An Efficient Emotion Classification System using EEG

Anuchin Chatchinarat

B.Sc. Engineering (Computer Engineering)

M.Sc. Engineering (Computer Engineering)

This thesis is presented for the Degree of

Doctor of Philosophy

Murdoch UNIVERSITY

2019

DECLARATION

I declare that this thesis is my own account of my research and contains as its main content work which has not previously been submitted for a degree at any tertiary education institution.

Anuchin Chatchinarat

April, 2019

ACKNOWLEDGEMENTS

I wish to express my deepest gratitude and appreciation to my academic supervisor, Associate Professor Dr. Kevin Wong, for providing advice, assistance, and encouragement throughout this study, and especially for critically reviewing this thesis.

I would also like to thank my co-supervisor, Emeritus Professor Dr. Lance Fung, for his close association and advice, as well as providing useful comments on my work. My extended thanks go to the staff at the Discipline of Information Technology, Mathematics and Statistics, Murdoch University.

I am grateful to Mahasarakham University for the financial support and opportunity for my study. Without this support, my PhD study would not be possible.

Finally, I am very grateful to my wife, family and friends for their companionship, support and inspiration during the course of my study. I apologize if I have inadvertently forgotten to acknowledge those who have assisted me in any way.

ABSTRACT

Emotion classification via Electroencephalography (EEG) is used to find the relationships between EEG signals and human emotions. There are many available channels, which consist of electrodes capturing brainwave activity. Some applications may require a reduced number of channels and frequency bands to shorten the computation time, facilitate human comprehensibility, and develop a practical wearable. In prior research, different sets of channels and frequency bands have been used. In this study, a systematic way of selecting the set of channels and frequency bands has been investigated, and results shown that by using the reduced number of channels and frequency bands, it can achieve similar accuracies. The study also proposed a method used to select the appropriate features using the ReliefF method. The experimental results of this study showed that the method could reduce and select appropriate features confidently and efficiently. Moreover, the Fuzzy Support Vector Machine (FSVM) is used to improve emotion classification accuracy, as it was found from this research that it performed better than the Support Vector Machine (SVM) in handling the outliers, which are typically presented in the EEG signals. Furthermore, the FSVM is treated as a black-box model, but some applications may need to provide comprehensible human rules. Therefore, the rules are extracted using the Classification and Regression Trees (CART) approach to provide human comprehensibility to the system. The FSVM and rule extraction experiments showed that The FSVM performed better than the SVM in classifying the emotion of interest used in

the experiments, and rule extraction from the FSVM utilizing the CART (FSVM-CART) had a good trade-off between classification accuracy and human comprehensibility.

List of Publications

Conference Proceeding

(P1) **Chatachinarat**, A., Wong KW, Fung CC "Emotion classification from electroencephalogram using fuzzy support vector machine". In: 24th International Conference on Neural Information Processing ICONIP, 2017. Springer, pp 455-462

(P2) **Chatchinarat A**, Wong KW, Fung CC, "Rule Extraction from Electroencephalogram Signals Using Support Vector Machine". In: 2017 9th International conference on knowledge and smart technology: crunching information of everything, KST 2017, pp 106–110.

(P3) **Chatchinarat A**, Wong KW, Fung CC, "A comparison study on the relationship between the selection of EEG electrode channels, frequency bands used in emotion classification for emotion recognition". In: International Conference on Machine Learning and Cybernetics (ICMLC), Korea, Jul 10-12, 2016. IEEE, pp 251-256

(P4) **Chatchinarat A**, Fung CC, Wong KW, "Emotion Recognition using EEG data with a Multiple Classification Framework". In: Thammaboosadee S (ed) The 2nd Management Innovation Technology International Conference (MITiCON2015), Bangkok, Thailand, 2015. Information Technology Management, Faculty of Engineering, Mahidol University, pp 135-138

Contributions of the Thesis

An efficient emotion classification system using EEG signals has been investigated into and the solutions to the research questions have been proposed and developed. The contributions of this thesis have been published in referred conference proceedings, as shown in Table 0-1.

Table 0-1 Summary of contributions

Chapter	Contribution	Paper No
II. Background	Survey on previous research work on emotion models, EEG emotion, channel and sub-frequency band selections, classification techniques, and noise reduction in EEG emotion classification.	(P4)
III. Channel and Frequency Band Selections for Features in the Efficient EEG Emotion Classification System	Channels and sub-frequency bands were investigated for the selection, and optimized using the Support Vector Machine (SVM) to construct an efficient EEG emotion classifier.	(P3)
IV. Fuzzy Support Vector Machine for EEG Emotion Classification	1) Selecting appropriate features from the findings of Chapter 2 using the Relief technique. 2) Developing a weighted function in the FSVM to build a more robust EEG emotion classifier,	(P1)

	by better handling outliers from the EEG signals.	
V. Rule extraction technique from the FSVM	Developing a rule extraction technique from the established EEG FSVM emotion.	(P2)

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

Abbreviations and Acronyms

aBCI	Affective brain-computer interface
ANN	Artificial neural network
BCI	Brain-computer interface
BP	Back-Propagation
CART	Classification and regression tree
D4	Daubechies 4
DA	Discriminant Analysis
DEAP	A Database for Emotion Analysis using Physiological Signals
DH	High Dominance
DNA	Deoxyribonucleic Acid
DWT	Discrete Wavelet Transform
ECG	Electrocardiogram
EEG	Electroencephalography
EOG	Electrooculography
ERG	Electroretinography
FC	Fuzzy Clustering
FCM	Fuzzy C-Mean Clustering
FS	Feature Selection

FSP	Feature Selection - Perceptron
FSVM	Fuzzy support vector machine
FSVM-CART	Fuzzy support vector machine using Classification and regression tree
HA	High Arousal
HCI	Human–computer interaction
HV	High Valence
Hz	Hertz
ICA	Independent component analysis
KM	K Means Clustering
KNN	K-nearest neighbors
KNN	K-Nearest Neighbor
LA	Low Arousal
LD	Low Dominance
LDA	Linear Discriminant Analysis
LIBSVM	A Library for Support Vector Machines
LV	Low Valence
LVQ	Learning Vector Quantization
MD	Mahalanobis Distance
MLP	Multi-Layer Perception
NB	Naïve Bayes
RBF	Radial Basis Function

RV	Ranking Values
SAM	Self-Assessment Manikin
SVM	Support vector machine
SVM-CART	Support vector machine using Classification and regression tree
SVM-RFE	Recursive Feature Elimination for Support Vector Machines
VAD	Valence, Arousal and Dominance

CHAPTER 1

Introduction

1.1 Emotion Classification from EEG

Recently, affective computing has been considered as one of the key areas of interest in Human-Computer Interaction (HCI). Affective computing comprises three cognition processes, which are attention, memory and decision-marking [1]. Affective computing provides the ability for computers to observe, interpret and generate affective features [2]. These abilities can significantly improve HCI by creating the interaction between computers and humans [3]. Affective computing combines knowledge from areas such as psychology, signal processing and, machine learning. The kind of affective computing that uses neurophysiological signals is known as affective Brain-Computer Interfaces (aBCI) [4].

In 1924, Hans Berger, a neurologist, captured the first electroencephalogram (EEG) using an electrode from a human brain. The EEG revealed electrical signal activities of human brains shown as wave patterns. With the advancement of computing power and the improvement of EEG equipment, the EEG signal can be better used to interpret the states of the cognitive process and behavior such as selective attention, working memory, and mental calculations. [5]

EEG systems can be used to detect human emotions and form an important area in the research of HCI [6]. Emotion is one of the critical factors that can affect human decision and behavior, as well as enhance user experience. In the case of the classification of emotion using human brain electrical signals, the tasks are to analyze the EEG signals such that the behavior can be classified into pre-defined emotional classes [7]. During the past decades, an exponential growth of aBCI publications has been observed, and various applications have been developed in the areas such as medical treatments, entertainment, education, marketing, and robotic control [8-14]. However, according to the reference [15] in the thesis, A. Al-Nafjan, M. Hosny, Y. Al-Ohali and A. Al-Wabil indicated that "*Some examples of limitations in current algorithms and approaches involve time constraints, accuracy, the number of electrodes, the number of recognized emotions, and benchmark EEG affective databases.*" Consequently, an efficient EEG emotion classification system for aBCI applications should be developed.

The effectiveness of EEG emotion classification depends on many factors. One of the essential tasks is the ability to perform real-time emotion classification using efficient techniques. Some studies [16] [17] suggested that portable and EEG systems for real-time applications such as detecting emotion conditions for airplane pilots and bus drivers, as well as the desire to reduce the response time in EEG medical applications, should be developed. However, most of the studies in aBCI were proposed for off-line applications and required a large number of electrode channels [15, 18].

Another limitation that has been reported in EEG emotion classification is related to classification accuracy which is affected by noise [19]. In Brain-Computer Interfaces

(BCI), noise is one of the leading issues affecting the performance of classification [20]. In fact, the EEG signal is noisy, and as such, noise and outliers are normally unavoidable [23]. Therefore, the identification and removal of signals due to artifactual activities is a challenge [4]. Although Independent Component Analysis (ICA) was suggested to deal with different signal sources [21], ICA is inefficient as it requires many reference channels and massive offline training samples [22]. Thus, these two requirements affect the development of real-time EEG applications.

Furthermore, for some EEG medical applications, such as medical diagnosis from EEG [23, 24], it is desirable to create an interpretable model to be used by human experts for decision-making [25]. Nevertheless, most classification modeling used in EEG emotion classification are black-box models, which lack the ability to provide human explanation.

As a result, these three challenges lead to the need for a system, which requires low computation requirements, possesses the ability to handle outliers effectively, and provides human comprehensibility. The objectives of this thesis are to addresses these limitations and to enable the development of an efficient system. First of all, an efficient emotion classification system using EEG should be able to use fewer features, by reducing the number of electrode channels and sub-frequency bands. Therefore, the complexity of the system is reduced and real-time aBCI applications in the future can be developed more easily. Next, noise and outliers in EEG signals should be better managed in order to increase classification accuracy. Finally, the system should be transformed into a white-box model, by extracting the rules from its corresponding black-box model. Consequently, expert users will then be able to interpret and evaluate the model for the need of the respective EEG applications. The following section describes in detail the three problems concerning EEG emotion classification.

1.2 Problem Statements

In this thesis, the efficient emotion classification system using EEG focuses on three problems, namely computational challenge, outlier handling, and an interpretable model.

1.2.1 Computational Challenge

Recently, EEG emotion classification has become one of the popular topics in aBCI. However, majority of the aBCI studies were aimed for offline applications [15]. On the other hand, some applications require real-time responses. For example, in the development of portable medical support applications for epilepsy patients, there is a need to reduce the complexity of the system because using less computational resources and a shorter respond time will assist patients promptly. To reduce the computational time, one way is to use fewer electrode channels, which are appropriate for the purpose of the application. Furthermore, using many and sometimes redundant channels may cause an overfitting problem in classification, and a problem in finding the optimal model using machine learning techniques. Therefore, there is a need to reduce the number of electrode channels for use in real-time applications in the future. [15, 26]

Most previous studies used various datasets, and appropriate channels were suggested differently. For example, 64 channels [27, 28], 32 channels [29, 30] and five channels were used [31] respectively for similar purposes. Some studies [32, 33] selected channels based on brain-activity built on the assumptions of using three or four channels such as the frontal lobe lateralization. In contrast, another study [34] conflicted previous studies by mentioning that the parietal and central lobes are recommended to acquire the signals, rather than the occipital and frontal lobes for the same purpose. There is no consistent or heuristic way of channel selection in EEG emotion classification. Therefore, EEG channel selection is an area of research interest in this thesis. This thesis studies the relationship between the number of channels and frequency bands for features regarding the same benchmark database and classifier for a fair comparison [26]. The set of selected channels is then processed by a selected feature selection method (ReliefF) to choose the appropriate features. This provides a systematic and effective way of analyzing the channels and frequency bands which are suitable for use in EEG emotion classification.

1.2.2 Outlier Handling

Most of the time, the EEG is affected by noise, and noise could affect classification accuracies. Inconsistent samples in the datasets are normally known as noise [35]. This issue can reduce the performance of machine learning techniques because of the complexity of data and an increase of computation time. Consequently, dealing with noise or outliers of the EEG signals is one of the focus in this research. To deal with noise and outliers in EEG signals, ICA seems to be a popular method. However, it requires many electrodes and some reference channels to deal with the noise. Therefore, it is not suitable for real-time computation [36]. Another approach, Another approach, which is more noise-tolerant, is the Fuzzy Support Vector Machine (FSVM), and it is proposed to be used to deal with the outliers in this thesis.

The SVM has been reported to be a commonly used method to provide good recognition accuracy in aBCI [15, 37, 38]. It was recommended to be used in aBCI because of its ability of regularization. The SVM has a regularization parameter C to deal with the misclassification issue in the training set [20]. Nevertheless, traditional SVM has been reported to be quite sensitive to noise and outliers [39]. Even though the SVM has the ability of regularization, it assigns the same value of C to all training samples, which might include misclassification samples. The FSVM was therefore introduced to cope with the outlier issue by assigning various membership values on uncertain instances during its learning process [40]. The FSVM also enhances the performance of classification when challenged with the outlier issue in the EEG data.

1.2.3 Interpretable Model

Using black-box models, such as Artificial Neural Network (ANN), SVM and FSVM, may not meet the requirements of some real-world applications in aBCI. [23, 24, 41]. Typically, the black-box model is difficult for humans to understand. For real-world applications, an understanding on how the model generates the output is important for applications such as medical diagnosis and prognosis [42]. There is a need for a machine learning model, which is interpretable and capable to interpret the prediction from EEG signals, especially in medical applications [43]. Although the SVM has been popular in building EEG prediction models, it is difficult to interpret. As a result, rule extraction from a black-box model is required because it can provide reasonable rules for a human expert to understand how such predictions are made [44]. Consequently, one of the objectives in this thesis is to develop a rule extraction method that can extract rules from the FSVM to provide human interpretability to the model and at the same time, maintain emotion classification accuracies.

1.3 Objectives

In order to develop an efficient emotion classification system using EEG with human comprehensibility, the objectives of this research are presented as follows:

1) To investigate a number of features for EEG emotion classification, in order to reduce the complexity of the emotion recognition system.
2) To propose and investigate a robust technique to enhance the classification accuracy, by effectively handling outliers in EEG data.
3) To extract interpretable rules from the proposed classifier, so as to allow human comprehensibility on the EEG-based emotion classifier.

1.4 Contributions

The significance of this research is to create an efficient emotion classification using EEG. First of all, the essential contribution is a rule extraction technique that can extract knowledge from a machine learning model (FSVM) to provide human interpretable EEG emotion classification. Next, an appropriate set of EEG channels and frequency bands is presented for reducing the complexity of EEG emotion classification. This reduction could also assist the rule extraction step in providing appropriate rules to interpret. The final contribution is the development of a FSVM framework to handle the outlier problem in the

EEG data and increase accuracy performance of EEG emotion classification and its rule extraction.

1.5 Overview of the Thesis

The structure of the thesis is as follows. This chapter provides a brief introduction to the EEG emotion classification system, problem statements, objectives and contributions of this thesis. Figure 1-1 shows the framework of efficient emotion classification using EEG.

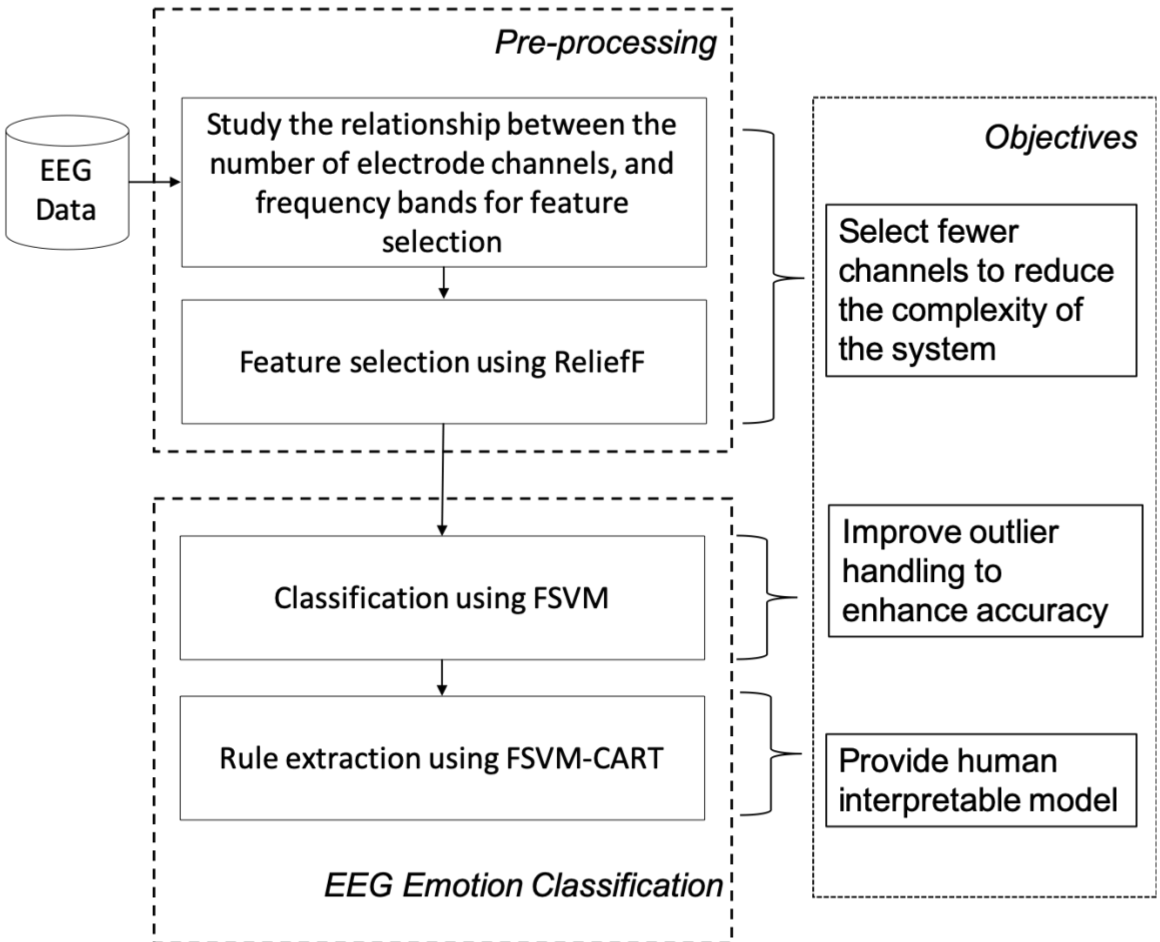

Figure 1-1 Efficient emotion classification using EEG

Chapter 2 is the background of this research, in which emotional models and EEG signals are defined. Related work with channel and frequency band selections are also presented. Previous machine learning techniques used in the EEG system are also explored, and the problem of outliers in the SVM is discussed. Finally, the discussion of channel and frequency band selections from other studies is presented.

In Chapter 3, a relationship between channels and frequency bands for the features is investigated by comparing channel selection of various studies from past literature. The SVM and EEG benchmark dataset are used for the experiments. After the investigation, suggestions and recommendations of the reduced set of channels are presented.

There are two parts in Chapter 4. The first part involves the use of recommendations from Chapter 3 to find appropriate channels and frequency bands for features using the ReliefF technique. Secondly, a framework using the FSVM to deal with outliers in the database is proposed. A FSVM weight function is presented and used to enhance the classification performance of the EEG database. The weight function is used to assign less values to the samples which are defined as outliers. Furthermore, a framework using the FSVM is compared with the SVM and other classification models in order to evaluate the performance. After that, a discussion is presented.

Chapter 5 presents the rule extraction from EEG signals using FSVM. A technique, which is rule extraction from EEG using SVM by Classification and Regression Trees (SVMCART), is applied to the framework. The experimental results of CART, FSVMCART (rule extraction of FSVM using CART), are then compared with each other and discussed.

Chapter 6 is the thesis conclusion. It summarizes the major significant contributions of this research. The limitations and recommendations for future studies are also presented.

CHAPTER 2

Background

This chapter discusses the background and relevant research works on EEG emotion classification. In this chapter, emotion models, EEG signals, placement channels, and the process of EEG emotion classification are presented. This serves to explain the concept of EEG emotion classification. This chapter also discusses channel and sub-frequency selections, noise reduction and machine learning techniques in the EEG emotion classification system. The SVM model is then described. Finally, a summary of the chapter is presented.

2.1 Emotion Models

Aristotle stated human emotion as, "*The Emotions are all those feelings that so change men as to affect their judgements, and that are also attended by pain or pleasure. Such are anger, pity, fear and the like, with their opposites*" [5]. Scherer [45] referred to William James's study that emotion in terms of modern experimental psychology is, "…*that the bodily changes follow directly the perception of the exciting fact, and that our feeling of the same changes as they occur is the emotion*". Both quotes are definitions from early and modern perspectives respectively. Interestingly, they both state that emotion invokes human's perception and reaction. The study of emotion can provide many benefits, especially in HCI [4, 15]. However, emotion is subjective and controversial. For instance, emotion can be classified as cognitive or non-cognitive and emotions can be analyzed using discrete or continuous models [46]. In addition, there are a wide variety of emotion definitions from psychologists, but discrete and dimension models have been used widely in EEG emotion classification systems [4].

2.1.1 Discrete model

Discrete models are based on basic emotions that can be found universally and they are distinguished from one another via different physiological theories. Examples of the emotions that have been identified are happiness, surprise, anger, fear, sadness, and disgust [47]. In addition, Ekman and Friesen interceded six basic discrete emotions which are surprise, happiness, anger, fear, sadness, and disgust [48]. This definition was developed on the assumption that those emotions can be found in every culture in the world.

Although discrete models are one of the more popular models that have been used in aBCI to identify human emotions, Wang et al. [7] pointed out that the issue of discrete models is the question as to which emotions are basic emotions. For example, Ekman et al. added a number of basic emotions from six to fifteen in 1999 [49]. In addition, De Sousa argued that two basic emotions, namely surprise and disgust, are too easy to be defined as emotions [50]. Moreover, Liu et al. added another issue, that although basic emotions are often found in most countries, not all of them can be found in some countries. For example, in Poland, the Polish do not have the emotion of disgust. Due to the issues found in discrete models, this thesis uses dimensional models for classifying emotions instead [51].

2.1.2 Dimensional model

To allow for a generalization of emotion models, the dimensional model has been introduced as a combination of multi-psychological dimensions [15]. This is another popular model that has been used widely. The models are defined by plotting a scale of 'core affect' on several dimensions. Scherer [45] reported that there are several pairs of emotions which can be plotted, such as pleasure and pain, agreeableness and disagreeableness, or positive and negative. These models are called bi-polar dimensions [5]. The Russel's model is a popular dimensional model [52]. It is commonly used and usually has two dimensions: valence and arousal on the two-axes. The valence axis defines the range from negative to positive feelings, whereas the arousal axis defines the emotions from calm to excited. The two-dimensional representation of emotional terms (vertical dimension: active/passive; horizontal dimension: positive/negative) is shown in Figure 2-1. In addition, a three-dimensional system was proposed by Wundt [45] for more complex emotions. The three-dimensional system is represented in three axes, including excitement vs. depression, tension vs. relaxation and pleasantness vs. uncleanness. An example of a three-dimensional model has sleep-tension, attention-rejection and pleasantness-unpleasantness [53]. There is another called the PAD-space [54]. It adds a third axis (dominance axis) to the original Russel model.

In this thesis, the dimensions of *Valence, Arousal* and *Dominance (VAD)* are used to scale emotions because they have been reported to be fundamental dimensions, which are widely used [4, 15]. Moreover, Wyazesany et al. found that VAD is clearer and more understandable than discrete emotions because discrete emotions are more difficult to be monitored precisely, as they are subject to individual perception [55]. Consequently, each dimension is divided into two emotions: positive and negative. Mehrabian [56] explained that arousal is used to measure how enthusiastic or soporific someone is, valence is used to measure how pleasant or unpleasant the human mind is, and dominance is used to measure how dominant and submissive a person feels. In other words, positive arousal can be excited and negative arousal can be calm, whereas positive valence is probably pleasant or joyful and negative valence might be unpleasantness, anger or fear. Finally, positive dominance can be a dominant emotion, such as anger. In contrast, fear is a negative dominance and submissive emotion [4, 56]. Moreover, a pair of bi-polar dimensions can be represented on two dimension axes and merely interpreted to a group of discrete emotions, as in Figure 2-1.

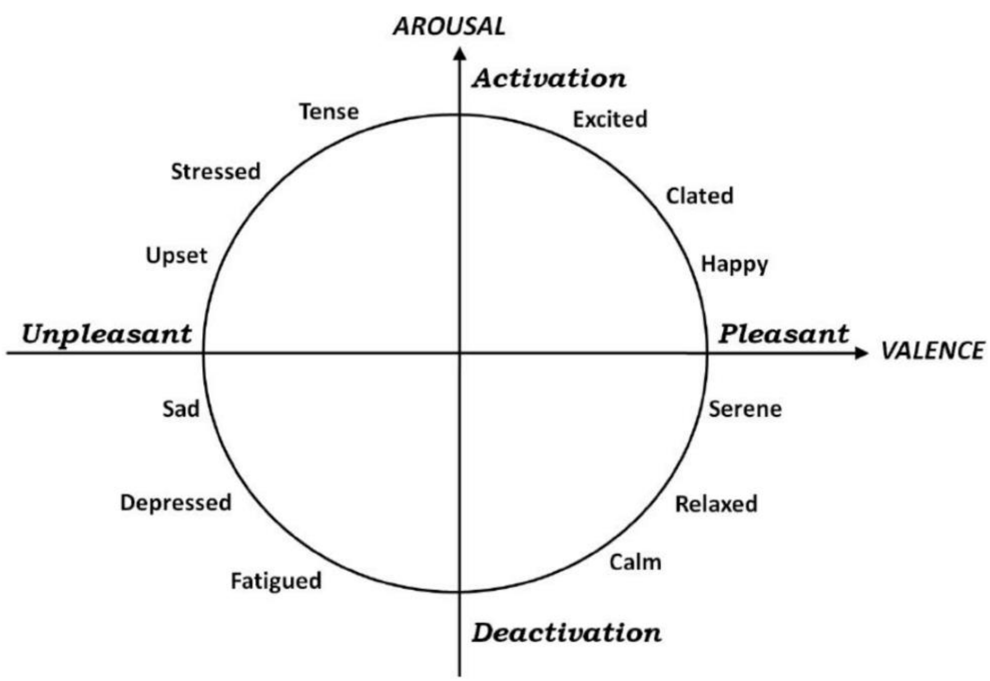

Figure 2-1 A two-dimensional representation of emotion terms [source from [57]

To measure an emotional response, the Self-Assessment Manikin (SAM) was developed to state what participants feel using a picture-oriented questionnaire [58].

2.1.3 Self-Assessment Manikin (SAM)

There are many standard measurements to rate the emotion scales. One of them is known as Self-Assessment Manikin (SAM). This measurement has dominated many studies of EEG emotion classification [59]. The SAM is used to measure the degree of arousal, pleasure, and dominance from the participants. The SAM is a non-verbal pictorial assessment technique used to obtain affective data from participants after stimuli were presented to them [60]. An example of the SAM assessment is shown in Figure 2-2.

