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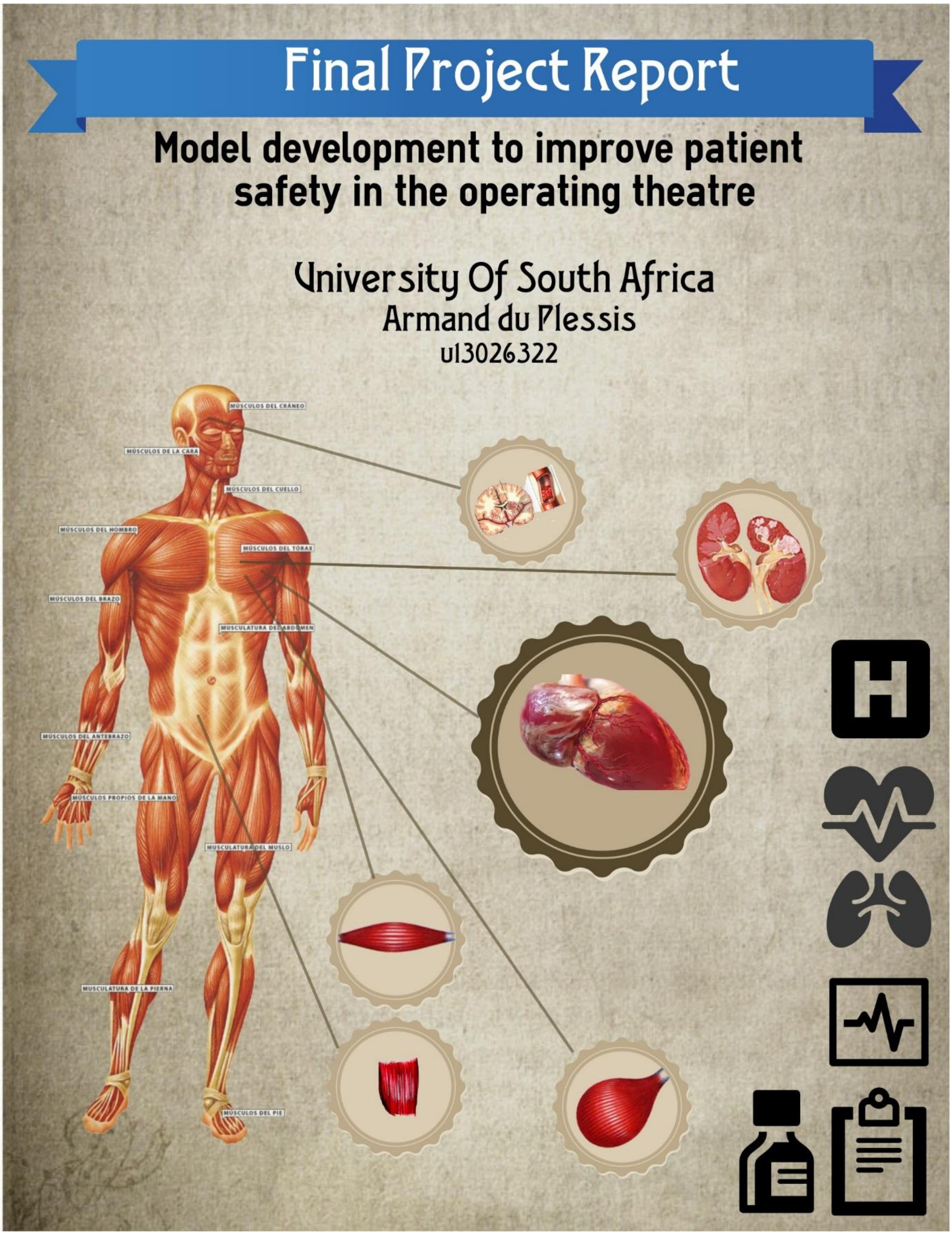

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DEPARTEMENT BEDRYFS- EN SISTEEMINGENIEURSWESE
DEPARTMENT OF INDUSTRIAL AND SYSTEMS ENGINEERING

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Datum **Date**	28/09/2016

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Executive summary

This project considers the need to use machine learning for supporting anaesthesiologists to predict and detect patient issues. Anaesthesiologists play a vital role within medical care and, especially in South Africa, are involved in nearly all medical care practices. This project is the first of its kind to look holistically at the entire anaesthesiology process, where previous papers have aimed at controlling and investigating only a small portion of the process. It was seen that in South Africa hospitals do not capture live patient data electronically, but rather on paper format. After testing and considering live patient data it was opted to construct an artificial data set as to take the sensitivity of the data into account and aim for a higher model accuracy. An artificial patient data set was constructed using interviews, medical knowledge available to the masses and intuition. This data set was described in detail and the deep complex nature of interrelations of the different variables were highlighted. The data set consisted of a 1000 patients, 500 male patients, 500 female patients, age distributions between 20 and 80 years old, patient heights in metres, patient weights in kilograms, heart rates in beats per minute and lastly, systolic and diastolic blood pressures in millimetres mercury. The data set was analysed by a number of machine learning algorithms and it was found that: J48 decision tree achieved a prediction accuracy of 98.9%, logistic regression 97.8%, k-nearest neighbour 98.3% and lastly, neural networks obtained a 99.7% accuracy. Validation and verification was done via the J48's decision tree and the models were proven to be fit for use and accurate. From the data it could be seen that future projects that would aim to use machine learning in the pre-,intra- and post-operative care sections of anaesthesiology; that they would have to gather a large data set as to make the models more accurate. Unlike other projects that aim to control the amount of anaesthesia or predict the patient risk beforehand, this project has proven that it is possible to continuously predict patient's current health status while the operation is under way. The report concluded by stating that the neural networks can be used as a second opinion to classify the patient's current health status and will be run live with current patient information.

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List of abbreviations and acronyms

BP	Blood pressure
ML	Machine learning
SVM	Support vector machines
ERP	Enterprise resource planning
AIMS	Anaesthesia information management system
BMI	Body mass index

1. Introduction

1.1 Background

The mid-year estimation of South Africa's population in 2014 was 54 million people (Statistics South Africa, 2014). Another report, also from Statistics South Africa, indicated that 70.6% of households used public sector health care. Thus 27.9% off all households use private sector healthcare and 9.5% of South Africa's populous used public hospitals, whereas 2% used private hospitals. 61.2% of South African's used public clinics and 24.3% used private doctors and some of those patients are referred to hospitals (Statistics South Africa, 2011). With regard to hospitals it is estimated that about 80% of procedures (keeping in mind hospitals mostly do critical operations) need an anaesthesiologist (Matthee, 2016). This statistic suggests that anaesthesiologists interact with at least 5 million South Africans annually. Considering the fact that anaesthesiologists keep patients alive during operations, they are indeed very important to critical healthcare in South Africa and the rest of the world.

1.2 Anaesthesiology

As mentioned, anaesthesiologists are important. They deal with the perioperative care of patients, which entails pre-operative care (care before an operation), intra-operative care (care during an operation) and post-operative care (care after a surgery) (Celestino et al., 2015).

More specifically:

1. Anaesthesiologists meet with patients before an operation and record their personal data (weight, height, age, medical history etc.) to prepare for any unseen events during an operation.
2. Anaesthesiologists provide anaesthesia for the pain (and maintain the anaesthesia throughput throughout the operation).
3. Anaesthesiologists paralyzes the patient's muscles to provide the doctor with the opportunity to work on the patient without harming them.
4. Anaesthesiologists monitor vitals during the operation in order to manipulate the patient's body and keep them alive. The reason for this paralysis is that anaesthesia represses normal human body behaviour. For instance, the human body shivers to keep a patient warm. Instead, an anaesthesiologist will warm the patient with blankets. Also patients cannot breathe on their own during operations. During the operation anaesthesiologists assist the patient with breathing either manually or mechanically, to list only one of many examples.
5. Anaesthesiologists takes care of the whole patient (their heart, lungs, brain, kidneys, even their eyes and skin) during the surgery so that the surgeon can focus completely on their area of expertise. This care is performed while optimizing the operating conditions for the surgical team.
6. Lastly, anaesthesiologists provide patients the right type and quantity of medicine for post-operative care. This care enables patients to wake up easily after a long operation and still be able to eat within two hours.

Thus anaesthesiologists are of cardinal importance to any operation whether major or minor.

1.3 Context

Figure 1 below clearly shows on a macro level where this project is positioned. It should be noted that this is a very high level and somewhat generalized view, as this project impacts anaesthesiologists and hospitals word wide (Dussmann, 2016; Gupta and Orbe, 2016; Mater, 2016). Each hospital has its own management style and departments may operate differently at different hospitals.

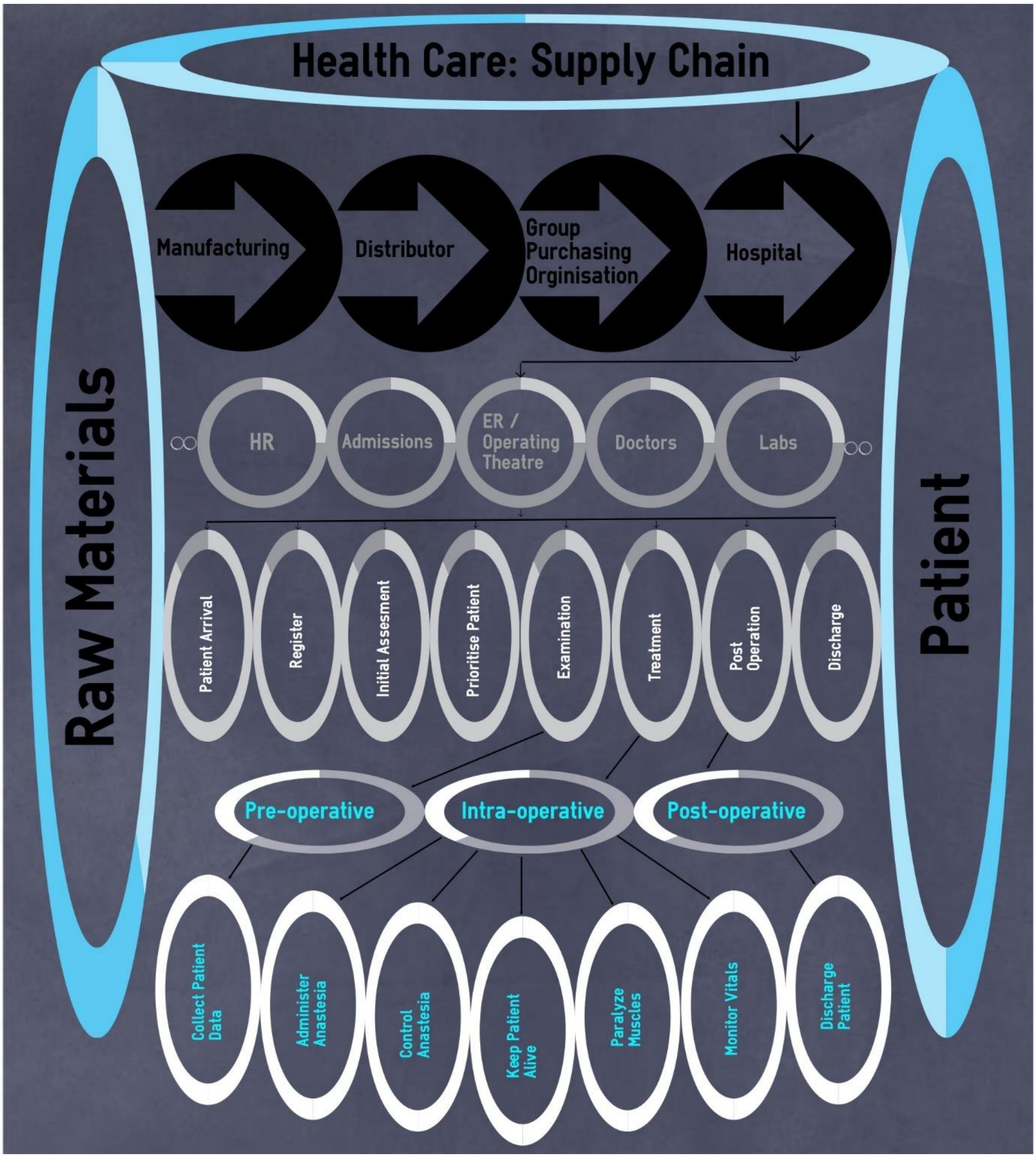

Figure 1: Systems perspective of where anaesthesiology is positioned

On the first level the organisations involved within the health care supply chain are provided. The hospital is featured at the very right as it is predominantly a service organisation and as such needs to be located near the customer. Hospitals are the main focus of the project and as such the next level flows directly out from it. The next level indicates the departments that can be found within a hospital. However, only the emergency and operation services are of interest. From them we see the general process a patient experiences when arriving at a hospital. This project focuses on the examination, treatment and post operation part of the process. The next two levels are highlighted in blue because they directly pertain to the process, steps and work that an anaesthesiologist does. These are critical processes, on the very lowest level, that are of importance. Raw materials and patients are involved in all the levels and such are displayed all along the sides of Figure 1.

1.4 Importance of topic

It has already been shown how directly anaesthesiologists affect the lives of South Africans. Since anaesthesiologists are part of 80% of activities within hospitals they directly affect the lives of many patients. Furthermore, the fact that anaesthesiologists have a "life or death" influence during operations, further emphasizes their importance. This topic is more geared towards patient safety, however, money always has a role to play in improvement projects. The topic of anaesthesia and cost saving by reducing the amount of anaesthesia used is controversial. Too much anaesthesia can kill the patient and drives up the recovery cost, too little anaesthesia and the patient experience pain. A study in the American Society of Anaesthesiology, showed that anaesthetic procedures using less anaesthesia than general anaesthesia, resulted in 75% less expenditures, as patient recovery and incidents were reduced (Memtsoudis et al., 2013).

1.5 Need requirement

Anaesthesiologists have a very rewarding but dangerous profession. The profession is rewarding because a wide range of medical knowledge is applied in very high pressure environments and creative ways. The profession is dangerous because anaesthesiologists have to constantly monitor many different variables during an operation.

The following is an incomplete list of variables that have to be monitored during operations (Celestino, 2016):

- BP (blood pressure)
- Pulse oximetry – how much oxygen the current amount of blood in the body is actually delivering
- EKG (Electrocardiogram) pattern – measures the heart's electrical activity to verify whether it is expanding and contracting correctly
- End-tidal CO_2 – the amount of carbon dioxide exhaled after each breath
- Train-of-four reflex – stimulates nerves to see if they are blocked or not
- EEG (Electroencephalogram) readings – measures the electrical activity in the brain
- BIS (Bi-spectral index) monitoring – monitors the depth of anaesthesia
- Invasive BP – a direct measurement of blood pressure by inserting a small needle in the artery
- CSF pressure (Intracranial pressure) – pressure inside the skull
- Blood pH – refers to the acidity of the blood
- Aesthetic vapour concentration – concentration of vapour in the lungs
- Random blood sugar – level of glucose in blood
- Urine output
- Tidal volume – volume of air that the lungs can push out when exhaling
- Etc...

It has been shown through history that when any human has to do complex work under extreme conditions, that they may and eventually will, falter (Gaba, 1989). The sound judgement of an anaesthesiologist can never be replaced, but it can be supported. This project proposes the need to aid anaesthesiologists in responding quicker and more accurately to the change in patient conditions that might affect them negatively. The aim then for this project is to investigate the use of machine learning for supporting anaesthesiologists to predict and detect patient issues.

1.6 Project Rationale

According to an article from Deloitte, South Africa's health care spending is estimated to reach $39 billion near 2018 (www2.deloitte.com, 2016). Figure 2 below is an info-graphic showing the size of industries using users on LinkedIn as direct reference (Vidani, 2016). This comparable figure, yet again shows how important the health care industry is.

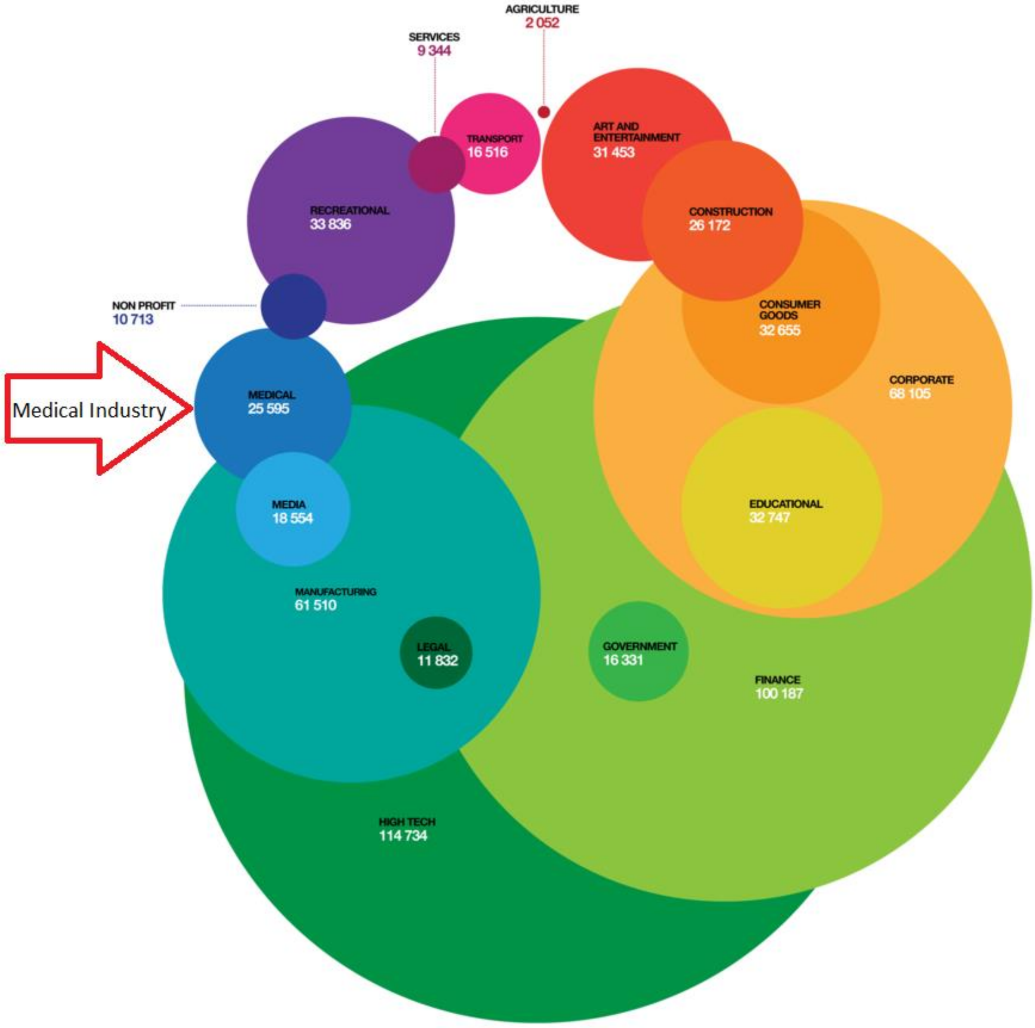

Figure 2: Size of South African health care (Vidani, 2016)

Health care expenditure might be affected by many different factors, but when considering how directly involved anaesthesiology is, it is easy to see how this discipline can directly impact that number. A large part of patient cost is the recovery time, as every day spent in the hospital is fairly expensive. To just name one example: the quicker the patient recovers from their anaesthesia and the quicker they start healing, the less recovery cost will be incurred and the more space is available for another patient.

On a completely different level, this project is crucial because of quality: quality of the patient's life. Every moment that passes, a variable of the patient is changing and effected by many different factors. If the anaesthesiologists can detect changes sufficiently early and determine what the impact is on the patient, then reaction time can be reduced and a life can be saved. Machine learning, artificial intelligence, neural networks, fuzzy logic, swarm intelligence or evolutionary computing, are but a few techniques that can assist in detecting and predicting these changes (Engelbrecht, 2007).

