# CA400 - Final Year Computer Applications Project

*Functional Specification*


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# 1 Introduction

## 1.1 Overview

Human Activity Recognition (HAR) is a challenging task and even more so when trying to Infer activity from low information sources such as: *body worn sensors* used conventionally for physiological monitoring. In such cases, the signal is a time series and inferring different activity classes from changes in the time series is by no means trivial. This Project aims to use sensor data to build a machine learning model to identify common human activities. These activities include: **Walking**, **Running**, **Cycling slowly**, **Cycling fast** and also an **Idle** state.

This project also will act as research for the insight centre in DCU. Human Activity Recognition has been achieved through PPG (Photoplethysmogram) data before, however, we will be using a new approach involving a technique known as: **Symbolic Aggregate Approximation** (SAX) - the details of which I will explain later in the document. We want to contrast whether using SAX will be more beneficial than more traditional approaches. The project aims to showcase how we can learn a lot about human activity recognition from cheap PPG technology.

Typically PPG technology is used to measure the heart rate usually at the fingertip or wrist, however recently it has been successful in measuring HAR via motion artefact Characteristics on the raw optical signal. A definition and better understanding of what a PPG is can be found below in the Glossary (**1.3)**.

The application's design is intended to be desktop-based. To construct a desktop application which will act as a medium between the PPG input stream and the visual output stream determining the activity performed. The application will allow people to view the activity of the PPG sensor wearer. The text will update as well as the animation reflecting what the wearer is doing.
For example: when the user is running, the text will update to 'running' and the animation will also update to reflect this activity.

The desktop application will also display the user's PPG data in a visual graph further motivating the concept behind the application. In addition, we intend to offer a research section to showcase what we learned from taking this SAX approach as well as how I developed the application.

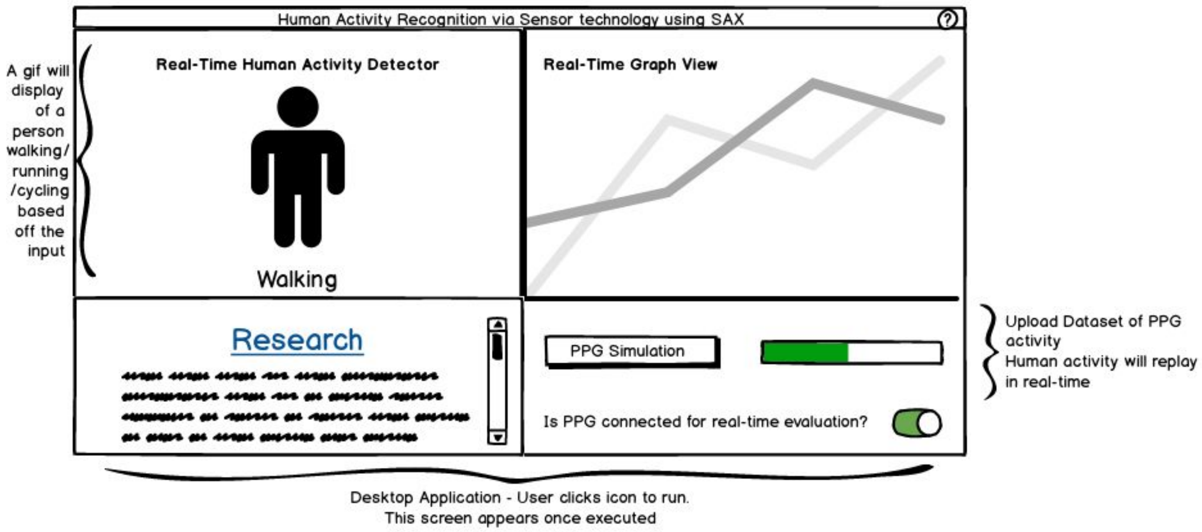
Why is this application useful?
This sort of application has many different areas where it could be incredibly useful.

For example:

- Personal trainer client tracking.
- Diabetes patient exercise tracking
- Elderly healthcare

***Note:*** Data will be extracted from a PPG sensor through the user of an arduino board. This will initially be done using a USB serial port and eventually using a bluetooth module offered via wireless Arduino. It should also be noted that wearable activity recognition is often achieved through inertial sensor technology but in this case, we use the much less complex sensor approach in the form of an optical sensor typically used for measuring the heart rate. By using such a modality for also recognising different activities, we could greatly simplify the design and hence cost of wearable trackers for fitness and other applications.

**Fig 1.0 - Basic Early Design Concept**




The above figure is a basic early design for the desktop application. Many of these design details most likely will change come release in May 2019.

## 1.2 Business Context

**Product Selling Point:**
This project has many areas where it could be involved. Primarily in relation to exercise Tracking. As previously mentioned, personal trainers could track their clients in relation to quantitative exercise performance, ensuring they get enough exercise. Specifically, trainer's could track for how long someone is exercising.

Another large selling point would be in the case of diabetics. Through scientific research It is greatly advised that individuals with diabetes should exercise at least five days per week, if not every day. This ensures that the muscles draw sugar from the bloodstream Continuously. Otherwise, the patient's blood sugar (glucose) levels will be escalating. This product can help regulate such an exercise regime. Diabetic patients can be tracked to ensure they are receiving enough exercise on a weekly basis. Otherwise, a dedicated team can step in upon seeing the low exercise recording from the application to help remedy the situation.

The application also has other reasons for existing based on the Insight Centre DCU. Insight brings together more than 400+ researchers from these institutions, 100m+ funding, and with over 80+ industry partners, to position Ireland at the heart of global data analytics research. My supervisor is part of the Insight Centre in DCU and hopes to use this project for comparison in the study of Human Activity Recognition. I will be using a somewhat underused technique of Symbolic Aggregate Approximation (SAX) to cluster my data into windows of commonality. We will be comparing this approach to the standard approach from training a model directly from a raw time-series. I will be recording the accuracy, the pros', the cons' and constructing a blog to detail my findings.

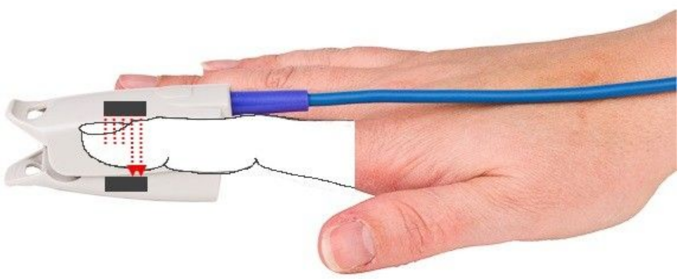
**Product Advertisement:**
Currently there is no plan to bring advertisement measures to this product. There is no Financially-driven motive. Considering the product design is primarily for research purposes, we have no intention of adding any form of product advertisement.

# 1.3 Glossary

**Human Activity Recognition (HAR)**
Human activity recognition, or HAR, is a challenging time series classification task. It involves predicting the movement of a person based on sensor data and traditionally involves deep domain expertise and methods from signal processing to correctly engineer features from the raw data in order to fit a machine learning model.

**Photoplethysmogram (PPG)**
A photoplethysmogram (PPG) is an optically obtained plethysmogram, a volumetric measurement of an organ. A PPG is often obtained by using a pulse oximeter which illuminates the skin and measures changes in light absorption.

**Fig 1.1 - A standard fingertip PPG**



**Inertial Sensor**
Built-in to many smart watches and fitbit watches are both PPG technology and Inertia technology. This is to ensure motion, generally focused on the wrist does not corrupt the datastream from the PPG. In the case of this project, it is the lack of the Inertia Sensor that allows us to build a predictive model on recognising human activity.

**Symbolic Aggregate Approximation (SAX)**
SAX is a way of transforming a time series to a sequence of symbols. The basic idea is that each symbol will represent some interval of values and that the symbol will be chosen so that each symbol appear approximately equally often in the time series.

**Bitmap Image**
A bitmap (also called "raster") graphic is created from rows of different colored pixels that together form an image. In their simplest form, bitmaps have only two colors, with each pixel being either black or white. With increasing complexity, an image can include more colors; photograph-quality images may have millions. In the case of this project, we will be converting the SAX time-series string into bitmap images. We do this so that we can apply machine vision approaches to time series classification. The images will look somewhat similar to the below figure.