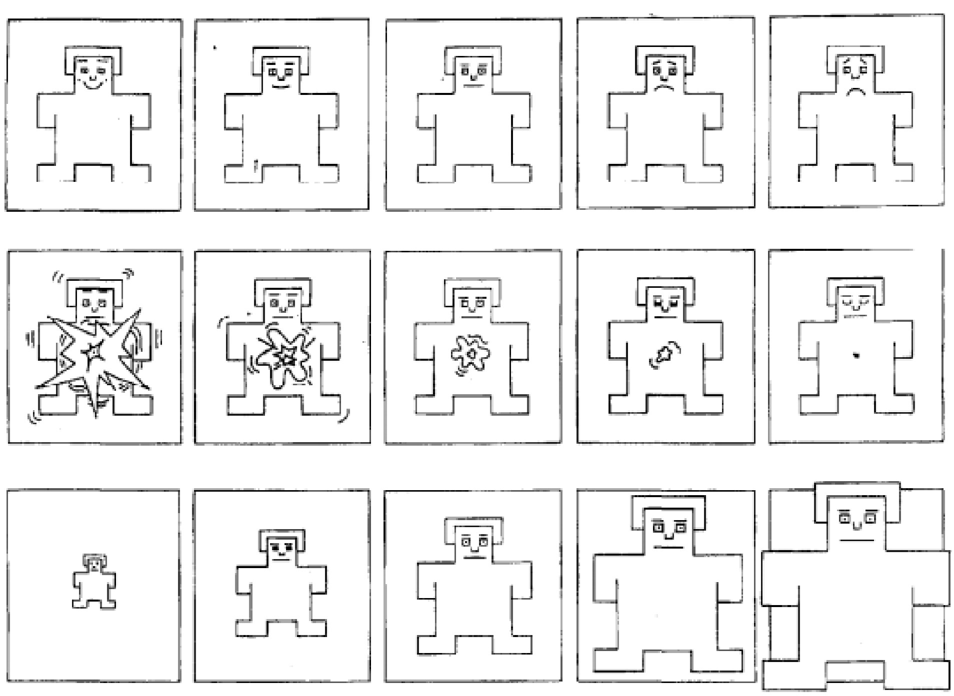

Figure 2-2 The Self-Assessment Manikin (SAM) used to rate the affective dimensions of valence (top panel), arousal (middle panel), and dominance (bottom panel) [source from [60]

There are a few ways to express emotion, namely via facial images, speech and more recently, biological signals [61]. Besides facial and speech expressions, biological signals are another type of input for classifying emotions. EEG is categorized under the biological signals group. Although emotion recognition and classification from facial or speech has provided satisfactory prediction, in some situations, it may not be so accurate. For example, facial expression is easy to be made up and speech expression, in terms of the tone, can also be faked easily [38, 62]. Therefore, it is getting more popular for physiological signals to be used as an alternative way for emotion classification.

2.2 Biopotential Signals

Thakor [63] mentioned that the human body is a combination of various organs. Some of the organs, for example, heart, brain, muscles and eyes, produce electrical signals when they are performing their functions. Out of these signals, the brain produces Electroencephalography (EEG). Secondly, eye movements produce a signal called Electrooculography (EOG) and the Electroretinography (ERG) signal is created by the retina in the eyes. Thirdly, every movement of the muscles generates signals known as Electromyography (EMG). Finally, the heart produces a signal called Electrocardiography (ECG). [63] For instance, sample waveforms of ECG, EEG, and EOG are shown in Figure 2-3 and the amplitude and bandwidth of the bio-signals is shown in Table 2-1.

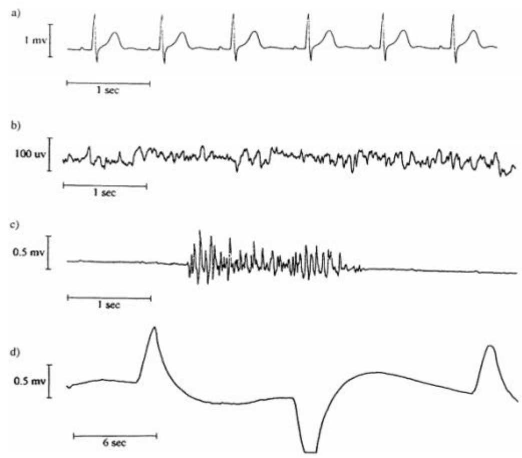

Figure 2-3 Sample waveforms: (a) ECG (b) EEG (c) EMG (d) EOG [source from [63]

Table 2-1 The bandwidth of the bio-signals

Source	**Amplitude (mV)**	**Bandwidth (Hz)**
ECG	1-5	0.05-100
EEG	0.001-.01	0.5-40
EMG	1-10	20-2000
EOG	0.01-0.1	dc-10

These signals have been acquired and used to interpret participants' emotions. For example, ECG and EOG [64], EMG [65], and EEG [30, 66] have been used in respective studies. However, using EEG to classify and recognize human emotions has been studied widely because it is inexpensive, fast and non-invasive [67]. Moreover, it supplies a good resolution; therefore, researchers can study phase changes in response to emotional stimuli [68]. As a result, EEG equipment is wearable, economical, portable and useable. Furthermore, EEG-based emotion applications can be developed in areas such as e-healthcare, e-learning and entertainment [69, 70]. Consequently, this study investigated EEG emotion classification based on EEG signals.

2.3 Electroencephalogram (EEG) and Human Emotion

Specifically, Mühl et al. [4] indicated that human emotions can be detected by interpreting EEG data in terms of time and frequency domains of EEG. For the frequency domain, there are five-frequency bands that can be associated with the emotion states. They include: delta, theta, alpha, beta and gamma frequency bands, as shown in Figure 2-4.

2.3.1 The delta band

The delta band frequencies range from 0.5 to 4 Hz. This range can be found during the last state of sleep [71] and motivational states [72]. Medial prefrontal cortex, ventral tegmental and nucleus accumbens are parts of the brain that create the delta frequency. A few studies [73-75] reported that the more arousal stimuli users receive, the higher the power of the delta band signal.

2.3.2 The theta band

The theta band frequencies range from 4 to 8 Hz. This range can be found during cognitive processes [4], working memory tasks [76, 77] and responding to pleasurable stimuli [78]. The theta band power signal has been found on the frontal [74] and parietal [73] regions when receiving arousing stimuli. Moreover, feelings of pleasure and displeasure are involved with positive valence during the listening to music [79] [80] and in such cases, the fronto-medical theta is normally increased.

2.3.3 The alpha band

The alpha band frequencies range from 8 to 13 Hz. This range can be found over the parietal, occipital [81] regions and frontal asymmetries [82]. Coan and Allen [82] also claimed that frontal alpha asymmetries associate with affective states and neurophysiology. Moreover, Niedermeyer [78] has reported that the alpha range plays an important role in terms of relaxed and wakeful states of mind. Additionally, a few studies [83, 84] indicated that during the states of relaxation, the alpha power increases.

2.3.4 The beta band

The beta band frequencies range from 13 to 30 Hz. This range can be found over the central regions of the human brain. This band is related with the sensory-motor system during motor activity, motor imagination or sense of touch [85]. In terms of affective states, the beta band power increases over temporal regions due to the response to self-induced positives and visuals [86, 87]. On the other hand, a decrease of the band power depends on the subjective experience [88].

2.3.5 The gamma band

The gamma band frequencies range above 30 Hz. The range can be found in different sensory and non-sensory cortical networks [89]. The gamma range is relevant to a wide variety of cognitive processes including: attention [90], memory [91], consciousness [92], and multi-sensory integration [93]. Concerning affective states, a few studies [87, 94] found that the amplitude of the gamma frequency increases with increasingly positive valence. Furthermore, in terms of arousal, high and low arousing visual stimuli affect the gamma band power by increasing the value [95-97]. Additionally, it was found that gamma activity increases over somatosensory cortices, when an awareness of painful stimuli is represented [98, 99].

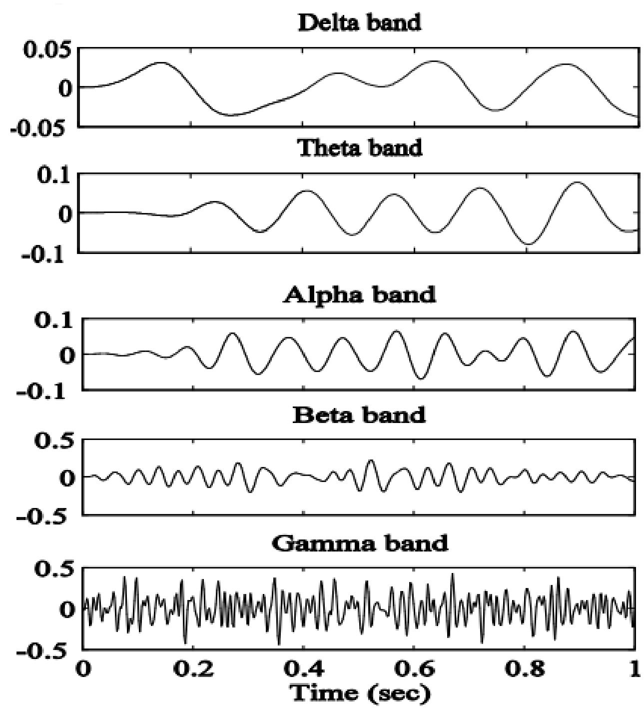

Figure 2-4 Examples of delta, theta, alpha, beta, and gamma frequencies [source from [100]

To capture raw EEG signals, there are many EEG devices which have been used in medical and academic purposes, such as Quik-cap [101], Active-electrodes [10] and EPOC [102]. These devices have a number of electrodes. In addition, the International 10-20 system has been used to locate placement position spatially [103].

2.4 International 10-20 EEG Placement System

During the affective stimulus process, electrodes are used to capture EEG signals. Although there are two main types of electrodes, namely gel and dry electrodes [104], the fundamentals behind them are the same. The electrical activities of the brain are captured to input the circuits of the electrodes. The signals are then amplified and recorded onto memory devices. The number of electrodes used depends on the number of positions on a scalp and the activities of the brain functions that need to be examined.

The standard used to position the electrodes on the scalp is called the 10/20 System or the International 10/20 System. Figure 2-5 shows the 10/20 system positions of the electrode placement with 21 electrodes, and the letters to identify the lode is shown in Table 2-2. The ‘C’ letter in Table 2-2 is used for identification purposes only. Also, the International 10/20 System, with intermediate 10% electrode positions, was extended from the original 10/20 System by the American Electroencephalographic Society [104], as shown in Figure 2-6. In this thesis, this modified 10/20 System is used to identify the positions of EEG electrode placement.

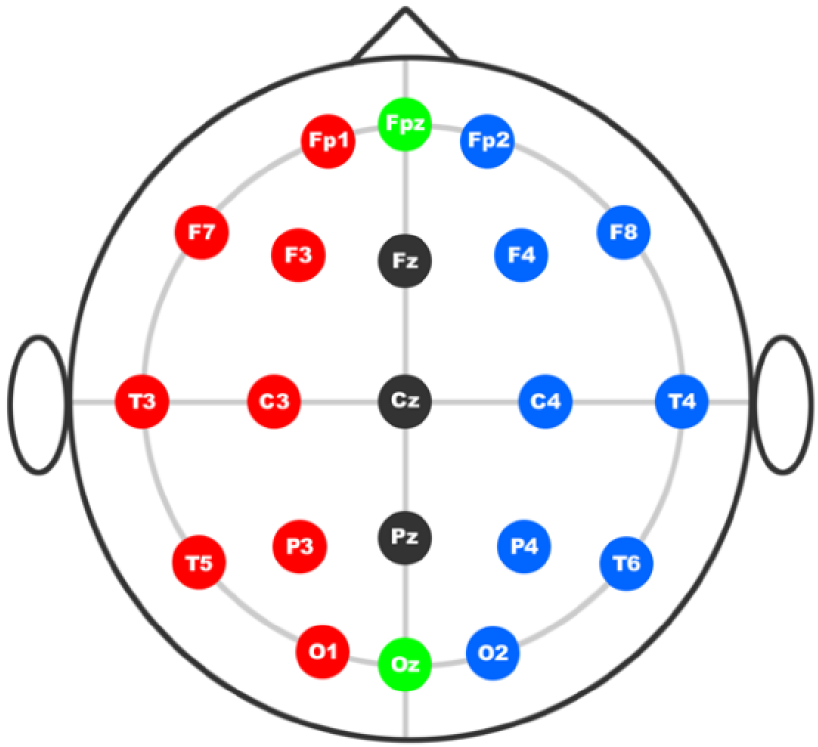

Figure 2-5 10/20 International positions of placement

Table 2-2 Letters to identify the lode position

Electrode	**Lobe**
F	Frontal
T	Temporal
C	Central
P	Parietal
O	Occipital

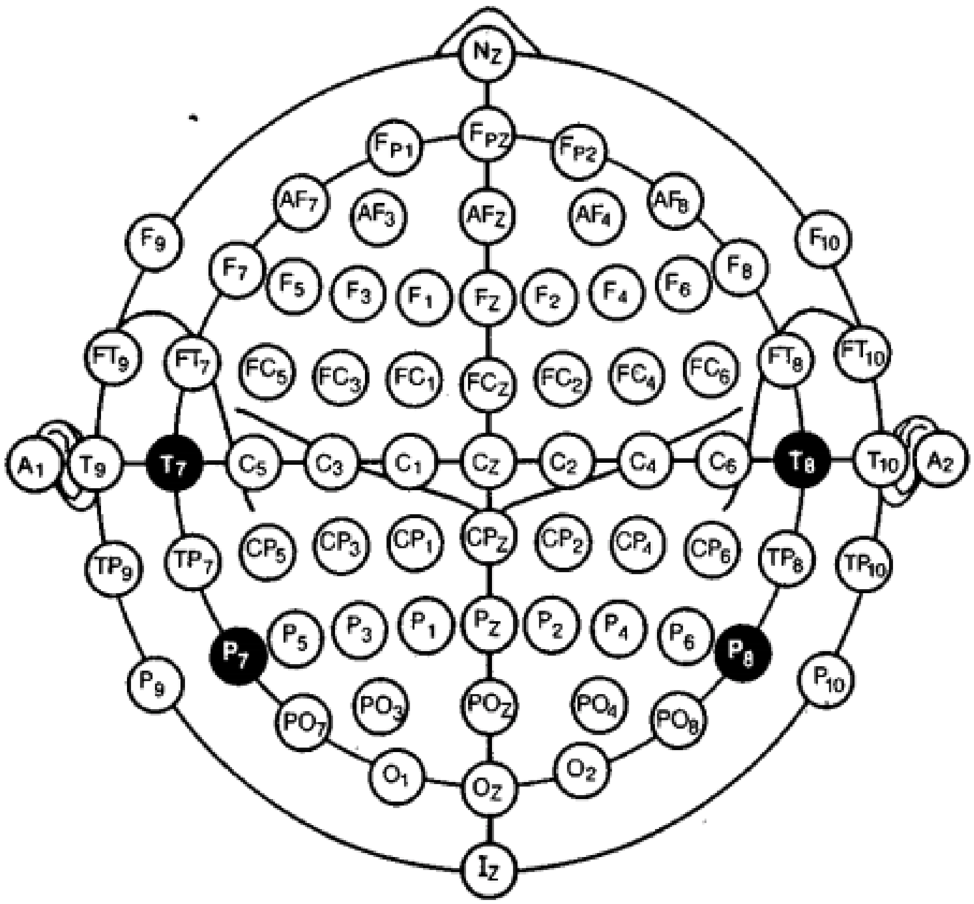

Figure 2-6 Modified 10/20 System [source from [104]

2.5 Channel and Frequency Band Selections in EEG Emotion Classification

EEG classification is a process that involves the selection of placements and appropriate data acquisition electrode channels on the skull, in order to obtain optimal signals. The signals are then decomposed into sub-frequency bands used for the selection of various features.

Al-Nafjan et al. [15] mentioned that there should be fewer channels used in the EEG system because of the comfort level of users, system usability and number of features to be processed. However, a large number of electrode channels has been required from most current EEG devices [15]. Mühl et al. [4] reported that the average accuracies of arousal and valence classifications are 68% and 65% respectively. In their survey, a number of features had been used. For example, 230 features of 5 bands of 32 channels and 14 asymmetry pairs [29], 216 features of 14 asymmetry pairs of 4 bands, 32 channels of 5 bands [30], and 3 channels of 3 bands [32]. Yet, very few studies used only one or two band(s) for the features [62, 105]. Nonetheless, these studies may not compare the relationship of the channels and frequency bands appropriately because they used different datasets and features. In order to improve the computation time for real-world applications, the reduction of frequency bands and channels is one of the objectives of this study (as based on the same dataset and settings).

Computation time is another concern for an efficient system. Rached and Perkusich [106] recommended that choosing techniques and channels of acquiring the EEG signal is the issue for improving performance significantly in terms of classifying affective states. Supporting this idea, Cheemalapati et al. [16] suggested that developing a portable system, of one channel only, is very important for real-time applications to measure stressful conditions in the case of airplane pilots and bus drivers. However, their study was a mere demonstration of signal detection and the rest of their objectives will only be achieved in the future. In addition, Mahajan et al. [17] also claimed that an inexpensive design of the EEG system is crucial to assist real-time medical tools to reduce the difficulties and reaction time of the EEG system. Nevertheless, the paper showed a design of the framework, but it did not present its experiment and results. Furthermore, Szibbo et al.

[107] indicated that some limited channels of EEG applications need real-time processing, low computation, such as BCI, sleep scoring programs, and Alzheimer's disease recognition. Nonetheless, the study presented a technique to deal with blink artifacts to contribute towards real-time EEG applications. Therefore, channel and frequency-band selection is one of the purposes in this thesis, in order to reduce the complexity of the EEG classification system and enable human comprehensibility.

The electrode channels, placement positions, and frequency bands are some of the controversial topics in aBCI. First of all, there are many studies selecting different numbers and locations of EEG placements. Some studies used several electrode channels to acquire EEG signals [108, 109], whereas others used only a few channels [105, 110]. Moreover, more than twenty channels had been selected in many studies [7, 111]. Secondly, there are a few placement positions to be recommended for aBCI. Frontal lobe positions have presented a decent performance [4]. In contrast, another study [34] mentioned that the parietal and central lobes are recommended for acquiring the signals, rather than the occipital and frontal lobes. Finally, there is the issue of the number of sub-frequency bands of EEG signals that should be selected for feature extraction. Five sub-frequency bands are decomposed and selected widely, including delta, theta, alpha, beta and gamma [7, 108]. However, some studies indicated that using a few sub-frequency bands are adequate for feature extraction. For example, Bos's study used only two sub-frequency bands: alpha and beta, and they were sufficient for emotion recognition [62]. In general, as observed from prior studies, there is no consistent way of determining the channel and frequency band selections. As a result, the experiments in Chapter 3 are designed to investigate the relationship of the number of electrode-channels, sub-frequency band selections and placement positions. The same benchmark dataset, feature extraction, and classification techniques are set for fair comparisons. Furthermore, in the beginning of Chapter 4, appropriate features are selected using a feature selection technique.

2.6 Noise Reduction

As mentioned in Chapter 1, there is the challenge of noise reduction. As such, noise removal is essential to improve classification performance and avoid the overfitting issue [112]. There are two main approaches in noise tolerant and noise elimination techniques [113]. The difference between both approaches is the way in which noisy data is considered and avoided. While the noise tolerant approach focuses on an internal improvement of the mechanism in a classifier model, the noise elimination approach focuses on a pre-processing process to remove noise from a training set [112].

Mühl et al. [4] stressed that noise filtering is important to filter noise from relevant EEG signals for an effective emotion system. Normally, EEG signals come up with non-emotional signals, such as power-line and other bio-signal noise, such as eye blink and eye movement artifacts called EOG artifacts. There are many techniques that have been applied recently to deal with the noise problems, such as those based on Principle Component Analysis (PCA) and Independent Component Analysis (ICA) [36]. PCA and ICA can be considered as noise elimination approaches because they perform a data pre-possessing task. There are many studies using these techniques in EEG classification [66] and [114]. Kroup et al. [36] made some conclusions as follows. First of all, ICA seems to have the best performance in terms of accuracy, but it is not the fastest in terms of speed. Therefore, it is suitable for offline computation. The second one is PCA. This technique is less accurate, but the time required is lesser than ICA. In addition, the requirements of real-time EEG systems have increased recently. One of these requirements is the number of channels. Matiko et al. [115] criticized the issue that for existing techniques of regression, PCA and ICA are not suitable for removing eye blink from the channel in non-medical applications. Supporting the issue of both PCA and ICA based methods, Khatwani and Tiwari [19] highlighted the limitations of both methods, as that of only analyzing in the time domain. Moreover, PCA depends on the size of EEG signals for its performance.

This thesis focuses on noise, which are outliers. In the literature, as mentioned earlier, the noise elimination approach might be unsuitable for the outliers in this thesis. To develop an efficient EEG emotion classification, a number of features must be reduced because of computation time. In other words, a number of channels might not be enough for ICA and PCA to provide a good training dataset. Moreover, time consumption is another purpose in this thesis. A number of processes should be reduced in the efficient EEG emotion classification system.

2.7 Emotion Classification

There are many processes for the EEG emotion classification system. First of all, participants' emotions are elicited using external stimulus. Some materials are provided to elicit human emotions, such as sounds [109], movies [7, 116] and pictures [117]. These materials will be used as training or testing data. After that, the EEG signals can be recorded by the electrode devices. Examples of commonly used systems are Emotive [109] and NeuroSky's MindWave [8]. The number of channels and positions between these systems are different, according to the devices and researchers. Nevertheless, many studies [82, 118-121] suggested that the human frontal lobe is an informative and affective area to measure EEG activities. Next, some digital signal pre-processing techniques are used to process EEG raw signals, in order to reduce complexity and remove noise and artifacts. For example, the raw signals may be reduced by different sampling rates [7, 108, 122]. Another example is the decomposition technique. The raw signals, which are within 0.1-70 Hz, can be decomposed into various sub-frequency bands, such as the delta, theta, alpha, beta, and gamma bands [37, 116, 122]. In addition, the raw signals contain not only EEG, but also other bio-signals, such as electrooculogram (EOG) and electromyogram (EMG) [123]; therefore, artifact removal techniques may be required in this process. After that, the feature extraction process, involving the pre-processed signals, is carried out. This stage is very important to achieve good results for emotion classification [117]. There are many methods to extract the EEG data. Examples of such techniques are *Power Spectrum Feature* [7, 117], *Fourier transform* [37, 108] and *Fractal Dimension* [109, 124]. The next process is classification. The feature data is trained by one of the many machine learning techniques, such as *Support Vector Machine* [7, 37, 109], *Naïve Bayes* [8, 108], *Fuzzy C-Mean Clustering* or *K-means* [7], so as to generate a classifier model. Finally, the classifier model can be used to benefit applications of EEG emotion classification; for example, in treatment (music therapy), providing of pleasure (computer game), marketing, education and art [8, 9, 18, 125, 126].

2.7.1 Machine Learning Techniques in EEG Emotion Classification

Many machine learning techniques have been applied for EEG emotion classification. For example, Mühl et al. [4] showed in their literature study that the Support Vector Machine (SVM), Naïve Bayes (NB), Linear Discriminant Analysis (LDA), K-Nearest Neighbor (k-NN), Fuzzy Clustering (FC) and Multi-Layer Perception (MLP) were used. Moreover, another study by Kim et al. [127] reported that Discriminant Analysis (DA), k-NN, Mahalanobis Distance (MD) and SVM were applied. Among these techniques, the SVM is used most widely. In addition, Valenzi et al. [37] claimed that the SVM performed the best in terms of accuracy over Back-Propagation (BP), Learning Vector Quantization (LVQ), Vector Quantization (VQ), Fuzzy C-Mean Clustering (FCM), k-means and k-medians. Moreover, Jatupaiboon et al. [38] indicated that the SVM performed better than other techniques because of the better generalization properties and dealing with the issue of dimensionality in emotion classification, as compared to the other methods in the comparison studies.

Consequently, although the SVM has been used by many studies [30, 32, 111, 117, 128, 129], outliers and noise might decrease the performance of the SVM. The SVM has been reported to be quite sensitive to noise and outliers [39]. EEG consists of non-stationary signals and contains many noises and outliers. For example, Lotte et al. [20] reported that poor signal-to-noise ratio is a characteristic of BCI. Consequently, regular SVM can face a problem from EEG data because it can change over time. Besides, Barua and Begun [130] claimed that EEG has the same issues as other bio-signals, such as noise and artifacts. Moreover, Barakat and Diederich claimed that some applications, such as medical diagnosis, require a better understanding of how a classifier makes a decision [131]. For example, Zhou and Jiang applied C4.5, which is a decision tree, to extract rules from an artificial neural network ensemble for three cases of medical diagnosis including hepatitis, diabetes, and breast cancers [132]. Likewise, Martens et al. indicated that some applications, like a credit score application, need a proven validation before actual implementation. Consequently, explanation capabilities are very important [133]. Nevertheless, most classifiers in EEG emotion classification are black-box models, which lack the ability to provide a human explanation. However, for some expert systems, such as medical diagnosis [17], a statement is very crucial for users to consider the procedure of the classification. Over the last decades, the SVM has dominated in many applications and also in aBCI, as this study mentioned earlier. Even though the SVM has been considered a good classifier, Fung et al. [44] mentioned that it is difficult for humans to understand the SVM and other linear classifiers, as compared to the rules that can be mapped in terms of variable space. Therefore, another objective of this study is to extract rules from the FSVM, to provide human comprehensibility, as seen in Chapter 5. Although the SVM may face outlier and human comprehensibility issues, it is commonly used successfully in the EEG emotion classification system. The next section presents the SVM method and a description of how it works.