A preliminary literature study has indicated that there is no exact project like this. There are projects that are similar in that they consider one variable within anaesthesiology and apply one machine learning method to the data (Saraoglu and Sanlı, 2007). However, no evidence thus far has shown projects that try to address all the variables, find the correlation between variables and apply the best method for detection and prediction. In that regard this project is very unique and revolutionary. One such example is a team of researchers that were able to use ML, more specifically reinforced learning in closed-loop control of anaesthesia using the bispectral index (L Moore et al., 2014). Another research group looked to pre-operative assessments to identify the patients risk level based on the American Society of Anaesthesiologists (ASA). They used three ML algorithms within the *Weka* environment: C4.5 decision tree classifier, Naïve Bayes and Multilayer Perceptron. The focus here is much different than this report as they looked at the preoperative assessment area and as this project looks at all three areas (pre-, intra- and post-operative). As can be seen with these two examples of research within this area that other projects either focused on controlling one variables ,as in the first case where they controlled the level of anaesthesia output to the patient or they use patient information to assess the patients risk before an operation. Although these projects will share much of the same input data, the outlook of the project is much larger and the output is to be used real time while busy with the operation not as a risk estimator beforehand.

1.7 Project Approach

At its very core, this project has three phases. The first is to identify the variables (both static and dynamic). Correlation between the variables should be identified and final selection of variables should be made that are the most important and will be used to apply the algorithms to. The second phase will be to identify what kind of algorithm to use, for example neural networks, support vector machines, regression analysis, k-nearest neighbour etc. The type, complexity and number of variables will influence that decision. The last phase will be to run and test the algorithms to prove their accuracy. The phases are shown graphically in the next Figure:

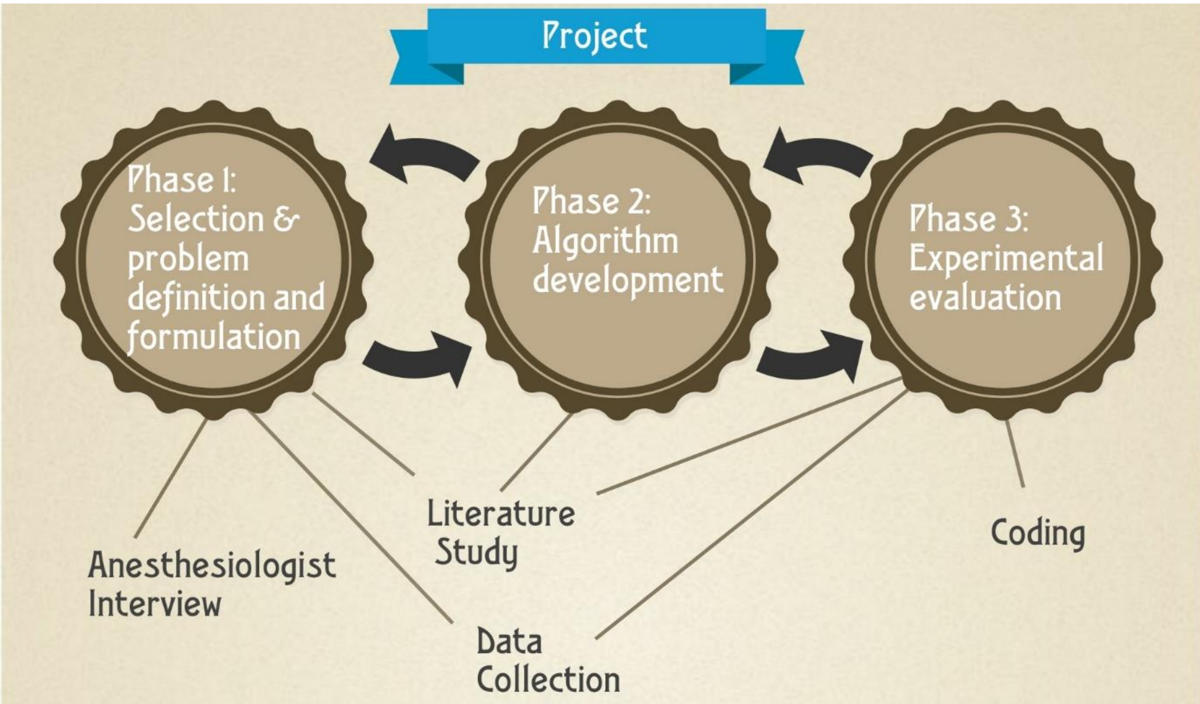

Figure 3: Phases of the project

1.8 Scope

Logically speaking, from the perspective of a product, the project life cycle will be: Literature review, coding, evaluation, trials (tested in actual operations) and commercialisation. This project will finish at the evaluation stage. The coding section suggest commercial prototype coding for product creation. This project will have coding involved when it comes to the simulation, but only that of the algorithms.

The scope of this project will involve all the variables anaesthesiologists work with. During the literature review it will be decided whether to use all of them, some of them or only one. The variables will include all generic data collected post-operation (weight, age, height etc.) as well as dynamic variables that change during the operation and post-operation.

2. Literature review

2.1 An introduction to machine learning

According to Pedro Domingos, who instructs the University of Washington's machine learning course, ML can be describes in two words: "automating automation". It is the most popular up and coming field within computer science where computers do the programming themselves. This is exactly the reverse of programming and the reason so many computers scientist are able to this is because of data. Data drives the very heart of machine learning and this field very closely relates to big data analysis. Domingos goes on to very cleverly describe the difference between machine learning and traditional programming in the next figure (Domingos, 2016):

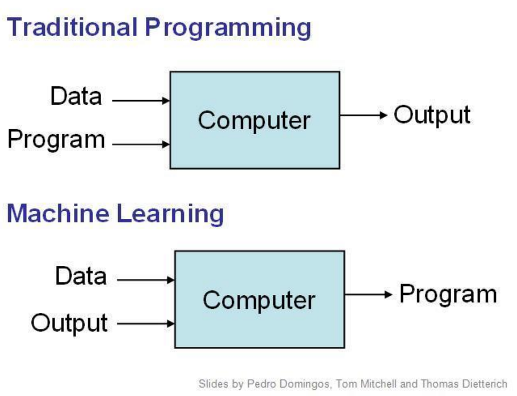

Figure 4: The difference between traditional programming and machine learning (Domingos, 2016)

Figure 4 clearly shows the core of machine learning. Data, in large quantities, which already contains an example of what the end user desires, is run through an algorithm to teach it. The end result is a program that has been trained to do some specific task via real life examples (big data).

There are four types of ML, very broadly defined as (Sas.com, 2016):

1. Supervised (inductive) learning: This is used where the output of the data is known and labelled. Thus an input is given to the algorithm which could be emails, but the corresponding correct output is also given to the algorithm as a label, in this case if the email at hand is spam or not.
2. Unsupervised learning: This is used where only the output is known and the data has no labels connected to it. For instance it could be used on a dataset where only the raw customer data is known, but not whether they are profitable or not. The algorithms are tasked with finding structure within the data and making more sense from the data.
3. Semi-supervised learning: This type is the same as supervised learning. The only difference is a small portion of the data is labelled and the rest is not. The labelled portion of the data is used to train the data and the algorithm is run on the rest of the unlabelled data to label it automatically.

As it is labour intensive and very expensive to label data manually, this method then works well where there is a large dataset and few resources to label them.

4. Reinforced learning: This type of ML learning uses rewards to drive the trial and error way of searching for the best answers. It is mostly used in gaming, robotics and navigation. Reinforced learning uses an agent, an environment and actions to maximise the reward.

The rest of the literature study will focus on supervised and unsupervised learning as this will maximise the use of the expected data that will be obtained.

2.2 Review of ML within the field of anaesthesia

The latest in ML research (2015 – 2016) all consider the depth of anaesthesia. Published in 2016, the computer science team at the University of La Laguna created an adaptive fuzzy predictive controller for anaesthesia delivery (Méndez et al., 2016). This complex adaptive model controls the hypnoses level, keeping it within a safe bound for the patient. Using the bi-spectral index as a measure, the model regulates the hypnotic depth of anaesthesia. This study resulted in an increase in patient safety and a cost reduction as patients recovered faster because they were given just the right amount of anaesthesia.

Controlling the depth of anaesthesia is not an old idea. In 2000 the journal (Drummond, 2016), "Monitoring Depth of Anaesthesia" discussed whether depth of anaesthesia could fully be controlled via the BIS (Bi-spectral index). Drummond had a greater interest in under-dosage and the effects it had on cost of anaesthetics and hospital discharge. He clearly states that this cost would reduce with just the right amount of anaesthesia. In this journal he was more concerned with the effect of patient reflexes and provides an in depth discussion of the different levels of awareness a patient experiences during an operation. Ultimately, he concluded that if there was a machine that could monitor and highlight dangerous situations where the patient may experience awareness, such a machine would still not be 100% effective and situations of awareness would still arise. This study highlighted the concern in other ML anaesthesia implementations of just how deep and complex anaesthesia really is.

Since then other researchers have tried varied approaches to anaesthesia control. Reinforced learning has also been proposed for closed-loop control of propofol-induced hypnosis (Moore et al., 2016). Under controlled situations and with test data only, this technique proposed to be an effective measure.

Research has also waded into the area of post-operative care (Hu et al., 2012). Decision based tree-learning was used on pain management and yielded an accuracy of 80.9%. ML and data mining techniques were used in depth on a large number of variables. The study found that neural networks, support vector machines, random forest, rotation forest and naïve Bayesian classifiers all performed less well than decision tree-based learning.

The above mentioned studies are all concerned with the control of anaesthesia. Other journals have more specific focuses like the control or the prediction of a specific type of disease or surgery (Tighe et al., 2011). This observation, firstly suggests that machine learning can be used in anaesthesia and secondly, that ML can be used in varied degrees and forms, depending on the circumstances. The literature also suggest that the more specific the question that is answered and the narrower the scope of the research or project, the more in depth knowledge of anaesthesia practices and theory is required to capture the nuances of the problem. Fortunately a few articles were also found more in the vein of large data sets with many variables that assists in decision support.

There were however, a few articles more in line with this idea. ML has been used in preoperative anaesthetic risk prediction before (S, KS and MS, 2016). The researchers used the American Society of

Anaesthesiology (ASA) scores in three different ML algorithms to predict patient safety and morbidity states. These algorithms were a C4.5 decision tree classifier, a naïve Bayes and a multilayer perceptron classifier using the *WEKA* toolkit. *WEKA* is short for Waikato Environment for Knowledge Analysis and it is a software workbench that hosts many different kinds of machine learning algorithms that can automatically be used on datasets. Using a preoperative assessment dataset of 362 patients and measuring predictive accuracy and ease of learning, the researchers found that the multilayer perceptron classifier outperformed the decision tree and naïve Bayes algorithms. In 2013, another group of researchers again set out to test ML to obtain more accurate ASA scores (El Amine Lazouni et al., 2013). This team again tested a C4.5 decision tree classifier and multilayer perceptron, except this time they used support vector machines (SVM) and a larger dataset of 989 patients with 17 variables. These algorithms were all tested in a Matlab environment and it was found that SVM was the most accurate at 93.25%. In this journal and the previous one testing, and accuracy of algorithms where performed via the 10-fold cross-validation method. Cross validation is a statistical method used to compare learning algorithms with each other that are used for predicting future outcomes (Ross et al., 2009).

From the review it is clear that ML definitely has its place within anaesthesia, but that each segment of research that was performed was something specific within one of the perioperative fields. None of the research shows ML or integrated forms of ML that span over all three categories of pre, intra and post-operative care. In that regard this project is unique and the only thing that could possibly limit its scope is the quality and quantity of data that is received. Hereafter follows a review of only a select few ML algorithms. The algorithms consist mainly of supervised learning and unsupervised learning.

2.3 Neural Networks

It is estimated that the human brain is made up of 10 to about 500 billion neurons (Engelbrecht, 2005) and that this supercomputer is powered by nothing more than the Watts of a lamp. Neurons might have more connections and use less power than computer chips, but the fast processing power and the amount transistors available are a force to be reckoned with. This fact is quite extraordinary and in that regard it is only natural that people look to the human brain to improve computer processing power.

The next figure illustrates a schematic representation of a single human neuron:

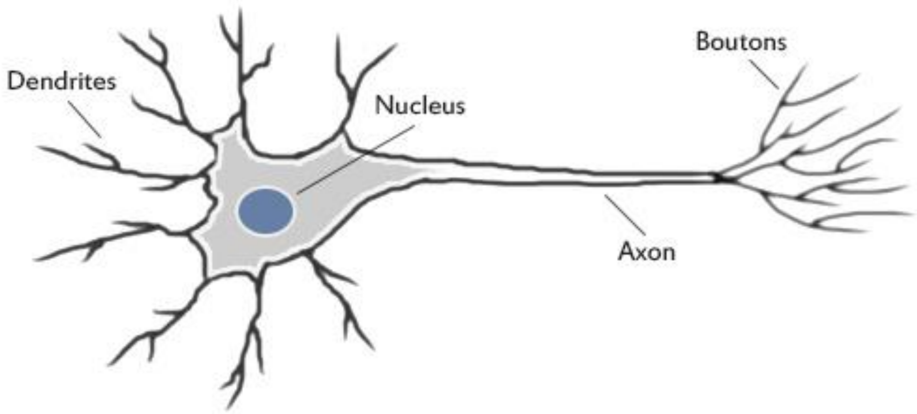

Figure 5: A single neuron (Jacobson, 2016)

The nucleus is found within the cell body. All around this nucleus are dendrites. They are the bushy tentacles that connect to other axons of other neurons to form synapses. This is where intelligence is stored and the learning takes place. The axon fires a jolt of electricity to send a signal to the other dendrites. If that signal is strong, learning took place (Computational Intelligence: An Introduction, 2005). That is how a neuron works, but that is also how the learning concept of the algorithms work.

The most basic neural network algorithm is a perceptron. The next figure illustrates the mathematics behind it:

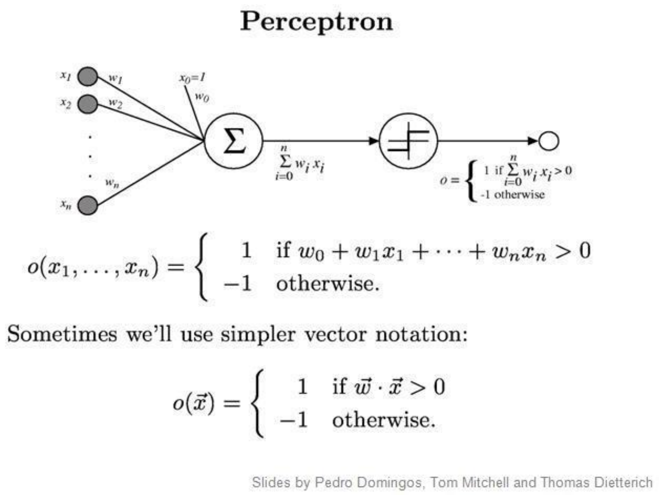

Figure 6: The perceptron schematic and formulae (Domingos, 2016)

This perceptron illustrates the use of one neuron for learning. The left hand side of the figure (X1, X2...Xn) illustrates the inputs. To the right of them are the connection that signify the weights (W1, W2....Wn). The inputs and weights are multiplied with each other and summed together and if their sum is more than 0 the output is 1 (i.e. the axon fires), otherwise the output is -1 and the axon does not fire (Domingos, 2016).

That, in a nutshell, is the very basic idea of a neural network. From there it becomes much more complex with different combinations of neurons and different activation functions to build up a unique algorithm. Neural networks can also be used as supervised or unsupervised algorithms and can also be used in the case of the intra-operative care which is time series data (Touretzky and Laskowski, 2016). Some of the strengths of neural networks are: that a theoretically infinite number of neurons can be used in computations to increase accuracy, no prior knowledge pertaining to the data is needed before using a neural network, using a wrong "model" to fit data is not penalised as neural networks can be tuned to fit the past data and the neural network has the capability to learn hidden structures within the data. The weaknesses are: adding too many neurons to the algorithm can cause it to over fit the data, creating a neural networks structure is time consuming because it goes hand in hand with trial and error tuning of the weights and that it cannot be used for all problems and is certainly not the best solution in certain ones.

2.4 SVM (support vector machines)

SVM is a class in machine learning that falls under supervised learning and is used for classification and regression analysis. The basic idea is that the training data is used as vectors or support vectors that guide the algorithm in the right direction. This will be explained via a simple illustration:

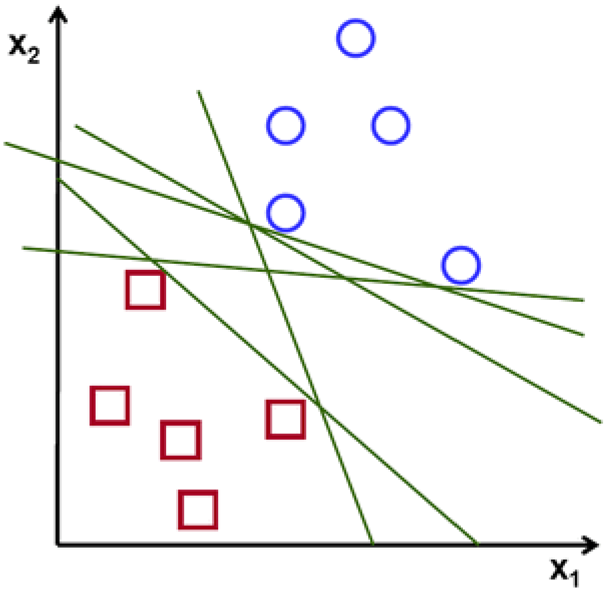

Figure 7: SVM example 1 (Docs.opencv.org, 2016)

Figure 7 illustrates a two-dimensional plane containing circles and squares. What SVM attempts to do is separate the circles and squares via a line to create two different planes or boundaries. As Figure 7 suggest there are many lines that could fit that description, but the line with the most equal amount of space between either sides of the circles and squares would be optimal. That is exactly the line that SVM attempts to find using the current or historical data as vectors in a plane. This optimum line can be seen in Figure 8:

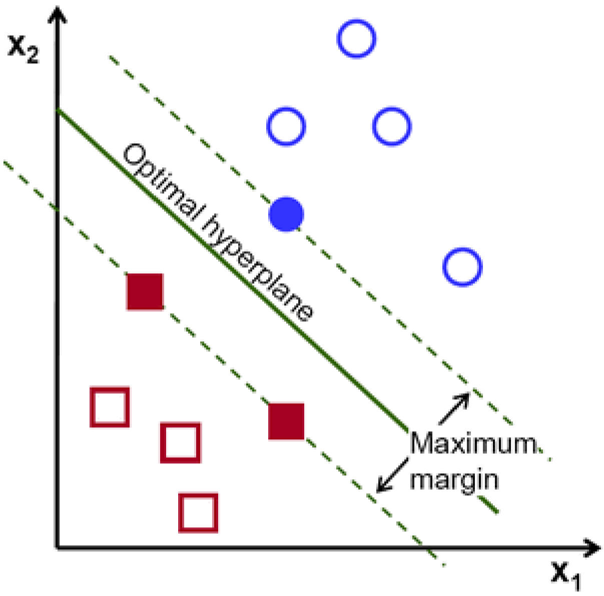

Figure 8: SVM example 2 (Docs.opencv.org, 2016)

If a new data point enters the plane and falls on the left side of the line, the equation will categorise that data point as a square (Docs.opencv.org, 2016). Some of the advantages of SVM are: effective in high dimensional spaces, if the number of dimensions is higher than the number of samples it is still an effective tool to use, the support vectors make the algorithm memory efficient and the technique can be versatile because of the decision functions that can be specified. The disadvantages include: if there are more features than there are samples the algorithm performs poorly and it doesn't include probability estimates (Scikit-learn.org, 2016).

