Using Machine Learning to Locate Personally Interesting Images Based on Biometric Response Measures

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Abstract

It is now possible to capture visual diaries of one's daily life, using a device such as the SnapCam which can be clipped to one's clothes and used to automatically capture multiple photos per minute; However, locating the interesting photos within such a collection is difficult. This research project explores the use of biometric response and machine learning techniques in this regard.

Biometric response provides a measure of an individual's arousal levels or engagement with a life situation, e.g. a person's biometric response would be different when their football team scored the winning game of a match than when they lost a match. This biometric response can be measured using devices worn on one's arm.

We investigated the development of a system that extracts the SnapCam photos a person is most interested in viewing from their visual diary based on their biometric response levels when the photos were captured across different categories of life events, and the use of machine learning techniques (Artificial Neural Networks, Support Vector Machine, and k-Nearest Neighbour) applied to the biometric responses to predict the photos a person will want to view in the future for different categories of events. In conducting this investigation, we recorded individuals' biometric responses when they were capturing photos with the SnapCam and manually logging life events.

An experiment methodology was designed and implemented to facilitate automatic and remote runners of experiments by multiple experiment subjects. The implementation is reliable due to the results of JUnit tests. Experiments to evaluate both the research investigation and the dependability of the generated software were setup, conducted, and reported on. The results of these experiments suggest that the k-Nearest Neighbour technique with accuracy of 62.2% is the most useful approach in regards to the prediction of important photos in a visual lifelog based on biometric responses.

I declare that the material submitted for assessment is my own work, except where credit is explicitly given to others by citation or acknowledgement. The main text of this dissertation is 12,577 words long.

Acknowledgements

I would first like to express my gratitude to my supervisor, Dr Liadh Kelly for the continuous support of my study and her patience, motivation, enthusiasm and immense knowledge. One simply could not wish for a better or friendlier supervisor.

I also would like to thank my loved ones who have supported me throughout entire process by their friendship, understanding and continuous encouragement. I will be grateful forever for your love.

I dedicate this dissertation to my husband,

Kamran

for his remarkable patience and unwavering love and support.

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Chapter 1

Introduction

1.1 Problem Statement

Nowadays, there are numerous people who tend to record and archive all information in their lives including their physical biological data and visual information in order to monitor their health, improve the quality of their lives, capture moments they might miss, pass their legacies on to their family and children and etc.

Personal lifelogging technologies automatically store artifacts from a person's life in a digital archive. Personal lifelogs include digital records captured from events of people's lives which can contain materials such as items read, written, or downloaded, photographs taken, videos seen, music heard, details of places visited, details of people met together with details of location and social context [40].

There are innumerable technologies by which people collect personal lifelogs namely using wearable gadgets (e.g. Autographer [1] which is a wearable camera that takes photos automatically), mobile apps (e.g. Sleepbot [2] which is for logging sleeping pattern), web apps (e.g. RescueTime [3] which enables users to know how they are spending time on their computers), and standalone gadgets (e.g. CubeSensors [4] which can monitor user's surroundings by continuously measuring temperature, humidity, noise, light, air quality, and barometric pressure).

Although personal lifelogging technologies may offer several benefits, they also may bring some challenges in handling, analysing, indexing and providing content-based access to streams of multimodal information derived from lifelogging sensors [28]. Therefore, any additional information which can aid in identifying important items is of a huge

[1] https://en.wikipedia.org/wiki/Autographer
[2] https://www.mysleepbot.com
[3] https://www.rescuetime.com
[4] https://cubesensors.com

significance [39].

This project sets out to apply such information in order to extract interesting photos when browsing a visual lifelog collection across five different categories of life events (Eating, Walking, Working, Travelling, and Other) and to make use of such data to train machine learning algorithms in order to predict the future important life events.

1.2 Motivation and Objectives

Advances in digital technologies that produce personal information in digital formats combined with the growing size of digital data collections bring up the need to develop technologies to automatically handle, manage and analyse the items in the data collections. There is a scope to use automatically inferred indicators of item's importance to help with this process. Across the various types of data, user's biometric response associated with an item is one potential source of useful information [39].

It is known that individual's biometric response is related to their overall arousal levels [47]. The individual's arousal level rises by notable events that cause a measurable biometric response [57]. Changes in arousal level motivate physiological responses such as changes in heart rate (HR), increased sweat production, and decreased blood flow in peripheral vessels which can be measured by the skin conductance response (SCR) (also referred to as galvanic skin response (GSR)) and skin temperature (ST) [57][69]. Technologies such as BodyMedia SenseWear Pro II armband[5] allow the record of several biometric measures such as wearer's GSR and ST on a continuous basis.

Preliminary studies show relationship between an individual's biometric response levels and the importance of items in a personal lifelog, using a basic technique [38]. To the best of our knowledge, there is no study contributing to presenting an efficient method and a reliable application to identify the interesting items related to measured biometric responses.

In this dissertation, we describe our findings to date which may guide future research in this field. We report our study in designing an efficient method to apply biometric response measures namely GSR, HF, and ST to specific life events (Eating, Walking, Working, Travelling, and Other) found within visual lifelogs in order to make use of such biometric responses to automatically categorise life events. To put it simply, we first make use of biometric measures of GSR, HF, and ST in order to extract interesting photos within a visual lifelog across the five different life event categories. Then, we make use of such data in a machine learning context in order to train our system and predict the future important and

[5] http://www.bodymedia.com.

memorable events; We chose machine learning approaches for the prediction due to the fact that machine learning algorithms are one of the most widely used predictive models and they can be trained to respond to new data.

The objectives of this project can be stated as follows:

- To create an efficient method capable of using biometric response levels to extract the photos a person is most interested in across the five different life event categories and to use machine learning techniques to automatically predict and categorise future important life events based on biometric response measures.

- To develop a dependable and reliable application that implements the method created and is capable of extract the most interesting photos.

- To design experiments to test the application and the method.

1.3 Ethics Approval

This project utilises SnapCam which is a wearable camera that takes photographs without user intervention and BodyMedia armband which is a wearable body monitoring system that records biometric responses provided by Dr Liadh Kelly, a lecturer at the Department of Computer Science of the Maynooth University. An Internal ethics process was followed within the department, as per Maynooth University's guidelines. See Appendix 1 for details, including the informed consent form and plain language statement.

1.4 Thesis Structure

This dissertation is structured in six different chapters. Chapter 1 provides an introduction to the background, the motivation and the problem that this project attempts to solve. Chapter 2 contains a survey of personal lifelogging research and introduces the devices of interest for this investigation together with a description of the utility of affective response in search of personal lifelogs. We also provide an overview of machine learning and its supervised techniques along with the related work in this chapter. Chapter 3 reports the structure of the test set used for the purpose of this study and describes the setup of the experiment designed as the methodology of this investigation. Chapter 4 provides a description of the implementation of our method and introduces the technologies and libraries that were used. Chapter 5 details the evaluation of the method and its implementation on a dataset. Finally, Chapter 6 presents the conclusions and future work for this study.

Chapter 2

Context and Related Work

This chapter provides the technical background required for this study. We start with a survey over personal lifelogs and the devices of interest for this investigation to collect such data. Next, we present an overview of the potential for improving the effectiveness of locating important events using the individuals biometric responses data associated with past interactions with these events. We also discuss machine learning as a technique to predict events of interest for individuals. We conclude the chapter with a summary of the related work being done in the extraction of important events in a personal lifelog using biometric response data.

2.1 Personal Lifelog

Throughout history, people used to store data about their personal activities within a catalogue such as calendars, books, diaries, letters and paintings. Over the last century, new lifelogged information such as photos, sounds and videos were added to the above list. With the widespread founding of the Internet at the end of the 90s and the beginning of the 20th century, personal data including email accounts, gaming data, login accounts, favourite web pages, personal documents, digital photo albums, online web services and applications were stored in personal devices. Recently, social networks have lured a large number of users who share personal moments, photos, achievements, news, and data [64].

There is no universal definition of lifelogging and there are various amounts of activities which are mentioned as falling into the personal lifelogging sphere including quantified-self analytics[1], life blogs, life glogs[2], personal digital memories, lifetime stores, the human black box, for example [28].

[1] http://quantifiedself.com.
[2] https://edu.glogster.com.

In adopting an appropriate definition, we refer to the description of lifelogging by Dodge and Kitchin, 2007 [21], where lifelogging is introduced as “a form of pervasive computing, consisting of a unified digital record of the totality of an individuals experiences, captured multi-modally through digital sensors and stored permanently as a personal multimedia archive”.

To put the matter another way, personal lifelogging represents a phenomenon through which people can collect digital records of information associated with their own daily lives in various levels of details for diverse purposes [28].

This information can contain elements such as photos, videos, music, emails received and sent, every event, every conversation, web content and other documents with which they have communicated, and logs of phone calls and text messages. They also can include personal data namely location recorded by GPS sensors, persons and objects present collected via Bluetooth, and physiological state measured by biometric sensors [36].

The unified digital record uses multi-modally captured data which has been collected and processed into retrievable information that are accessible through an interface [28]. Such information can potentially support a wide variety of use-cases including helping people recover their partially forgotten information, sharing experiences with friends or relatives, narrating the story of an individual’s life, clinical employment for the memory impaired, and fundamental psychological investigations of memory [36].

All profits of lifelogging in smart environments confront new challenges that can be divided into two parts: the information capture and the post-processing [53].

In order to capture the information, lifelog devices are required to be stable, have reliability in measurements, a long battery life, sufficient on-device storage, and unobtrusive wearability. Lifelog systems also need a secure central storage to collect and process the data from different devices. Moreover, considering the privacy of users and their near surrounding, as well as applicable privacy laws is a crucial issue that may bring several difficulties [53].

To process the captured multimodal and multimedia data, elaborate algorithms are required to make it searchable and usable. These algorithms should synchronize multiple devices, convert the data into usable formats by extracting low-level features such as the heart rate, filter and cluster the data based on similarity, rejecting low-quality and redundant data, transform the data into an interpretable format, and augment the data by adding input from new external sources such as weather information [53].

One important challenge to process lifelog archives is segmenting continuous content streams into indexable units for analysis, retrieval and presentation [27]. The core concept of a document is the base for indexing units in most retrieval systems. Due to the continuous nature of lifelog data, the document is not clearly defined and efforts are required to impose a unit of retrieval [26].

There have been a significant minority of dedicated individuals who actively attempt to log the entirety of their lives. For instance, Richard Buckminster-Fuller who collected his activities in detail every 15 minutes day by day from 1920 until 1983 into a lifetime archive called the Dymaxion Chronofile [28]. Another example of active logging is Annual Reports by Nicholas Felton[3], in which lifelog data that is collected manually is converted into a yearly book of semantically meaningful objects and experiences [22].