2.7.2 SVM

This section briefly reviews the fundamental principles of the basics of the Support Vector Machine (SVM) and discusses a few of its classification problems [40, 134-137]. A binary classification problem can be represented by a dataset as follows:

$$\{(x_1, y_1), (x_2, y_2), (x_3, y_3), \dots, (x_l, y_l)\} \tag{1}$$

Each $x_i \in \mathcal{R}^{\mathcal{N}}$ represents n-dimensional feature points, and it belongs to only one class in y_i when $y_i \in \{-1, 1\}$ for $i = 1,2,3, \dots, l$. The objective of the SVM learning algorithm is that it tries to find an optimal hyperplane to separate all x_i, which maps the feature inputs of a higher dimensional feature space $\mathcal{Z}$, into two classes. In order to find an optimal hyperplane, let Φ be a mapping function, and a possible optimal hyperplane can be written as:

$$w \cdot \Phi(x) + b = 0 \tag{2}$$

where $w \in \mathcal{Z}$ and $b \in \mathcal{R}$, each x_i can be separated by:

$$f(x_i) = sign(w \cdot \Phi(x_i) + b) = \begin{cases} 1 & when\ y_i = 1 \\ -1, & when\ y_i = -1 \end{cases} \tag{3}$$

Finding the optimal hyperplane of linear separation is to find the hyperplane with the maximum margin between the two classes.

$$\text{Minimum} \left(\tfrac{1}{2} |w|^2 \right)$$

$$\text{Subject to } y_i(w \cdot \Phi(x_i) + b) \geq 1 \,;\, i = 1,2,3, \dots, l. \tag{4}$$

In fact, the linear separation is not suitable for most real-world problems because "the datasets are not completely linearly separable [134]". Then equation (4) is modified by adding a non-negative variable ξ to:

$$\text{Minimum}\left(\tfrac{1}{2} |w|^2 + C \textstyle\sum_{i=1}^{l} \xi_i\right)$$

$$\text{Subject to } y_i(w \cdot \Phi(x_i) + b) \geq 1 - \xi_i \,;\; i = 1,2,3, \dots, l; \;\; \xi_i \geq 0. \qquad (5)$$

A measurement of the misclassification can be defined by the term $\sum_{i=1}^{l} \xi_i$ because the non-negative variable ξ is designed for all input x_i, which are misclassified. Moreover, the parameter C is a free parameter to be adjusted for maximizing the margin and minimizing the misclassification. Therefore, finding the optimal hyperplane is a quadratic optimization problem, and the Lagrangian technique was applied by constructing and transforming (5) into the dual problem:

$$\text{Maximum } \mathrm{W}(\alpha) \sum_{i=1}^{l} \alpha_i - \frac{1}{2} \sum_{i=1}^{l} \sum_{j=1}^{l} \alpha_i \alpha_j y_i y_j \Phi(x_i) \Phi(x_j)$$

$$\text{Subject to} \sum_{i=1}^{l} y_i \alpha_i = 0, 0 \;\leq\; \alpha_i \;\leq C, i = 1, \dots, l \qquad (6)$$

where $\bar{\alpha}_i s = (\bar{\alpha}_1, \dots, \bar{\alpha}_l)$ are vectors of Lagrange multipliers. After that, to satisfy equation (6), the Karush-Kuhn-Tucker conditions were applied.

$$\bar{\alpha}_i\big(y_i(\bar{w} \cdot \Phi(x_i) + \bar{b}\big) - 1 + \bar{\xi}_i) = 0, \; i = 1, \dots, l \qquad (7)$$

$$(C - \bar{\alpha}_i)\bar{\xi}_i = 0, \; i = 1, \dots, l \qquad (8)$$

According to the unknown mapping function Φ, a function $K(\cdot,\cdot)$ was introduced for the computation of the dot product of each data point in the feature space $\mathcal{Z}$ as follows:

$$\Phi(x_i) \cdot \Phi\big(x_j\big) = K\big(x_i, x_j\big) = \big(1 + x_i \cdot x_j\big)^d \qquad (9)$$

where d is the polynomial kernel. Thus, the dual problem in equation (6) is transformed into:

$$\text{Maximum } W(\alpha) \sum_{i=1}^{l} \alpha_i - \frac{1}{2} \sum_{i=1}^{l} \sum_{j=1}^{l} \alpha_i \alpha_j y_i y_j K(x_i, x_j)$$

$$\text{subject to} \sum_{i=1}^{l} y_i \alpha_i = 0, 0 \leq \alpha_i \leq C, i = 1, \dots, l \quad (10)$$

A solution to find the optimal hyperplane values for $\bar{\alpha}_i, \bar{w}$ is:

$$\bar{w} = \sum_{i=1}^{l} \bar{\alpha}_i y_i \Phi(x_i) \quad (11)$$

Finally, the decision function of the SVM is given as follows:

$$f(x) = sign(w \cdot \Phi(x) + b) = sign\left(\sum_{i=1}^{l} \alpha_i y_i K(x_i, x) + b\right) \quad (12)$$

2.8 Benchmark Database

Recently, many EEG devices are available for research purposes and some of these are Emotive EPOC, MindWave, MindSet, and OpenBCI [15]. The differences between these devices are its prices, the number of electrodes, types of electrodes, and their applications. Moreover, instead of capturing EEG signals directly, there are three benchmark datasets which are available for research, as shown in Table 2-3. The Database for Emotion Analysis using Physiological Signals (DEAP) is used in this study because it provides the largest datasets among the three. Moreover, it has three emotion dimensions including arousal, valence and dominance.

Table 2-3 EEG benchmark datasets [source from [4]

Name/Link	Stimuli	Emotions	Participants
eNTERFACE http://www.enterface.net/results/	Images IAPS	Happiness, disgust, valence, and arousal	5
MANHOB-HCI (emotive part) http://mahnob-db.eu/hct-tagging/	Videos (film clips)	Valence, arousal, dominance, and predictability	27
DEAP (Database for Emotion Analysis using Physiological Signals) http://www.eecs.qmul.ac.uk/mmv/datasets/deap/	Music video clips	Valence, arousal, dominance, familiarity, and likeliness	32

2.9 Summary

This chapter began with the related areas of emotion classification. After that, literature reviews of the channel and frequency band selections, classification techniques and noise reduction in EEG emotion classification were presented. The problems with these topics were highlighted to provide the background to the aim of the thesis, which are EEG placement channel and sub-frequency band selections, outliers and noise reduction, and inability of human comprehensibility in some machine learning techniques. Also, the general concept of the SVM was described. Finally, a few benchmark datasets were presented.

CHAPTER 3

The Investigation of Channel and Frequency Band Selections for Features in the Efficient EEG Emotion Classification System

3.1 Introduction

Mühl et al. mentioned that devising a standard for aBCI is one of the challenges [4]. To achieve efficient EEG emotion classification, the appropriate channels and sub-frequency bands have to be selected. However, the knowledge concerning the relationship between the selection of the channels and sub-frequency bands has shown to be inconsistent with channel selection in EEG emotion classification. This chapter aims to investigate the relationship between the number of electrode channels and frequency bands, using the same benchmark dataset with the same feature extraction and classification technique in EEG emotion classification. The objective of this chapter is to determine the relationship between the number of channels and frequency bands, in order to find the appropriate electrode positions and number of sub-frequency bands to be used.

This chapter is organized as follows. Section 3.2 describes the benchmark dataset used in this thesis. Section 3.3 presents channel selection. The feature extraction approach used: Discrete Wavelet Transform (DWT) is shown in Section 3.4. Section 3.5 describes emotion labels. The experimental methodology is presented in Section 3.6. Sections 3.7 and 3.8 show the results from the use of a number of electrodes channels and positions, as well as the number of sub-frequency bands used, respectively. Finally, Section 3.9 is the summary of this chapter.

3.2 Database for Emotion Analysis using Physiological Signals: DEAP

DEAP [59] is a benchmark dataset for analyzing human affective states. Thirty-two participants watched 40 one-minute excerpts of music videos. Meanwhile, they recorded EEG signals at a sample rate of 512 Hz from 32 channels after each video finished and they had to rate levels of emotions including arousal, valence, and dominance. Having said that, like/dislike and familiarity were also rated, but in this thesis, only the three aforementioned emotions were used. The SAM was utilized to deliver each emotion level on a continuous scale between 1 and 9. Consequently, there were some processes for a pre-processed dataset. First of all, the raw dataset was sampled at a frequency rate down to 128Hz. Secondly, eye-blink artifacts were detected and removed. Next, the frequencies between 4 and 45Hz was selected. Finally, the signals were segmented into a one-minute trials and three seconds of each trial was removed from the beginning. In this thesis, the pre-processed dataset was used in all experiments.

3.3 Channel Selection

There are two categories of channel selection used in this chapter. The first category is based on the position lobes of the International System, as shown in Table 3-1 [138]. The positions of the human lobes are investigated by comparing each position against the other. Therefore, the best placement positions of the human lobe can be identified, so as to acquire the EEG signals. The second category is based on numerous previous studies, as shown in Table 3-2. A wide variety of channel selection from different lobes have been selected in the second category.

Table 3-1 Category I: Divided by letters of lode positions

Sub-group	Letter of Position Name (number of channels)	Lobe
1-1	All F(13)	All channels on Frontal
1-2	F3 F4 Fz F7 F8 (5)	Some channels on Frontal
1-3	FC1 FC2 FC5 FC6 (4)	Some channels on Frontal
1-4	Fp1 Fp2 (2)	Some channels on Frontal
1-5	AF3 AF4 (2)	Some channels on Frontal
1-6	All T(2)	All channels on Temporal
1-7	All P(7)	All channels on Parietal
1-8	P7 P3 Pz P4 P8 (5)	Some channels on Parietal
1-9	PO3 PO4 (2)	Some channels on Parietal
1-10	All O(3)	All channels on Occipital
1-11	All C(7)	All channels on Central
1-12	All Letters (32)	All channels

Table 3-2 Category II: Divided by selecting channels from previous studies

Sub-Group	Position Name (number of channels)	Reference
2-1	F3 F4 (2)	[139]
2-2	F3 F4 Fz (3)	[62]
2-3	AF3 F7 F3 FC5 FC6 F4 F8 AF4 P7 P8 (10)	[140]
2-4	Fp1 AF3 F7 P7 P3 Pz PO3 O1 CP2 C4 T8 FC6 (12)	[141]
2-5	Fp1 Fp2 F7 F3 Fz F4, F8 T7 C3 Cz C4 T8 P7 P3 Pz P4 T8 O1 Oz O2 (20)	[111] *
2-6	All (32)	[142]

3.4 Feature Extraction

In EEG emotion classification, a spectral feature is one of the popular techniques to extract a feature, as shown in Table 3-3. Discrete Wavelet Transform (DWT) is a spectral estimation technique [143]. It is one of many signal-processing techniques (which consists of several sub-signals) used to decompose signals into different frequency bands [34]. In this study, the DWT [7] was selected for decomposing the pre-processed DEAP dataset into five frequency bands including delta, theta, alpha, beta, and gamma. Moreover, *db4* was chosen as mother wavelets according to the good results in the EEG feature extraction [144]. Also, Amin et al. reported that this wavelet energy is suitable and appropriate for classifying EEG signals regarding medical applications [145]. Figure 3-1 shows the DWT orders and Table 3-4 shows the results.

Table 3-3 Some Feature Extraction Techniques in EEG Emotion Classification

Reference	Features
[26]	*Spectral features*, PCA
[17]	*Spectral features*, Coherence measures
[146]	*Spectral features*
[28]	*Spectral features*, Hemispheric asymmetry
[59]	*Spectral features*, Hemispheric asymmetry
[111]	Spectral turbulence
[33]	Signal averaged per participant, Adaptive filtering high-order crossing
[30]	*Spectral features*, Hemispheric asymmetry
[147]	Time frequency features, Mutual information between electrodes pair

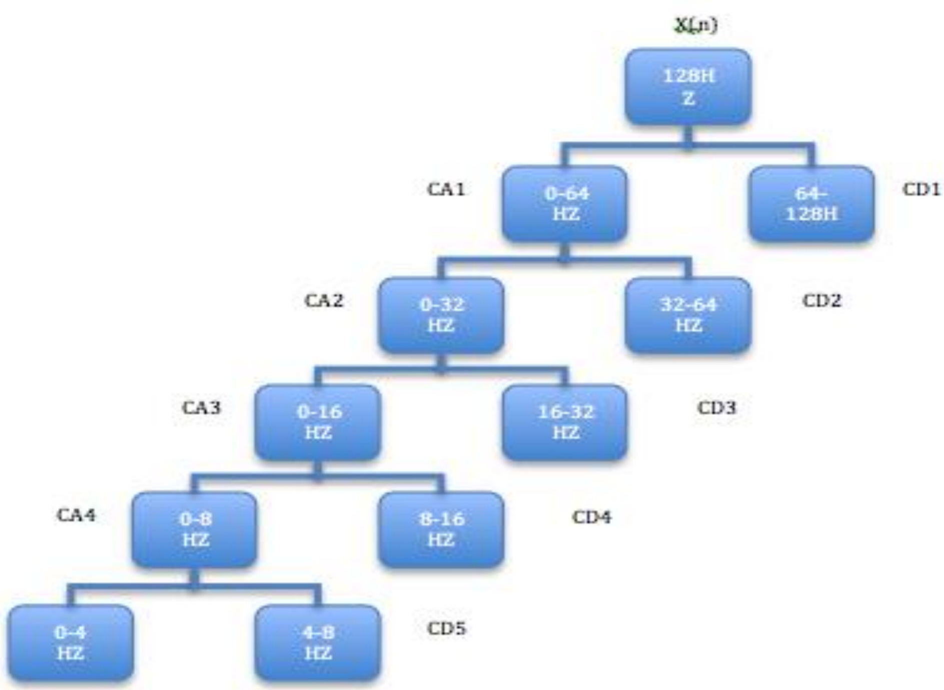

Figure 3-1 DWT orders

Table 3-4 Sub-Frequency Bands

Orders	Name of Frequency	Frequency Range (Hz)
CA5	Delta	0-4
CD5	Theta	4-8
CD4	Alpha	8-16
CD3	Beta	16-32
CD2	Gamma	32-64
CD1	Noise	64-128

According to Section 2.3 Electroencephalogram (EEG) and Human Emotion in Chapter 2, human emotion can be interpreted from the delta, theta, alpha, beta, and gamma frequency bands. After that, to measure the energy as a function of frequency, the conventional technique is spectral analysis. Therefore, the average powerband of each band has been selected to be a feature in the thesis.

The average power band of each sub-band is calculated for the features as follows. For example, the average power band of Delta is expressed as follows:

$$Avg.powerband\ \ of\ Delta = \frac{\sum_{i=1}^{length\ of\ CA_5}\left(CA_5(i)\right)^2}{length\ of\ CA_5} \tag{13}$$

3.5 Emotion Labels

Dimensional models are selected in this chapter for the emotion model, as mentioned in Chapter 2. There are three dimensions, namely arousal, valence, and dominance. Each emotion dimension will be further classified into two emotions: low or high. The emotion that the participant gives a rating of greater than or equal to 5 is a high emotion, whereas the emotion which is below 5 is a low emotion. Also, the maximum emotion is eight. There are three criteria of emotion as shown in Table 3-4.

Table 3-5 Names of Emotions

Emotion Model	The Number of Emotions	Emotion Name
Arousal	2	Low Arousal (LA) / High Arousal (HA)
Valence	2	Low Valence (LV) / High Valence (HV)
Dominance	2	Low Dominance (LD) / High Dominance (HD)

3.6 Methodology

In this thesis, four tasks are carried out in order to achieve an efficient emotion classification system, as shown in Figure 3-2. The first task is to study the relationship between the number of electrode channels, and frequency bands for feature selection. After that, feature extraction is conducted to select the appropriate features. The next task is the classification process using a technique to improve handling with the outliers. The final task is rule extraction. Task 1 is the focus in this chapter.

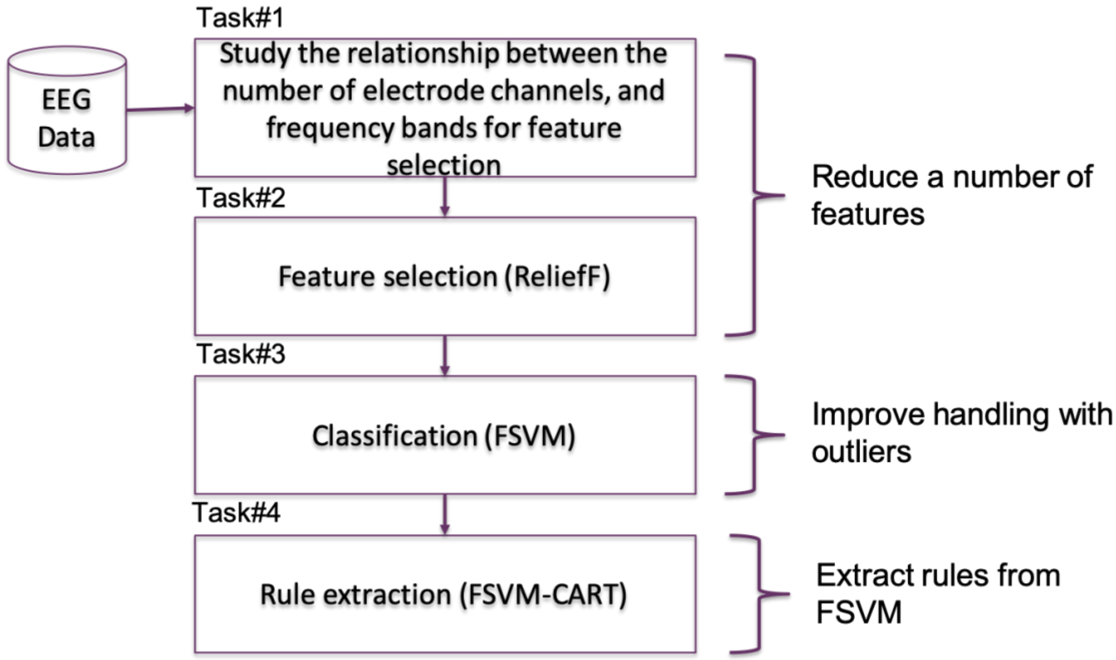

Figure 3-2 The efficient emotion classification system

The DEAP is the dataset used with 32 participants. Each participant has 40 trials. The same thirty-two trials were randomly selected for a training set, and eight trials became the testing set. The SVM is selected as a classifier in this chapter, via LIBSVM [148], because it was recommended for EEG emotion classification (as mentioned in Chapter 2). There are optimum 10 times of the experiment and the best result was selected. Moreover, 10-fold cross-validation was used each run. Dependent classification is used because of the higher accuracy [4]. Dependent classification means that each user has their own training and testing processes. As a result, each user has their own classifier model. There are two categories, as mentioned in Section 3.3, on Channel Selection. For feature extraction, the average power bands of sub-frequency bands are used.

There are two experiments used to study the relationship between the channel and sub-frequency band selections as the features in the EEG emotion classification system. In experiment one, a relationship of channel selection is studied to find the most appropriate electrode placements. After that, a relationship between the number of sub-frequency bands and feature selections is investigated in order to recommend the number of sub-frequency bands that should be used. The choices between two and five channels are shown in experiment two (Figure 3-3).

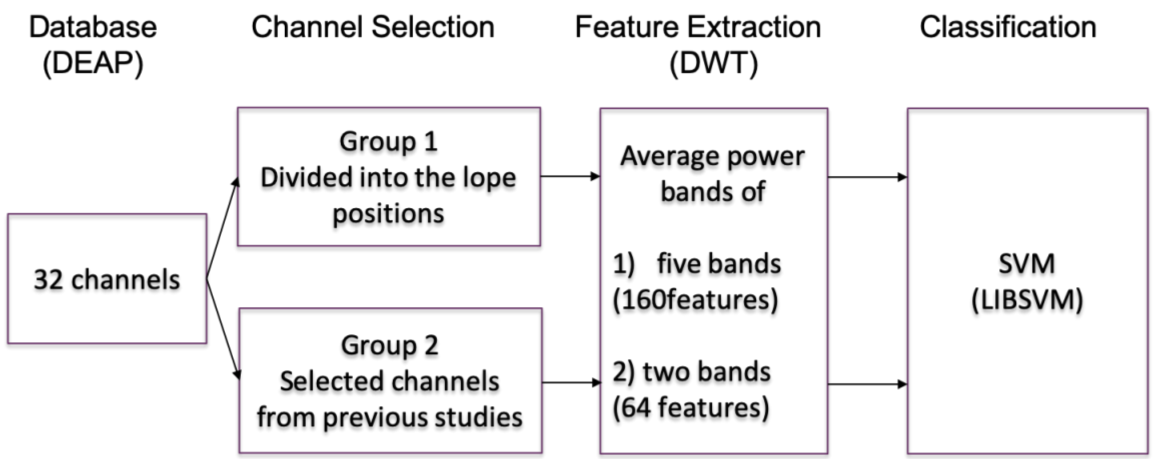

Figure 3-3 Experimental Methodology

3.7 Results from the determination of the Number of Electrode Channels and Positions

In this experiment, two results, which are Categories I and II, are presented based on the channel selection. Both are two-emotion classification for each dimension model. The average power band of each sub-frequency band is used as a feature. As a result, there are five features per channel.

Table 3-6 shows the results of the two-emotion classification from Category I. The best result of arousal is sub-group 1-5, which is a pair of AF3-AF4. The best result of valence and dominance is sub-group 1-8, which is a combination of P7-P3-Pz-P4-P8. Consequently, it seems that the channels on the frontal lobe are useful for arousal emotion, whereas the channels on the parietal lobe are crucial for valence and dominance classifications. Furthermore, using more channels for classification did not guarantee a better result. In contrast, using fewer channels showed better results in this experiment.

Table 3-6 Result of Category I

Sub-Group	Accuracy		
	Arousal	Valence	Dominance
1-1	57.8	56.77	61.98
1-2	54.69	52.08	56.77
1-3	52.60	55.73	63.02
1-4	57.29	47.40	61.98
1-5	59.90	54.17	52.60
1-6	56.77	56.25	60.42
1-7	55.21	53.65	65.63
1-8	58.33	58.85	66.15
1-9	54.69	51.56	61.98
1-10	55.21	56.25	56.77
1-11	55.21	56.77	61.46
1-12	57.29	54.69	59.90
Avg.	**56.25**	**54.51**	**60.72**

Table 3-7 presents the results of the two-emotion classification from various selected channels of Category II. The best result for arousal classification is sub-group 2-5, which is a combination of 20 channels from different lobe zones. The best results for valence and dominance are sub-group 2-6 (which is all 32 channels) and sub-group 2-3 (which combines ten channels between the frontal and parietal lobes). Surprisingly, the best results in this experiment for Category II are different from Category I. Both best results of Category II were mixed from various positions to provide the best results.

Table 3-7 Result of Category II

Sub-Group	Accuracy		
	Arousal	Valence	Dominance
2-1	51.56	49.48	57.81
2-2	49.48	50.52	53.65
2-3	52.08	53.13	64.06
2-4	54.17	51.56	63.54
2-5	60.94	51.56	60.42
2-6	57.29	54.69	59.90
Avg.	**54.25**	**51.82**	**59.90**

For the overall classification from Tables 3-6 and 3-7, sub-group 2-5 is the best for two-emotion classification of the arousal model by using 20 channels from many positions on the human lobe. Nevertheless, it is better than the second best, which is sub-group 1-5. Interestingly, the two channels of sub-group 1-5 can provide an equal classification performance when compared with the 20 channels. For valence and dominance classifications, sub-group 1-8, using five channels from the parietal lobe, is the best.

Therefore, although this experiment cannot indicate the exact channel positions that should be chosen as the best positions of two-emotion classification, frontal and parietal channels seem to be crucial for better classification. Also, using a few channels can provide a decent performance of emotion classification. These results are useful for feature selection.

3.8 Results from determination of the Number of Sub-Frequency Bands

The last experiment in this chapter is to investigate the relationship of the number of sub-frequency bands for the features. There are two types: using two (alpha, beta) [62, 105] and five (delta, theta, alpha, beta, gamma) bands per channel as the features. Table 3-8 shows two-emotion classification for each dimensional model of Category I and Table 3-9 shows two-emotion classification of each dimensional model of Category II.

For Table 3-8, the average accuracy of using five sub-frequency bands as the features is better than using two bands for valence and dominance emotions. In contrast, the average accuracy of using two sub-frequency bands as the features is better than using five bands for the arousal emotion. Similarly, Table 3-9 indicates the same trend as Table 3-8. Although the results cannot suggest precisely the best sub-frequency band for the features, it appears that the results generated from the models using only two bands is similar to that of five bands.

To sum up, in this experiment, using more channels does not guarantee a higher accuracy. In contrast, it might reduce the classification performance. However, the results reveal that using fewer sub-frequency bands for the features in this environment did not reduce the performance significantly. This information will be used to find appropriate sub-frequency bands for the features in Chapter 4.

Table 3-8 Two-emotion classification of each dimensional model of Category I

Sub-Group	Accuracy					
	Arousal		Valence		Dominance	
	5 bands	2 bands	5 bands	2 bands	5 bands	2 bands
1-1	57.81	58.33	56.77	53.65	61.98	55.21
1-2	54.69	58.33	52.08	53.65	56.77	56.25
1-3	52.60	62.50	55.73	54.17	63.02	64.58
1-4	57.29	57.81	47.40	53.65	61.98	57.29
1-5	59.90	56.77	54.17	52.08	52.60	53.65
1-6	56.77	57.81	56.25	57.29	60.42	56.77
1-7	55.21	51.04	53.65	56.77	65.63	62.50
1-8	58.33	58.33	58.85	56.77	66.15	56.77
1-9	54.69	57.29	51.56	48.44	61.98	56.25
1-10	55.21	57.81	56.25	47.40	56.77	54.69
1-11	55.21	63.54	56.77	56.25	61.46	55.21
1-12	57.29	58.33	54.69	53.65	59.90	61.46
Avg.	**56.25**	**58.16**	**54.51**	**53.65**	**60.72**	**57.55**

Table 3-9 Two-emotion classification of each dimensional model of Category II

Sub-Group	Accuracy					
	Arousal		Valence		Dominance	
	5 bands	2 bands	5 bands	2 bands	5 bands	2 bands
2-1	51.56	59.38	56.77	53.65	61.98	55.21
2-2	49.48	57.29	52.08	53.65	56.77	56.25
2-3	52.08	58.33	55.73	54.17	63.02	64.58
2-4	54.17	57.81	47.40	53.65	61.98	57.29
2-5	60.94	56.25	54.17	52.08	52.60	53.65
2-6	57.29	58.33	56.25	57.29	60.42	56.77
Avg.	54.25	57.90	53.73	54.08	59.46	57.29

Nevertheless, the classification results in this chapter are lower, as compared to some previous studies, as shown in Table 3-10. The reason for the lower classification results is because the model used a smaller number of channels, bands and features. Moreover, no parameter optimization was applied in the SVM technique and it is also sensitive to noise, as mentioned in Chapter 2; whereas EEG signals normally contain some noise. These issues will be addressed in the next chapter.

Table 3-10 A comparison of classification results

Emotion	Accuracy	
	Best results	Previous Study [[4]]*
Arousal	63.54%	68%

Valence	58.85%	65%
Dominance	66.15%	-

* The average accuracies of arousal and valence classifications of five studies

3.9 Summary

In this chapter, the relationship of the number of EEG electrode placements (channels), emotions, and sub-frequency bands for the features has been investigated. Various channels and sub-frequencies were compared with the same database, features, and classifier. There are three observations made in the chapter. The first investigation began with the relationship of the number of channels in EEG emotion classification. The results could not indicate exactly the best combination of channels for all emotion classifications. However, the EEG signals from a few frontal positions can be considered for arousal emotion and some parietal positions are appropriate for valence and dominance emotions. Therefore, the channels from both groups will be selected for feature selection in the next chapter. Moreover, using fewer channels did not drop the classification performance significantly. Next, the number of sub-frequencies for the features between two and five bands was compared. Interestingly, this study revealed that using two bands was sufficient for two emotion classification using EEG. This observation can confirm that an emotion system can use fewer sub-frequency bands instead of all bands for the features. As a result, some features can be reduced. These observations will be useful to design an efficient emotion classification framework for the rest of the thesis because of the possibility of a reduction of channel and sub-frequency selections. As a result, there are two outcomes that have been identified. 1) In EEG emotion classification, the channels of the frontal and parietal should be considered in the selection. 2) Using several channels and sub-frequency bands for features is sufficient for the purpose of the EEG emotion classification in this thesis. Thus, the objective of this chapter has been achieved.