2.5 K-nearest neighbour

The K-nearest neighbour algorithm is the easiest algorithm to use and the easiest way to describe the K-nearest neighbour algorithm is with an example (How kNN algorithm works, 2016).

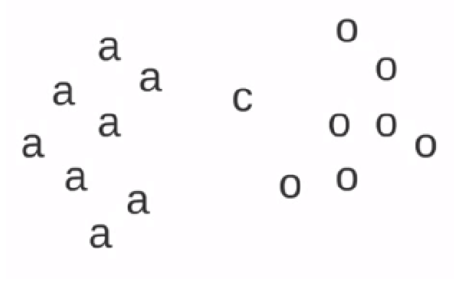

Figure 9: K-nearest neighbour example

Figure 9 represents a two dimensional plane that originally consisted of a's and o's (the a's and o's represent the training data that was originally captured). The algorithm's functionality is exactly as stated in the name – for every new query it finds the k-nearest neighbours. If the new query in this instance is c and k = 3 then the algorithm would find that one a and two o's are the nearest data points to c (shown in the circle in Figure 10), because of this c (the query data point that has to be predicted) will be o.

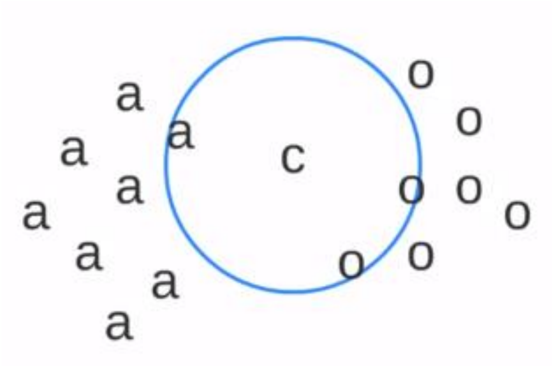

Figure 10: K-nearest neighbour example continued

This very simplistic example is what the algorithm is all about. All the data is stored and at its core, when a request is made to identify a new point, the nearest point to the new point is identified and the requested point is then "guessed" to belong to the same class. If more points are considered (k number of points), the k nearest ones are found and the more there are of a certain type of point, the higher the likelihood that the requested point belongs to the same class.

There are more powerful versions of this algorithm in use, but for the most part the biggest aspect that can be adapted is the closeness factor (how the nearest neighbour is measured). The nearest neighbour can be measured by means of the Euclidian, Manhattan or L^n-norm distances (Domingos, 2016). The k-nearest neighbour algorithm can also be used for discrete and continuous datasets.

The advantages of this algorithms are: the training itself is very fast, it can learn a complex target function easily and that none of the original dataset is lost. On the other hand k-nearest neighbour has some disadvantages: the algorithm has a slow query time because it has to use the original data set and filter through the data to find the answer (this problem obviously increases as the dataset increases), the algorithm needs significant memory and because the algorithm uses the original data and does not remove outliers or "noise" within the data; the algorithm can very easily use irrelevant data.

2. 6 Regression analysis

Regression is a statistical method that finds the relationship among all the variables. The technique shows how the dependant and independent variables interact with each other and if one changes how the relationship changes (Armstrong, N.D.). The most basic regression analysis technique, linear regression, functions much like a straight line equation:

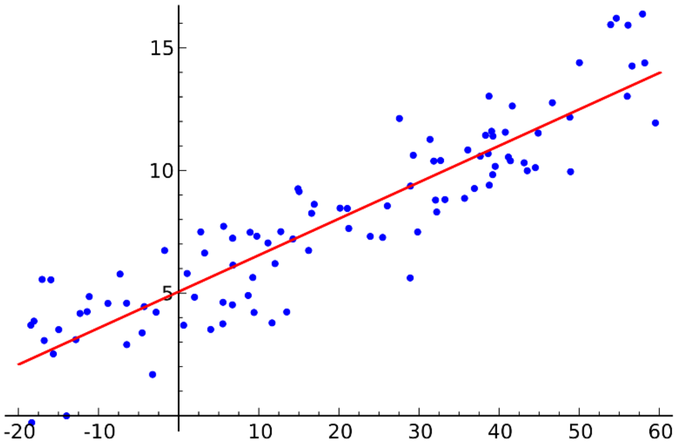

Figure 11: Linear regression illustration (Wikipedia, 2016)

This is not just a statistical technique steeped in books, it has close ties with ML (Brownlee, 2013). Some of the regression models available are:

- Ordinary least squares regression (OLSR)
- Linear regression
- Logistic regression
- Stepwise regression
- Multivariate adaptive regression splines (MARS)
- Legally estimated scatterplot smoothing (LOESS)

The advantages and disadvantages of this category relies, like all the other categories, solely on the specific algorithm used. For instance, linear regression is simple, easy to interpret and is easy to use and effective on data that has a linear relationship. However the opposite can also be said. Many real world problems just do not abide by this linear relationships and data that has little to no linear correlation between the points will be null and void with this technique (Chambers and Dinsmore, 2016). There are, however, regression models which can model more complicated equations such as polynomial functions etc.

2.7 Time series analysis

A time series consists of data that is dependent and recorded over time. This data has the following characteristics: continuous time intervals, measurement taken successively, measurements taken with equal spacing' between each other and for every time unit there is at least one corresponding data point. Examples are: arrival of cars at an undercover parking recorder over time, patient vitals with constant increments and ocean tides.

Time series analysis can be used in weather, economics, forecasting etc. This analysis use statistics to look at historical data to predict future values (Zissis, Xidias and Lekkas, 2015).

The next figure clearly shows the difference between time series and regression analysis, in regression analysis it is all about the relationship between the variables, in time series it is all about the relationship of the data point within the specific time frame that it happened. Thus the data has to be dependent on when it happened in time.

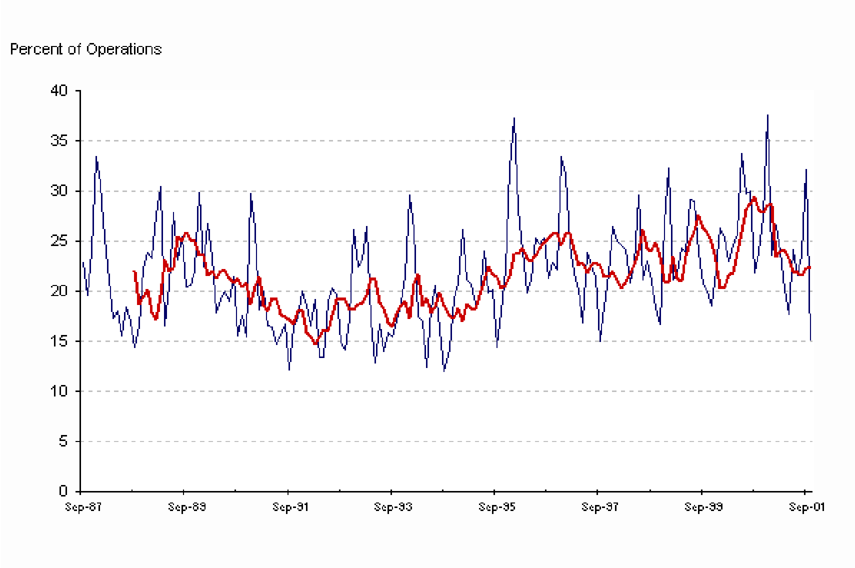

Figure 12: Example of a time series graph (bureau of transportation and statistics, 2012)

Yet again this analysis can be used within ML. Some of the algorithms harnessing time series analysis are: hidden Markov model, recurrent neural network and autoregressive integrated moving average (Quora.com, 2016). The advantages of time series analysis are: the analysis can help in identifying seasonal variations, the forecasting can be very accurate in the short term and the fitted line can adjust quite closely to varying data points. The disadvantages are: it relies heavily on historical data for prediction (some instances are case specific), it is not very good at long term forecasting and there can be quite a lot of calculations if large period moving averages are used (business studies online, 2016).

2.8 J48 Decision Tree

As the name suggests this algorithm is a type of decision tree. Decision trees fall under the category of statistical classifiers. These are classifiers that have to pinpoint how to classify a new observation and to which category or sub-population does this observation belong to, using statistical methods (Kim, 2010).

The first version of this algorithm was named ID3, created by Ross Quinlan. After that he created the C4.5 algorithm. The J48 algorithm is based on the C4.5 with the only difference being that the J48 algorithm is used in a different data mining toolkit than the original (Girones, 2016).

The basic premise of a decision tree is that it breaks up all the data connected to an outcome or classifier into logical smaller parts or in this case trees. If the data set being used was used to describe what a sunny day was like then the outcomes would be sunny or not-sunny. One of the inputs to this data set would be temperature and the way a tree is formed is by looking at what temperatures are the outcomes sunny and at what temperatures are they not. It would for example look like this:

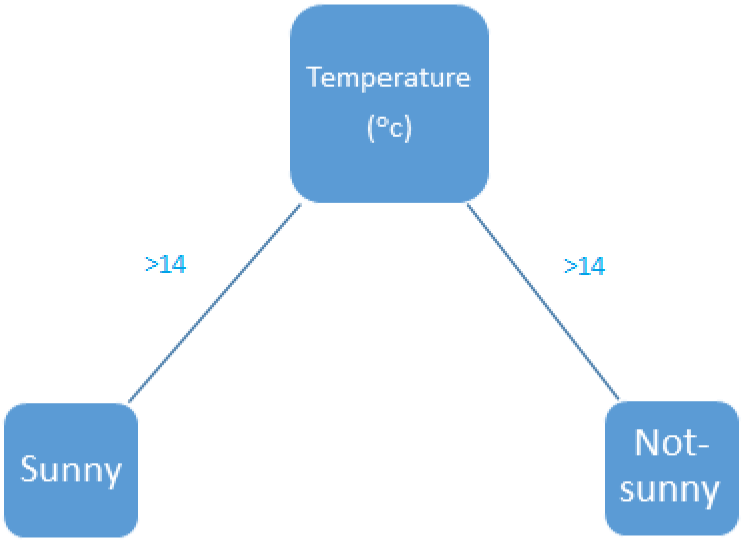

Figure 13: Example decision tree

The algorithm would work through the data and find, as in this case, that in most cases if the temperature is above 14 degrees then it will be a sunny day, otherwise not. This is the common theme behind this type of algorithm and the more data inputs there are the larger the tree structure can break down into.

2.9 Software

As machine learning can be build using any programming language and the field of study being in high demand as of late, there are no shortage of software to choose from (Yegulalp, 2016). For the purposes of this project two types of software/languages were looked at: *Python* and *Weka*. *Python* is the most commonly known programming language out there and enjoys one of the larges open source communities to date. The platform or module on which machine learning applications are executed is known as scikit-learn (Scikit-learn.org, 2016).

Weka on the other hand is specifically build for researchers who want to quickly prototype and tune their algorithms. It runs on java and has algorithm built in and thus does not require any programming (Cs.waikato.ac.nz, 2016). The negative of using *Weka* is that algorithm cannot be programed to specifically meet the need of the user. On the other hand it is much quicker to use *Weka* than it is to programme it from scratch, that and the massive roster of algorithms that come pre-built allow the researcher to quickly run the data through all the algorithms and identify which algorithms will work their best. Most scholarly articles that did ML research within the field of anaesthesia used *Weka* as their software of choice (refer to section 3.2).

2.10 Medical legislation

The South African Medical Device Industry Association (SAMED) is a non-profit association managing the interests of 160+ companies and members of the medical device industry. According to SAMED there are currently no regulations in South Africa pertaining to the sale and use of medical devises, except for electro medical devices that are used for radiation control (SAMED – South African Medical Device Industry Association, N.D.). This causes a problem as any medical device used in industry needs to be tested and have an accuracy associated with its use. SAMED goes on to describe what a medical device is and that among the intended uses for these instrument are "diagnoses" and "prevention". SAMED also describes the poor local manufacturing industry in terms of medical devices and that 90% of the market is catered for by imports. As the report focuses heavily on the vital machines that anaesthesiologists work with and that any improvement within this field is closely tied to the use of those machines (any new measurement or algorithm will be either using these machines exclusively or interface with them from other smart devices like computers or smart phones), knowing the lay of the medical device industry within the country is important. SAMED estimates the value of the South African medical device industry in 2013 to be 1.2 billion dollars. This means this project is definitely entering an area of interest and that the strong importing rates most likely suggests external app development that would have to interface with foreign medical devices.

3. Problem Investigation

Figure 14: Muelmed hospital ICU hallway

On Friday the 22nd of April the student observed an ICU operation at Muelmed Hospital in Pretorius street Arcadia (Figure 14). The patient had just been in a bike crash and had broken his legs in two places. The patient was already anaesthetized by the time the student had entered the operating room. Obviously, by this time the pre-operative assessment had been made by the nurse. Figure 32: Pre-operative form 1 and Figure 33: Pre-operative form 2 (Appendix B) shows the information the anaesthesiologist usually completes before an operation. In this instance the patient was an emergency case and therefore these forms were not filled in, but it is routine for the anaesthesiologist to meet with the patient before an operation and fill out these forms. For the most part these forms contain the patient's previous medical information and current health status such as previous operations undergone, smoking habits, medication etc. The most important information contained in all these forms are the weight, height and age of the patient as the anaesthesiologist calculates the correct amount of anaesthesia to give to the patient with this information and thus they have direct relationships to one another.

Figure 15: Medical drug tray

Figure 15 shows a picture of a medical drug tray, where the anaesthesiologists store their drugs that they are going to use during an operation. By this time the operation was already underway. Interestingly, the doctor routinely refers to the anaesthesiologist to hear if the patients is still stable. The anaesthesiologist's main focus was the patient's oxygen content and blood flow. This makes sense as blood transport the oxygen all over the body and if there is too little blood or the blood is clotted or running too fast the patient is going to be in real trouble. In that regard the anaesthesiologist's main focus is blood and oxygen control. That is why most of what they monitor during an operation has to do with blood pressure and the flow of blood and oxygen through the patient's body. Figure 35 and 36 in Appendix C shows the Intra-operative forms. Here the anaesthesiologist jots down patient and operation specific events that happened during an operation like the positioning of the patient and if a tourniquet was used or not.

Figure 16 shows a vital monitoring machine that the anaesthesiologist used to monitor the patients vitals:

Figure 16: Vital monitoring machine

On this machine they monitor heart rate, two measures of blood pressure, amount of oxygen intake, amount of oxygen out, minute volume, tidal volume etc. A printout is shown in Figure 17, which containing all of these variables:

Muelmed TH THEATRE T2
Tabular Trend Report

Page 2/2
10-Apr-2016

		Apr 10 10:55	11:00	11:05	11:10	11:15	11:20	11:25	11:30	11:35	11:40	11:45	11:50
HR	bpm	ASY	67	59	80	62	64	63	128	99	88	73	***
SpO2	%	97	***	92	***	***	97	***	***	***	100	***	***
PLS	bpm	73	***	61	***	***	65	***	***	***	90	***	***
NBP S	mmHg	***					***					***	
NBP M	mmHg	***					***					***	
NBP D	mmHg	***					***					***	
		10:54					11:19					11:44	
etCO2*	mmHg	30	35	36	40	39	39	40	21	36	33	32	27
iCO2*	mmHg	0	1	1	1	1	0	1	0	1	1	1	3
RRc*	1/min	11	11	11	11	11	11	11	11	21	25	20	29
iO2	%	57	57	56	56	56	56	56	58	54	54	97	100
etO2	%	51	49	48	47	47	47	47	50	48	48	85	96
iSEV	%	2.4	2.5	2.6	2.6	2.6	2.6	2.6	2.8	2.5	2.4	0.0	0.0
etSEV	%	1.9	2.0	2.0	2.1	2.1	2.1	2.1	2.5	2.1	2.1	0.6	0.3
N2O	%	0	0	0	0	0	0	0	0	0	0	0	0
etN2O	%	0	0	0	0	0	0	0	0	0	0	0	0
PIP	cmH2O	19	16	16	16	16	16	16	15				
PEEP	cmH2O	6	6	6	6	6	6	6	4				
MAP	cmH2O	9	9	9	9	9	9	9	1	0	0	1	1
MVe	L	4.5	3.2	3.2	3.2	3.2	3.2	3.2	1.1	6.2	5.6	4.9	8.1
TVe	ml	409	289	280	290	288	287	291	138	319	221	243	258
RRv	1/min	11	11	11	11	11	11	11	13	20	25	20	29
STII	mm	-0.2	-0.4	-0.3	-0.5	-0.6	-0.4	-0.4	-0.3	-0.7	-0.5	-0.4	***
%PACED	%												
PVC/min	bpm												
ART S	mmHg	75	125	94	122	90	99	54	121	88	77	+++	
ART M	mmHg	65	106	80	104	77	83	47	109	79	70	+++	
ART D	mmHg	55	87	67	87	63	68	37	95	69	61	+++	
STI	mm												
STIII	mm												
STaVR	mm												
STaVF	mm												
STaVL	mm												
STV	mm												
STV+	mm												
MVi	L/min												
TVi	ml												

Figure 17: Intra-operative vitals printout

The patients receive their anaesthesia in a machine that gives it to them with the air they inhale. These machines breathe for the patients during an operation and circulates the oxygen between the body and itself. Figure 18 shows the oxygen machine used by the anaesthesiologist during the operation:

Figure 18: Oxygen machine

Lastly when the operation has concluded successfully the bike crash patient is transferred to the surgical ICU where the post-operative care takes place. Figure 37 and 38 in Appendix D shows the post-operative care forms that also contain the patient's vitals and general post-operative care information that is monitored after and operation.

4. Data analysis

A first set of patient data was acquired through an anaesthesiologist (Dr Christo De Jager), who was kind enough to allow the usage of his patient data. A first review of the real patient data yielded an accuracy of 39%. Granted this was all the inputs except time series data. However this small glimpse into real patient data showed that real patient data has a very high variability within its data. The low accuracy can also be attributed to the small data set (only a 100 patients) that had a large number of complex variables. The rule often with complex data is the more data the algorithm has the easier it becomes to find the correlations in the data.

In the problem investigation, an intra-operative vital printout was shown (Figure 15). The availability of these printouts made analysing prospective variables easier, but this also poses a problem. The printouts are the only form of data that is captured and in an interview with a doctor it was found that hospitals in South Africa do not capture live data on ERP or any kind of smart hospital system like AIMS (Rantloane, 2016). This means that the project is entirely dependent on what data can be captured. After all a project without data is no project at all. Keeping in mind how difficult it is to capture data and the sensitivity and complexity of the data, it was opted in this project to reconstruct a data set using empirical knowledge.

It should be noted that the students' knowledge in the medical domain is scarce, thus the data set was constructed using interviews (Matthee, 2016), knowledge available to the public and pure intuition. To build the data set, variables were considered from the printout form in Figure 17. The data set was built one variable at a time until complete enough, large enough and complex enough to mimic that of an actual patient data set. Each variable was added with great care to ensure that the overall set of variables would interrelate with one another and form deep complex associations and rules that would quite clearly manifest themselves within the logic of the ML algorithm to be used.

