**	**TN**	**FN**	**Loss**	**Accuracy**	**TP**	**FP**	**TN**	**FN**
0.437	0.835	3487	696	190	31	0.381	0.870	952	124	14	20
0.318	0.888	3439	416	470	79	0.298	0.896	966	109	29	6
0.278	0.899	3435	362	524	83	0.313	0.897	969	111	27	3
0.235	0.921	3460	290	596	58	0.328	0.905	967	100	38	5
0.214	0.922	3434	258	628	84	0.227	0.923	959	72	66	13
0.173	0.938	3444	199	687	74	0.269	0.919	967	85	53	5
0.165	0.940	3439	186	700	79	0.190	0.937	961	59	79	11
0.146	0.946	3444	164	722	74	0.197	0.936	963	62	76	9
0.147	0.948	3444	155	731	74	0.163	0.944	947	37	101	25
0.142	0.947	3431	145	741	87	0.378	0.912	970	96	42	2
0.142	0.950	3443	147	739	75	0.178	0.947	960	47	91	12
0.136	0.952	3445	139	747	73	0.171	0.937	965	63	75	7
0.138	0.950	3448	148	738	70	0.158	0.940	947	42	96	25
0.130	0.954	3457	143	743	61	0.171	0.938	954	51	87	18
0.124	0.952	3443	135	751	75	0.230	0.923	962	76	62	10
0.144	0.948	3446	156	730	72	0.185	0.932	949	53	85	23
0.141	0.947	3435	149	737	83	0.151	0.948	961	47	91	11
0.121	0.957	3445	116	770	73	0.233	0.939	968	64	74	4
0.124	0.958	3453	118	768	65	0.146	0.952	956	37	101	16
0.120	0.958	3455	122	764	63	0.177	0.939	962	58	80	10
0.120	0.958	3465	132	754	53	0.183	0.938	961	58	80	11
0.144	0.947	3450	164	722	68	0.176	0.941	955	49	89	17
0.142	0.948	3430	140	746	88	0.161	0.943	938	29	109	34
0.128	0.955	3457	139	747	61	0.201	0.918	920	39	99	52
0.118	0.961	3448	100	786	70	0.156	0.950	960	44	94	12
0.102	0.962	3463	111	775	55	0.173	0.941	961	54	84	11
0.094	0.969	3465	85	801	53	0.160	0.950	960	44	94	12
0.090	0.967	3464	91	795	54	0.146	0.951	957	39	99	15
0.088	0.970	3466	79	807	52	0.146	0.952	957	38	100	15
0.083	0.970	3464	79	807	54	0.148	0.956	960	37	101	12
0.083	0.970	3459	72	814	59	0.151	0.950	955	39	99	17
0.096	0.965	3442	77	809	76	0.174	0.948	960	46	92	12
0.087	0.970	3466	80	806	52	0.143	0.952	956	37	101	16
0.078	0.972	3462	69	817	56	0.150	0.949	955	40	98	17
0.081	0.971	3467	78	808	51	0.166	0.949	960	45	93	12
0.072	0.975	3473	65	821	45	0.150	0.947	957	44	94	15
0.071	0.977	3471	55	831	47	0.158	0.948	957	43	95	15
0.072	0.975	3472	65	821	46	0.148	0.952	955	36	102	17
0.066	0.976	3469	56	830	49	0.151	0.952	958	39	99	14
0.060	0.980	3482	51	835	36	0.156	0.950	958	42	96	14
0.065	0.977	3480	64	822	38	0.149	0.948	955	41	97	17
0.062	0.981	3482	47	839	36	0.154	0.949	957	42	96	15
0.058	0.979	3478	51	835	40	0.153	0.950	957	40	98	15

K fold = 4											
Training						Validation					
Loss	**Accuracy**	**TP**	**FP**	**TN**	**FN**	**Loss**	**Accuracy**	**TP**	**FP**	**TN**	**FN**
0.453	0.823	3467	717	159	62	0.375	0.874	967	136	2	4
0.345	0.873	3481	510	366	48	0.319	0.894	964	110	28	7
0.363	0.871	3461	500	376	68	0.325	0.893	966	114	24	5
0.323	0.887	3459	428	448	70	0.264	0.913	962	87	51	9
0.295	0.898	3457	377	499	72	0.270	0.909	966	96	42	5
0.300	0.894	3447	387	489	82	0.259	0.917	964	85	53	7
0.261	0.912	3476	335	541	53	0.239	0.918	960	80	58	11
0.264	0.913	3465	321	555	64	0.238	0.923	952	66	72	19
0.250	0.918	3449	283	593	80	0.252	0.910	943	72	66	28
0.250	0.919	3467	295	581	62	0.215	0.920	953	71	67	18
0.213	0.928	3475	262	614	54	0.209	0.922	937	52	86	34
0.204	0.933	3460	224	652	69	0.284	0.918	967	87	51	4
0.205	0.931	3468	242	634	61	0.189	0.938	955	53	85	16
0.213	0.925	3450	251	625	79	0.218	0.925	947	59	79	24
0.210	0.927	3461	252	624	68	0.207	0.925	964	76	62	7
0.217	0.928	3478	266	610	51	0.217	0.923	940	54	84	31
0.200	0.932	3466	237	639	63	0.215	0.926	959	70	68	12
0.203	0.927	3453	245	631	76	0.202	0.927	957	67	71	14
0.177	0.936	3461	215	661	68	0.182	0.929	959	67	71	12
0.161	0.938	3452	197	679	77	0.164	0.938	956	54	84	15
0.155	0.944	3463	179	697	66	0.174	0.935	961	62	76	10
0.149	0.945	3462	176	700	67	0.150	0.942	956	49	89	15
0.140	0.949	3478	174	702	51	0.149	0.938	956	54	84	15
0.138	0.948	3475	175	701	54	0.144	0.945	957	47	91	14
0.137	0.954	3476	151	725	53	0.160	0.940	959	55	83	12
0.134	0.951	3473	158	718	56	0.149	0.941	956	50	88	15
0.124	0.956	3472	139	737	57	0.139	0.948	955	42	96	16
0.118	0.960	3478	127	749	51	0.134	0.946	951	40	98	20
0.118	0.959	3476	129	747	53	0.140	0.946	954	43	95	17
0.117	0.959	3469	119	757	60	0.132	0.950	950	34	104	21
0.114	0.959	3467	118	758	62	0.142	0.950	958	43	95	13
0.113	0.960	3472	119	757	57	0.139	0.949	958	44	94	13
0.114	0.959	3472	122	754	57	0.129	0.950	954	38	100	17
0.105	0.964	3479	110	766	50	0.138	0.951	957	40	98	14
0.107	0.963	3479	114	762	50	0.135	0.950	955	40	98	16
0.103	0.964	3473	103	773	56	0.142	0.951	957	40	98	14
0.100	0.967	3482	100	776	47	0.155	0.948	959	46	92	12
0.100	0.966	3479	101	775	50	0.143	0.954	957	37	101	14
0.096	0.966	3476	95	781	53	0.142	0.951	959	42	96	12
0.091	0.968	3486	99	777	43	0.138	0.952	958	40	98	13
0.089	0.969	3480	87	789	49	0.132	0.954	957	37	101	14
0.090	0.970	3481	86	790	48	0.134	0.955	959	38	100	12
0.084	0.972	3479	73	803	50	0.134	0.953	957	38	100	14

K fold = 5											
		Training						Validation			
Loss	Accuracy	TP	FP	TN	FN	Loss	Accuracy	TP	FP	TN	FN
0.460	0.818	3477	753	127	48	0.379	0.872	967	138	0	4
0.367	0.867	3474	533	347	51	0.354	0.881	969	130	8	2
0.317	0.887	3460	432	448	65	0.326	0.893	965	113	25	6
0.275	0.902	3465	370	510	60	0.273	0.909	951	81	57	20
0.247	0.916	3463	308	572	62	0.397	0.849	850	47	91	121
0.241	0.916	3460	303	577	65	0.248	0.919	949	68	70	22
0.221	0.924	3462	272	608	63	0.246	0.924	956	69	69	15
0.206	0.928	3467	258	622	58	0.230	0.930	948	55	83	23
0.200	0.931	3459	240	640	66	0.200	0.940	957	53	85	14
0.177	0.938	3463	210	670	62	0.199	0.940	940	35	103	31
0.169	0.940	3458	199	681	67	0.202	0.936	961	61	77	10
0.171	0.937	3456	207	673	69	0.175	0.950	952	37	101	19
0.150	0.948	3457	163	717	68	0.185	0.935	961	62	76	10
0.147	0.950	3464	160	720	61	0.195	0.929	952	60	78	19
0.151	0.946	3463	176	704	62	0.175	0.942	962	55	83	9
0.147	0.947	3457	167	713	68	0.176	0.936	945	45	93	26
0.140	0.952	3469	157	723	56	0.173	0.942	952	45	93	19
0.151	0.947	3448	158	722	77	0.197	0.931	958	63	75	13
0.155	0.942	3442	172	708	83	0.164	0.943	959	51	87	12
0.131	0.955	3470	144	736	55	0.168	0.940	953	49	89	18
0.143	0.950	3453	149	731	72	0.180	0.946	957	46	92	14
0.132	0.952	3443	130	750	82	0.151	0.947	945	33	105	26
0.124	0.955	3457	131	749	68	0.211	0.934	960	62	76	11
0.128	0.956	3461	132	748	64	0.205	0.928	930	39	99	41
0.149	0.950	3471	165	715	54	0.183	0.947	958	46	92	13
0.137	0.950	3454	148	732	71	0.211	0.938	958	56	82	13
0.133	0.953	3462	142	738	63	0.166	0.947	947	35	103	24
0.126	0.954	3461	138	742	64	0.165	0.947	949	37	101	22
0.112	0.956	3456	124	756	69	0.162	0.950	950	35	103	21
0.108	0.959	3457	111	769	68	0.164	0.955	957	36	102	14
0.103	0.960	3460	112	768	65	0.166	0.950	958	43	95	13
0.104	0.963	3466	105	775	59	0.160	0.954	949	29	109	22

