LEARNER'S EMOTION PREDICTION USING PRODUCTION RULES CLASSIFICATION ALGORITHM THROUGH BRAIN COMPUTER INTERFACE TOOL

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ABSTRAK

Perkembangan teknologi neurosains kognitif dan pengimejan otak seperti teknologi Interaksi Manusia- Komputer telah membolehkan manusia berinteraksi secara langsung dengan otak. Penggunaan pengesan Antaramuka Otak-Komputer boleh mengawasi keadaan fizikal dan mental di dalam otak. Pengecaman emosi merupakan aspek penting di dalam interaksi antara manusia di mana emosi mempengaruhi manusia di dalam kehidupan seharian. Para penyelidik telah mengkaji pelbagai metod bagi mendapatkan dan mengenali emosi seperti melalui percakapan, ekpresi wajah dan juga melalui isyarat fisiologi. Isyarat *electroencephalogram* (EEG) adalah isyarat fisiologi terbaik yang mengandungi maklumat berkaitan keadaan mental manusia. Walau bagaimanapun, isyarat-isyarat EEG tersebut melibatkan banyak data yang perlu dilombong dan dianalisis dengan baik supaya menjadi maklumat yang berguna dan berharga. Kepentingan pengenalan emosi kebanyakannya diabaikan kerana sukar untuk dikira dan difahami. Di Malaysia, tiada penyelidikan berasaskan EEG yang dijalankan ke atas kanak- kanak sekolah bagi mengkaji kelakuan emosi mereka semasa pembelajaran. Klasifikasi dan ramalan data merupakan dua fungsi teknik penggalian data yang sesuai di dalam pemprosesan isyarat EEG. Objektif kajian ini adalah untuk mengklasifikasi ciri-ciri emosi pengguna melalui isyarat EEG berasaskan tingkah laku kanak-kanak, untuk membangunkan sebuah sistem prototaip ramalan emosi yang dinamakan MYEmotion dan mengesahkan sistem prototaip tersebut dalam meramalkan emosi positif dan negatif kanak-kanak. Set data bacaan tahap perhatian dan meditasi telah dikumpul daripada satu persampelan kualitatif di dalam kalangan pelajar sekolah di Pekan, Pahang yang berumur 10 tahun menggunakan pengesan Antara muka Otak-Komputer. Setiap responden menjalani dua sesi permainan berasaskan matematik menggunakan telefon pintar yang disertakan dengan rehat selama 2 minit di antara kedua sesi yang dijalankan. Analisis data menggunakan perisian WEKA menunjukkan pengelas berasaskan peraturan (PART) merupakan algoritma klasifikasi yang paling tepat untuk mengelaskan keadaan emosi positif dan negatif dengan peratusan ketepatan paling tinggi sebanyak 99.6% berbanding J48 (99.5%) dan Naïve Bayes (96.2%). Senarai keputusan oleh pengelas PART yang mewakili kebiasaan tahap perhatian dan meditasi dalam kalangan kanak-kanak telah ditukar kepada beberapa set peraturan. Kemudian, set peraturan ini telah diimplementasi ke dalam MYEmotion menggunakan persekitaran MATLAB. MYEmotion meringkaskan keseluruhan prosedur dari pra pemprosesan sehinggalah ke akhir. Set asas yang diagunapakai dari nilai meter eSense yang diiktiraf oleh penyelidik lepas juga dikod ke dalam MYEmotion. Analisis data daripada set asas dan set ramalan peraturan menunjukkan bahawa tiada banyak perbezaan di antara peratusan keadaan emosi positif dan negatif bagi kedua set. Hubungan di antara isyarat EEG dengan perhatian dan meditasi kanak-kanak semasa pembelajaran berpotensi untuk mengenal pasti keadaan mental semasa proses pembelajaran seperti kefahaman, keterlibatan dan hasil pembelajaran. Kajian ini berupaya menjadi permulaan di dalam pengautomasian tutorial keputusan yang boleh disesuaikan dengan tingkah laku pelajar berdasarkan keadaan mental. Oleh itu, lebih banyak maklumat yang relevan berkenaan pelajar boleh disediakan kepada pihak sekolah dan guru untuk meningkatkan hasil pembelajaran.

ABSTRACT

Enhancements in cognitive neuroscience and brain imaging technologies such as Human-Computer Interaction (HCI) have started to provide human with the ability to interact directly with the brain. The use of sensors known as Brain-Computer Interface (BCI) tool can monitor the physical processes and mental states that occur in the human brain. Emotion recognition is found to be an important aspect of the interaction between human being where emotion influences human in daily life. Researchers investigated many methods to capture and recognise emotion, such as through speech, facial expression, and physiological signals. Electroencephalogram (EEG) signals are found to be the best physiological signals that contain valuable information about human mental state. However, these EEG signals involve a lot of data and need to be mined efficiently in order to make it valuable and meaningful. The crucial parameter of emotion recognition has largely been ignored because it is always misunderstood and is hard to measure. No EEG studies in Malaysia has been done on school children to study their emotional behaviour while learning. Classification and prediction are the functions provided by the data mining techniques that suit in EEG signal processing. The objectives of this research are to classify the user emotion characteristics by using EEG signals based on children's behaviour, to develop a prototype of an emotion prediction system named as MYEmotion and to validate the developed prototype in predicting the positive and negative emotions of the children. 16 datasets of attention and meditation levels were collected from a qualitative sampling of 10 years old school children in Pekan, Pahang using a BCI headset tool. Each respondent underwent two mathematical game sessions using a smartphone with a two-minute break in between each session. From the data analysis using WEKA software, the production rules classifier (PART) is found to be the most accurate classification algorithm in classifying the emotion which yields the highest precision percentage of 99.6% compared to J48 (99.5%) and Naïve Bayes (96.2%). The decision lists generated by PART classifier that represent the regularities of the attention and meditation levels among children are converted into several rule sets of positive and negative emotions. These rule sets was implemented in the MYEmotion using MATLAB environment. MYEmotion summarises the entire procedure starting from the pre-processing to the end. A baseline set which is adopted from an established eSense meter value was also coded into the prototype. The data analysis of the both baseline and rule-based prediction sets have shown that there are not many differences between the trend of the positive and negative emotions percentage of both sets. The reliable relationship between EEG signals of the attention and meditation and their impact towards the positive and negative emotions among children while learning illustrates the potentials in detecting mental states which are relevant to tutoring such as comprehension, engagement and learning impact. In future, this research can be an initial work in automating tutorial decisions in an intelligent tutoring system which are able to adapt to the behaviour of the learners based on the detected mental states. Therefore, more relevant information about the students can be provided to the schools and teachers in order to increase the learning impacts.

TABLE OF CONTENT

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1

INTRODUCTION

1.1 Research Background

Human-Computer Interaction (HCI) is prospected to make the computers and any other related devices to be designed with an understanding that people with specific tasks in mind will want to use them in assisting and accomplishing their everyday work. In an interaction with a computer, the user receives information from the computer and responds by providing input to the computer. According to Dix et al. (2004), HCI draws on many disciplines and may be an option specializing in a particular area, such as cognitive modeling of brain-based skills. For example, HCI can help in capturing human brain signals which can be beneficial to medical, educational and psychological fields.

There are more data produced in human daily life from time to time and the number of users has also increased tremendously. Such data refers to data stream which arrive in time and sequence (Guha et al., 2001). The vast amount of the data needs to be processed and stored efficiently in order to make it valuable and meaningful. Data can be in various formats such as texts, graphics, audio and video. Human is limited in their capacity and ability to process the information. Therefore, it had been found that data mining concept can be a good option to handle the data stream. Data stream and data mining are correlated with each other. Data streams are the data arrived in time and in sequence. Data mining is the technique that is used to mine the data stream for decision making. According to Deepashri & Ashwini (2017), data mining or also known as Knowledge Discovery Database (KDD) is used in the data stream for data retrieval and decision making.

Data mining has become one of the most popular tools for extracting, manipulating and discovering patterns of data to produce meaningful information in order to help the organisation conduct decision-making processes. It analyses the data from different perspectives and then summarises it into meaningful information for specific purposes. It is a powerful new technology with great potential to help an individual or organisation to retrieve important information from their data warehouses. By using data mining tools, prediction of future trends and behaviour contribute to helping organisations or companies in decision making. Data mining has been used widely in various fields such as disaster forecasting, brain signal processing, healthcare, education, credit scoring, sports, intelligent agencies, e-commerce, digital library retrieval and predictions in engineering application. It has been studied that the fundamental algorithms in data mining and analysis form the basis of the emerging field of data science, which includes automated methods to analyse the patterns and models for all kinds of data, with applications ranging from scientific discovery to business intelligence and analytics (Zaki & Jr, 2014).

Data mining is the extraction of useful information from raw data. It will go into the databases automatically and seek regularities or patterns. The descriptive function, as well as classification and prediction function are the main functions in data mining, where the classification and prediction function will be the main highlights in this research. Classification algorithms represent the set of supervised learning techniques, where a set of dependent variables needs to be predicted based on another set of input attributes. There were many researchers that did prediction modeling using data mining in their research. For example, Luan (2002), who discussed about the application of data mining in higher education. He explained how data mining saves resources while maximising efficiency in academic. Another example is Nandeshwar & Chaudhari (2009) who initiated the enrolment of prediction models based on student admission data by applying different data mining methods in maximising students recruitment and retention. This thesis will discuss the classification and prediction of electroencephalograph (EEG) signals which are closely related to human mental states. Measuring EEG data results in huge amount of data and by using the data mining concept, there are many patterns that can be mined from the brain signals.

As mentioned earlier, one of the fields that apply data mining is the brain signal processing. The brain is a fascinating organ that regulates almost all of the human activity. Therefore the activity of the brain contains a lot of information about an individual. This brain signal is also known as electroencephalograph (EEG) signals which was discovered by a German scientist named Hans Berger about 80 years ago. This research will study EEG signals in order to identify the positive and negative emotions of a respondent while learning. Scientists agree on the fact that the human brain is the main source of emotion and has been selected to be the input signal for emotion detection, as EEG is one of the useful bio signals from the brain to detect the human emotion (Murugappan et al., 2007).

Emotion is an important aspect of the psychological changes of a human being. Emotion adjusts the state of the human brain and influences several processes. People's emotion heavily influences their way of communicating, acting and producing something. Many studies were done in regard to emotion recognition. For example, there were few researches done to make computers recognise emotion from speech (Bhatti et al., 2004; Dellaert et al., 1996; Patel et al., 2017; Trigeorgis et al., 2016), from facial expressions or from both, emotion and facial expressions (Catherine et al., 2017; Fasel & Luettin, 2003; Pantic & Rothkrantz, 2000). Another method of measuring human emotion is by using physiological signals such as heartbeat rate, skin temperature, skin conductance, blood volume pressure and EEG. These physiological signals are available at any moment, and it has been shown that emotional markers are present in EEG, and can also be deduced from heartbeat rates and skin conductivity (Haag et al., 2004; Kim et al., 2004; Mcgonigal et al., 2017). These physiological signals can hardly be deceived by voluntary control and are available all the time, without needing any further action of the user. Literature suggests that emotion recognition should be possible from EEG signals (Shemiakina and Dan’ko, 2004; Tickle et al., 2016; Zheng et al., 2016).

Nowadays, there are new methods for exploring this EEG through invasive and non-invasive approaches. An invasive approach requires physical implants of electrodes in humans or animals, making it possible to measure single neurons. A non-invasive approach makes use of magnetic resonance imaging (MRI) and EEG equipment or Brain Computer Interface (BCI) tools to do measurements. Both give different perspectives and enable us to look and observe what happens inside the brain (Kropotov et al., 2016). As for this research, a BCI headset tool is used. BCI tools are becoming more available on the public market, and this enables research to be done in many areas, more diversely. For example, paralysed or disabled patients can interact with the external world by the mapping of brain signals to human cognitive or sensory-motor functions (Bos et al., 2010). BCI tools development is no longer restricted to medication or treatment purposes only, but it has been extended to normal people as well. For instance, lots of BCI tool applications had been developed for educational and gaming purposes. Some of the developers made use of BCI tools to develop game-based learning to enhance the learning experience through gameplay.

With the advance in both hardware and software technologies, automated data generation and storage has become faster than ever. Streaming of the numerous data has been often a challenging, in terms of storing, analysing and visualising. The most conventional data mining techniques have to be adapted to run in a streaming environment, because of the underlying resource constraints in terms of memory and running time. One important conventional data mining problem is the classification. Raw EEG signals involve lots of readings captured from the brain. There will be difficulties to read and understand the readings. Therefore, by using the right algorithms in data mining, all the raw data can be processed and analysed properly and converted into meaningful information. The discussion above gives a motivation to the researcher to look into the ignored aspects of affective behaviour while learning in term of the techniques to assess and mine the human (specifically towards children) EEG signals into a relevant knowledge in education nowadays.

1.2 Problem Statement

Emotion is fundamental to human experience. It influences cognition, perception, and everyday tasks such as learning, communication, and rational decision-making. Literature has suggested that most studies in affective computing are related to emotion blended learning and interactive games. This will lead in the way of teaching and learning and the user behaviour when using a computer to learn and play games. Despite the importance of the educational and gaming system, this crucial parameter seems to have been ignored by a certain group of technologists and educational theorists. They failed to acknowledge the important role of emotion in academic achievement and learning. Pekrun et al. (2011) reported that human knowledge about students' emotion in educational environments remained limited eventhough the conventional theories of achievement and motivation posited emotions such as pride and shame as central components. The relationship between emotion and learning achievement was rarely analysed empirically as stated by Bandura (2014). He believed that the existing and future affective aspect of the human brain (emotion) and cognitive research needs to be adapted and applied on the learning activity nowadays.

EEG signals has been always easily misunderstood and hard to measure. However, by using the suitable and appropriate techniques such as prediction and classification, these EEG signals will be meaningful and informative. In addition, it was found that no EEG studies in Malaysia had been applied on school children to study their emotional behaviour while learning. Most of the researches focus on adults or elders in order to study human emotion. One possible reason for the lack of research in learning involves ethical consideration, such as the direct assessment of student's emotions during their learning process. This might negatively influence their learning outcomes and interrupt their problem solving effort (Goetz et al., 2008). Therefore, we aim in this research to help the academic practitioners and parents by investigating the positive and negative emotion states of the children after a learning session by capturing their EEG signals without interrupting their normal process of learning. It is believed that children will have different ability while coping with their learning environment and their emotion changes might also differ from elders.

1.3 Research Objectives

The objectives of this research are outlined as follows:

1. To classify user emotion characteristics on children's behaviour using EEG signals.
2. To develop a prototype of emotion prediction system using the best tested classification algorithm.
3. To validate the prototype of emotion prediction system in predicting the positive and negative emotions of the children.

1.4 Research Scopes

This research will specifically focus on the qualitative sampling of eight 10 years old Malaysian primary school children. These eight (8) subjects were the key respondents in this research. Any qualitative study needs to keep its sample size to a reasonably small scale depending on the targeted population. A larger number of respondents will be difficult to manage in terms of the quality of data collection and analysis that can be achieved (Ritchie & Lewis, 2014). An experimental study was set to collect the EEG signal datasets of the attention and meditation levels of the children's brainwaves in order to determine their positive and negative emotions while answering mathematic questions using a BCI headset tool in Session 1 and 2. Further explanation about these sessions can be referred in Section 3.2. Then, a preliminary study was done, where the same datasets are analysed by WEKA software to compare three classification algorithms of production rules classifier using PART type, decision tree system (also known as J48) and Naïve Bayes classifier. The most accurate algorithm in predicting the positive and negative emotions is chosen and will be used in the development of the positive and negative emotions prediction prototype using MATLAB. These three classification algorithms had been used by many former researchers who did EEG signals studies with different datasets.

1.5 Thesis Organisation

This thesis is organised into five chapters. The brief explanation of the research background, problem statement, objectives and the scopes of the research are covered in Chapter 1.

Chapter 2 discusses the literature reviews of every scopes and elements covered in this study. The review of the role of emotion in learning has been introduced in this chapter. The brief review of EEG signals and frequency bands are also presented. In addition, this chapter discusses the emotional system of representing the positive and negative emotions of the children while learning by capturing their attention and meditation level. The features, architecture and measurement of the BCI tool are also described in this chapter. The classification and prediction methods and the related works are being addressed in the last section of this chapter.