One thousand patients generated for the data set. The literature review clearly showed studies using 300 to 800 patients. The 1000 patients were divided into 500 men and 500 women patients. After the gender variable, the age variable was added. It was decided to only generate ages between 20 and 80 years old because very young and very old patients have their own unique reaction to anaesthesia that is different from a normal person. *Stat assist* in excel was used to generate random variables which were used to generate the patient information (Baxter, 2004). As gender depends on regions and different economic settings, it was assumed the distribution of ages would be normally distributed. A normal distribution with a mean of 50 and a standard deviation of 8 was used to generate the ages of the men and woman populations respectively. Refer to Figures 19 and 20:

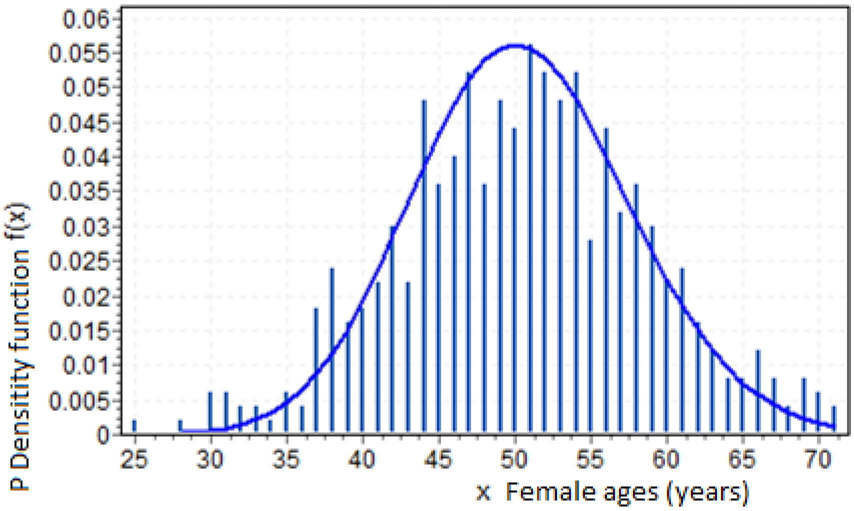

Figure 19: Female age distribution (Baxter, 2004)

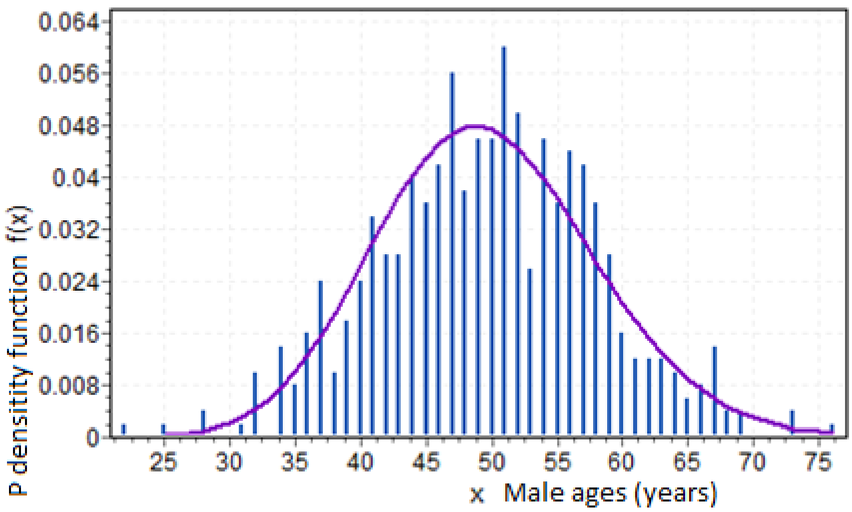

Figure 20: Male age distribution (Baxter, 2004)

As expected for both the male and female patients most of the ages were between 45 and 55 years. Weight is the next variable that was added. According to Rachel Blumenfeld (a Nutrition Specialist) average weight is related to age as follows (Blumenfeld, 2016):

Female		Male	
Age (years)	Weight (Kg)	Age (years)	Weight (Kg)
20 – 29	73.44	20 - 29	83.42
30 – 39	76.70	30 - 39	90.49
40 – 49	76.20	40 - 49	90.99
50 – 59	77.11	50 - 59	91.31
60 – 69	77.34	60 - 69	90.45
70 – 79	74.80	70 - 79	86.46

Table 1: relation of age to average weight for men and woman

Again the actual distributions of weights to ages that were randomly generated for both male and female are shown in Figures 21 and 22:

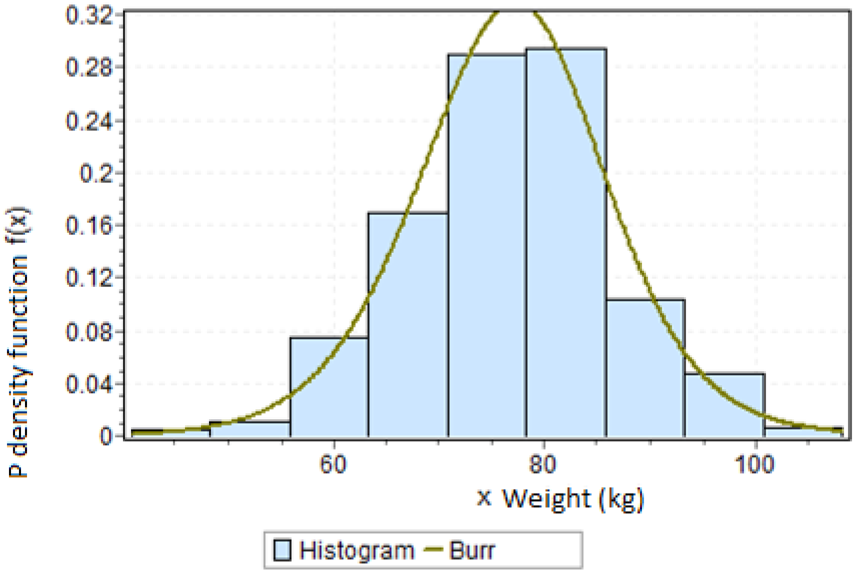

Figure 21: Distribution of patient weight for woman (Baxter, 2004)

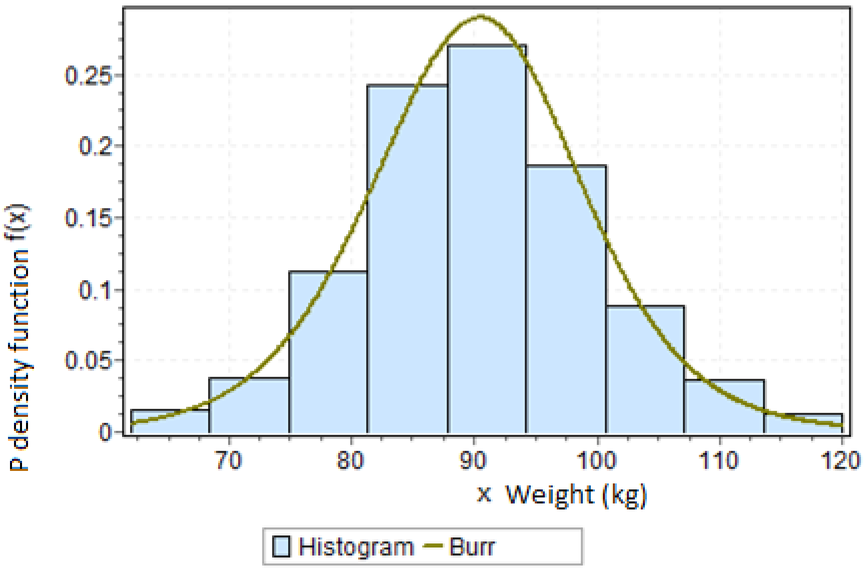

Figure 22: Distribution of patient weight for men (Baxter, 2004)

It can be noted that on average men are heavier than woman, which is a realistic assumption. Height is the next variable to be added and according to Doctor Halls the relation of average length to age for male and female are (Moose and Doc, 2016):

Woman		Men	
Age (years)	Height (m)	Age (years)	Height (m)
20 – 30	1.778	20 - 30	1.642
30 – 40	1.78	30 - 40	1.64
40 – 50	1.776	40 - 50	1.63
50 – 60	1.762	50 - 60	1.625
60 – 70	1.42	60 - 70	1.6
70 – 80	1.72	70 - 80	1.58

Table 2: relation of age to average height for men and woman

The random values that were attributed to the patients are shown in Figures 23 and 24:

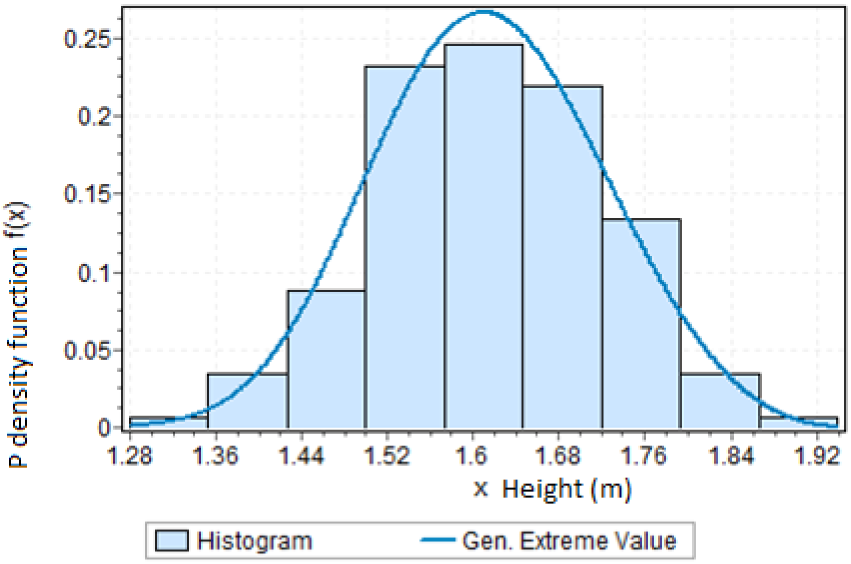

Figure 23: Distribution of patient height for woman (Baxter, 2004)

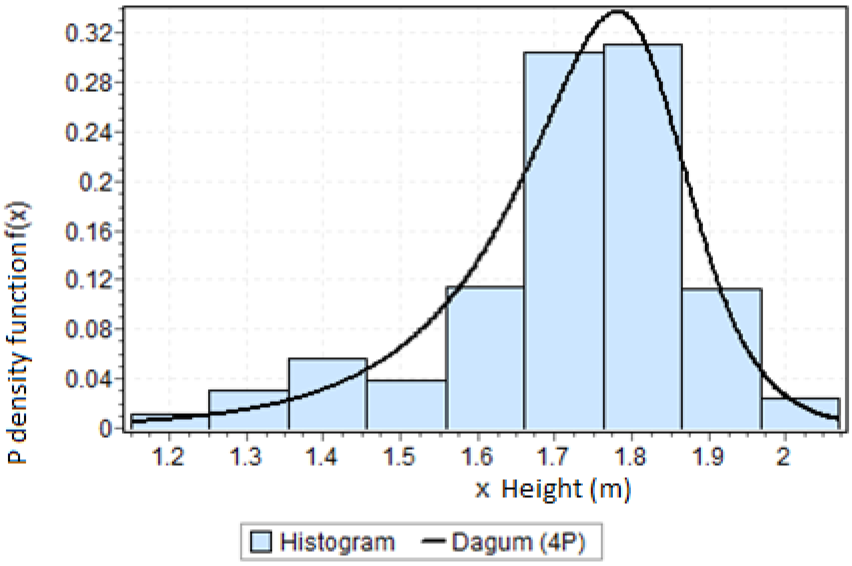

Figure 24: Distribution of patient height for men (Baxter, 2004)

As expected, on average men are taller than woman, but both sets display a rise and fall in patient height as they grow older.

The next association to be made was the classes. There are three classes and each one represents the "health state" that the patient finds him or herself in. Class one represents the healthiest patient that reacted well to the anaesthesia during an operation. Class two represents a patients that is neither healthy nor at risk. These patients can quickly become critical or fall back into the safe regions were the doctor would like them to be. Obviously, class three is the most dangerous patients. They are at-risk patients that are either near death or dying. Body mass index (BMI) was used to attribute classes based on weight and height and because age is already connected to both height and weight, all the variables were taken into account to attribute the classes. There are many other types of indices out there similar to BMI, all with their respective flaws. BMI is no exception and its biggest flaw is that it cannot differentiate between body fat and body muscle. Thus a body builder who has very little body fat, but whose muscles weigh a great deal will be seen as an obese person. BMI was used as it is a fairly common and well known index and relating the weight and height to the index is easy. The formula for BMI is follows:

$$BMI = \frac{weight\ (kg)}{[Height\ (m)]^2} \qquad (1)$$

Formula (1) was used to relate the existing patient information, calculate their BMI and then assign a class based on if the patient had a normal body composition or an overweight body composition. The assumption made here was that heavily overweight or underweight patients would react poorly to anaesthesia and thus be categorised as either class 2 or class 3 patients, whereas a normal weight composition would more likely be a class 1 patient. Table 3 shows what the BMI number mean (Bmi3d.com, 2016):

Meaning of BMI index	BMI index
Underweight	≥ 19
Normal weight	19–24,9
Overweight	25–29,9
Obesity level I	30–34,9
Obesity level II	35–39,9
Obesity level III	≥ 40

Table 3: Meaning of each body mass index number

Table 4 shows how the classes were attributed to the different BMI numbers:

BMI	Class
10 – 20	2,3
20 – 25	1
25 – 30	1,2
30 – 35	1,2,3
35 – 40	2,3
≥ 40	3

Table 4: Relation of body mass index to classes

In Table 4, for the BMI bracket of 30 – 35 a class of 1, 2 and 3 were given. The assumption made here is that patients of obesity level 1 (Table 3) could be any of the three classes and as such a class was randomly allocated to the patient. A BMI of 20 to 25, which corresponds to a normal weight (the assumption made here was that normal body to weight distribution would represent a healthy patient) could thus only be a class 1 healthy patient. Likewise patients with BMI's over 40 would be categorised as the most obese patients. The chance that these patients react badly to the anaesthesia is much higher and thus the assumption was made that they could only represent a class 3 patient. The resulting distributions of classes for the male and female patients are shown in Figure25 and 26.

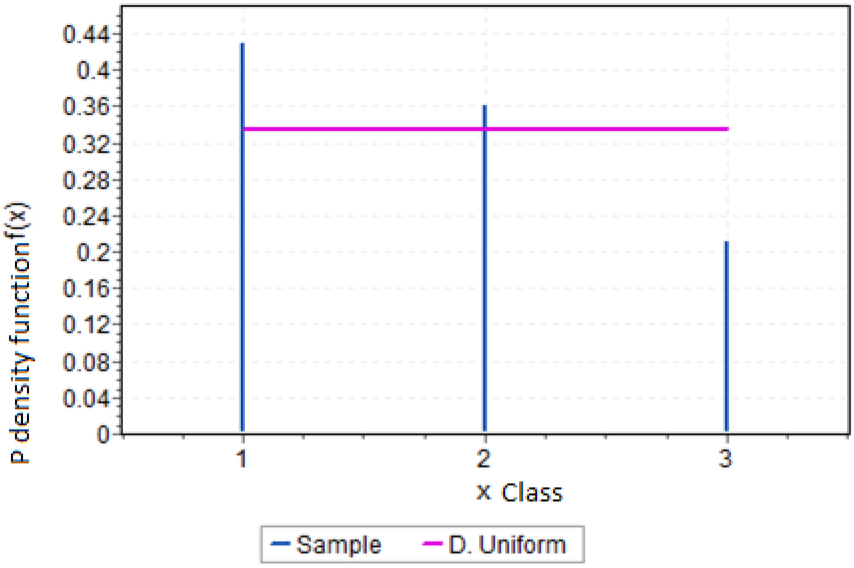

Figure 25: Distribution of classes for the woman patients

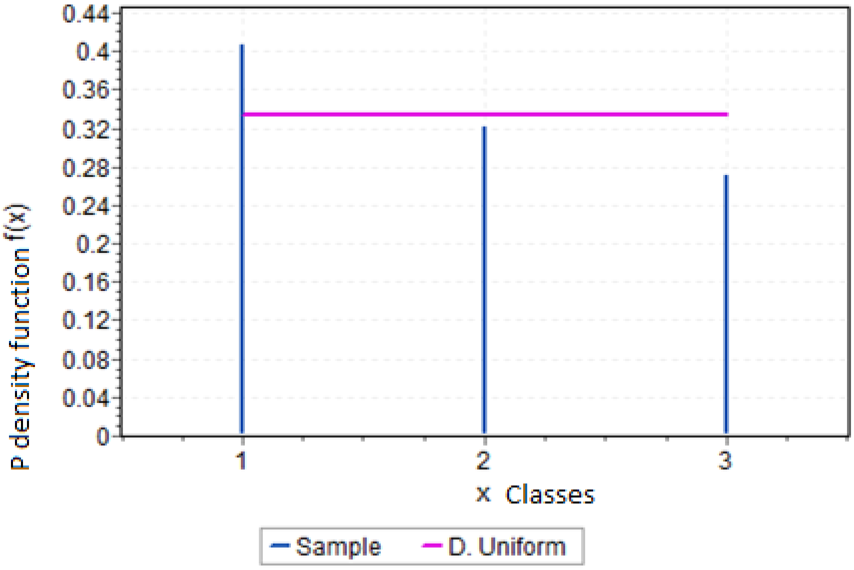

Figure 26: Distribution of classes for the men patients

There are more class 1 patients, followed by class 2 patients with the least being class 3 patients as can be seen for both the male and female patients. This makes intuitive sense as Table 4 attributed more class 1s in the middle of the BMI regions of 20 to 35 and as we have seen from the ages, weights and heights, most of the patients lie in the middle regions. Just as a normal distribution would be.

The next variable to be added was heart rate (HR), which is measured in heart beats per minute. The resting heart rate was used to attribute average heart rates to patients via age and classes. Resting heart represent the number of times a person's heart beats per minute while at complete rest (Verywell, 2016). Even though the resting rate is used more commonly for sport and exercise the assumption made here was that the patient will be asleep and their heart rate would be similar to that of a resting heart rate of a person not under anaesthesia. Table 5 represents how the heart rates were allocated based on age and class (Sportsscience.co, 2016):

HR	Age 18 – 25		Age 26 – 35		Age 36 – 45		Age 46 – 55		Age 56 – 65		Age ≥ 66	
	Class	Des	Class	Des	Class	Des	Class	Des	Class	Des	Class	Des
49		At		At		At		At		At		At
50		At		At		At		At		At		At
51		At		At		At		At		At		At
52		At		At		At		At		At		At
53		At		At		At		At		At		At
54		At		At		At		At		At		At
55	1	At	1	E	1	At		At	1	At	1	At
56		E		E		At	1	At		At		E
57		E		E		E		At		E		E
58		E		E		E		E		E		E
59		E		E		E		E		E		E
60		E		E		E		E		E		E
61		E		E		E		E		E		E
62		G		G		E		E		G		G
63		G		G		G		E		G		G
64		G		G		G		G		G		G
65		G		G		G		G		G		G
66		AA		AA		G		G		G		AA
67		AA		AA		AA		G		G		AA
68	2	AA	2	AA		AA		AA	2	AA	2	AA
69		AA		AA	2	AA		AA		AA		AA
70		Av		AA		AA	2	AA		AA		Av
71		Av		Av		Av		AA		AA		Av
72		Av		Av		Av		Av		Av		Av
73		Av		Av		Av		Av		Av		Av
74		BA		Av		Av		Av		Av		BA
75		BA		BA		Av		Av		Av		BA
76		BA		BA		BA		Av		BA		BA
77		BA		BA		BA		BA		BA		BA
78		BA		BA		BA		BA		BA		BA
79	3	BA	3	BA		BA		BA		BA	3	BA
80		BA		BA	3	BA	3	BA	3	BA		P
81		BA		BA		BA		BA		BA		P
82		P		P		BA		BA		P		P
83		P		P		P		BA		P		P
84		P		P		P		P		P		P

Key	Key description
HR	Hear Rate
Des	Description
At	Athlete heart rate
E	Excellent heart rate
G	Good heart rate
AA	Above Average heart rate
Av	Average heart rate
BA	Below Average heart rate
P	Poor heart rate

Table 5: Relation of resting heart rate to class and age

For Table 5: if a patient has an age of 22 and has already been given a class 1 label then a heart rate of 49 to 61 could be randomly assigned to the patient. Otherwise if the patient of 22 years of age had a class 3 label then a heart rate of 74 to 84 would randomly be assigned to the patient. The actual heart rate distributions for both the male and female can be found in Appendix E Figure 39 and 40.