A.5 Total Atrial Fibrillation = 622 , 0:100 (Real:Sim)

K fold = 1											
		Training						Validation			
Loss	Accuracy	TP	FP	TN	FN	Loss	Accuracy	TP	FP	TN	FN
0.428	0.836	3346	666	439	77	0.374	0.876	970	136	2	2
0.339	0.879	3385	512	593	38	0.354	0.875	961	128	10	11
0.282	0.895	3341	393	712	82	0.336	0.882	971	130	8	1
0.242	0.913	3360	333	772	63	0.279	0.910	968	96	42	4
0.213	0.929	3363	263	842	60	0.235	0.918	961	80	58	11
0.169	0.940	3362	211	894	61	0.234	0.925	936	47	91	36
0.159	0.938	3332	189	916	91	0.197	0.932	948	52	86	24
0.138	0.954	3367	154	951	56	0.194	0.929	960	67	71	12
0.140	0.950	3357	160	945	66	0.169	0.943	961	52	86	11
0.136	0.953	3362	153	952	61	0.180	0.942	951	43	95	21
0.142	0.950	3344	149	956	79	0.165	0.945	955	44	94	17
0.120	0.958	3363	128	977	60	0.173	0.945	940	29	109	32
0.114	0.962	3367	114	991	56	0.150	0.958	957	32	106	15
0.105	0.965	3380	114	991	43	0.159	0.945	956	45	93	16
0.106	0.964	3367	109	996	56	0.137	0.953	953	33	105	19
0.102	0.965	3373	107	998	50	0.167	0.950	954	38	100	18
0.106	0.963	3364	107	998	59	0.184	0.945	964	53	85	8
0.127	0.956	3350	126	979	73	0.189	0.934	959	60	78	13
0.143	0.949	3355	161	944	68	0.182	0.944	961	51	87	11
0.145	0.948	3342	154	951	81	0.219	0.928	966	74	64	6
0.109	0.964	3371	113	992	52	0.167	0.944	959	49	89	13
0.102	0.965	3370	104	1001	53	0.167	0.948	963	49	89	9
0.090	0.968	3371	95	1010	52	0.167	0.949	962	47	91	10
0.089	0.969	3377	96	1009	46	0.153	0.953	957	37	101	15
0.082	0.973	3384	85	1020	39	0.147	0.957	955	31	107	17

K fold = 2											
		Training						Validation			
Loss	Accuracy	TP	FP	TN	FN	Loss	Accuracy	TP	FP	TN	FN
0.431	0.826	3352	713	389	74	0.359	0.876	972	138	0	0
0.313	0.885	3370	463	639	56	0.279	0.894	947	93	45	25
0.270	0.909	3375	362	740	51	0.313	0.899	957	97	41	15
0.220	0.924	3366	286	816	60	0.222	0.910	963	91	47	9
0.180	0.934	3349	223	879	77	0.189	0.933	961	63	75	11
0.162	0.939	3341	193	909	85	0.178	0.938	962	59	79	10
0.153	0.943	3350	184	918	76	0.185	0.929	961	68	70	11
0.142	0.949	3357	161	941	69	0.175	0.944	956	46	92	16
0.125	0.955	3350	130	972	76	0.182	0.940	961	56	82	11
0.140	0.952	3351	143	959	75	0.182	0.932	961	64	74	11
0.134	0.950	3349	148	954	77	0.169	0.945	956	45	93	16
0.130	0.955	3360	137	965	66	0.175	0.937	958	56	82	14
0.138	0.951	3344	139	963	82	0.168	0.946	943	31	107	29
0.137	0.948	3354	165	937	72	0.162	0.941	943	36	102	29
0.129	0.953	3359	145	957	67	0.162	0.943	953	44	94	19
0.130	0.953	3349	138	964	77	0.187	0.924	912	24	114	60
0.132	0.953	3347	132	970	79	0.153	0.950	958	42	96	14
0.126	0.953	3346	132	970	80	0.154	0.945	952	41	97	20
0.134	0.952	3350	142	960	76	0.172	0.943	958	49	89	14
0.124	0.956	3350	123	979	76	0.187	0.937	965	63	75	7
0.121	0.958	3353	118	984	73	0.160	0.945	956	45	93	16
0.138	0.953	3359	146	956	67	0.195	0.932	938	42	96	34
0.112	0.959	3360	118	984	66	0.167	0.944	960	50	88	12
0.095	0.965	3359	91	1011	67	0.163	0.950	959	43	95	13
0.092	0.968	3367	88	1014	59	0.153	0.951	953	35	103	19
0.086	0.972	3367	70	1032	59	0.154	0.947	951	38	100	21
0.083	0.973	3380	78	1024	46	0.165	0.950	957	40	98	15
0.083	0.972	3372	71	1031	54	0.162	0.950	957	41	97	15
0.076	0.975	3386	72	1030	40	0.155	0.950	955	38	100	17
0.074	0.974	3382	72	1030	44	0.151	0.954	954	33	105	18
0.076	0.974	3381	73	1029	45	0.156	0.954	957	36	102	15
0.074	0.973	3375	69	1033	51	0.151	0.951	955	37	101	17
0.075	0.975	3384	70	1032	42	0.163	0.949	957	42	96	15
0.074	0.975	3380	66	1036	46	0.152	0.950	955	38	100	17
0.071	0.975	3378	64	1038	48	0.157	0.950	956	40	98	16
0.070	0.977	3384	62	1040	42	0.153	0.950	955	38	100	17
0.071	0.976	3382	66	1036	44	0.153	0.955	954	32	106	18
0.067	0.978	3388	63	1039	38	0.153	0.956	954	31	107	18
0.070	0.977	3378	58	1044	48	0.151	0.955	955	33	105	17
0.064	0.978	3385	58	1044	41	0.152	0.954	955	34	104	17

K fold = 3											
		Training						Validation			
Loss	Accuracy	TP	FP	TN	FN	Loss	Accuracy	TP	FP	TN	FN
0.415	0.841	3345	634	464	85	0.372	0.876	972	138	0	0
0.341	0.879	3381	498	600	49	0.313	0.891	961	110	28	11
0.278	0.906	3361	355	743	69	0.258	0.914	966	90	48	6
0.240	0.922	3377	302	796	53	0.261	0.912	967	93	45	5
0.205	0.932	3385	265	833	45	0.205	0.929	961	68	70	11
0.167	0.944	3378	200	898	52	0.175	0.935	968	68	70	4
0.173	0.936	3349	209	889	81	0.185	0.928	935	43	95	37
0.146	0.949	3357	159	939	73	0.188	0.935	966	66	72	6
0.137	0.948	3357	161	937	73	0.131	0.946	955	43	95	17
0.161	0.941	3350	189	909	80	0.176	0.932	962	66	72	10
0.176	0.940	3341	183	915	89	0.191	0.930	967	73	65	5
0.161	0.941	3364	199	899	66	0.156	0.941	961	55	83	11
0.135	0.949	3351	153	945	79	0.180	0.937	965	63	75	7
0.147	0.945	3352	173	925	78	0.136	0.945	958	47	91	14
0.116	0.957	3370	136	962	60	0.141	0.946	961	49	89	11
0.104	0.962	3383	124	974	47	0.128	0.958	958	33	105	14
0.100	0.966	3380	106	992	50	0.138	0.950	967	50	88	5
0.089	0.968	3385	102	996	45	0.130	0.954	963	42	96	9
0.090	0.968	3380	94	1004	50	0.124	0.957	957	33	105	15
0.092	0.968	3376	92	1006	54	0.142	0.951	966	48	90	6
0.083	0.970	3384	90	1008	46	0.147	0.944	966	56	82	6
0.076	0.975	3404	87	1011	26	0.129	0.951	964	46	92	8
0.079	0.973	3384	77	1021	46	0.126	0.958	966	41	97	6
0.078	0.973	3392	85	1013	38	0.137	0.951	966	48	90	6
0.072	0.975	3396	81	1017	34	0.139	0.951	966	48	90	6
0.067	0.978	3400	69	1029	30	0.128	0.958	965	40	98	7
0.066	0.978	3395	63	1035	35	0.133	0.953	966	46	92	6
0.065	0.977	3394	67	1031	36	0.133	0.956	966	43	95	6
0.062	0.978	3402	70	1028	28	0.133	0.955	965	43	95	7