The entire flow of the whole research, hardware tools, software tools, the preliminary study and the experimental setup are discussed in Chapter 3. The approach taken to construct the prototype and the management algorithm of the emotion prediction system of MYEmotion are also being stated in this chapter.

The result and analysis of the procedures listed in Chapter 3 is discussed briefly in Chapter 4. The analysis and the performance of MYEmotion prediction system is discussed in this chapter in details.

Chapter 5 concludes this thesis and exhibits the future works and recommendations. Finally, this thesis is completed with references and appendices.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

This chapter introduces the literature review for this thesis. A brief review of HCI and the overview of the BCI tool are presented. To recognise emotion from the brain activity, the information on how the brain handles emotion and to measure the brain activity need to be understood. These are well covered in this section. A substantial literature has been studied on emotion recognition followed by the influences of emotion in learning. A review about EEG signals and the power spectrums are also provided. The review is organised chronologically to offer insight on how emotion recognition contributes to this research. The related works by other researchers will be described in the last section of this chapter.

2.2 Human–Computer Interaction (HCI)

Parmar (2003) stated that HCI is an area concentrated on the design, evaluation, and implementation of interactive computing systems to assist human in daily life. HCI application provides a major responsibility in the development of remarkable new user interface software and technology by providing the most extensive scale of important research which will transform the HCI experience. Thus, computers will no longer be known as a disturbance towards attention and focus but instead, as an invisible tool that assures the individual users experience a natural and effective human-computer collaboration. The major goal of HCI is to figure out how human interacts with computers and to signify the best way on how information is transmitted between human and computers (Garrett et al., 2003). Errity (2016) supported that the goal of HCI in creating an interactive computer mediated experiences that are satisfying and effective, where human can interact with computers to develop newer and better interaction paradigms. Satyavathy & RachelBlessie (2017) stated that HCI also focuses on the interfaces between people (users) and computers.

HCI experts constantly make efforts to improve the communication speed and quality between mankind and computer systems. They have investigated visualizations as well as multimodal presentations to ensure computers to use as many sensory channels as possible to send information to a human being. Correspondingly, they have invented both hardware and software innovations to improve the information and facts where people can easily input into computers, such as moving a mouse, hitting buttons, using hand gestures, or talking. By utilizing HCI, experts strive to presume information regarding user state and intention of monitoring their physiology, behaviour patterns or the surroundings in which they work on. With this particular information and facts, systems will be able to dynamically accommodate on their own in order to help out the user in completing the tasks.

2.3 Brain Computer Interface (BCI) Tool

Advancement of HCI interactions in cognitive neuroscience and brain imaging technological innovations have started to enable humans with the capability to interact straight away with their brains (Bos et al., 2010). This capability is possible by making use of the sensors which are able to keep track a number of the physical processes that take place within the human brain that correspond to several kinds of thoughts. Experts have tried and used these kinds of technologies to develop brain-computer interfaces (BCI) tool, the communication tools which do not rely on the brain’s regular output pathways of peripheral nerves and muscles. Through these tools, end users will be able to manipulate their brain activity rather than motor movements to generate signals which can be used to handle computers or any communication device.

Nijholt et al. (2008) believed that there is a vast possibility to bridge the study in BCI and HCI. Additionally, they also believed that BCI tool experts will certainly benefit from the body of expertise designed in the HCI area since they developed the systems that depend on interaction with the human brain as the control system. In addition, BCI tools are becoming trustworthy as the HCI experts preferably attach them to the tool belt when creating new input procedures which most notably in surroundings with limitations on routine motor movement.

2.3.1 BCI Headset Tool to Detect the Mental States

The EEG signal is a voltage signal from synchronised neural activity of millions of neurons in the brain. As a way to capture all the activities, a non-invasively device known as BCI tool is needed by placing an electrode on the scalp. As stated by Mostow et al. (2011), synchronised neural activity varies into development, mental state, cognitive activity accordingly, and the EEG signal can detect such variation. For example, rhythmic fluctuations in the EEG signal occur within several particular frequency bands, and the relative level of activity within each frequency band has been associated with specific brain states such as focused attentional processing, engagement, and frustration (Berka et al., 2007; Lutsyuk et al., 2006; Marosi et al., 2002) which in turn are important for predictive learning (Baker et al., 2010).

As stated by Wolpaw (2010), BCI is an approach to communication-based on neural activity of the brain. The aim of BCI tool is not to figure out a person by eavesdropping on brain activity , but to render an upgraded channel of the human brain output which requires voluntary adaptive control by the user alternatively. Mostow et al. (2011) used BCI tool to record EEG of adults and children reading various types of easy and hard sentences purposing to induce various mental states. Then, they trained classifiers to predict the type of the text read from the reader's EEG signal.

The EEG-based BCI includes several standard parts which will execute a unique critical function (Bos, 2006; Murugappan et al., 2007). Figure 2 .1 shows the BCI tool process cycle:

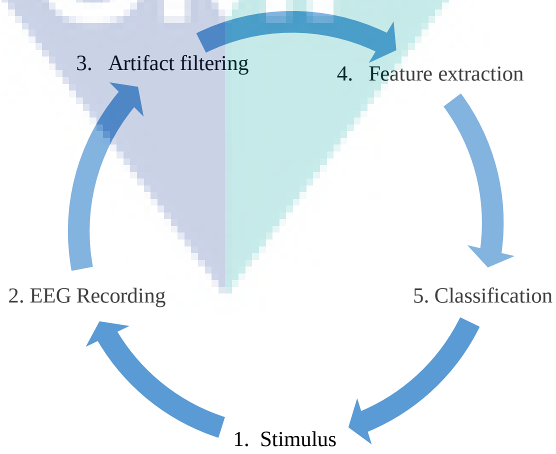


Figure 2.1 BCI tool process cycle

Source: Bos (2006)

Firstly (1) a stimulus is set and the test procedure is required. Throughout the experimental phase, the test respondent will be subjected to the stimuli in line with the test protocol. The resulting voltage changes within the brainwaves are then recorded (2) as an electroencephalogram, from which noise, as well as artifacts, is cleaned (3). The data will be analysed (4), and the appropriate characteristics will be calculated. Based on a test set of these characteristics a classifier will be trained (5), and the remaining of the data will be classified using this classifier. This step offers an interpretation of the original raw brain signals. The common BCI tool structure is illustrated in Figure 2.2.

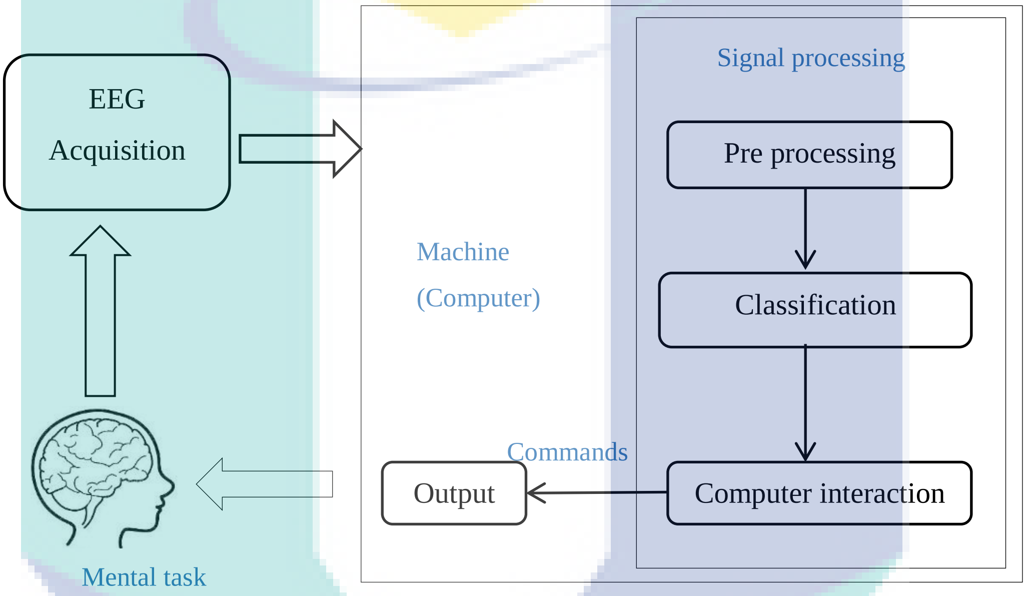


Figure 2.2 Common BCI tool structure

Source: Turnip et al. (2013)

(i) Signal acquisition: The EEG signals are obtained from the brain through invasive or non-invasive methods. After that, the signal is amplified and sampled.

(ii) Signal pre-processing: It is necessary to clean and filter all the signals obtained.

(iii) Signal classification: All filtered signals will be processed and classified in order to find out which kind of mental task the respondent is performing.

(iv) Computer interaction: The classified signals will be used by an appropriate algorithm for the development of a certain application.

2.3.2 Architecture Design of BCI

The BCI headset used in this research is a device to measure the brainwave and outputs the power spectra EEG in the form of the attention and meditation signal values. As mentioned by Rebolledo & Freitas (2008), the signals captured are used as the input in the algorithms to determine the attention and meditation levels. The algorithm returns one value per second in a range from 0 to 100, representing the respondent's level of attention and meditation.

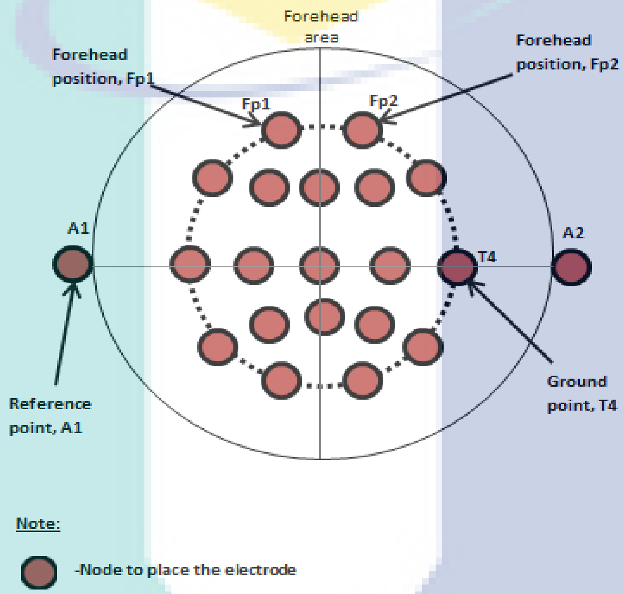


Figure 2.3 10-20 electrode placement guide
Source: Shen et al. (2009)

Inside every BCI device, there is a ThinkGear chip to collect and process the signal in a sequence of usable data and the interference that may occur are digitally filtered. This chip enables the device to interact with the wearer's brainwaves by amplifying the raw brainwave signal and removing the ambient noise and artifacts. The headset consists of a headset, an ear-clip, a sensor arm and containing the silver electrode created to read brain signals, touching the forehead above the eye at Fp1 position in accordance with the American Electroencephalographic Society. 10-20 system of electrode placement (Guðmundsdóttir, 2011). Sanei and Chambers (2013) stated that the headset's reference and ground electrodes on the ear clip at A1 and T4 help in ensuring the accuracy of the brain signals as illustrated in Figure 2.3.

Recent advances in EEG technology have led to the development of the cheaper and easier to set up products which use dry electrode-based EEG hardware with a single electrode at the forehead. It is lower in cost with greater portability and does not require any special surgery (Hassan, 2015). The measuring and analysis of the brain states become less complex and more comfortable for the respondent (Yasui, 2009). The headset used for this research is a low cost single-electrode EEG headset, which has been proven effective in detecting user's mental states and comfortable for children usage (Chee-Keong & Chia, 2015). It is very important to help the respondents who are among the primary school children to avoid any terrified feeling during the experimental session which can cause interferences in their brain wave signals.

The single point electrode means that any changes in the brainwave activity of different parts of the brain cannot be monitored. However, volume conduction makes it possible to measure electrical potentials at some distance from their source generators (Guðmundsdóttir, 2011). Therefore, the single point electrode is able to monitor a substantial part of the entire brain's activity. The sensing electrode is positioned on the forehead. There is no hair between the electrode and the scalp, which makes the signal stronger and steadier. Moreover, the cognitive signals linked to the higher states of consciousness originating from the frontal cortex, which lies directly under the forehead.

The main drawback of a single electrode system is its susceptibility to artifacts. Since there is only one sensor in place, separating brainwaves from artifacts becomes a challenge. Whenever the headset is not fastened properly to the head such as during yawning, the headset will shift a little and cause muscle movements which will result in a momentary decrease in signal quality. To avoid this, the BCI used in this research includes a ThinkGear chip which enables the device to interface with the wearer's brainwaves by amplifying the raw brainwave signal and removing the ambient noise and the artifacts mentioned above. The noise is filtered out of the raw EEG before the calculation of the eSense values. This noise elimination is performed by a proprietary noise cancellation algorithm that eliminates known noise frequencies from muscle movements and electrical devices. When the ThinkGear chip detects too much noise to be filtered out in a satisfactory way, the same eSense meter values are repeated. Therefore, all meter values that are consecutive and equal need to be marked as noise and removed before data analysis begins. Therefore, the headset is usable and suitable for this research.

2.3.3 BCI Tool Measurement

The measurements of the BCI headset tool used for this research is eSense meter for attention-meditation value scale which has been established and used by former researchers (Guðmundsdóttir, 2011; Larsen & Wang, 2011; Méndez-Gordillo et al., 2015; Shirazi et al., 2014). The headset will compute and deliver the attention and meditation eSense meter readings which these measures are trade secrets of the manufacturer and cannot be described publicly . This eSense meter can determine how effective the user is engaging to attention which also identical to concentration or meditation which similar to relaxation. The electric signals will be decoded and an algorithm is implemented to provide readings on a scale from 0 to 100. By using meter values return by the headset, it is easier for the researchers to understand thousands of data captured by the BCI headset. The eSense attention meter indicates the degree of a user's mental focus in order to determine the level of concentration. Wandering thoughts, minimal focus, distraction from surroundings or anxiousness will reduce the readings of the attention meter level (Guðmundsdóttir, 2011).

The eSense meditation meter resembles the active mental processes in the brain and signifies the intensity of a user's degree of mental calmness or relaxation. Thus, by relaxing the body and closing one's eyes often helps the mind to relax and increase the reading of meditation meter level. Moreover, Guðmundsdóttir (2011) and Hassan (2015) stated that anxiety, wandering thoughts and agitation will also reduce the meditation meter level. Hence, sensory stimulations such as smelling the unpleasant smell, touching by other people, listening to noise and disturbing sound from the surrounding and seeing other objects around are profound to be the unwanted distractions in maintaining the meditation state. Table 2.1 describes the relative eSense attention-meditation value scale that has been used by the headset.

Table 2.1 eSense attention - meditation value scale

Value	Levels
1-20	Strongly lowered
21-40	Reduced
41-60	Neutral
61-80	Slightly elevated
81-100	Elevated

Sources: Guðmundsdóttir (2011), Larsen & Wang (2011), Méndez-Gordillo et al. (2015), Shirazi et al.(2014)

From Table 2.1, the attention and meditation values are ranging from 1 to 100 at a sampling rate of 1 Hz for which these values are determined via the provided unrevealed proprietary algorithms by the developer. The values between 41 and 60 are appeared to be neutral or similar in notion to baselines state, 60 to 80 are slightly elevated levels, and 81 to 100 refer to strongly elevated attention-meditation levels. A value between 21 to 40 indicates reduce levels of the eSense, while a value between 1 to 20 indicates strongly lowered levels of the attention-meditation value (Shirazi et al., 2014). These lowered levels may indicate states of distraction, agitation, or abnormality in a user's condition. A zero eSense value means the ThinkGear is unable to calculate an eSense level with a reasonable amount of reliability due to background noise and should be removed or ignored (Hassan, 2015).

Crowley et al. (2011) reported that the readings will return high if the respondent is relaxed and not under stress condition. However, if the respondent becomes stress as a result of performing a task, the readings will return low for both attention and meditation levels. They also reported that the attention readings captured respondent's level of effort. If the respondent's effort level is high while performing a task, then the output can reach up to 100. However, the output will be near to 0 if the respondent makes no effort at all.