The last two variables to be added was the systolic and diastolic blood pressure. Blood pressure is always represented as one number over another (e.g. 180/70). The top number refers to the systolic blood pressure and represents the pressure in a patients arteries during contraction of the heart muscle. The bottom number then refers to diastolic blood pressure and represents a patient's blood pressure when the patient's heart muscle is between beats. These blood pressure readings are measured in millimetres of mercury (mmHg). A low blood pressure reading means the heart is not supplying the body with enough blood and a high reading means the heart is working too hard to supply the body with enough oxygenated blood (Healthline, 2016). According to blood pressure UK the different kinds of blood pressure readings for adult are (Bloodpressureuk.org, 2016):

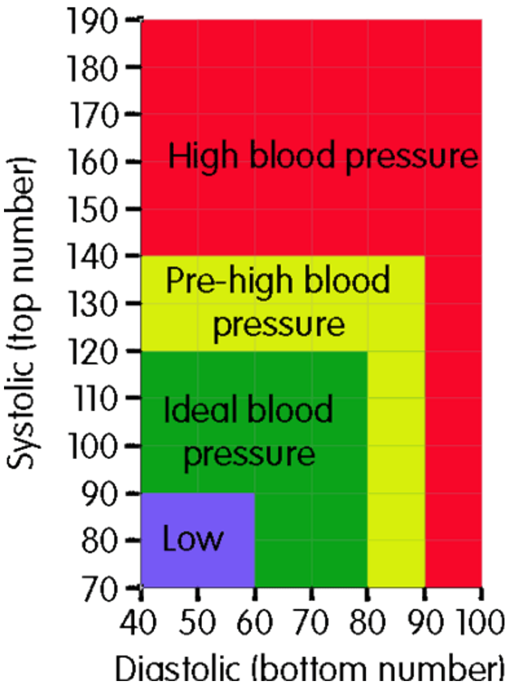

Figure 27: Systolic and Diastolic blood pressure ranges for adults (Healthline, 2016)

However these values mean nothing if they cannot be related to age. Figure 28 relates the average BP as well as the minimum and maximum systolic and diastolic pressures according to age groups (Lifescript.com, 1995):

2015 BLOOD Pressure BY AGE

lifescript

AGE	Average	Minimum	Maximum
14-19	117/77	105/73	120/81
20-24	120/79	108/75	132/83
25-29	121/80	109/76	133/84
30-34	122/81	110/77	134/85
35-39	123/82	111/78	135/86
40-44	125/83	112/79	137/87
45-49	127/84	115/80	139/88
50-54	129/85	116/81	142/89
55-59	131/86	118/82	144/90

Figure 28: Blood pressure values according to age (Lifescript.com, 1995)

The previous two figures were used to relate the class, age and gender of patients to give them their specific systolic and diastolic blood pressure, as shown in Table 6:

Systolic blood pressure ranges			
Age:	20 – 25	Age:	25 - 30
Class	Pressure values	Class	Pressure values
Class 1	108 – 132	Class 1	109 – 133
Class 2	132 – 152	Class 2	133 – 153
Class 3 Males	152 – 190	Class 3 Males	153 – 190
Class 3 Females	70 - 108	Class 3 Females	70 - 109
Age:	30 – 35	Age:	35 - 40
Class	Pressure values	Class	Pressure values
Class 1	110 – 134	Class 1	111 – 135
Class 2	134 – 154	Class 2	135 – 155
Class 3 Males	154 – 190	Class 3 Males	155 – 190
Class 3 Females	70 – 110	Class 3 Females	70 - 111
Age:	40 – 45	Age:	45 - 50
Class	Pressure values	Class	Pressure values
Class 1	112 - 137	Class 1	115 – 139
Class 2	137 – 157	Class 2	139 – 159
Class 3 Males	157 – 190	Class 3 Males	159 – 190
Class 3 Females	70 - 112	Class 3 Females	70 - 115
Age:	50 – 55	Age:	≥ 55
Class	Pressure values	Class	Pressure values
Class 1	116 – 142	Class 1	118 – 144
Class 2	142 – 162	Class 2	144 – 164
Class 3 Males	162 – 190	Class 3 Males	164 – 190
Class 3 Females	70 - 116	Class 3 Females	70 - 118
Diastolic blood pressure values			
Age:	20 – 25	Age:	25 - 30
Class	Pressure values	Class	Pressure values
Class 1	75 – 83	Class 1	76 – 84
Class 2	83 – 93	Class 2	84 – 94
Class 3 Males	93 – 103	Class 3 Males	94 – 104
Class 3 Females	40 - 75	Class 3 Females	40 - 76
Age:	30 - 35	Age:	35 – 40
Class	Pressure values	Class	Pressure values
Class 1	77 – 85	Class 1	78 – 86
Class 2	85 – 95	Class 2	86 – 96
Class 3 Males	95 – 105	Class 3 Males	96 – 106
Class 3 Females	40 - 77	Class 3 Females	40 - 78
Age:	40 - 45	Age:	45 - 50
Class	Pressure values	Class	Pressure values
Class 1	79 – 87	Class 1	80 – 88
Class 2	87 – 97	Class 2	88 – 98
Class 3 Males	97 – 107	Class 3 Males	98 – 108
Class 3 Females	40 - 79	Class 3 Females	40 - 80
Age:	50 - 55	Age:	≥ 55
Class	Pressure values	Class	Pressure values
Class 1	81 – 89	Class 1	82 – 90
Class 2	89 – 99	Class 2	90 – 100
Class 3 Males	99 – 109	Class 3 Males	100 – 110
Class 3 Females	40 - 81	Class 3 Females	40 - 82

Table 6: Systolic and diastolic pressure values related to age, gender and class

From Table 6 it can be seen that a patient of 23 years of age who is a class one patient, will have a systolic pressure lying between 110 and 134. It should also be noted that class 3 patients are divided into male and female patients. The male values will always exhibit the highest blood pressure and the female the lowest blood pressure. Usually men have a higher blood pressure than woman before the age of 50. After that it switches. However for the sake of calculations it was kept as men of class 3 health will always have higher blood pressure than woman of class 3 health (Lifescript.com, 2016). In Appendix E Figures 37 to 40 shows the distributions of systolic and diastolic pressures for the patients in the data set.

5. Solution

In the previous section the data set was constructed. In this section the data set will be analysed by a number of ML algorithms and the models adjusted for accuracy. At first the data set was run through all of *Weka*'s on board algorithms, without adjusting the algorithms to obtain an average base line accuracy. Refer to Table 7 for the results.

Classifier type	Algorithm	Accuracy (%)
Bayesian	BayesNet	99.5
	NaiveBayes	99.5
	NaiveBayesUpdateable	99.5
Functions	Logistic	97.3
	MultilayerPerceptron	99.7
	SimpleLogistic	97
	SMO	97.3
Lazy	IBK	100
	KStar	99.7
	LWL	80.3
Meta	AdaBoostM1	95.3
	AttributeSelectedClassifier	98.7
	Bagging	99.1
	ClassificationViaRegression	99.3
	CVParameterSelectio	41.7
	FilteredClassifier	99
	IterativeClassifierOptimizer	99.4
	LogitBoost	99.4
	MultiClassClassifier	97.2
	MultiClassClassifierUpdateable	76.3
	RandomCommittee	99.6
	RandomizableFilteredClassifier	99.6
	RandomSubSpace	99.4
	Stacking	41.7
	Vote	41.7
	WeightedInstancesHandlerWrapper	41.7
Rules	DecisionTable	98.3
	JRip	98.6
	OneR	95.5
	PART	99.8
	ZeroR	41.7
Trees	DecisionStump	73.7
	HoeffdingTree	99.2
	J48	98.9

	LMT	99.6
	RandomForest	99.6
	RandomTree	98.5
	REPTree	98.1

Table 7: First algorithm run accuracy through most of Weka's algorithms

The algorithms used in Table 7 in shortly described in Table 8:

Classifier type	**Algorithm**	***Weka* description of algorithm**
Bayesian	BayesNet	"Bayes Network learning using various search algorithms and quality measures. Base class for a Bayes Network classifier. Provides data-structures (network structure, conditional probability distributions, etc.) and facilities common to Bayes Network learning algorithms like K2 and B."
	NaiveBayes	" Class for a Naive Bayes classifier using estimator classes. Numeric estimator precision values are chosen based on analysis of the training data. For this reason, this classifier is not an Updateable Classifier (which in typical usage are initialized with zero training instances)."
	NaiveBayesUpdateable	"Class for a Naive Bayes classifier using estimator classes. This is the updateable version of NaiveBayes. This classifier will use a default precision of 0.1 for numeric attributes when build-Classifier is called with zero training instances."
Functions	Logistic	"Class for building and using a multinomial logistic regression model with a ridge estimator. There are some modifications, however, compared to the paper of leCessie and van Houwelingen(1992). Although the original Logistic Regression does not deal with instance weights, we modify the algorithm a little bit to handle the instance weights."
	MultilayerPerceptron	"A Classifier that uses backpropagation to classify instances. This network can be built by hand, created by an algorithm or both. The network can also be monitored and modified during training time. The nodes in this network are all sigmoid (except for when the class is numeric in which case the output nodes become unthresholded linear units)."
	SimpleLogistic	"Classifier for building linear logistic regression models. LogitBoost with

		simple regression functions as base learners is used for fitting the logistic models. The optimal number of LogitBoost iterations to perform is cross-validated, which leads to automatic attribute selection. For more information see: Niels Landwehr, Mark Hall, Eibe Frank (2005). Logistic Model Trees.”
	SMO	“Implements John Platt's sequential minimal optimization algorithm for training a support vector classifier.This implementation globally replaces all missing values and transforms nominal attributes into binary ones. It also normalizes all attributes by default. (In that case the coefficients in the output are based on the normalized data, not the original data --- this is important for interpreting the classifier.) Multi-class problems are solved using pairwise classification (i.e. 1-vs-1). To obtain proper probability estimates, use the option that fits calibration models to the outputs of the support vector machine. In the multi-class case, the predicted probabilities are coupled using Hastie and Tibshirani's pairwise coupling method.”
Lazy	IBK	“K-nearest neighbours classifier. Can select appropriate value of K based on cross-validation. Can also do distance weighting.”
	KStar	“KStar is an instance-based classifier, that is, the class of a test instance is based upon the class of those training instances similar to it, as determined by some similarity function. It differs from other instance-based learners in that it uses an entropy-based distance function.”
	LWL	“Locally weighted learning. Uses an instance-based algorithm to assign instance weights which are then used by a specified Weighted Instances Handler. Can do classification (e.g. using naive Bayes) or regression (e.g. using linear regression).”
Meta	AdaBoostM1	“Class for boosting a nominal class classifier using the Adaboost M1 method. Only nominal class problems can be tackled. Often dramatically

		improves performance, but sometimes over-fits."
	AttributeSelectedClassifier	"Dimensionality of training and test data is reduced by attribute selection before being passed on to a classifier."
	Bagging	"Class for bagging a classifier to reduce variance. Can do classification and regression depending on the base learner."
	ClassificationViaRegression	"Class for doing classification using regression methods. Class is binarized and one regression model is built for each class value."
	CVParameterSelectio	"Class for performing parameter selection by cross-validation for any classifier."
	FilteredClassifier	"Class for running an arbitrary classifier on data that has been passed through an arbitrary filter. Like the classifier, the structure of the filter is based exclusively on the training data and test instances will be processed by the filter without changing their structure."
	IterativeClassifierOptimizer	"Optimizes the number of iterations of the given iterative classifier using cross-validation."
	LogitBoost	"Class for performing additive logistic regression. This class performs classification using a regression scheme as the base learner, and can handle multi-class problems."
	MultiClassClassifier	"A meta-classifier for handling multi-class datasets with 2-class classifiers. This classifier is also capable of applying error correcting output codes for increased accuracy."
	MultiClassClassifierUpdateable	"A meta-classifier for handling multi-class datasets with 2-class classifiers. This classifier is also capable of applying error correcting output codes for increased accuracy. The base classifier must be an updateable classifier."
	RandomCommittee	"Class for building an ensemble of randomizable base classifiers. Each base classifiers is built using a different random number seed (but based on the same data). The final prediction is a straight average of the predictions generated by the individual base classifiers."

	RandomizableFilteredClassifier	"A simple variant of the FilteredClassifier that implements the Randomizable interface, useful for building ensemble classifiers using the RandomCommittee meta learner. It requires that either the filter or the base learner implement the Randomizable interface."
	RandomSubSpace	"This method constructs a decision tree based classifier that maintains the highest accuracy on training data and improves on generalization accuracy as it grows in complexity. The classifier consists of multiple trees constructed systematically by pseudo-randomly selecting subsets of components of the feature vector, that is, trees constructed in randomly chosen subspaces."
	Stacking	"Combines several classifiers using the stacking method. Can do classification or regression."
	Vote	"Class for combining classifiers. Different combinations of probability estimates for classification are available."
Rules	DecisionTable	"Class for building and using a simple decision table majority classifier."
	JRip	"This class implements a propositional rule learner, Repeated Incremental Pruning to Produce Error Reduction (RIPPER), which was proposed by William W. Cohen as an optimized version of IREP."
	OneR	"Class for building and using a 1R classifier; in other words, it uses the minimum-error attribute for prediction, discretizing numeric attributes."
	PART	"Class for generating a PART decision list. Uses separate-and-conquer. Builds a partial C4.5 decision tree in each iteration and makes the "best" leaf into a rule."
	ZeroR	"Class for building and using a 0-R classifier. Predicts the mean (for a numeric class) or the mode (for a nominal class)."
Trees	DecisionStump	"Class for building and using a decision stump. Usually used in conjunction with a boosting algorithm. Does regression (based on mean-squared error) or classification (based on entropy). Missing values is treated as a separate value."

	HoeffdingTree	“A Hoeffding tree (VFDT) is an incremental, anytime decision tree induction algorithm that is capable of learning from massive data streams, assuming that the distribution generating examples does not change over time. Hoeffding trees exploit the fact that a small sample can often be enough to choose an optimal splitting attribute. This idea is supported mathematically by the Hoeffding bound, which quantifies the number of observations (in our case, examples) needed to estimate some statistics within a prescribed precision (in our case, the goodness of an attribute). A theoretically appealing feature of Hoeffding Trees not shared by other incremental decision tree learners is that it has sound guarantees of performance. Using the Hoeffding bound one can show that its output is asymptotically nearly identical to that of a non-incremental learner using infinitely many examples.”
	J48	“Class for generating a pruned or unpruned C4.5 decision tree.”
	LMT	“Classifier for building 'logistic model trees', which are classification trees with logistic regression functions at the leaves. The algorithm can deal with binary and multi-class target variables, numeric and nominal attributes and missing values.”
	RandomForest	“Class for constructing a forest of random trees.”
	RandomTree	“Class for constructing a tree that considers K randomly chosen attributes at each node. Performs no pruning. Also has an option to allow estimation of class probabilities (or target mean in the regression case) based on a hold-out set (back-fitting)”
	REPTree	“Fast decision tree learner. Builds a decision/regression tree using information gain/variance and prunes it using reduced-error pruning (with back-fitting). Only sorts values for numeric attributes once. Missing values are dealt with by splitting the corresponding instances into pieces (i.e. as in C4.5).”

Table 8: Short description of Weka's algorithms (Wiki.pentaho.com, 2016)

Most of these algorithms serve as reference to the reader of all the types of algorithms that can be used. It also serves as a raw first run that equated to an average accuracy of 89.48% (Table 7), which will serve as the baseline accuracy. Any accuracy significantly lower than this means there is either a problem somewhere, the algorithm is not adjusted correctly or the model is not suited to this type of data. An abnormally high accuracy usually stems from overfitting. Overfitting is when a model is so accurately adjusted to the data that it can perfectly predict any current data point that falls within its bounds. The problem is that if new data points (which is the interest for ML practitioners) that have to be identified, fall outside of the algorithms search space, then the model will not be able to predict the new point because the search space is too tightly defined around the original data set.

The four algorithms of choice that this project focussed on was K-nearest neighbour (IBK in *Weka*), neural networks (Multilayer perceptron's in *Weka*), logistic regression model (logistic in *Weka*) and finally a decision tree (J48 in *Weka*). Table 9 shows the final model results after the models have been adjusted for maximum accuracy:

Evaluation Criteria	Classifiers			
	IBK	J48	Log	MLP
Time to build the model (sec)	0	0.01	0.13	2.26
Correctly classified instances	983	989	978	997
Incorrectly classified instances	17	11	22	3
Prediction accuracy (%)	98.3	98.9	97.8	99.7
Model complexity (1-5) 5 being the highest	1	3	3	5
IBK	K-nearest neighbour			
J48	Decision tree			
Log	Logistic regression			
MLP	Multilayer perceptron			

Table 9: Predictive performance of the classifier (Hall et al., 2016)

As can be seen from the results, Multilayer perceptron has the highest accuracy followed by J48, K-nearest neighbour and lastly logistic regression. Multilayer perceptron might have the highest prediction accuracy, but the run is almost 1700 times longer than that of the logistic regression algorithm which was found to be the third slowest. In terms of complexity the multilayer perceptron is the most complex out of the four algorithms with j48 and logistic algorithms being average and k-nearest neighbour having the simplest built. In terms of big data this is very important because complex and bulky algorithms like the multilayer perceptron run slower than simple algorithms like the k-nearest neighbour. For implementation purposes if the model has to instantly give feedback on a continual basis then the simpler model would be a better choice. It should also be noted that the high prediction accuracy is accredited to the fact that, although complicated, a set number of rules were pre-built into data. Real life patient data will exhibit much more chaotic and non-linear data. Since the multilayer perceptron had the highest prediction accuracy out of all of the algorithms, it is chosen as the solution model and will be described more in detail. We are primarily interested in higher predication accuracy models because patients' lives are at risk. Figure 29 is a physical representation of the network structure.

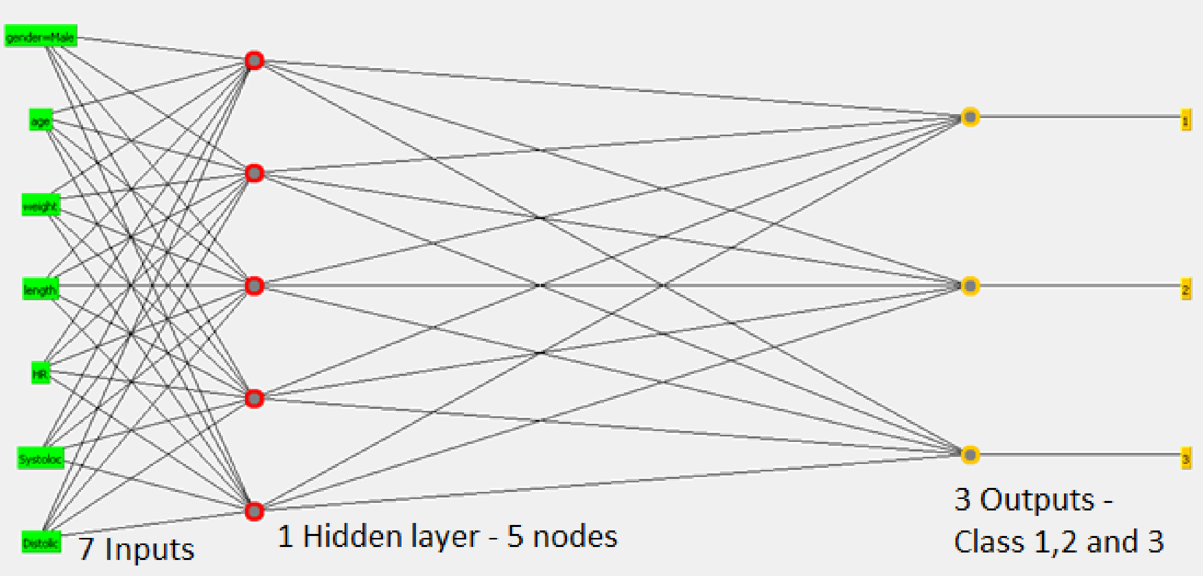

Figure 29: Multilayer neural network design (Hall et al., 2016)

As can be seen from the figure, there are 7 inputs that represents the variables that were created in the data section. This network features 1 hidden layer with 5 nodes. A hidden layer adds more learning weights (or "neurons") to the network that will be able to learn more. The more nodes are added the heavier the computation and the longer the run time of the model. The learning rate is 0.1, which is how quickly the network "learns". Learning rate dictates how much a weight is adjusted when learning. A large learning rate mean the network learns faster, but not necessarily better. The momentum was set to 0.2. Momentum is an extra term added to the weights that allow the change to persist for a number of cycles.