K fold = 4											
Training						Validation					
Loss	Accuracy	TP	FP	TN	FN	Loss	Accuracy	TP	FP	TN	FN
0.438	0.827	3338	695	409	87	0.500	0.847	913	112	26	58
0.333	0.880	3373	490	614	52	0.422	0.876	969	136	2	2
0.287	0.900	3373	401	703	52	0.281	0.897	935	78	60	36
0.259	0.912	3362	337	767	63	0.286	0.897	950	93	45	21
0.244	0.917	3356	309	795	69	0.252	0.914	963	87	51	8
0.226	0.925	3373	287	817	52	0.261	0.912	940	67	71	31
0.205	0.930	3360	251	853	65	0.238	0.908	940	71	67	31
0.206	0.929	3359	254	850	66	0.245	0.911	961	89	49	10
0.179	0.939	3377	227	877	48	0.200	0.921	946	63	75	25
0.171	0.942	3364	201	903	61	0.250	0.913	908	34	104	63
0.154	0.949	3359	167	937	66	0.205	0.921	959	76	62	12
0.151	0.947	3361	174	930	64	0.188	0.930	958	65	73	13
0.150	0.949	3359	165	939	66	0.170	0.938	961	59	79	10
0.158	0.946	3348	169	935	77	0.196	0.929	960	68	70	11
0.147	0.948	3366	176	928	59	0.206	0.930	948	55	83	23
0.167	0.943	3349	184	920	76	0.208	0.931	958	63	75	13
0.182	0.935	3335	204	900	90	0.177	0.926	933	44	94	38
0.137	0.952	3350	142	962	75	0.241	0.924	964	77	61	7
0.123	0.959	3378	138	966	47	0.187	0.935	959	60	78	12
0.112	0.964	3374	112	992	51	0.155	0.941	944	38	100	27
0.100	0.967	3376	101	1003	49	0.163	0.947	958	46	92	13
0.094	0.968	3381	102	1002	44	0.170	0.941	957	51	87	14
0.095	0.967	3375	98	1006	50	0.151	0.947	955	43	95	16
0.090	0.970	3376	85	1019	49	0.152	0.946	952	41	97	19
0.094	0.969	3376	92	1012	49	0.150	0.948	954	41	97	17
0.086	0.970	3380	89	1015	45	0.157	0.942	945	38	100	26
0.079	0.974	3387	80	1024	38	0.148	0.948	946	33	105	25
0.083	0.974	3383	74	1030	42	0.143	0.949	952	38	100	19
0.080	0.972	3384	85	1019	41	0.138	0.951	946	29	109	25
0.084	0.972	3377	78	1026	48	0.149	0.950	951	36	102	20
0.071	0.977	3385	64	1040	40	0.144	0.953	952	33	105	19
0.069	0.978	3388	61	1043	37	0.144	0.952	946	28	110	25
0.072	0.976	3383	67	1037	42	0.151	0.945	947	37	101	24
0.063	0.979	3386	54	1050	39	0.150	0.950	950	35	103	21
0.063	0.978	3384	57	1047	41	0.153	0.946	953	42	96	18
0.060	0.981	3393	55	1049	32	0.152	0.950	953	38	100	18
0.059	0.981	3390	52	1052	35	0.159	0.944	953	44	94	18
0.057	0.981	3389	49	1055	36	0.149	0.949	952	38	100	19
0.059	0.981	3390	53	1051	35	0.158	0.946	956	45	93	15

K fold = 5											
Training						Validation					
Loss	Accuracy	TP	FP	TN	FN	Loss	Accuracy	TP	FP	TN	FN
0.399	0.848	3345	613	496	75	0.344	0.875	964	132	6	7
0.297	0.893	3361	425	684	59	0.288	0.893	956	104	34	15
0.241	0.915	3357	320	789	63	0.245	0.913	950	76	62	21
0.206	0.927	3364	276	833	56	0.213	0.922	957	73	65	14
0.177	0.939	3363	221	888	57	0.214	0.918	959	79	59	12
0.157	0.941	3342	189	920	78	0.184	0.932	952	56	82	19
0.148	0.948	3354	169	940	66	0.240	0.916	963	85	53	8
0.143	0.946	3338	164	945	82	0.191	0.931	963	69	69	8
0.146	0.951	3355	158	951	65	0.194	0.937	938	37	101	33
0.135	0.953	3356	147	962	64	0.169	0.936	958	58	80	13
0.143	0.952	3359	158	951	61	0.162	0.937	948	47	91	23
0.143	0.948	3334	149	960	86	0.166	0.943	949	41	97	22
0.124	0.956	3359	139	970	61	0.175	0.936	955	55	83	16
0.137	0.950	3348	154	955	72	0.165	0.939	956	53	85	15
0.149	0.947	3331	150	959	89	0.186	0.934	931	33	105	40
0.155	0.949	3340	153	956	80	0.174	0.937	937	36	102	34
0.119	0.958	3355	123	986	65	0.156	0.944	952	43	95	19
0.105	0.963	3363	110	999	57	0.171	0.941	955	49	89	16
0.098	0.967	3367	98	1011	53	0.144	0.947	949	37	101	22
0.092	0.967	3371	100	1009	49	0.138	0.948	946	33	105	25
0.087	0.968	3366	91	1018	54	0.149	0.948	953	40	98	18
0.085	0.970	3374	90	1019	46	0.151	0.950	953	37	101	18
0.081	0.972	3370	76	1033	50	0.147	0.947	952	40	98	19
0.084	0.971	3370	83	1026	50	0.146	0.951	954	37	101	17
0.081	0.969	3364	85	1024	56	0.136	0.955	954	33	105	17
0.074	0.974	3380	79	1030	40	0.138	0.955	948	27	111	23
0.071	0.974	3374	74	1035	46	0.132	0.956	952	30	108	19
0.071	0.975	3376	68	1041	44	0.137	0.953	949	30	108	22
0.069	0.978	3386	67	1042	34	0.133	0.957	956	33	105	15
0.065	0.977	3375	60	1049	45	0.133	0.956	953	31	107	18
0.063	0.977	3379	64	1045	41	0.132	0.958	954	30	108	17
0.060	0.980	3382	54	1055	38	0.146	0.958	959	35	103	12
0.055	0.980	3387	59	1050	33	0.137	0.957	957	34	104	14
0.053	0.981	3389	54	1055	31	0.134	0.959	955	29	109	16
0.052	0.981	3384	50	1059	36	0.135	0.960	956	29	109	15
0.049	0.984	3389	41	1068	31	0.140	0.957	957	34	104	14
0.051	0.983	3388	43	1066	32	0.139	0.960	959	32	106	12

A.6 Total Atrial Fibrillation = 777 , 80:20 (Real:Sim)

K fold = 1											
Training						Validation					
Loss	**Accuracy**	**TP**	**FP**	**TN**	**FN**	**Loss**	**Accuracy**	**TP**	**FP**	**TN**	**FN**
0.432	0.844	3866	696	12	20	0.372	0.868	942	116	22	30
0.376	0.870	3852	563	145	34	0.323	0.895	957	101	37	15
0.332	0.886	3833	473	235	53	0.274	0.911	958	85	53	14
0.287	0.902	3823	388	320	63	0.249	0.918	967	86	52	5
0.262	0.912	3835	353	355	51	0.238	0.913	940	65	73	32
0.237	0.918	3829	320	388	57	0.217	0.917	959	79	59	13
0.227	0.920	3819	302	406	67	0.199	0.922	966	81	57	6
0.204	0.928	3823	270	438	63	0.177	0.932	966	69	69	6
0.178	0.934	3805	220	488	81	0.163	0.937	949	47	91	23
0.168	0.936	3807	216	492	79	0.169	0.933	958	60	78	14
0.168	0.937	3818	222	486	68	0.193	0.927	950	59	79	22
0.187	0.933	3790	211	497	96	0.249	0.895	889	33	105	83
0.177	0.939	3824	218	490	62	0.204	0.928	952	60	78	20
0.169	0.934	3777	193	515	109	0.177	0.929	954	61	77	18
0.138	0.948	3817	169	539	69	0.165	0.938	946	43	95	26
0.123	0.957	3828	141	567	58	0.144	0.944	947	37	101	25
0.119	0.958	3817	124	584	69	0.149	0.947	951	38	100	21
0.112	0.961	3819	112	596	67	0.142	0.945	948	37	101	24
0.111	0.960	3811	110	598	75	0.139	0.956	955	32	106	17
0.107	0.963	3824	110	598	62	0.142	0.951	954	36	102	18
0.111	0.959	3813	115	593	73	0.145	0.949	954	39	99	18
0.104	0.963	3828	114	594	58	0.142	0.948	953	39	99	19
0.099	0.964	3822	100	608	64	0.151	0.945	946	35	103	26
0.099	0.964	3819	97	611	67	0.159	0.946	954	42	96	18
0.092	0.969	3836	91	617	50	0.155	0.944	948	38	100	24
0.087	0.970	3832	83	625	54	0.151	0.943	947	38	100	25
0.085	0.972	3831	75	633	55	0.149	0.946	949	37	101	23
0.085	0.970	3830	80	628	56	0.154	0.948	953	39	99	19
0.085	0.971	3838	85	623	48	0.150	0.946	952	40	98	20