CHAPTER 4

Fuzzy Support Vector Machine for EEG Emotion Classification

4.1 Introduction

Many machine learning algorithms have been applied in aBCI, but the most used classification method is the SVM [130]. The SVM has shown to provide a higher accuracy than many conventional learning methods, when dealing with classification problems [149]. Furthermore, the SVM has worked successfully in many real-world classification problems in different domains [134]. However, conventional SVM has to be improved when used in the aBCI field due to the characteristic of EEG signals, which are non-stationary and contain noise or outliers [20]. The SVM has shown to be sensitive to noise and outliers [39]. Lin and Wang [40] introduced a fuzzy approach on the SVM to handle these problems and it has been called Fuzzy Support Vector Machines (FSVMs). The difference between the traditional SVM and FSVM is that the samples in the SVM are treated equally, whereas the samples are treated with different fuzzy membership values in the FSVM [150]. To the best of the author’s knowledge, the application of the FSVM to aBCI has not been investigated. Furthermore, some studies suggested that portable and EEG systems for real-time applications should be developed for practical uses; for example, detecting emotion conditions in airplane pilots and bus drivers [16], and the need to reduce the response time in EEG medical applications [17]. Consequently, these goals inspired this chapter, that of reducing the number of EEG features. This investigation will assist in real-time and practical EEG applications in the future, by suggesting an appropriate set of channels and frequency bands for feature extraction in an efficient EEG emotion classification system, with a focus on accuracy and computation time. With respect to accuracy, the FSVM, with a weight function, is used in this chapter to deal with the outliers amongst the EEG data. The idea behind the weight function is to give less informative weights for the samples, which are considered outliers. In other words, samples, which are further from the class centers, should be considered as less important for training in the FSVM model. For effective calculation, the determination of appropriate channels and bands are selected in order to reduce the number of features associated with the FSVM.

As a result, this chapter is divided into two main parts. The first part focuses on the feature selection technique. The objective of this part is to reduce and find the best combination of bands and channels as the features using the feature selection technique. The second part is the FSVM which is enhanced for dealing with outliers in the EEG emotion classification.

4.2 Feature Selection

After channel zone and frequency band selections in Chapter 3, many features remain, and a large number of features may cause an increase in computation cost and overfitting in a learning model [151]. Besides, from the results in Chapter 3, it is indicative that using less channels and bands could work for two-emotion classification. However, there are differences as to how the channels and bands can be selected. Therefore, the next step is to use a Feature Selection (FS) technique to find an appropriate set of features. FS is one of the crucial processes for the learning machine, so as to acquire better accuracy. The attempt of FS is to find a subset of features that are relevant to the target class [152], and eliminate irrelevant and redundant features in the process. An irrelevant feature means that the feature does not induce the target class, while a redundant feature means that the feature adds nothing to the target class [153]. Therefore, FS is used to reduce irrelevant and redundant features. Consequently, FS can enhance prediction performance by facilitating data visualization and data understanding, reducing training and computational times, decreasing storage and measurement requirements and addressing the curse of high dimensional data [154]. As a result, FS has been widely applied in various applications such as text categorization, information retrieval, and DNA micro-array analysis [155]. FS has also been used in many EEG emotion classification and recognition applications [as illustrated in references [10, 30, 156, 157]. There are three main approaches to FS: *Filter*, *Wrapper*, and *Embedded* methods. Before determining which technique is used for FS in this research, some advantages and disadvantages of these methods are explained below.

4.2.1 Filter Models

In the filter models, the features are evaluated without the utilization of classification algorithms but these techniques depend on the characteristics of the training data [151]. In other words, filter methods are independent of any specific classifiers. The advantages of this category are the independence of the learning machine, lower computational cost and good generalization ability [155]. This category has a lower time consumption because it is a pre-processed technique which ranks the features based on specific criteria. In contrast, the other two methods need to evaluate performance together with the classifier, and therefore the computation is more complex. However, some useful features could be missed with the filter methods, especially when used alone. Those features could be crucial when combined with other features [158] due to the lack of interaction with the classifier [155]. Some examples of filter methods include INTERACT [159], ReliefF [160], and Information Gain [161].

4.2.2 Wrapper Models

The significant disadvantage of filter methods is that they completely ignore the selected feature set on the evaluation of the learning algorithm [162, 163]. Wrapper methods were designed to solve this issue by interacting with a classifier as a part of the selection algorithm [155]. Based on this assumption, the classifier evaluates and selects a feature subset according to its predictive power [154]. Wrapper methods typically use cross-validation to estimate the accuracy of the learning machine. Therefore, it is an iteration process. Although it can capture feature dependencies, there are a few disadvantages of this category; namely the fact that it is expensive, there is a risk of overfitting and it is a classifier-dependent selection [155]. Wrapper-C4.5 and Wrapper SVM [164] are examples of this category.

4.2.3 Embedded Models

Embedded models are a function of feature selection in the training process of a selected learning machine [155]. In other words, the feature selection process is embedded in the classifier construction. Embedded models have a few benefits over filter and wrapper approaches [151]. They can capture feature dependencies as well as wrapper methods but the computation time is lower than the wrapper approach [158]. For example, Recursive Feature Elimination for Support Vector Machines (SVM-RFE) performs feature selection in itself and removes incompetent features, which are indicated by the SVM, during the iteratively training process [165]. Another example is Feature Selection - Perceptron (FS-P). It has an embedded selecting method based on a perceptron which is the interconnection weights. These weights are used to decide which features will be used [166]. However, the embedded approach has a lack of independence from the classifier [155].

Most researchers agree that there is no perfect method for all problems, but for a specific problem setting, there might be one approach that suits the environment [155]. In this study, the filter approach is used to find the appropriate features for the emotions. Filter methods are the fastest in terms of computation cost, and it is independent of the classifiers. This study tries to find the significant features in a process prior to the selected classifier. Moreover, due to the potential real-time applications of EEG emotion classification, an independence from the classifier in filter methods could be beneficial, as compared to wrapper and embedded approaches. In addition, Bolon-Canedo et al. [155] indicated that one of the filter methods, which is the ReliefF technique, was faster than the embedded and wrapper methods in their study. Furthermore, it had a good generalization ability, and it was the best approach to deal with noise in the datasets of their experiments. Therefore, this technique was selected in this thesis. The next section presents the conceptual and algorithmic descriptions of the original Relief-based.

4.2.4 Relief-based Feature Selection

The original Relief algorithm was developed by Kira and Rendell based on instance-based learning [167]. Chikhi and Benhammada [168] explained the main idea of the algorithm to be, " *... to estimate the quality of attributes according to how well their values distinguish between instances that they are near each other"*. Figure 4-1 shows the pseudo code of the Relief algorithm. R_i is a randomly selected instance, called *target instance* R_i, and there are two instances to be searched. *H* is the nearest instance from the same target class of R_i, called *nearest hit H*. In contrast, *M* is the nearest instance from the deferent target class of R_i, called *nearest miss M*. The algorithm updates the quality estimation, which is a feature weight W for all attributes *A* (*W[A]* = weight of feature '*A*'). The quality of estimation *W[A*] is decreased when instances R_i and *H* have different values of attribute *A*, and the attribute *A* separates two instances with the same class. Therefore, *A* is not desirable. On the other hand, *W[A]* is increased when instances R_i and *M* have different values of attribute *A*, and the attribute *A* separates two instances with the same class. As a result, *A* is desirable. The whole process is complete when it repeats *m* times, where *m* is a user-defined parameter.

The difference between the values of attribute A for two instances, I_1 and I_2, can be calculated by the distance function $diff(A, I_1, I_2)$, where $I_1 = R_i$ and I_2 is either *H* or *M*. *diff()* is defined as (14) for nominal attributes and (15) for numerical attributes:

$$diff(A, I_1, I_2) = \begin{cases} 0, & if\ value(A, I_1) = value(A, I_2) \\ 1, & if\ otherwise \end{cases} \tag{14}$$

$$diff(A, I_1, I_2) = \frac{|value\ (A, I_1) - value\ (A, I_2)|}{\max(A) - \min(A)} \tag{15}$$

Input: for each training instance a vector of attribute values and the class value

Output: the vector W of estimations of the qualities of attributes

1: set all weight $W[A]$:= 0:0;

2: **for** $i \coloneqq 1$ **to** m **do** begin

3: randomly select an instance R_i;

4: find nearest hit H and nearest miss M;

5: **for** $A \coloneqq 1$ t**o** a **do**

6: $W[A] \coloneqq W[A] - \frac{diff(A,R_i,H)}{m} + \frac{diff(A,R_i,M)}{m}$

7: **end**

Figure 4-1 Pseudo code of Relief algorithm [168]

The max and min are respectively the maximum and minimum value of A over the entire set of instances. The first Relief can deal with a two-class problem, nominal and numerical attributes, but it cannot work with incomplete and noisy data. [168] Nevertheless, the EEG signal may contain noise. Therefore, the original algorithm may not cope with the noise issue in the EEG data.

Kononenko et al. [160] developed the ReliefF (Relief-F) algorithm to increase the ability of the original one. As a result, it can deal with incomplete and noisy data. Figure 4-2 shows the algorithm of ReliefF. In the algorithm, R_i is selected randomly, the same way as in the case of Relief. The difference between both algorithms is that the ReliefF searches for k-nearest neighbours of R_i within the same class, whereas the Relief searches for only one.

These k nearest neighbours are called nearest hits H_j. In the opposite target class of R_i, k nearest neighbours are called nearest misses $M_j(C)$. As a result, ReliefF searches for k nearest hits and misses. In addition, it makes the algorithm more robust in terms of decreasing redundant and noisy attributes because of the usage of average values of both H_j and $M_j(C)$ [168]. Consequently, ReliefF may suit the EEG data due to noise handling. Moreover, ReliefF can deal with a multi-class problem according to the prior probability of that class P(C). However, this thesis focuses on two-class problems. For more information, the multi-class problem can be found in [168]. Consequently, ReliefF is selected as a feature selection in this chapter.

Input: for each training instance a vector of attribute values and the class value

Output: the vector W of estimations of the qualities of attributes

1: set all weight $W[A]$:= 0:0;

2: **for** $i \coloneqq 1$ **to** m **do** begin

3: randomly select an instance R_i;

4: find k nearest hit Hj;

5: **for** $each\ class\ C\ \neq classe(R_i)$ **do**

6: from class C find k nearest misses $Mj(C)$;

7: **for** $A \coloneqq 1$ **to** a **do**

8: $W[A] \coloneqq W[A] - \sum_{j=1}^{k} \frac{diff(A,R_i,H_j)}{(m.k)} + \sum_{\neq class(R_i)} \frac{P(c)}{1-P(class(R_i))} \sum_{j=1}^{k} \frac{diff(A,R_i,M_j(C))}{(m.k)}$

9: **end**

Figure 4-2 Pseudo code of ReliefF algorithm [168]

4.2.5 Methodology for Selecting Appropriate Features

The results from Chapter 3 recommended that frontal and parietal channels are appropriate for the selection in EEG emotion classification. Moreover, a number of sub-frequency bands can be reduced. Therefore, the channels from both groups are selected in task 2, FS, as shown in Figure 3-2. These channels use five features per channel, including the average powerband of the delta, theta, alpha, beta, and gamma as input features. All features are presented in Table 4-1, while Figure 4-3 shows the methodology of FS. There are four processes in this task, as shown in Figure 4-4, using the proposed feature selection technique.

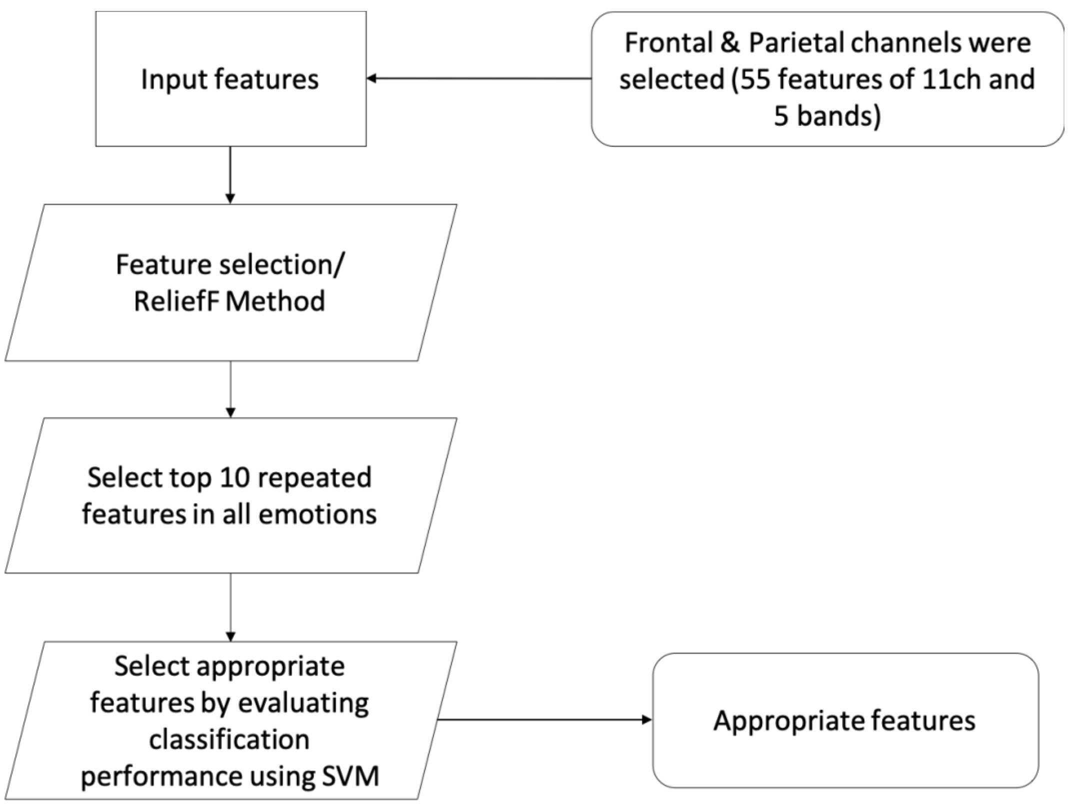

Figure 4-3 Methodology of feature selection

Table 4-1 Input features

Feature Number	Feature Name	Feature Number	Feature Name
1	Fp1-Delta	29	Fp2-Alpha
2	AF3-Delta	30	Af4-Alpha
3	P3-Delta	31	P4-Alpha
4	P7-Delta	32	P8-Alpha
5	Po3-Delta	33	Po4-Alpha
6	Pz-Delta	34	Fp1-Beta
7	Fp2-Delta	35	AF3-Beta
8	Af4-Delta	36	P3-Beta
9	P4-Delta	37	P7-Beta
10	P8-Delta	38	Po3-Beta
11	Po4-Delta	39	Pz-Beta
12	Fp1-Theta	40	Fp2-Beta
13	AF3-Theta	41	Af4-Beta
14	P3-Theta	42	P4-Beta
15	P7-Theta	43	P8-Beta
16	Po3-Theta	44	Po4-Beta
17	Pz-Theta	45	Fp1-Gamma
18	Fp2-Theta	46	AF3-Gamma
19	Af4-Theta	47	P3-Gamma
20	P4-Theta	48	P7-Gamma
21	P8-Theta	49	Po3-Gamma
22	Po4-Theta	50	Pz-Gamma
23	Fp1-Alpha	51	Fp2-Gamma

24	AF3-Alpha	52	Af4-Gamma
25	P3-Alpha	53	P4-Gamma
26	P7-Alpha	54	P8-Gamma
27	Po3-Alpha	55	Po4-Gamma
28	Pz-Alpha		

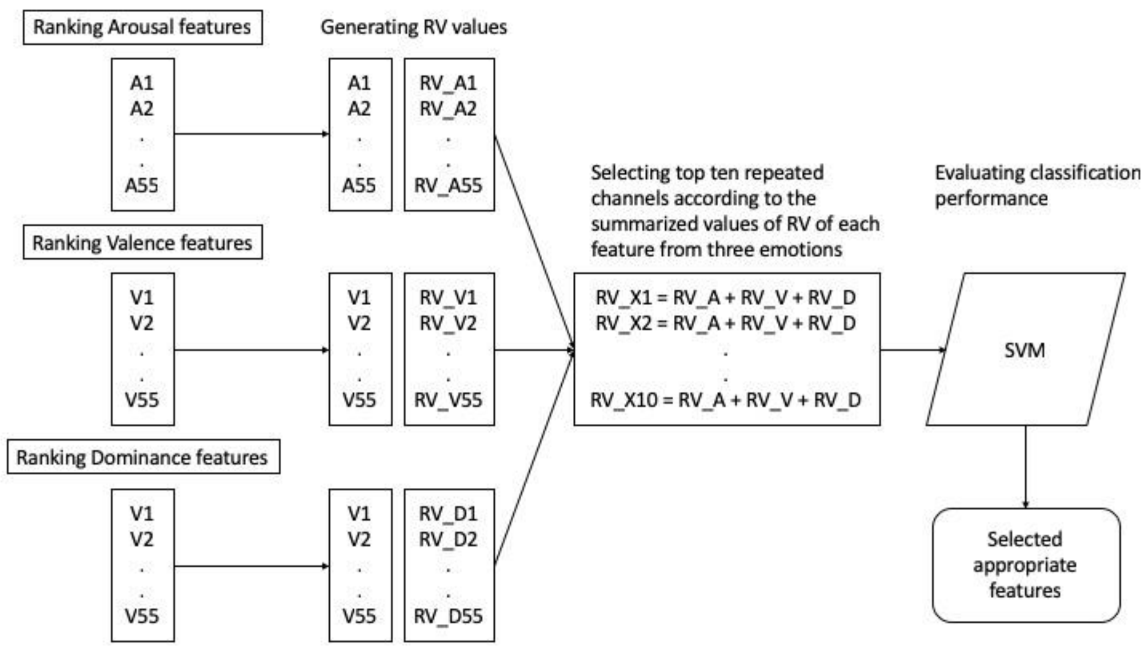

Figure 4-4 Proposed feature selection method

1) The ReliefF method ranks all features from the most to the least important for each emotion. In the first process, the channel, which is more important, is assigned a higher-ranking value (weight value of ReliefF) for a particular emotion. In contrast,

a lower-ranking value is assigned to the channel which has less importance for classifying that emotion, according to ReliefF.

2) In the second process, Ranking Values (RVs) can then be assigned by equation (16). RVs are designed to indicate how important a particular feature is for that specific emotion. Although a weight value of ReliefF method can interpret meaning in the same way as RVs, the weight value may give an extreme value due to the distance function of the ReliefF method. Consequently, a summation of weight values of each feature from all emotions might not indicate the essential features. In contrast, RVs present how important the features are using a gradual ratio. As a result, RVs do not provide extreme values.

$$Ranking\ Value\ (RV) = \left(1 - \frac{Ranking}{a\ number\ of\ channels}\right) \tag{16}$$

3) The third process is to select the top ten repeated features from all emotions using the summation of the RVs of each feature from the three emotions. After that, according to the summation values, the top ten features are chosen as a starting point for the trial and error process, so as to select the best set of features for the three emotions.

4) Finally, the SVM is used to select appropriate features by evaluating the classification performance. There are optimum ten runs of the experiments and the best result was selected. Moreover, 10-fold cross-validation was used each run. In this process, the top ten selected features are reduced one by one to evaluate a

classification result. After reducing the ten features to just one, all classification results are compared against one another. The best classification result will indicate how many features should be selected in EEG emotion classification.

4.2.6 Feature Selection Experiments: Results and Discussion

Table 4-2 shows all features, after the ReliefF method ranked the features for each emotion, as well as the RVs. The results reveal that the top ten best features for each emotion are not identical. Therefore, the best features for one emotion may not be the best for another emotion. However, one objective of this thesis is to find fewer appropriate features for all emotions according to the objective of the reduction of a number of features, as mentioned in Chapter 1. To achieve the objective, the proposed RVs were used instead of weight values.

Table 4-2 ReliefF method results and ranking values

Emo-tion	Arousal			Valence			Dominance		
Rank	Feature	Weight ([w])	RV	Feature	Weight ([w])	RV	Feature	Weight ([w])	RV
1	Fp1-Gamma	0.0010989	0.98	AF4-Theta	0.0014483	0.98	Fp1-Delta	0.0015706	0.98
2	Fp2-Gamma	0.0010006	0.96	Po4-Beta	0.0013475	0.96	P4-Gamma	0.00125051	0.96
3	Fp2-Alpha	0.0009388	0.95	Po4-Theta	0.0012785	0.95	AF3-Gamma	0.0012361	0.95
4	AF3-Alpha	0.0009041	0.93	AF4-Gamma	0.0012624	0.93	Fp1-Theta	0.00120495	0.93
5	Fp2-Theta	0.0008345	0.91	Fp2-Gamma	0.0012289	0.91	Po3-Gamma	0.00120387	0.91
6	Fp2-Beta	0.0007145	0.89	Po4-Alpha	0.0012195	0.89	AF4-Delta	0.00106671	0.89
7	AF4-Gamma	0.0006941	0.87	AF4-Beta	0.0012168	0.87	Fp1-Alpha	0.00102631	0.87
8	Pz-Beta	0.0006838	0.85	AF4-Delta	0.0011555	0.85	AF4-Gamma	0.00088118	0.85
9	P3-Alpha	0.0005703	0.84	Fp1-Gamma	0.0011355	0.84	Af4-Theta	0.00086518	0.84

10	Pz-Alpha	0.0005434	0.82	Fp1-Beta	0.0010326	0.82	AF4-Alpha	0.00076665	0.82
11	P7-Alpha	0.0005112	0.80	Fp2-Beta	0.0009768	0.80	Fp1-Gamma	0.00068639	0.80
12	AF3-Theta	0.0004621	0.78	Fp2-Alpha	0.000949	0.78	Fp1-Beta	0.00060159	0.78
13	Pz-Theta	0.0004184	0.76	Fp1-Delta	0.0008988	0.76	AF3-Alpha	0.00055928	0.76
14	Pz-Gamma	0.0004074	0.75	P4-Gamma	0.0008811	0.75	Af4-Beta	0.00055601	0.75
15	P3-Theta	0.0003897	0.73	Po4-Gamma	0.000845	0.73	Po4-Gamma	0.00051553	0.73
16	P8-Delta	0.0003655	0.71	Fp2-Theta	0.0008432	0.71	Af3-Theta	0.00043053	0.71
17	Pz-Theta	0.0003512	0.69	Fp1-Theta	0.0008342	0.69	Fp2-Alpha	0.00041468	0.69
18	P8-Beta	0.0003266	0.67	AF4-Delta	0.0008138	0.67	P4-Theta	0.00037933	0.67
19	P8-Theta	0.0002872	0.65	P3-Beta	0.0007818	0.65	Fp2-Gamma	0.0003657	0.65
20	P7-Delta	0.0002268	0.64	P4-Alpha	0.0007618	0.64	P4-Beta	0.00035404	0.64
21	Pz-Delta	0.0002242	0.62	Fp1-Alpha	0.0007559	0.62	AF3-Beta	0.00025546	0.62
22	P8-Alpha	0.0001722	0.60	P4-Beta	0.0007487	0.60	Po3-Delta	0.0002076	0.60
23	P4-Alpha	0.0001649	0.58	AF3-Alpha	0.0007272	0.58	P4-Delta	0.00018868	0.58
24	AF3-Delta	0.0001302	0.56	AF3-Beta	0.0006966	0.56	Po3-Alpha	0.00012439	0.56
25	Fp2-Delta	0.0001113	0.55	Pz-Beta	0.000683	0.55	Fp2-Theta	0.00005669	0.55
26	P7-Gamma	0.0000619	0.53	AF3-Gamma	0.0006656	0.53	P7-Gamma	0.00002903	0.53
27	Po3-Theta	0.0000598	0.51	Po3-Alpha	0.0006135	0.51	Fp2-Beta	0.0000286	0.51
28	AF3-Beta	0.00003	0.49	Po3-Gamma	0.0006092	0.49	AF3-Delta	0.00001299	0.49
29	P7-Theta	0.000013	0.47	P4-Theta	0.0005934	0.47	Fp2-Delta	0.0000025	0.47
30	Fp1-Alpha	-0.0000374	0.45	AF3-Theta	0.0004932	0.45	P4-Theta	-0.00001132	0.45
31	Fp1-Theta	-0.000062	0.44	Po3-Beta	0.0004833	0.44	Po3-Beta	-0.00008482	0.44
32	AF3-Gamma	-0.0001247	0.42	Pz-Deta	0.0003868	0.42	Po4-Alpha	-0.00010995	0.42
33	P3-Delta	-0.0001371	0.40	P3-Gamma	0.0003418	0.40	Po3-Theta	-0.00038863	0.40
34	Po3-Beta	-0.0001374	0.38	P8-Delta	0.0003338	0.38	Po4-Theta	-0.00047968	0.38
35	P8-Gamma	-0.0001447	0.36	P7-Theta	0.000272	0.36	Po4-Delta	-0.000618	0.36
36	Fp1-Beta	-0.0002204	0.35	Po3-Theta	0.0002614	0.35	Pz-Delta	-0.00094622	0.35
37	P4-Theta	-0.0002745	0.33	P3-Alpha	0.0002559	0.33	P8-Gamma	-0.0010701	0.33
38	P7-Alpha	-0.0003422	0.31	Pz-Alpha	0.0002453	0.31	Po4-Beta	-0.00113852	0.31
39	Po4-Alpha	-0.0003667	0.29	Pz-Theta	0.0001621	0.29	P7-Beta	-0.00138872	0.29

40	Po3-Delta	-0.0003908	0.27	P3-Delta	0.000135	0.27	P3-Delta	-0.0014874	0.27
41	P3-Gamma	-0.0004411	0.25	P7-Delta	0.0001302	0.25	P8-Beta	-0.00152243	0.25
42	P4-Gamma	-0.000446	0.24	Pz-Gamma	0.0001196	0.24	P3-Gamma	-0.00164649	0.24
43	P4-Beta	-0.0004636	0.22	P7-Alpha	0.0000421	0.22	P7-Alpha	-0.00165847	0.22
44	Po4-Gamma	-0.000506	0.20	p3-Theta	0.0000273	0.20	P7-Theta	-0.00175907	0.20
45	P4-Delta	-0.0006233	0.18	Fp2-Delta	-0.0000242	0.18	P8-Alpha	-0.00201386	0.18
46	Po3-Gamma	-0.0006292	0.16	P7-Beta	-0.0000699	0.16	Pz-Gamma	-0.0020182	0.16
47	AF4-Alpha	-0.0006691	0.15	Po4-Delta	-0.0000858	0.15	P8-Delta	-0.00202974	0.15
48	Po4-Delta	-0.0006794	0.13	P4-Delta	-0.0001267	0.13	Pz-Theta	-0.00247542	0.13
49	Fp1-Delta	-0.0007042	0.11	P7-Gamma	-0.0002077	0.11	P8-Theta	-0.00266481	0.11
50	P7-Beta	-0.0007324	0.09	AF3-Delta	-0.0002299	0.09	P3-Theta	-0.00266776	0.09
51	AF4-Theta	-0.0008262	0.07	Po3-Delta	-0.0002832	0.07	Pz-Alpha	-0.00268228	0.07
52	AF4-Beta	-0.0008444	0.05	P8-Alpha	-0.0003924	0.05	P3-Alpha	-0.00303989	0.05
53	Po4-Theta	-0.0009669	0.04	P8-Beta	-0.0004812	0.04	P3-Beta	-0.00315271	0.04
54	Po4-Beta	-0.0011026	0.02	P8-Theta	-0.0004914	0.02	P7-Delta	-0.00320384	0.02
55	AF4-Delta	-0.0017565	0.00	P8-Gamma	-0.0006128	0.00	Po4-Gamma	-0.00371719	0.00

To select the appropriate features for classifying all emotions, a summation of RVs for all emotions is calculated for each feature. Table 4-3 shows the results of the summation values of RVs. Then, the top ten appropriate features are selected as an initial number of features for the next process. The SVM is a classifier used to evaluate a classification result. Five random participants of the DEAP dataset are selected to classify all emotions using simple random sampling. The reason the process does not use all samples is because of generalization and the need to prevent any selection bias [169]. Then, each random participant does a 10-fold cross-validation. The top ten selected appropriate features are AF4-Gamma, Fp1-Gamma, Fp2-Gamma, Fp2-Alpha, AF3-Alpha, Fp2-Beta, Fp2-Theta, Fp1-Theta, P4-Gamma, and Fp1-Beta. Table 4-4 and Figure 4-5 show the classification results using one to ten features. Some accuracy results in Table 4-4 cannot be generated because of no recall value for the positive or negative emotion. In other words, a classification model has no recall value. This is not practical because the model can only predict one target class. Consequently, there are some with no accuracy results in Table 4-4. The result of this experiment shows that six features provide the best results. After using less than six features, the classification accuracies dramatically decreased. The result can be interpreted that as the features are less than six, they are not enough to distinguish two classes properly. In contrast, while using more than six features, the extra features may not have new information to enhance the ability of the classification. Moreover, the extra features may cause an overfitting issue. As a result, this experiment can conclude that using six features, which are AF4-Gamma, Fp1-Gamma, Fp2-Gamma, Fp2-Alpha, AF3-Alpha, Fp2-Beta, is appropriate for classifying all emotions using the EEG data.