**Fig 1.2 - Bitmap Images representing a string of characters**

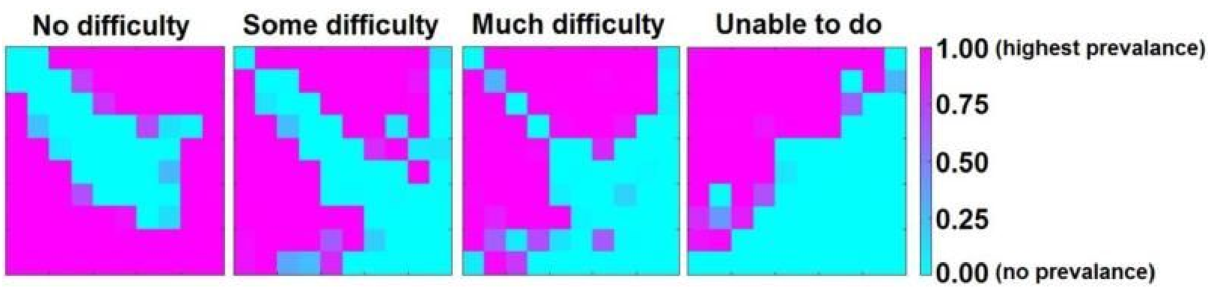



**Image Classification**
Image classification is a supervised learning problem: define a set of target classes (objects to identify in images), and train a model to recognize them using labeled example photos. In our case, we'll use bitmap images to train on.

**Machine Vision**
Machine vision (MV) is the technology and methods used to provide imaging-based automatic inspection and analysis for such applications as automatic inspection, process control, and robot guidance, usually in industry.

# 2 General Description

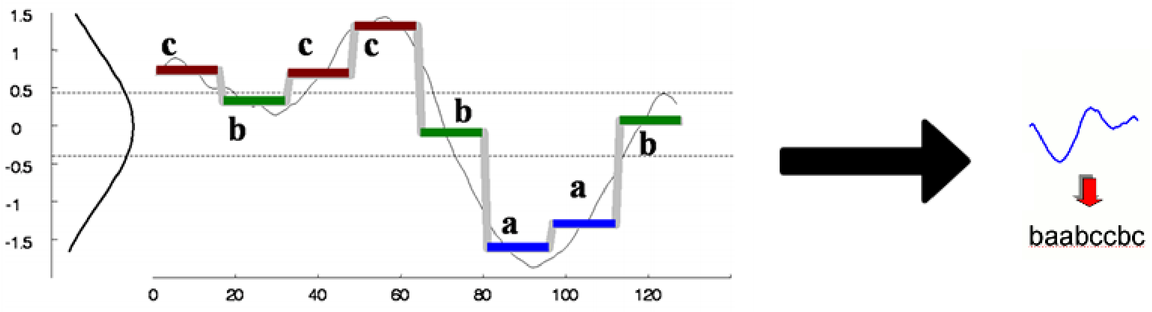
## 2.1 Product/System functions

The goal of this project is to build a desktop application demonstrating the ability to recognise human activity through the use of a PPG. The design of the desktop application will be tailored towards data science and research such that we can compare and contrast this method of machine vision against another more standard approach. Through using the SAX transformation process, we hope to compare the accuracy of the model and also its longevity in the HAR field.

In order to build the predictive model to recognise human activity, I plan to train our model using various exercise datasets from https://www.physionet.org/. Once the model is complete, I aim to use it to detect human activity from a real-time PPG sensor equipped at the wrist. Now, we can expect a lot of variation from the datasets online compared to a real-time sensor so many tweaks and adjustments will need to be made to suit our exact dilemma.

The five activity states we hope to recognise through this application are: **Walking, Running, Slow Cycle, Fast Cycle** and an **Idle** state**.** The goal of the project revolves around tracking of patients / elderly healthcare. As stated above the product has usefulness in many areas but primarily for research in the field of Machine Learning and Human Activity Recognition.

**Fig 2.0 - How the SAX (Symbolic Aggregate Approximation) transformation works**




We can see from the above diagram how a curve is split into windows of commonality. We can see values in the range 0.5 - 1.5 determine the letter ‘c’ as output. The window size here between letters is 1 unit. This principle applies throughout the transformation. In addition to this, it is necessary for the curve to remain in that range for the equal length of 20 time units (We determine the time unit the SAX transformation uses).

This is how I will generate the string of characters as shown on the right of the **fig 2.0** and it is from this string of characters how we will generate bitmap images to perform image classification from.

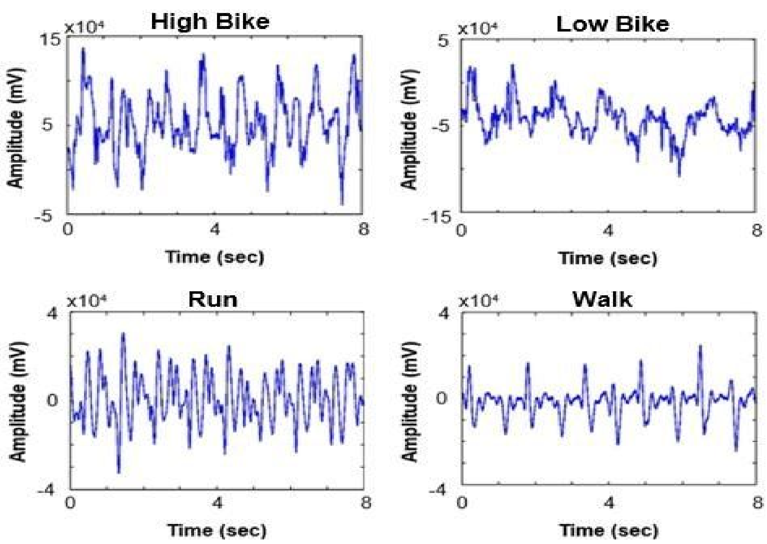
**Recognise Human Activity**
Through the desktop application, we want to show what activity an individual is performing based on the PPG datastream equipped at the wrist. This will be connected via Bluetooth or via a Wired approach. The desktop application will show both an animation representing the activity performed as well as a textual subtitle.

**Follow research progress**
A research section will be implemented which will offer insights into how the application was built, into how the predictive model was created, information about the SAX transformation technique and more. This segment of the application will also offer knowledge into how this method compares to more traditional Human Activity Recognition approaches. Specifically, we'll be looking at the accuracy of the models in addition to variable parameters such as: how 'deep' they are or how 'wide' they are in terms of layers and neurons.

**Visualise real-time data view**
The desktop application will also hone a view pane which showcases the data flow of the PPG in real-time. This will offer another view into how the data is being perceived and will show a correlation between the activity performed with the flow of the data. In other words, the fluctuation in the data view will be representative of the activity performed (High fluctuations could be indicative of running or fast cycle).

**PPG Simulation for real-time Activity Recognition Playback**
This function will allow users to submit pre-recorded PPG data, e.g. the data you get on Physionet and the application will take this data and play it back in real time as if a real PPG sensor were connected.

**Fig 2.1 - Different PPG data states representing the activity**



**Check PPG connection**
As shown by the early design concept diagram above (**Fig 1.0**), the application will also determine whether or not a PPG is actively connected. In cases where a PPG is not connected to the system, the application will have a **PPG player/simulator** built-in. This will take existing PPG datasets and replay what activities were done throughout the time-series of the data.

# 2.2 User Characteristics and Objectives

The user community of this application can be split into 3 categories. Elderly healthcare, fitness industry experts and researchers of Machine Vision and Human Activity Recognition fields. There may be more user community types.

Users of the desktop application are not expected to have a technical expertise. Simply, users will have to start the application and they can access the various features above. The design of the application will be entirely my own as there is nothing really like this at the moment.

The application will be accessible by anyone with a desktop/laptop. The user will require an internet connection to download the application. The intention is to build a website to host the application's download and also provide research and findings. Hyperlink anchors to other references on the topic in addition to the development blog, user manual and video walkthrough will also be found on the website.

The requirements for the system from the user's perspective will be about research and understanding. The computer will be able to recognise what activity an individual is performing and report that back to the screen. A real-time data graph will also forecast this. Finally, there will be a research section on the application to compare and contrast this approach against more traditional approaches as previously stated in the overview.

More feasible solutions would involve reverting our approach to a traditional machine learning approach on the dataset. If our combination of using the Symbolic Aggregate Approximation (SAX) and bitmap image classification falls through and somehow is not feasible by May 2019, we will revert to this traditional ML approach, however we think this is highly unlikely.

# 2.3 Operational Scenarios

**User Downloads Application from Website**
Users will download the application from the website available online. The name of the website has yet to be determined but will exist for this purpose. Additionally, other information based around the research obtained from the project can be found on the site.