K fold = 2											
Training						Validation					
Loss	**Accuracy**	**TP**	**FP**	**TN**	**FN**	**Loss**	**Accuracy**	**TP**	**FP**	**TN**	**FN**
0.438	0.845	3878	706	2	8	0.400	0.876	972	138	0	0
0.437	0.846	3886	708	0	0	0.375	0.876	972	138	0	0
0.433	0.845	3881	707	1	5	0.383	0.876	972	138	0	0
0.432	0.846	3886	708	0	0	0.375	0.876	972	138	0	0
0.434	0.846	3886	708	0	0	0.379	0.876	972	138	0	0
0.432	0.846	3886	708	0	0	0.400	0.876	972	138	0	0
0.417	0.848	3880	694	14	6	0.329	0.886	971	125	13	1
0.344	0.875	3813	503	205	73	0.267	0.901	946	84	54	26
0.302	0.893	3788	394	314	98	0.248	0.917	963	83	55	9
0.279	0.899	3811	391	317	75	0.256	0.914	942	66	72	30
0.278	0.901	3819	388	320	67	0.239	0.918	972	91	47	0
0.273	0.907	3827	369	339	59	0.269	0.919	948	66	72	24
0.263	0.909	3805	336	372	81	0.237	0.924	969	81	57	3
0.254	0.912	3805	323	385	81	0.237	0.924	955	67	71	17
0.263	0.909	3803	333	375	83	0.224	0.929	968	75	63	4
0.252	0.910	3789	315	393	97	0.218	0.932	969	73	65	3
0.265	0.908	3811	348	360	75	0.222	0.929	970	77	61	2
0.250	0.914	3816	326	382	70	0.249	0.923	971	85	53	1
0.251	0.913	3816	329	379	70	0.222	0.931	963	68	70	9
0.246	0.911	3785	306	402	101	0.218	0.933	966	68	70	6
0.241	0.915	3800	306	402	86	0.222	0.918	971	90	48	1
0.225	0.918	3828	317	391	58	0.207	0.933	970	72	66	2
0.216	0.921	3842	321	387	44	0.199	0.938	964	61	77	8
0.218	0.922	3815	289	419	71	0.199	0.940	965	60	78	7
0.213	0.921	3825	302	406	61	0.196	0.935	962	62	76	10
0.214	0.924	3822	283	425	64	0.197	0.939	965	61	77	7
0.208	0.924	3814	278	430	72	0.192	0.939	967	63	75	5
0.204	0.928	3827	274	434	59	0.199	0.940	960	55	83	12
0.203	0.925	3823	281	427	63	0.186	0.941	966	60	78	6
0.201	0.927	3823	271	437	63	0.189	0.941	968	61	77	4
0.199	0.928	3829	272	436	57	0.187	0.942	965	57	81	7
0.196	0.929	3819	258	450	67	0.184	0.939	962	58	80	10
0.196	0.930	3819	256	452	67	0.193	0.941	968	62	76	4
0.197	0.929	3808	248	460	78	0.185	0.941	965	59	79	7
0.190	0.930	3801	238	470	85	0.182	0.940	963	58	80	9
0.189	0.931	3808	240	468	78	0.187	0.939	966	62	76	6
0.186	0.933	3820	243	465	66	0.180	0.941	964	57	81	8
0.183	0.933	3816	236	472	70	0.179	0.941	965	58	80	7
0.184	0.935	3811	225	483	75	0.185	0.940	966	61	77	6
0.184	0.934	3819	236	472	67	0.184	0.941	963	57	81	9
0.185	0.932	3808	236	472	78	0.183	0.939	959	55	83	13
0.186	0.931	3820	253	455	66	0.182	0.942	967	59	79	5
0.184	0.933	3830	253	455	56	0.185	0.940	968	63	75	4
0.176	0.936	3829	237	471	57	0.179	0.941	961	54	84	11
0.175	0.935	3823	234	474	63	0.180	0.942	961	53	85	11
0.173	0.935	3813	226	482	73	0.180	0.945	961	50	88	11
0.171	0.936	3814	222	486	72	0.179	0.943	962	53	85	10
0.169	0.936	3820	226	482	66	0.179	0.944	962	52	86	10
0.169	0.936	3802	212	496	84	0.178	0.942	961	53	85	11
0.170	0.937	3824	227	481	62	0.179	0.946	963	51	87	9
0.171	0.936	3815	223	485	71	0.178	0.943	963	54	84	9
0.166	0.938	3817	215	493	69	0.179	0.945	963	52	86	9
0.169	0.936	3820	227	481	66	0.177	0.945	962	51	87	10
0.164	0.937	3810	215	493	76	0.179	0.944	960	50	88	12
0.166	0.941	3812	195	513	74	0.178	0.943	963	54	84	9
0.166	0.935	3817	230	478	69	0.177	0.941	962	55	83	10
0.167	0.939	3814	209	499	72	0.178	0.944	962	52	86	10
0.168	0.938	3809	210	498	77	0.176	0.945	962	51	87	10
0.164	0.938	3821	221	487	65	0.178	0.946	963	51	87	9
0.162	0.939	3818	211	497	68	0.180	0.946	963	51	87	9

K fold = 3											
Training						Validation					
Loss	**Accuracy**	**TP**	**FP**	**TN**	**FN**	**Loss**	**Accuracy**	**TP**	**FP**	**TN**	**FN**
0.437	0.841	3859	703	5	27	0.392	0.876	972	138	0	0
0.404	0.856	3866	641	67	20	0.372	0.876	972	138	0	0
0.359	0.874	3833	524	184	53	0.369	0.878	970	133	5	2
0.322	0.889	3813	435	273	73	0.329	0.898	968	109	29	4
0.283	0.904	3837	394	314	49	0.293	0.905	954	88	50	18
0.266	0.910	3829	358	350	57	0.276	0.907	965	96	42	7
0.257	0.911	3829	351	357	57	0.285	0.905	971	105	33	1
0.254	0.913	3844	359	349	42	0.256	0.906	935	67	71	37
0.246	0.916	3824	326	382	62	0.262	0.913	966	91	47	6
0.246	0.915	3835	339	369	51	0.269	0.916	963	84	54	9
0.270	0.913	3824	336	372	62	0.258	0.916	964	85	53	8
0.284	0.900	3804	379	329	82	0.258	0.913	953	78	60	19
0.272	0.910	3792	320	388	94	0.258	0.907	952	83	55	20
0.236	0.919	3820	305	403	66	0.235	0.912	951	77	61	21
0.225	0.923	3829	299	409	57	0.232	0.914	948	71	67	24
0.220	0.923	3818	285	423	68	0.228	0.916	947	68	70	25
0.217	0.927	3826	276	432	60	0.231	0.921	948	64	74	24
0.210	0.929	3826	268	440	60	0.245	0.912	954	80	58	18
0.211	0.928	3818	265	443	68	0.236	0.916	954	75	63	18
0.211	0.929	3820	258	450	66	0.229	0.919	944	62	76	28
0.205	0.927	3817	267	441	69	0.231	0.919	941	59	79	31
0.194	0.933	3829	249	459	57	0.229	0.916	955	76	62	17
0.197	0.931	3829	259	449	57	0.222	0.916	948	69	69	24
0.200	0.930	3808	244	464	78	0.221	0.916	948	69	69	24
0.194	0.933	3830	251	457	56	0.221	0.917	948	68	70	24
0.194	0.933	3818	238	470	68	0.222	0.917	946	66	72	26
0.195	0.934	3825	242	466	61	0.222	0.917	946	66	72	26
0.193	0.934	3827	246	462	59	0.222	0.919	950	68	70	22
0.192	0.934	3821	239	469	65	0.221	0.917	944	64	74	28
0.191	0.933	3818	239	469	68	0.218	0.918	945	64	74	27
0.195	0.933	3825	247	461	61	0.218	0.919	949	67	71	23
0.192	0.933	3812	233	475	74	0.215	0.920	948	65	73	24
0.190	0.932	3813	239	469	73	0.216	0.921	950	66	72	22
0.190	0.933	3819	241	467	67	0.215	0.921	948	64	74	24
0.188	0.935	3831	243	465	55	0.217	0.921	951	67	71	21
0.186	0.937	3832	236	472	54	0.213	0.919	946	64	74	26
0.190	0.934	3811	230	478	75	0.216	0.916	941	62	76	31
0.188	0.933	3811	231	477	75	0.214	0.920	945	62	76	27
0.188	0.934	3822	238	470	64	0.213	0.920	950	67	71	22
0.185	0.936	3824	232	476	62	0.212	0.922	952	67	71	20
0.184	0.933	3817	237	471	69	0.212	0.923	948	62	76	24
0.182	0.936	3814	224	484	72	0.212	0.923	948	62	76	24
0.186	0.932	3818	246	462	68	0.216	0.920	953	70	68	19
0.183	0.936	3818	228	480	68	0.213	0.923	947	61	77	25
0.179	0.937	3812	215	493	74	0.215	0.923	949	63	75	23
0.179	0.939	3823	217	491	63	0.215	0.924	952	64	74	20
0.184	0.935	3814	225	483	72	0.213	0.924	951	63	75	21
0.182	0.937	3815	217	491	71	0.213	0.924	950	62	76	22
0.185	0.937	3816	220	488	70	0.213	0.923	950	63	75	22
0.183	0.937	3818	223	485	68	0.212	0.924	950	62	76	22
0.179	0.938	3821	219	489	65	0.213	0.924	951	63	75	21