6. Validation and Verification

In terms of verification, there is extensive proof that the model can be verified. From the literature study it was shown that many research institutes used *Weka* as it can be used for both industry and research purposes.

Next a discussion will follow about whether the algorithms used can be verified by the data itself. Table 10 shows 4 patient instances from the built data set.

Number	Gender	Age	Weight (kg)	Length (m)	HR (bmp)	Systolic (mmHg)	Diastolic (mmHg)	Class
1	Female	53	66.2	1.57	53	119	83	1
2	Female	54	98.41	1.64	80	99	71	3
3	Male	54	95.16	1.78	74	149	92	2
4	Male	22	88.81	1.73	70	145	83	2

Table 10: Four patient instances used for verification

It should be noted that these four patient instances have four different colours. These four different colours correspond to the four different paths traced out in Figure 29. Number 1 (from Table 10) will now be explained with regards to Figure 30. At the very top heart rate has two paths to follow. Patient number 1 in this instance has a heart rate of 53 which Is lower than 62, thus the left path is followed. There the branch considers the systolic attribute. Patient number 1 has a systolic pressure of 119 which is larger than 143, thus the left branch is taken. According to the tree this patient has to have a class of 1. Matching up with the data that was extracted it can be seen from Table 10 that patient number 1 indeed has a class of 1. This can be done for the other 3 patients as well and their respective logical paths are shown in the decision tree. The J48 only had 11 incorrectly classified instances, which means only 11 patients classes will be incorrectly guessed by this model.

As the J48 algorithm was the second best algorithm in terms of prediction accuracy, it serves as a fair verification for all the other models as well.

Lastly in terms of validation the student obtained the professional opinion of a Doctor from the medical department of the University of Pretoria. The doctor suggested that it would be a feasible project as long as adequate real life data were to be found.

This project has succeeded in two thirds of its initial project aims. The initial aim of the project was to investigate the use of machine learning for supporting anaesthesiologists to predict and detect patient issues. Firstly, with this report it was proven that machine learning definitely should be considered for future implementations of this type of project. Secondly, this project succeeded in terms of prediction and accuracy as proven in the previous two sections. However, it should be noted that custom built patient data was used and not real data. Real life patient data will be much more volatile and will definitely increase the variability of the data and decrease the accuracy of the algorithms. The prediction that the algorithms can actually do is that of validating the current patient status, thus giving the anaesthesiologist a second opinion. This prediction does not refer to patient health status N-minutes from the current situation.

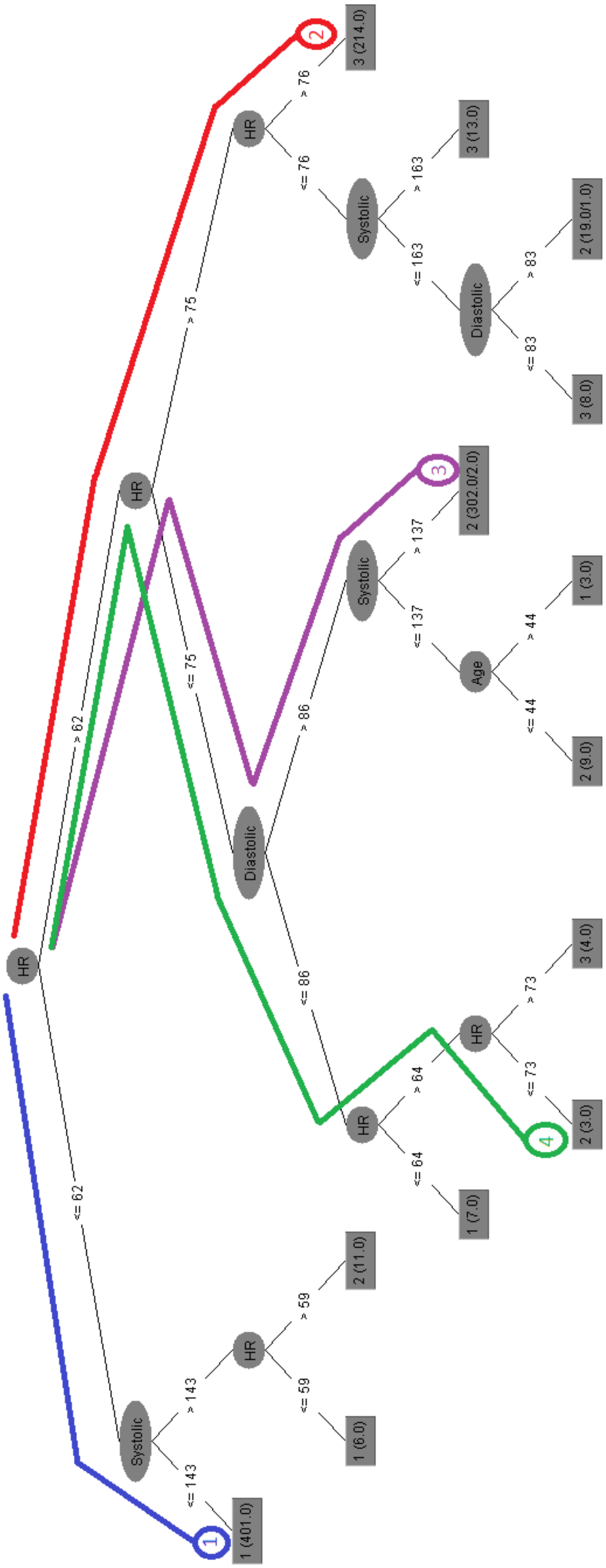

Figure 30: J48 decision tree used for verification (Hall et al., 2016)

Lastly a sensitivity analysis was done to see how responsive the model parameters are. The algorithm used for the sensitivity analysis was the multilayer perceptron, as its model had the highest accuracy, the parameters that was taken into account for the sensitivity analysis were the number of hidden layers, the learning rate and the momentum. Table 11 shows the analysis:

1st Hidden layer (k-nodes)	0	1	2	3	4	5	6	7	8	9	10
Accuracy (%)	86.8	92.6	97.6	99.6	99.6	99.7	99.7	99.7	99.7	99.7	99.7
2nd hidden layer (k-nodes, 1st layer = 5)	0	1	2	3	4	5	6	7	8	9	10
Accuracy (%)	99.7	99.5	99.6	99.6	99.6	99.6	99.6	99.6	99.6	99.6	99.6
3rd hidden layer (k-nodes, 1st layer = 5, 2nd layer = 2)	0	1	2	3	4	5	6	7	8	9	10
Accuracy (%)	99.6	99.4	99.6	99.6	99.6	99.6	99.6	99.6	99.6	99.6	99.6
Learning rate (small increments)	0.01	0.02	0.03	0.04	0.05	0.06	0.07	0.08	0.09	0.1	0.11
Accuracy (%)	98.2	99.6	99.5	99.5	99.6	99.6	99.6	99.6	99.6	99.7	99.7
Learning rate (large increments)	0.00001	0.0001	0.001	0.01	0.1	1	10	100	1000	10000	100000
Accuracy (%)	41.7	41.7	95.6	98.2	99.7	99.7	99.7	99.7	99.7	99.7	99.7
Momentum	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
Accuracy (%)	99.6	99.6	99.7	99.7	99.7	99.7	99.7	99.7	99.7	99.6	45.5

Table 11: Sensitivity analysis for the neural network model (Hall et al., 2016)

The analysis start out at the very top with 1 hidden layer and increasing amount of nodes. The accuracy of the model is fairly sensitive to an increment of just 1. The next parameter to be tested is the 2nd hidden layer, here the first hidden layer was kept at 5 as it achieved the highest results. No significant improvement was observed and this section was not very sensitive to change but did have longer running times as a result of adding more nodes. The next section was the third hidden layer, here the first layer was set to 5 and the second layer set to 2 (for convenience). Again no significant change was observed. In the end one hidden layer with only 5 nodes proved to be effective enough for this data set. A large incremental change in learning rate had a larger effect on the accuracy up to about 0.01, from there only small incremental changes could be observed to have an effect. Lastly a change in momentum did not have a large effect on the accuracy of the model. In the end the parameters having the largest effect on the model accuracy were hidden layers (up to certain extent) and learning rate.

7. Proposed implementation and recommendations

As was briefly mentioned in the previous section, the algorithm will be used to track real time the current health status of the patient or class the patient's falls in. This has the benefit that the doctor can make his/her own observation and conclusion and if they feel they need a second opinion quickly, especially in cases where there is little to no patient information, they can consult with and compare with the algorithm. Although the neural network far outmatched the rest of the algorithms in terms of prediction accuracy it was also much slower than any of the other algorithms.

Boosting the neural network and adjusting it with the help of and in conjunction with other algorithms might take the load of off the model building time. Only live testing with continuously running patient variables will provide a clear picture as to how slow the algorithms updating time would be in real life situations.

For future studies and research projects, it is recommended that large quantities of real life patient data be gathered. For future reference, collecting the data is difficult, especially in South Africa. Here all patient data is still captured via paper and not saved in any kind of electronic format. The amount, detail and quality of patient data being captured also varies from hospital to hospital. One hospital might be content with only the bare basic variables like: age, heart rate, systolic and diastolic blood pressures and mean blood pressure. However, another hospital, because of newer machines, might use significantly more detailed variables as was shown in the printout form of Figure 17.

It was also briefly mentioned in the previous section that real life patient data will be much more volatile and thus the variance of the data will increase and the prediction accuracy of the model decrease, because the algorithms have a harder time finding linearly separable rules to fully divide and describe the data by. Real life patient data should have much more jumbled up and non-linear planes. Therefore it is advised for future projects that smaller sample spaces be considered; not smaller data sets. With this it is meant that a future project should focus on, for example, an age range of 20 to 30 years of age and patients with much more similar injuries. It will be much easier to find correlations in the data with a 10 year age gap in the patient data set than one with an age range of 20 to 80 years old. Such a data set in real life would especially increase the variability of the data. Thus the larger the sample size being considered and the more variables added to the data set the more patients are needed to find correlations in the data.

Finally, future projects should consider an algorithm or algorithms that can span the entire operation range of pre, intra and post-operative care. Also the potential uses of forecasting should be investigated to detect future anomalies in patients and provide accurate feedback as to what will happened and how it might be prevented.

8. Conclusion

This project started off by specifying the need for machine learning to be used as a second opinion in aiding anaesthesiologists, to provide them with a second opinion when making on-the-fly decisions. The literature review discussed and proved that previous research within anaesthesiology using machine learning has been done before, just with smaller scopes and singular objectives in mind. A quick look into South Africa's medical landscape and a visit to Muelmed hospital showed that hospitals do not save patient data electronically. Initially a data set of a 100 patients were gather, but because the model accuracy were low and data sensitivity was taken into account, it was opted to intelligently design a data set containing a 1000 patients. Of the plethora of machine learning algorithms in existence it was suggested that J48 decision trees, logistic regressions models, K-nearest neighbour and neural networks might perform the best. After testing the prediction accuracies were as follows: J48 – 98.9%, Logistic – 97.8%, k-nearest neighbour – 98.3% and neural networks – 99.7%. The neural network algorithm performed the best but was also the slowest and took 2.26 seconds to build its model, which was later discussed to have future implications as the model will be used for real time classifications of patients. After using the J48 decision tree model to validate the models, it was found that the algorithms along with the software being used (*Weka*) to be accurate and suitable for the use of this project and its implementations. Unlike other research projects in this area that only focused on controlling one aspect of the anaesthesia procedure like the amount of anaesthesia administered to the patient this projects initial focus was to take as much variable into account as possible. Also unlike most of the research topics that focused on pre-operative assessment of risk this projects concluded by assessing intra-operative risk assessment, with the intent of monitoring patients risk level continuously real time while the operation is being conducted. Unlike all other projects out there this project took a macro approach to anaesthesiology to see where ML could be effectively used, thus the depth and breadth of the anaesthesia landscape covered is much larger than other projects and will serve as a catalyst for future projects. The report was concluded by stating that the model will be used as a second opinion, real time, when anaesthesiologists are making decisions on-the-fly.

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Special software citation (Weka):

Hall, M., Frank, E., Holmes, G., Pfahringer, B., Reutemann, P. and Witten, I. (2016). *The WEKA Data Mining Software: An Update*. Hamilton, New Zealand: University of Waikato.

Appendix A: Industry sponsorship form

Department of Industrial & Systems Engineering
Final Year Projects
Identification and Responsibility of Project Sponsors

Final Year Projects may be published by the University of Pretoria on *UPSpace* and may thus be freely available on the Internet. These publications portray the quality of education at the University, but they have the potential of exposing sensitive company information. It is important that both students and company representatives or sponsors are aware of such implications.

Key responsibilities of Project Sponsors:

A project sponsor is the key contact person within the company. This person should thus be able to provide guidance to the student throughout the project. The sponsor is also very likely to gain from the success of the project. The project sponsor has the following important responsibilities:

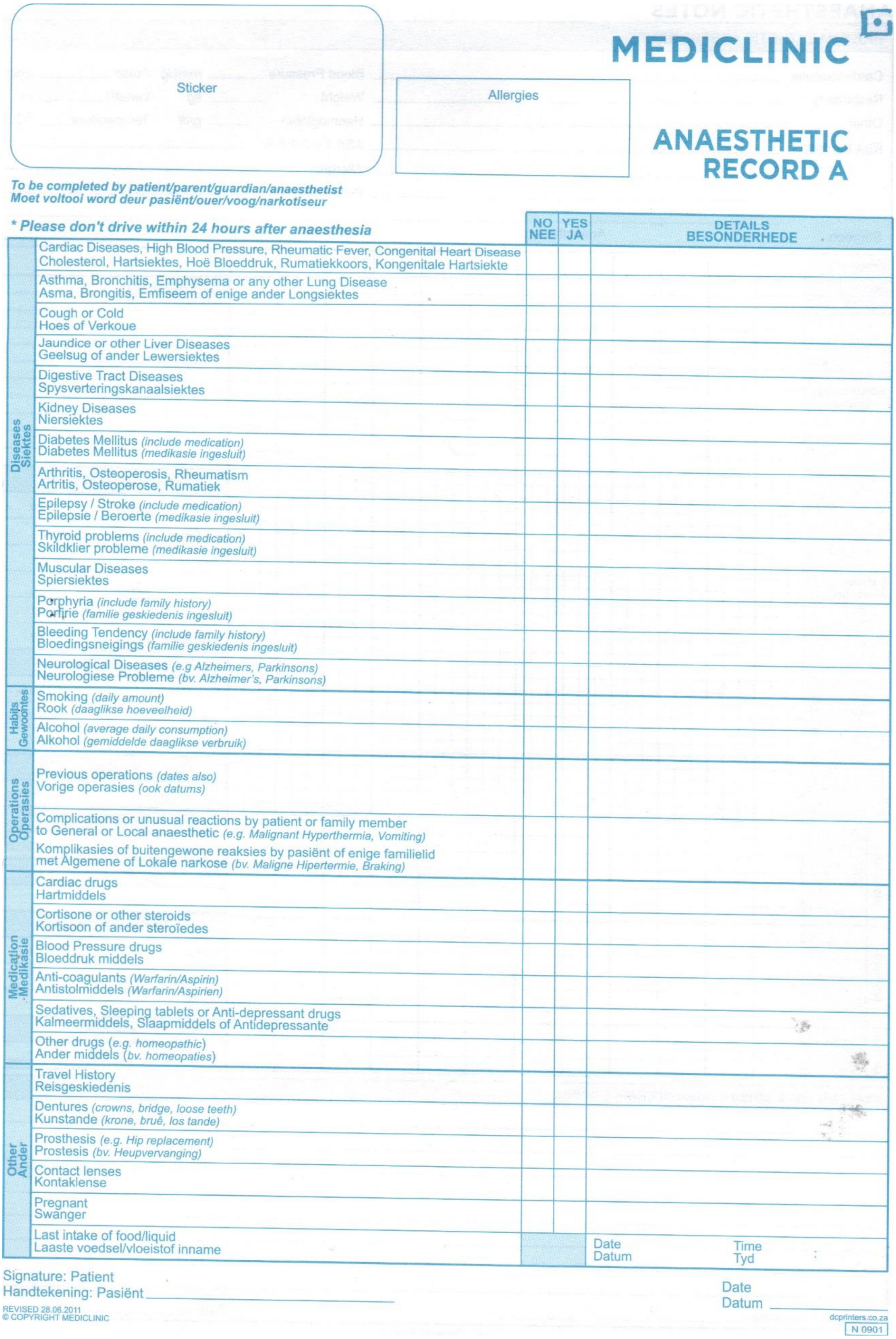
1. Confirm his/her role as project sponsor, duly authorised by the company. Multiple sponsors can be appointed, but this is not advised. The duly completed form will considered as acceptance of sponsor role.
2. Review and approve the Project Proposal, ensuring that it clearly defines the problem to be investigated by the student and that the project aim, scope, deliverables and approach is acceptable from the company's perspective.
3. Review the Final Project Report (delivered during the second semester), ensuring that information is accurate and that the solution addresses the problems and/or design requirements of the defined project.
4. Acknowledges the intended publication of the Project Report on UP Space.
5. Ensures that any sensitive, confidential information or intellectual property of the company is not disclosed in the Final Project Report.