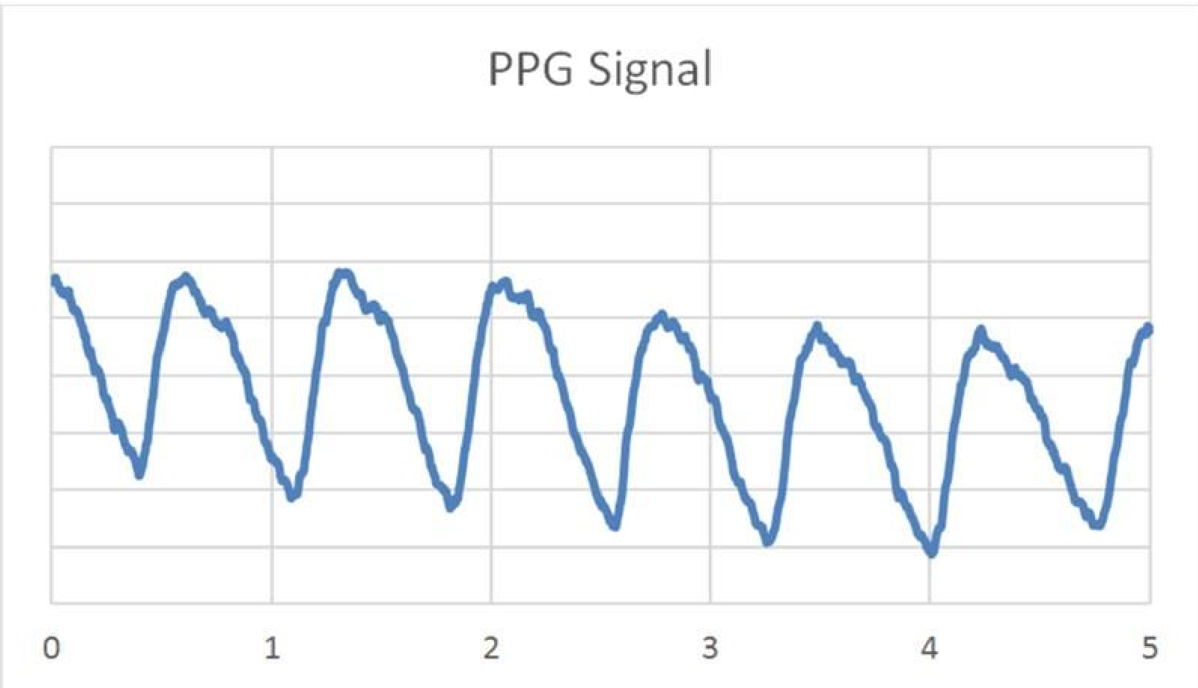
**User Connects PPG**
Users will need to connect a PPG to their computer to experience the application’s primary purpose. At a minimum a wired approach will be used, but we are hoping to utilise a wireless approach. Once connected, the application should visually tell the user that the connection has been found and is working correctly. This is showcased above in the early design diagram.

**Observation of Detected Human Activity in Real-Time**
The primary purpose of the application. The desktop application will reflect the activity performed by users equipped with PPG technology at the wrist. The detected activity from the PPG data plugged into our predictive model will be displayed via an animation as well as a textual title. For example: When an individual is running while equipped with the PPG sensor, the animation will show an avatar running with the text ‘Running’ underneath.
**Fig 1.0** above is a good indication of this.

**Observation of Real-Time Datastream**
The datastream from the PPG will also be displayed. The current plan is for the concurrent visualisation of the detected human activity and the PPG data stream recorded at the wrist. The datastream will look similar to **Fig 2.2** as found below.

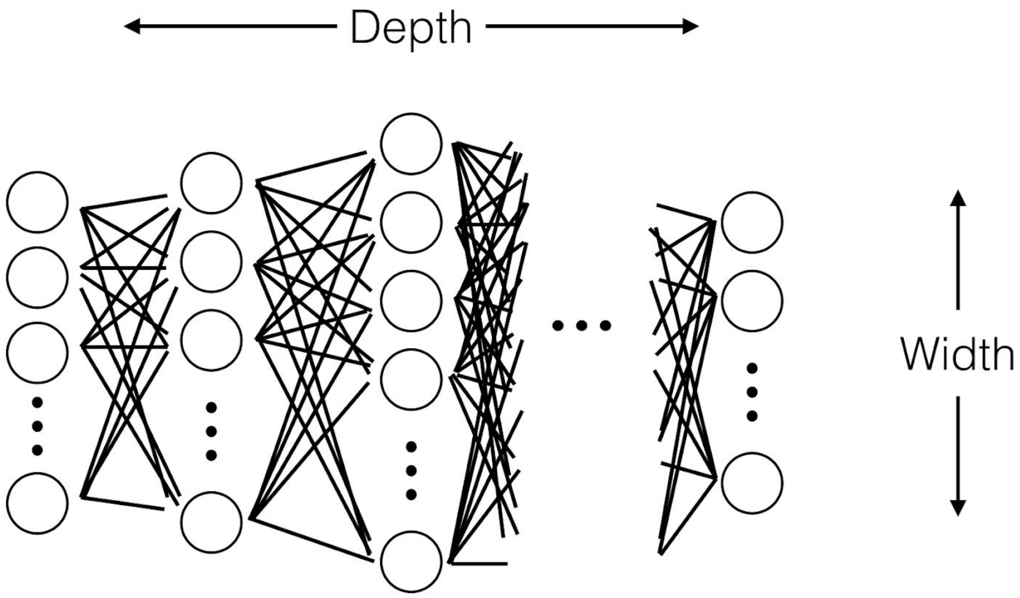
**PPG Simulation for real-time Activity Recognition Playback**
Users will be able to submit a file containing the PPG datastream recording and the application will play back in real-time what activity is being performed.

**Fig 2.2 - Basic PPG Heart-Rate Signal**



**Explanation of Research and Findings**
Finally, I plan to add a research and findings section embedded within the application. This pane is primarily for the findings I gather throughout building my predictive model. Any interesting facts found throughout the building of the application will also be noted. Some things included may be: How does having a ‘deep’ neural network fair against a ‘wide’ neural network. Another interesting parameter we can influence to test for the best accuracy would be the SAX transformation window size.

**Fig 2.3 - Neural network parameter comparison for research**




The diagram above shows how varying different parameters like network-width and network-depth can result in unique findings and potentially a better accuracy score.

# 2.4 Constraints

**Processor Power**
When building our Machine Learning Model via Artificial Neural Networks, there are 4 significant stages the model must endure before it can be tested. Those stages are:

- Preprocessing input data
- Training the deep learning model
- Storing the trained deep learning model
- Deployment of the model

Out of all of these stages, the second stage involving training the deep learning model will take by far the longest. GPUs are very good for training predictive models like this, far better than CPU power. For this reason, it is essential I have a powerful GPU to perform this step of the build. For this constraint, I aim to work alongside DCU’s Insight Department to allow me to make use of available GPUs or the Google GPU system now available by DCU.

**Quasi Real-Time Predictive Model Ability**
Another constraint I may find myself facing is the ability to recognise human activity in real-time. Myself and Tomas (Project Supervisor) had ideas about quasi real-time such that the activity could be detected shortly after the activity was performed. For example, when someone walks for 3 seconds, it may take the program 2 seconds to realise they are walking based on the PPG data. Influencing the window size of the SAX transformation may allow for more varied readings in terms of accuracy.

**Human Activity Recognition Accuracy**
I hope to achieve the highest accuracy level possible for my predictive model, however considering we are taking a new approach to recognise human activity using the SAX transformation combined with bitmap image classification, our accuracy results may be better or worse than a more traditional approach.

**PPG data quality (Variation with tightness etc…)**
We plan to build and train our model using available walking, running, slow cycling and fast cycling datasets found online at [https://physionet.org/](https://physionet.org/). However, a constraint that concerns myself is how well a real PPG equipped at the wrist would match with the data found in these online datasets. For example: How tightly the PPG is wrapped at the wrist would play a factor into how the results would be returned.

**TensorFlow constraint**
Finally, using frameworks like TensorFlow or Keras can be constraining in terms of how I build the application. These provide a high-level methodology for building machine learning based projects but abstract some of the low level detail which may be required.

# 3 Functional Requirements

## 3.1.0 Recognition of Human Activity

*Description:*
This is the main function of the application. Any user who downloads the application will desire this requirement. The design of the application should be intuitive and natural to use. When the user starts up the application, they should be greeted with an application window through which they can see if there activity is being recognised. This will be displayed via an an avatar animation with also a textual title indicative of the action performed. It is essential the user has a PPG device connected. This is discussed in another requirement below.

*Criticality:*

This is by far the most crucial aspect of the system and is the most challenging and time-sinking portion. This part of the project will take me months but ultimately, I hope to achieve a high model accuracy alongside an intuitive design for the application.

*Technical Issues:*

Some technical issues embodied in this requirement involve improving the accuracy to an acceptable point such that the application is worth using. Other design issues could be rendering an animation to reflect the action of the user through the PPG device. Finally, changing the variables and parameters of the artificial neural network is a design decision i want to be fully conscious about. To achieve the best accuracy I can in my model, I will need to do a plethora of research to grow my knowledge of Deep Learning methodologies.

*Dependencies on other requirements:*

This requirement is the most crucial to the system and as a result has many dependencies on other requirements. This requirement is dependent on 3.1.1 below discussing how accuracy of our model is a requirement. 3.1.2 is also a dependant of this requirement as we hope to achieve quasi real-time activity recognition (Walking, Running, Slow Cycle, Fast Cycle, Idle). This requirement also depends on 3.5 below which sheds light on how an active PPG connection is required to determine the human activity.

*Other details:*

Recurrent vs Convolutional Neural Networks is a question i'll have to ask myself when building the model. Understanding the advantages of both and which would be better suited to my problem is an important question I'll need to answer. Other questions may include bitmap size and alternative machine vision approaches to the problem that we could utilise.