Table 4-3 Summation values of RVs

Rank	Feature	Summation of RVs	Rank	Feature	Summation of RVs
1	AF4-Gamma	2.65	29	Po4-Delta	1.37
2	Fp1-Gamma	2.62	30	Po4-Beta	1.29
3	Fp2-Gamma	2.52	31	Po3-Beta	1.26
4	Fp2-Alpha	2.42	32	Po3-Delta	1.26
5	AF3-Alpha	2.27	33	P4-Theta	1.25
6	Fp2-Beta	2.2	34	P8-Delta	1.24
7	Fp2-Theta	2.17	35	P3-Alpha	1.22
8	Fp1-Theta	2.06	36	Pz-Alpha	1.2
9	P4-Gamma	1.95	37	Fp2-Delta	1.2
10	Fp1-Bata	1.95	38	Pz-Theta	1.18
11	Fp1-Alpha	1.94	39	P7-Gamma	1.17
12	Af3-Theta	1.94	40	Pz-Gamma	1.15

13	AF3-Gamma	1.9	41	AF3-Delta	1.14
14	P4-Alpha	1.89	42	P7-Theta	1.03
15	AF4-Theta	1.89	43	P3-Theta	1.02
16	Po3-Alpha	1.87	44	P8-Alpha	0.96
17	Fp1-Delta	1.85	45	Po3-Delta	0.94
18	AF4-Alpha	1.82	46	P3-Delta	0.94
19	Af4-Beta	1.67	47	P7-Delta	0.91
20	Af3-Beta	1.67	48	P3-Gamma	0.89
21	Po4-Gamma	1.66	49	P4-Delta	0.89
22	Po4-Alpha	1.6	50	P8-Alpha	0.83
23	Po3-Gamma	1.56	51	P8-Theta	0.78
24	AF4-Delta	1.56	52	P7-Alpha	0.75
25	P4-Beta	1.46	53	P8-Gamma	0.69
26	Pz-Beta	1.4	54	Po4-Delta	0.64
27	Pz-Delta	1.39	55	P7-Beta	0.54
28	P3-Beta	1.38			

Table 4-4 Classification results using one feature to ten features

Participant	Emotion	Number of Features / Accuracy (%)									
		1	2	3	4	5	6	7	8	9	10
s01	Arousal	-	-	62.5	62.5	62.5	75	62.5	37.5	62.5	50
s01	Valence	37.5	50	50	50	50	62.5	37.5	50	50	62.5
s01	Dominance	-	-	-	-	75	50	62.5	75	62.5	62.5
s05	Arousal	50	37.5	37.5	62.5	50	50	37.5	37.5	50	50
s05	Valence	62.5	50	62.5	37.5	62.5	75	62.5	62.5	37.5	75
s05	Dominance	37.5	75	62.5	75	75	75	75	75	75	37.5
s07	Arousal	-	37.5	37.5	12.5	62.5	62.5	62.5	50	62.5	12.5
s07	Valence	-	-	-	62.5	75	75	50	50	50	50
s07	Dominance	-	25	-	37.5	25	37.5	37.5	37.5	37.5	37.5

s21	Arousal	-	-	-	-	-	75	75	75	75	75
s21	Valence	50	62.5	50	37.5	37.5	50	87.5	87.5	75	75
s21	Dominance	-	-	62.5	62.5	75	62.5	62.5	62.5	50	62.5
s31	Arousal	75	62.5	62.5	37.5	62.5	62.5	62.5	62.5	75	75
s31	Valence	-	-	62.5	37.5	75	50	50	37.5	62.5	50
s31	Dominance	-	50	50	37.5	37.5	62.6	37.5	37.5	50	50
Avg.		19.59	28.25	37.69	38.53	51.88	58.19	54.34	52.84	55.25	52.19

Nevertheless, the six selected appropriate features for classifying all emotions are different from the best six features for classifying each emotion as shown in Table 4-5. In other words, the selected six appropriate features from this experiment may not be optimal to classify each emotion. Consequently, this chapter compares the classification results of these features, as shown in Table 4-6.

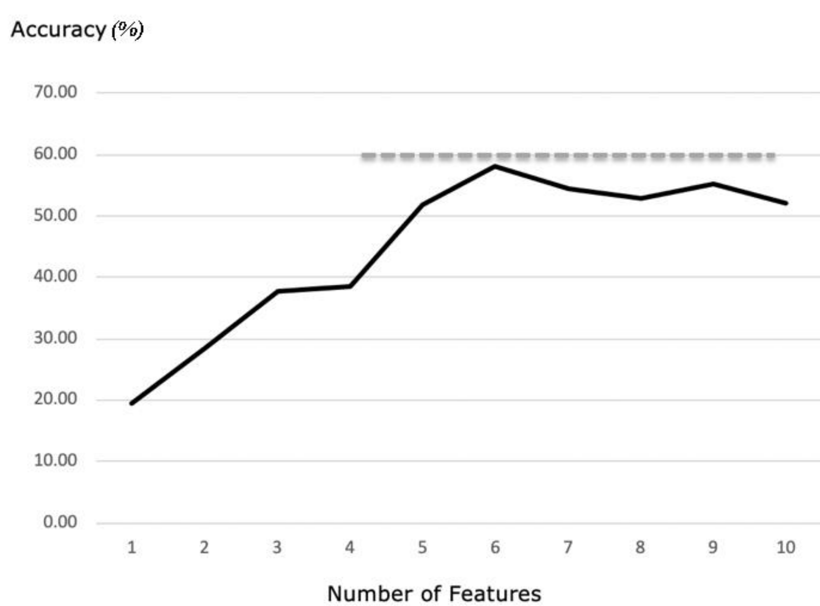

Figure 4-5 Classification results using one feature to ten features

Table 4-5 Top six features

Rank	All Three Emotions (Six selected appropriate features)	Arousal (Six best features)	Valence (Six best features)	Dominance (Six best features)
1	AF4-Gamma	Fp1-Gamma	AF4-Theta	Fp1-Delta
2	Fp1-Gamma	Fp2-Gamma	PO4-Beta	P4-Gamma
3	Fp2-Gamma	Fp2-Alpha	PO4-Theta	AF3-Gamma
4	Fp2-Alpha	AF3-Alpha	AF4-Gamma	Fp1-Theta
5	AF3-Alpha	Fp2-Theta	Fp2-Gamma	PO3-Gamma
6	Fp2-Beta	Fp2-Beta	PO4-Alpha	AF4-Delta
#channels #bands #features	- 4 Channels (AF4, Fp1, Fp2, and AF3) - 3 Bands (Gamma, Alpha, and Beta) - 6 features	- 8 Channels (Fp1, Fp2, AF3, Fp2, AF4, PO4, P4, and PO3 - 5 Bands (Delta, Theta, Beta, Gamma, and Alpha) - 17 features		

Table 4-6 Classification results for each emotion between proposed feature selection and top six feature selections

Emotion	Proposed selected appropriate six features (%)	Top best six features for each emotion (%)
Arousal	68.36	69.53
Valence	70.31	71.09
Dominance	68.55	69.76

The result shows that the six selected appropriate features using the proposed feature selection technique are not the best results for each emotion. Instead, it is slightly lower than using the top six best features in each emotion by around one percent. In addition, the proposed six appropriate features have four channels and three sub-frequency bands to provide the complete results for each emotion. On the other hand, to provide the best results in all emotions, there are seventeen features to be collected from eight channels and five sub-frequency bands, which are Fp1-Gamma, Fp2-Gamma, Fp2-Alpha, AF3-Alpha, Fp2-Theta, Fp2-Beta AF4-Theta, PO4-Beta, PO4-Theta, AF4-Gamma, PO4-Alpha Fp1-Delta, P4-Gamma, AF3-Gamma, Fp1-Theta, PO3-Gamma, and AF4-Delta. Even though the selected appropriate features, which are AF4-Gamma, Fp1-Gamma, Fp2-Gamma, Fp2-Alpha, AF3-Alpha, and Fp2-Beta, do not perform the best in each emotion's classification, the classification results using these features are quite similar as when using the best features. In contrast, the EEG emotion classification system using the selected appropriate features uses fewer channels and sub-frequency bands. As a result, one of the objectives of this thesis, which is to reduce the complexity of the EEG system, can be achieved. In Mühl's survey, previous studies have used many features and channels. For example, they utilized five sub-bands and 14 symmetrical pairs of the left and right hemisphere with four sub-bands. In comparison, only four channels with three sub-bands are used in this study. Moreover, using fewer features in this research could have many benefits such as avoiding the overfitting problem, making it easier to select the optimal model, and reducing computational complexity.

Table 4-7 shows the comparison results between task 1 in Chapter 3, and task 2 in this chapter. After selecting the appropriate features, the classification performance is notably better in arousal and valence emotions and slightly better in the dominance emotion.

Table 4-7 The comparison between Task 1 and Task 2

Emotion	Accuracy	
	Task#1 Feature selection (previous studies)	Task#2 Feature selection (ReliefF)
Arousal	60.94%	68.36%
Valence	58.85%	70.31%
Dominance	66.15%	68.55%

Nevertheless, all earlier experiments used the SVM classifier, but the SVM has been reported to be quite sensitive to noise and outliers [170]. Meanwhile, the EEG has non-stationary signals and contains noise and outliers [20, 130]. Therefore, the SVM might not perform the best, as EEG data normally contains outliers. Having said that, the outlier issue is one of the objectives of this thesis. Consequently, the FSVM has been investigated for the EEG emotion classification in this chapter to deal with the problem.

4.3 FSVM

Due to the SVM's issue, the FSVM was used to cope with the problem. This section briefly describes the details of the FSVM and its formulations according to [40, 134]. For implementing the FSVM, there are two main approaches. The first one is based on Lin and Wang [40]. In the SVM training process, a fuzzy membership value is assigned to different values. It depends on how crucial each sample is for the SVM learning process. Therefore, these samples can contribute differently during the learning process for separating the hyperplane [134]. Secondly, Wang et al. [171] applied the FSVM by assigning two membership values for each class. One is for the positive class, while the other is for the negative one. In this research, the first approach is used because this thesis focuses on dealing with outliers. Lin and Wang [40] indicated that outlier and noise issues could be resolved by assigning the fuzzy membership, s_i, where $0 < s_i \leq 1$, for each training sample x_i. The meaning of s_i is the attitude of the importance of its class in the classification problem. Batuwita and Palade [134] called the fuzzy membership s_i as weight m_i because it is more common that the higher weight that is assigned to the more important point. Therefore, in this thesis, it is also called weight m_i because it is easy to understand that m_is represents the importance of those samples in the FSVM training algorithm.

Let S be a set of labeled training points:

$$(y_1, x_1, m_1), (y_2, x_2, m_2), \dots, (y_l, x_l, m_i) \quad (16)$$

where $x_i \in \mathcal{R}^N$. Each x_i belongs to a class label $y_i \in \{-1,1\}$. Each x_i also has a weight (a fuzzy membership value), $\sigma \leq m_i \leq 1$, with $i = 1,2, \dots, l$ and σ is a small number, which is greater than zero. The reformulation of the SVM is shown as follows:

$$\text{Minimum}\left(\frac{1}{2}|w|^2 + C\sum_{i=1}^{l} m_i \xi_i\right)$$

$$\text{Subject to } y_i(w \cdot \Phi(x_i) + b) \geq 1 - \xi_i$$

$$i = 1,2,3, \dots, l; \;\; \xi_i \geq 0. \quad (17)$$

After that, the Lagrangian technique [40] was applied to equation (17) and it transforms the problem of FSVM optimization into:

$$\text{Maximum } W(\alpha) \sum_{i=1}^{l} \alpha_i - \frac{1}{2}\sum_{i=1}^{l}\sum_{j=1}^{l} \alpha_i \alpha_j y_i y_j K(x_i, x_j)$$

$$\text{Subject to} \sum_{i=1}^{l} y_i \alpha_i = 0$$

$$0 \leq \alpha_i \leq m_i C, \quad i = 1, \dots, l \tag{18}$$

There is only one turning parameter and only one difference between the SVM (10) and FSVM (18). In the SVM, there is only one way to control the margin by turning the only C, but there are many free parameters to be assigned in the FSVM due to $m_i C$. In other words, a number of free parameters in the FSVM is equal to a number of training samples. In the SVM, C is used to balance the margin for maximizing a distance between two classes, and it is considered the cost of misclassifications. A larger C allows for a narrower margin. Therefore, it gives a small number of misclassifications for the training set. In contrast, a wider margin can be assigned by a smaller C, and it disregards more training samples. On the other hand, in the FSVM, weight m_i plays a significant role in controlling how crucial the sample x_i is in the FSVM training process. A bigger m_i makes a narrower margin due to $m_i C$. It consequently means that x_i is vital in the training set. Conversely, a smaller m_i makes a wider margin, and x_i has less significance in the FSVM training algorithm. [40, 134]

As a result, this thesis investigates the FSVM for EEG emotion classification. The FSVM has the ability to control the priority of each instance during the training process. Therefore, for instances, which are considered as outliers, they can be assigned less informative values or be ignored during the training process. The fundamental FSVM is adapted and extended by using a weight function for the fuzzy membership values in the efficient EEG emotion classification.

Uncertain data, which locates further from class centers, is identified as outliers. This data will be assigned a smaller amount of fuzzy membership values (weight values). Therefore, during the learning process, the outliers can be reduced. The primary objective of this section is to improve the classification accuracy of EEG emotion classification by dealing with the outliers on the selected appropriate features using the FSVM.

4.3.1 Weight Assignment

Lin and Wang [40] introduced a fuzzy membership function to deal with outliers. It uses the class center to reduce the effects of outliers. The function calculates the distance between a point and its class center, in order to assign a membership value s_i. However, in this study, s_i is called a weight value m_i, as mentioned earlier.

Suppose there is a sequence of training points:

$$(y_1, x_1, m_1), \dots, (y_2, x_2, m_2). \tag{19}$$

Denote x_+ is the mean of class positive, whereas x_- is the mean of class negative. Let r_+ be the radius of class positive as:

$$r_+ = \max_{\{x_i : y=+1\}} |x_+ - x_-| \tag{20}$$

and r_{-} is the radius of class negative as:

$$r_{-} = \max_{\{x_i : y=-1\}} |x_{-} - x_{+}| \tag{21}$$

Let weight m_i be a function of the mean and radius of each class:

$$m_i = \begin{cases} 1 - \frac{|x_{+} - x_i|}{r_{+} + \delta}, \ if \ y_i = +1 \\ 1 - \frac{|x_{-} - x_i|}{r_{-} + \delta}, \ if \ y_i = -1 \end{cases} \tag{22}$$

Where δ is a small number to avoid the case $m_i = 0$.

Consequently, equation (22) can generate a weight value for each instance and assign them to the FSVM model, which is equation (17). As a result, an instance with a smaller value of m_i is considered as an outlier and has less importance during the training process. In contrast, when an instance has a bigger value of m_i, it is considered a very important instance during the training process.

4.4 Methodology

This section deals with task 3, which uses the FSVM to deal with outliers in EEG data, as shown in Figure 3-2. The FSVM for EEG Emotion Classification (FSVM-EEGEC) is explained. The six selected appropriate features (selected from the feature selection task) are assigned as input data in the classification process. The FSVM utilizes weight values from the weight function, as per equation (22). The weight function, using the class center

[40], is applied to deal with outliers. After that, the classification results of the FSVM are compared with the SVM with the same parameters (Appendix I) using 10-fold cross-validation. Moreover, the FSVM is compared to other machine learning techniques which have been used in EEG emotion classification. Figure 4-6 shows the methodology of task 3. LIBSVM has been used for both models with a radial basis function (RBF) [148]. The experiment uses dependent classification. There is only one difference between these two models. The FSVM uses the weight function for m_i, whereas SVM assigns 1 to every m_i, as shown in Figure 4-7.

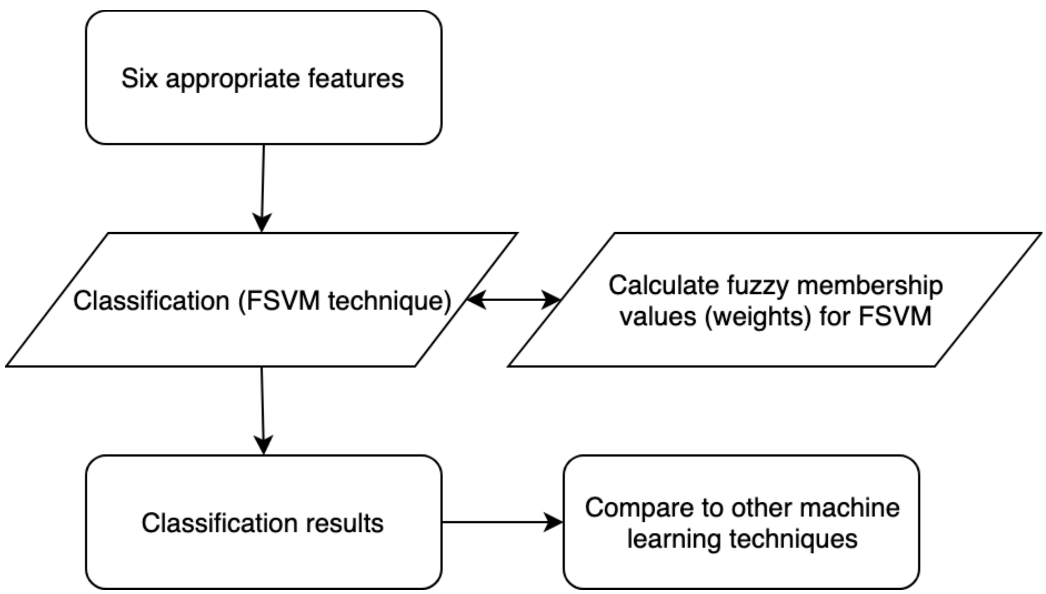

Figure 4-6 FSVM methodology

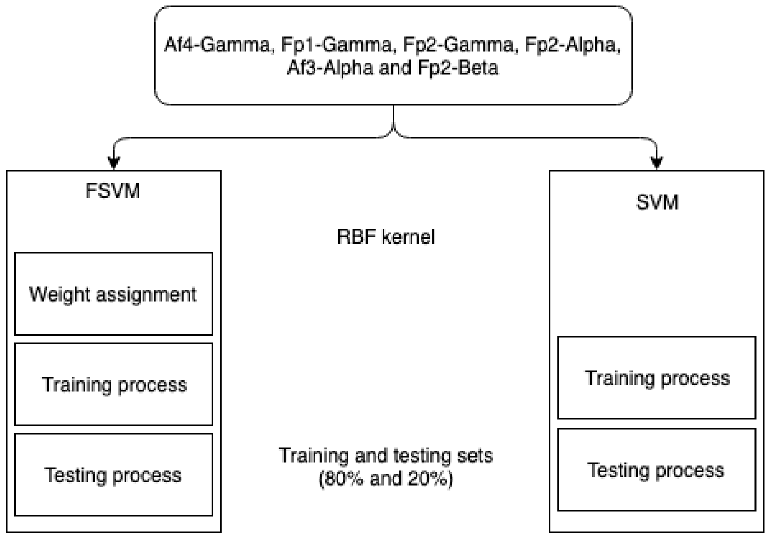

Figure 4-7 The experiment of Task 3

4.4.1 Feature Extraction

In this case, pre-processed DEAP EEG data was used. The signals of the six selected appropriate channels had been selected using the feature selection technique, as discussed at the beginning of the chapter, including AF4, Fp1, Fp2, and AF3. The DWT was used to decompose the EEG signal, which was combined from five sub-frequency bands into a single frequency band. Daubechies 4 (*D4)* was selected as the mother wavelet of the DWT as Amin et al. [145] reported that this wavelet energy is suitable and appropriate for classifying EEG signals regarding medical applications. Then, three sub-frequency bands of the selected appropriate channels were selected including Gamma, Alpha, and Beta. As a result, there are six appropriate features, AF4-Gamma, Fp1-Gamma, Fp2-Gamma, Fp2-Alpha, AF3-Alpha, and Fp2-Beta. After that, the average power band of the selected appropriate features was calculated.

4.4.2 FSVM Training and Testing Processes

Before the FSVM training process, there is one pre-processing step. The objective of this process is to generate the weight values. For each participant, the whole data was randomly divided into training and testing sets of 80% and 20%, respectively. The training set is divided into positive, and negative groups depending on their target class labels. After that, the weight values of both groups are carried out by weight equation (22). Next, the FSVM training process uses the weight values. The FSVM has an ability to decrease the importance of the samples, which are considered outliers. As mentioned earlier, during the training process, these samples are assigned lower values of weight, m_i (17). In contrast, the traditional SVM training process does not provide a parameter to level the significance of each sample in equation (5). Therefore, every sample in the SVM has the same effect in the SVM training process.

4.5 Experimental Settings

This section describes the experiment settings. There are two experiments. Both experiments use the selected appropriate features, which are AF4-Gamma, Fp1-Gamma, Fp2-Gamma, Fp2-Alpha, AF3-Alpha, and Fp2-Beta. Each participant data was divided into the 80% training and 20% testing sets randomly. First of all, the FSVM and the SVM are compared with each other in terms of accuracy performance for all emotions. Only participant number 27 cannot generate models because there is only one target class. Therefore, it is not necessary to build a model that can predict only one result. Both FSVM and SVM models use the LIBSVM with the same set of parameters. Moreover, the FSVM uses the weight values m_i with parameter C (m_iC), whereas the SVM has only one value for parameter C. Secondly, the FSVM and other classifiers were compared with respect to the performance based on the appropriate features.

4.6 Results and Discussions

Table 4-8 shows the classification performances between the FSVM and SVM models using the selected appropriate features. The results indicate that the FSVM is significantly better than the SVM in all emotions. Based on the average results, using the FSVM provides a better performance than the SVM on the arousal, valence, and dominance emotions at around 8.20%, 8.98%, and 7.26% respectively. As a result, the FSVM could deal with outliers which they usually associate with EEG signals. The FSVM can handle the issue by giving the degree of priority for the samples in the learning process. The samples, which are indicated as outliers, have fewer valuable weights during the learning process. FSVM gives a higher priority for each sample close to its class center and less importance for a sample further from its class center. However, some results show that the SVM is better than the FSVM. For example, in arousal and valence, the FSVM is worse than the SVM for participant number 27. The reason probably depends on a data characteristic because the data of this participant may not be too noisy. Nevertheless, the FSVM attempts to decrease the importance of some data during the learning process because it gives fewer valuable weights for samples that are further from its class center. As a result, due to this allocation of weights, the noise or outliers of this participant could be minimized, but the FSVM could also remove some significant information which are minority (treated as outliers). Therefore, the SVM is better than the FSVM in this case.

Table 4-8 Classification results between FSVM and SVM using the six selected appropriate features

Emotion	Arousal(%)		Valence(%)		Dominance(%)	
Participant#	SVM	FSVM	SVM	FSVM	SVM	FSVM
1	75	87.5	50	75	87.5	75
2	62.5	75	62.5	62.5	87.5	87.5
3	75	87.5	75	87.5	62.5	75
4	62.5	75	50	87.5	62.5	75
5	75	75	75	75	87.5	87.5
6	50	50	75	75	50	75
7	62.5	62.5	62.5	75	50	62.5
8	62.5	75	87.5	87.5	62.5	75
9	62.5	75	62.5	75	62.5	75
10	75	75	62.5	87.5	75	100
11	100	100	62.5	75	62.5	87.5
12	75	87.5	62.5	75	87.5	87.5
13	62.5	62.5	87.5	87.5	75	75
14	62.5	75	75	87.5	75	75
15	37.5	87.5	75	75	62.5	62.5
16	50	62.5	62.5	87.5	50	50
17	87.5	100	37.5	75	75	100
18	62.5	75	100	100	87.5	75
19	62.5	62.5	62.5	75	75	75

20	75	75	87.5	87.5	50	75
21	62.5	62.5	75	62.5	50	62.5
22	62.5	87.5	62.5	75	62.5	87.5
23	75	75	87.5	87.5	50	62.5
24	87.5	87.5	87.5	87.5	62.5	62.5
25	62.5	75	75	75	75	87.5
26	62.5	75	62.5	75	62.5	62.5
27	75	62.5	100	87.5	-	-
28	75	75	62.5	87.5	87.5	75
29	62.5	75	87.5	87.5	62.5	75
30	75	87.5	62.5	62.5	75	75
31	62.5	75	62.5	62.5	75	75
32	87.5	87.5	50	75	75	75
Avg.	**68.36**	**76.56**	**70.31**	**79.30**	**68.55**	**75.81**

Table 4-9 shows the classification results between the FSVM and other machine learning techniques using EEG in emotion classification. The conventional machine learning methods used for the comparison study include Naïve Bayes[8], KNN[65], MLP[146], Fisher LDA[156] and SVM [111, 128, 129]. The purpose of this experiment is to compare the proposed FSVM classifier with other established classifiers. The selected appropriate features were used in the comparison based on the same dataset, which is the DEAP. Moreover, each classifier had been run ten times to obtain a set of training and testing accuracies. The best results of each classifier were then selected for the comparison. The results of these methods were compared with the FSVM using the weight function. The results demonstrate that the FSVM is the best model for EEG emotion classification in this research.