Project Sponsor Details:

Company:	Deloitte
Project Description:	Model development to improve patient safety in the operating theatre and post OP
Student Name:	Armand
Student number:	13026322
Student Signature:	
Sponsor Name:	Andre Liebenberg
Designation:	Consultant
E-mail:	industrial.andre@gmail.com
Tel No:	
Cell No:	072 319 3278
Fax No:	
Sponsor Signature:	

Figure 31: Industry sponsorship form

Appendix B: Pre-operative records



MEDICLINIC

ANAESTHETIC RECORD A

Sticker

Allergies

To be completed by patient/parent/guardian/anaesthetist
Moet voltooi word deur pasiënt/ouer/voog/narkotiseur

*** Please don't drive within 24 hours after anaesthesia**

		NO NEE	YES JA	DETAILS BESONDERHEDE
Diseases Siektes	Cardiac Diseases, High Blood Pressure, Rheumatic Fever, Congenital Heart Disease Cholesterol, Hartsiektes, Hoë Bloeddruk, Rumatiekkoors, Kongenitale Hartsiekte			
	Asthma, Bronchitis, Emphysema or any other Lung Disease Asma, Brongitis, Emfiseem of enige ander Longsiektes			
	Cough or Cold Hoes of Verkoue			
	Jaundice or other Liver Diseases Geelsug of ander Lewersiektes			
	Digestive Tract Diseases Spysverteringskanaalsiektes			
	Kidney Diseases Niersiektes			
	Diabetes Mellitus *(include medication)* Diabetes Mellitus *(medikasie ingesluit)*			
	Arthritis, Osteoperosis, Rheumatism Artritis, Osteoperose, Rumatiek			
	Epilepsy / Stroke *(include medication)* Epilepsie / Beroerte *(medikasie ingesluit)*			
	Thyroid problems *(include medication)* Skildklier probleme *(medikasie ingesluit)*			
	Muscular Diseases Spiersiektes			
	Porphyria *(include family history)* Porfirie *(familie geskiedenis ingesluit)*			
	Bleeding Tendency *(include family history)* Bloedingsneigings *(familie geskiedenis ingesluit)*			
	Neurological Diseases *(e.g Alzheimers, Parkinsons)* Neurologiese Probleme *(bv. Alzheimer's, Parkinsons)*			
Habits Gewoontes	Smoking *(daily amount)* Rook *(daaglikse hoeveelheid)*			
	Alcohol *(average daily consumption)* Alkohol *(gemiddelde daaglikse verbruik)*			
Operations Operasies	Previous operations *(dates also)* Vorige operasies *(ook datums)*			
	Complications or unusual reactions by patient or family member to General or Local anaesthetic *(e.g. Malignant Hyperthermia, Vomiting)* Komplikasies of buitengewone reaksies by pasiënt of enige familielid met Algemene of Lokale narkose *(bv. Maligne Hipertermie, Braking)*			
Medication Medikasie	Cardiac drugs Hartmiddels			
	Cortisone or other steroids Kortisoon of ander steroïedes			
	Blood Pressure drugs Bloeddruk middels			
	Anti-coagulants *(Warfarin/Aspirin)* Antistolmiddels *(Warfarin/Aspirien)*			
	Sedatives, Sleeping tablets or Anti-depressant drugs Kalmeermiddels, Slaapmiddels of Antidepressante			
	Other drugs *(e.g. homeopathic)* Ander middels *(bv. homeopaties)*			
Other Ander	Travel History Reisgeskiedenis			
	Dentures *(crowns, bridge, loose teeth)* Kunstande *(krone, brue, los tande)*			
	Prosthesis *(e.g. Hip replacement)* Prostesis *(bv. Heupvervanging)*			
	Contact lenses Kontaklense			
	Pregnant Swanger			
	Last intake of food/liquid Laaste voedsel/vloeistof inname			Date / Datum Time / Tyd

Signature: Patient
Handtekening: Pasiënt ____________________

Date
Datum ____________

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Figure 32: Pre-operative form 1

ANAESTHETIC NOTES

PRE ANAESTHETIC ASSESSMENT

Cardiovascular ______ Blood Pressure ______ *mmHg* Pulse ______ */min*
Respiratory ______ Weight ______ *kg* Length ______ *m*
Other ______ Haemoglobin ______ *g/dl* Temperature ______ °C
Risk Factors ______ ASA 1 2 3 4 5 E ______
Allergies ______
Pre-Medication ______
Surgeon Anaesthetist Operation

Time		
Inhalation %		Inhalation Agent
$N_2O : O_2$		$N_2O : O_2$
Intravenous Drugs	1	1
	2	2
	3	3
	4	4
	5	5
	6	6
	7	7
	8	8
	9	9
Blood Pressure *mmHg*	200	
	180	
	160	
	140	
	120	
	100	
Pulse */min*	90	
	80	
	70	
	60	
	50	
	40	
	30	
Monitoring	S_aO_2	
	F_iO_2	
	Et CO_2	
	Paw	
IV Fluids		
Output	Urine	
	Blood	
	Other	

Anaesthetic Technique

Airway:	*Mask*	*L. Mask*
ET Tube:	*Oral*	*Nasal*
Rubber	*Latex*	*Plastic*
Size:	Type:	
Pack:	*Cuff*	*Topical*
Intubation:	*Easy*	*Difficult*

Intravenous Therapy

Butterfly	Cannula
Internal Jugular	Subclavian
Site:	Size:

Ventilation

Spontaneous Controlled

Circuit

T. Tube ADE C Circuit

Position

Regional Technique

Spinal
Epidural
Other

Duration

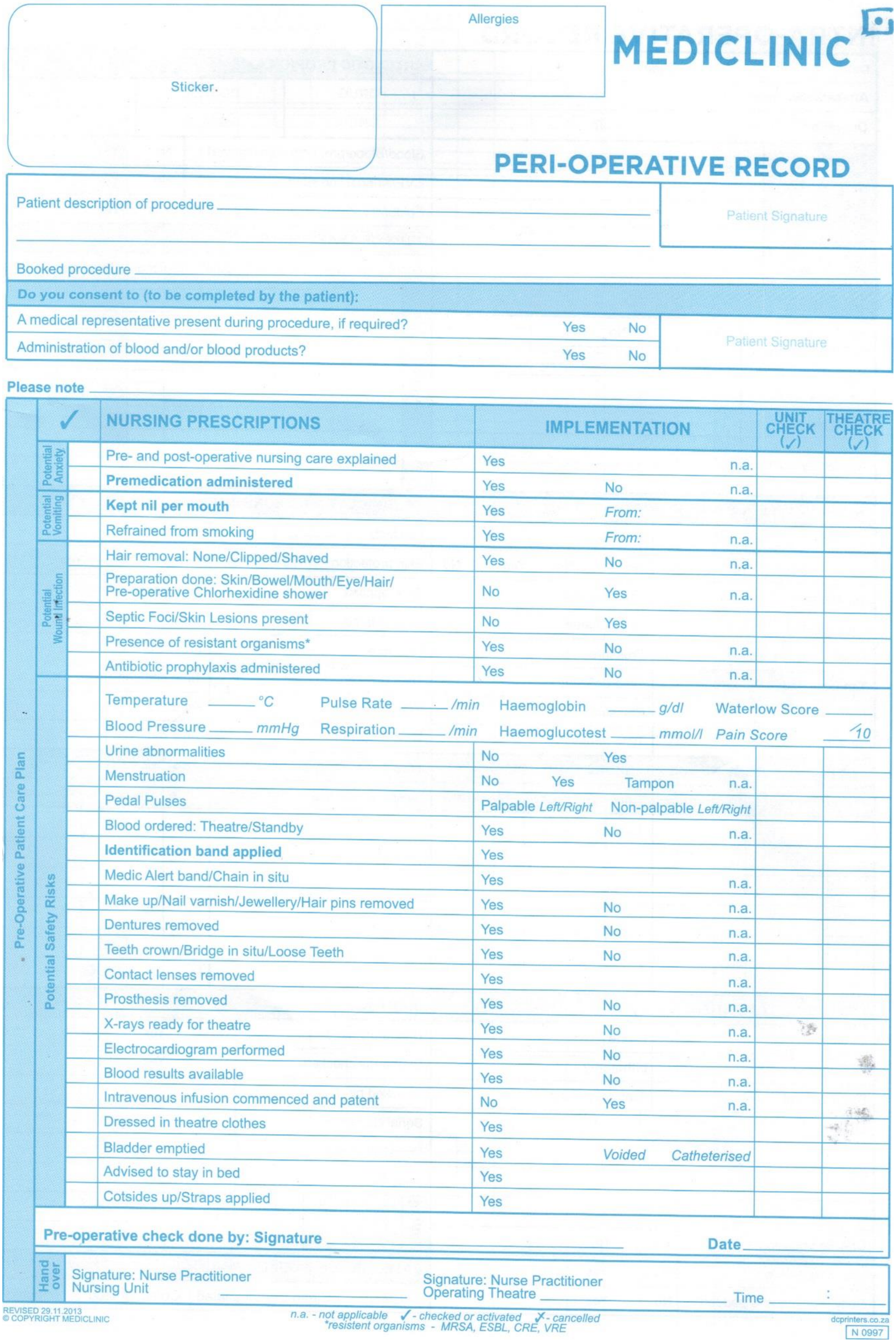
In ______ Out ______

ANAESTHETIST'S NOTES & INTRA-OPERATIVE DRUGS

Signature: Anaesthetist ______ Date: ______

Paw - Pressure Airway

Figure 33: Pre-operative form 2



MEDICLINIC

PERI-OPERATIVE RECORD

Sticker.

Allergies

Patient description of procedure ____________________

Patient Signature

Booked procedure ____________________

Do you consent to (to be completed by the patient):

A medical representative present during procedure, if required?	Yes	No	Patient Signature
Administration of blood and/or blood products?	Yes	No	

Please note ____________________

Pre-Operative Patient Care Plan

	✓	NURSING PRESCRIPTIONS	IMPLEMENTATION			UNIT CHECK (✓)	THEATRE CHECK (✓)
Potential Anxiety		Pre- and post-operative nursing care explained	Yes		n.a.		
		Premedication administered	Yes	No	n.a.		
Potential Vomiting		**Kept nil per mouth**	Yes	From:			
		Refrained from smoking	Yes	From:	n.a.		
Potential Wound Infection		Hair removal: None/Clipped/Shaved	Yes	No	n.a.		
		Preparation done: Skin/Bowel/Mouth/Eye/Hair/ Pre-operative Chlorhexidine shower	No	Yes	n.a.		
		Septic Foci/Skin Lesions present	No	Yes			
		Presence of resistant organisms*	Yes	No	n.a.		
		Antibiotic prophylaxis administered	Yes	No	n.a.		

Potential Safety Risks					
Temperature ____ °C	Pulse Rate ____ /min	Haemoglobin ____ g/dl	Waterlow Score ____		
Blood Pressure ____ mmHg	Respiration ____ /min	Haemoglucotest ____ mmol/l	Pain Score ____ /10		

✓	NURSING PRESCRIPTIONS	IMPLEMENTATION				UNIT CHECK (✓)	THEATRE CHECK (✓)
	Urine abnormalities	No		Yes			
	Menstruation	No	Yes	Tampon	n.a.		
	Pedal Pulses	Palpable Left/Right		Non-palpable Left/Right			
	Blood ordered: Theatre/Standby	Yes		No	n.a.		
	Identification band applied	Yes					
	Medic Alert band/Chain in situ	Yes			n.a.		
	Make up/Nail varnish/Jewellery/Hair pins removed	Yes		No	n.a.		
	Dentures removed	Yes		No	n.a.		
	Teeth crown/Bridge in situ/Loose Teeth	Yes		No	n.a.		
	Contact lenses removed	Yes			n.a.		
	Prosthesis removed	Yes		No	n.a.		
	X-rays ready for theatre	Yes		No	n.a.		
	Electrocardiogram performed	Yes		No	n.a.		
	Blood results available	Yes		No	n.a.		
	Intravenous infusion commenced and patent	No		Yes	n.a.		
	Dressed in theatre clothes	Yes					
	Bladder emptied	Yes		Voided	Catheterised		
	Advised to stay in bed	Yes					
	Cotsides up/Straps applied	Yes					

Pre-operative check done by: Signature ____________________ **Date** ____________

Hand over — Signature: Nurse Practitioner Nursing Unit ____________ Signature: Nurse Practitioner Operating Theatre ____________ Time ____ : ____

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n.a. - not applicable ✓ - checked or activated ✗ - cancelled
*resistent organisms - MRSA, ESBL, CRE, VRE

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Figure 34: Pre-operative nurse form

Appendix C: Intra-operative records

INTRA-OPERATIVE RECORD

Date		Theatre	
Anaesthetic: *From*	:	*To*	:
Operation: *From*	:	*To*	:

Surgeon (1)	
Surgeon (2)	
Assistant (1)	
Assistant (2)	
Anaesthetist	

TOURNIQUET

Tourniquet used	Yes	No	n.a.
Type			
Serial Number			
Applied by Doctor			

TOURNIQUET PRESSURE CONTROL n.a.

Left limb		Right limb	
Skin protection: Yes No		Skin protection: Yes No	
Time applied	:	Time applied	:
Time inflated	:	Time inflated	:
Pressure		Pressure	
Time deflated	:	Time deflated	:
Pressure		Pressure	
Time removed	:	Time removed	:

TOURNIQUET CONTINUOUS PRESSURE CONTROL n.a.

Time	Pressure	Signature	Time	Pressure	Signature
:			:		
:			:		
:			:		
:			:		
:			:		
:			:		

POSITIONING OF PATIENT

Supine	Prone
Left Lateral	Lithotomy
Right Lateral	Trendellenburg
Other:	

Checked position	Yes	No
Warming device	No	Yes
Bony prominences padded	No	Yes

ANTIBIOTIC PROPHYLAXIS Yes No n.a.

DRUG	DOSAGE	TIME
DRUG	DOSAGE	TIME

Blood/Blood products administered	No	Yes	
CVP/Arterial line sited	No	Yes	
Epidural catheter removed in theatre	Yes	No	n.a.

TYPE OF ANAESTHETIC

Local	General	Epidural	Spinal	Regional	Conscious Sedation

Drugs

TOURNIQUET PRESSURE CONTROL n.a.

Left limb		Right limb	
Skin protection: Yes No		Skin protection: Yes No	
Time applied	:	Time applied	:
Time inflated	:	Time inflated	:
Pressure		Pressure	
Time deflated	:	Time deflated	:
Pressure		Pressure	
Time removed	:	Time removed	:

TOURNIQUET CONTINUOUS PRESSURE CONTROL n.a.

Time	Pressure	Signature	Time	Pressure	Signature
:			:		
:			:		
:			:		
:			:		
:			:		
:			:		

DIATHERMY

Diathermy used	No	Yes	n.a.
Diathermy checked	No	Yes	
Checked by			
Serial Number			
Plate Batch Number			
Plate Site			

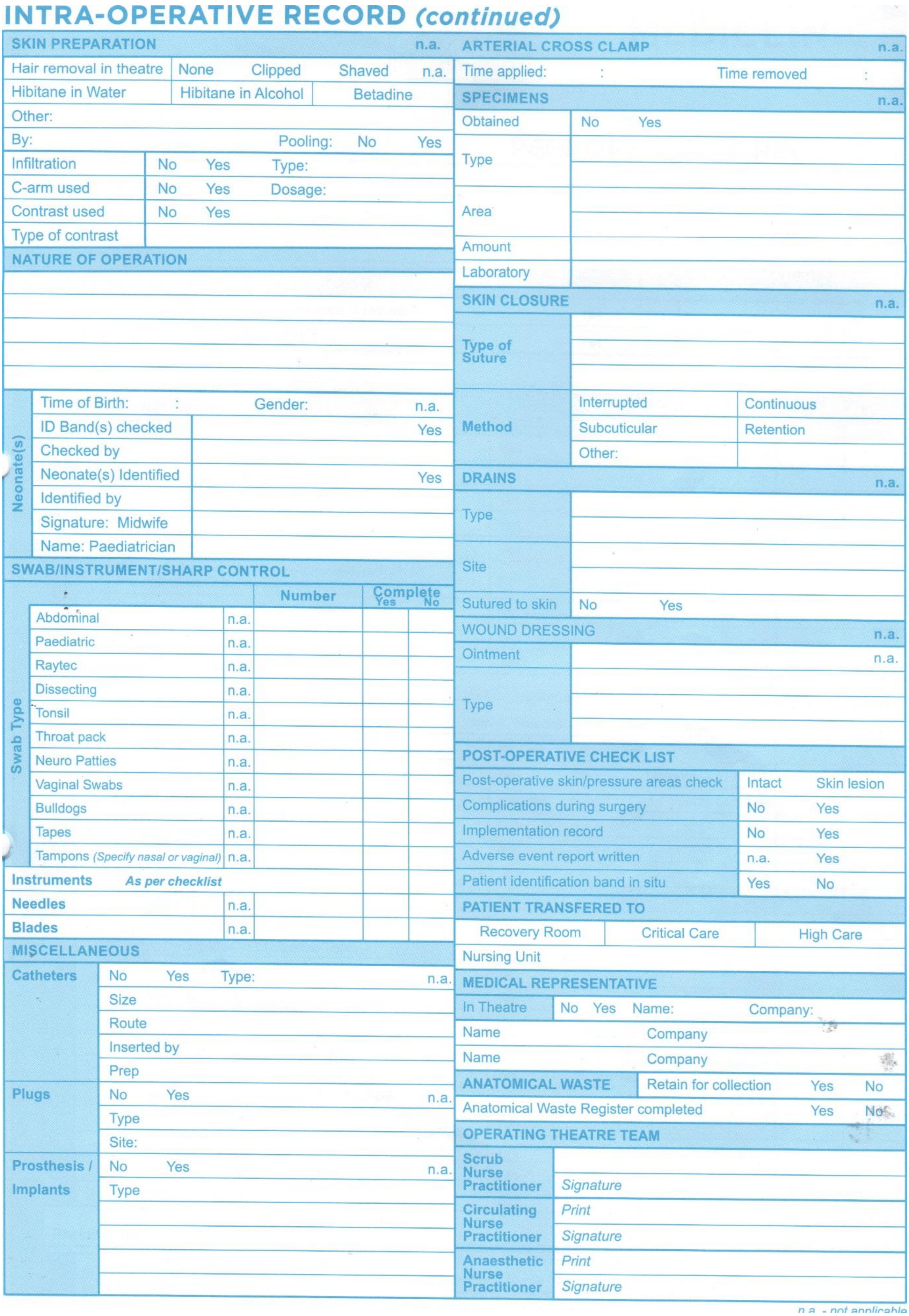
Setting			
	Monopolar	Cutting:	Coagulation:
	Bipolar		

CATEGORY OF WOUND

Clean	Clean Contaminated	Contaminated	Infected

n.a. - not applicable

Figure 35: Intra-operative form 1



INTRA-OPERATIVE RECORD *(continued)*

SKIN PREPARATION n.a.

Hair removal in theatre	None	Clipped	Shaved	n.a.
Hibitane in Water	Hibitane in Alcohol	Betadine		
Other:				
By:		Pooling:	No	Yes
Infiltration	No	Yes	Type:	
C-arm used	No	Yes	Dosage:	
Contrast used	No	Yes		
Type of contrast				

NATURE OF OPERATION

Neonate(s)

Time of Birth: :	Gender:	n.a.
ID Band(s) checked		Yes
Checked by		
Neonate(s) Identified		Yes
Identified by		
Signature: Midwife		
Name: Paediatrician		

SWAB/INSTRUMENT/SHARP CONTROL

Swab Type		Number	Complete Yes	Complete No
Abdominal	n.a.			
Paediatric	n.a.			
Raytec	n.a.			
Dissecting	n.a.			
Tonsil	n.a.			
Throat pack	n.a.			
Neuro Patties	n.a.			
Vaginal Swabs	n.a.			
Bulldogs	n.a.			
Tapes	n.a.			
Tampons *(Specify nasal or vaginal)*	n.a.			
Instruments	***As per checklist***			
Needles	n.a.			
Blades	n.a.			

MISCELLANEOUS

Catheters	No	Yes	Type:	n.a.
	Size			
	Route			
	Inserted by			
	Prep			
Plugs	No	Yes		n.a.
	Type			
	Site:			
Prosthesis / Implants	No	Yes		n.a.
	Type			

ARTERIAL CROSS CLAMP n.a.

Time applied: : Time removed :

SPECIMENS n.a.

Obtained	No	Yes
Type		
Area		
Amount		
Laboratory		

SKIN CLOSURE n.a.

Type of Suture		
Method	Interrupted	Continuous
	Subcuticular	Retention
	Other:	

DRAINS n.a.

Type		
Site		
Sutured to skin	No	Yes

WOUND DRESSING n.a.