## 3.1.1 Predictive Model Accuracy

*Description:*

This requirement is labeled 3.1.1 as it is a continuation of the previous requirement but places more emphasis on the accuracy of the predictive model. This is a performance requirement such that we want to achieve the best accuracy possible for the model.

*Criticality:*

This is very important to the system as a whole. I am not certain what accuracy is acceptable for the problem of Human Activity Recognition but I will strive for as high as possible.

*Technical Issues:*

There are many parameters and variables that can be adjusted to test for an improved accuracy. Some of these may involve how ‘wide’ a neural network is against how ‘deep’ it is. Other parameters we can experiment with to improve accuracy might be how we build our bitmap images from our SAX transformation output. Another being how we specify the SAX transformation. In other words, how the string of letters is generated and how the rules behind the transformation are governed.

These are only a handful of the parameters we can vary to try improve the accuracy of our model and I will need to do countless research to understand the benefit of each. These are some technical implementation details I have accounted for.

*Dependencies on other requirements:*

The accuracy of our model does not depend on any requirements listed here.  What it does depends on is the preprocessing of the input data and the training of the deep learning model.

*Other details:*

To achieve the quasi real-time recognition requirement listed below, we want to acquire the best accuracy possible, otherwise the activity determination could be incorrect. I.E. Walking could be regarded as running or vice versa which is not what we want.

## 3.1.2 Quasi Real-Time Activity Recognition

*Description:*

Similarly to the above requirement, this requirement is also an extension of 3.1.0 ‘Recognising of Human Activity’. This requirement not only involves the recognition portion of the project but also offers the ability for it to be done in quasi real-time. In other words, the human activity can be detected in almost real-time with out model. This requirement is incredibly challenging but we hope to achieve it come May next year.

*Criticality:*

This feature is quite critical to the overall application. Considering this application is for research purposes and may hold potential for future applications wanting to perform Human Activity Recognition, it is quite important we achieve activity recognition in quasi real-time. Also for the demonstration portion of the DCU 4th year project, it would look brilliant if we could achieve this aspect in real-time or quasi real-time.

*Technical Issues:*

The system will need to be very reactive to the PPG data that is read as input. It will need to make a logical choice on what the activity is based on our predictive model. The level of difficulty required to achieve this is ambiguous and it will be quite challenging from an implementation standpoint.

### *Dependencies on other requirements:*

The quasi real-time aspect of the project is dependant on the accuracy of our model. This is mentioned above in 3.1.1 - It is also dependent on the input stream from the PPG as described in 3.5.

### *Other details:*

Our model is built using exercise datasets from https://physionet.org/ but the tightness of the equipped PPG and other factors that may differentiate the datasets from an in-person PPG signal are a concern. These environmental factors may cause trouble when determining the activity of an individual in quasi real-time.

## 3.2 Real-Time PPG datastream Visualisation

### *Description:*

While the PPG is actively connected and attached at the wrist/finger, this requirement specifies a datastream which showcases blood-volume changes in a graphical form. As shown by Fig **1.0** in the initial section of this document, the goal is to show a graphical view of the data outputted from the PPG. This will be useful for determining the blood-volume changes and as a result, show the correlation between the blood-volume changes and the recognised activity performed by an individual.

### *Criticality:*

This requirement is not critical to the application’s overall purpose and design philosophy but will help in understanding the PPG data. It will also shed some light on the correlation between the PPG data and the detected human activity as when the blood-volume rate is high, there will be strong fluctuations in the PPG reading.

### *Technical Issues:*

Technical issues in relation to this requirement may be how the graph is displayed, how the data on the graph is depicted, how we can show the correlation between the graphical data and the recognised human activity.

### *Dependencies on other requirements:*

This requirement only depends on the active PPG connection as discussed in requirement 3.5 below. If there is no connected PPG device, the visualisation pane will most likely inform the user that there is no PPG connected.

### *Other details:*

The graphical format may change throughout development. Currently in mind is a line graph representative of the PPG input stream.

## 3.3 User Downloads Application

### *Description:*

Unrelated to the above requirements but, this requirement will discuss how users will be able to download and utilise the desktop application for their own research and knowledge. To download the application, there will be a constructed website to display research and findings as well as a download to the actual application.

### *Criticality:*

This is hugely critical. It is essential that we have an easy and intuitive way for people to get access to the application.

### *Technical Issues:*

The site will most likely need some form of cloud hosting in the form of a web server. The desire here is that the server will host the website which will enable online users to visit and review my findings and research and download the application for their own enjoyment and experimentation.

### *Dependencies on other requirements:*

This requirement has no dependencies on any other requirement listed.

### *Other details:*

The website URL has not yet been decided. I will also need to look into Search Engine Optimisation (SEO) for high website recognition but this is quite minor in the grand scheme of things.

## 3.4 Read research obtained from project

### *Description:*

As stated throughout this document, one of the primary reasons behind the projects existence is research and learning. I want to compare and contrast this approach against more traditional Machine Learning approaches in relation to Human Activity Recognition. Embedded within the application, there will be a research/knowledge pane through which will describe my findings and design of the predictive model.

The online portion of the project which is primarily to host the download of the application (mentioned in 3.3 above) will also have a section dedicated to research and design philosophies of the application and internal predictive model.

### *Criticality:*

The research aspect is crucial in the overall purpose of the project. The goal is to evaluate this method of building a machine learning model against more traditional approaches and compare the accuracy levels. This method could potentially be more lucrative in terms of predictive accuracy in the HAR field.

### *Technical Issues:*

Some technical issues involve building the embedded research pane within the desktop application. I have not built a desktop application before and coming to grips with it will be technically challenging.

### *Dependencies on other requirements:*

Any knowledge I discover relating to this method of human activity recognition will be documented thoroughly. This research is all about all of the other requirements. So, therefore I can say that this requirement is dependent on all other requirements. The research is about the core design of the predictive model and the PPG sensor itself. There will also be documented knowledge on the visualisation graph of the PPG discussed in requirement 3.2.

## 3.5 PPG connected correctly for activity recognition

### *Description:*

This requirement simply specifies if the PPG is connected correctly to the computer such that the application recognises it. Shown in the early design concept diagram in section 1, there will be some visual aid to tell the user if the PPG is adequately connected to begin Activity Recognition.

### *Criticality:*

This requirement is somewhat important. In terms of design, it would be nice for there to visually show if the device is recognised in the context of the application. The PPG sensor is how we will get our input and should be equipped at the wrist/finger to measure optically blood-volume levels.

### *Technical Issues:*

Enabling the application to recognise when the PPG is connected is challenging. Currently I am not sure how I will implement this but I am confident it can be done. I will also need to acquire a PPG, potentially from DCUs School of Computing, to use as input into the neural network.

### *Dependencies on other requirements:*

This requirement doesn't depend on any other requirement but has many dependants.

### *Other details*

Through this requirement, the project's aim is to demonstrate how very cheap optical sensors (cheaper than inertial sensors plus optical sensor used in a Fitbit or Apple Watch) can allow us to understand more about a person than simply their heart rate and this has applications in understanding health and behavior. So for example if we see that people after diagnosis with diabetes initially do a lot of running but that over time they spend more time walking or walking more slowly then we know we should perhaps intervene and encourage them to do more exercise for the sake of managing their condition.

## 3.6 PPG Simulation for real-time Activity Recognition Playback

### *Description:*

This requirement simply specifies that a PPG datastream file can be submitted and real-time playback of the human activities representing that data will be showcased. This is an interesting requirement as it allows us to learn more about historical PPG recordings than simply ones recording in real-time at that given moment. Testing is also another reason as to why this requirement is crucial. We'll be able to know if our system is working correctly when inputting *ground truth* data and expecting a certain result.

### *Criticality:*

This requirement is not essential to the entire application but would be great considering it would enable us to understand what activities were performed from a historic point of view.

### *Technical Issues:*

The application will need to read the datastream from a PPG file in blocks of X units per second. This will give it the real-time activity recognition effect. This will be technically challenging to achieve.

### *Dependencies on other requirements:*

This requirement depends on **3.5** given that the PPG is connected correctly. This requirement is also dependant on **3.1.0, 3.1.1, 3.1.2** which determine how accurate the model is and that human activity recognition can be performed.