The following sections will detail two wearable lifelog devices namely iON SnapCam Lite and BodyMedia SenseWear Pro2 armband which are the devices of interest for this project.

2.1.1 iON SnapCam Lite

The iON SnapCam Lite is a mini wearable fisheye camera, typically attached directly to clothes with a clip or magnet, designed to take photographs without user intervention. The device is shown in Figure 2.1. Anything in the view of the wearer can be captured by the SnapCam.

Figure 2.1: iON SnapCam Lite

The device weighs 1.16 ounces and captures photos of 5mp resolution. The battery enables user the taking of 3000 photos on a single charge and works 7-days on stand-by mode. For storing the data SnapCam requires Micro SD or Micro SDHC cards[4].

The camera has Time Lapse mode that uses a timer to automatically take a new image approximately every 30 seconds, resulting in up to 2880 images per day. Wearing a Snap-

[3] http://feltron.com.
[4] https://uk.ioncamera.com/snapcam-lite/.

Cam, a wearer can very swiftly create large and rich photo collections. Worn daily, this adds up to nearly 1 million images per year.

2.1.2 BodyMedia SenseWear Pro2 Armband

The SenseWear Pro2 armband that was developed by BodyMedia, Inc (Pittsburgh, PA, USA), is a wearable device wrapped around the upper arm to monitor metabolic physical activity and total energy expenditure [6]. The device is represented in Figure 2.2.

Figure 2.2: BodyMedia SenseWear Pro2 Armband [6]

Information presented by the manufacturer indicates that the SenseWear armband applies non-invasive biometric sensors to continuously measure physical parameters including heat flux (HF), GSR, ST, near-body temperature, and two-axis accelerometry and demographic characteristics consisting of gender, age, height, weight to estimate energy expenditure [33][54].

Employing such data the BodyMedia device can calculate energy expenditure interpretations at a rate of once per minute by applying proprietary algorithms which calculate energy expenditure based on the demographic characteristics of the individual coupled with the activity of the user, inferred from the on-device data [6].

The validity of the BodyMedia SenseWear Pro2 armband's energy expenditure calculation has been confirmed in several investigations including Cole et al., 2004 [18], Fruin and Rankin, 2004 [23], Jakicic et al., 2004 [34], King et al., 2005 [44], Mealey et al., 2007 [58], and St-Onge et al., 2007 [75].

The armband has memory for almost two weeks of wear. Using the device, a carefully chosen set of features are captured including both basic statistics of the data streams such as averages and variances as well as more complex features including peaks and steps. The stored data on the armband are then sent to a PC via either a USB cable using the provided software [6]. This software produces analytics and graphs to enable the user to analyse their recorded biometric data and the ability to export their data into a csv file format for future employment.

The provided BodyMedia software runs only on Windows XP resulting in the required use of Virtual Box. A Virtual Box [5] is a general purpose virtual machine monitor that enables different versions and derivations of operating systems to be run on a computer. Since Virtual Box can make use of all external drives and ports on the computer it runs on, the BodyMedia Biometric armband can successfully connect to the software for data exportation and analytics via Virtual Box.

2.2 Biometric Response and the Digital Environment

As mentioned in Section 1.2, there is a relationship between an individual's biometric response and their overall arousal levels [47]. Significant or important events lead to raising an individual's arousal level, generating a measurable biometric response [57]. Events that are important or emotional in our lives are the ones which individuals can often remember clearly in the future [24].

Since changes in arousal level evoke physiological responses including variations in HR or increase in sweat production, one way of observing an arousal response is by measuring GSR. The GSR reveals the changes in the activity of the sweat glands (even if this change is only subtle and transient and the individual concerned is not obviously sweating) by a variation in the electrical conductivity of the skin [24][12].

Another indicator of an individual's arousal levels is the rate of heat exchange from a person's body to the outside environment, termed HF. The ST is the additional way of observing arousal responses. The decrease in blood flow in peripheral vessels is a result of increases in sympathetic nervous activity caused by increases in arousal levels [37][69].

A challenge for arousal level detection using biometric response is that several circumstances including defective sensors and food consumption can provoke noise in biometric data [32]. Such noises in biometric data can also be produced by external factors consisting of physical activity that can similarly change the biometric levels [62][77].

[5] https://www.virtualbox.org

One approach toward measuring levels of physical activity is through an energy expenditure calculation which considers individuals' characteristics consisting of motion, age, weight and height. Energy expenditure is an estimate of the energy that human body uses, according to physical activity, resting metabolic rate and the thermic effect of food (expense of processing food for storage and use) [3][4][11]. Digital devices such as the BodyMedia SenseWear Pro 2 armband provide the opportunity to enter individual's weight, age and height along with biometric interpretations [6].

A significant research effort has been made to correctly identify the relationship between biometric response and individuals' arousal and emotional levels, namely: Bradley et al., 2001a [13], Bradley et al., 2001b [14], Kim et al., 2004 [43], Kim and Andre, 2008a [41], Kim and Andre, 2008b [42], Lang et al., 1993 [48], Lang,1995 [47], Lisetti et al., 2003 [50], Lisetti and Nasoz, 2004 [51], and Maltzman and Boyd, 1984 [55]. Efforts have also been made in the detection of emotion for HCI using an individual's biometric response, For instance, Allanson, 2002 [5], Anttonen and Surakka, 2005 [7], Klein et al., 2002 [45], Partala and Surakka, 2004 [63], Picard, 2000 [65], Picard et al., 2001 [66], Scheirer et al., 2002 [70], and Ward and Marsden, 2003 [80] and in extracting of emotional response to movies and movie scenes, for example Canini et al., 2010 [15], Chen and Segall, 2009 [17], Hettema et al., 2000 [29], Mooney et al., 2006 [60], Rothwell et al., 2006 [68], Smeaton and Rothwell, 2009 [73], Soleymani et al., 2008 [74].

Researchers have also begun looking at how the observed biometric response may be used to detect tasks or items in the various test sets that are of current relevance or importance to the individual. One example of the research in this field is Arapakis et al., 2009 [8] which is a study through the selection and elicitation of topical relevance for impersonal multimedia collections (TRECVid [72] and TREC Web track [9] collections).

According to Arapakis et al., 2009 [8], there is a relationship between the topical relevance of search results and an individual's emotional response in which an emotional response is identified over passing biometric measures through a support vector machine. This work represents that individuals' affective responses, as learned from the observation of their facial expressions and other peripheral physiological signals, will diversify over the importance of perused information items.

Moshfeghi et al., 2011 [61] also propose an approach for collaborative filtering by combining semantic and emotion information with rating information. The results of this study show that emotion and semantic features consistently play a role in improving the performance of a model-based collaborative filtering system. Furthermore, the sparsity of the dataset increases the effectiveness of emotion spaces, especially in a cold start situation.

Most recently White and Ma (2017) [82] explored the use of a large cohort of people's heart rate levels (23k people) as an implicit indicator of the importance of web pages to queries. Their results show support for the use of heart rate in this regard.

2.3 Machine Learning

The term machine learning is dedicated to the domain of study involved in the development of computer algorithms to convert data into intelligent action [49]. With the growing size of data, the need for additional computing power is also raised which consequently yields the need for the development of statistical techniques to analyse large datasets. Machine learning is introduced in such environments where available data, statistical methods, and computing power quickly and concurrently grow [49]. Figure 2.3 demonstrates the cycle of such a system that allows even larger and more interesting data to be collected.

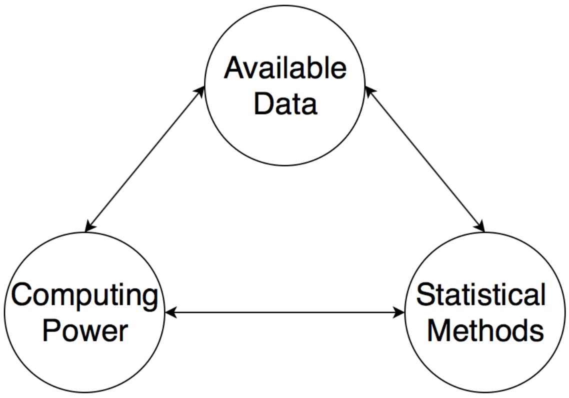


Figure 2.3: The Cycle of Advancement in Data Processing [49].

The objectives of machine learning centre around three fundamental research themes [16]:

- ***Task-Oriented Studies*** that are also being referred to as the engineering approaches and contribute towards the development and analysis of learning systems to enhance performance in a proposed set of tasks.
- ***Cognitive Simulation*** that investigate and simulate the human learning processes.
- ***Theoretical Analysis*** that theoretically investigate the space of potential learning techniques and algorithms independent of the application domain.

A research towards one of these objectives can often lead to improvement towards another. For example, to explore the scope of possible learning methods, considering human as the only identified instance of robust learning behaviour is a logical starting point. Likewise, the theoretical analysis which can present several learning models may help psychological studies of human learning [16].

An equally primary scientific objective of machine learning is the investigation of alternative learning mechanisms that consist of a broad range of knowledge including the exploration of different induction algorithms, the scope and limitations of particular methods, the information that must be available to the learner, the issue of coping with deficient training data, and the creation of general techniques applicable in many task areas [16].

Machine learning has various applications amongst which data mining is the most important one. Problems that involve analyses or establishment of relationships between multiple features are often difficult to solve due to the fact that people are often prone to make mistakes in such areas. Machine learning is often a successful solution for these problems by improving the performance of systems and the designs of machines [46].

Machine learning algorithms use datasets with the instances that are represented employing the same set of features including continuous, categorical or binary. The learning procedure is termed supervised if instances are provided with known labels (the corresponding correct outputs). Many machine learning applications comprise tasks that can be structured as supervised; Although, conversely there are unsupervised machine learning methods in which learning instances are unlabeled [46]. Researchers wish to identify unknown, but beneficial, classes of elements applying unsupervised algorithms [31].

Reinforcement learning is another type of machine learning in which the learning system uses the training information given by an external trainer [76]. Such information is in the form of a scalar reinforcement signal that develops a measurement for the operation of the system. In this technique, the learner does not receive any instruction of which action to practise; However, it must try each action successively to determine which actions produce the greatest achievement [76] [46].

The process of learning rules from instances that are cases in a training set is called inductive machine learning. This method generates a classifier that can be employed to generalise from new instances. Figure 2.4 demonstrates the procedure of employing supervised machine learning to solve real-world problems.