Table 4-9 FSVM compared with other machine learning techniques

Emotion	Naïve Bayes [8]	KNN [65]	MLP (NN) [146]	Fisher LDA [156]	SVM [111, 128, 129]	FSVM
Arousal	60.78%	65.89%	62.87%	60.93%	68.36%	76.56%
Valence	60.31%	64.79%	57.19%	65.27%	70.31%	79.30%
Dominance	60.95%	65.20%	66.22%	56.47%	68.55%	75.81%

The reason FSVM and SVM perform much better than MLP is due to the small data size used in this thesis. Generally, ANN is worse than SVM when the data size is smaller [172]. In order to prove this point, the best result from the ten experiments using optimized parameters was reported in this thesis. As a result, due to the small database in this thesis, MLP is based on ANN, so it did not perform well as SVM. However, the FSVM has the same problem as the SVM in terms of human comprehensibility. They are both black-box models and lack the ability of human understanding. The next chapter will focus on rule extraction from the FSVM to provide information that enables human comprehensibility.

4.7 Summary

This chapter focused on reducing the number of features and improving the handling of outliers. First of all, ReliefF was used in a feature selection process. ReliefF method is a technique used to estimate the quality of attributes, and it can distinguish a pair of instances that are near to each other. Therefore, it was used to rank the features in each emotion.

After that, the top ten repeated features from all emotions were selected using the summation of RVs. Then, the SVM was used as a classifier to evaluate the classification performance of these features. To select an appropriate number of features, the top ten selected appropriate features were used at the beginning. Then, the classification process was repeated by reducing the number of features from ten to one. After that, all classification results were compared against one another. The features that provided the best results were selected. The experiment indicated that using the six features: AF4-Gamma, Fp1-Gamma, Fp2-Gamma, Fp2-Alpha, AF3-Alpha, and Fp2-Beta, is appropriate for EEG emotion classification. These features come from four channels and three sub-frequency bands. Even though the selected appropriate features do not provide the best results for each emotion, when compared with the top best six features of each emotion, the selected appropriate features can then be used to substitute for the best features. In addition, it provides only slightly worse classification results (by around 1-2%) than the best features for each emotion classification. However, in the real world, we would not know the emotion beforehand and thus, by using the best set of the selected appropriate features for all emotions, we would then be able to classify all emotions correctly. Therefore, one of the objectives of this thesis, to contribute the efficient emotion classification using EEG by reducing the number of features and complexity of the system using a feature selection technique, has been achieved.

The second focus of this chapter is to improve the handling of outliers using the FSVM. The SVM is one of the most popular techniques in EEG emotion classification but it has been reported that it is quite sensitive to outliers, as EEG normally contains some noise and outliers. The FSVM was utilized in this research to deal with outliers because it can assign a fuzzy membership. The fuzzy membership is used for each data point and the FSVM is reformulated such that different input points can make different contributions to the learning of the decision surface. The weight function, which calculates a distance between a point to the point's class center, assigns values for every fuzzy membership value in this study. Consequently, a point which is further from its class center, is assigned a lower weight value, whereas a point which is closer to its class center, is assigned a higher weight value. In other words, the point which has a lower weight is considered an outlier. In contrast, the point which has a higher weight is considered a good point for training. As a result, the FSVM can deal with the outliers in the EEG data. The classification results confirmed that the FSVM is better than the SVM in arousal, valence, and dominance emotions around 8.20%, 8.98%, and 7.26% respectively. The best results using the FSVM are 76.56% in arousal, 79.30% in valence and 75.81 in dominance. Therefore, another objective of this thesis, that of improving the handling with outliers in order to enhance classification accuracy for the efficient emotion classification, has also been achieved. Additionally, based on the same settings, the FSVM provided the best accuracy among Naïve Bayes, KNN, MLP, Fisher LDA, and SVM techniques, while using the appropriate features. These observations are useful for the development of an effective EEG emotion classification system because the reduction of sub-bands and channels for features will reduce the computation time, and the handling of outliers will provide compatible results in EEG emotion classification

CHAPTER 5

Rule Extraction from EEG Signals using Fuzzy Support Vector Machine for Emotion Classification

5.1 Introduction

The FSVM was used in the previous chapter as a classifier in EEG emotion classification. However, the FSVM is similar to the SVM in terms of human comprehensibility. Barakat and Diederich claimed that some applications, such as medical diagnosis, require a better understanding of how a classifier makes a decision [131]. For example, Zhou and Jiang applied C4.5, which is a decision tree, to extract rules from an artificial neural network ensemble for three cases of medical diagnosis including hepatitis, diabetes, and breast cancers [132]. Likewise, Martens et al. indicated that some applications, like a credit score application, need a proven validation before implementation. Consequently, explanation capabilities are very important [133]. Nevertheless, techniques with comprehensible inability, such as the SVM, have dominated in many applications and also in aBCI, as this study mentioned earlier. Even though the SVM has been considered a good classifier, Fung et al. [44] mentioned that the SVM and other linear classifiers are difficult to be understood by humans, as compared to rules that can be mapped in terms of variable space. As mentioned earlier, the FSVM was developed from the SVM. Thus, the FSVM also has the same issue. Therefore, the aim of this chapter is EEG rule extraction from the FSVM to provide human comprehensibility.

This chapter is organized as follows: Section 5.2 briefly describes four SVM rule extraction methods that can be applied to the FSVM. In addition, it discusses the advantages and disadvantages of each technique. The Classification and Regression Tree (CART) is briefly described in Section 5.3. Section 5.4 presents the methodology for rule extraction using the FSVM with the CART. Section 5.4 consists of experimental results and discussions. Finally, a summary is presented in Section 5.5.

5.2 Rule Extraction Techniques

Martens et al. [133] indicated that there are two objectives of rule extraction. First, the common usage of rule extraction is to understand the classification of a black box model of data and then generate rules that explain it. The second usage is to enhance the performance of rule induction by removing noise in the data. This chapter aims to gain the benefit of rule extraction for understanding the black box model of the FSVM and to obtain the rules from the EEG data. As the structure and implementation of the FSVM is similar to that of the SVM, SVM rule extraction methods can be applied to the FSVM in this research. Barakat and Bradley published a survey study of rule extraction from SVMs, which were divided into four categories [42]. First of all, the SVM is a closed-box. Secondly, the rules are extracted directly from the model support vectors (SVs). Next, the rules are extracted from the utilization of the decision function and SVs. Finally, SVs, the separating hyperplane and training data are added to the list of considerations in order to obtain the rules. However, they reorganized these categories into region-based rules, fuzzy rule extraction, sequential covering rule extraction and decision tree-based rules, according to the analysis of the algorithms as follows.

5.2.1 Region-based rules

The input space is mapped into regions by utilizing the SVM decision function and/or the model SVs. After that, the regions can be refined and translated into rules. There are three types of regions: ellipsoids such as SVM+ [173], hyper-rectangles such as HRE [174] and hyper-cubes such as MK-SVMII [175]. However, extracting rules from ellipsoids hyper-rectangles might suffer in terms of comprehensibility because these techniques use all the input features of their processes, although some features do not contribute to the classification decision. Moreover, in case of hyper-cube regions, it is specific for the SVM kernel, even if it is comprehensible and efficient. [42]

5.2.2 Decision tree-based rules

The idea in this technique is to learn what the SVM model has learned by using a decision tree learner. The main concept is an artificial dataset which is generated by the SVM model. In other words, the class of the training set is replaced by the output of the SVM model. Then, one of the decision tree learners is used to learn the artificial dataset and generate a tree that can devise rules from the data [131, 176, 177]. These methods create a useful number of rules along with decent accuracy. However, Martens's method [177] might generate some cases which are non-existence in reality because the method creates many extra samples close to the SVM and SVs. [42]

5.2.3 Fuzzy rule extraction

This method [178] is different from previous techniques because it generates fuzzy rules. However, Barakat and Bradly [42] indicated that it provided low accuracy and comprehensibility. The reason why it lacks comprehensible expressions is because the fuzzy rules need the knowledge of fuzzy theory and fuzzy set to understand the rules. In contrast, the rules of region-based and decision tree-based are easier to understand because the rules show directly the relationship between inputs and outputs.

5.2.4 Sequential covering rule extraction

Barakat and Bradly [42] recommended the use of the SQRex-SVM [179] because of a good trade-off between performance and comprehensibility. The rules of the SQRex-SVM are extracted directly from SVs using a modified sequential covering method [180]. Nevertheless, Reddy et al. [170] claimed that the SQRex-SVM would suffer from noise. Also, Chen et al. [170] indicated that "*the main disadvantage of this method is that it is prone to having binary classification difficulty*."

In this research, the decision tree-based rule technique is used to extract rules from the SVM and FSVM because it provides concise rules and good performance, whereas the region-based rules technique might lack human comprehensibility because of the redundancy of the features. Moreover, the region-based rules technique is dependent on the FSVM and SVM kernel, whereas the decision tree-based rule technique is flexible because it can be used for every kernel. Furthermore, the sequential covering rule extraction technique is not selected in this study because it is quite sensitive to noise, while the EEG data typically contains noise and outliers. There is only one disadvantage of using the decision tree-based rule. It might not have any existing case in reality [181], but emotion classification is not a serious case of security-related issues. This study aims to understand the black-box model for emotion classification and generate rules that humans can understand easily.

The idea of the decision tree-based rule technique is to treat the SVM as a black-box by using another machine learning technique, which is a decision tree learner, to learn what the SVM has learned [179]. Figure 5-1 shows the process of this approach. The basic concept is to create artificial labeled samples which are created by the SVM. Then, the artificial labels are replaced instead of the original target class. Therefore, the new artificial dataset represents the knowledge of the FSVM. [131] Similarly, the FSVM follows the same method in this chapter.

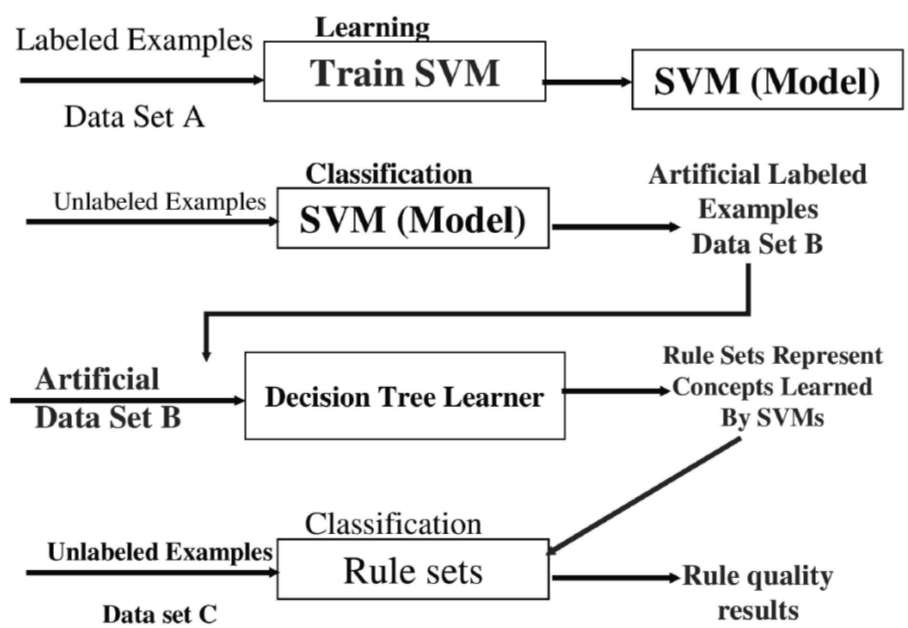

Figure 5-1 Learning-based rule extraction approach [179]

5.3 CART

In this chapter, a machine learning technique, the Classification and Regression Tree (CART), is being used as a second classifier to extract rules from the FSVM. There are many decision tree algorithms such as C4.5 [182] and ID3 [183]. The CART [184] is another popular decision tree. The main difference amongst these algorithms is the approach to grow and prune a tree. In this study, the CART was selected to extract rules from the FSVM, as recommended by Lavanya and Ku-Rani, who claimed when comparing ID3, C4.5 and CART for medical datasets, that the larger the size of the data, the better the performance of the CART [185]. Moreover, Singh et al. [186] indicated that the CART is the most powerful to handle the outliers, whereas ID3 and C4.5 are susceptible to the outliers.

The CART, a binary tree, was introduced by Breiman. The Gini Index is used for the splitting criterion by measuring how pure a node is. Equation (23) shows the Gini Index [187].

$$1 - \sum_i p^2(i) \tag{23}$$

Where $p(i)$ is the observed fraction of class i ($p(i)$ = Count of specific class / Total count of members). If the Gini index equals zero, a node contains samples which belong to only one class i. In other words, the node is a purity data set. The Example 1 shows the use of Gini index as follow:

The Example 1

Assume there are two regions to be selected by CART. Region one contains {1,1,1,0,0} and Region two contains (1,1,1,1,1). Gini Index is used to select the best region between them by measuring the purity of each area.

$$Gini_{region1} = 1 - \left(\frac{3}{5}\right)^2 - \left(\frac{2}{5}\right)^2 = 0.48$$

$$Gini_{region2} = 1 - \left(\frac{5}{5}\right)^2 - \left(\frac{0}{5}\right)^2 = 0$$

The Region two has been split by CART because the Gini index of region two is lower than the Gini index of the region one. In other words, region two is purer than the region one because it contains only positive class members, whereas region one contains three positive class and two negative class members.

Due to the ability of the CART in terms of human comprehensibility, it is utilized as a decision tree leaner for the FSVM, as shown in Figure 5-1.

5.4 Methodology for Rule Extraction using FSVM with CART

There are several steps for the FSVM-CART. Most of the steps follow the methods utilizing the SVM model as a closed-box [42], as seen in Figure 4-1. First of all, a benchmark database was used, which is the pre-processed database of the DEAP. In this study, arousal, valence and dominance emotions were classified. Each main emotion was divided into two targets: positive and negative emotions. There were 32 participants and 40 samples per participant for each main emotion. Next, the appropriate features, AF4-

Gamma, Fp1-Gamma, Fp2-Gamma, Fp2-Alpha, AF3-Alpha, and Fp2-Beta, were selected because of the highest average accuracy of the three emotions from the FSVM classifier in the previous chapter. After that, the selected features and their labels from both channels were randomly divided into two groups, which are training and unseen sets respectively, with a ratio 8:2 (32 samples for the training set and 8 samples for the unseen set). Then, the training set was used to build the FSVM classifier using the LIBSVM [148] with a radial basis function kernel. A ten-fold cross-validation was applied to find the best model during the learning process. After that, due to the limitations of the training set per participant (32 samples), an unlabeled set was created from the input range of the training set with a normal distribution for each participant. The unlabeled set is a set for the FSVM classifier to predict, so the result of this process is called an artificial set. The idea of the artificial set is similar to that of synthetic data [131]. Finally, a new classifier model was built from the artificial dataset by the CART. In addition, the Gini Index was used to estimate the probability to split a node with weight $w = \frac{1}{n}$, when the sample size is n [187], and a pruning method was cut off because the aim of this study is using the CART to extract rules from the SVM. The Example 2 shows the relationship of w and equation 23 as follow:

<u>The Example 2</u>

Region A contains {0,1}

$$Gini_{regionA} = 1 - \left(\frac{1}{2}\right)^2 - \left(\frac{1}{2}\right)^2 = 0.5$$

Region A is not pure because $Gini_{regionA} = 0.5$ so w = ½ = 0.5; n = 2. As a result, w does not equal one so region A must be split by CART.

After splitting, there two subregions; A1 contains {1} and A2 contains {0}. Both subregions are pure, and therefore do not need to be split further.

Consequently, the if/then rules and a decision tree of the CART will reveal what the FSVM has learned. All the steps are shown in Figure 4-2.

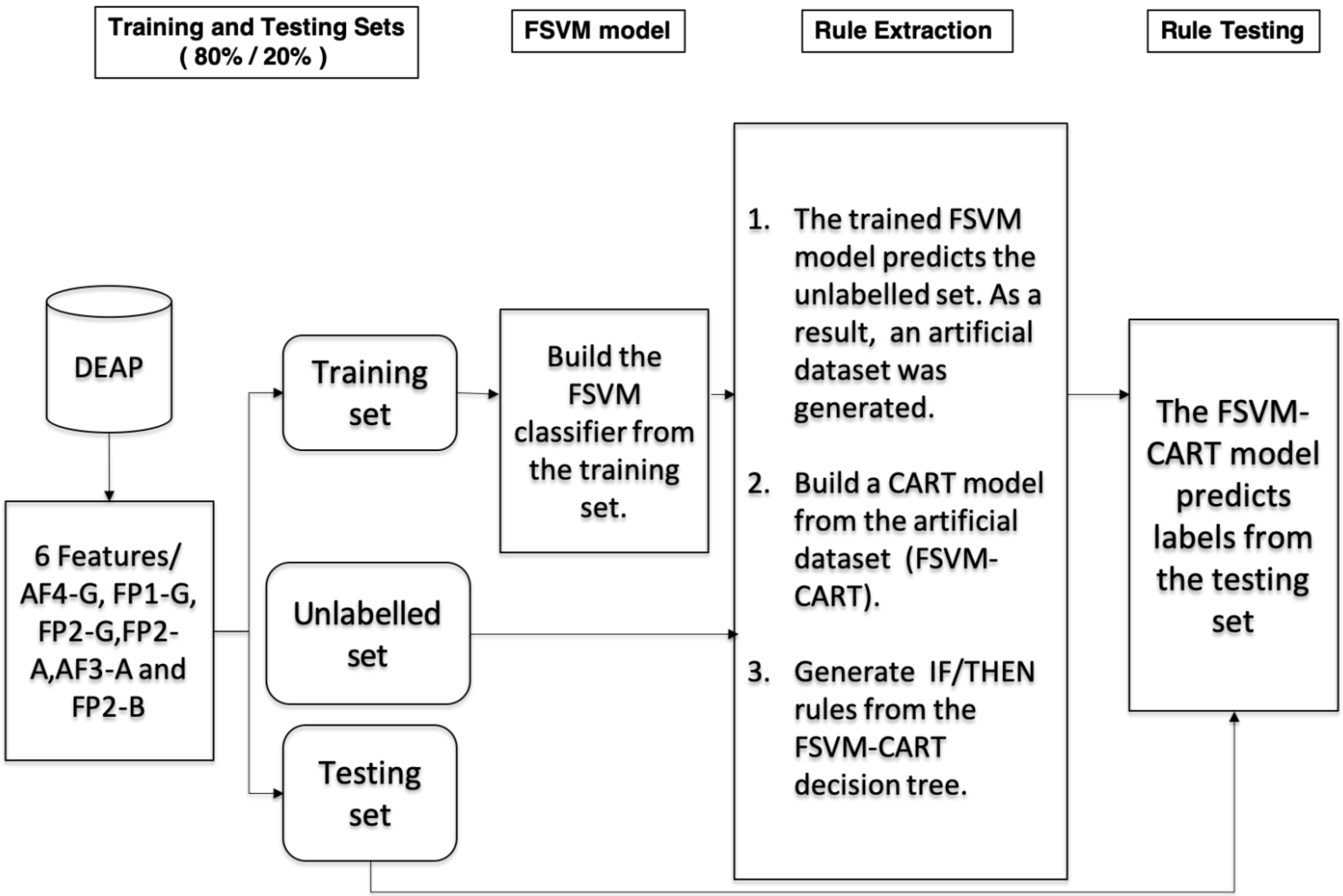

Figure 5-2 Steps of SVM-CART processing [modified from [42]

5.5 Experiments, Results, and Discussion

Besides the results from the FSVM-CART model, the same training dataset and unseen datasets were experimented by the SVM, CART, FSVM and SVM-CART models for comparison purposes. All experiments in this study are of the dependent classification because of the higher accuracy [4] and noting of exact rules from each participant. Tables 5-1, 5-2 and 5-3 show the results of arousal, valence and dominance emotions. In the dominance experiment, participant number 27 was removed because there is only one target class. Table 5-4 shows an average accuracy of each emotion. Figure 5-3 and Table 5-5 show an example of the decision tree and IF/THEN rules of participant number 1 for the arousal emotion respectively.

Table 5-1 Arousal emotion (%)

Participant no.	SVM	FSVM	CART	CART-SVM	CART-FSVM
1	75	87.5	62.5	87.5	100
2	62.5	75	50	62.5	75
3	75	87.5	62.5	50	87.5
4	62.5	75	50	62.5	62.5
5	75	75	50	62.5	62.5
6	50	50	25	75	75
7	62.5	62.5	50	75	75
8	62.5	75	25	50	50
9	62.5	75	62.5	75	75
10	75	75	87.5	87.5	87.5

11	100	100	50	50	75
12	75	87.5	87.5	87.5	100
13	62.5	62.5	87.5	62.5	62.5
14	62.5	75	75	50	50
15	37.5	87.5	75	50	87.5
16	50	62.5	37.5	50	62.5
17	87.5	100	75	75	75
18	62.5	75	37.5	62.5	75
19	62.5	62.5	87.5	50	62.5
20	75	75	87.5	75	75
21	62.5	62.5	62.5	62.5	62.5
22	62.5	87.5	62.5	50	62.5
23	75	75	25	62.5	87.5
24	87.5	87.5	75	100	100
25	62.5	75	37.5	75	75
26	62.5	75	37.5	50	62.5
27	75	62.5	50	62.5	75
28	75	75	62.5	62.5	75
29	62.5	75	62.5	50	62.5
30	75	87.5	75	75	62.5
31	62.5	75	37.5	50	62.5
32	87.5	87.5	75	87.5	87.5
Average	**68.36**	**76.56**	**58.98**	**65.23**	**73.44**

Table 5-2 Valence emotion (%)

Participant no.	SVM	FSVM	CART	CART-SVM	CART-FSVM
1	50	75	75	50	62.5
2	62.5	62.5	50	50	75
3	75	87.5	50	50	75
4	50	87.5	25	62.5	75
5	75	75	50	75	75
6	75	75	62.5	100	100
7	62.5	75	50	75	75
8	87.5	87.5	50	75	75
9	62.5	75	25	75	87.5
10	62.5	87.5	87.5	87.5	87.5
11	62.5	75	37.5	62.5	62.5
12	62.5	75	50	62.5	87.5
13	87.5	87.5	100	50	87.5
14	75	87.5	87.5	75	75
15	75	75	50	87.5	87.5
16	62.5	87.5	50	62.5	100
17	37.5	75	62.5	50	87.5
18	100	100	100	75	75
19	62.5	75	50	75	87.5
20	87.5	87.5	87.5	75	87.5
21	75	62.5	62.5	62.5	62.5
22	62.5	75	75	50	50

23	87.5	87.5	50	50	50
24	87.5	87.5	75	50	62.5
25	75	75	75	62.5	62.5
26	62.5	75	75	62.5	75
27	100	87.5	87.5	75	75
28	62.5	87.5	75	62.5	87.5
29	87.5	87.5	50	87.5	100
30	62.5	62.5	75	62.5	62.5
31	62.5	62.5	50	50	50
32	50	75	62.5	75	75
Average	**70.31**	**79.30**	**62.89**	**66.41**	**76.17**

Table 5-3 Dominance emotion (%)

Participant no.	SVM	FSVM	CART	CART-SVM	CART-FSVM
1	87.5	75	75	75	75
2	87.5	87.5	50	75	100
3	62.5	75	62.5	62.5	75
4	62.5	75	62.5	75	75
5	87.5	87.5	75	87.5	87.5
6	50	75	62.5	62.5	62.5
7	50	62.5	62.5	62.5	50
8	62.5	75	75	50	75
9	62.5	75	75	62.5	75
10	75	100	75	62.5	75

11	62.5	87.5	87.5	75	75
12	87.5	87.5	75	75	75
13	75	75	62.5	62.5	62.5
14	75	75	37.5	62.5	62.5
15	62.5	62.5	62.5	62.5	75
16	50	50	62.5	75	75
17	75	100	87.5	87.5	87.5
18	87.5	75	75	87.5	87.5
19	75	75	50	75	75
20	50	75	75	62.5	87.5
21	50	62.5	37.5	62.5	62.5
22	62.5	87.5	25	50	62.5
23	50	62.5	62.5	75	87.5
24	62.5	62.5	50	50	50
25	75	87.5	87.5	87.5	87.5
26	62.5	62.5	62.5	50	62.5
27	-	-	-	-	-
28	87.5	75	37.5	50	50
29	62.5	75	50	50	62.5
30	75	75	75	25	62.5
31	75	75	50	75	87.5
32	75	75	87.5	87.5	87.5
Average	**68.55**	**75.81**	**63.71**	**66.53**	**73.39**

Table 5-4 Average performances (%)

Emotion	FSVM	FSVM-CART	SVM	SVM-CART	CART
Arousal	76.56	73.44	68.36	65.23	58.98
Valence	79.30	76.17	70.31	66.41	62.89
Dominance	75.81	73.39	68.55	66.53	63.71

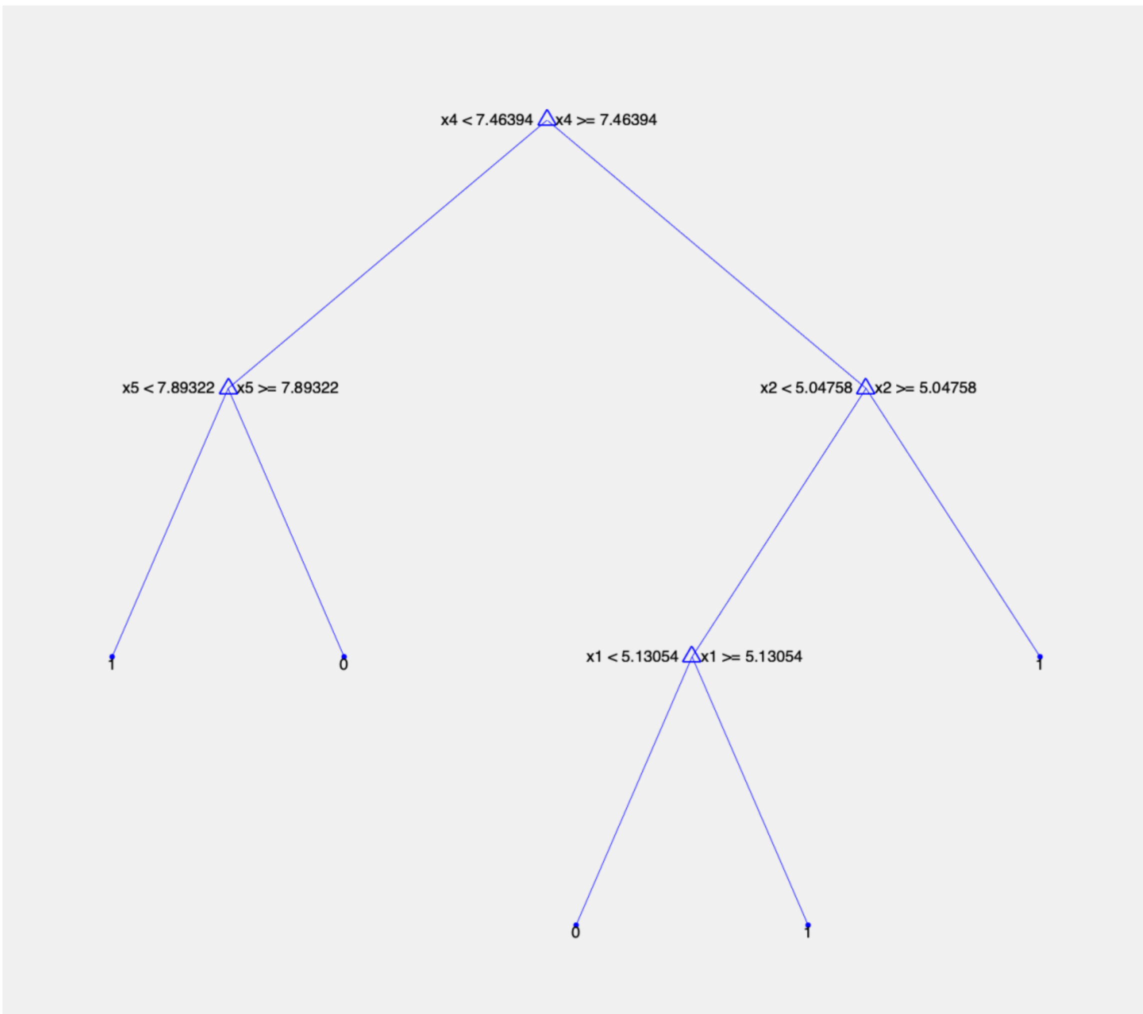

Figure 5-3 The decision tree of participant number 1 from FSVM-CART on Arousal emotion while 0 is negative arousal and 1 is positive arousal (x1, x2, x4 and x5 are AF4-Gamma, Fp1-Gamma, Fp2-Beta and AF3-Alpha respectively)

Table 5-5 IF/THEN rules of participant #1 from FSVM-CART on arousal emotion

Rule#	Rule
1	If Fp2-Beta < 7.46 then *Rule#2* else if Fp2-Beta >= 7.46 then *Rule#3*.
2	If Fp2-Beta < 7.89 then *Positive Arousal* else if Fp2-Beta >= 7.89 then *Negative Arousal*.
3	If Fp1-Gamma < 5.04 then *Rule#4* else if Fp1-Gamma >= 5.04 then *Positive Arousal*.
4	If AF4-Gamma < 5.13 then Negative Arousal else if AF4-Gamma >= 5.13 then *Positive Arousal.*

From Table 5-4, the best results of arousal, valence, and dominance emotions are from the FSVM model. The second-best model is the FSVM-CART and the worst model to classify each emotion is the CART. These results came from the same unseen dataset. The results indicate that the FSVM is the most suitable for emotion classification (in terms of accuracy), but it is only better than the FSVM-CART by 3.12%, 3.13%, and 2.42% for arousal, valence, and dominance respectively. In contrast, the FSVM-CART, SVM-CART and CART have an ability of comprehensibility, whereas the FSVM and SVM do not.