K fold = 4											
		Training						Validation			
Loss	Accuracy	TP	FP	TN	FN	Loss	Accuracy	TP	FP	TN	FN
0.431	0.843	3868	702	6	19	0.355	0.878	970	134	4	1
0.309	0.889	3811	434	274	76	0.344	0.899	969	110	28	2
0.257	0.911	3829	350	358	58	0.251	0.916	964	86	52	7
0.213	0.925	3822	280	428	65	0.257	0.906	967	100	38	4
0.176	0.935	3819	231	477	68	0.167	0.943	960	52	86	11
0.174	0.933	3788	211	497	99	0.172	0.938	962	60	78	9
0.152	0.944	3805	177	531	82	0.178	0.939	965	62	76	6
0.168	0.939	3804	196	512	83	0.170	0.942	964	57	81	7
0.150	0.946	3817	180	528	70	0.179	0.941	956	50	88	15
0.152	0.946	3800	161	547	87	0.209	0.930	966	73	65	5
0.123	0.954	3818	141	567	69	0.160	0.940	959	55	83	12
0.107	0.963	3830	112	596	57	0.160	0.950	963	48	90	8
0.098	0.963	3829	110	598	58	0.162	0.949	961	47	91	10
0.090	0.969	3835	89	619	52	0.151	0.950	959	43	95	12
0.083	0.969	3837	92	616	50	0.144	0.951	957	40	98	14
0.087	0.970	3838	89	619	49	0.129	0.955	957	36	102	14
0.079	0.970	3835	87	621	52	0.162	0.948	961	48	90	10
0.076	0.972	3843	84	624	44	0.162	0.950	963	47	91	8
0.071	0.974	3837	70	638	50	0.141	0.952	956	38	100	15
0.065	0.978	3851	67	641	36	0.156	0.950	959	44	94	12
0.061	0.979	3851	62	646	36	0.138	0.956	960	38	100	11
0.057	0.982	3856	52	656	31	0.150	0.952	960	42	96	11
0.053	0.983	3859	48	660	28	0.143	0.953	959	40	98	12
0.054	0.983	3858	51	657	29	0.148	0.952	958	40	98	13
0.052	0.982	3859	54	654	28	0.146	0.953	958	39	99	13
0.050	0.984	3862	47	661	25	0.148	0.952	957	39	99	14

K fold = 5											
		Training						Validation			
Loss	Accuracy	TP	FP	TN	FN	Loss	Accuracy	TP	FP	TN	FN
0.439	0.841	3858	701	7	29	0.376	0.876	971	138	0	0
0.389	0.857	3844	614	94	43	0.346	0.885	971	128	10	0
0.307	0.894	3825	425	283	62	0.341	0.894	966	113	25	5
0.290	0.900	3839	411	297	48	0.296	0.904	949	85	53	22
0.267	0.911	3830	354	354	57	0.281	0.905	946	80	58	25
0.244	0.916	3822	323	385	65	0.255	0.921	950	67	71	21
0.243	0.916	3816	315	393	71	0.286	0.907	920	52	86	51
0.212	0.928	3825	269	439	62	0.213	0.924	960	73	65	11
0.195	0.928	3808	254	454	79	0.217	0.922	965	81	57	6
0.181	0.934	3819	234	474	68	0.189	0.927	963	73	65	8
0.163	0.940	3824	214	494	63	0.164	0.934	942	44	94	29
0.161	0.941	3812	196	512	75	0.174	0.937	959	58	80	12
0.160	0.941	3796	179	529	91	0.151	0.946	955	44	94	16
0.155	0.944	3814	184	524	73	0.155	0.940	957	52	86	14
0.153	0.944	3803	175	533	84	0.237	0.919	964	83	55	7
0.175	0.934	3787	202	506	100	0.198	0.935	950	51	87	21
0.165	0.940	3789	177	531	98	0.160	0.937	947	46	92	24
0.135	0.952	3822	156	552	65	0.170	0.942	954	47	91	17
0.130	0.955	3821	139	569	66	0.139	0.952	956	38	100	15
0.114	0.958	3817	125	583	70	0.140	0.951	957	40	98	14
0.108	0.961	3818	110	598	69	0.143	0.949	958	44	94	13
0.102	0.962	3829	118	590	58	0.128	0.955	957	36	102	14
0.103	0.965	3836	111	597	51	0.132	0.952	947	29	109	24
0.097	0.964	3825	104	604	62	0.152	0.950	958	43	95	13
0.101	0.963	3834	118	590	53	0.139	0.950	954	38	100	17
0.098	0.965	3831	106	602	56	0.147	0.947	955	43	95	16
0.094	0.968	3832	92	616	55	0.138	0.950	957	42	96	14
0.085	0.970	3833	83	625	54	0.131	0.952	956	38	100	15
0.083	0.972	3839	81	627	48	0.125	0.956	957	35	103	14
0.082	0.974	3837	70	638	50	0.133	0.951	957	40	98	14
0.081	0.970	3837	86	622	50	0.126	0.959	956	31	107	15
0.082	0.971	3841	88	620	46	0.127	0.957	956	33	105	15
0.079	0.973	3841	76	632	46	0.127	0.956	956	34	104	15
0.079	0.972	3839	81	627	48	0.137	0.950	957	41	97	14
0.076	0.973	3847	84	624	40	0.133	0.953	957	38	100	14
0.076	0.975	3839	67	641	48	0.133	0.953	957	38	100	14
0.074	0.974	3834	67	641	53	0.132	0.954	957	37	101	14
0.072	0.974	3847	81	627	40	0.131	0.954	957	37	101	14
0.075	0.973	3841	77	631	46	0.130	0.956	957	35	103	14

A.7 Total Atrial Fibrillation = 887 , 70:30 (Real:Sim)

K fold = 1											
Training						Validation					
Loss	**Accuracy**	**TP**	**FP**	**TN**	**FN**	**Loss**	**Accuracy**	**TP**	**FP**	**TN**	**FN**
0.432	0.835	3824	715	103	62	0.331	0.889	963	114	24	9
0.339	0.882	3825	493	325	61	0.324	0.897	969	111	27	3
0.267	0.910	3807	346	472	79	0.309	0.903	966	102	36	6
0.244	0.912	3818	347	471	68	0.313	0.910	968	96	42	4
0.208	0.925	3815	281	537	71	0.260	0.917	950	70	68	22
0.193	0.929	3796	243	575	90	0.232	0.922	966	81	57	6
0.166	0.941	3798	190	628	88	0.201	0.928	965	73	65	7
0.163	0.937	3793	205	613	93	0.197	0.934	942	43	95	30
0.157	0.940	3793	191	627	93	0.254	0.928	968	76	62	4
0.152	0.946	3798	164	654	88	0.172	0.943	954	45	93	18
0.153	0.941	3782	174	644	104	0.199	0.935	964	64	74	8
0.147	0.945	3800	173	645	86	0.197	0.931	960	65	73	12
0.147	0.947	3807	170	648	79	0.191	0.939	960	56	82	12
0.149	0.946	3806	172	646	80	0.192	0.932	931	35	103	41
0.139	0.948	3796	153	665	90	0.265	0.928	963	71	67	9
0.117	0.957	3814	131	687	72	0.180	0.940	953	48	90	19
0.103	0.961	3815	114	704	71	0.179	0.941	959	53	85	13
0.095	0.964	3816	101	717	70	0.160	0.945	956	45	93	16
0.097	0.966	3827	102	716	59	0.157	0.949	957	42	96	15
0.089	0.967	3818	89	729	68	0.180	0.940	958	53	85	14
0.087	0.967	3825	93	725	61	0.160	0.949	955	40	98	17
0.081	0.972	3833	81	737	53	0.171	0.945	954	43	95	18
0.077	0.972	3833	80	738	53	0.173	0.947	958	45	93	14
0.078	0.970	3828	84	734	58	0.189	0.943	960	51	87	12
0.074	0.973	3843	82	736	43	0.172	0.947	956	43	95	16
0.070	0.977	3839	63	755	47	0.170	0.949	957	42	96	15
0.070	0.974	3839	75	743	47	0.171	0.950	957	41	97	15
0.068	0.975	3835	66	752	51	0.172	0.949	956	41	97	16
0.067	0.976	3842	68	750	44	0.181	0.943	956	47	91	16