To begin to deal with a problem employing a supervised machine learning method, collecting the dataset is the first step which is crucial. The dataset collection could be done by several approaches including to make use of an expert who could recommend which attributes or features are the most instructive ones or to make use of the "brute-force" method [46]. The aforementioned approach aims to recognise the informative features by measuring every single instance that is available; Nevertheless, since a dataset gathered

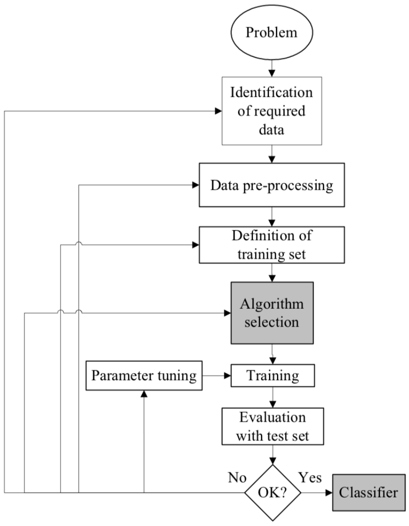


Figure 2.4: The Process of Supervised Machine Learning [46].

by the brute-force method carries noise and missing feature values in most cases, it is not straight suitable for induction; Hence, the dataset needs vital pre-processing [85].

The second step is the data preparation and data pre-processing. Considering the conditions, researchers can pick an approach from several methods to handle missing data [10]. In 2004, Hodge and Austin [30] proposed a review of present methods for noise detection and distinguished advantages and disadvantages of such techniques.

In accordance with Liu and Motoda, 2012 [52], instance selection is practised to handle noise as well as coping with the infeasibility of learning from massive datasets. Instance selection in datasets is an optimisation problem that tries to sustain the mining quality whilst minimising the sample size by decreasing the size of data and allowing a data mining algorithm to perform efficiently with very large datasets.

There is a diversity of methods for sampling instances from a large dataset [67]. Feature subset selection is a process that permits data mining algorithms to function quicker and more effectively by recognizing and eliminating as much irrelevant and redundant features as possible [84].

The indisputable truth that numerous features depend on each other often improperly affects the accuracy of supervised machine learning classification models [46]. As Markovitch and Rosenstein stated in 2002 [56], this problem can be approached by creating new features from the basic feature collection. This technique is named feature construction/transformation that may lead to the production of more concise and precise classifiers.

Algorithm selection is another step which is of great importance. A specific learning algorithm can be chosen using a preliminary testing for which the classifier (mapping from unlabeled instances to classes) is accessible for routine use [46].

The accuracy of a prediction that is most often used for the evaluation of a classifier, is the percentage of accurate prediction divided by the absolute number of predictions [46]. In order to calculate the classifier's accuracy at least three techniques exist one of which is breaking the training set employing two-thirds for training and the other third for predicting performance. One more technique named cross-validation is to divide the training set into mutually independent and equal-sized subsets and train the classifier for each subset based on the union of all the other subsets; Hence, the mean of the error rate of each subset is an approximation of the error rate of the classifier. A particular case of cross-validation is leave-one-out validation in which each test subset consists of a single instance. This kind of validation, although more costly computationally, is beneficial when the most precise estimation of a classifier's error rate is needed [46].

As represented in Figure 2.4, if the error rate evaluation is undesirable, a return to a former step of the supervised machine learning process is required. A diversity of factors can affect this parameter including the size of the training set, selection of the features, the dimensionality of the problem, choice of the algorithm, and balance of the database [35] [46].

Intelligent systems frequently make use of supervised classification; Therefore, a great number of methods have been developed based on artificial intelligence (logical/symbolic techniques), perceptron-based techniques, and statistics (Bayesian networks, instance-based techniques) [46].

In the following sections, we will describe three of the supervised machine learning algorithms that we aim to use for the purpose of this investigation, namely: Artificial Neural Networks (ANN), Support Vector Machine (SVM), and k-Nearest Neighbours (kNN).

2.3.1 Artificial Neural Networks

The ANN is a perceptron-based technique that has been developed as a generalisation of mathematical models of biological nervous systems and has been applied to numerous real-world problems [46] [1].

Artificial neurons, or simply neurons or nodes are the primary processing units of neural networks that are joined together in a pattern of connections. The basic architecture of a neural network consists of three types of neuron layers: input, hidden, and output layers. The feed-forward ANNs enable the signals to flow in only one-way directions, from input to output units [1].

Figure 2.5 represents a typical artificial neuron (a) and the modelling of a multi-layered neural network (b). As illustrated in this Figure, the signal flow from inputs $x_1, \cdots, x_n$ and the output signal flow are considered to be unidirectional and both of them are shown by arrows.

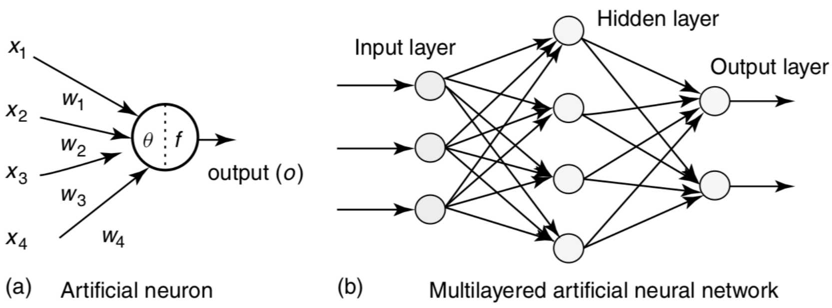


Figure 2.5: The Architecture of ANNs [1].

The neuron output signal (O) is calculated by the following relationship [1]:

$$O = f(net) = f(\sum_{j=1}^{n} w_j x_j) \tag{2.1}$$

where the parameter w is the weight vector that represents the effects of the synapses and modulates the impact of the correlated input signals and the function $f(net)$ is indicated to as an activation (transfer) function which is a representation of nonlinear characteristic exhibited by neurons.

As given in equation 2.2, the variable net is determined as a scalar product of the weight and input vectors [1],

$$net = w^T x = w_1 x_1 + \cdots + w_n x_n \tag{2.2}$$

where T is the transpose of a matrix, and, in the uncomplicated case, the output value O is calculated as:

$$O = f(net) = \begin{cases} 1 & if\ w^T x \geq \theta \\ 0 & otherwise \end{cases} \tag{2.3}$$

where the name of the parameter θ is threshold level and this kind of node is termed a linear threshold unit.

A neural network has to be configured in order to generate the desired set of outputs from a set of inputs. Several techniques exist in regards to setting the strengths of the connections. One way is to employ a priori knowledge and set the weights explicitly. The other way is to feed the neural network by teaching patterns and train the network by enabling it to change its weights according to some learning rule [1].

The feed-forward ANNs are most often trained by employing the original back propagation algorithm or by some variant. The greatest challenge in such kind of networks is that they are extremely slow for most applications [1]. There exist several approaches to speed up the training rate one of which is to estimate optimal initial weights [83]. One other technique for training multi-layered feed-forward ANNs is the weight-elimination algorithm. Applying this method, it automatically determines the appropriate topology and consequently, it withdraws also the challenges with over-fitting [81]. Genetic algorithms [71] and Bayesian methods [79] have also been used to train the weights of neural networks.

To sum up, although ANNs have been employed to solve numerous real-world problems, they still have some disadvantages. The most noticeable weakness in such techniques is their lack of ability to reason about their output in a way that can be efficiently communicated. Several researchers have attempted to address this issue and they have proposed various solutions among which extraction of symbolic rules from trained neural networks is the most attractive one [46].

2.3.2 Support Vector Machine

In recent times, one of the most significant directions both in theory and application of learning is proposed by the SVM margin control techniques [78]. Cristianini and Shawe Taylor [46] in 2000 published a book that is an excellent survey of SVMs. SVMs rely on the concept of a margin which is either side of a hyperplane(linear surface) that separates two data classes [46]. Although classical techniques of statistics concentrated on the decrease of the dimensionality of a feature space to control the performance, the SVM focuses on the increase of dimensionality and depends on the so-called large margin factor [78].

In SVM techniques, the upper bound on the expected generalisation error has been proven to be reduced by maximising the margin and generating the greatest possible distance between the separating hyperplane and the instances on either side of it [46].

Melgani and Bruzzone(2004) [59] explained the mathematical formulation of SVMs; Since the mathematical description is beyond the scope of this study, we will not go through the details and we will confine this section to a short explanation.

When the case is two linearly separable classes, one can find an optimum separating hyperplane by minimising the squared norm of the separating hyperplane. This minimisation can be treated as a convex quadratic programming problem. As pictured in Figure 2.6, the points that lie on the margin of the optimum separating hyperplane are known as support vector points and the solution is designed as a linear combination of only these points and other data points are ignored. That is to say that since the number of support vector points chosen by the SVM learning algorithms is most often small, the number of features encountered in the training data cannot affect the model complexity of an SVM. Therefore, in regards to the number of training instances, SVMs are well suited to deal with learning tasks in which the number of features is large [46].

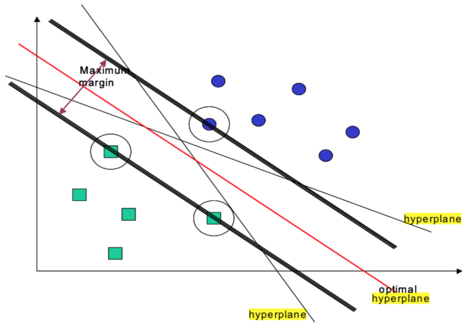


Figure 2.6: The Maximum Margin [46].

2.3.3 K-Nearest Neighbour

The nearest neighbour algorithm is one of the most straightforward instance-based learning algorithms. Aha (1997) [2] and De Mantaras and Armengol (1998) [20] gave a revision over instance-based learning classifiers.

As stated by Cover and Hart (1967) [19], the basis of kNN is on the principle that the instances in a dataset usually exist in the adjacent vicinity to other instances that have similar characteristics.

In kNN algorithms, if the instances are marked with a classification label, then witnessing the class of nearest neighbours of an unclassified instance can determine the value of the label of such instance [46]. Figure 2.7 illustrates a pseudo-code sample for the instance-based learning methods. As demonstrated in this example, the kNN algorithms place the k nearest instances to the query instance and distinguish the single most frequent class label to determine its class.

```
procedure    InstanceBaseLearner(Testing
Instances)
    for each testing instance
    {
    find the k most nearest instances of
    the  training  set  according  to  a
    distance metric
    Resulting Class= most frequent class
    label of the k nearest instances
    }
```

Figure 2.7: The Pseudo-code for Instance-based Learners [46].

Although kNN is powerful in several real domains, there are some doubts about the usefulness of it. Two of such reservations are that the kNN algorithms have huge storage demands and they are sensitive to the selection of the comparison function that is employed to compare instances [46]. The selection of k affects the performance of the kNN algorithm; therefore the kNN approaches also require a principled method to choose k, such as cross-validation or similar computationally-expensive technique [25].