For a better understanding, these meter values will be simplified into a baseline of positive and negative emotions where the readings above 40 represent the positive emotion and the readings below 40 represent the negative emotion. Further explanation of applying this baseline set will be explained in Section 4.3.1. In order to observe the trends and differences between the results of the baseline set and prediction (production rules) set, the dataset of the respondent will be run in MATLAB and the results are discussed in Section 4.3.2.

2.4 Emotional System

The human emotional system is a complex, widely distributed, and error-prone system that defines our basic personality in life and is quite resistant to change. Recent evolution in the cognitive sciences is unlocking the mysteries of how and where the brain processes the emotion. The human emotional response can affect human in their everyday life. For instance, positive emotion makes it possible for a human to think more creatively and enable them to solve the complex problems. Meanwhile, negative emotion pushes into the narrow focused thinking. If someone is frustrated or afraid to something, he or she will not be able to solve even a simple problem compared to a condition where he or she is relaxed. Psychologists have studied emotional response for many years and there are many theories such as what is happening when we feel an emotion and why such response occurs. While in learning, this unique combination of the biology and psychology of emotion promises to the powerful educational applications. Thus, emotion is important in learning which enables people to drive attention which can affect the learning process and memory (Siegel, 2012; Sylwester, 1994).

2.4.1 Representing Emotion

In order to represent the emotion, some models have been proposed. There are two dominant models of the basic emotion and dimensional view models which had been used by few researchers before.

2.4.1.1 Basic Emotion Model

One of the models uses the idea that all emotion can be composed of some basic emotions, just like colors can be derived from primary colors. Plutchik (1962) related eight basic emotion to evolutionary precious characteristics and he claimed anger, fear, sadness, disgust, surprise, curiosity, acceptance, and joy to be the basic emotions. Some researchers argued for the basic emotions, stipulating that happiness is one of a number of basic emotions, including anger, sadness, happiness, fear, and disgust (Frijda, 1988; Oatley and Johnson-laird, 1987). Ekman (1999) had chosen other emotion to be the basic and found that these emotions and expressions are universal. Ekman's list of basic emotions are anger, fear, sadness, happiness, disgust and surprise.

2.4.1.2 Dimensional View Model

This model is composed of multiple dimensions and places every emotion on a multidimensional scale. Figure 2.4 is a graphical representation of the model, with the valence dimension represented horizontally on the x-axis and arousal is vertically on the y-axis. Past researches had suggested that positive and negative emotions may be associated with greater activation in the left and right hemispheres of the brain respectively. A meta-analysis by Murphy et al. (2003) found that neural activity associated with positive and negative emotions was found to be relatively symmetrical.

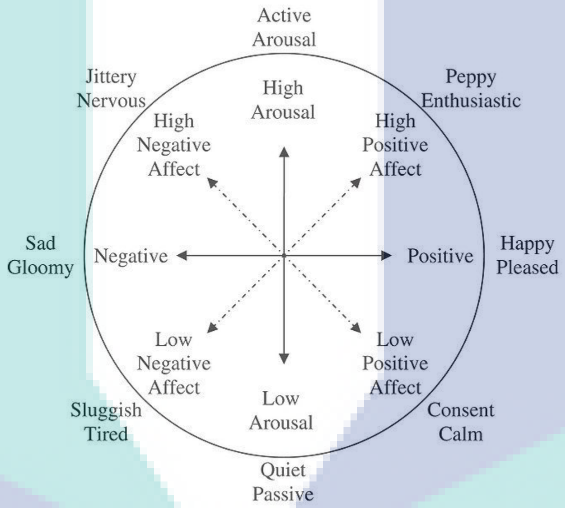


Figure 2.4 Dimensional view model
Source: Horlings (2008)

Most literatures on emotion recognition use the dimensional model of emotion because of its simplicity. It is easy to express an emotion in terms of arousal and valence or positive and negative emotions, while it is much more difficult to decompose an emotion into basic emotion. Basic emotion is more difficult to use, and there is an agreement only about a small number of basic emotions. Therefore, the dimensional model will be used in this research to represent and differentiate between the positive and negative emotions of children while perceiving learning. In accordance with the dimensional view model, the positive and negative emotions can be represented as in Figure 2.5.

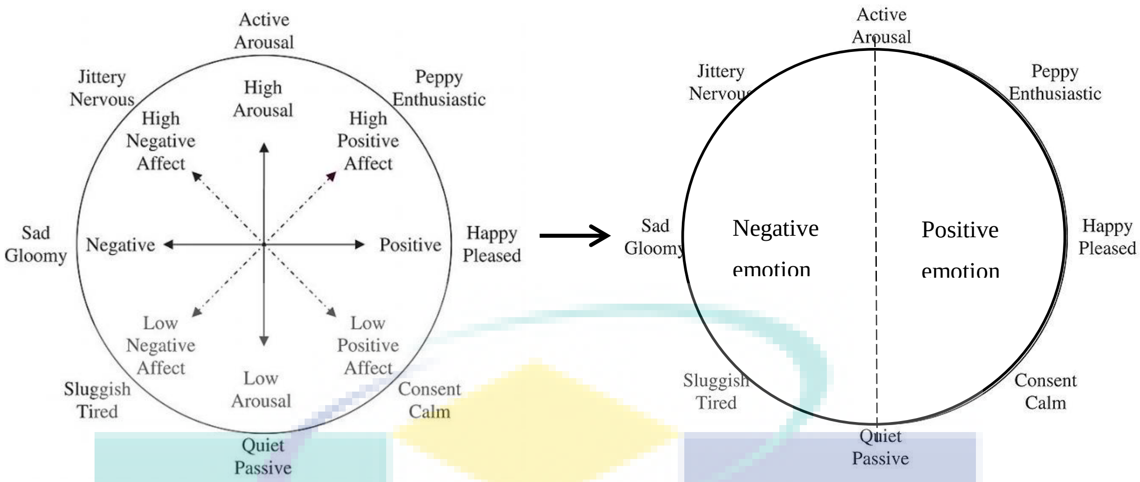


Figure 2.5 Representation of the positive and negative emotion

2.4.2 The Effect of Positive Emotion State in Learning

The positive emotional state allows an individual to become more creative, flexible, and efficient (Fredrickson & Losada, 2005). LeBlanc et al. (2014) reported that positive emotions improve the integration of information in problem solving and decision making. Likewise, evidence from the study conducted by Isen & Reeve (2005) shows that people experiencing positive emotion display patterns of thoughts that are notably unusual, flexible and efficient. The second advantage of students being in a positive emotional state is broadening students' scope for action. Hidi & Renninger (2006) studied children's reactions when playing with objects that elicited interest. He found that children in a positive emotional state showed a wider range of types of play, more variations of action within play types and longer play episodes when dealing with elicited interest objects. Positive emotions have the ability to correct, restore, and undo the after- effects of negative emotions (Lazarus, 2015). Fredrickson & Levenson (1998) reported that participants in a positive emotional state exhibited faster recovery. This finding indicates that positive emotions have the ability to reduce a negative emotional arousal.

There is also research on dysfunctional of positive emotions. For example Tiba & Szentagotai (2005) argued that uncontrolled strong positive emotions such as pride, joy and contentment can influence individual behaviour to deploy unrealistic expectation, cognitive bias leading to inappropriate action and strategies, reduce creativity in decision-making, and appraisal components (Lazarus, 1991). In high level sports such as the Olympic Games, positive emotions are perceived as dysfunctional.

Positive emotional states such as calm, relaxed, satisfied or too confident can affect the athlete's performance (Ruiz & Hanin, 2014).

In a learning context, positive emotions may also sometimes require regulation. For example, getting the correct answer to a difficult question could elicit positive emotions such as joy and pride, but lead to inappropriate learning activities if too much attention is given to the elicited emotions. Without regulation, excessive positive emotions can direct the student to focus on the euphoria and underestimate the effort needed to attain a good result. Consequently, they become overconfident and less likely to increase their effort in learning. In summary, the findings suggest that a careful approach on positive emotion regulation should be considered in an affective tutorial system framework so that the positive emotion can be nurtured to optimize learning.

Emotions resulted from an appropriate attention, self-regulation and motivation strategies can lead to a positive effect on learning and achievement. For example, positive emotions promote a more inclusive form of thinking that permits a person to be more creative and willing to take risks that could guide him to produce better learning outcomes. Negative emotions such as fear and anxiety can assist students in learning. These elicited emotional states may alert students to become more careful and analytic in their learning so that a better learning outcome can be produced which, in turn, improves their negative affective states. However, excessive negative emotions may reduce the student's problem-solving ability in learning (Bandura, 2014).

2.4.3 The Effect of Negative Emotion State in Learning

Yusoff & Zin (2013) highlights four potential effects of negative emotional state among students. Firstly, students in a negative emotional state sometimes cannot recognise the exact emotions they are experiencing as stated by Pekrun et al.(2011). This may lead to a student sometimes ignoring or denying his emotional state. As a result, the student may fail to engage in adaptive strategies for regulating his negative emotions, thereby prolonging his distress.

Secondly, they are inclined to misinterpret the causes of problems associated with their learning and may lead them to seek inappropriate solutions to their problem or not to seek any solution at all. Thirdly, a student in this negative emotional state may have adequate knowledge but is unable to use it while in a negative emotional state.

This knowledge deficit may be a result of never having learned effective strategies for managing negative effect. Finally, a student in a negative emotional state may experience inability to execute or exercise the necessary responses of his selected solutions of a problem. This is due to the general skills deficit or a temporary deficit resulting from their negative effect (Pekrun et al., 2011). Students with negative effect have been found to generate significantly more irrelevant strategies than students with positive effect, although they did not differ with regard to the total number of alternative strategies generated.

2.4.4 Recognizing the Emotion

Emotion recognition could be done from text, speech, facial expression, gestures or physiological signals. There were various research examples by former researchers to this kind of emotion recognition. However, it was proven that the physiological signals generated from the human brain wave (EEG) were much more meaningful and valid as humans could control their expression or vocal intonation (Liu et al., 2010). Cohen (2017) stated in his paper that EEG is one of the most important non-invasive brain imaging tools in neuroscience. According to Chee-Keong & Chong (2015), the first report on electrical brain activity in 1929 had allowed the clinicians and scientists to monitor the brain in a meaningful way. Blanchard et al. (2009) stated that there were many other physiological signals that can be considered to study the human emotion, mainly heart rate (HR) and blood volume pressure (BVP) for cardiovascular activity, skin temperature (ST) (Ward & Ingleby, 2009), respiration (Ley, 1994; Morrissey, 2006), galvanic skin response (GSR) (Lang, 1995), surface electromyography (SEMG) and EEG (Blanchard et al., 2009).

There were few studies concerning the emotion recognition from these biological or psychological signals. Picard et al. (2001) recognised emotion by collecting electromyographic data, blood volume pressure, skin conductance, and respiration information from one person during a number of weeks from eight emotion categories. Kim et al. (2004) did a user independent study using information from the skin temperature, skin conductance, and heart rate. Meanwhile, Haag et al. (2004) used data from electrocardiography, electromyographic signals, blood volume pressure, skin conductance, respiration, and skin temperature. There were numbers of studies implemented physiological signals for emotion classification and recognition, but only a few made used the EEG signals (Blanchard et al., 2009).

2.4.5 Electroencephalogram (EEG) Signals

EEG signals are a representation of the neural electrical activities present throughout the brain called brain wave. Generally, these different brainwaves are set in groups of Delta, Theta, Alpha, Beta and Gamma bands to indicate the mental state of the brain at a given moment as illustrated in Table 2.3. The frequency of each wave is measured in Hertz (Hz) unit.

Leins et al. (2007) found that different electrical frequencies could be linked to actions and different stages of consciousness. This was done by observing respondents performing different tasks, such as solving mathematical problems while capturing their EEG readings. Human brain puts off waves of energy that can be traced and recorded These brainwaves are placed into categories that can tell how the brain is functioning and what a person is doing very often based on of their brainwaves (Horlings et al., 2008) as illustrated in Table 2.2.

Table 2.2 Frequency bands

Wave	Frequency	Mental State
Delta	0.5-4Hz	Deep sleep, unconsciousness.
Theta	4-8 Hz	Creativity, dream sleep, drifting thoughts, inefficiency state, daydreaming, drowsiness.
Alpha	8-13 Hz	Relaxation, calmness, abstract thinking, meditate.
Beta	13-30Hz	Relaxed focus, high alertness, hyperexcitable, agitation, anxiety, attention state.
Gamma	Above 30Hz	Consciousness.

2.4.5.1 Gamma Wave

Gamma waves are in the frequency range of 30Hz and above. It reflects the mechanism of consciousness. Rangaswamy et al. (2002) stated that beta and gamma waves have been associated with attention, perception, and cognition.

2.4.5.2 Beta Wave

Beta waves are in the frequency range between 13 to 30 Hz , but are often divided into Beta 1 (β1) and Beta 2 (β2). Beta waves are associated with focus, concentration and best defined in central and frontal areas of the brain. When a person is very well involved, active or engaged in challenging mental activities, their brainwaves are actually operating in beta level. Beta waves are often associated with active conversation when mental and verbal skills need to engage to each other at the same time. When avoiding or suppressing movement or solving a math task, there is an increase in beta activity (Zhou et al., 2009).

2.4.5.3 Alpha Wave

Alpha waves are ranging from 8 to 13 Hz. These waves are slower but have a higher amplitude. These waves are associated with relaxation and disengagement. Larsen & Wang (2011) reported that thinking of something peaceful with eyes closed should give an increase of alpha activity which most profound in the back of the head and in the frontal lobe. Several studies have found a significant rise in alpha power after smoking marijuana (Lukas et al., 1995). The people who are in a resting state or coming down from a busy set of activities are often in the alpha brainwave state. The people who practise light meditation will also be functioning in the alpha brain level. It was found that the low alpha frequencies relate to attention and high alpha frequencies relate to some cognitive processes such as memory (Guðmundsdóttir, 2011; Klimesch, 1999)

2.4.5.4 Theta Wave

Theta waves are waves that ranging between 4 to 8 Hz. These waves are correlated with inefficiency, daydreaming and the smallest and weakest waves of theta represent by the borderline between being awake and in a sleep state. Theta waves are normally recorded in someone who is zoning out, a state where someone is losing the concentration and consciousness. For example, if someone does not remember the details of his car trip after driven home from work, then his brain is actually functioning at a theta level. A deeper meditation is often recorded in this state are trance states and hypnosis. Theta wave arises from emotional stress, especially frustration or disappointment (Li et al., 2005). It has also been associated with access to unconscious material, creative inspiration, and deep meditation. High levels of theta are considered abnormal in adults and much more related to Attention Deficit Hyperactivity Disorder (AD/HD) (Heinrich & Gevensleben, 2007).

The brainwave that can connect to psychic abilities is from this theta pattern. People will often receive insight, message, or creative ideas through this theta pattern where it may seem these ideas pop out of nowhere but surprisingly, it actually happens as the busy mind in the beta level is quiet and a person is able to listen to a deeper wisdom by tapping into his or her theta brainwave pattern with practice. People who have been proven to have psychic abilities have learned to tap into this brain pattern and the most interesting part is anyone can do it.

2.4.5.5 Delta Wave

The slowest and deepest of the brainwave levels is the delta pattern. Delta waves are ranging from 0.5 to 4 Hz. These waves are the slowest waves and occur when sleeping (Hammond, 2007). The delta pattern will reflect two different speeds of a dreaming and non-dreaming conditions. In daydreaming, for example after about 90 minutes of sleep, typically everyone will enter a delta brain pattern state. This is considered the most restorative time for the brain. However, if these waves happen to occur in the awake state, it indicates the physical defects in the brain. Larsen & Wang (2011) stated that the movement can make artificial delta waves, but this can be verified with an instant analysis by just observing the raw EEG records.

Based on the above literature review regarding the waves in the human brain, it can be deduced that meditation and attention are the emotion in alpha and beta waves categories respectively. This research will focus towards capturing attention and meditation information of children while learning. The next section will further discuss the significance and the relationship between the attention and meditation information in predicting the children’s positive and negative emotions while learning.

2.4.6 Relationship between the Attention and Meditation Level

Attention indicates the level of mental focus while meditation is an indicative of the level of the mental calmness. Behavioural and neurophysiological studies have shown that meditation improves attention performance. A five days training of 20 minutes of meditation per day improved conflict scores on the Attention Network Test relative to a relaxation control group (Tang et al., 2007). Meditation experience is associated with reduced interference during the Stroop task (Chan & Woollacott, 2007) and meditators have a better attention performance in the Stroop task compared to a meditation-naïve control group (Moore & Malinowski, 2009). These findings suggest that meditation training results in better attention performance.