K fold = 2											
		Training						**Validation**			
Loss	**Accuracy**	**TP**	**FP**	**TN**	**FN**	**Loss**	**Accuracy**	**TP**	**FP**	**TN**	**FN**
0.424	0.843	3851	703	115	35	0.394	0.867	945	121	17	27
0.339	0.875	3827	531	287	59	0.285	0.908	962	92	46	10
0.284	0.898	3820	412	406	66	0.252	0.917	954	74	64	18
0.229	0.918	3818	318	500	68	0.241	0.914	969	92	46	3
0.195	0.929	3814	264	554	72	0.183	0.936	962	61	77	10
0.172	0.939	3804	204	614	82	0.169	0.940	947	42	96	25
0.167	0.940	3813	208	610	73	0.193	0.924	963	75	63	9
0.156	0.945	3810	184	634	76	0.157	0.944	959	49	89	13
0.141	0.949	3808	161	657	78	0.167	0.944	960	50	88	12
0.141	0.949	3810	162	656	76	0.158	0.949	958	43	95	14
0.153	0.942	3813	198	620	73	0.175	0.932	927	30	108	45
0.150	0.944	3805	183	635	81	0.144	0.950	950	33	105	22
0.137	0.951	3805	151	667	81	0.154	0.943	933	24	114	39
0.137	0.949	3800	154	664	86	0.151	0.942	958	50	88	14
0.153	0.947	3821	182	636	65	0.148	0.943	951	42	96	21
0.137	0.950	3815	162	656	71	0.167	0.941	932	26	112	40
0.145	0.949	3809	164	654	77	0.165	0.945	954	43	95	18
0.108	0.963	3844	133	685	42	0.159	0.946	958	46	92	14
0.099	0.965	3834	114	704	52	0.142	0.950	949	33	105	23
0.090	0.970	3842	95	723	44	0.145	0.950	948	32	106	24
0.091	0.968	3834	100	718	52	0.140	0.953	945	25	113	27
0.088	0.970	3837	94	724	49	0.136	0.952	948	29	109	24
0.083	0.969	3833	93	725	53	0.136	0.953	946	26	112	26
0.084	0.971	3837	87	731	49	0.147	0.950	956	39	99	16
0.084	0.971	3837	87	731	49	0.146	0.948	948	34	104	24
0.078	0.972	3848	92	726	38	0.136	0.954	944	23	115	28
0.075	0.976	3839	66	752	47	0.135	0.953	946	26	112	26
0.072	0.978	3855	74	744	31	0.139	0.953	953	33	105	19
0.072	0.976	3847	76	742	39	0.137	0.953	954	34	104	18
0.072	0.976	3841	69	749	45	0.136	0.956	953	30	108	19
0.068	0.977	3849	69	749	37	0.136	0.949	949	34	104	23
0.070	0.976	3847	75	743	39	0.140	0.950	950	33	105	22
0.063	0.980	3853	60	758	33	0.137	0.953	951	31	107	21
0.062	0.979	3846	58	760	40	0.139	0.955	953	31	107	19
0.061	0.980	3852	62	756	34	0.138	0.955	951	29	109	21
0.060	0.980	3854	64	754	32	0.139	0.954	950	29	109	22
0.055	0.983	3857	53	765	29	0.141	0.952	951	32	106	21

K fold = 3											
		Training						**Validation**			
Loss	**Accuracy**	**TP**	**FP**	**TN**	**FN**	**Loss**	**Accuracy**	**TP**	**FP**	**TN**	**FN**
0.464	0.826	3869	803	15	17	0.383	0.863	934	114	24	38
0.337	0.874	3800	507	311	86	0.298	0.896	945	88	50	27
0.282	0.905	3830	390	428	56	0.280	0.908	962	92	46	10
0.251	0.916	3832	343	475	54	0.228	0.923	955	68	70	17
0.209	0.927	3820	277	541	66	0.277	0.906	934	66	72	38
0.172	0.935	3813	232	586	73	0.168	0.947	952	39	99	20
0.155	0.946	3807	177	641	79	0.217	0.923	965	79	59	7
0.171	0.936	3802	216	602	84	0.204	0.936	953	52	86	19
0.168	0.939	3794	196	622	92	0.190	0.934	957	58	80	15
0.147	0.946	3804	172	646	82	0.161	0.942	961	53	85	11
0.136	0.950	3807	155	663	79	0.225	0.926	966	76	62	6
0.134	0.952	3815	153	665	71	0.149	0.950	955	39	99	17
0.128	0.955	3812	140	678	74	0.135	0.955	955	33	105	17
0.128	0.956	3814	135	683	72	0.160	0.939	961	57	81	11
0.115	0.960	3819	121	697	67	0.155	0.946	958	46	92	14
0.135	0.955	3821	147	671	65	0.154	0.950	964	47	91	8
0.129	0.953	3811	146	672	75	0.144	0.949	959	44	94	13
0.131	0.952	3818	160	658	68	0.152	0.942	955	47	91	17
0.113	0.961	3822	121	697	64	0.145	0.946	958	46	92	14
0.101	0.964	3833	114	704	53	0.143	0.950	954	38	100	18
0.092	0.967	3826	93	725	60	0.140	0.954	956	35	103	16
0.089	0.966	3823	95	723	63	0.162	0.948	958	44	94	14
0.086	0.971	3829	81	737	57	0.137	0.960	948	20	118	24

K fold = 4											
Training						Validation					
Loss	Accuracy	TP	FP	TN	FN	Loss	Accuracy	TP	FP	TN	FN
0.431	0.841	3863	725	93	24	0.764	0.670	697	92	46	274
0.366	0.872	3846	562	256	41	0.300	0.891	948	98	40	23
0.304	0.894	3825	438	380	62	0.305	0.898	969	111	27	2
0.282	0.901	3827	407	411	60	0.267	0.913	961	86	52	10
0.256	0.911	3829	363	455	58	0.267	0.907	969	101	37	2
0.248	0.914	3826	344	474	61	0.252	0.922	965	80	58	6
0.224	0.922	3821	303	515	66	0.230	0.922	964	79	59	7
0.214	0.925	3824	291	527	63	0.221	0.929	966	74	64	5
0.212	0.926	3815	277	541	72	0.232	0.917	926	47	91	45
0.214	0.923	3794	271	547	93	0.203	0.922	960	75	63	11
0.200	0.924	3799	268	550	88	0.189	0.926	955	66	72	16
0.203	0.924	3793	262	556	94	0.206	0.931	953	58	80	18
0.180	0.935	3806	223	595	81	0.227	0.924	966	79	59	5
0.181	0.933	3796	223	595	91	0.217	0.919	932	51	87	39
0.185	0.934	3812	235	583	75	0.181	0.937	958	57	81	13
0.179	0.942	3818	206	612	69	0.187	0.936	966	66	72	5
0.191	0.934	3820	243	575	67	0.231	0.917	969	90	48	2
0.196	0.928	3788	241	577	99	0.298	0.908	969	100	38	2
0.207	0.927	3802	258	560	85	0.191	0.930	955	62	76	16
0.181	0.938	3803	210	608	84	0.169	0.944	956	47	91	15
0.197	0.926	3794	253	565	93	0.179	0.925	954	66	72	17
0.180	0.936	3811	225	593	76	0.201	0.924	964	77	61	7
0.195	0.930	3813	256	562	74	0.219	0.923	933	47	91	38
0.205	0.928	3806	259	559	81	0.178	0.931	948	54	84	23
0.178	0.939	3827	225	593	60	0.174	0.942	955	48	90	16
0.151	0.949	3828	181	637	59	0.164	0.941	960	54	84	11
0.137	0.954	3832	162	656	55	0.159	0.944	959	50	88	12
0.132	0.952	3834	172	646	53	0.172	0.940	961	56	82	10
0.126	0.958	3829	140	678	58	0.162	0.940	957	52	86	14
0.124	0.954	3834	162	656	53	0.151	0.943	957	49	89	14
0.124	0.955	3834	158	660	53	0.146	0.950	962	47	91	9
0.123	0.956	3825	145	673	62	0.181	0.939	953	50	88	18
0.127	0.955	3815	140	678	72	0.142	0.954	956	36	102	15
0.115	0.957	3829	144	674	58	0.142	0.950	958	43	95	13
0.117	0.958	3822	133	685	65	0.150	0.950	958	43	95	13
0.111	0.959	3814	120	698	73	0.152	0.950	962	47	91	9
0.110	0.961	3831	129	689	56	0.139	0.952	948	30	108	23
0.107	0.959	3821	127	691	66	0.140	0.951	958	41	97	13
0.109	0.960	3828	128	690	59	0.141	0.950	947	31	107	24
0.113	0.961	3810	108	710	77	0.153	0.944	953	44	94	18
0.110	0.961	3816	113	705	71	0.153	0.942	953	46	92	18
0.104	0.965	3840	120	698	47	0.148	0.951	949	32	106	22
0.101	0.965	3827	106	712	60	0.150	0.950	955	40	98	16
0.099	0.963	3821	107	711	66	0.137	0.953	951	32	106	20
0.096	0.965	3829	106	712	58	0.140	0.950	951	35	103	20
0.096	0.966	3826	100	718	61	0.154	0.947	955	43	95	16
0.097	0.964	3825	106	712	62	0.147	0.947	954	42	96	17
0.096	0.966	3841	113	705	46	0.145	0.952	956	38	100	15
0.092	0.967	3836	103	715	51	0.144	0.950	955	39	99	16
0.095	0.965	3822	101	717	65	0.141	0.953	953	34	104	18
0.092	0.965	3835	112	706	52	0.140	0.952	956	38	100	15
0.092	0.967	3834	100	718	53	0.143	0.950	955	39	99	16
0.092	0.967	3825	93	725	62	0.136	0.957	955	32	106	16
0.090	0.966	3828	101	717	59	0.138	0.957	955	32	106	16
0.090	0.966	3831	102	716	56	0.138	0.950	954	38	100	17
0.091	0.966	3823	98	720	64	0.135	0.956	953	31	107	18
0.089	0.967	3827	93	725	60	0.137	0.954	955	35	103	16
0.088	0.967	3834	100	718	53	0.134	0.959	953	28	110	18
0.091	0.964	3818	99	719	69	0.140	0.953	955	36	102	16
0.090	0.970	3831	87	731	56	0.140	0.953	956	37	101	15