2.4 Related Work

Although there is not a solution that can take a photo archive recorded with the SnapCam device (or similar) and produce an archive consisting photos of interest based on biometric responses, there is research directed to the utility of affective response in search of personal lifelogs. This section aims to present an overview of the work being done in this area.

Kelly and Jones, 2009 [39] investigated using biometric responses such as GSR, ST, and HR as a tool to recognise and extract significant items from personal lifelog collections. For the purpose of this investigation, three subjects captured their biometric responses data such as GSR and ST data, using a BodyMedia SenseWear Pro2 armband (introduced in Section 2.1.2), and their HR data, using a Polar Heart Rate Monitor [6], for the duration of one month.

In addition to the biometric data, their experimental lifelog collections contained computer activities such as web pages viewed, files created or accessed, emails sent and received, etc, recorded using the Slife package [7] and MyLifeBits [8]. The subjects also captured SMSs, all using Nokia N95 mobile phones [9]. Logs of SMSs sent and received were produced employing scripts installed on N95s. A visual log of individual's activities was also captured using a Microsoft Research SenseCam [10].

Kelly and Jones made use of this dataset and designed an experiment to examine whether biometric data can be helpful in recognising significant and memorable events. The procedure for extraction of the SenseCam and computer/SMS items/events in their study comprises of three steps: Firstly, they calculated the maximum, minimum and average GSR, HR, and ST data and they determined the begin and end timestamps of maximum GSR, HR and ST, begin and end timestamps of minimum GSR, HR and ST, and begin and

[6] https://www.polar.com/
[7] http://www.slifeweb.com
[8] https://www.microsoft.com/en-us/research/project/mylifebits/
[9] https://www.nokia.com/en_gb/phones
[10] https://www.microsoft.com/en-us/research/project/sensecam/

end timestamps of average GSR, HR and ST. For the next step, they used the begin and end timestamps from the previous step to extract SenseCam, and computer/SMS events/items as follows: if computer or mobile activity happened during the begin and end timestamps, these items were extracted; otherwise, if SenseCam images occurred within the begin and end timestamps, these images were extracted. Finally, they removed duplicates by removing items from all but their highest occurring threshold. For instance, if a computer file is currently in the minimum collection to be displayed to the subject and it generated a maximum biometric response on a different occasion, then it was removed from the minimum collection.

They analysed the result of their experiment by asking the subjects to complete a provided questionnaire and they observed that GSR and ST appear potential sources of evidence for determination of photos, particularly, ST proved to be the most beneficial factor for retrieving important and interesting items from such collections.

The following year, in 2010, Kelly and Jones [40] studied GSR, in particular, that is identified to change with an individual's arousal level. They hypothesised that items related to important GSR responses are likely to be similarly of more importance and interest to the user in later reflection. The dataset that they used for this study included the lifelogs for three postgraduate students, for a one month period accompanied with corresponding GSR data. The results of their experiments proposed preliminary support for the utilisation of maximum GSR as a jump in point to personal lifelog applications supporting self-reflection.

Kelly dedicated much of her PhD thesis in 2011 [38] to explore the role of biometric response in detecting significant items within lifelogs. She studied if items coinciding with the maximum observed biometric GSR, HF and HR and with minimum observed ST readings were more important to subjects and if this would mean they would be most beneficial or interesting for subjects to view in the future.

Kelly used a one month period from three subjects' lifelog databases which include SenseCam images and computer items (consisting of emails, webpages and textual files) annotated with biometric data for her experiment. She observed the relationship between biometric levels and both SenseCam event and computer item importance.

According to the results of Kelly's experiment, HF levels with periods of high energy expenditure removed are most useful for identifying SenseCam events that subjects may wish to view in the future. Moreover, ST levels showed the greatest utility in detecting computer items individuals may wish to view in the future.

Overall Kelly concluded that factoring of energy expenditure into the individual biometric readings is significant; However, it is difficult to draw conclusions on a biometric measure which may prove most beneficial in discovering interesting events/items. She also declared that future work was required to investigate the nature of biometric response associated with lifelog items and the role of this response in identifying important lifelog items in greater detail.

It is these three studies in particular that form the basis of this project and we hope to build our investigations on their findings by concentrating on categories of life events within the personal lifelogs. We will describe our test set and experiment setup in the following chapter.

Chapter 3

Methodology

In this chapter, we first introduce the structure of the test set that we used for the purpose of our investigation. This test set contains biometric response measures of GSR, HF, and ST, SnapCam photos, and manually logged life events. We then describe the setup of our experiments in order to apply biometric responses to the five different categories of life events for extracting important photos within a visual collection and to make use of such data in order to train three of the supervised machine learning algorithms named ANN, SVM, and kNN to make predictions for the future interesting events and automatically categorise future life events.

3.1 Test Set Structure

Due to the timescale of this investigation, the somewhat cumbersome nature of the devices adopted, and the technical difficulties in using biometric devices running on Windows XP (as described in Section 2.1.2), this study makes use of a personal digital data collection collected by two subjects over a limited time. The subjects involved in this project were two females computer science students in their early twenties. The ethical forms (provided in Appendix 1) were signed by the subjects, the nature of the experiment explained, and the opportunity to ask questions provided.

The subjects collected a visual lifelog using the SnapCam device (introduced in Section 2.1.1) covering 4 hours of a typical day in their lives resulting in over 1000 photos. Along with this visual lifelog the subjects' biometric response data was captured employing the BodyMedia device (as presented in Section 2.1.2) resulting in a total number of 30906 biometric records. This biometric response data was measured once every second and involved GSR, ST, and HF data. The subjects also manually collected a log providing life event information complementing their image-based personal lifelog. In other words, the goal of this log was for it to be applied in combination with the visual lifelog to recognise the life events within the collection.

As demonstrated in Figure 3.1, we stored both the subjects' biometric response data and their manually logged life events in databases. In order to achieve this goal, we employed Java code (provided in Appendix 2) to import the CSV file of biometric response data which was generated by the BodyMedia software into a database. We also made use of Java code (provided in Appendix 2) to import the CSV file of the manually logged life events into the database and we kept the SnapCam photos in a folder. Moreover, we developed Java code (provided in Appendix 2) to make use of the timestamp of each biometric response data and each manually logged life event and find the associated SnapCam photo. The following sections provide details and structures of each component.

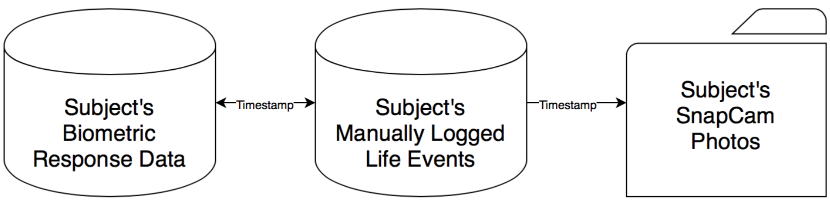


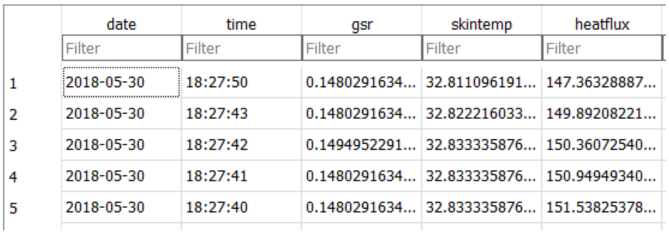
Figure 3.1: The System Architecture Involved in The Process of Data Collection.

3.1.1 Biometric Responses

The biometric response data was collected using a BodyMedia SenseWear Pro2 armband. As we thoroughly described in Section 2.1.2, the BodyMedia armband is worn on the upper arm and records a range of psychological data. The data collected using such device for the purpose of this investigation includes GSR, HF, and ST.

As we also discussed in Section 2.1.2, due to the age of the BodyMedia armband, a VirtualBox had to be employed to run the associated Windows XP based software. This software was required to export and store the recorded biometric response data. The device was connected to the subject's personal computer via a USB cable. The BodyMedia software exported and saved the data as a CSV file through a VirtualBox on a subject's personal computer.

We made use of existing Java code (described in Section 4.2.1) to import this CSV file into an SQLite database. This code firstly takes the individual's path to each of the multiple CSV files, each CSV file contains a day of biometric data. Then, it reads the biometric responses data from the CSV file and puts it into a hash map. Since the beginning 45 minutes of data are most often less reliable, the code eliminates such data from each day



	date	time	gsr	skintemp	heatflux
	Filter	Filter	Filter	Filter	Filter
1	2018-05-30	18:27:50	0.1480291634...	32.811096191...	147.36328887...
2	2018-05-30	18:27:43	0.1480291634...	32.822216033...	149.89208221...
3	2018-05-30	18:27:42	0.1494952291...	32.833335876...	150.36072540...
4	2018-05-30	18:27:41	0.1480291634...	32.833335876...	150.94949340...
5	2018-05-30	18:27:40	0.1480291634...	32.833335876...	151.53825378...

Figure 3.2: An Example of the Table of Biometric Response Data in a Database.

of biometric responses. Finally, once such data are removed, the code writes the remaining biometric data into an SQLite database and stores the collected biometric responses in a table. Figure 3.2 illustrates an example of the table of biometric responses data in a database.

The process of biometric responses data collection in this study encountered challenges. Firstly, due to the cumbersome nature of the BodyMedia armband and the psychological burden placed on subjects from the continuous biometric data recording, they needed breaks from the recording process. This need was also as a result of the discomfort experienced by subjects from prolonged contact of the device with the skin, visibility through individual's clothing and the knowledge that one's biometric response data (even though only available to the test subject) was being recorded; As a result, it was only possible to record biometric data for a limited time period in this study. New devices would alleviate much of these burduns, as discussed in Section 6.2.

3.1.2 Manually Logged Life Events

Along with the biometric response data, we asked our subjects to keep a log providing life events information to complement their image-based personal lifelog. To put it differently, we made use of the contextual information through this life event log to later interpret the visual lifelog.

Based on the activities of an individual during a day, we grouped the events that happened most frequently into appropriate categories resulting in the 5 categories named: Eating, Walking, Working, Travelling, and Other. We asked our subjects to log their information regarding which of the five events best explained what they were doing. To make sure that we do not miss any information, we explained to our subjects to log their information whenever had a change of event within the logging period.

The subjects made use of a spreadsheet placed on their mobile phone which was kept in sync online through Microsoft OneDrive to log their information. We imported the manually logged data into a database using the SQLite database manager. Figure 3.3 demonstrates an example of the table of such data in a database.

	mydate	clock	activity
	Filter	Filter	Filter
1	2018-05-30	14:06:00	Working
2	2018-05-30	15:06:00	Working
3	2018-05-30	16:06:00	Working
4	2018-05-30	16:50:00	Walking
5	2018-05-30	17:06:00	Travelling

Figure 3.3: An Example of the Table of Manually Logged Life Events in a Database.