Several recent researches have suggested that meditation training may change brain morphology and function, which particularly in areas associated with attention and response selection (Hölzel et al., 2011; Jang et al., 2010). Long-term meditation practice was in connection with an elevated cortical thickness in respondents who practise insight meditation, which involves focused attention on internal experience. It can be concluded that these attention and meditation levels are both related to each other and meditation can improve memory and attention performances.

According to Keller's ARCS model, both low and high levels of attention could be detected and reaction feedback could be provided so that the learner could improve or sustain their attention (Rebolledo & Freitas, 2008). From the literature study, it was found that meditation level is correlated to attention state of a human brain (Chan & Woollacott, 2007). Short-term meditation training was found to improve attention and self-regulation (Tang et al., 2007), enhance attention stability (Lutz et al., 2009), reduce stress and increase mental focus (Chan & Woollacott, 2007). Lutz et al. (2009) also stated that the attention state is cultivated by meditation state at the first place. Crowley et al. (2011) reported that meditation state represents the user's state of arousal or the state when a person is active or attentive to a certain situation.

Meditation acts as a control and will occur as early as before the attention state could arise from any activity, meaning that people need to have a meditation state in order to sustain the attention state. However, the differences and inconsistency in meditation readings between people still can occur as different people will have different mental training practices as mentioned by Slagter et al. (2007). Some people tend to meditate themselves by focusing on objects, paying attention to the present moment, relaxing their body and closing their eyes. Breathing practice and mental imagery also can help people to access the meditative states.

2.5 Data Mining

The electroencephalograph (EEG) data are not easy to understand as they involve a lot of readings. Data mining concept can be a good option to handle this kind of data. Data mining is defined as the process of discovering meaningful patterns in data. Data mining is also a powerful new technology with great potential to help an individual or an organisation to retrieve the important information from their data warehouses. According to Padhy et al. (2012), most of the data mining applications are being used for prediction of the future state of data. In prediction, the current and past states of attributes and prediction of future states will be analysed. The data is stored electronically and the search is automated and augmented by the computer. The enormous growth of databases in recent years has brought data mining to the forefront of new business technologies. It has been estimated that the amount of data stored in the world's database doubles every 20 months and increase the opportunities for data mining to take place. Data mining solves problems by analysing data that already present in the database. For example, in the database of customer choices, patterns of behaviour of former customer can be analysed to identify a different characteristic of those likely to switch products and those likely to remain loyal.

2.5.1 Data Mining Algorithms

An algorithm in data mining (or machine learning) is a set of heuristics and computations that generate a model from data. To build a model, the algorithm initially will be analysing the data provided, searching for specific types of patterns or trends. The algorithm uses the results of this analysis over a number of iterations to find the best parameters for developing the mining model. These types of parameters are then applied to the entire data set to extract actionable patterns and detailed statistics. The mining model that an algorithm creates from your data can take various forms. For examples:

(i) A set of clusters that describes how the cases in a dataset are related.

(ii) A decision tree that predicts an outcome, and describes how different criteria affect that outcome.

(iii) A mathematical model that forecasts sales.

(iv) A set of rules that describes such as how products are grouped together in a transaction and the probabilities that products are purchased together.

This research will focus on the rules set generation from the attention and meditation datasets obtained from the experiment to predict the positive and negative emotions of the children while learning.

2.5.2 Functions of Data Mining

Data mining deals with various kinds of patterns that can be mined. There are two categories of functions that involved in data mining, which are descriptive as well as classification and prediction.

2.5.2.1 Descriptive Function

Descriptive data mining deals with the general properties of data in the database. There are several types of descriptive data mining such as:

(i) Class/concept description
(ii) Mining of frequent pattern
(iii) Mining of association
(iv) Mining of correlation
(v) Mining of clusters

2.5.2.2 Classification and Prediction

Classification and prediction provide the capability to discover a model that represents the data clause or concepts. The goal is to be able to use this model to predict the class of respondents whose class label is unknown. There are various classification algorithms which can be used to classify the data sets . This research will focus on three of the classification algorithms of production rules classifier (PART), Naive Bayes and decision tree (J48). The detail explanation of these three classifiers will be discussed further in Section 2.5.3. There were few researchers who did classification and prediction of different datasets using the selected classification algorithm of the decision tree, Naïve Bayes, and production rules classifiers. Table 2.3 illustrates a short review of the related works involving classification of various datasets. From Table 2.3, it can be seen that the selected classification algorithm, especially the production rules classifier was widely used by the former researchers to classify and predict their data. The datasets might be different to each other, but the process flow that had been done could be used for further research works with another type of datasets.

Table 2.3 Related works of classification

Researchers	Respondents	Dataset	Classification algorithm	Efficiency rate (%)
Kabakchieva (2013)		Students' achievement & pre-university characteristics	-Production rules (OneR, JRip) -Decision Tree (J48) -Naive Bayes -BayesNet -Nearest Neighbor (k=100,k=250)	-OneR 48.1% -JRip 62.1% -J48 63.1% -Naive Bayes 59% -BayesNet 59.6% -Nearest Neighbor (k=100) 57% -Nearest Neighbor (k=250) 56.1%
Mahajan and Ganpati (2014)		Chess end	Rule based system: -OneR -PART -Decision Table -DTNB -Ridor	-OneR 67.5% -PART 99.1% -Decision Table 97.2% -DTNB 96.6% -Ridor 98.6%
Srinivas (2012)	286 cancer patients	Breast cancer	RIPPER -Decision Table -DTNB	-RIPPER 72.27% -DT 72.72% -DTNB 75.17%

Table 2.3 Continued

Researchers	Respondents	Dataset	Classification algorithm	Efficiency rate (%)
Palanisamy (2006)		-Sonar -Census income -Mushroom -Forest cover	-Association Rule (CBA) -ZeroR -Decision Tree (J48)	-Sonar CBA 74.65% ZeroR 54.93% J48 70.43% -Census income CBA 83.5% J48 84.07% ZeroR 76.27% -Mushroom CBA 99.02% J48 100% ZeroR 50.4% -Forest cover CBA 62.53% J48 88% ZeroR 61%

Table 2.3 Continued

Researchers	Respondents	Dataset	Classification algorithm	Efficiency rate (%)
Shirazi et al. (2014)	20 respondents (8 female), average age of 23.3 years	Reading & relaxing task	Naive Bayes	-Reading task 97% -Relaxing task 79%
Serasiya and Chaudhary (2012)		Weather	Decision Tree (J48)	-Training set 100% -Supplied test set 55.5 % -Cross-validation (folds=10) 57.14 % -Percentage split (40%) 62.5%
Sabeti et al.(2007)	20 schizophrenic patient 20 age-matched respondents of (18-55 years old)	Schizophrenia	Association Rule (CBA)	80 %
Chanel et al.(2006)	3 males and 1 female		Naive Bayes	50-72%
Sharif et al. (2015)	8 children (7-12 years old)	Attention and meditation level	-Production rules (PART) -Decision Tree (J48) -Naive Bayes	-PART 99.6% -J48 99.5% -Naive Bayes 96.2%

2.5.3 Classification Algorithms (Classifiers)

There are various classification algorithms in data mining. This research only focuses to 3 main classifiers of the decision tree (J48), Naïve Bayes and production rules (PART) classifiers because they were applied by most of the former researchers to classify and predict their data (Chanel et al., 2006; Kabakchieva, 2013; Mahajan & Ganpati, 2014; Palanisamy, 2006; Sabeti et al., 2007; Serasiya & Chaudhary, 2012; Sharif et al., 2015; Shirazi et al., 2014; Srinivas, 2012).

2.5.3.1 Decision Tree Classifier (J48)

A decision tree is a tree-like structure, which starts from root attributes, and ends with leaf nodes. The decision tree resembles a flowchart that has the nodes that contain attribute values. Generally, the branch represents the outcomes of the test and the leaves represent a class of distribution (Jain & Srivastava, 2013; Kabakchieva, 2013).

A decision tree can be categorized as a predictive model to be used for classification. It is also able to generate rules and favored techniques to build an understanding model because of the nature of the tree structure: understandable and relatively fast. Other advantages of decision trees are that they represent rules which could easily be understood and interpreted by users, do not require complex data preparation, and perform well for numerical and categorical variables. This is supported by Kabakchieva (2013) who reported that decision trees are powerful and popular tools for classification. There are many different types of decision trees such as Chi-Square Automatic Interaction Detection (CHAID) (Kass, 1980), Classification and Regression Trees (CART) (Breiman, 1996) and C4.5 (J48) (Quinlan, 1996). This research will only highlight J48 for the data analysis and comparison purposes.

Figure 2.6 illustrates a dataset containing data which related to lifestyle and heart disease. Each row has a person, sex, age, Smoker (Yes/No), Diet (Good/Poor), and a label Risk (Less Risk/More Risk). The data indicates that the biggest influence on Risk turns out to be the Smoker attribute. The Smoker will be the first branch in the tree. For Smokers, the next influential attribute happens to be Age. However, the data indicates that diet for non-smoker (Smoker=No) has a bigger influence on the risk . The tree will part into two different nodes until the classification reached the maximum depth that has been established.

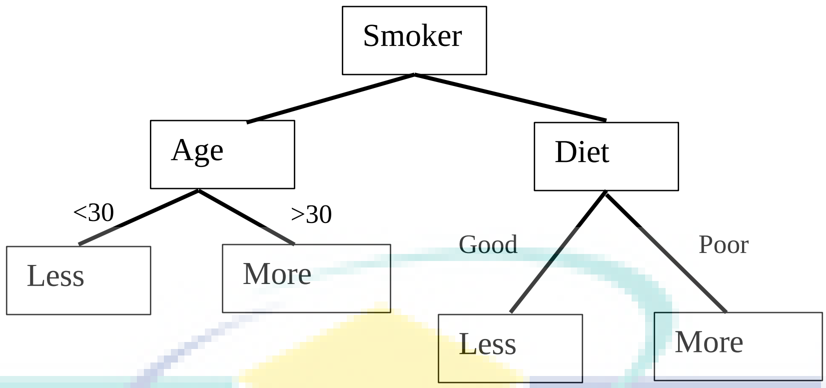


Figure 2.6 Example of a decision tree

According to Li & Wong (2004), a decision tree is a good learning algorithm that can induce classification rules that use a small number of features. For example, suppose a gene expression cancer diagnosis dataset have *n* number of features, but by using a tree induction algorithm such as C4.5, the value of *n* could be reduced to a very small *n* number of features. This small number of features may help biomedical experts to understand the medical mechanism in a better way.

2.5.3.2 Naïve Bayes Classifier

A Naïve Bayes classifier is a simple probabilistic classifier. This classifier computes the probability that some data points belong to a specific class. To perform the classification, the algorithm chooses the class with the highest probability, as its result (Horlings, 2008). Based on the precise nature of the probability model, Naïve Bayes classifier can be trained efficiently in a supervised learning setting. In many practical applications, parameter estimation for Naïve Bayes model uses the method of maximum likelihood; in other words, one can work with the Naïve Bayes model without believing in Bayesian probability or using any Bayesian methods. In spite of the naïve design and apparently over-simplified assumptions, Naïve Bayes classifiers have worked quite well in many complex real-world situations.

An advantage of the Naïve Bayes classifier is it only requires a small amount of training data to estimate the parameters (means and variances of the variables) that are necessary for the classification. Because independent variables are assumed, only the variances of the variables for each class need to be determined and not the entire covariance matrix.

2.5.3.3 Production Rules Classifier (PART)

The rules are known as an option to the decision tree. Each leaf of a tree will generate one rule. A condition for every node is an antecedent of the rule on the path from the root to the leaf while the class assigned by the leaf is the consequent of the rule. In general, the rule sets are more clearly expressed compared to a decision tree, rules derived from the trees are usually prone to remove redundant tests, easy to understand and read. The production rules classifier classifies records by using a collection of if-then rules. It is much easier to understand and need a very limited calculation. It can be described in several characteristics:

(i) Mutually exclusive rules:

Classifier contains mutually exclusive rules if the rules are independent of each other and every record is covered by at most one rule

(ii) Exhaustive rules

Classifier has exhaustive coverage if it accounts for every possible combination of attribute values where each record is covered by at least one rule.

Some other classifier, may not always achieve the above two properties. There are many types of production rules classification algorithm such as PART, OneR, ZeroR, Decision Table and RIDOR. This research will only include PART for the classification process because it is found to be the most accurate algorithm compared to the others (Mahajan & Ganpati, 2014). PART is a separate-and-conquer rule learner proposed by Frank & Witten (1998). A new data entry is compared to each rule in the list and the first matching rule will assign the data to the right category. A default is applied if no rules are successfully match the new data entry. PART builds a partial C4.5 decision tree in its each iteration and makes the best leaf into a rule. This classifier is a combination of C4.5 and RIPPER rule learning which can be represented in Equation 2.1 (Ali & Smith, 2006).

$$Rule\ \boldsymbol{n}: \quad (Condition) \rightarrow y \qquad 2.1$$

n refers to the number of rules generated where ***n*** = *1,2,3,* While *Condition* is a conjunction of attributes tests *and y* is the decided class label of a certain condition. Let say, the following Table 2.4 of animals’ categories dataset is given:

Table 2.4 Animal categories dataset

Name	Blood Type	Give Birth	Can Fly	Live in Water	Class
Human	warm	yes	no	no	Mammals
Python	cold	no	no	no	Reptiles
Salmon	cold	no	no	yes	Fishes
Whale	warm	yes	no	yes	Mammals
Frog	cold	no	no	sometimes	Amphibians
Komodo	warm	no	no	no	Reptiles
Bad	warm	yes	yes	no	Mammals
Pigeon	warm	no	yes	no	Birds
Cat	warm	yes	no	no	Mammals
Shark	cold	yes	no	yes	Fishes
Turtle	cold	no	no	sometimes	Reptiles
Penguin	warm	no	no	sometimes	Birds
Porcupine	warm	yes	no	no	Mammals
Eel	cold	no	no	yes	Fishes
Salamander	cold	no	no	sometimes	Amphibians
Gila monster	cold	no	no	no	Reptiles
Platypus	warm	no	no	no	Mammals
Owl	warm	no	yes	no	Birds
Dolphin	warm	yes	no	yes	Mammals

From the table, five rules can be learnt from the dataset:

R1: (Give Birth = no) ∧ (Can Fly = yes) → Birds

R2: (Give Birth = no) ∧ (Live in Water = yes) → Fishes

R3: (Give Birth = yes) ∧ (Blood Type = warm) → Mammals

R4: (Give Birth = no) ∧ (Can Fly = no) → Reptiles

R5: (Live in Water = sometimes) → Amphibians

So, when new animals and their characteristics are added into the table, the class of the animals can be determined easily. For example, if new data of animals: hawk and grizzly bear are added as illustrated in Table 2.5.

Table 2.5 New data of animal categories dataset

Name	Blood Type	Give Birth	Can Fly	Live in Water	Class
Hawk	warm	no	yes	no	?
Bear	warm	yes	no	no	?

It can be deduced that R1 covers a hawk and make the hawk in 'Bird' class while R3 covers the grizzly bear and return the 'Mammal' class.

Table 2.6 summarises the characteristics and the former researchers who used the above three classifiers.

Table 2.6 Comparisons between the classifiers

Classifiers	Characteristics	Authors
Production rules classifier	-As an option to the decision tree - Rule sets are more clearly expressed compared to a decision tree - Easy to understand - Easy to read and much more simpler than decision tree - Easy to generate and interpret - Need a very limited calculation and can classify new instances rapidly	-Kabakchieva (2013) -Mahajan and Ganpati (2014) -Srinivas (2012) -Palanisamy (2006) -Sabeti et al.(2007)
Decision Tree	- Understandable - Fast - Represent rules which could easily be understood by the users - Do not require complex data preparation - Perform well for numerical and categorical variables - A good learning algorithm that can induce classification rules that use a small number of features	-Kabakchieva (2013) -Palanisamy (2006)
Naïve Bayes	- Simple probabilistic classifier - Requires a small amount of training data to estimate the parameters that are necessary for the classification	-Kabakchieva (2013) -Shirazi et al. (2014) -Chanel et al.(2006

2.6 Summary

A review of the related research highlighted that it is possible to measure any emotional response from EEG activity by using different platforms, techniques, datasets, and tools. The significance of the attention and meditation data in predicting positive and negative emotions in learning session is understood to be important in education nowadays. These data are not easy to understand as they involve a lot of readings. Thus, the classification and prediction techniques in data mining will play an important role to turn the data into meaningful and understandable information. Chapter 3 will discuss the methods used in this research.