### *Other details*

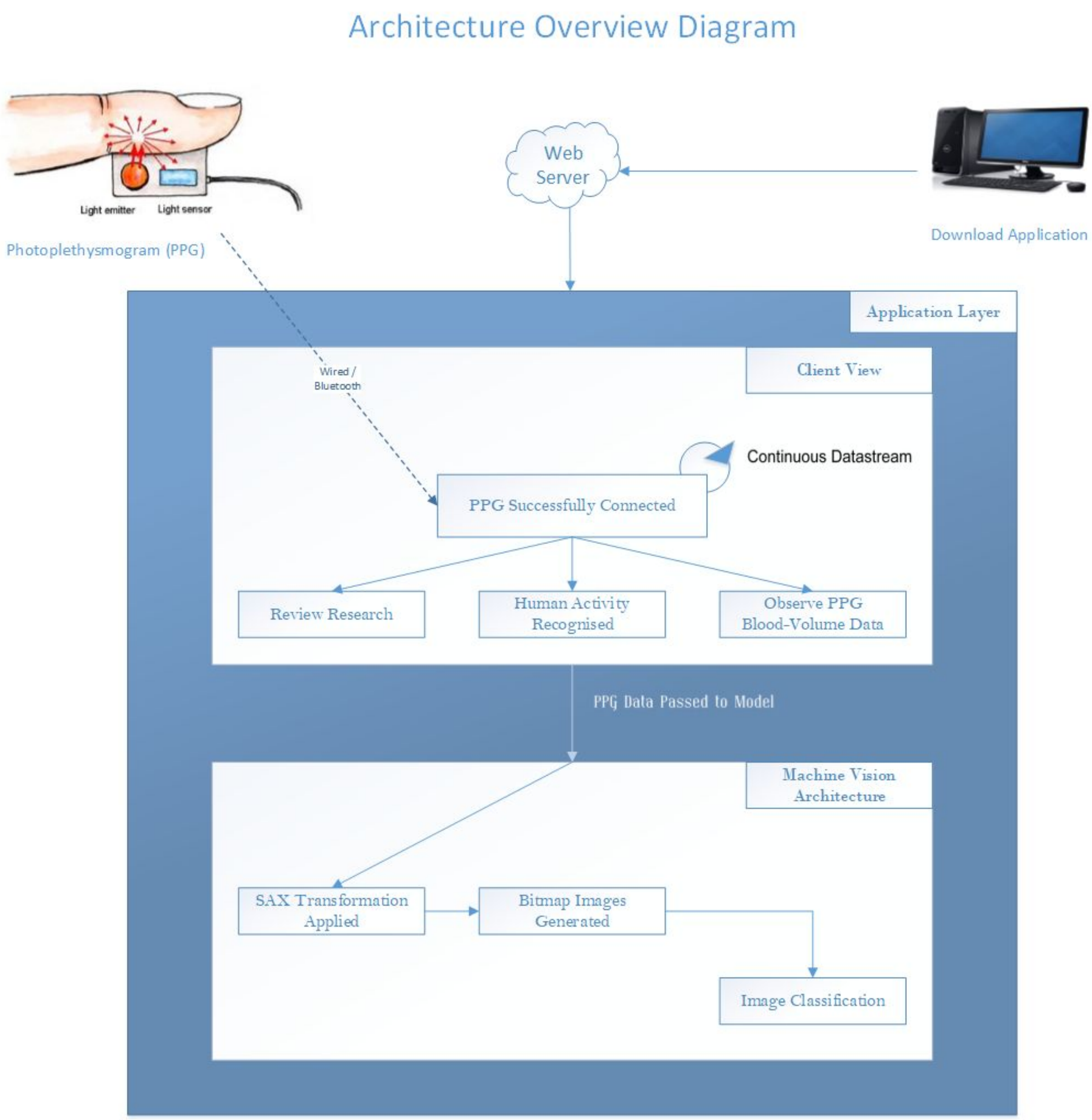
Through this requirement, the project's aim is to demonstrate how very cheap optical sensors (cheaper than inertial sensors plus optical sensor used in a Fitbit or Apple Watch) can allow us to understand more about a person than simply their heart rate and this has applications in understanding health and behavior.

So for example if we see that people after diagnosis with diabetes initially do a lot of running but that over time they spend more time walking or walking more slowly then we know we should perhaps intervene and encourage them to do more exercise for the sake of managing their condition.

# 4 System Architecture

When referring to **System Architecture**, high level structures of a software system and the discipline of creating such structures and systems come to mind. The below diagram shows how these structures communicate and work together to allow the system to perform the functional requirements.

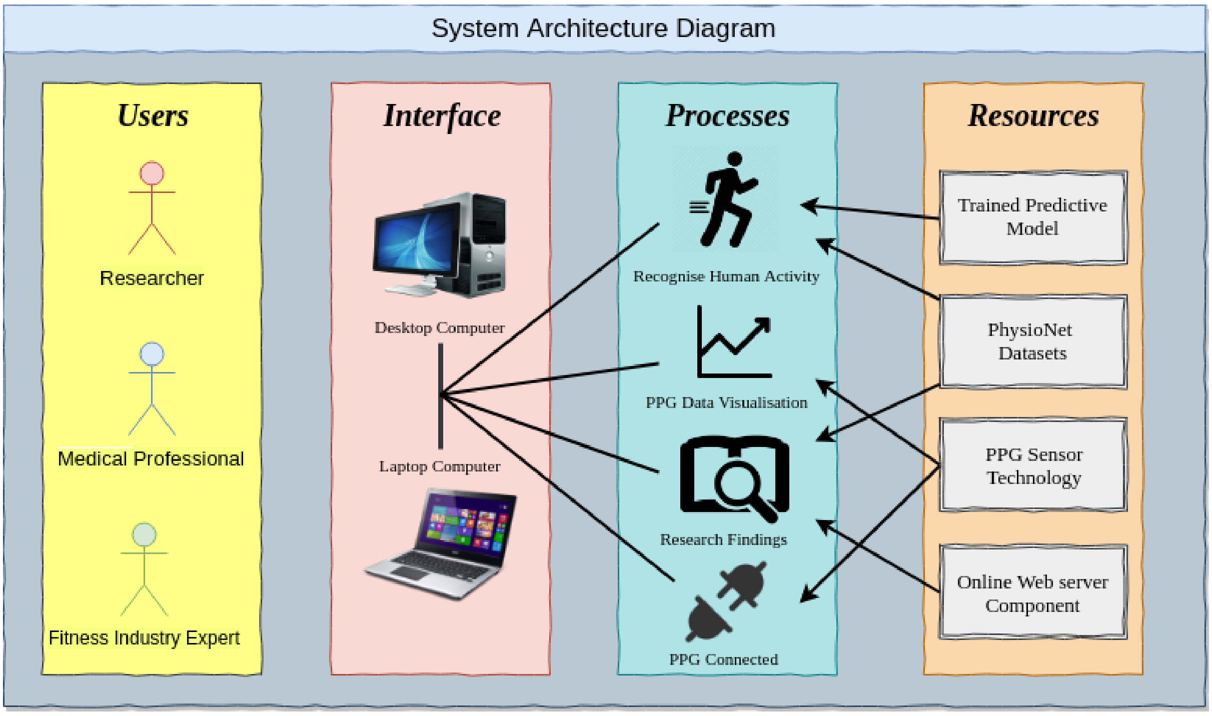
**Fig 4.0 - Architectural Overview Diagram**




The above diagram shows a coordinated overview of all the components of the system. We can see each of the functional requirements represented here as well as the internal machine learning model we'll be using the recognise human activity.

The diagram was designed with an intuitive flow in mind such that any technical reader should be able to understand. We have split our application layer into two views. One pertaining to what the client will see once the application is open. The other being the more internal workings behind how our version of human activity recognition is performed.

**Fig 4.1 - System Architecture Diagram**




A **system architecture diagram** would be used to show the relationship between different components within the scope of the system. Inclusive of hardware and software components, these components are represented in the diagram to show the interaction between them. Generally, there is a linear flow from **left-to-right** or **top-to-bottom** depending on how it's designed.

From our diagram above, we can see:

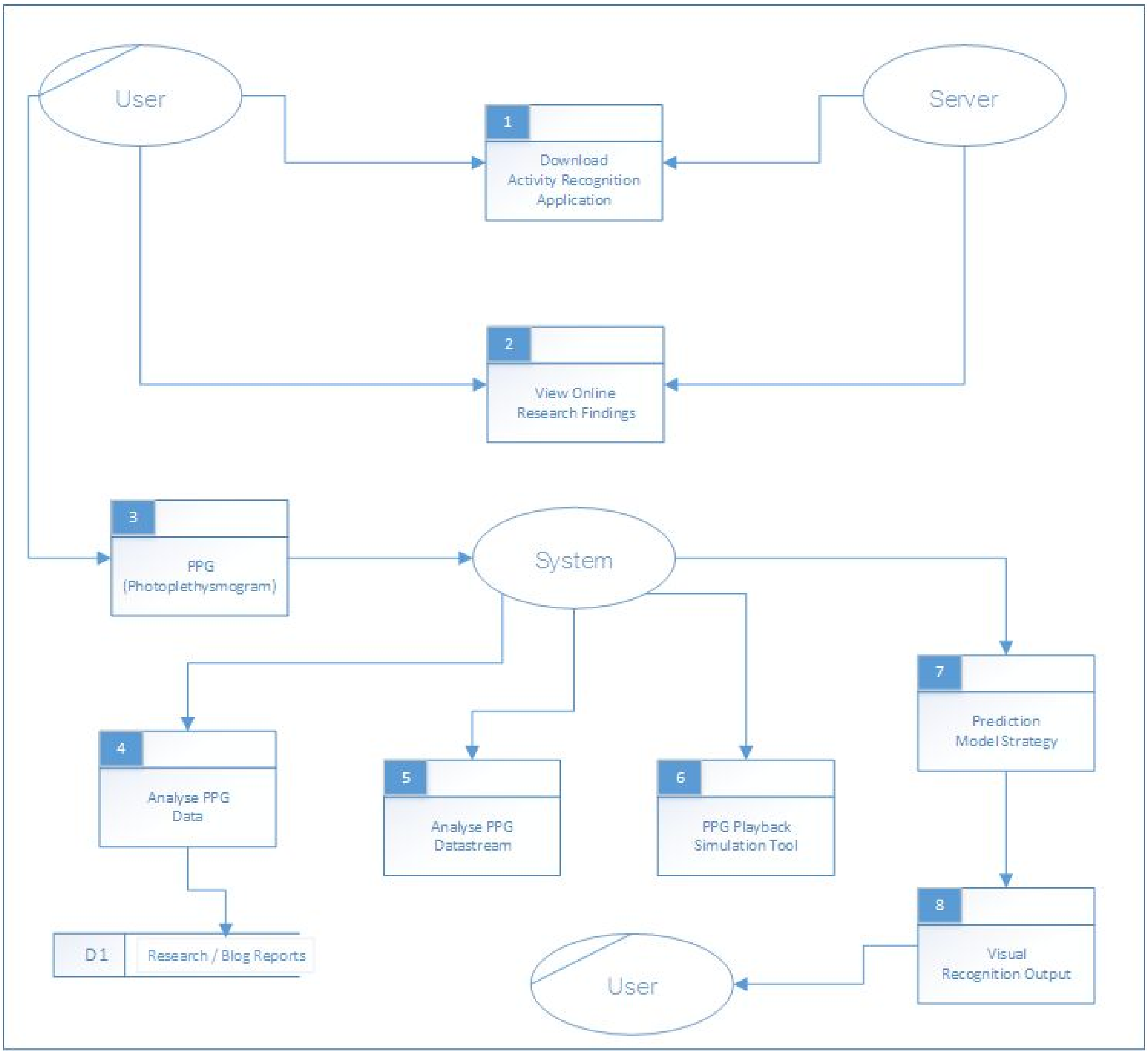
1. which users interact with our system
2. what device they will interact with
3. what processes they will utilise in their experience with the application.
4. The resources required to fuel the application's processes.

Application processes can only be interacted with through either a desktop device or a laptop device. There are four crucial processes the application must perform.

# 5 High-Level Design

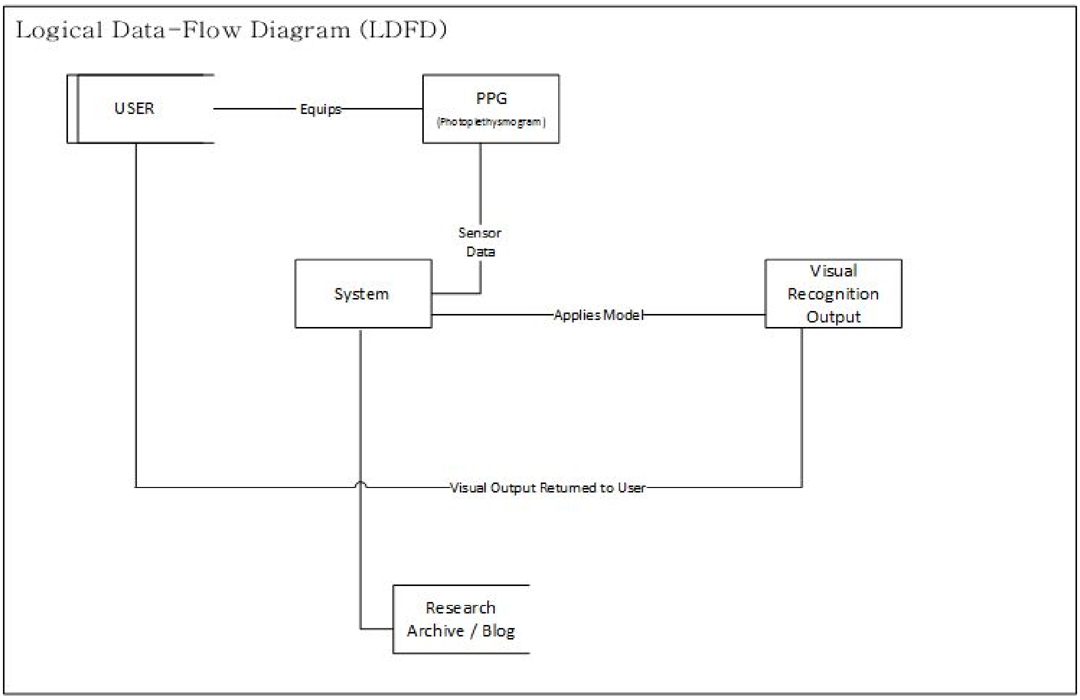
This section will show myriad of diagrams to represent the design philosophies behind the proposed system. I have constructed three DFD diagrams to reflect various different viewpoints of the system (**Physical DFD, Logical DFD, Machine Learning DFD**).
There will also be a general **use case diagram** in addition to a **class diagram** to visually describe the project in detail.

**Fig 5.0 Physical Data Flow Diagram (PDFD)**



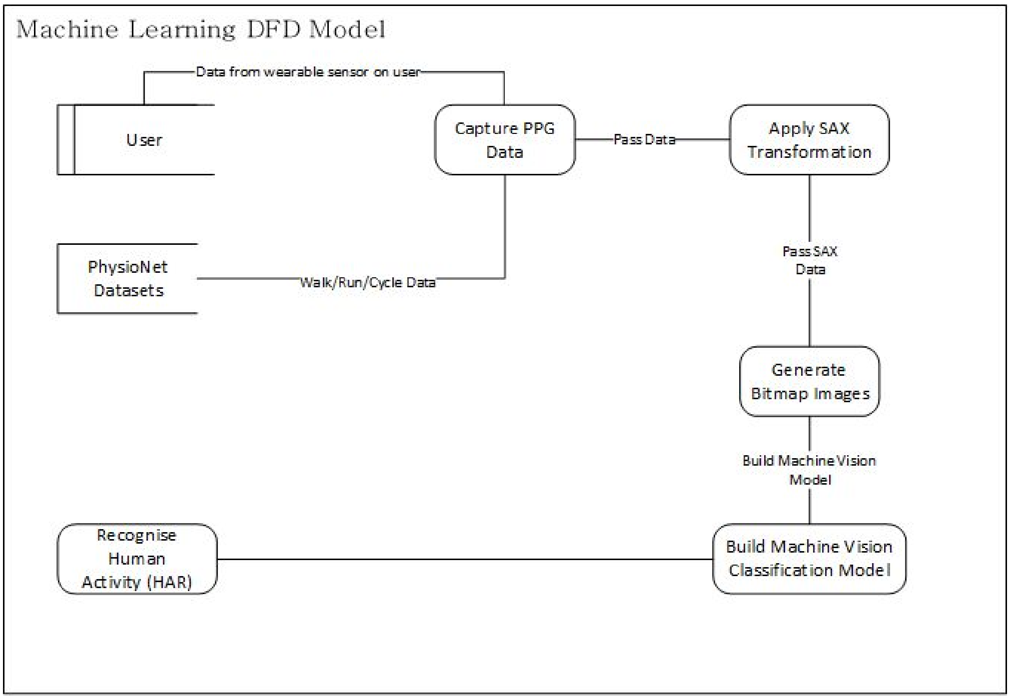

The physical DFD above depicts how the system will be implemented. It depicts a direct flow through which the user must follow to interact with the system. The sensor data is the main form of input into the system and will be utilised when performing the quasi real-time activity recognition.

### Fig 5.1 Logical Data Flow Diagram (LDFD)




Our logical DFD above shows **what** are system is going to do and gives a high-level overview of that. From a business standpoint, the primary activity the application will perform is human activity recognition so hence why the diagram has been simplified in comparison to the physical DFD. The research findings section of the application is also a key component. This is why it is shown within the diagram from a business perspective.