It should be noted that all details of subjects lives may not be logged due to the fact that manually logging events is a daunting task and the subjects may easily forget to log some events.

3.1.3 SnapCam Photos

A visual lifelog of our subjects' activities was held using the SnapCam device (described in Section 2.1.1). The collected lifelog photos were exported from the SnapCam using a Micro SD card reader or via a USB cable from the device to the subject's personal computer. Such photos were stored to the subject's personal computer within a folder.

Each photo in such folder has a unique name and a timestamp. We developed Java code (described in Section 4.4) to search within this folder and find the related photos based on their timestamps.

Data collection using SnapCam device involved several challenges including subjects' need for privacy, subjects' need for psychological break from the recording process, unwillingness of some people encountered to be captured by the SnapCam, and subjects' feeling of being uncomfortable wearing the SnapCam in some social settings. As a result of such problems, all details of subjects lives are not captured in SnapCam photos.

3.2 Experiment Setup

In this section, we describe the setup of our study to examine whether biometric response levels can be useful in identifying future important and memorable events across the five different life event categories.

As fully reported in Section 3.1, we made use of the one day period from our subjects' lifelogs which contain biometric response data, manually logged life events, and SnapCam photos as the test set for this experiment. We read both the biometric data and manually logged life events from the biometrics table and manually logged life events table in the databases. These tables are respectively described in Section 3.1.1 and Section 3.1.2. We also accessed the SnapCam photos through a folder placed in the subjects' personal computers (section 3.1.3).

The remainder of this section describes our use of biometric responses data to extract important SnapCam events and describes the user study conducted to determine the utility of our approach.

3.2.1 Extracting Important Events

As discussed earlier in Section 2.2, biometric responses always vary and numerous factors can make such changes including internal thinking processes of the individual, external temperature, a fear provoked by a sudden noise, and eating. For this reason, it is an extremely complicated process to use biometric response data associated with a former experience of lifelogging items to identify the items that individuals might be interested to view in the future. In this section, we attempt to make use of the relationship between biometric response and interesting events to extract the events that an individual will later reflect on.

In the extraction of life events from the subjects' personal lifelog collections, we hypothesised that the important events were those of maximum GSR and HF responses and minimum ST response. The basis of this postulation is the results of Kelly et al's investigations (detailed in Section 2.4) which declared preliminary support of this study.

In order to extract these events from the personal lifelog collections, two factors are required to be considered; Firstly, the intensity of GSR, HF, and ST biometric responses (minimum, average, and maximum) and secondly, the type of life event (Eating, Walking, Working, Travelling, and Other). In regards to measuring the relationship between biometric responses and life events, we extracted no more than 45 events in total. As demonstrated in Figure 3.4, these events include 9 biometric responses event for each of the 5 types of life events.

As illustrated in Figure 3.5, each of these 9 biometric responses events was divided up into 3 events including minimum, average and maximum responses for each of the three biometric responses types: GSR, HF, and ST.

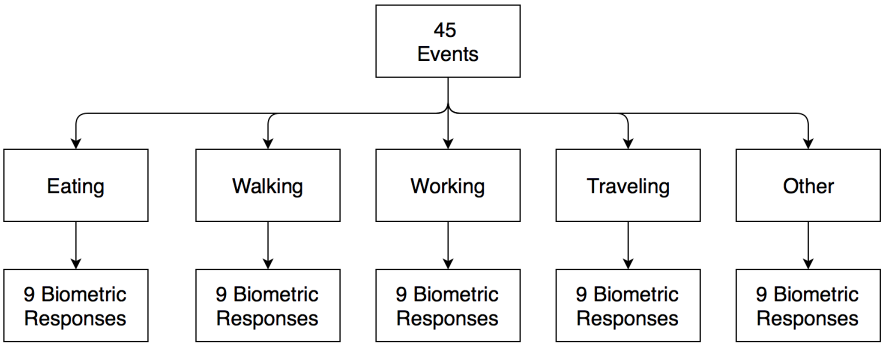


Figure 3.4: The Structure of the Events.

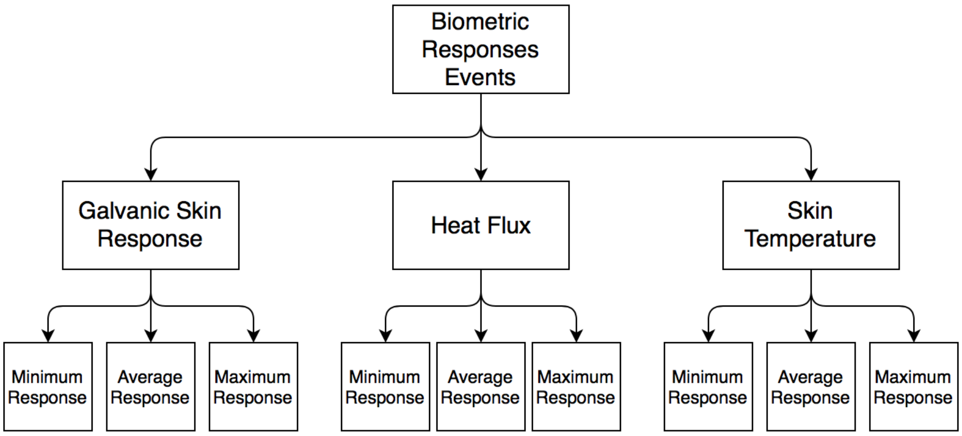


Figure 3.5: The Structure of the Biometric Response Events.

Each of the 45 events had an extracted item based on their recorded timestamp which is not necessarily unique. Life event extraction was achieved using two tables of data, the subjects' biometric response data and the subjects' manually logged life events. We displayed the examples of these two tables respectively in Figure 3.2 and Figure 3.3. Since the BodyMedia armband recorded the data every single second, then there definitely is a common timestamp between the subjects' manually logged life events and their biometric responses data. We made use of this common timestamp as a primary key to join the life events data with the subjects' associated biometric responses data. Section 4.4 will later precisely describe the implementation of such extraction.

We made use of Java code to retrieve the appropriate SnapCam photo based on the timestamps of the associated biometric responses extracted above. We will also describe the details of this implementation later in Section 4.4.

3.2.2 Experiment Procedure

The goal of this investigation is to establish the relationship between biometric response levels and future significance of events across the five different life event categories. In this section, as an initial investigation into this new field of research, we attempt to set up an experiment to make use of machine learning algorithms and the relationship between biometric response levels and interesting items to predict such events. Figure 3.6 demonstrates the procedure of these experiments.

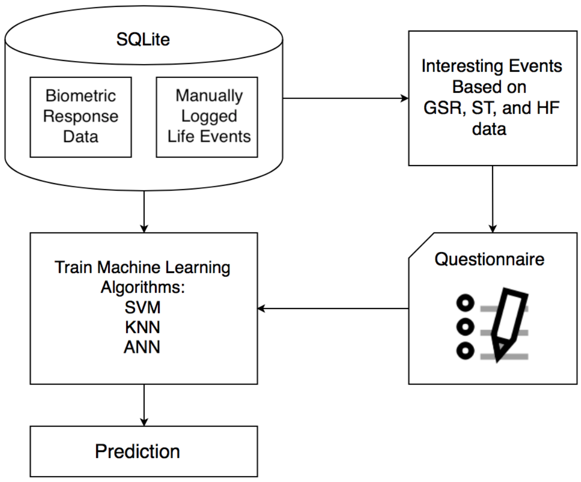


Figure 3.6: The Architecture of the Training System.

As illustrated in this figure, to begin with, we extracted the interesting photos based on varying GSR, HF, and ST responses for each of the 5 types of life events (Eating, Walking, Working, Travelling, and Other). Section 3.2.1 thoroughly described such extraction. Afterwards, we presented these extracted events to subjects and asked them to complete a questionnaire to discover whether GSR, HF, and ST carried any evidence of the memorableness and importance of specific life events or whether the subjects' had any desire to retrieve such events again.

Each of the subjects was presented with their set of no more than 45 SnapCam events in no particular order and a questionnaire. Subjects were not informed that the sets presented to them included events with varying associated biometric levels. There were 7 different questions in the questionnaire and each of these questions had a categorical information as the choice of response. We explained this questionnaire to subjects. Each of the subjects completed the questionnaire for their no more than 45 events and they returned the results to the investigator for analysis. The questions posed in the questionnaire are listed blow:

1. Is this event memorable? (Very Memorable/ Memorable/ Not Very Memorable/ Not Memorable)

2. Was the event important to you at the time? (Very Important/ Important/ Not Very Important/ Not Important)

3. Is the event important to you now? (Very Important/ Important/ Not Very Important/ Not Important)

4. Can you remember the event now? (Very Well Remembered/ Well Remembered/ Not Very Well Remembered/ Not Well Remembered)

5. How did you feel at the time this event occurred? (Don't Remember/ Stressed/ Excited/ Happy/ Sad)

6. How do you feel on being re-presented with this event now? (Feel Nothing/ Stressed/ Excited/ Happy/ Sad)

7. Do you think you would want to re-retrieve the event? (Yes/ Maybe/ No)

Next, we made use of the collected biometric data together with the subjects' manually logged life events and results of the questionnaire in supervised machine learning techniques (described in Section 2.3) to study what could be predicted given such data. We used the statistical language R (introduced in Section 4.2.3) to implement three of such techniques named ANN, SVM, and kNN which are respectively explained in Section 2.3.1, Section 2.3.2, and Section 2.3.3. We will thoroughly present the details of this implementation in Section 4.5.

The training data presents the machine learning algorithms the information from which they can train a model. In order to collect such training data, we developed Java code to create a training table using the subjects' biometric response data, subjects' manually logged life events and results of the questionnaire. Figure 3.7 demonstrates an example of such table. As illustrated in this figure, the training table makes use of the information in the biometric responses table (reported in Section 3.2) together with the information of manually logged life events table (reported in Section 3.3), and the results of the questionnaire.