CHAPTER 3

METHODOLOGY

3.1 Introduction

This chapter discusses the experimental design to obtain the data from the headset tool. Data preprocessing and data classification as the essential steps are briefly presented. The model used to develop the prototype is illustrated in this chapter. Finally, the process flow towards the prototype development of MYEmotion are also explained in this chapter. For a better understanding, the conceptual framework used in this research to outline the preferred methods is shown in Figure 3.1.

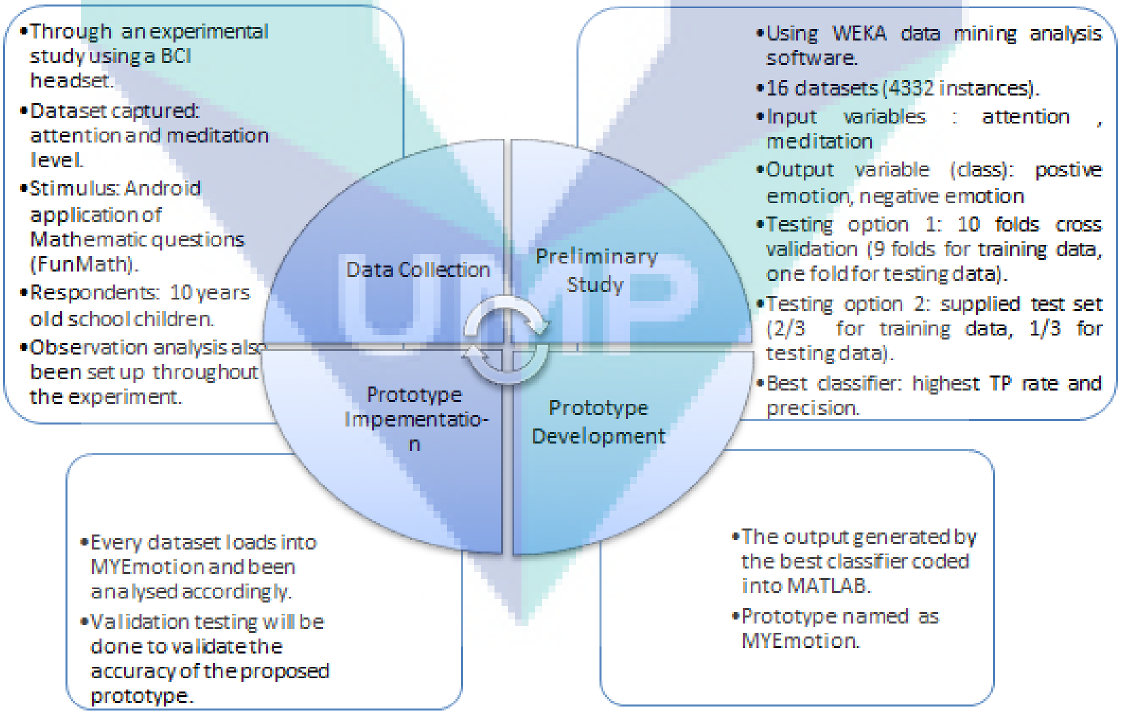


Figure 3.1 Research method framework

There are four processes used in this research which are the data collection, preliminary study, prototype development and finally the prototype implementation. During the data collection, a BCI headset was used to capture the attention and meditation data of the children through an experimental study. The stimulus was an Android application of Mathematic questions named Fun Math. The respondents selected were among the 10 years old children. The observation analysis to support the findings also had been set up throughout the experiment.

After that, a preliminary study was conducted using WEKA data mining analysis software to classify all the data captured into the positive and negative emotions. This preliminary study was also intended to find for the best among three classification algorithm/classifier (production rule classifier, Naïve Bayes classifier and decision tree classifier) in classifying and predicting the positive and negative emotions of the children while learning. There were 16 datasets involved with 4332 instances. The example of the dataset runs in WEKA will be explained in Section 3.5. The input variables were the attention and meditation levels while the output variables or the classes were the positive and negative emotions. Two testing options implemented in each classifier were 10 fold cross validation and supplied test set. The best classifier was decided based on the highest true positive (TP) rate and its precision value.

During the prototype development, the output generated by the best classifier was coded in MATLAB to predict the positive and negative emotions of the children while learning. The prototype is named as MYEmotion.

The last process is the prototype implementation where the datasets to be tested are loaded into MYEmotion and analysed accordingly. A validation testing using similarity (*Sim*) function was done to validate the accuracy of the proposed prototype in predicting the positive and negative emotions of the children while learning.

Table 3.1 illustrates the summary of the methods used in this research. Generally, this research has seven phases comprises problem identification, data acquisition processes, data mining analysis process, preliminary analysis, development of MYEmotion, implementation of MYEmotion and finally the validation testing of MYEmotion. All phases fulfilled the research objectives and will be discussed in a specific section as highlighted in Table 3.1.

Table 3.1 Summary of the study phases

Objective	Phase	Method	Process	Section	Tool/material/data
Objective 1	Phase 1	Problem Identification		3.2	
	Phase 2	Data Acquisition	Experimental study	3.3.1	-Eight 10 years old children -Fun Math -EEG Analyzer
			Observation analysis	3.3.2	-Eight 10 years old children -Observation form
	Phase 3	Data Mining Analysis Process	Data Preprocessing	3.4.1	16 datasets of attention and meditation level
			Classification of positive and negative emotion	3.4.2	16 datasets of attention and meditation level
	Phase 4	Preliminary Analysis		3.5	-16 datasets of attention and meditation level WEKA
Objective 2	Phase 5	MYEmotion Development	Rapid prototyping development model	3.6	-A set of production rules prediction set -MATLAB
	Phase 6	Implementation of MYEmotion		3.7	MATLAB
Objective 3	Phase 7	Validation Testing		3.8 4.4	Sim function

3.2 Phase 1: Problem Identification

This phase involves the problem identification defined from the research problems, scopes and objectives. A very comprehensive study about the problem is needed before the solution could be provided accordingly. As for this research, the problem that arose was, how EEG signals can be measured by using the data mining methods of classification and prediction.

3.3 Phase 2: Data Acquisition Processes

An experimental study and observation analysis had been done in order to obtain the required amount of data for this research.

3.3.1 Experimental Study

The respondents of this study were eight 10 years old children of a primary school in Pekan, Pahang. They were all normal children without any history of medical, neurological or psychiatric illness. All participants were given a sufficient and clear introduction on the test sessions. The experimental setup was a desktop PC or laptop, BCI headset, webcam, comfortable chair, controlled room with typical room temperature, mouse, and keyboard. Figure 3.3 shows the setup of the experiment.

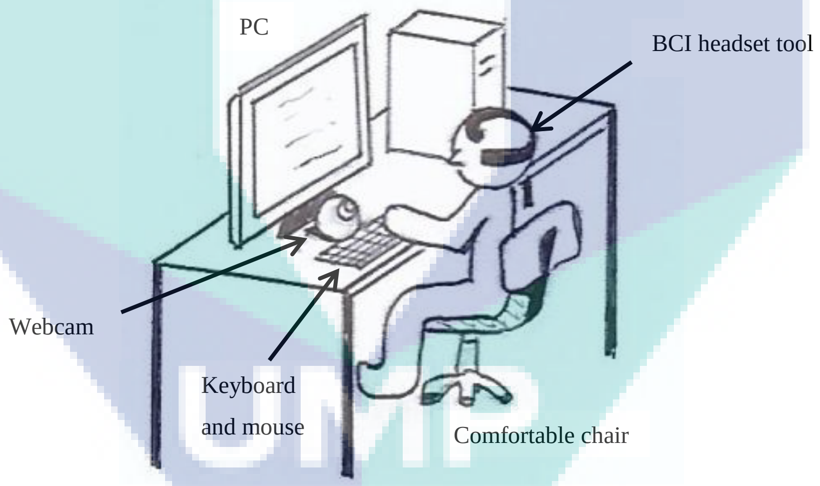
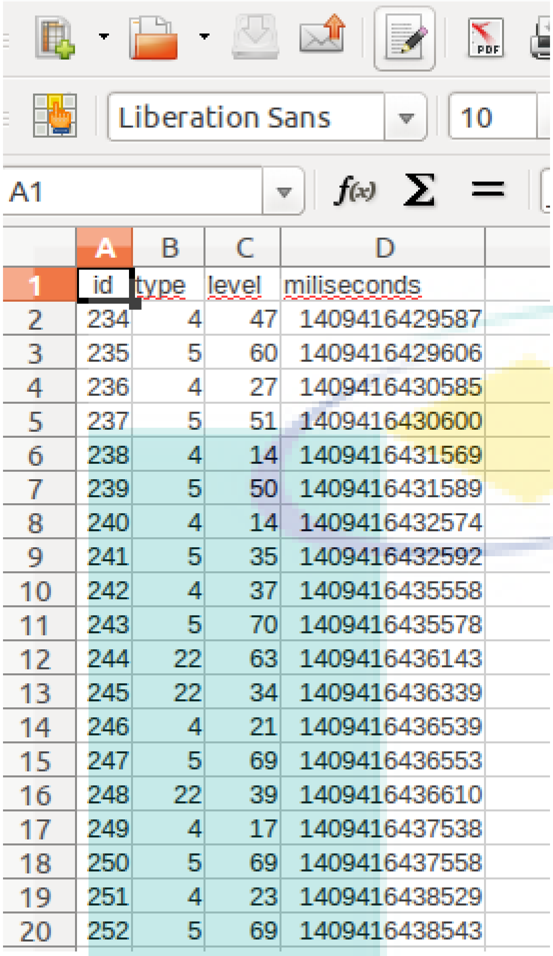


Figure 3.2 Experiment setup

The respondent wore a BCI headset tool with the front electrode resting on her or his forehead and the ear clip was properly in contact with the lower part of the earlobe to provide a ground reference as shown in Figure 3.3. The device worn by the respondent should be correctly connected via Bluetooth to the Android device that has been used to capture the attention and meditation data. Each respondent took part in two sessions of mathematical games. There were many other stimulus that had been used by former researchers to induce the attention and meditation readings using the same headset tool. Crowley et al. (2011) used mathematical game (Towers of Hanoi), Mostow et al. (2011) asked his respondents to do the reading tasks, while Crowley et al. (2011) and Robbins et al. (2014) used a word-inference test which requires the subject to name the color that is displayed on the screen and not the word known as Stroop Test. This experiment was done in 2 sessions because the researcher would like to record if there are any changes in children's positive and negative emotions with and without any prior preparation. From the literature, it was found that emotion is not discrete as the state of the brain signals can change in split seconds. As mentioned by Denham (2007), children regulate and deal their emotions with their own norms and values.

Figure 3.3 A respondent wears the BCI headset tool

Session 1 began with respondents completing a 5 minute session of answering mathematical game, without any prior preparation. They sat in front of the computer and immediately requested to start answering an Android interactive mathematical game, Fun Math. Their brain readings were recorded by the headset and transmitted to the Android device via Bluetooth system. An EEG recording software named EEG Analyzer was installed on the Android device. After the session ended, the software will allow the researchers to export all the readings into the Dropbox storage before it can be viewed in comma separated value (.csv) format. The example of the raw output generated from the EEG Analyzer can referred in Figure 3.4.



	A	B	C	D
1	id	type	level	miliseconds
2	234	4	47	1409416429587
3	235	5	60	1409416429606
4	236	4	27	1409416430585
5	237	5	51	1409416430600
6	238	4	14	1409416431569
7	239	5	50	1409416431589
8	240	4	14	1409416432574
9	241	5	35	1409416432592
10	242	4	37	1409416435558
11	243	5	70	1409416435578
12	244	22	63	1409416436143
13	245	22	34	1409416436339
14	246	4	21	1409416436539
15	247	5	69	1409416436553
16	248	22	39	1409416436610
17	249	4	17	1409416437538
18	250	5	69	1409416437558
19	251	4	23	1409416438529
20	252	5	69	1409416438543

Figure 3.4 Sample raw output from EEG Analyzer

After completing the first session, the respondent was given 2 minutes rest before they were asked to play the game again for Session 2. The session of answering questions from Fun Math lasted over 5 minutes. His or her EEG signal was recorded and the same procedures took place as in the first session. There are 16 datasets collected from all respondents. The researcher will observe the respondents' behaviour by observing and asking few simple questions to the children throughout the experiment to determine the current states of respondent emotion before and after the learning sessions which will also be discussed in Section 3.3.2. The observation form can be referred to Appendix A.

This experimental study was not conducted as a one-off event, as the researcher at the first place need to study the experiences and exposure of the targeted respondents towards computers and gadgets. This was done due to the different backgrounds of each respondent, to eliminate nervousness, build confidence and to ensure a positive learning environment. The researcher has to make sure all the respondents to get familiar with the devices before the real experiment takes place. This experiment involved a lot of efforts and enthusiasm, time consuming and a very challenging task for the researchers. Children tend to have a learning refusal problem, especially for children with learning disabilities. Therefore, the element of trust and friendship to attract the children's attention and interest is needed. Children emotion is genuine. Garner (1999) asserted that after the age of five, children have increasing familiarity with even complex emotion terms like pride and embarrassment, and are capable of the self-reflection needed to accurately report their occurrence. Therefore, there was no emotion induction through provocations involved in this research as the researchers will let the children to naturally deal with their own emotions while answering the mathematical game.

3.3.2 Observation Analysis

An observation analysis was done to all respondents by using 11 questions based on emotion state (by referring to the dimensional view model as explained in Section 2.4.1.2) to determine the current states of respondent emotion before and after learning sessions (as for this research, they will answer mathematical game using Android learning application).The questions were asked to each participant in 2 different sessions of Session 1 (before answering mathematical game) and Session 2 (after finished answering all the questions) with no time limit was imposed. The observation form can be referred to Appendix A. Researchers helped to explain the questions briefly to the respondent in an understandable way. The observation analysis can be referred in Appendix B

3.3.3 Hardware and Software Tools

In order to recognise the positive and negative emotions of the children, the datasets were gathered using several hardware and software tools. The following Table 3.2 and Table 3.3 illustrate the hardware and software tools which had been used in this research respectively.

Table 3.2 Hardware tools

Hardware	Function
BCI headset	To record the brain wave
Bluetooth USB	To connect the computer (with no built-in Bluetooth system) to the headset
PC or laptop	To run the BCI headset tool driver and game stimulus for the experiment
Web camera	To capture and record the facial expression and movement of the respondent
Smartphone/ tablet phone	To record the attention and meditation readings from the headset tool in CSV format

Table 3.3 Software tools

Software	Function
WEKA 3.7	To view and analyse the raw data
FunMath	A mathematic game stimulus to induce the attention and meditation readings
MATLAB R2011b	To perform preprocessing and raw data analysis obtained from the BCI headset
EEG Analyzer	To view and analyse the raw data (for Android mobile)
Microsoft Office Project 2016	To design the research Gantt chart
Microsoft Office Word	For report write-up
Microsoft Office Excel	To tabulate the result
Dropbox	To store the data captured by the headset tool

3.4 Phase 3: Data Mining Analysis Processes

This phase involves the data preprocessing and data classification processes.

3.4.1 Data Preprocessing

Data preprocessing is one of the most critical steps in a data mining process which deals with the preparation and transformation of the initial dataset. It represents any type of processing procedures performed on the raw data to prepare it for another procedure of analysis. Data collection may lose control, result in out-of-range values, impossible data combination or may contain missing values. Raw data is also highly susceptible to noise, missing values, and inconsistency. In order to improve the quality, efficiency and to make further processes easier, the preprocessing procedure is a must.