K fold = 5											
Training						Validation					
Loss	Accuracy	TP	FP	TN	FN	Loss	Accuracy	TP	FP	TN	FN
0.469	0.819	3847	811	7	40	0.388	0.876	971	138	0	0
0.402	0.849	3831	656	162	56	0.361	0.880	971	133	5	0
0.318	0.887	3810	454	364	77	0.297	0.903	971	108	30	0
0.280	0.904	3829	393	425	58	0.283	0.909	970	100	38	1
0.262	0.911	3836	367	451	51	0.256	0.911	958	86	52	13
0.255	0.916	3827	337	481	60	0.251	0.915	958	81	57	13
0.261	0.913	3823	346	472	64	0.257	0.918	967	87	51	4
0.241	0.921	3830	317	501	57	0.231	0.925	965	77	61	6
0.240	0.920	3820	309	509	67	0.232	0.921	965	82	56	6
0.238	0.919	3823	319	499	64	0.226	0.922	959	75	63	12
0.221	0.921	3782	267	551	105	0.227	0.922	963	78	60	8
0.254	0.915	3802	314	504	85	0.229	0.920	947	65	73	24
0.241	0.920	3807	296	522	80	0.244	0.919	967	86	52	4
0.232	0.922	3808	290	528	79	0.218	0.921	958	75	63	13
0.222	0.925	3805	270	548	82	0.246	0.921	967	84	54	4
0.233	0.921	3798	283	535	89	0.213	0.926	933	44	94	38
0.226	0.925	3819	285	533	68	0.236	0.906	912	45	93	59
0.209	0.928	3816	268	550	71	0.220	0.928	951	60	78	20
0.199	0.933	3812	240	578	75	0.189	0.927	950	60	78	21
0.200	0.931	3801	239	579	86	0.200	0.931	959	64	74	12
0.204	0.934	3831	254	564	56	0.217	0.926	937	48	90	34
0.211	0.924	3778	250	568	109	0.216	0.927	968	78	60	3
0.233	0.917	3812	316	502	75	0.205	0.927	961	71	67	10
0.220	0.926	3830	291	527	57	0.223	0.916	967	89	49	4
0.205	0.929	3846	291	527	41	0.199	0.931	953	59	79	18
0.188	0.938	3832	239	579	55	0.193	0.931	956	62	76	15
0.174	0.939	3837	235	583	50	0.190	0.933	951	54	84	20
0.175	0.940	3816	212	606	71	0.187	0.932	953	57	81	18
0.169	0.939	3834	233	585	53	0.190	0.931	941	46	92	30
0.173	0.940	3821	217	601	66	0.181	0.938	955	53	85	16
0.162	0.944	3832	208	610	55	0.180	0.941	954	48	90	17
0.162	0.945	3827	197	621	60	0.208	0.931	965	70	68	6
0.162	0.944	3820	196	622	67	0.183	0.943	965	57	81	6
0.156	0.946	3833	199	619	54	0.172	0.946	958	47	91	13
0.151	0.948	3831	188	630	56	0.176	0.943	963	55	83	8
0.150	0.946	3809	177	641	78	0.172	0.944	953	44	94	18
0.145	0.950	3822	169	649	65	0.170	0.946	956	45	93	15
0.142	0.947	3826	187	631	61	0.169	0.944	953	44	94	18
0.148	0.950	3835	182	636	52	0.188	0.935	964	65	73	7
0.144	0.950	3834	181	637	53	0.171	0.950	960	45	93	11
0.142	0.951	3836	178	640	51	0.164	0.946	958	47	91	13
0.136	0.953	3828	163	655	59	0.165	0.944	953	44	94	18
0.138	0.952	3823	161	657	64	0.173	0.947	955	43	95	16
0.130	0.953	3827	159	659	60	0.163	0.947	957	45	93	14
0.133	0.950	3821	167	651	66	0.177	0.942	964	57	81	7
0.130	0.952	3817	154	664	70	0.175	0.943	963	55	83	8
0.131	0.953	3844	179	639	43	0.179	0.942	964	57	81	7
0.124	0.958	3818	130	688	69	0.168	0.944	956	47	91	15
0.121	0.956	3829	150	668	58	0.174	0.943	961	53	85	10
0.113	0.961	3842	138	680	45	0.165	0.944	957	48	90	14
0.116	0.960	3833	134	684	54	0.159	0.948	956	43	95	15
0.114	0.962	3840	132	686	47	0.165	0.950	958	43	95	13
0.113	0.959	3819	127	691	68	0.166	0.945	959	49	89	12
0.113	0.957	3821	134	684	66	0.165	0.949	959	45	93	12
0.110	0.964	3836	120	698	51	0.168	0.948	960	47	91	11
0.111	0.960	3833	133	685	54	0.162	0.950	960	45	93	11
0.111	0.961	3827	123	695	60	0.161	0.949	956	42	96	15
0.111	0.962	3837	127	691	50	0.171	0.947	961	49	89	10
0.110	0.960	3834	136	682	53	0.165	0.949	960	46	92	11
0.108	0.962	3835	129	689	52	0.169	0.949	960	46	92	11

A.8 Total Atrial Fibrillation = 1244 , 50:50 (Real:Sim)

K fold = 1											
		Training						Validation			
Loss	Accuracy	TP	FP	TN	FN	Loss	Accuracy	TP	FP	TN	FN
0.422	0.837	3817	758	416	69	0.354	0.868	958	133	5	14
0.297	0.890	3798	468	706	88	0.340	0.896	969	112	26	3
0.245	0.917	3819	354	820	67	0.269	0.906	926	58	80	46
0.224	0.920	3808	325	849	78	0.233	0.923	958	72	66	14
0.190	0.931	3813	277	897	73	0.187	0.932	958	61	77	14
0.180	0.933	3793	246	928	93	0.219	0.916	963	84	54	9
0.151	0.947	3813	197	977	73	0.169	0.940	956	51	87	16
0.146	0.950	3808	175	999	78	0.183	0.929	959	66	72	13
0.142	0.950	3810	177	997	76	0.156	0.941	956	49	89	16
0.133	0.952	3804	162	1012	82	0.169	0.941	954	47	91	18
0.146	0.948	3794	173	1001	92	0.170	0.941	954	47	91	18
0.136	0.952	3810	166	1008	76	0.167	0.939	950	46	92	22
0.137	0.949	3797	169	1005	89	0.209	0.930	955	61	77	17
0.138	0.951	3798	159	1015	88	0.240	0.915	960	82	56	12
0.113	0.959	3809	132	1042	77	0.166	0.939	941	37	101	31
0.098	0.965	3828	119	1055	58	0.161	0.942	944	36	102	28
0.092	0.966	3822	109	1065	64	0.182	0.937	951	49	89	21
0.092	0.966	3820	108	1066	66	0.157	0.949	946	31	107	26
0.084	0.969	3829	100	1074	57	0.160	0.943	950	41	97	22

K fold = 2											
Training						Validation					
Loss	**Accuracy**	**TP**	**FP**	**TN**	**FN**	**Loss**	**Accuracy**	**TP**	**FP**	**TN**	**FN**
0.418	0.841	3797	717	457	89	0.387	0.861	952	134	4	20
0.308	0.882	3800	510	664	86	0.268	0.908	961	91	47	11
0.252	0.911	3816	380	794	70	0.247	0.907	966	97	41	6
0.211	0.925	3815	307	867	71	0.196	0.932	950	54	84	22
0.180	0.937	3812	246	928	74	0.189	0.936	964	63	75	8
0.167	0.940	3799	219	955	87	0.170	0.940	955	50	88	17
0.161	0.942	3803	208	966	83	0.172	0.935	965	65	73	7
0.147	0.949	3805	176	998	81	0.160	0.941	961	55	83	11
0.141	0.951	3805	168	1006	81	0.200	0.924	965	77	61	7
0.137	0.950	3807	174	1000	79	0.145	0.946	954	42	96	18
0.132	0.955	3812	155	1019	74	0.188	0.938	966	63	75	6
0.148	0.946	3792	179	995	94	0.155	0.950	961	45	93	11
0.153	0.943	3775	179	995	111	0.164	0.943	964	55	83	8
0.172	0.937	3774	206	968	112	0.199	0.928	964	72	66	8
0.142	0.949	3808	178	996	78	0.168	0.943	933	24	114	39
0.122	0.959	3811	134	1040	75	0.151	0.945	963	52	86	9
0.104	0.967	3839	122	1052	47	0.151	0.947	964	51	87	8
0.103	0.966	3831	118	1056	55	0.162	0.947	964	51	87	8
0.091	0.970	3842	106	1068	44	0.138	0.956	959	36	102	13
0.092	0.968	3828	106	1068	58	0.127	0.954	957	36	102	15
0.087	0.971	3832	92	1082	54	0.136	0.955	958	36	102	14
0.085	0.971	3835	98	1076	51	0.132	0.957	957	33	105	15
0.086	0.968	3825	100	1074	61	0.155	0.953	963	43	95	9
0.085	0.971	3834	95	1079	52	0.136	0.959	963	37	101	9
0.081	0.972	3838	93	1081	48	0.123	0.962	960	30	108	12
0.076	0.975	3837	78	1096	49	0.129	0.959	965	39	99	7
0.076	0.973	3834	85	1089	52	0.129	0.953	959	39	99	13
0.072	0.976	3848	83	1091	38	0.128	0.955	958	36	102	14
0.072	0.975	3842	83	1091	44	0.122	0.956	954	31	107	18
0.071	0.976	3837	74	1100	49	0.130	0.959	960	33	105	12
0.071	0.976	3838	71	1103	48	0.142	0.955	963	41	97	9
0.066	0.978	3846	72	1102	40	0.130	0.956	955	32	106	17
0.068	0.977	3839	70	1104	47	0.155	0.954	965	44	94	7
0.062	0.979	3850	68	1106	36	0.122	0.955	960	38	100	12
0.054	0.982	3851	57	1117	35	0.120	0.961	959	30	108	13
0.055	0.983	3856	57	1117	30	0.122	0.959	959	32	106	13
0.055	0.982	3852	55	1119	34	0.126	0.962	964	34	104	8
0.055	0.981	3845	54	1120	41	0.125	0.959	962	36	102	10
0.051	0.984	3860	53	1121	26	0.125	0.960	964	36	102	8
0.053	0.984	3856	53	1121	30	0.120	0.960	962	34	104	10
0.053	0.982	3854	60	1114	32	0.124	0.961	963	34	104	9
0.050	0.983	3851	51	1123	35	0.123	0.961	962	33	105	10
0.050	0.984	3854	51	1123	32	0.122	0.961	961	32	106	11
0.048	0.985	3859	50	1124	27	0.123	0.959	960	33	105	12
0.052	0.982	3851	56	1118	35	0.121	0.959	959	32	106	13
0.048	0.985	3849	40	1134	37	0.122	0.959	959	32	106	13
0.049	0.984	3857	50	1124	29	0.123	0.959	959	33	105	13
0.047	0.985	3855	45	1129	31	0.125	0.959	960	33	105	12
0.046	0.987	3858	40	1134	28	0.126	0.959	960	33	105	12
0.046	0.984	3853	47	1127	33	0.126	0.959	960	33	105	12