1	Time in Bio	Time in Log	Date	HF	GSR	ST	Activity	Intensity	Biometric	Photo Name	Memorable	Important that Time	Important Now	Remember	Feel that Time	Feel Re-Presented	Retrieve the Event
2	18:31:40	18:25:00	30/05/2018	174.445	0.14363	32.2795	Walking	MIN	ST	SNAP1175.JPG	Not Memorable	Not Important	Not Important	Not Well Remembered	Stressed	Sad	No
3	16:50:00	16:50:00	30/05/2018	126.568	0.14363	34.7748	Walking	MAX	ST	SNAP1087.JPG	Memorable	Important	Important	Well Remembered	Happy	Excited	Yes
4	14:06:00	14:06:00	30/05/2018	96.5057	0.0315	27.7462	Working	MIN	ST	SNAP0759.JPG	Very Memorable	Very Important	Important	Not Well Remembered	Sad	Feel Nothing	Maybe
5	15:47:34	15:06:00	30/05/2018	95.904	0.17809	35.1658	Working	MAX	ST	SNAP0962.JPG	Not Memorable	Not Important	Not Important	Not Well Remembered	Don't Remember	Feel Nothing	No

Figure 3.7: An Example of the Training Table.

This experiment attempts to predict the subjects' questionnaire responses and the type of event logged by them. As displayed in Figure 3.8, once the machine is trained using each of the ANN, SVM, and kNN techniques, it can predict such data using biometric responses data without any additional step.

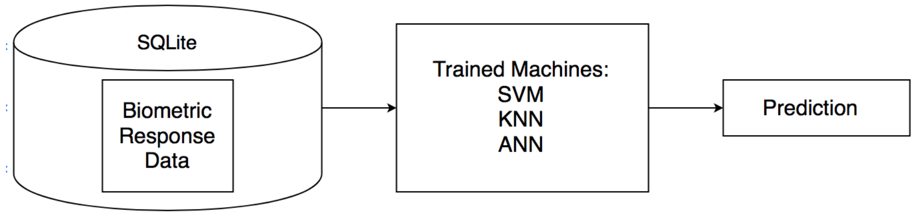


Figure 3.8: The Architecture of the Trained System.

We will thoroughly discuss the results of this experiment later in Section 5. The following chapter will report the implementation of the aforementioned method.

Chapter 4

Implementation

In this chapter, we present the implementation of our method (described in the previous chapter) to attempt solving the problem that we stated in Section 1.1. To start with, this chapter gives a survey over the implementation process and introduces the programming languages and libraries that we used to develop the code needed for this project. Next, we report the requirements of the project (as a post-condition) together with the assumptions we made (as a pre-condition) and the design of the whole system. We conclude this chapter with a detailed description of the steps of this implementation.

4.1 Implementation Overview

The aim of this investigation is to locate personally important events within categories based on biometric response measures and to predict such events using machine learning algorithms. In order to implement our methodology (described in Section 3.2), we separated the project into two different phases. In the first phase, we developed an application that extracts important events using biometric responses and in the second one, we employed machine learning algorithms to make predictions. The following sections will report the details of such implementation.

4.2 Programming Languages and Libraries

We implemented the application of Phase I using the Java language and SQL. Java was originally created in the 1990s by James Gosling at Sun Microsystems and has since then become a simple, yet powerful, programming language. The Java programming language has rich API supports that enable developers to run their code on all platforms without the need for recompilation which makes it an attractive choice for the implementation of this phase. Additionally, we had access to some existing Java code. Since Java is a modular language, we could change this code and make use of it for a part of this phase.

We made use of the R programming language to implement Phase II. R was designed in the 1990s by Ross Ihaka and Robert Gentleman at the University of Auckland, New Zealand, and is currently developed by the R Development Core Team. We chose R for this phase of the project due to the fact that R has several powerful machine learning packages and makes it straightforward to implement such techniques. The remainder of this section describes the application of these languages and their libraries in this study.

4.2.1 Java Language

We made use of an existing Java[1] (version 9.0.1) code (provided in Appendix 2) to store the collected biometric data into a database. For the purpose of this investigation, we altered the Java code to satisfy the requirements of this study by changing the type of database fields needed to store the biometric responses. This code extracts the reliable data by eliminating the inaccurate data which is located at the beginning 45 minutes of a collection period and writes such data into a particular database.

This Java code uses two libraries for the insertion and management of the SQL database. These two libraries are listed as follows:

- *java.util*[2] that affords the collections framework and legacy collection classes while also giving event model, date and time facilities, and internationalization together with other miscellaneous utility classes. The utility of this library in this study is to provide iterators, hash map, tree map and calendar functionality for extracting CSV format of recorded biometric data and writing them.

- *java.sql*[3] that affords the API to access and process the data stored in a data source (usually a relational database). The benefit of the aforementioned library in this investigation is to provide the connection management, result sets and statements required for the insertion and management of the SQL database.

We also developed Java code (provided in Appendix 2) to automate the process of getting paths to the biometric responses CSV file, manually logged life events CSV file, SnapCam directory, a SQLite database, and an empty CSV file from the user and generate the

[1] https://www.java.com/
[2] https://docs.oracle.com/javase/7/docs/api/java/util/package-summary.html
[3] https://docs.oracle.com/javase/7/docs/api/java/sql/package-summary.html

extracted data into this empty CSV file. This code stores the manually logged life events into the database and next, it runs the modified Java code to store the biometric data into the database as well. Then, the code makes use of these data to automatically extract no more than 45 events (described in Section 3.2.1) and their associated SnapCam photos. Finally, the code exports such data into the empty CSV file. This Java code makes use of the *opencsv*[4] library to read and write CSV files.

4.2.2 Structured Query Language

We made use of SQL as a standard language for storing, managing, manipulating, and retrieving the data stored in databases. In order to achieve the goal of this study, we employed SQLite[5] (version 3.22.0) which is a self-contained, high-reliability, public-domain, SQL database engine and has the widest usage amongst other engines around the world. We wrote several queries to extract a variety of information associating with the events and biometric response data stored in SQLite.

4.2.3 R Language

We made use of the R[6] (version 3.4.4) programming language for statistical computing and graphics. In regards to the aim of this project, we adopted R in a machine learning context (provided in Appendix 3) to predict several results based on the subject's biometric response data, manually logged life events and their responses to a questionnaire. For this reason, we also made use of the following libraries:

- *readxl*[7] that makes it simple to get data out of an Excel file and put it into R. The benefit of this library in our investigation is to read the training data from the CSV file and make use of this information in R code.

- *nnet*[8] that fits feed-forward single-hidden-layer neural networks, probably with skip-layer connections. The usage of nnet library for this study is to implement the ANN technique.

- *e1071*[9] that has various functions for potential class analysis, short time Fourier transform, fuzzy clustering, SVMs, shortest path computation, bagged clustering, naive

[4] http://opencsv.sourceforge.net
[5] https://www.sqlite.org/
[6] https://www.r-project.org
[7] https://readxl.tidyverse.org
[8] https://cran.r-project.org/web/packages/nnet/
[9] https://cran.r-project.org/web/packages/e1071/

Bayes classifier, etc. The profit of e1071 library for this investigation is to implement the SVM technique.

- *class*[10] that has several functions for classification, including kNN, learning vector quantization and self-organizing maps. The advantage of this library for our project is to implement the kNN technique.

4.3 Requirements

A successful run of the code should:

- find the needed files from the user's given paths.
- be able to process biometric response data of any length.
- be able to process manually logged life events of any length.
- be able to extract the important biometric responses.
- be able to find the related SnapCam photos.
- be able to generate the user CSV file.
- be able to predict the answers of the questions in the questionnaire.
- be able to predict the user's activity (Eating, Walking, Working, Travelling, and Other).

For the code to carry out such activities, we made some assumptions which we will explain in the next section.

4.3.1 Assumptions

Given the requirements declared in the previous section, we made the following assumptions regarding the input values during the development of the code:

- Paths to the required files and folders are correct.
- Biometric Response data are in a CSV file with the same format as BodyMedia software generates.

[10] https://cran.r-project.org/web/packages/class/

- Manually logged life events are in a CSV file which contains 3 columns respectively containing the date, time, and activity information.
- The activities in manually logged life events are one of the Eating, Walking, Working, Travelling, or Other events.
- Answers to the questionnaire have at least three different responses for each question.

4.3.2 Design

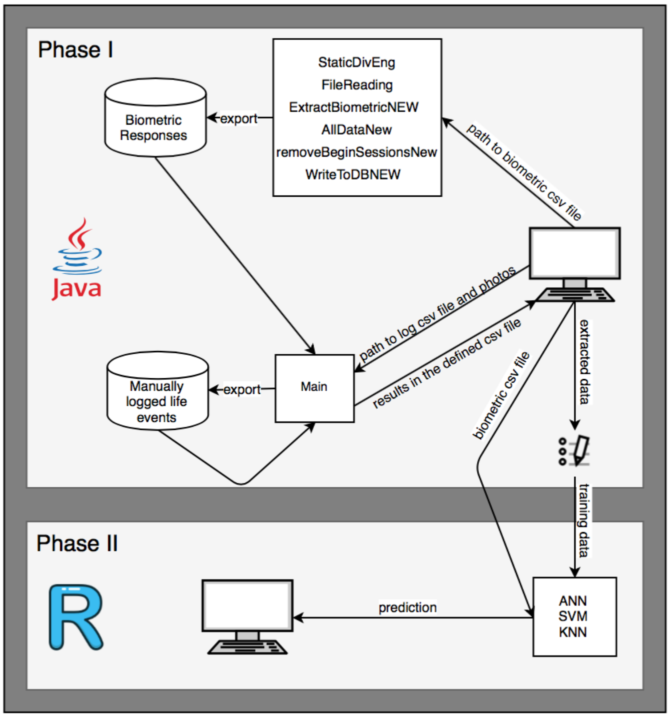


Figure 4.1: The Architecture of the System.

Figure 4.1 demonstrates the architecture of the system we used to process a lifelog. As we mentioned earlier, this system consists of two different phases. Phase I starts with using the Java programming language to receive paths from the user and create SQLite tables. This Phase ends with the extraction of important events and their associated SnapCam photos. Phase II receives the combination of outputs of Phase I and results of the questionnaire as a training set. This phase uses the R programming language to implement ANN, SVM, and kNN techniques and predict the future important events. We will describe details of each phase thoroughly in the following sections.