There are various methods that can be used for preprocessing such as data cleaning, data integration, data transformation and data reduction. This research has included the data cleaning, which removes the unwanted data and feature extraction to pull out any specified data that is significant in some particular context. Raw data may contain errors and outliers values which deviate from the expected. Data cleaning helps to filter unnecessary sources of variation for the analysis process. The data collection instruments used may also be faulty, which which leads to errors in the transmission of the data entry. Misleading results can occur in a condition where the data has not been carefully filtered. This may cause confusion to the classification procedure. For example, by using the dataset provided by the headset tool, there are three types of records that are recorded: Type 4 (level of attention), Type 5 (level of meditation) and Type 22 (level of eye blinking). Type 22 data was ignored and excluded from the analysis. A zero value means the signal cannot be calculated reliably due to background noise and should be removed or ignored (Shirazi et al., 2014).

The headset has a noise filter in place in order to filter the noise of the head movements, muscle artifact, and others out of the raw EEG before the calculation of the eSense value can be made. The headset records the repeated meter values when there is too much noise to be filtered out properly. Thus, the consecutive meter values were removed. This critical step of data preprocessing were coded in the prototype as in Appendix E.

3.4.2 Data Classification

After extracting the desired features, the positive or negative emotion should be identified. This process was done by a classifier or the classification algorithm. A classifier is a system that divides some data into different classes which are able to learn the relationship between the features and the emotion that belongs to that part of the EEG signal. Three (3) classification algorithms were used in this research: production rules system (PART), Naïve Bayes and decision tree. In this research, WEKA data mining software was used to compare the data and the pattern analysis of the three different techniques in terms of their accuracy in classifying and predicting children's positive and negative emotions while learning. The output information from the most accurate classification algorithm will be chosen for further process of the prototype development.

3.5 Phase 4: Preliminary Analysis

A preliminary study as an initial work was conducted in order to find the best classifier to be used in this research. Several different algorithms are applied for building the classification model which aimed at analysing the performance of the algorithms on the provided dataset of the attention and meditation levels in order to predict the positive and negative emotions of children while learning. For this purpose, three classifiers of production rule classifier (PART), decision tree (J48) and Naïve Bayes classifier were compared to each other. They were selected and have been applied to the dataset because they have the potential to yield good results based on the previous literature reviews.

The WEKA software is used at this stage since it is freely available to the public and widely used for research purposes in the data mining field. The performance of each classifier was analysed accordingly. The data set is acquired through the previous experimental study using a BCI tool and the experimental setup can be referred in Section 3.3.2. The data set used for the evaluation contains 4332 instances (3265 for 'positive' emotion and 1067 for 'negative' emotion). The number of instances used is adequate for WEKA for the analysis process. A table of data in comma separated value (CSV) format of one output and two (2) input variables will be set in WEKA. In this case, the attention and meditation attributes will be the input variables (in numeric value) while emotion attribute (in nominal value) of 'positive' and 'negative' is chosen as the output or class for the classification purpose. Table 3.4 shows the example of the CSV table runs in WEKA. All 4332 data were combined together in a table to be analysed by WEKA to find the regularities in the data trends. The mean value of meditation and attention (meditation and attention are summed up together and divided by 2) indicates the value of the emotion either positive or negative that occur in every second which will be discussed further in Section 4.3.

Table 3.4 Sample data runs in WEKA

Attention level	Meditation level	Emotion
54	54	Positive
37	44	Negative
17	26	Negative
7	24	Negative
13	29	Negative
54	41	Negative
96	51	Positive
100	57	Positive
100	38	Positive
83	74	Positive
83	56	Positive
94	64	Positive
94	64	Positive
74	77	Positive

Each classifier was applied for two testing options from 10-fold cross-validation and percentage split. 10-folds cross-validation randomly divided the data set into k subsamples of 10 and k-1 subsamples used as the training data and another one sub-sample as the test data. The algorithm was repeated 10 times. Extensive experiments had shown that k=10 was the best choice to get an accurate estimate. However, another split such as k=5 are also popular. The supplied test set used 2/3 of the dataset as a training set and the remaining 1/3 of the dataset as a test set to evaluate the training set. It is important that the test data is not used in any way to create the classifier. The separate test set can be used to confirm the performance of the model computed during the cross-validation testing. Using separate test set and technique like cross-validation ensures a more accurate and reasonable picture of the performance of the model. Moreover, it is usually suggested to use a supplied test set because the accuracy that gained from the model generated from the cross-validation test is better studied on new instances.

This classification knowledge explains the evaluation measures towards the predictive ability. True Positive (TP) rate and precision were two performance parameters that had been considered for the experimental evaluation of all classifiers. TP rate (or also known as sensitivity) is a rate of true positives (instances correctly classified as a given class) and precision represents the ability of the model to correctly predict the class label of new or previously unseen data. Further discussions on the preliminary analysis can be referred in Section 4.2. The table of results generated from

PART, J48, and Naïve Bayes can be referred to Appendix C while the WEKA output can be referred to Appendix D.

3.6 Phase 5: Development of MYEmotion

A prototype will summarise the entire process involved starting from preprocessing to the end. This research developed an emotion prediction prototype system, namely MYEmotion. MYEmotion is an automation system of the whole process involved in this research using MATLAB environment. This system will be able to classify children's positive and negative emotions in the learning process which is depending on the readings of children's brain signal of the attention and meditation value scales. The graphical user interfaces of MYEmotion can be referred in Appendix F.

3.6.1 MYEmotion Development Model: Rapid Prototyping

A prototype is a model of a system which displays limited but typical functionality. Rapid prototyping involves the early development of a prototype, either paper or computer-based.

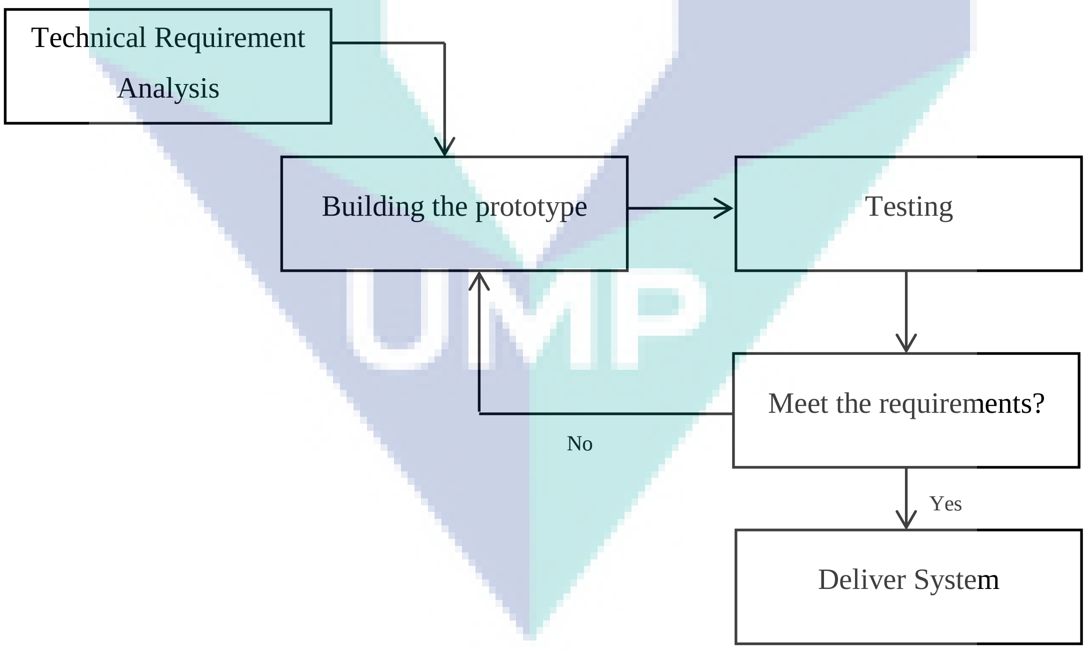


Figure 3.5 Rapid prototyping model

The prototype has been developed to a stage which allows normal people to get a reasonable idea of how the prototype system will look and function. Figure 3.5 illustrates the rapid prototyping model. In rapid prototyping, the prototype-feedback cycle is much shorter compared to the other models such as system development life cycle (SDLC) model, waterfall model, and spiral model. The developer attempts to understand, analyse and document the problem faced by the clients or users in order to develop the outline specification. The goals and functions of the proposed system or prototype must be clearly identified.

Once the technical requirements of the proposed system such as the hardware and software platforms, the databases to be used are understood and agreed, a design of the prototype will be developed accordingly. To test the developed prototype is essential to ensure it meets the requirements and performs to a satisfactory level. If the prototype matches the requirements, then it will be delivered. Otherwise, the process of building the prototype will be repeated once or more until the prototype is ready to be delivered.

3.7 Phase 6 : Implementation of MYEMOTION

The flowchart for the implementation process of the prediction of positive and negative emotions in MYEmotion is depicted in Figure 3.6. The raw dataset in comma separated value format (.csv) will be loaded into the MYEmotion. Then, once the ‘start’ button is clicked, MYEmotion will filter and remove unwanted data (outliers or artifacts) such as zero value readings and Type 22 (eye blinking readings). After the dataset has been cleaned, MYEmotion calculates the filtered data and classify the data into the positive and negative emotions. Finally, MYEmotion will display the final output of current dataset tested in the form of graphs and percentage values. The results of the implementation can be referred in Section 4.3.

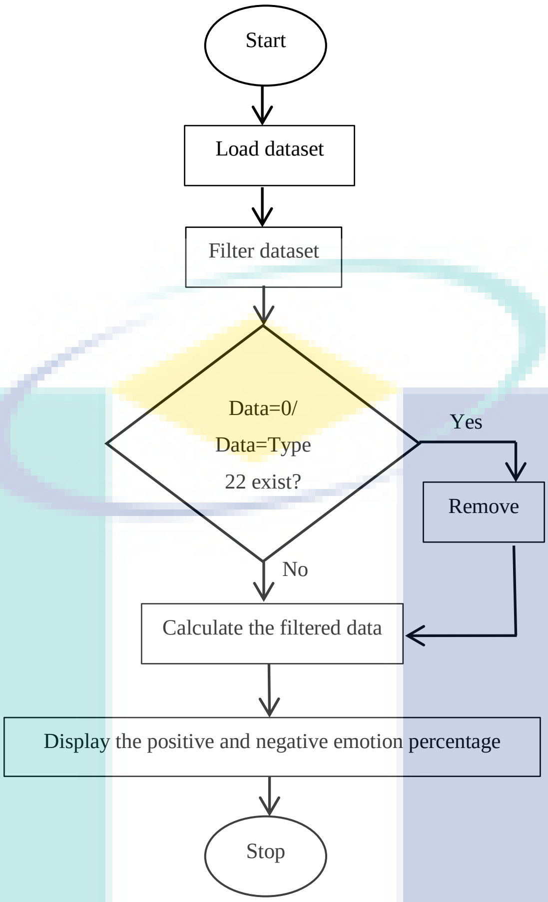


Figure 3.6 Flowchart of MYEmotion

3.8 Phase 7: Validation of MYEmotion through Similarity Comparison, $\sum(\boldsymbol{Sim})$

The purpose of this testing is to test the ability of MYEmotion in predicting positive and negative emotions of the children in learning process. The dataset of each respondent was run into MYEmotion and the graph output was observed in order to record the trend of the positive and negative emotions percentage of each respondent in Session 1 and 2. An accuracy-based equation using similarity function (*Sim)*, as shown in Equation 3.1 was applied in order to validate the emotion prediction by MYEmotion, where ***n*** is the number of the respondents. This part is discussed further in Section 4.4.

$$\sum(Sim) = \frac{\sum_{i=1}}{n} \times 100 \qquad 3.1$$

3.9 Summary

This chapter provides information about all the processes that involved in this research. Based on the literature review, all the techniques were applied and an emotion prediction prototype system had been developed. The result of the implementation can be further referred in Chapter 4.

CHAPTER 4

RESULTS AND DISCUSSION

4.1 Introduction

This chapter discusses the results of the preliminary analysis that had been done in order to identify the best classification algorithm to be implemented in this research. This chapter also discusses the implementation of MYEmotion and analysis of the results obtained. The rule sets generated from the decision list of the production rules classifier using WEKA is presented and leads to the development of the emotion prediction system (MYEmotion).The results of the tested data using both production rules prediction set and baseline set in MYEmotion were observed and have been presented in a table of comparison in order to find their degree of similarities. An accuracy-based equation using a similarity (*Sim*) function was applied in order to validate the emotion prediction by MYEmotion.

4.2 Preliminary Analysis: The Performance of Classifiers

As mentioned earlier in Chapter 3, a preliminary study was conducted in order to find the best classifier for this research. The results for the preliminary study showed that J48 classifier classifies correctly about 99.54% of the instances for the 10-fold cross-validation testing and 98.55% for the supplied test set, produces a classification tree with a size of 77 nodes and 39 leaves.

Table 4.1 illustrates the performance of the three classifiers run in WEKA. The results for the detailed accuracy by class, including the True Positive (TP) rate and precision are presented. The results reveal that the TP rate of J48 is high for the two of the classes for both test option of 10-fold cross-validation and supplied test set. Positive (99.4-99.8%), Negative (95-99 %) and the weighted average is 98-100%. The precision is very high for the positive (98.8-99.6 %), high for the negative (97.2-99.2 %) and weighted average (98.5-99.5 %) classes.

Naïve Bayes classifier classifies 96.01% of the instances correctly for the 10-fold cross-validation testing and 98.2% for the supplied test set. The detailed accuracy results for the Naïve Bayes classifiers reveal that the TP rate is very high for the positive class (almost 100%) and high for the negative class (84.2-90 %). The precision is high for the negative class (almost 100%), high for the weighted average (99.6-100 %) and good for the positive class (95.1-97.9 %).

PART correctly classifies 99.58% of all the instances using cross-validation test option and 99.45% using supplied test set. The precision and TP rate of the weighted average of PART for both test options is about 99-100%. It shows that PART performs well in classifying positive and negative emotions for both testing options. Figure 4.1 and 4.2 present the graphical analysis of each test option of 10-fold cross-validation and supplied test set.