Regarding human understanding, the FSVM cannot provide a comprehensible expression. Consequently, the FSVM-CART plays a crucial role to deliver information that the FSVM has learned in a way that humans can understand. Unlike the FSVM, the FSVM-CART can express information in the form of the decision tree, as shown in Figure 5-3. Moreover, this decision tree can be transformed to IF/THEN rules, as shown in Table 5-5. Apart from human understanding, the FSVM-CART is also better than the SVM-CART and CART in terms of accuracy, as can be seen from the results in Table 5-4. It may, therefore, be concluded that if accuracy is the most important factor of EEG emotion applications, then the FSVM should be applied. In contrast, if human comprehensibility and accuracy are considered, the FSVM-CART is a reasonable choice for that application. Furthermore, this proposed framework could be applied to other classifiers that cannot express the relationship between the input and output of the system. The reason why the accuracy of FSVM-CART is slightly lower than the FSVM may be the fact that the FSVM-CART in this study wasn’t optimized in the CART process. For example, there is no optimization for a number of leaf nodes in the FSVM-CART. Therefore, the overfitting issue might occur in the model. Moreover, for the example as shown in Figure 5-3, the number of appropriate features is decreased from six features in the FSVM down to four features in the FSVM-CART. In the process of the FSVM-CART, it tries to split the criterion by measuring how pure a node is. This process might cut out some crucial information of the input features. Therefore, two features were cut off in the FSVM-CART. Moreover, the objective of the FSVM-CART is to extract human interpretable rules from the trained FSVM model. As demonstrated in past researches from the literature, the optimization between interpretability and accuracies is always a challenge. In this thesis, the FSVM-CART has been optimized to generate a set of interpretable rules. However, the performance is still slightly lower than the original trained FSVM model.

5.6 Summary

This chapter was undertaken to design a system which can explain how the black-box model of the FSVM works in terms of human comprehensibility. The proposed combination method of rule extraction between Fuzzy Support Vector Machines and the Classification and Regression Tree (FSVM-CART) was used for EEG emotion classification. There are two contributions to this thesis. First of all, the FSVM-CART can extract rules from the FSVM classifier into the form of a decision tree, so that human comprehensibility can be achieved. The second benefit of the FSVM-CART is the improvement of accuracy over the CART. While the CART can directly extract rules from the data, the proposed technique performed significantly better than the CART. Even though the FSVM was slightly better than the FSVM-CART concerning the accuracy, the FSVM-CART could be better than the FSVM for applications that require both human understanding and accuracy. The findings of this study will help developers to produce efficient EEG emotion classification applications in terms of the white-box model. Therefore, the objective of this chapter has been achieved.

CHAPTER 6

Conclusion and Future Work

6.1 Research Summary and Contributions

The primary objective of the current research was to develop an efficient emotion classification system using EEG with human comprehensibility. This was evaluated through three sub-objectives. First of all, a number of feature selections were investigated and efficiently selected, in order to reduce the complexity of the system. Secondly, a robust technique was used to enhance classification accuracy, by effectively handling the outliers in EEG data. Finally, interpretable rules were extracted from the proposed classifier to allow for human comprehensibility on the EEG emotion system. To archive the sub-objectives, four tasks had to be carried out (as shown in Figure 6-1).

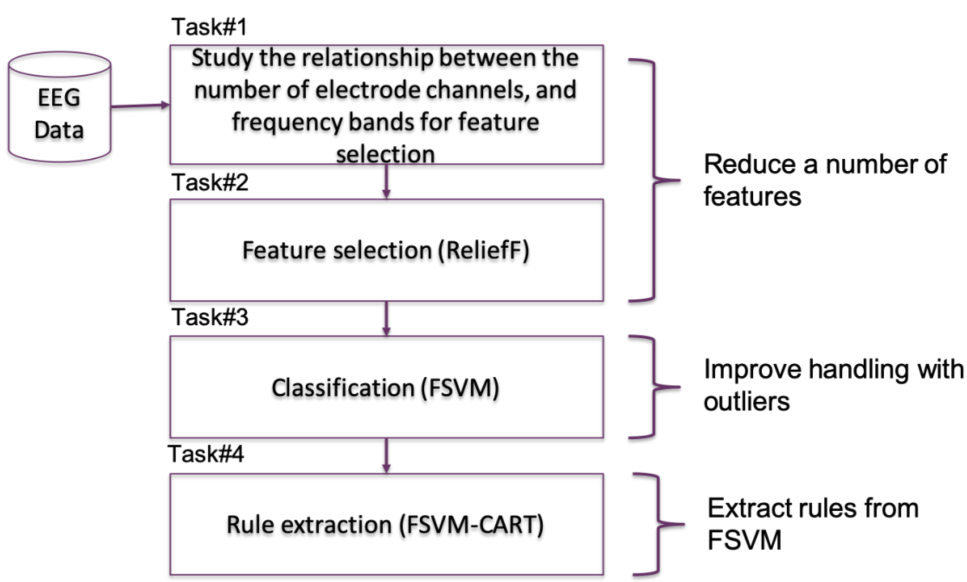

Figure 6-1 An efficient emotion classification framework

A summary of each task is as follows:

- In task 1, Chapter 3, the comparative experimental results suggested that by using fewer channels and sub-frequency bands for the features, it does not significantly drop the classification accuracies. Moreover, the results revealed that some frontal channels are useful for arousal emotion. In contrast, the channels on the parietal lobe are crucial for valence and dominance emotions. As a result, only 55 features from some frontal and parietal channels were selected as inputs. These observations can be used in the next task, feature selection, in order to reduce the number of features.
- Task 2, the first part of Chapter 4, consists of feature selection. The proposed method using the ReliefF technique is applied to reduce and select appropriate features for building the model. The results of this study indicate that AF4-Gamma, Fp1-Gamma, Fp2-Gamma, Fp2-Alpha, AF3-Alpha, as well as Fp2-Beta are appropriate features used to classify three emotions, namely arousal, valence, and dominance. Consequently, tasks 1 and 2 can reduce the number of features from 160 to six, using four channels and three sub-frequency bands. The findings from this task clearly present the appropriate set of EEG channels and sub-frequency bands for reducing the complexity of the EEG emotion classification, which may suit real-time applications in the future. Moreover, this reduction could also assist the rule extraction step by providing compact rules to interpret.
- In task 3, the second part of Chapter 4, it establishes an efficient and effective classification technique. Due to the sensitivity of the SVM with the outliers, the FSVM was used to improve the classification accuracy in the EEG data. The distance function

between a point and its class center was utilized. It assigned the weight value (fuzzy membership value) to each point during the learning process. The experimental results showed that the FSVM is significantly better than the SVM in arousal, valence, and dominance; around 8.20%, 8.98%, and 7.26% respectively.

- In the final task, Chapter 5, the proposed combination method, FSVM-CART, was developed to extract human comprehensible rules and provide a better understanding of the FSVM model for impending practical applications. Like the SVM, the FSVM is a black-box model, and it lacks the ability of human comprehensibility. The idea of the proposed method is to use another white-box machine learning technique to learn what the FSVM has learned. The experimental results indicate that the FSVM-CART can extract rules from the FSVM. It can generate a binary tree and transform to If/Then rules instead of the black-box one. However, the FSVM provides slightly better classification results as compared to the FSVM-CART (around 2-3% better), but the FSVM-CART has a good trade-off between classification accuracy and human comprehensibility. As a result, the rule extraction technique, which can extract knowledge from the FSVM to provide human interpretable EEG emotion classification, is the essential contribution of this study.

Consequently, the contributions of each task can develop an efficient emotion classification system using EEG with human comprehensibility. In particular, portable applications which require fewer features and a white-box model can be derived from the findings of this study.

6.2 Recommendations for Future Research

Future work of the current study may be extended as follows:

- A proposed method for rule extraction, the FSVM-CART, can be developed. The classification accuracy of the FSVM-CART is slightly lower than the FSVM. This is probably because the CART in the FSVM-CART is not optimized. It is suggested that by using a pruning method, it will likely increase the classification performance of the FSVM-CART.
- All experiments in this study are participant-dependent classifications. As such, the limitation is that the proposed system required a training process for each user. In the future, participant-independent classifications should be studied and developed with generalization.

Appendix I

There are SVM/FSVM parameters.

Participant Number	Arousal emotion			Valence emotion			Dominance		
	Kernel	c	gamma	Kernel	c	gamma	Kernel	c	gamma
1	RBF	10000	0.0005	RBF	10000	0.0005	RBF	10000	0.0005
2	RBF	10000	0.0000005	RBF	10000	0.0000005	RBF	10000	0.0000005
3	RBF	10000	0.000005	RBF	10000	0.0000005	RBF	10000	0.0000005
4	RBF	10000	5E-10	RBF	10000	5E-10	RBF	10000	0.000000005
5	RBF	10000	0.00005	RBF	10000	0.00005	RBF	10000	0.00005
6	RBF	10000	0.00005	RBF	10000	0.00005	RBF	10000	0.00005
7	RBF	10000	0.00005	RBF	10000	0.00005	RBF	10000	0.00005
8	RBF	10000	0.00000005	RBF	10000	0.0000005	RBF	10000	0.0000005
9	RBF	10000	0.00000005	RBF	10000	0.00000005	RBF	10000	0.0000005
10	RBF	10000	0.000005	RBF	10000	0.0000005	RBF	10000	0.0000005
11	RBF	10000	0.000005	RBF	10000	0.0000005	RBF	10000	0.0000005
12	RBF	10000	0.0005	RBF	10000	0.0005	RBF	10000	0.0005
13	RBF	10000	0.0005	RBF	10000	0.0005	RBF	10000	0.0005
14	RBF	10000	0.000005	RBF	10000	0.0000005	RBF	10000	0.0000005
15	RBF	10000	0.000005	RBF	10000	0.0000005	RBF	10000	0.0000005
16	RBF	10000	0.000005	RBF	10000	0.0000005	RBF	10000	0.0000005
17	RBF	10000	0.00000005	RBF	10000	0.00005	RBF	10000	0.00005
18	RBF	10000	0.00000005	RBF	10000	0.00000005	RBF	10000	0.00000005
19	RBF	10000	0.0000005	RBF	10000	0.0000005	RBF	10000	0.0000005
20	RBF	10000	0.00005	RBF	10000	0.00005	RBF	10000	0.00005
21	RBF	10000	0.00005	RBF	10000	0.00005	RBF	10000	0.00005
22	RBF	10000	0.000000005	RBF	10000	5E-10	RBF	10000	5E-10
23	RBF	10000	0.0005	RBF	10000	0.0005	RBF	10000	0.0005

24	RBF	10000	0.00000005	RBF	10000	0.00000005	RBF	10000	0.00000005
25	RBF	10000	0.0000005	RBF	10000	0.0000005	RBF	10000	0.0000005
26	RBF	10000	0.00000005	RBF	10000	0.00000005	RBF	10000	0.00000005
27	RBF	10000	0.00005	RBF	10000	0.00005	RBF	10000	0.00005
28	RBF	10000	0.000005	RBF	10000	0.000005	RBF	10000	0.000005
29	RBF	10000	0.0000005	RBF	10000	0.0000005	RBF	10000	0.0000005
30	RBF	10000	0.0000005	RBF	10000	0.0000005	RBF	10000	0.00005
31	RBF	10000	0.00005	RBF	10000	0.00005	RBF	10000	0.00005
32	RBF	10000	0.0005	RBF	10000	0.0005	RBF	10000	0.005

REFERENCES

[1] E. L. van den Broek, "Affective computing: a reverence for a century of research," in Cognitive Behavioural Systems: Springer, 2012, pp. 434-448.

[2] J. Tao and T. Tan, "Affective computing: A review," in International Conference on Affective computing and intelligent interaction, 2005, pp. 981-995: Springer.

[3] P. Lemmens, A. De Haan, G. Van Galen, and R. Meulenbroek, "Stimulus–response compatibility and affective computing: A review," Theoretical Issues in Ergonomics Science, vol. 8, no. 6, pp. 583-600, 2007.

[4] C. Mühl, B. Allison, A. Nijholt, and G. Chanel, "A survey of affective brain computer interfaces: principles, state-of-the-art, and challenges," Brain-Computer Interfaces, vol. 1, no. 2, pp. 66-84, 2014.

[5] S. P. Kvaale, "Emotion Recognition in EEG: A neuroevolutionary approach," Institutt for datateknikk og informasjonsvitenskap, 2012.

[6] J. Kumar, "Affective modelling of users in HCI using EEG," Procedia Computer Science, vol. 84, pp. 107-114, 2016.

[7] X.-W. Wang, D. Nie, and B.-L. Lu, "Emotional state classification from EEG data using machine learning approach," Neurocomputing, vol. 129, pp. 94-106, 2014.

[8] H. Yoon, S.-W. Park, Y.-K. Lee, and J.-H. Jang, "Emotion recognition of serious game players using a simple brain computer interface," in ICT Convergence (ICTC), 2013 International Conference on, 2013, pp. 783-786: IEEE.

[9] D. P.-O. Bos et al., "Brain-computer interfacing and games," in Brain-Computer Interfaces: Springer, 2010, pp. 149-178.

[10] G. Chanel, C. Rebetez, M. Bétrancourt, and T. Pun, "Emotion assessment from physiological signals for adaptation of game difficulty," Systems, Man and Cybernetics, Part A: Systems and Humans, IEEE Transactions on, vol. 41, no. 6, pp. 1052-1063, 2011.

[11] V. Gandhi, G. Prasad, D. Coyle, L. Behera, and T. M. McGinnity, "EEG-based mobile robot control through an adaptive brain–robot interface," Systems, Man, and Cybernetics: Systems, IEEE Transactions on, vol. 44, no. 9, pp. 1278-1285, 2014.

[12] S. Kar and A. Routray, "Effect of sleep deprivation on functional connectivity of EEG channels," IEEE Transactions on Systems, Man, and Cybernetics: Systems, vol. 43, no. 3, pp. 666-672, 2013.

[13] D. Vasavi and R. Krishnaiah, On-line detection of drowsiness using brain and visual information. IEEE Transactions on systems, man, and cybernetics-part A: systems and humans, 42, 764-775.

[14] W. A. Chaovalitwongse, R. S. Pottenger, S. Wang, Y.-J. Fan, and L. D. Iasemidis, "Pattern-and network-based classification techniques for multichannel medical data signals to improve brain diagnosis," IEEE Transactions on Systems, Man, and Cybernetics-Part A: Systems and Humans, vol. 41, no. 5, pp. 977-988, 2011.

[15] A. Al-Nafjan, M. Hosny, Y. Al-Ohali, and A. Al-Wabil, "Review and Classification of Emotion Recognition Based on EEG Brain-Computer Interface System Research: A Systematic Review," Applied Sciences, vol. 7, no. 12, p. 1239, 2017.

[16] S. Cheemalapati, M. Gubanov, M. Del Vale, and A. Pyayt, "A real-time classification algorithm for emotion detection using portable EEG," in Information Reuse and Integration (IRI), 2013 IEEE 14th International Conference on, 2013, pp. 720-723: IEEE.

[17] R. Mahajan, D. Bansal, and S. Singh, "A real time set up for retrieval of emotional states from human neural responses," International Journal of Medical, Health, Pharmaceutical and Biomedical Engineering, vol. 8, no. 3, pp. 142-147, 2014.

[18] Y. Liu, O. Sourina, and M. K. Nguyen, "Real-time EEG-based emotion recognition and its applications," in Transactions on computational science XII: Springer, 2011, pp. 256-277.

[19] P. Khatwani and A. Tiwari, "A survey on different noise removal techniques of EEG signals," International Journal of Advanced Research in Computer and Communication Engineering, vol. 2, no. 2, pp. 1091-1095, 2013.

[20] F. Lotte, M. Congedo, A. Lécuyer, F. Lamarche, and B. Arnaldi, "A review of classification algorithms for EEG-based brain–computer interfaces," Journal of neural engineering, vol. 4, no. 2, p. R1, 2007.

[21] I. Winkler, S. Haufe, and M. Tangermann, "Automatic classification of artifactual ICA-components for artifact removal in EEG signals," Behavioral and Brain Functions, vol. 7, no. 1, p. 30, 2011.

[22] C. Zhang et al., "Automatic artifact removal from electroencephalogram data based on a priori artifact information," BioMed research international, vol. 2015, 2015.

[23] U. R. Acharya, V. K. Sudarshan, H. Adeli, J. Santhosh, J. E. Koh, and A. Adeli, "Computer-aided diagnosis of depression using EEG signals," European neurology, vol. 73, no. 5-6, pp. 329-336, 2015.

[24] G. M. Bairy, U. Niranjan, and S. D. Puthankattil, "Automated classification of depression EEG signals using wavelet entropies and energies," Journal of Mechanics in Medicine and Biology, vol. 16, no. 03, p. 1650035, 2016.

[25] P. Shukla and S. Verma, "A compact fuzzy rule interpretation of SVM classifier for medical whole slide images," in Region 10 Conference, TENCON 2017-2017 IEEE, 2017, pp. 1588-1592: IEEE.

[26] T. Alotaiby, F. E. A. El-Samie, S. A. Alshebeili, and I. Ahmad, "A review of channel selection algorithms for EEG signal processing," EURASIP Journal on Advances in Signal Processing, vol. 2015, no. 1, p. 66, 2015.

[27] A. Ponz et al., "Emotion processing in words: a test of the neural re-use hypothesis using surface and intracranial EEG," Social Cognitive and Affective Neuroscience, vol. 9, no. 5, pp. 619-627, 2013.

[28] Y.-P. Lin et al., "EEG-based emotion recognition in music listening," Biomedical Engineering, IEEE Transactions on, vol. 57, no. 7, pp. 1798-1806, 2010.

[29] S. Koelstra and I. Patras, "Fusion of facial expressions and EEG for implicit affective tagging," Image and Vision Computing, vol. 31, no. 2, pp. 164-174, 2013.

[30] M. Soleymani, M. Pantic, and T. Pun, "Multimodal emotion recognition in response to videos," Affective Computing, IEEE Transactions on, vol. 3, no. 2, pp. 211-223, 2012.

[31] M. Naji, M. Firoozabadi, and P. Azadfallah, "Emotion classification during music listening from forehead biosignals," Signal, Image and Video Processing, vol. 9, no. 6, pp. 1365-1375, 2015.

[32] C. A. Frantzidis, C. Bratsas, C. L. Papadelis, E. Konstantinidis, C. Pappas, and P. D. Bamidis, "Toward emotion aware computing: an integrated approach using multichannel neurophysiological recordings and affective visual stimuli," Information Technology in Biomedicine, IEEE Transactions on, vol. 14, no. 3, pp. 589-597, 2010.

[33] P. C. Petrantonakis and L. J. Hadjileontiadis, "Emotion recognition from brain signals using hybrid adaptive filtering and higher order crossings analysis," IEEE Transactions on affective computing, vol. 1, no. 2, pp. 81-97, 2010.
[34] R. Jenke, A. Peer, and M. Buss, "Feature Extraction and Selection for Emotion Recognition from EEG," Affective Computing, IEEE Transactions on, vol. 5, no. 3, pp. 327-339, 2014.
[35] R. Pruengkarn, C. C. Fung, and K. W. Wong, "Using misclassification data to improve classification performance," in Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology (ECTI-CON), 2015 12th International Conference on, 2015, pp. 1-5: IEEE.
[36] E. Kroupi, A. Yazdani, J.-M. Vesin, and T. Ebrahimi, "Ocular artifact removal from EEG : a comparison of subspace projection and adaptive filtering methods," in Proceedings of 19th European Signal Processing Conference (Eusipco 2011), 2011, no. EPFL-CONF-167489.
[37] S. Valenzi, T. Islam, P. Jurica, and A. Cichocki, "Individual Classification of Emotions Using EEG," Journal of Biomedical Science and Engineering, vol. 2014, 2014.
[38] N. Jatupaiboon, S. Pan-ngum, and P. Israsena, "Real-time EEG-based happiness detection system," The Scientific World Journal, vol. 2013, 2013.
[39] X. Zhang, "Using class-center vectors to build support vector machines," in Neural Networks for Signal Processing IX, 1999. Proceedings of the 1999 IEEE Signal Processing Society Workshop., 1999, pp. 3-11: IEEE.
[40] C.-F. Lin and S.-D. Wang, "Fuzzy support vector machines," Neural Networks, IEEE Transactions on, vol. 13, no. 2, pp. 464-471, 2002.
[41] S. L. G. Andino, R. G. de Peralta Menendez, A. Khateb, T. Landis, and A. J. Pegna, "Electrophysiological correlates of affective blindsight," NeuroImage, vol. 44, no. 2, pp. 581-589, 2009.
[42] N. Barakat and A. P. Bradley, "Rule extraction from support vector machines: a review," Neurocomputing, vol. 74, no. 1, pp. 178-190, 2010.
[43] G. J. Katuwal and R. Chen, "Machine Learning Model Interpretability for Precision Medicine," arXiv preprint arXiv:1610.09045, 2016.
[44] G. Fung, S. Sandilya, and R. B. Rao, "Rule extraction from linear support vector machines," in Proceedings of the eleventh ACM SIGKDD international conference on Knowledge discovery in data mining, 2005, pp. 32-40: ACM.
[45] K. R. Scherer, "Psychological models of emotion," The neuropsychology of emotion, vol. 137, no. 3, pp. 137-162, 2000.
[46] M. Li and B.-L. Lu, "Emotion classification based on gamma-band EEG," in Engineering in Medicine and Biology Society, 2009. EMBC 2009. Annual International Conference of the IEEE, 2009, pp. 1223-1226: IEEE.
[47] P. Ekman, "Are there basic emotions?," 1992.
[48] P. Ekman and W. V. Friesen, "Constants across cultures in the face and emotion," Journal of personality and social psychology, vol. 17, no. 2, p. 124, 1971.
[49] P. Ekman, T. Dalgleish, and M. Power, "Handbook of cognition and emotion," Chihester, UK: Wiley, 1999.
[50] R. de Sousa, "Emotion (Electronic version.)," ed: Stanford encyclopedia of philosophy. Stanford: Stanford University Press, 2012.
[51] Y.-H. Liu, C.-T. Wu, W.-T. Cheng, Y.-T. Hsiao, P.-M. Chen, and J.-T. Teng, "Emotion Recognition from Single-Trial EEG Based on Kernel Fisher's Emotion Pattern and

Imbalanced Quasiconformal Kernel Support Vector Machine," Sensors (Basel, Switzerland), vol. 14, no. 8, pp. 13361-13388, 07/24.

[52] J. A. Russell, "A circumplex model of affect," Journal of personality and social psychology, vol. 39, no. 6, p. 1161, 1980.

[53] H. Schlosberg, "Three dimensions of emotion," Psychological review, vol. 61, no. 2, p. 81, 1954.

[54] A. Mehrabian and J. A. Russell, An approach to environmental psychology. the MIT Press, 1974.

[55] M. Wyczesany and T. S. Ligeza, "Towards a constructionist approach to emotions: verification of the three-dimensional model of affect with EEG-independent component analysis," Experimental brain research, vol. 233, no. 3, pp. 723-733, 2015.

[56] A. Mehrabian, "Basic Dimensions for a General Psychological Theory Implications for Personality, Social, Environmental, and Developmental Studies," 1980.

[57] G. Valenza, A. Lanata, and E. P. Scilingo, "The role of nonlinear dynamics in affective valence and arousal recognition," IEEE transactions on affective computing, vol. 3, no. 2, pp. 237-249, 2012.

[58] D. Garcia, N. Lester, K. Cloninger, and C. Cloninger, "Encyclopedia of personality and individual differences," 2017.

[59] S. Koelstra et al., "Deap: A database for emotion analysis; using physiological signals," Affective Computing, IEEE Transactions on, vol. 3, no. 1, pp. 18-31, 2012.