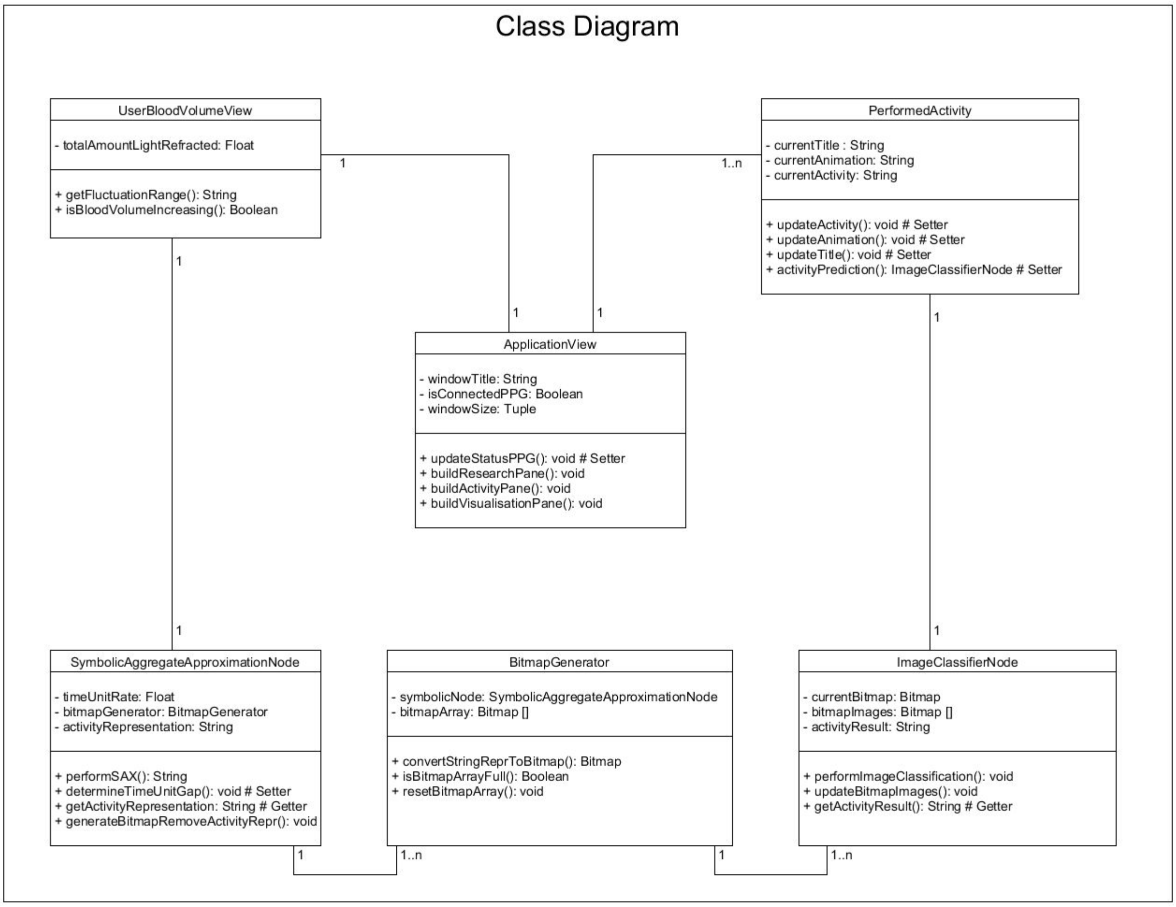
### Fig 5.2 Machine Learning Data Flow Diagram (MLDFD)



The above diagram specified as figure **5.2** explains the flow of data among the machine learning portion of the project, In summary, the data is captured via the PPG. This data is passed into our system and the Symbolic Aggregate Approximation (SAX) transformation is applied, resulting in a string of characters representing the data. From the string representation, we generate a set of bitmap images, each image based on a time-period over the PPG data.

The bulk of the project lies in the next step, in which the building of a predictive model will be carried out. Through using neural network image classification techniques, we plan to apply image classification to these set of bitmap images to determine what activity the person wearing the PPG is performing.

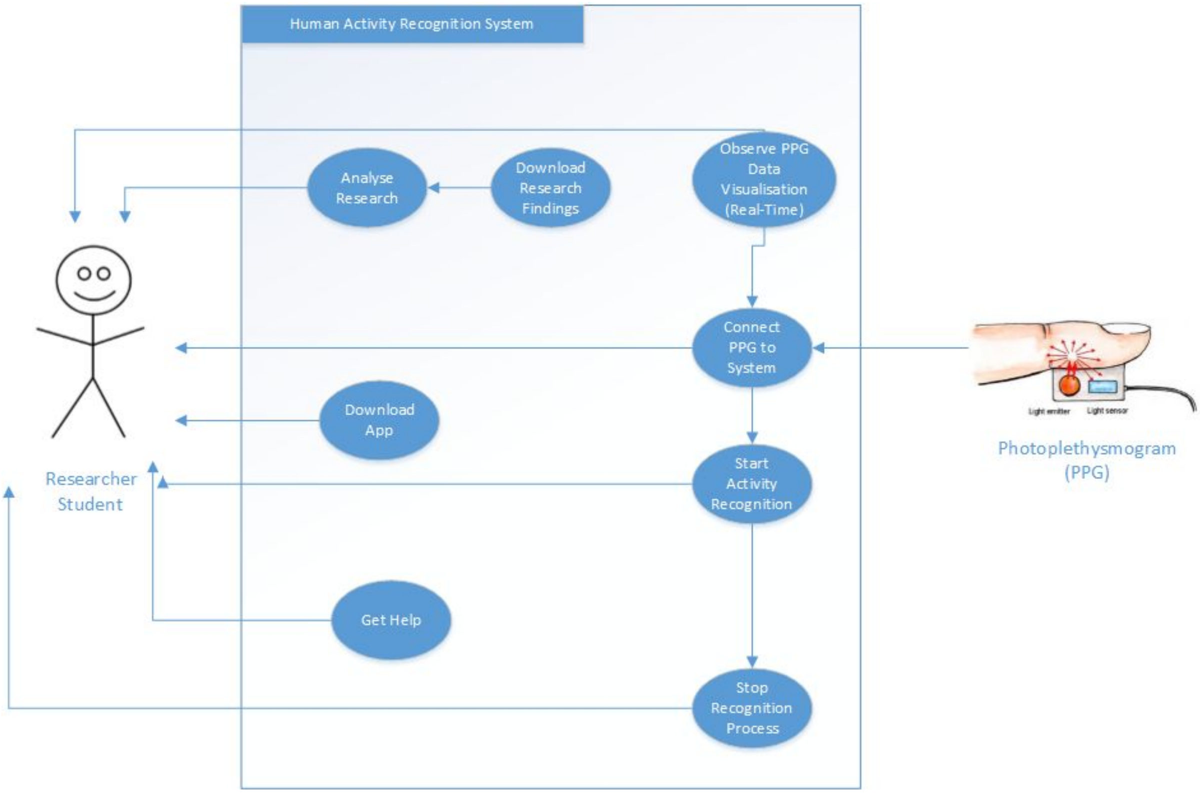
**Fig 5.3 Class Diagram**




The class diagram above gives us a basic impression of how each class interacts with one another. This class diagram shows us the relationship between our classes and how data is passed between them to allow them to perform their various functions.

The **ApplicationView** is the primary class where we create all our panes within the desktop application. Each pane represents a functional requirement as specified above in section 3, therefore this class is essential to the application as a whole

**Fig 5.4 Use Case Diagram**



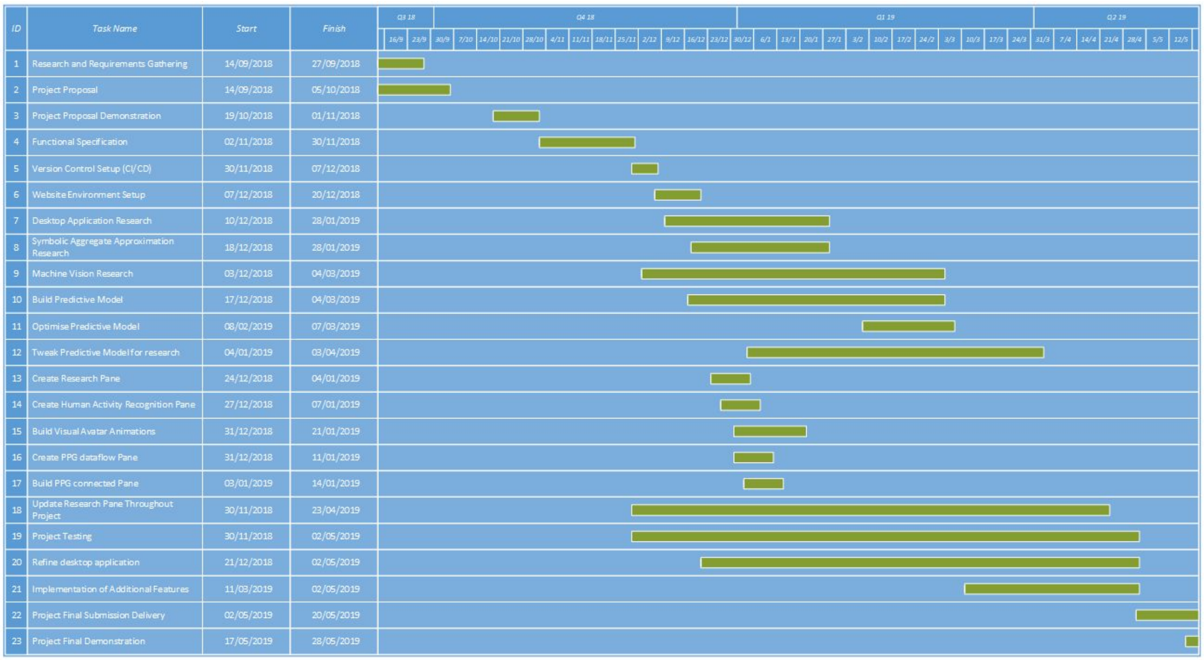

A user such as a research student will interact with the application through **downloading** it online. Once downloaded, users can **Get Help** in order to understand how to use the application, however, it will be intuitive to use from a design point of view.