4.4 Phase I: Extraction of Important Events

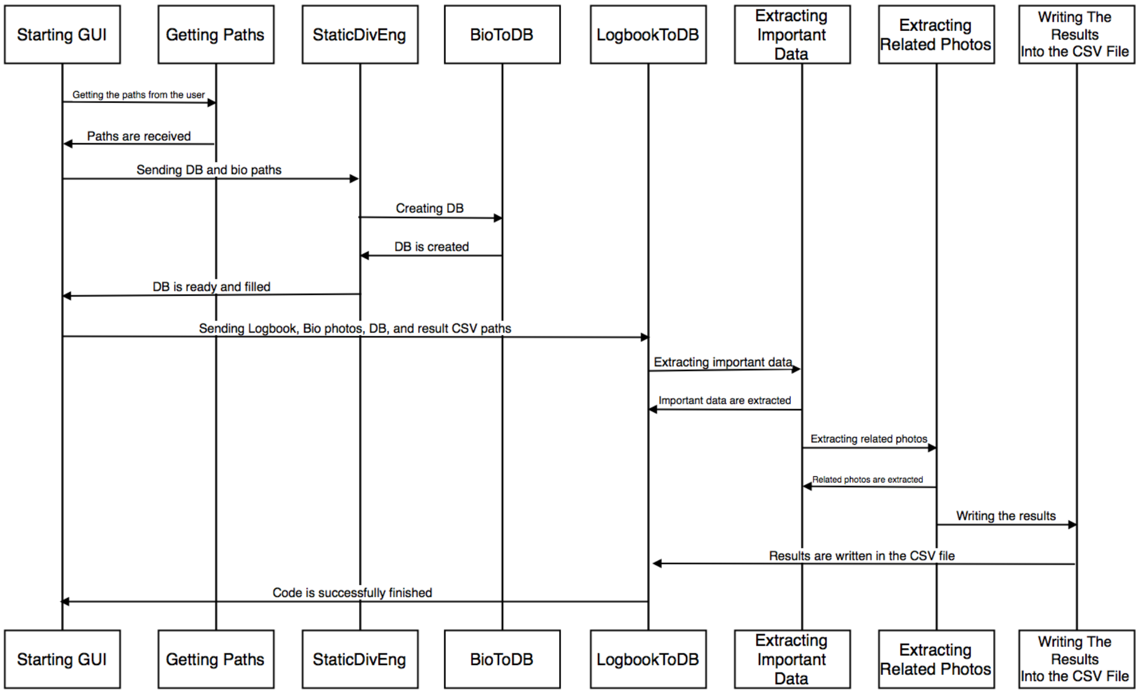


Figure 4.2: The Sequence Diagram for Phase I.

The goal of this phase is to locate personally important events based on biometric response data (described in Section 3.2.1) and extract their related photos. Figure 4.2 demonstrates the sequence diagram for this phase. As represented in this Figure, this phase starts with a GUI that collects paths for required directions from the user (illustrated in Figure 4.3).

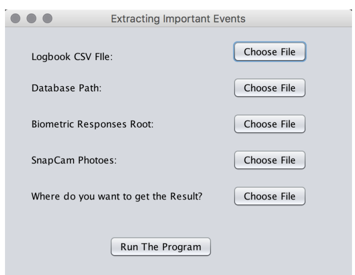


Figure 4.3: Extracting Important Events GUI.

Once the paths are collected, this phase makes use of the modified version of existing Java code containing 6 classes named *staticDivEng*, *FileReading*, *ExtractBiometricNEW*, *AllDataNEW*, *removeBeginSessionsNEW*, and *WriteTODBNEW* to read the biometric response data, remove the beginning 45 minutes of it and export it into the SQLite as a table named *AllBio* (shown in Figure 3.2).

We developed a class named *Main* for this phase to export manually logged life events into SQLite as a table named *logbook* (shown in Figure 3.3). Next, we made use of this code to use timestamps of such tables as a primary key and send queries to SQLite to join the manually logged life event with the subject's associated biometric responses and extract important events. These queries are of two types: the first type is for finding the minimum and maximum of each GSR, HF, and ST responses and their associated activities and the other one is for finding the average of such data. Figure 4.4 represents an example of a query from the first type that find all the information for the minimum ST and Walking activity.

```
SELECT logbook.activity, AllBio.time as DataTime, logbook.clock as LogTime, logbook.mydate, AllBio.date, AllBio.heatflux, AllBio.skintemp, Allbio.gsr
FROM AllBio INNER JOIN logbook ON substr(logbook.clock, 0,3) == substr(AllBio.time, 0,3) AND logbook.mydate == AllBio.date
WHERE logbook.activity = "Walking"
AND ((substr(AllBio.time, 4,2) >= substr(logbook.clock, 4,2)) or (substr(AllBio.time, 4,2) < (substr(logbook.clock, 4,2) + 30)))
ORDER BY AllBio.skintemp ASC limit 1
```

Figure 4.4: A Sample Query Example.

In addition, the *Main* class makes use of the timestamp of the SnapCam photos to automatically find the related photos to the aforementioned extracted events. Figure 4.5 demonstrates the function doing such extraction.

```
public void names(String[][] data) {
    File[] images = new File(IMAGES_PATH).listFiles();
    SimpleDateFormat sdf = new SimpleDateFormat("h:m:s");

    for (int i = 0; i < data.length; i++) {
        if (data[i][0] == null)
            return;
        String time = data[i][0];
        long min = Long.MAX_VALUE;
        String fn = "";
        for (File image: images) {
            BasicFileAttributes attr = null;
            try {
                attr = Files.readAttributes(Paths.get(image.getPath()), BasicFileAttributes.class);
            } catch (IOException e) {
                e.printStackTrace();
            }
            String mt = attr.lastModifiedTime().toString().substring(11, attr.lastModifiedTime().toString().length() - 1);
            try {
                if (Math.abs(sdf.parse(time).getTime() - sdf.parse(mt).getTime()) < min) {
                    min = Math.abs(sdf.parse(time).getTime() - sdf.parse(mt).getTime());
                    fn = image.getName();
                }
            } catch (ParseException e) {
                e.printStackTrace();
            }

        }
        data[i][9] = fn;

    }
}
```

Figure 4.5: The Function of Photo Extraction.

Lastly, this code generates a CSV file (demonstrated in Figure 4.6) containing important events with their related information in both *AllBio* and *logbook* tables and the name of their associated SnapCam photos. This file also contains 7 empty columns for results of the questionnaire to be filled later and be used as an input for the next phase.

Time in Bi	Time in Lc	Date	HF	GSR	ST	Activity	Intensity	Biometric	Photo Nar	Memorab	Important	Important	Remembe	Feel that	Feel Re-Pi	Retrieve the Event
18:31:40	18:25:00	30/05/2018	174.4449	0.143631	32.2795	Walking	MIN	ST	SNAP1175.JPG							
16:50:00	16:50:00	30/05/2018	126.568	0.143631	34.7748	Walking	MAX	ST	SNAP1087.JPG							
14:06:00	14:06:00	30/05/2018	96.50568	0.031504	27.7462	Working	MIN	ST	SNAP0759.JPG							
15:47:34	15:06:00	30/05/2018	95.90401	0.178085	35.16583	Working	MAX	ST	SNAP0962.JPG							
17:37:10	17:06:00	30/05/2018	211.6891	0.194948	32.52264	Travelling	MIN	ST	SNAP1175.JPG							

Figure 4.6: The CSV File Generated by the Application.

The investigator is required to extract the "Photo Name" column of this CSV file and give the names together with the questionnaire to the user. Once the user completed the questionnaire, the investigator fills the empty columns based on the results of this questionnaire and makes use of it as an input for the next phase. We will provide details of the next phase in the following section.

4.5 Phase II: Prediction

Phase II receives the CSV file which is generated by the application in the previous phase and completed by results of the questionnaire as an input. This phase uses the R language to implement three of the supervised machine learning languages namely ANN (described in Section 2.3.1), SVM (described in Section 2.3.2), and kNN (described in Section 2.3.3). Figure 4.7 demonstrates a sample code for implementing the ANN technique. This code uses a function named *predictMNL* to predict the important events based on the ANN model.

```
a <- trainset$`Skin Temp`
b <- trainset$Heatflux
c <- trainset$GSR
d <- as.factor(trainset$`Feel that Time`)
modelD <- multinom(d ~ a + b + c, trainset)
a = testdata$Skin.Temp; b = testdata$Heatflux; c = testdata$GSR;
mytestdata = data.frame(a,b,c)
predictMNL <- function(model, newdata) {
  if (is.element("nnet",class(model))) {
    probs <- predict(model,newdata,"probs")
    cum.probs <- t(apply(probs,1,cumsum))
    vals <- runif(nrow(newdata))
    tmp <- cbind(cum.probs,vals)
    k <- ncol(probs)
    ids <- 1 + apply(tmp,1,function(x) length(which(x[1:k] < x[k+1])))
    return(ids)
  }
}
predD <- predictMNL(modelD, mytestdata)
```

Figure 4.7: A Sample Code for the ANN Implementation.

Figure 4.8 illustrates a sample code for implementing the SVM technique. This code collects the training set information and designs a model based on such information. Next, the code gets test set information and imputes the events using the designed model.

```
a <- trainset$`Skin Temp`
b <- trainset$Heatflux
c <- trainset$GSR
g <- as.factor(trainset$`Important Now`)

modelSVMG <- svm(g ~ a + b + c, trainset, probability = TRUE)

a = testdata$Skin.Temp; b = testdata$Heatflux; c = testdata$GSR;
mytestdata = data.frame(a,b,c)

predSVMG <- predict(modelSVMG, mytestdata, decision.values = TRUE,probability = TRUE)
```

Figure 4.8: A Sample Code for the SVM Implementation.

Figures 4.9 demonstrates a sample code for implementing the kNN approach. The implementation of this technique is almost similar to the implementation of the SVM technique. This code trains the system using the information in the training set and makes use of the kNN method in order to predict life events.

```
a <- trainset$`Skin Temp`
b <- trainset$Heatflux
c <- trainset$GSR
act <- as.factor(trainset$Activity)

a_ <- c(testdata$Skin.Temp)
b_ <- c(testdata$Heatflux)
c_ <- c(testdata$GSR)
act_ <- c(as.factor(testdata$Activity))

train <- cbind(a,b,c)
test <- cbind(a_,b_,c_)

actRes = knn(train = train , test = test, cl = act, k = 3, prob = T)
```

Figure 4.9: A Sample Code for the kNN Implementation.

In the following chapter, we will report the results of these experiments together with an evaluation of our system.

Chapter 5

Evaluation

In this chapter, we report results of the experiment described in Section 3.2. We also provide a discussion regarding the experimental results, and the strengths and limitations identified of the proposed approach.

5.1 Experiment Results

As discussed in Section 3.2, in this experiment, we extracted important events within a visual lifelog based on biometric response measures across five different life event categories (Eating, Walking, Working, Travelling, and Other). We then asked the subjects to complete a questionnaire on the extracted events. Next, we made use of the extracted events, biometric response levels, and results of the questionnaire in a machine learning system in order to predict the events that would be important to the subjects in the future.