Ointment	n.a.
Type	

POST-OPERATIVE CHECK LIST

Post-operative skin/pressure areas check	Intact	Skin lesion
Complications during surgery	No	Yes
Implementation record	No	Yes
Adverse event report written	n.a.	Yes
Patient identification band in situ	Yes	No

PATIENT TRANSFERED TO

Recovery Room | Critical Care | High Care

Nursing Unit

MEDICAL REPRESENTATIVE

In Theatre	No	Yes	Name:	Company:
Name				Company
Name				Company

ANATOMICAL WASTE Retain for collection Yes No

Anatomical Waste Register completed Yes No

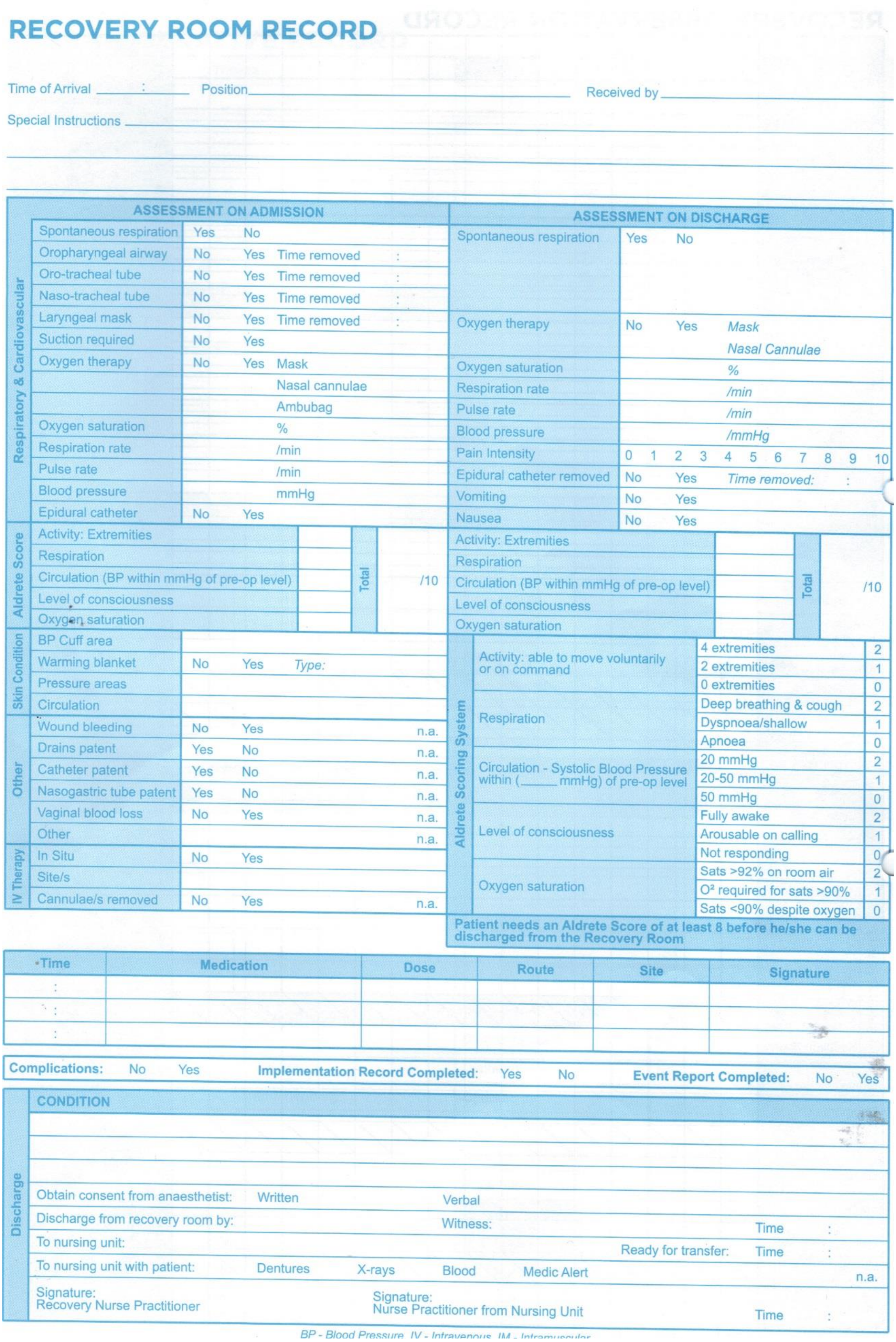
OPERATING THEATRE TEAM

Scrub Nurse Practitioner	*Signature*
Circulating Nurse Practitioner	*Print*
	Signature
Anaesthetic Nurse Practitioner	*Print*
	Signature

n.a. - not applicable

Figure 36: Intra-operative form 2

Appendix D: Post-operative records



RECOVERY ROOM RECORD

Time of Arrival ___ : ___ Position ___ Received by ___

Special Instructions ___

ASSESSMENT ON ADMISSION			
Respiratory & Cardiovascular	Spontaneous respiration	Yes No	
	Oropharyngeal airway	No Yes	Time removed :
	Oro-tracheal tube	No Yes	Time removed :
	Naso-tracheal tube	No Yes	Time removed :
	Laryngeal mask	No Yes	Time removed :
	Suction required	No Yes	
	Oxygen therapy	No Yes	Mask
			Nasal cannulae
			Ambubag
	Oxygen saturation		%
	Respiration rate		/min
	Pulse rate		/min
	Blood pressure		mmHg
	Epidural catheter	No Yes	
Aldrete Score	Activity: Extremities		Total /10
	Respiration		
	Circulation (BP within mmHg of pre-op level)		
	Level of consciousness		
	Oxygen saturation		
Skin Condition	BP Cuff area		
	Warming blanket	No Yes	Type:
	Pressure areas		
	Circulation		
Other	Wound bleeding	No Yes	n.a.
	Drains patent	Yes No	n.a.
	Catheter patent	Yes No	n.a.
	Nasogastric tube patent	Yes No	n.a.
	Vaginal blood loss	No Yes	n.a.
	Other		n.a.
IV Therapy	In Situ	No Yes	
	Site/s		
	Cannulae/s removed	No Yes	n.a.

ASSESSMENT ON DISCHARGE		
Spontaneous respiration	Yes No	
Oxygen therapy	No Yes	Mask
		Nasal Cannulae
Oxygen saturation		%
Respiration rate		/min
Pulse rate		/min
Blood pressure		/mmHg
Pain Intensity	0 1 2 3 4 5 6 7 8 9 10	
Epidural catheter removed	No Yes	Time removed: :
Vomiting	No Yes	
Nausea	No Yes	
Activity: Extremities		Total /10
Respiration		
Circulation (BP within mmHg of pre-op level)		
Level of consciousness		
Oxygen saturation		

Aldrete Scoring System			
	Activity: able to move voluntarily or on command	4 extremities	2
		2 extremities	1
		0 extremities	0
	Respiration	Deep breathing & cough	2
		Dyspnoea/shallow	1
		Apnoea	0
	Circulation - Systolic Blood Pressure within (___ mmHg) of pre-op level	20 mmHg	2
		20-50 mmHg	1
		50 mmHg	0
	Level of consciousness	Fully awake	2
		Arousable on calling	1
		Not responding	0
	Oxygen saturation	Sats >92% on room air	2
		O² required for sats >90%	1
		Sats <90% despite oxygen	0

Patient needs an Aldrete Score of at least 8 before he/she can be discharged from the Recovery Room

Time	Medication	Dose	Route	Site	Signature
:					
:					
:					

Complications: No Yes **Implementation Record Completed:** Yes No **Event Report Completed:** No Yes

Discharge

CONDITION

Obtain consent from anaesthetist: Written Verbal

Discharge from recovery room by: Witness: Time :

To nursing unit: Ready for transfer: Time :

To nursing unit with patient: Dentures X-rays Blood Medic Alert n.a.

Signature: Recovery Nurse Practitioner Signature: Nurse Practitioner from Nursing Unit Time :

BP - Blood Pressure IV - Intravenous IM - Intramuscular

Figure 37: Pots-operative form 1

RECOVERY OBSERVATION RECORD

	Time	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..		
																		Temperature °C	
	220																	41	
	210																	40	
	200																	39	
	190																	38	
	180																	37	
	170																	36	
Blood Pressure mmHg	160																	35	
	150																		
	140																		
	130																		
	120																		
	110																		
	100																		
Pulse /min	90																		
	80																		
	70																		
	60																		
	50																		
	40																		
	30																		
Respiration	/min																		
Oxygen Saturation*	%																		
Oxygen Administered	/min																	RA	Room Air
Peripheral Temperature	L R																	W L C	Warm Lukewarm Cold
Peripheral Pulses Present	L R																	Y N	Yes No
Aldrete Score	Activity: Extremities																	2 1 0	4 Extremities 2 Extremities 0 Extremities
Aldrete Score	Respiration																	2 1 0	Deep breathing & cough Dyspnoea / Shallow Apnoea
Aldrete Score	Circulation (BP *)																	2 1 0	20mmHg 20 - 50mmHg 50 mmHg
Aldrete Score	Level of Consciousness																	2 1 0	Fully awake Arousable on calling Not responding
Aldrete Score	Oxygen Saturation																	2 1 0	Sats >92% on room air O² required for Sats >90% Sats <90% despite oxygen
Spinal / Epidural	Sensory Level																	T4 T6 T10	Nipples Rib Margin Umbilicus
Spinal / Epidural	Chest Movement																	0 1	Superficial Deep
Spinal / Epidural	Cough Reflex																	0 1	Weak Strong
Spinal / Epidural	Limb Movement L R																		
Spinal / Epidural	Sedation Score																	0 1 2 3 4	Not rousable hardly rousable Sedated difficult to rouse Sedated, easy to rouse Fully awake/alert
Pain Intensity																		1 - 10	
Haemorrhage																		Y N	Yes No
Hb/HGT	g % mmol/l																		
Uterus																		C A	Contracted Atonic
Lochia																		+++ ++ +	Heavy Moderate Mild
Foetal Heart Rate																		Y N	Yes No
Nausea/ Vomiting																		N Y	No Yes
Intial																			

* Systolic blood pressure within (______ mmHg) of pre-op level L - Left R - Right

Figure 38: Post-operative form 2

Appendix E: Data

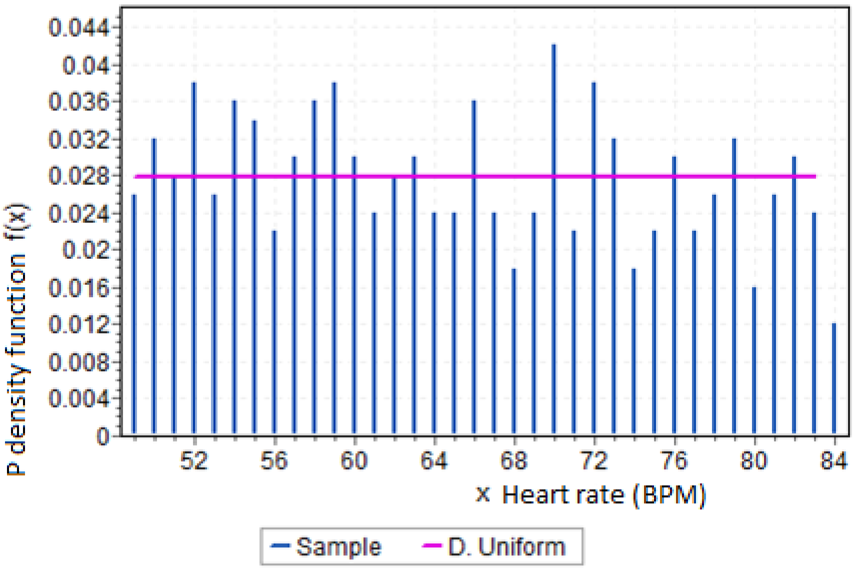


Figure 39: Distribution of heart rates for women

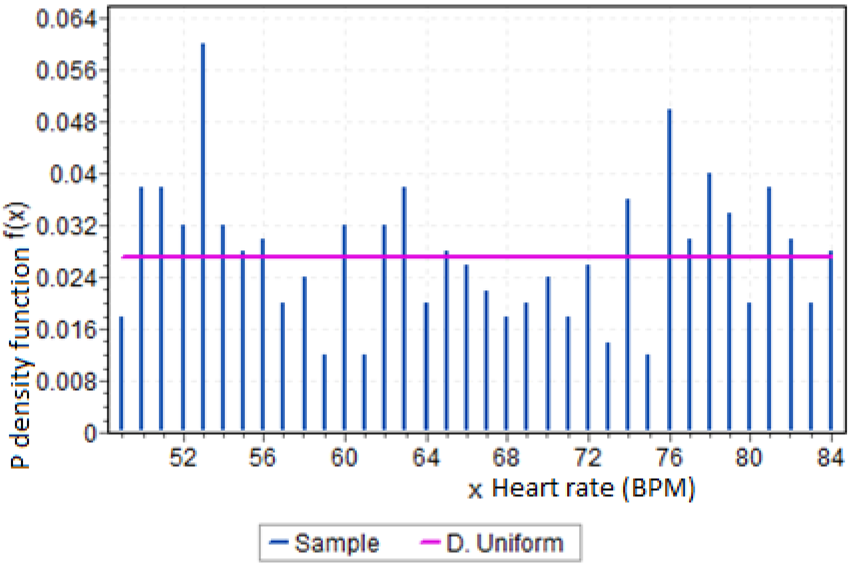


Figure 40: Distribution of heart rates for men

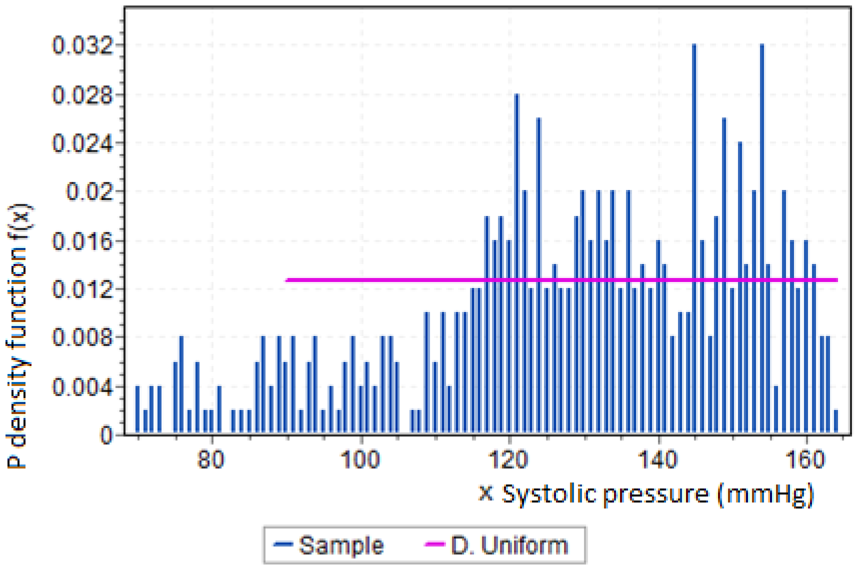


Figure 41: Distribution of systolic blood pressures for woman

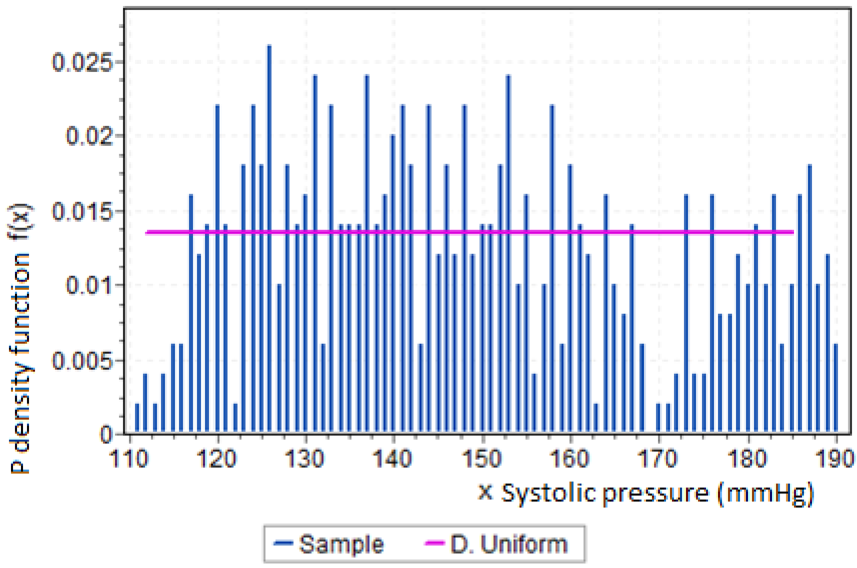


Figure 42: Distribution of systolic blood pressures for men

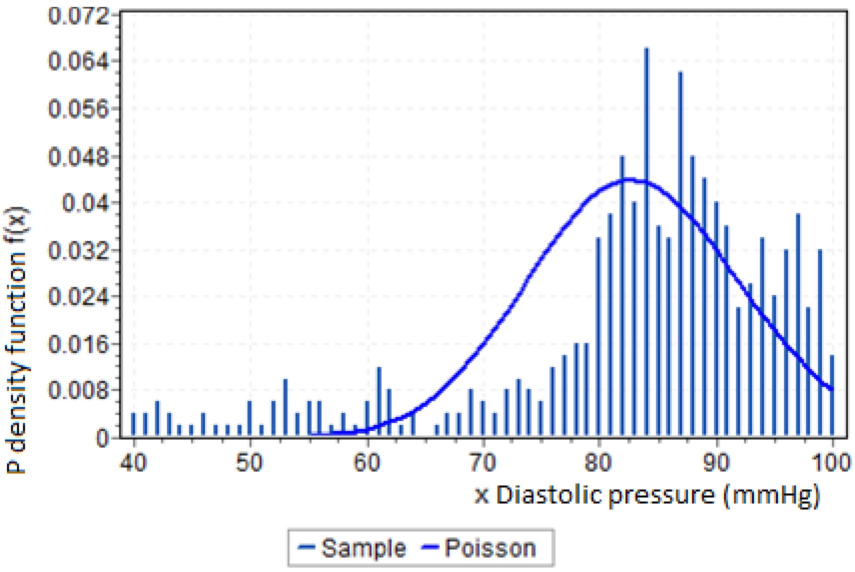


Figure 43: Distribution of diastolic blood pressures for woman

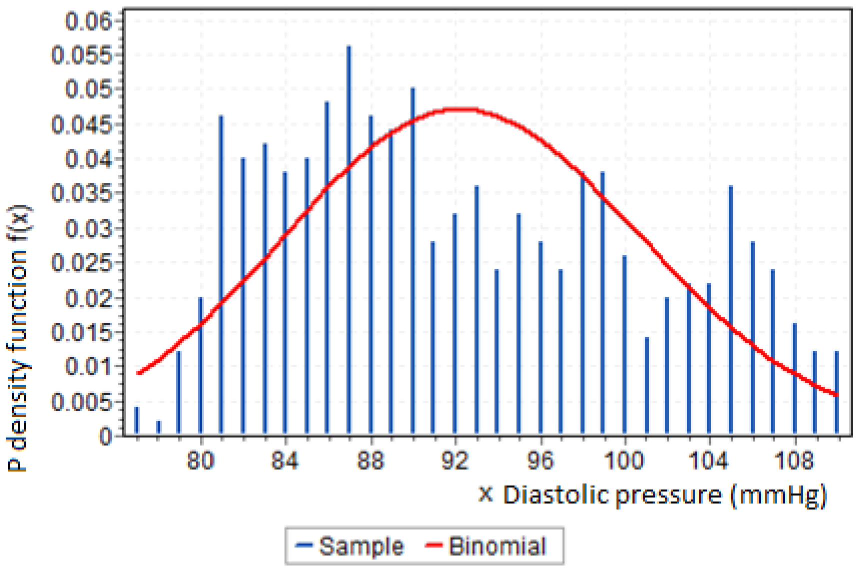


Figure 44: Distribution of diastolic blood pressures for men