Table 4.1 Performance of classifiers

Test options	**Classes**	**Classifiers**	**Precision**	**TP rate**
10-fold cross-validation	Positive	J48	0.996	0.998
		NB	0.951	0.999
		PART	0.997	0.998
	Negative	J48	0.992	0.989
		NB	0.996	0.842
		PART	0.993	0.99
	Weighted average	J48	0.995	0.995
		NB	0.962	0.96
		PART	0.996	0.996
Supplied test set	Positive	J48	0.988	0.994
		NB	0.979	1
		PART	0.997	0.997
	Negative	J48	0.972	0.946
		NB	1	0.9
		PART	0.985	0.985
	Weighted average	J48	0.985	0.985
		NB	0.982	0.982
		PART	0.994	0.994

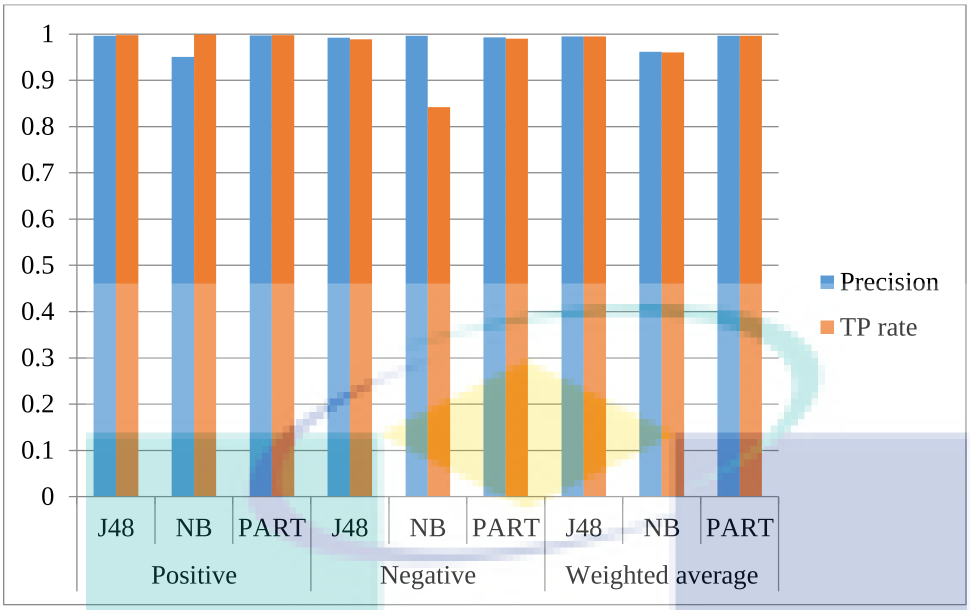


Figure 4.1 Result of test option 1: 10-fold cross-validation

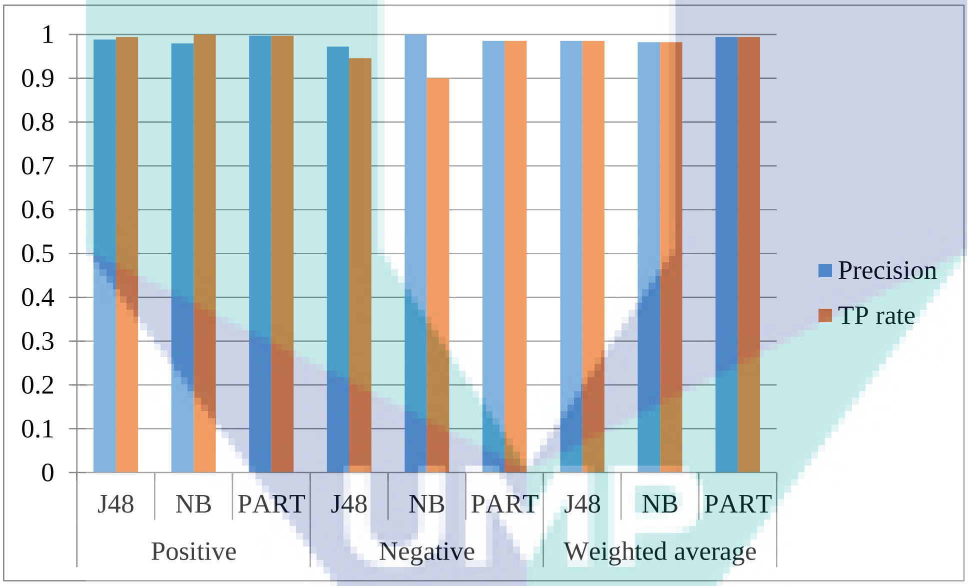


Figure 4.2 Result of test option 2: supplied test set

The production rules classifier (PART) performed the best with the highest overall accuracy (weighted average), followed by the decision tree (J48) and Naïve Bayes classifier. All tested classifiers performed with an overall accuracy of above 90% for both test options showing low error rate and reliable prediction. Therefore, the production rules classifier of PART was chosen as the best classifier to predict the positive and negative emotions of the children while learning.

4.3 Implementation of MYEmotion

An emotion prediction prototype is developed based on the best classification algorithm identified (production rules classifier) from the previous preliminary study as discussed in Chapter 3. MYEmotion is an automation of the whole processes involved in this research using MATLAB environment. It is able to predict the emotion of the children into two categories or classes, depending on the readings of their attention and meditation value scales from their brain signals.

As meditation and attention interrelated to each other as discussed in Section 2.4.6, this research considered both attention and meditation readings from the headset and the mean value of both readings will be calculated at every second (where each row of the data represent one-second interval). The meditation and attention are summed up together and divided by 2 as shown by Equation 4.1. The mean value indicates the value of the emotion either positive or negative that occur in every second (Chan & Woollacott, 2007; Crowley et al., 2011).

$$\text{Mean (Emotion)} = \frac{(\text{Attention} + \text{Meditation})}{2} \qquad 4.1$$

4.3.1 Applying Baseline Set in MYEmotion

A baseline set of the positive and negative emotions is adapted from eSense attention-meditation meter returned by the headset. For a better understanding of this research, the eSense meter was altered into a baseline set to differentiate between the positive and negative emotions as derived from the dimensional view model as explained in Chapter 2. Table 4.2 illustrates the baseline set where the positive emotion will represent the neutral, slightly elevated and elevated levels of the readings between 41 to 100 while negative emotion represents the reduced and strongly lowered levels and underlies within the value of 1 up to 40. Therefore, the positive and negative emotions will meet at a red dotted baseline of 40 as shown in Figure 4.3.

Table 4.2 Baseline set

Value	Levels	Emotion
1-20	Strongly lowered	Negative (below 40)
21-40	Reduced	
41-60	Neutral	Positive (above 40)
61-80	Slightly elevated	
81-100	Elevated	

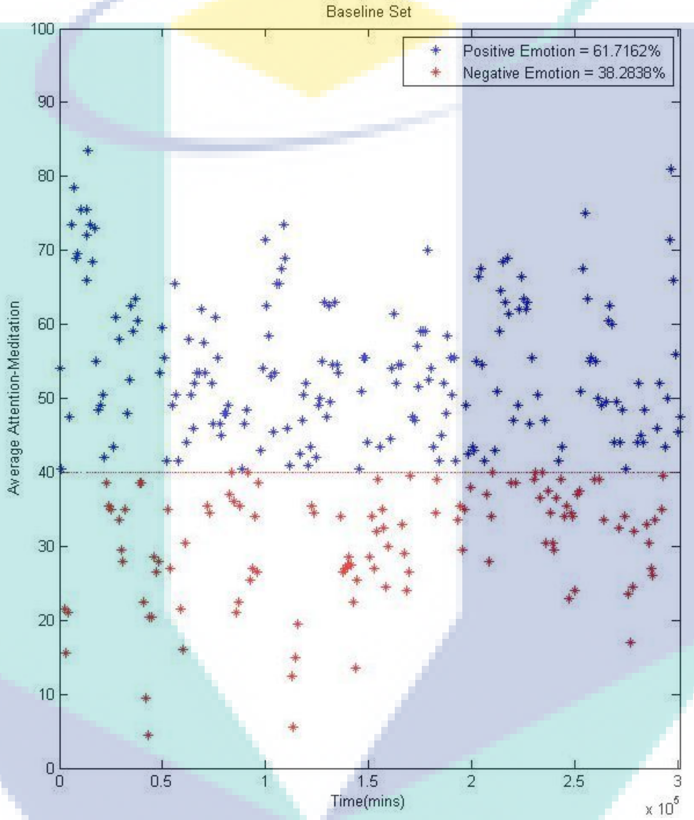


Figure 4.3 The output of the baseline set

The baseline set is applied in order to validate and compare the results of the applied prediction (production rules) set in the next section. The example of the results generated by MYEmotion after applying baseline state for Respondent 1 in Session 1 and 2 can be referred in Appendix G. The percentage of positive and negative emotions display on top of the graph indicates the percentage of a respondent who experiences positive and negative emotions while learning. Table 4.3 illustrates the percentage of the positive and negative emotions of all respondents in both sessions after applying the baseline set in the dataset.

Table 4.3 Respondents' performance of the baseline set

Respondents #	Session 1		Session 2	
	Positive (%)	Negative (%)	Positive (%)	Negative (%)
1	61.72	38.28	65.99	34.01
2	87.94	12.06	52.55	47.45
3	73.26	26.74	83.85	16.15
4	85.07	14.93	74.60	25.40
5	88.00	12.00	82.39	17.61
6	79.14	20.86	83.50	16.50
7	73.33	26.67	79.87	20.13
8	82.55	17.45	98.68	1.32

Table 4.3 shows that respondents #1, #3, #6, #7, and #8 have an increasing percentage of positive emotion while learning from Session1 to 2. By referring to the previous state of positive and negative emotions explained in Chapter 2, the data analysis of each respondent was studied individually through the observation held before and after the experiment. From the observation analysis, which can be referred in Appendix B, it is found that there was a decrease in stress levels from the first to the second session for the five respondents. After completing Session 1, the above respondents reported that they were very excited to start a new session and ready for the task. Relaxing the body and closing eyes often helps the mind to relax and increases the meditation level. It can be concluded that they were benefiting from the previous session and resulted in good improvement in their positive emotion.

However, another 3 respondents are reported to have decreasing level of positive emotion. From the observation, it is found that respondents #2, #4 and #5 had wandering thoughts and distraction from friends' voice while performing the second session. Respondent #4 claimed that he feels so sad after being scolded by his parent right before doing the task. They also reported that they are nervous to start the task. Their ability to stay focus was decreasing and reported such increasing negative emotion percentage from Session 1 to the next session. According to Robbins et al.(2014), the distractions, wandering thoughts, lack of focus, or anxiety may lower the attention and meditation levels. It can be seen from the results that the repetition of the task influences the outcomes of the respondents' emotion either to be negative or positive emotion. The capacity to stabilise the attention and meditation levels over time varies among individual, especially in children. They might need a longer time in order to sustain their attention and meditation state. Only then, their positive and negative emotions can be decided.

4.3.2 Applying Production Rules Prediction Set in MYEmotion

The implementation of the classification algorithms helps in acquiring new knowledge from the data collected from the human brain wave. Previously, the prediction of positive and negative emotions was possible through the baseline set highlighted by the former researcher. This research intended to reveal the potential application behind the readings of the attention and meditation and to extract how far the data can help in predicting positive and negative emotions of the children while learning. In this case, the regularities of the attention and meditation readings of the respondents were taken into account and production rules classifier was identified as the best classification algorithm which can help in the prediction of the positive and negative emotions. WEKA provides a list of decisions for the dataset that has been classified using the production rules classifier.

The entire decision list was converted into the following rule sets and coded into MATLAB.

```
R1:(Attention >30) and (Meditation >40)→ Positive
R2:(Attention >17) and (Meditation >60)→ Positive
R3:(Attention >43) and (Meditation >35)→ Positive
R4:(Attention >26) and (Meditation >37)→ Positive
R5:(Attention >53) and (Meditation >24)→ Positive
R6:(Attention <=40) and (Meditation <=40)→ Negative
R7:(Attention <=35) and (Meditation <=51)→ Negative
R8:(Attention <=23) and (Meditation <=69)→ Negative
R9:(Attention <=44) and (Meditation <=56)→ Negative
```

All of the above rule sets are represented by Equation 4.2:

$$\text{Rule } \mathbf{n}: \quad (\text{Condition}) \rightarrow \text{y} \tag{4.2}$$

There are two methods to generate the set of rules: direct and indirect methods. The direct method extract rules directly from the data while indirect method will extract the rules from other classification algorithm such as the decision tree. The above rule sets are generated by using the direct method because all data have been converted and simplified in the form of decision list by the production rules in WEKA. For example, by referring to the first decision list generated by the production rules classifier (see part C in Appendix D),

```
Attention level > 30 AND
Meditation level > 40 AND
Meditation level > 44: Positive
```

From the above decision list, it can be seen that the value of the attention level is >30 and there are 2 values for the meditation level; >40 and >44. In this case, the instance elimination process is needed where the covered decision in a same decision list will be eliminated to prevent the rule from being generated again. Therefore, ‘Meditation level > 44’ will be removed because it is already covered by ‘Meditation level > 40’. After the instance elimination has been done, the first rule that will be generated is :

```
R1:(Attention >30) and (Meditation >40)→ Positive
```

The rule sets (named as production rules prediction set) generated by the classifier summarise the regularities in the readings and help in the realization of the prediction system of the emotion. Figure 4.4 is the output before applying the production rules prediction set (in the baseline set) while Figure 4.5 is the output after applying the production rules prediction set. Both graphs indicate the differences between the scatter points of the positive and negative emotions after applying the baseline set and the production rules prediction sets generated by MYEmotion. The sample output displayed by MATLAB of a respondent in both sessions can be further referred to Appendix G as well.

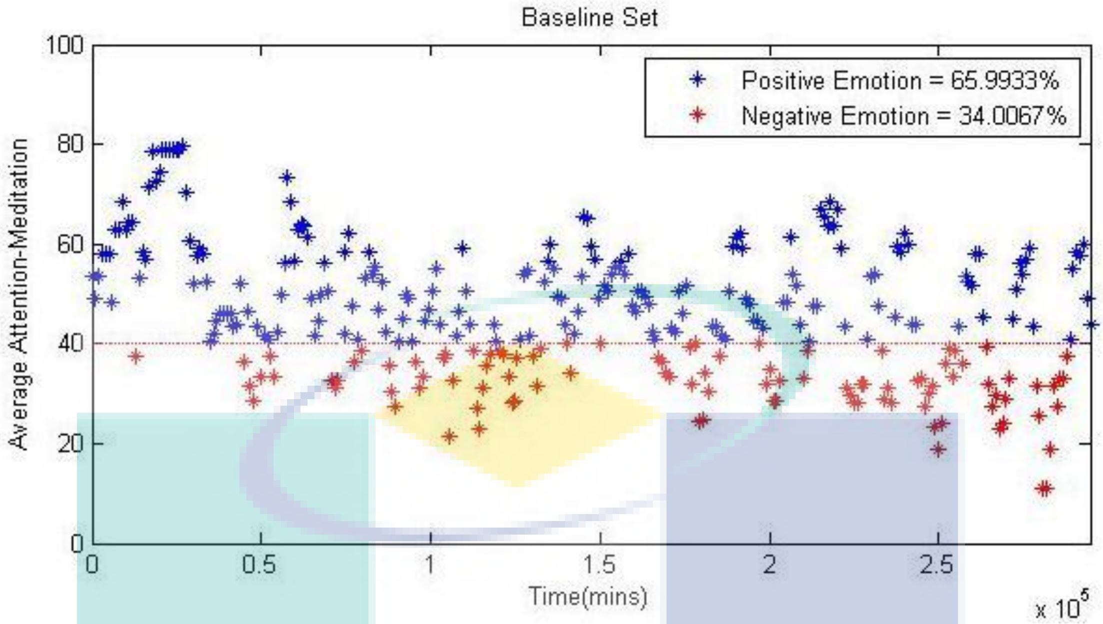


Figure 4.4 The output before applying the production rules prediction set

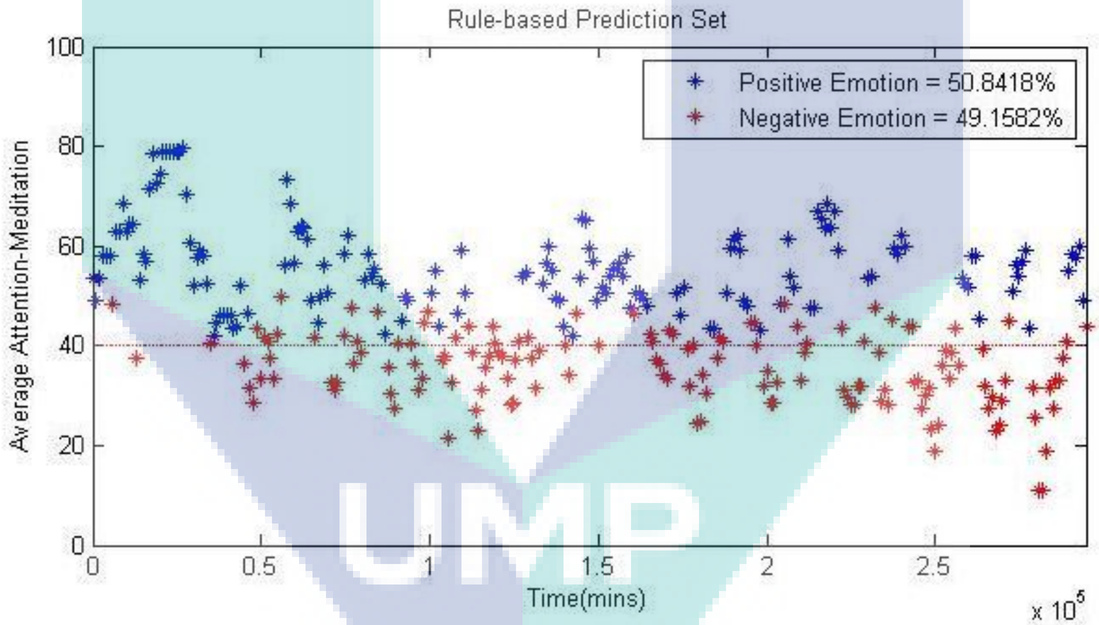


Figure 4.5 The output after applying the production rules prediction set

It can be seen clearly in Figure 4.5 that the points of negative emotion (in red dots) are also scattered in the positive emotion area (in blue dots). This is due to the set of rules which are no longer depending on the baseline of 40 to differentiate between the positive and negative emotions. As mentioned above, this rule sets will find the regularities in the attention and meditation datasets of the respondents. The information from the rule sets enable the system to automatically decide the emotion of the student either to be positive or negative within an allocated period as illustrated by the percentage displayed on the top right of the graph.