To evaluate our prediction system, we used the extracted important events and biometric responses together with the results of the questionnaire of our first subject as a training set, and we used the extracted important events and biometric responses of the second subject as a test set. The training set was used to train our machine learning algorithms to predict results of the questionnaire for the second subject. When the prediction was completed, we compared the predicted results with the actual results of the questionnaire provided by the second subject. As described in Section 3.2.2, there were different choices of responses for the 7 questions of the questionnaire. According to the questionnaire, 4 of these questions had 4 choices of responses, 2 of these questions had 5 choices of responses, and 1 of these questions had 3 choices of responses. In order to compare the predicted results with the actual results and analyse these results, we converted all of these responses to a 3-point scale (respectively maybe, no, yes) in order to automatically predict the answer to the question "Do you think you would want to re-retrieve the event?". For this reason, we combined the response of 3 and 4 for the questions that had 4 choices of responses while

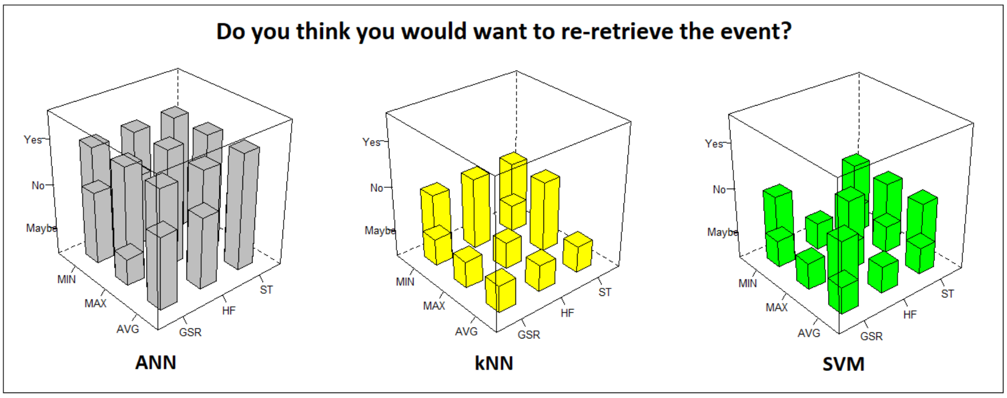


Figure 5.1: The Results of Predictions.

we combined the response of 2 and 3 and the response of 4 and 5 for the questions that had 5 choices of responses. Using this conversion, we chose the answer (maybe, no, yes) with the most number of occurrence in the results of the 7 question as the answer for the proposed question for each event. We also applied the same method to the result of the questionnaire provided by our second subject in order to compare such results with results of our predictions and calculate the accuracy of each technique.

Figure 5.1 presents the results of the predictions using the ANN, kNN, and SVM machine learning techniques, for the question that we were interested in automatically predicting ("Do you think you would want to re-retrieve the event?"). This figure shows the predicted results of the questionnaire in accordance with measures of GSR, HF, and ST responses and their intensity (MIN, MAX, AVG) across five different life event categories (Eating, Walking, Working, Travelling, and Other).

Figure 5.2 illustrates the accuracy of predictions for each of the ANN, SVM and the kNN approaches. As can be seen, the kNN technique proved to be the most accurate technique with accuracy of 62.2%.

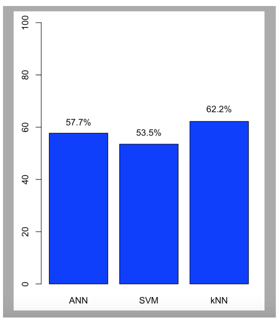


Figure 5.2: The Accuracy of Results.

Since the kNN technique had the highest accuracy, we used it to predict which of the 5 life event categories each photo represented, based on biometric response levels. Figure 5.3 demonstrates the results of such predictions together with the actual life event categories provided by the second subject in their manually logged life events. We also calculated the accuracy of the kNN technique for these predictions and it was 71.1%.

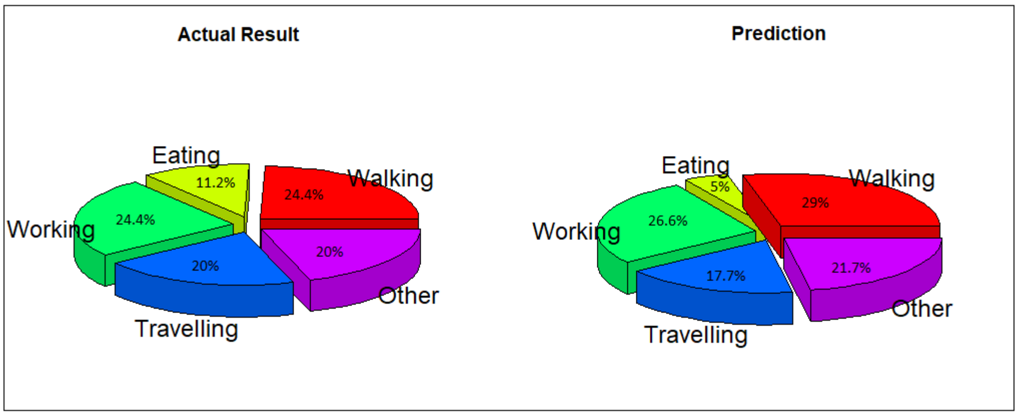


Figure 5.3: The Prediction of Life Event Categories using the kNN Technique.

In the following section, we will discuss reported results of our experiments combined with the strengths and limitations of our system.

5.2 Discussion

In accordance with the results of three machine learning techniques (ANN, SVM, and kNN) reported in the previous section, we observed that the predicted events of future interest for the subjects were mostly the ones related to the maximum GSR, maximum HF, and average ST. These observed correlations differ from those observed by Kelly [38] in their preliminary study in the ST measures. Although the accuracies of all three approaches were above 50% using our system, the results suggested that the kNN approach was the most powerful technique in comparison with the ANN and SVM techniques with accuracy of 62.2%. We also observed the accuracy of the kNN approach with regards to the prediction of different life event categories and it proved to be 71.1% which is a remarkable achievement.

We believe that our system is dependable as a result of having 5 software dependability attributes named availability, reliability, safety, integrity and maintainability. Firstly, the system is available 24x7 on local machines. Secondly, in order to ensure that our system is reliable, we developed unit tests (provided in Appendix 2) for testing our application throughout the development of the first phase (described in Section 4.4). Thirdly, the current state of our system does not involve security aspects. Fourthly, with regards to the integrity, our system has a backup of the datasets on databases. Lastly, our system welcomes maintenance and extensions.

Even though we believe our designed system is both dependable and reliable, we also consider our experiment to have some limitations. One such limitation is in regards to the number of subjects and the time-frame of the test set which results from the timescale of the project and the cumbersome nature of devices used. The second limitation is the lack of variety in life event categories as a result of having student subjects. However, our system is flexible enough to include new features and further refinements without notable differences (by changing the format of inputs or adding new functions to Java code) and it can be extended in future developments. In the following chapter, we will outline our conclusions and we will suggest potential future work.

Chapter 6

Conclusion and Future Work

Having described the context, problem, solution and evaluation of our investigation into the use of machine learning to locate personally interesting photos using biometric response, in this chapter we present the conclusions that were reached by the end of our investigation. We also analyse the completion of the objectives of this investigation. Lastly, we suggest future work to continue the research direction taken by this study.

6.1 Conclusions

This was an ambitious study that required substantial work regarding becoming familiar with new concepts in personal lifelogging and machine learning and it also demanded the use of two devices namely iON SnapCam Lite and BodyMedia SenseWear Pro2 armband. From a personal perspective, this investigation was remarkably rewarding both due to the knowledge gained and the results that were obtained.

This project achieved a novel solution to the problem stated in Section 1.1. This problem involved handling, analysing, indexing and providing content-based access to the data derived from lifelogging. In attempt to solve this, we implemented an application to make use of GSR, HF, and ST measures to extract important events within a visual collection across particular life events (Eating, Walking, Working, Travelling, and Other). Once important events were extracted, we asked our subjects to complete a questionnaire regarding such events. We then combined the important events and results of the questionnaire as a training set in order to train machine learning algorithms and predict the future important life events across the mentioned five different categories. Our system has the power to help researchers and individuals to retrieve their events of interest from a visual lifelog. The evaluation results fulfilled our primary objectives and demonstrated that this system could successfully be beneficial for the user. The following is a summary of key points in the thesis, along with key observations and findings.

Firstly, this thesis described the definition of personal lifelogging, its benefits and challenges that it may cause together with the description of two devices of interest for this study. The utility of biometric response measures in personal lifelog searches was also discussed along with a survey of machine learning approaches and related work.

Secondly, the test set structure used in this study and the methodology to extract important events in a visual collection across five different categories of life events using biometric responses and to predict future important life events were described. The setup of experiments and the procedure of implementing this system were also reported.

Finally, this thesis presented the results of our experiments and a discussion of these results. Using three different techniques of machine learning named ANN, SVM, and kNN, the kNN approach proved to be the most useful approach with accuracy of 62.2% for predicting the future photos of interest in a visual lifelog based on biometric measures across five different life event categories. The kNN technique also predicted the 5 categories of life events, Eating, Walking, Working, Travelling, and Other, with accuracy of 71.1%.

6.2 Future Work

Future work for this project includes:

- ***Scale up this study.*** One of the limitations of the current study (due to the circumstances mentioned in Section 3.1) was the number of subjects and the time-frame of the test set. An alternative experiment could be set up where the number of subjects is greater and the subjects collect their records over a longer period.

- ***Apply this technique to lifelogs created with other devices.*** There are newer biometric response recording devices than the BodyMedia SenseWear Pro2 armband in the market such as the E4 wristband from Empatica [1] that are more sophisticated and less clunky to wear. These devices could be used for the approach proposed in this investigation. An analysis of the characteristics of their output data could be performed to determine their accuracy and comparability to the BodyMedia armband in recording biometric response, and any resulting changes that are needed to process visual lifelogs based on such data using our method.

- ***Additional life events categories.*** To improve and create a more general approach to automatically categorise life events, a new approach could be developed to overcome the limitation of the number of life event categories. A suggestion would be

[1] https://www.empatica.com/research/e4/

to personalise life events for different types of people by dividing them into different categories such as students, workers, and housekeepers, for example.

- ***Improve the current machine learning approaches.*** The current machine learning techniques could be improved by increasing the number of training data in order to achieve a higher accuracy in predictions. Moreover, changing the number of neighbours in the kNN technique could lead to more accurate results.

- ***Use more machine learning approaches.*** The accuracy of predictions could be maximised if additional machine learning techniques are taken into consideration to predict future important life events within a visual lifelog based on biometric responses. These techniques could include “Deep Learning”, “Bayesian Networks”, “Clustering”, and “Decision Tree Learning”.

- ***Future research directions.*** Additionally, the current approach could be extended to extract other types of lifelog data such as emails, computer files, web pages viewed, Global Positioning System (GPS) that might be interesting for the user.

Appendix A

Attachments and Supporting Files

- *Appendix 1:* The Ethics Forms.
- *Appendix 2:* The Java Code.
- *Appendix 3:* The R Code.

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