Users can view historical data on **research findings.** Users will primarily want to **connect a PPG** to the system to begin human activity recognition. Once connected users can **Start Activity Recognition** and **Stop Activity Recognition**. Once started, users can view what activity is performed by the equipped PPG holder in **quasi real-time**.

Finally, users can **view the PPG blood-volume data flow in real-time** in one of the 4 panes visually shown in the application's UI.

# 6 Preliminary Schedule

**Fig 6.0 Gantt Chart**.



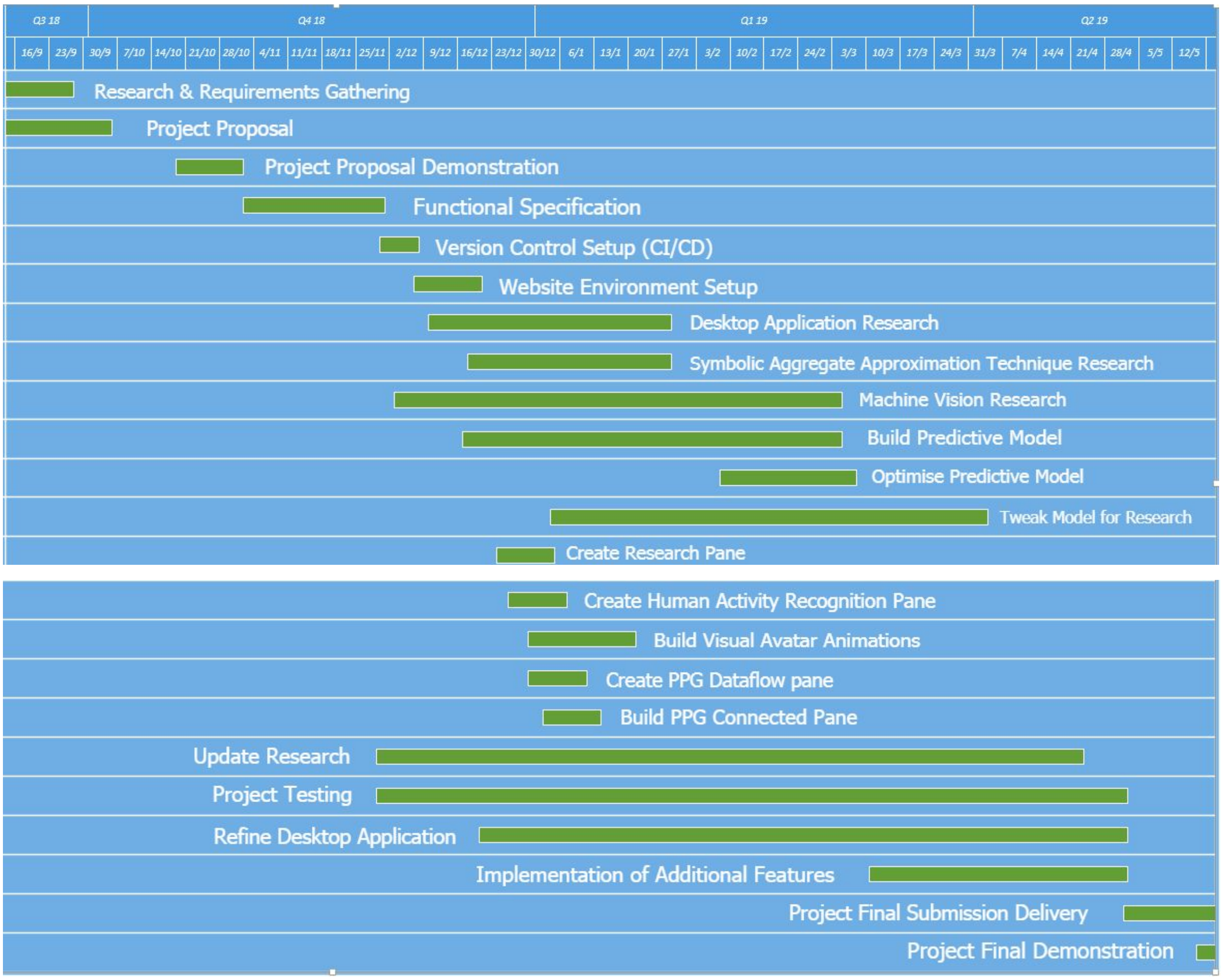

The above gantt chart shows the schedule of project activities over the course of the 4th year project timeline. Most of my time will be spent building the predictive model and refining it to get my accuracy as high as possible.

Other long requirements would be testing. There will be Continuous Integration running throughout the life of the project. Unit tests and Integration tests will be consistently added to the project as more features are added. The research pane will also be actively contributed to and refinement of the desktop application overall will take a long period of time.

Research among many different unique topics will take up a lot of time. To understand the material and then apply it to enable the ability to recognise human activity through PPG sensors data is the primary reason why this project will be time consuming.

Managing my time throughout the project will be important. Errors and hardships are prone around all corners of the project. Bundled into the **'Build Predictive Model'** phase of the gantt chart would be the synchronisation from the PhysioNet datasets into real PPG data extracted from the device. This is crucial to achieving quasi real-time activity recognition but will be very time consuming considering all the different environmental parameters at hand.

**Fig 6.1 Gantt Chart - A more detailed look**




(*Critical Task Date schedule & Appendices below)*

**Fig 6.1 - Critical Tasks Schedule**.

| ID | Task Name | Start | Finish |
|---|---|---|---|
| 1 | Research and Requirements Gathering | 14/09/2018 | 27/09/2018 |
| 2 | Project Proposal | 14/09/2018 | 05/10/2018 |
| 3 | Project Proposal Demonstration | 19/10/2018 | 01/11/2018 |
| 4 | Functional Specification | 02/11/2018 | 30/11/2018 |
| 5 | Version Control Setup (CI/CD) | 30/11/2018 | 07/12/2018 |
| 6 | Website Environment Setup | 07/12/2018 | 20/12/2018 |
| 7 | Desktop Application Research | 10/12/2018 | 28/01/2019 |
| 8 | Symbolic Aggregate Approximation Research | 18/12/2018 | 28/01/2019 |
| 9 | Machine Vision Research | 03/12/2018 | 04/03/2019 |
| 10 | Build Predictive Model | 17/12/2018 | 04/03/2019 |
| 11 | Optimise Predictive Model | 08/02/2019 | 07/03/2019 |
| 12 | Tweak Predictive Model for research | 04/01/2019 | 03/04/2019 |
| 13 | Create Research Pane | 24/12/2018 | 04/01/2019 |
| 14 | Create Human Activity Recognition Pane | 27/12/2018 | 07/01/2019 |
| 15 | Build Visual Avatar Animations | 31/12/2018 | 21/01/2019 |
| 16 | Create PPG dataflow Pane | 31/12/2018 | 11/01/2019 |
| 17 | Build PPG connected Pane | 03/01/2019 | 14/01/2019 |
| 18 | Update Research Pane Throughout Project | 30/11/2018 | 23/04/2019 |
| 19 | Project Testing | 30/11/2018 | 02/05/2019 |
| 20 | Refine desktop application | 21/12/2018 | 02/05/2019 |
| 21 | Implementation of Additional Features | 11/03/2019 | 02/05/2019 |
| 22 | Project Final Submission Delivery | 02/05/2019 | 20/05/2019 |
| 23 | Project Final Demonstration | 17/05/2019 | 28/05/2019 |

# 7 Appendices

1. **A machine vision approach to human activity recognition using photoplethysmography sensor data:** http://doras.dcu.ie/22433/

2. **Symbolic Aggregate Approximation:** http://www.cs.ucr.edu/~eamonn/SAX.htm

3. **Deep Learning and Convolutional Neural Networks:** https://medium.com/@ageitgey/machine-learning-is-fun-part-3-deep-learning-and-convolutional-neural-networks-f40359318721

4. **PhysioNet database:** https://physionet.org/

5. **Python GUI collection options** https://opensource.com/resources/python/gui-frameworks

6. **Human Activity Recognition using Convolutional Neural Networks** http://www.ecmlpkdd2018.org/wp-content/uploads/2018/09/706.pdf

7. **Physical Activity Identification using Supervised Machine Learning and based on Pulse Rate:** http://oru.diva-portal.org/smash/get/diva2:638278/FULLTEXT01.pdf