[60] M. M. Bradley and P. J. Lang, "Measuring emotion: the self-assessment manikin and the semantic differential," Journal of behavior therapy and experimental psychiatry, vol. 25, no. 1, pp. 49-59, 1994.

[61] H. Xu, "Towards Automated Recognition of Human Emotions using EEG," University of Toronto, 2012.

[62] D. Bos, "EEG-based Emotion Recognition: The Influence of Visual and Auditory Stimuli (2007)," ed, 2014.

[63] N. V. Thakor. Biopotentials and Electrophysiology Measurement. Available: http://mx.nthu.edu.tw/~yucsu/3271/p07.pdf

[64] M. K. Abadi, S. M. Kia, R. Subramanian, P. Avesani, and N. Sebe, "User-centric affective video tagging from MEG and peripheral physiological responses," in Affective Computing and Intelligent Interaction (ACII), 2013 Humaine Association Conference on, 2013, pp. 582-587: IEEE.

[65] F. Zhou, X. Qu, J. R. Jiao, and M. G. Helander, "Emotion prediction from physiological signals: A comparison study between visual and auditory elicitors," Interacting with computers, vol. 26, no. 3, pp. 285-302, 2014.

[66] Q. Zhang and M. Lee, "Emotion development system by interacting with human EEG and natural scene understanding," Cognitive Systems Research, vol. 14, no. 1, pp. 37-49, 2012.

[67] C. P. Niemic and K. Warren, "Studies of emotion," A Theoretical and Empirical Review of Psychophysiological Studies of Emotion.(Department of Clinical and Social Psychology). JUR Rochester, vol. 1, no. 1, pp. 15-19, 2002.

[68] S. M. Alarcao and M. J. Fonseca, "Emotions recognition using EEG signals: A survey," IEEE Transactions on Affective Computing, 2017.

[69] M. Ali, A. H. Mosa, F. Al Machot, and K. Kyamakya, "EEG-based emotion recognition approach for e-healthcare applications," in Ubiquitous and Future Networks (ICUFN), 2016 Eighth International Conference on, 2016, pp. 946-950: IEEE.

[70] C. Hondrou and G. Caridakis, "Affective, natural interaction using EEG: sensors, application and future directions," in Hellenic Conference on Artificial Intelligence, 2012, pp. 331-338: Springer.

[71] M. Steriade, D. A. McCormick, and T. J. Sejnowski, "Thalamocortical oscillations in the sleeping and aroused brain," Science, vol. 262, no. 5134, pp. 679-685, 1993.

[72] G. G. Knyazev, "EEG delta oscillations as a correlate of basic homeostatic and motivational processes," Neuroscience & Biobehavioral Reviews, vol. 36, no. 1, pp. 677-695, 2012.

[73] L. I. Aftanas, A. A. Varlamov, S. V. Pavlov, V. P. Makhnev, and N. V. Reva, "Time-dependent cortical asymmetries induced by emotional arousal: EEG analysis of event-related synchronization and desynchronization in individually defined frequency bands," International Journal of Psychophysiology, vol. 44, no. 1, pp. 67-82, 2002.

[74] M. Balconi and C. Lucchiari, "EEG correlates (event-related desynchronization) of emotional face elaboration: a temporal analysis," Neuroscience letters, vol. 392, no. 1, pp. 118-123, 2006.

[75] M. A. Klados et al., "A framework combining delta event-related oscillations (EROs) and synchronisation effects (ERD/ERS) to study emotional processing," Computational intelligence and neuroscience, vol. 2009, p. 12, 2009.

[76] W. Klimesch, R. Freunberger, P. Sauseng, and W. Gruber, "A short review of slow phase synchronization and memory: evidence for control processes in different memory systems?," Brain research, vol. 1235, pp. 31-44, 2008.

[77] M. Kawasaki, K. Kitajo, and Y. Yamaguchi, "Dynamic links between theta executive functions and alpha storage buffers in auditory and visual working memory," European Journal of Neuroscience, vol. 31, no. 9, pp. 1683-1689, 2010.

[78] E. Neidermeyer, "The normal EEG of the waking adult," Electroencephalography: basic principles, clinical applications and related fields, 4th ed. Baltimore, MD: Williams and Wilkins, pp. 149-173, 1999.

[79] D. Sammler, M. Grigutsch, T. Fritz, and S. Koelsch, "Music and emotion: electrophysiological correlates of the processing of pleasant and unpleasant music," Psychophysiology, vol. 44, no. 2, pp. 293-304, 2007.

[80] Y.-P. Lin, J.-R. Duann, J.-H. Chen, and T.-P. Jung, "Electroencephalographic dynamics of musical emotion perception revealed by independent spectral components," Neuroreport, vol. 21, no. 6, pp. 410-415, 2010.

[81] G. Pfurtscheller and F. L. Da Silva, "Event-related EEG/MEG synchronization and desynchronization: basic principles," Clinical neurophysiology, vol. 110, no. 11, pp. 1842-1857, 1999.

[82] J. A. Coan and J. J. Allen, "Frontal EEG asymmetry as a moderator and mediator of emotion," Biological psychology, vol. 67, no. 1, pp. 7-50, 2004.

[83] R. J. Barry, A. R. Clarke, S. J. Johnstone, C. A. Magee, and J. A. Rushby, "EEG differences between eyes-closed and eyes-open resting conditions," Clinical Neurophysiology, vol. 118, no. 12, pp. 2765-2773, 2007.

[84] R. J. Barry, A. R. Clarke, S. J. Johnstone, and C. R. Brown, "EEG differences in children between eyes-closed and eyes-open resting conditions," Clinical Neurophysiology, vol. 120, no. 10, pp. 1806-1811, 2009.

[85] C. Neuper, M. Wörtz, and G. Pfurtscheller, "ERD/ERS patterns reflecting sensorimotor activation and deactivation," Progress in brain research, vol. 159, pp. 211-222, 2006.

[86] H. W. Cole and W. J. Ray, "EEG correlates of emotional tasks related to attentional demands," International Journal of Psychophysiology, vol. 3, no. 1, pp. 33-41, 1985.

[87] J. Onton and S. Makeig, "High-frequency broadband modulations of electroencephalographic spectra," Frontiers in human neuroscience, vol. 3, 2009.

[88] I. Goncharova, D. J. McFarland, T. M. Vaughan, and J. R. Wolpaw, "EMG contamination of EEG: spectral and topographical characteristics," Clinical Neurophysiology, vol. 114, no. 9, pp. 1580-1593, 2003.

[89] P. Fries, "Neuronal gamma-band synchronization as a fundamental process in cortical computation," Annual review of neuroscience, vol. 32, pp. 209-224, 2009.

[90] T. Gruber, M. M. Müller, A. Keil, and T. Elbert, "Selective visual-spatial attention alters induced gamma band responses in the human EEG," Clinical Neurophysiology, vol. 110, no. 12, pp. 2074-2085, 1999.

[91] O. Jensen, J. Kaiser, and J.-P. Lachaux, "Human gamma-frequency oscillations associated with attention and memory," Trends in neurosciences, vol. 30, no. 7, pp. 317-324, 2007.

[92] L. M. Ward, "Synchronous neural oscillations and cognitive processes," Trends in cognitive sciences, vol. 7, no. 12, pp. 553-559, 2003.

[93] D. Senkowski, T. R. Schneider, F. Tandler, and A. K. Engel, "Gamma-band activity reflects multisensory matching in working memory," Experimental brain research, vol. 198, no. 2-3, pp. 363-372, 2009.

[94] M. M. Müller, A. Keil, T. Gruber, and T. Elbert, "Processing of affective pictures modulates right-hemispheric gamma band EEG activity," Clinical Neurophysiology, vol. 110, no. 11, pp. 1913-1920, 1999.

[95] M. Balconi and U. Pozzoli, "Arousal effect on emotional face comprehension: Frequency band changes in different time intervals," Physiology & behavior, vol. 97, no. 3, pp. 455-462, 2009.

[96] L. Aftanas, N. Reva, A. Varlamov, S. Pavlov, and V. Makhnev, "Analysis of evoked EEG synchronization and desynchronization in conditions of emotional activation in humans: temporal and topographic characteristics," Neuroscience and behavioral physiology, vol. 34, no. 8, pp. 859-867, 2004.

[97] A. Keil, M. M. Müller, T. Gruber, C. Wienbruch, M. Stolarova, and T. Elbert, "Effects of emotional arousal in the cerebral hemispheres: a study of oscillatory brain activity and event-related potentials," Clinical neurophysiology, vol. 112, no. 11, pp. 2057-2068, 2001.

[98] J. Gross, A. Schnitzler, L. Timmermann, and M. Ploner, "Gamma oscillations in human primary somatosensory cortex reflect pain perception," PLoS biology, vol. 5, no. 5, p. e133, 2007.

[99] D. Senkowski, J. Kautz, M. Hauck, R. Zimmermann, and A. K. Engel, "Emotional facial expressions modulate pain-induced beta and gamma oscillations in sensorimotor cortex," The Journal of Neuroscience, vol. 31, no. 41, pp. 14542-14550, 2011.

[100] M. Rashed-Al-Mahfuz, M. R. Islam, K. Hirose, and M. K. I. Molla, "Artifact suppression and analysis of brain activities with electroencephalography signals," Neural regeneration research, vol. 8, no. 16, p. 1500, 2013.

[101] M. Balconi and C. Cobelli, "Motivational mechanisms (BAS) and prefrontal cortical activation contribute to recognition memory for emotional words. rTMS effect on performance and EEG (alpha band) measures," Brain and language, vol. 137, pp. 77-85, 2014.

[102] J.-M. López-Gil et al., "Corrigendum: Method for Improving EEG Based Emotion Recognition by Combining It with Synchronized Biometric and Eye Tracking

Technologies in a Non-invasive and Low Cost Way," Frontiers in computational neuroscience, vol. 10, p. 119, 2016.
[103] V. L. Towle et al., "The spatial location of EEG electrodes: locating the best-fitting sphere relative to cortical anatomy," Electroencephalography and clinical neurophysiology, vol. 86, no. 1, pp. 1-6, 1993.
[104] S. E. P. Nomenclature, "American Electroencephalographic Society Guidelines for," Journal of clinical Neurophysiology, vol. 8, no. 2, pp. 200-202, 1991.
[105] J. W. Matiko, S. P. Beeby, and J. Tudor, "Fuzzy logic based emotion classification," in Acoustics, Speech and Signal Processing (ICASSP), 2014 IEEE International Conference on, 2014, pp. 4389-4393: IEEE.
[106] T. S. Rached and A. Perkusich, "Emotion Recognition Based on Brain-Computer Interface Systems," 2013.
[107] D. Szibbo, A. Luo, and T. J. Sullivan, "Removal of blink artifacts in single channel EEG," in Engineering in Medicine and Biology Society (EMBC), 2012 Annual International Conference of the IEEE, 2012, pp. 3511-3514: IEEE.
[108] Y.-P. Lin and T.-P. Jung, "Exploring day-to-day variability in EEG-based emotion classification," in Systems, Man and Cybernetics (SMC), 2014 IEEE International Conference on, 2014, pp. 2226-2229: IEEE.
[109] Y. Liu, O. Sourina, and M. K. Nguyen, "Real-time EEG-based human emotion recognition and visualization," in Cyberworlds (CW), 2010 International Conference on, 2010, pp. 262-269: IEEE.
[110] D. O. Bos, "EEG-based emotion recognition," The Influence of Visual and Auditory Stimuli, pp. 1-17, 2006.
[111] A. Hidalgo-Muñoz, M. López, A. Pereira, I. Santos, and A. Tomé, "Spectral turbulence measuring as feature extraction method from EEG on affective computing," Biomedical Signal Processing and Control, vol. 8, no. 6, pp. 945-950, 2013.
[112] P. Jeatrakul, "Enhancing classification performance over noise and imbalanced data problems," Murdoch University, 2012.
[113] D. Guan, W. Yuan, Y.-K. Lee, and S. Lee, "Identifying mislabeled training data with the aid of unlabeled data," Applied Intelligence, vol. 35, no. 3, pp. 345-358, 2011.
[114] G. Lee, M. Kwon, S. K. Sri, and M. Lee, "Emotion recognition based on 3D fuzzy visual and EEG features in movie clips," Neurocomputing, vol. 144, pp. 560-568, 2014.
[115] J. W. Matiko, S. Beeby, and J. Tudor, "Real time eye blink noise removal from EEG signals using morphological component analysis," in Engineering in Medicine and Biology Society (EMBC), 2013 35th Annual International Conference of the IEEE, 2013, pp. 13-16: IEEE.
[116] M. Stikic, R. R. Johnson, V. Tan, and C. Berka, "EEG-based classification of positive and negative affective states," Brain-Computer Interfaces, vol. 1, no. 2, pp. 99-112, 2014.
[117] Y.-H. Liu, W.-T. Cheng, Y.-T. Hsiao, C.-T. Wu, and M.-D. Jeng, "EEG-based emotion recognition based on kernel Fisher's discriminant analysis and spectral powers," in Systems, Man and Cybernetics (SMC), 2014 IEEE International Conference on, 2014, pp. 2221-2225: IEEE.
[118] S. G. Costafreda, M. J. Brammer, A. S. David, and C. H. Fu, "Predictors of amygdala activation during the processing of emotional stimuli: a meta-analysis of 385 PET and fMRI studies," Brain research reviews, vol. 58, no. 1, pp. 57-70, 2008.
[119] R. J. Davidson and N. A. Fox, "Asymmetrical brain activity discriminates between positive and negative affective stimuli in human infants," Science, vol. 218, no. 4578, pp. 1235-1237, 1982.

[120] H. Blaiech, M. Neji, A. Wali, and A. M. Alimi, "Emotion recognition by analysis of EEG signals," in Hybrid Intelligent Systems (HIS), 2013 13th International Conference on, 2013, pp. 312-318: IEEE.

[121] T. Holtgraves and A. Felton, "Hemispheric asymmetry in the processing of negative and positive words: A divided field study," Cognition and Emotion, vol. 25, no. 4, pp. 691-699, 2011.

[122] O. Sourina, Y. Liu, Q. Wang, and M. K. Nguyen, "EEG-based personalized digital experience," in Universal Access in Human-Computer Interaction. Users Diversity: Springer, 2011, pp. 591-599.

[123] J. Hu, C.-s. Wang, M. Wu, Y.-x. Du, Y. He, and J. She, "Removal of EOG and EMG artifacts from EEG using combination of functional link neural network and adaptive neural fuzzy inference system," Neurocomputing, vol. 151, pp. 278-287, 2015.

[124] A. Viet Hoang, V. Manh Ngo, H. Bang Ban, and Q. Thang Huynh, "A real-time model based Support Vector Machine for emotion recognition through EEG," in Control, Automation and Information Sciences (ICCAIS), 2012 International Conference on, 2012, pp. 191-196.

[125] B. Allison, B. Graimann, and A. Gräser, "Why use a BCI if you are healthy," in ACE Workshop-Brain-Computer Interfaces and Games, 2007, pp. 7-11.

[126] M. Cavazza, D. Pizzi, F. Charles, T. Vogt, and E. André, "Emotional Input for Character-based Interactive Storytelling," 2009.

[127] M.-K. Kim, M. Kim, E. Oh, and S.-P. Kim, "A review on the computational methods for emotional state estimation from the human EEG," Computational and mathematical methods in medicine, vol. 2013, 2013.

[128] D. Iacoviello, A. Petracca, M. Spezialetti, and G. Placidi, "A Classification Algorithm for Electroencephalography Signals by Self-Induced Emotional Stimuli," IEEE transactions on cybernetics, vol. 46, no. 12, pp. 3171-3180, 2016.

[129] S.-Y. Dong, B.-K. Kim, and S.-Y. Lee, "EEG-Based Classification of Implicit Intention During Self-Relevant Sentence Reading," IEEE transactions on cybernetics, vol. 46, no. 11, pp. 2535-2542, 2016.

[130] S. Barua and S. Begum, "A Review on Machine Learning Algorithms in Handling EEG Artifacts," in The Swedish AI Society (SAIS) Workshop SAIS, 14, 22-23 May 2014, Stockholm, Sweden, 2014.

[131] N. Barakat and J. Diederich, "Learning-based rule-extraction from support vector machines," in The 14th International Conference on Computer Theory and applications ICCTA'2004, 2004: not found.

[132] Z.-H. Zhou and Y. Jiang, "Medical diagnosis with C4. 5 rule preceded by artificial neural network ensemble," IEEE Transactions on information Technology in Biomedicine, vol. 7, no. 1, pp. 37-42, 2003.

[133] D. Martens, J. Huysmans, R. Setiono, J. Vanthienen, and B. Baesens, "Rule extraction from support vector machines: an overview of issues and application in credit scoring," in Rule extraction from support vector machines: Springer, 2008, pp. 33-63.

[134] R. Batuwita and V. Palade, "FSVM-CIL: fuzzy support vector machines for class imbalance learning," Fuzzy Systems, IEEE Transactions on, vol. 18, no. 3, pp. 558-571, 2010.

[135] V. N. Vladimir and V. Vapnik, "The nature of statistical learning theory," ed: Springer Heidelberg, 1995.

[136] C. Cortes and V. Vapnik, "Support-vector networks," Machine learning, vol. 20, no. 3, pp. 273-297, 1995.

[137] A. J. Smola and B. Schölkopf, "A tutorial on support vector regression," Statistics and computing, vol. 14, no. 3, pp. 199-222, 2004.
[138] V. Jurcak, D. Tsuzuki, and I. Dan, "10/20, 10/10, and 10/5 systems revisited: their validity as relative head-surface-based positioning systems," Neuroimage, vol. 34, no. 4, pp. 1600-1611, 2007.
[139] M. Othman, A. Wahab, I. Karim, M. A. Dzulkifli, and I. F. T. Alshaikli, "Eeg emotion recognition based on the dimensional models of emotions," Procedia-Social and Behavioral Sciences, vol. 97, pp. 30-37, 2013.
[140] Y. Liu and O. Sourina, "EEG-based dominance level recognition for emotion-enabled interaction," in Multimedia and Expo (ICME), 2012 IEEE International Conference on, 2012, pp. 1039-1044: IEEE.
[141] A. E. Vijayan, D. Sen, and A. Sudheer, "EEG-Based Emotion Recognition Using Statistical Measures and Auto-Regressive Modeling," in Computational Intelligence & Communication Technology (CICT), 2015 IEEE International Conference on, 2015, pp. 587-591: IEEE.
[142] E. Kroupi, A. Yazdani, and T. Ebrahimi, "EEG correlates of different emotional states elicited during watching music videos," in Affective Computing and Intelligent Interaction: Springer, 2011, pp. 457-466.
[143] P. Jahankhani, V. Kodogiannis, and K. Revett, "EEG signal classification using wavelet feature extraction and neural networks," in Modern Computing, 2006. JVA'06. IEEE John Vincent Atanasoff 2006 International Symposium on, 2006, pp. 120-124: IEEE.
[144] A. Chavan and M. Kolte, "Optimal Mother Wavelet for EEG Signal Processing."
[145] H. U. Amin et al., "Feature extraction and classification for EEG signals using wavelet transform and machine learning techniques," Australasian physical & engineering sciences in medicine, vol. 38, no. 1, pp. 139-149, 2015.
[146] A. Choppin, "EEG-based human interface for disabled individuals: Emotion expression with neural networks," Unpublished master’s thesis, 2000.
[147] G. Chanel, J. J. Kierkels, M. Soleymani, and T. Pun, "Short-term emotion assessment in a recall paradigm," International Journal of Human-Computer Studies, vol. 67, no. 8, pp. 607-627, 2009.
[148] C.-C. Chang and C.-J. Lin, "LIBSVM: A library for support vector machines," ACM Transactions on Intelligent Systems and Technology (TIST), vol. 2, no. 3, p. 27, 2011.
[149] C. J. Burges, "A tutorial on support vector machines for pattern recognition," Data mining and knowledge discovery, vol. 2, no. 2, pp. 121-167, 1998.
[150] H. Samma, C. P. Lim, J. M. Saleh, and S. A. Suandi, "A memetic-based fuzzy support vector machine model and its application to license plate recognition," Memetic computing, vol. 8, no. 3, pp. 235-251, 2016.
[151] J. Tang, S. Alelyani, and H. Liu, "Feature selection for classification: A review," Data Classification: Algorithms and Applications, p. 37, 2014.
[152] M. Dash and H. Liu, "Feature selection for classification," Intelligent data analysis, vol. 1, no. 3, pp. 131-156, 1997.
[153] G. H. John, R. Kohavi, and K. Pfleger, "Irrelevant features and the subset selection problem," in Machine Learning Proceedings 1994: Elsevier, 1994, pp. 121-129.
[154] I. Guyon and A. Elisseeff, "An introduction to variable and feature selection," Journal of machine learning research, vol. 3, no. Mar, pp. 1157-1182, 2003.
[155] V. Bolón-Canedo, N. Sánchez-Maroño, and A. Alonso-Betanzos, "A review of feature selection methods on synthetic data," Knowledge and information systems, vol. 34, no. 3, pp. 483-519, 2013.

[156] S. Moghimi, A. Kushki, S. Power, A. M. Guerguerian, and T. Chau, "Automatic detection of a prefrontal cortical response to emotionally rated music using multi-channel near-infrared spectroscopy," Journal of neural engineering, vol. 9, no. 2, p. 026022, 2012.
[157] D. Heger, R. Mutter, C. Herff, F. Putze, and T. Schultz, "Continuous recognition of affective states by functional near infrared spectroscopy signals," in Affective Computing and Intelligent Interaction (ACII), 2013 Humaine Association Conference on, 2013, pp. 832-837: IEEE.
[158] V. Kumar and S. Minz, "Feature selection," SmartCR, vol. 4, no. 3, pp. 211-229, 2014.
[159] Z. Zhao and H. Liu, "Searching for Interacting Features," in ijcai, 2007, vol. 7, pp. 1156-1161.
[160] I. Kononenko, "Estimating attributes: analysis and extensions of RELIEF," in European conference on machine learning, 1994, pp. 171-182: Springer.
[161] M. A. Hall and L. A. Smith, "Practical feature subset selection for machine learning," 1998.
[162] R. Kohavi and G. H. John, "Wrappers for feature subset selection," Artificial intelligence, vol. 97, no. 1-2, pp. 273-324, 1997.
[163] M. A. Hall and L. A. Smith, "Feature selection for machine learning: comparing a correlation-based filter approach to the wrapper," in FLAIRS conference, 1999, vol. 1999, pp. 235-239.
[164] H. Peng, F. Long, and C. Ding, "Feature selection based on mutual information criteria of max-dependency, max-relevance, and min-redundancy," IEEE Transactions on pattern analysis and machine intelligence, vol. 27, no. 8, pp. 1226-1238, 2005.
[165] I. Guyon, J. Weston, S. Barnhill, and V. Vapnik, "Gene selection for cancer classification using support vector machines," Machine learning, vol. 46, no. 1-3, pp. 389-422, 2002.
[166] M. Mejía-Lavalle, E. Sucar, and G. Arroyo, "Feature selection with a perceptron neural net," in Proceedings of the international workshop on feature selection for data mining, 2006, pp. 131-135.
[167] R. J. Urbanowicz, M. Meeker, W. La Cava, R. S. Olson, and J. H. Moore, "Relief-based feature selection: introduction and review," Journal of biomedical informatics, 2018.
[168] S. Chikhi and S. Benhammada, "ReliefMSS: a variation on a feature ranking ReliefF algorithm," International Journal of Business Intelligence and Data Mining, vol. 4, no. 3-4, pp. 375-390, 2009.
[169] K. Suresh, S. V. Thomas, and G. Suresh, "Design, data analysis and sampling techniques for clinical research," Annals of Indian Academy of Neurology, vol. 14, no. 4, p. 287, 2011.
[170] M. C. V.Siva Nagi Reddy, S.Chinna.Gopi, "A Comprehensive Review on Support Vector Rule Extraction," International Journal of Computer Sci ence And Technology, vol. 3, no. 2, pp. 502-506, 2012.
[171] Y. Wang, S. Wang, and K. K. Lai, "A new fuzzy support vector machine to evaluate credit risk," IEEE Transactions on Fuzzy Systems, vol. 13, no. 6, pp. 820-831, 2005.
[172] K.-S. Shin, T. S. Lee, and H.-j. Kim, "An application of support vector machines in bankruptcy prediction model," Expert systems with applications, vol. 28, no. 1, pp. 127-135, 2005.
[173] H. Núñez, C. Angulo, and A. Català, "Rule extraction from support vector machines," in Esann, 2002, pp. 107-112.
[174] Y. Zhang, H. Su, T. Jia, and J. Chu, "Rule extraction from trained support vector machines," in Pacific-Asia Conference on Knowledge Discovery and Data Mining, 2005, pp. 61-70: Springer.

[175] Z. Chen, J. Li, and L. Wei, "A multiple kernel support vector machine scheme for feature selection and rule extraction from gene expression data of cancer tissue," Artificial Intelligence in Medicine, vol. 41, no. 2, pp. 161-175, 2007.

[176] D. Torres and C. Rocco, "Extracting trees from trained SVM models using a TREPAN based approach," in Hybrid Intelligent Systems, 2005. HIS'05. Fifth International Conference on, 2005, p. 6 pp.: IEEE.

[177] D. Martens, B. Baesens, and T. Van Gestel, "Decompositional rule extraction from support vector machines by active learning," IEEE Transactions on Knowledge and Data Engineering, vol. 21, no. 2, pp. 178-191, 2009.

[178] A. d. C. F. Chaves, M. M. B. Vellasco, and R. Tanscheit, "Fuzzy rule extraction from support vector machines," in Hybrid Intelligent Systems, 2005. HIS'05. Fifth International Conference on, 2005, p. 6 pp.: IEEE.

[179] N. H. Barakat and A. P. Bradley, "Rule extraction from support vector machines: A sequential covering approach," IEEE Transactions on Knowledge and Data Engineering, vol. 19, no. 6, pp. 729-741, 2007.

[180] T. M. Mitchell, "Machine learning. WCB," ed: McGraw-Hill Boston, MA:, 1997.

[181] N. Barakat and J. Diederich, "Eclectic rule-extraction from support vector machines," International Journal of Computational Intelligence, vol. 2, no. 1, pp. 59-62, 2005.

[182] J. R. Quinlan, C4. 5: programs for machine learning. Elsevier, 2014.

[183] J. R. Quinlan, "Induction of decision trees," Machine learning, vol. 1, no. 1, pp. 81-106, 1986.

[184] L.Breiman, J.Friedman, R.Olshen, and C.Stone, Classification and Regression Trees. Monterrey, CA: WadsworthandBrooks, 1984.

[185] D. Lavanya and K. U. Rani, "Performance evaluation of decision tree classifiers on medical datasets," International Journal of Computer Applications (0975–8887 (, Volume 26–No. 4, 1-4, 2011.

[186] S. Singh and P. Gupta, "Comparative study ID3, cart and C4. 5 decision tree algorithm: a survey," Int J Adv Inf Sci Technol [Internet], vol. 27, pp. 97-103, 2014.

[187] I. The MathWorks. ClassificationTree class. Available: https://au.mathworks.com/help/stats/classificationtree-class.html