K fold = 3											
Training						Validation					
Loss	**Accuracy**	**TP**	**FP**	**TN**	**FN**	**Loss**	**Accuracy**	**TP**	**FP**	**TN**	**FN**
0.458	0.815	3819	870	304	67	0.388	0.874	969	137	1	3
0.331	0.882	3831	543	631	55	0.299	0.892	950	98	40	22
0.284	0.896	3808	450	724	78	0.304	0.895	917	62	76	55
0.261	0.911	3809	375	799	77	0.261	0.909	949	78	60	23
0.235	0.914	3802	351	823	84	0.224	0.921	967	83	55	5
0.196	0.929	3797	270	904	89	0.178	0.932	949	52	86	23
0.164	0.941	3807	219	955	79	0.189	0.932	966	70	68	6
0.150	0.948	3808	186	988	78	0.212	0.914	965	88	50	7
0.137	0.952	3814	171	1003	72	0.154	0.951	954	36	102	18
0.149	0.947	3791	172	1002	95	0.193	0.930	969	75	63	3
0.141	0.950	3811	180	994	75	0.164	0.951	936	18	120	36
0.134	0.954	3812	157	1017	74	0.141	0.950	964	48	90	8
0.141	0.952	3817	176	998	69	0.171	0.933	956	58	80	16
0.137	0.954	3820	169	1005	66	0.155	0.948	961	47	91	11
0.131	0.951	3800	160	1014	86	0.166	0.937	964	62	76	8
0.177	0.938	3780	208	966	106	0.157	0.940	951	46	92	21
0.159	0.942	3782	187	987	104	0.180	0.933	939	41	97	33
0.124	0.957	3801	132	1042	85	0.156	0.945	961	50	88	11
0.107	0.965	3829	121	1053	57	0.150	0.950	957	41	97	15
0.103	0.964	3825	119	1055	61	0.149	0.951	957	39	99	15
0.100	0.965	3818	111	1063	68	0.150	0.948	955	41	97	17
0.102	0.965	3813	104	1070	73	0.145	0.950	958	42	96	14

K fold = 4											
Training						Validation					
Loss	**Accuracy**	**TP**	**FP**	**TN**	**FN**	**Loss**	**Accuracy**	**TP**	**FP**	**TN**	**FN**
0.415	0.842	3796	708	466	91	0.376	0.874	965	134	4	6
0.319	0.882	3822	532	642	65	0.349	0.875	968	136	2	3
0.272	0.896	3797	436	738	90	0.404	0.845	859	60	78	112
0.227	0.917	3799	330	844	88	0.243	0.911	964	92	46	7
0.183	0.935	3806	250	924	81	0.215	0.922	942	58	80	29
0.171	0.938	3798	224	950	89	0.192	0.921	959	76	62	12
0.172	0.939	3795	217	957	92	0.198	0.923	964	78	60	7
0.141	0.948	3811	188	986	76	0.172	0.935	954	55	83	17
0.139	0.951	3804	166	1008	83	0.175	0.939	953	50	88	18
0.135	0.949	3801	170	1004	86	0.208	0.921	926	43	95	45
0.137	0.956	3824	162	1012	63	0.181	0.936	954	54	84	17
0.155	0.946	3799	186	988	88	0.199	0.933	955	58	80	16
0.133	0.955	3813	152	1022	74	0.199	0.930	952	59	79	19
0.116	0.959	3834	153	1021	53	0.177	0.935	946	47	91	25
0.104	0.963	3818	120	1054	69	0.176	0.939	952	49	89	19
0.096	0.964	3823	117	1057	64	0.167	0.939	950	47	91	21
0.094	0.968	3827	104	1070	60	0.160	0.943	948	40	98	23
0.090	0.969	3829	100	1074	58	0.167	0.940	955	51	87	16
0.083	0.973	3843	92	1082	44	0.160	0.945	956	46	92	15
0.085	0.970	3824	91	1083	63	0.158	0.947	951	39	99	20
0.075	0.974	3837	80	1094	50	0.158	0.946	952	41	97	19
0.076	0.974	3837	84	1090	50	0.161	0.946	953	42	96	18
0.071	0.976	3844	80	1094	43	0.167	0.950	958	43	95	13
0.073	0.974	3837	80	1094	50	0.169	0.941	948	42	96	23
0.071	0.974	3837	83	1091	50	0.175	0.941	956	50	88	15
0.063	0.979	3844	65	1109	43	0.162	0.945	951	41	97	20
0.060	0.981	3849	58	1116	38	0.163	0.945	952	42	96	19
0.057	0.981	3846	55	1119	41	0.163	0.946	952	41	97	19
0.058	0.980	3849	63	1111	38	0.163	0.946	951	40	98	20
0.057	0.982	3846	52	1122	41	0.169	0.946	954	43	95	17

K fold = 5											
Training						Validation					
Loss	**Accuracy**	**TP**	**FP**	**TN**	**FN**	**Loss**	**Accuracy**	**TP**	**FP**	**TN**	**FN**
0.431	0.832	3804	766	408	83	0.382	0.873	964	134	4	7
0.339	0.879	3822	545	629	65	0.355	0.865	900	79	59	71
0.280	0.900	3808	426	748	79	0.284	0.902	926	64	74	45
0.258	0.911	3799	362	812	88	0.224	0.923	961	75	63	10
0.214	0.927	3811	295	879	76	0.188	0.934	966	68	70	5
0.177	0.936	3817	254	920	70	0.161	0.948	957	44	94	14
0.166	0.939	3796	219	955	91	0.153	0.941	937	31	107	34
0.157	0.940	3781	198	976	106	0.163	0.940	962	57	81	9
0.158	0.943	3792	196	978	95	0.181	0.936	954	54	84	17
0.156	0.942	3783	188	986	104	0.161	0.950	961	46	92	10
0.125	0.953	3808	157	1017	79	0.142	0.950	957	42	96	14
0.118	0.955	3801	141	1033	86	0.150	0.954	966	46	92	5
0.135	0.951	3811	171	1003	76	0.153	0.949	937	23	115	34
0.137	0.952	3816	172	1002	71	0.154	0.940	963	58	80	8
0.132	0.949	3796	165	1009	91	0.153	0.944	956	47	91	15
0.138	0.949	3797	166	1008	90	0.179	0.940	961	57	81	10
0.126	0.955	3810	149	1025	77	0.155	0.950	956	40	98	15
0.112	0.961	3823	135	1039	64	0.143	0.952	956	38	100	15
0.103	0.963	3820	118	1056	67	0.145	0.951	961	44	94	10
0.102	0.962	3824	127	1047	63	0.138	0.952	954	36	102	17
0.097	0.964	3809	105	1069	78	0.146	0.953	959	40	98	12
0.092	0.967	3828	107	1067	59	0.138	0.949	945	31	107	26
0.092	0.966	3816	103	1071	71	0.145	0.954	957	37	101	14
0.085	0.972	3835	88	1086	52	0.147	0.955	958	37	101	13
0.083	0.971	3831	89	1085	56	0.139	0.956	954	32	106	17
0.082	0.973	3831	81	1093	56	0.137	0.957	959	36	102	12
0.075	0.976	3838	74	1100	49	0.142	0.954	957	37	101	14
0.072	0.978	3844	69	1105	43	0.133	0.956	958	36	102	13
0.075	0.975	3833	74	1100	54	0.143	0.953	958	39	99	13
0.073	0.975	3828	70	1104	59	0.138	0.957	958	35	103	13
0.070	0.975	3836	73	1101	51	0.140	0.958	956	32	106	15
0.069	0.976	3831	66	1108	56	0.135	0.961	959	31	107	12
0.068	0.977	3840	71	1103	47	0.141	0.959	959	34	104	12
0.062	0.977	3838	69	1105	49	0.134	0.959	956	31	107	15
0.060	0.978	3844	68	1106	43	0.137	0.956	956	34	104	15
0.058	0.981	3847	56	1118	40	0.135	0.959	956	31	107	15
0.055	0.982	3848	53	1121	39	0.139	0.956	956	34	104	15
0.058	0.981	3845	55	1119	42	0.140	0.957	956	33	105	15