Table 4.4 figures out the performance of all respondents in both sessions before and after applying the production rules prediction set in the dataset. It clearly illustrates the production rules prediction set retain the previous result of baseline set where respondents #1,#3, #7, and #8 have an increasing percentage of the positive emotion from Session1 to 2. Only respondent #6 is reported to have a slightly decrease in positive emotion from 67.88 to 65.35% after applying the production rules prediction set. From the previous baseline set implementation, the positive emotion percentage of respondent #6 was reported to be 79.14% in the first session and had increased to 83.50% in the second session. As mentioned earlier, this experiment was done in 2 sessions because the researcher would like to record if there are any changes in children's positive and negative emotions with and without any prior preparation. This can be seen by the trends of the results captured in Session 1 and 2. The percentage values between each session were changing and had proven that emotion is not discrete as the state of the brain signals can change in split seconds.

Table 4.4 Comparison between baseline set and production rules prediction set

Respondents #	Session 1				Session 2			
	Baseline set (%)		Production rules prediction set (%)		Baseline set (%)		Production rules prediction set (%)	
	Positive	Negative	Positive	Negative	Positive	Negative	Positive	Negative
1	61.72	38.28	49.84	50.16	65.99	34.01	50.84	49.16
2	87.94	12.06	77.04	22.96	52.55	47.45	36.86	63.14
3	73.26	26.74	64.47	35.53	83.85	16.15	64.60	35.40
4	85.07	14.93	74.63	25.37	74.60	25.40	55.24	44.76
5	88.00	12.00	79.33	20.67	82.39	17.61	64.78	35.22
6	79.14	20.86	67.88	32.12	83.50	16.50	65.35	34.65
7	73.33	26.67	52.33	47.67	79.87	20.13	60.40	39.60
8	82.55	17.45	67.11	32.89	98.68	1.32	94.37	5.63

4.4 Validation Testing through Similarity Comparison, $\sum(Sim)$

Sim function was used as the basic for the comparison (Atman et al., 2009). It is specified based on the differences between the prediction by the production rules prediction set, baseline set and the findings from the observation. The value of outcomes will return 1 if the value is similar or 0 if the value is different. Table 4.5 and 4.6 show the value of outcome between the production rules prediction set with the observation findings and baseline set with the observation findings for Session 1 and 2.

Table 4.5 Similarity comparison (Session 1)

Respondent (#)	Production rules prediction set	Baseline set	Observation	Value of outcomes	
				Baseline set & Observation	Production rules prediction set & Observation
1	Positive	Negative	Positive	0	1
2	Positive	Positive	Positive	1	1
3	Positive	Positive	Positive	1	1
4	Positive	Positive	Negative	0	0
5	Positive	Positive	Negative	0	0
6	Positive	Positive	Positive	1	1
7	Positive	Positive	Positive	1	1
8	Positive	Positive	Positive	1	1

Table 4.6 Similarity comparison (Session 2)

Respondent (#)	Production rules prediction set	Baseline set	Observation	Value of outcomes	
				Baseline set & Observation	Production rules prediction set & Observation
1	Positive	Positive	Positive	1	1
2	Negative	Negative	Positive	0	0
3	Positive	Positive	Positive	1	1
4	Positive	Positive	Negative	0	0
5	Positive	Positive	Positive	1	1
6	Positive	Positive	Positive	1	1
7	Positive	Positive	Positive	1	1
8	Positive	Positive	Positive	1	1

Notes:

1- If the prediction is similar
0- If the prediction is different

By using the *Sim* function, the similarity (the value of outcomes of 1) of the production rules prediction set and the observation in Session 1 are as in Equation 4.4 and 4.5:

$$\sum(Sim_{\text{rule-based prediction set, observation}}) = \frac{6}{8} \times 100 = 75\% \qquad 4.3$$

$$\sum(Sim_{\text{baseline set, observation}}) = \frac{5}{8} \times 100 = 62.5\% \qquad 4.4$$

While Equation 4. 6 and 4.7 show the similarity of the baseline set and the observation in Session 2.

$$\sum(Sim_{\text{rule-based prediction set, observation}}) = \frac{6}{8} \times 100 = 75\% \qquad 4.6$$

$$\sum(Sim_{\text{baseline set, observation}}) = \frac{6}{8} \times 100 = 75\% \qquad 4.7$$

According to Garcıa et al. (2007), the percentage that exceeds 65% is acceptable as a high value to show a good similarity. Based on Equation 4.4 and 4.5, it can be seen that the similarity between the production rules prediction set and the observation is higher compared to baseline set and the observation. While in Session 2, both production rules prediction and the baseline sets reported a same similarity percentage of 75% to observation. Therefore, the high similarity percentage of the production rules prediction set can be referred as a legal basis of acceptance towards the accuracy of the production rules prediction set in predicting children's positive and negative emotions instead of applying the baseline set or using conventional method of observation.

4.5 Discussions

This chapter presents the findings that it is possible to predict the class variable of the positive and negative emotions using the explanatory variables of the attention and meditation levels. Several different algorithms are applied for building the classification model which aimed at analysing the performance of the algorithms on the provided dataset of the attention and meditation levels in order to predict the positive and negative emotions of children while learning. The results of the preliminary analysis revealed that the production rules classification algorithm performed better compared to others in term of its precision.

MYEmotion prototype system implements the generated rule sets of the production rules classification algorithm. The output of the positive and negative emotions of the dataset shows that different children will have different adaptations towards learning session. This finding is in line with the results obtained from the observation during the data collection experiment. The results of the implementation of MYEmotion are encouraging and show that the headset tool has the potential not only to record brainwave activity, but also to differentiate between mental states or emotions. The reliable relationship between EEG signals of attention and meditation and their impact towards the positive and negative emotions of the children while learning illustrates the potential to detect mental states which relevant to tutoring such as comprehension, engagement, and learning.

In addition, this research highlights the importance of knowing the emotional state of the learners in learning session. The teachers will be able to decide or plan the suitable emotion-focused strategies to help students to regulate their emotional state in a self-regulating tutoring system.

4.6 Summary

This chapter discusses briefly the result and analysis of the procedures listed in Chapter 3. Chapter 5 will conclude this thesis and exhibits the future works and the recommendations.

CHAPTER 5

CONCLUSIONS AND RECOMMENDATIONS

5.1 Introduction

This chapter discusses the conclusion, highlights the contribution and provides recommendations for future works that has been reached from this research work in predicting children's positive and negative emotions while learning using rule-based classification algorithm.

5.2 Conclusion

This thesis describes the research works on the development of a prototype system to predict children's positive and negative emotions in learning process using EEG signals. In order to achieve the development phase, the theoretical information about the human brain and emotion were studied and described briefly in Chapter 2. This research focuses to classify the user emotion characteristics by using EEG signals based on children's attention and meditation data into an understandable knowledge of positive and negative emotions while learning. These are fulfilled by the first objective of this research. From the literature review, it was found that EEG seems to be an ideal way of measuring children's brain activity while learning as children could control their facial expression but not their feelings or inner emotions. Several researchers have shown that it is possible to measure emotional cues using EEG measurements. This research made use the data of the attention and meditation readings from a BCI headset tool and analysed them.

On top of that, this research held an experiment towards several school children in order to gather the attention and meditation readings of their brainwaves. After gathering the data and knowledge regarding the EEG signals, this thesis looked at the methods to use by referring to a few experts and former researchers. The methods for data preprocessing, classification and prototype development model were briefly discussed in Chapter 3.

This research finds out that the best classification algorithm to classify the positive and negative emotions is by using WEKA machine learning software. The WEKA software is used for the study implementation since it is freely available to the public and widely used for research purposes in the data mining field. The results had shown that production rules classification algorithm performs better than others in terms of its accuracy. The comparative analysis of the findings is given in Chapter 4. Based on the information provided by the production rules algorithm, a prototype of a prediction system of MYEmotion was built to automatically predict the positive and negative emotions of a new respondent in the future. The development of MYEmotion fulfills the second objective of this research. Finally, a validation process using Similarity, (Sim) function was done onto the prediction system in order to validate the effectiveness of production rules prediction set in predicting the positive and negative emotions of the children. The validation process fulfills the last objective of this research.

5.3 Research Contribution

This research has two main contributions. Firstly, it demonstrates the potential of exploiting the attention and meditation readings from the human brain using a BCI tool. It also shows that emotions can be easily predicted by finding the regularities of the trends in the attention and meditation readings.

Secondly, this research also highlights the solution upon the challenges faced by the academic practitioners in dealing with the children nowadays. By using the predictive system of the production rule prediction set, teachers, parents and other academic practitioners will be able to monitor and observe the current emotion of the student after involving in a learning session. This may be applicable to a child who needs high supervision of the teachers or any children with academic problems. These children may have a lack of confidence and having a low ability to stay focused and calm themselves in class whenever they feel hard and stress. Therefore, teachers might be able to monitor their progress in the class and deal with their positive and negative emotions during the learning session. In summary, this research will give hope and awareness that MYEmotion is another important learning aid in school that can capture and provide much relevant information to enhance the learning impacts among the children.

5.4 Future Recommendations

This research has come up with some recommendations for further research works as the field of emotion recognition with EEG signals is still new and remains challenging from time to time. This research can be extended to the next research phase by collecting more data rather than only depending on these attention and meditation data. It is much more proper to gain the human brain’s signals in the Hertz unit because it is easier to interpret emotion accordingly as discussed in the previous section of EEG frequency bands in Chapter 2. In addition, the classifier accuracy can be improved by collecting more data and by using more sophisticated training methods.

The next researchers should try to find other suitable BCI tools which can properly read these brain signal units as the tool used for this research is only capable of capturing the attention and meditation readings only. Another option for future research is using different methods to induce the emotion. This research used a mathematical game application to evoke the attention and meditation value, but it is not known whether the values are the same when the children are evoked by watching the movies or listening to a sound. These methods could raise different brain activity with the same values or results in better experiences. It is suggested that student’s emotions are influenced by their religion and culture especially in Malaysian context. Thus, it is important to conduct a comparison study of the emotion-focused implementation strategies based on student’s religion and cultural background.

This research can be an initial work in automating tutorial decisions in intelligent tutoring system which is able to identify and adapt to the specific behaviour of the learners either by responding or adapting immediately to a detected mental state. Finally, future researchers from various domains in EEG studies are all encouraged to improve and enhance this research works.

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APPENDIX A

OBSERVATION FORM

BORANG PEMERHATIAN PENYELIDIK

*Semua soalan akan ditanya oleh penyelidik kepada responden sebagai catatan pemerhatian kajian.

Responden : ________________________

Umur : ________________________

SEBELUM SESI 1

1. Apakah perasaan anda pada ketika ini?

   A. Gembira
   B. Sedih
   C. Marah
   D. Penat
   E. Bersemangat
   F. Mengantuk
   G. Berdebar
   H. Tidak pasti

2. Adakah anda tahu menggunakan komputer ?

   A. Ya
   B. Tidak

3. Adakah anda pernah bermain permainan matematik di telefon/ komputer?

   A. Ya
   B. Tidak

4. Adakah anda tahu operasi menambah dan menolak di dalam Matematik?

   A. Ya
   B. Tidak

SELEPAS SESI 1

5. Adakah permainan sebentar tadi menarik?

   A. Ya
   B. Tidak

6. Adakah soalan yang diberikan susah / senang?

   A. Senang
   B. Susah

7. Adakah anda memahami pembelajaran yang diberikan?

   A. Ya
   B. Tidak

SELEPAS SESI 2

8. Bagaimana perasaan anda sekarang?

   A. Gembira
   B. Sedih
   C. Marah
   D. Penat
   E. Bersemangat
   F. Mengantuk
   G. Bosan
   H. Berdebar
   I. Tidak pasti

9. Adakah soalan yang dikemukakan semakin senang daripada sesi pertama?
   A. Ya
   B. Tidak

10. Adakah anda ingin mengulangi permainan ini lagi?

   A. Ya
   B. Tidak

11. Jika (tidak). Mengapa? Senaraikan.

   A. ---------------------------
   B. ---------------------------

Pemerhatian (Diisi oleh penyelidik)

APPENDIX B

OBSERVATION ANALYSIS

#	SESSION 1														SESSION 2					
#	Q 1	Q 2		Q 3		Q4		Q 5		Q 6		Q 7		Q8	Q 9		Q 10		Q11
		Yes	No	Yes	No	Yes	No	Yes	No	Hard	Easy	Yes	No		Yes	No	Yes	No	
1	Happy, energetic, nervous	/		/		/		/			/	/		Happy, energetic, nervous	/		/		None
2	Energetic	/		/		/		/			/	/		Happy	/		/		None
3	Happy	/		/		/		/			/	/		Happy, nervous	/		/		None
4	Sad	/		/		/		/			/	/		Happy, sleepy	/		/		None
5	Happy	/		/		/		/		/		/		Happy	/		/		None
6	Happy	/		/		/		/			/	/		Happy, energetic	/		/		None
7	Happy, energetic, nervous	/		/		/		/			/	/		Happy, energetic	/		/		None
8	Happy, energetic, nervous	/		/		/		/			/	/		Happy, energetic	/		/		None

APPENDIX C

RESULT OF CLASSIFIERS

Table 1 Accuracy parameters of decision tree classifier (J48)

Class	J48-10 fold cross validation		J48-Supplied test set	
	TP rate	**Precision**	**TP rate**	**Precision**
Positive	0.998	0.996	0.994	0.988
Negative	0.989	0.992	0.946	0.972
Weighted average	0.995	0.995	0.985	0.985

Table 2 Accuracy parameters of Naïve Bayes classifier (NB)

Class	NB-10 fold cross validation		NB-Supplied test set	
	TP rate	**Precision**	**TP rate**	**Precision**
Positive	0.999	0.951	1	0.979
Negative	0.842	0.996	0.9	1
Weighted average	0.96	0.962	0.982	0.982

Table 3 Accuracy parameters of production rules classifier (PART)

Class	PART-10 fold cross validation		PART-Supplied test set	
	TP rate	**Precision**	**TP rate**	**Precision**
Positive	0.998	0.997	0.997	0.997
Negative	0.99	0.993	0.985	0.985
Weighted average	0.996	0.996	0.994	0.994

APPENDIX D

WEKA OUTPUT

A. DECISION TREE (J48)

```
=== Run information ===

Scheme:       WEKA.classifiers.trees.J48 -C 0.25 -M 2
Relation:     All Dataset
Instances:    4332
Attributes:   3
              Attention level
              Meditation level
              Emotion
Test mode:    10-fold cross-validation

=== Classifier model (full training set) ===

J48 pruned tree
------------------

Attention level <= 30
|   Meditation level <= 51: Negative (522.0/1.0)
|   Meditation level > 51
|   |   Attention level <= 17
|   |   |   Meditation level <= 64: Negative (102.0)
|   |   |   Meditation level > 64
|   |   |   |   Meditation level <= 70
|   |   |   |   |   Attention level <= 14
|   |   |   |   |   |   Meditation level <= 69: Negative (15.0)
|   |   |   |   |   |   Meditation level > 69
|   |   |   |   |   |   |   Attention level <= 10: Negative (4.0)
|   |   |   |   |   |   |   Attention level > 10: Positive (2.0)
|   |   |   |   |   Attention level > 14: Positive (9.0)
|   |   |   |   Meditation level > 70
|   |   |   |   |   Attention level <= 1: Negative (3.0/1.0)
|   |   |   |   |   Attention level > 1: Positive (29.0)
|   |   Attention level > 17
|   |   |   Meditation level <= 60
|   |   |   |   Attention level <= 26
|   |   |   |   |   Meditation level <= 54: Negative (42.0)
|   |   |   |   |   Meditation level > 54
|   |   |   |   |   |   Attention level <= 24
|   |   |   |   |   |   |   Meditation level <= 56: Negative (10.0)
|   |   |   |   |   |   |   Meditation level > 56
|   |   |   |   |   |   |   |   Attention level <= 23
|   |   |   |   |   |   |   |   |   Meditation level <= 57:
Negative (11.0)
|   |   |   |   |   |   |   |   |   Meditation level > 57
|   |   |   |   |   |   |   |   |   |   Attention level <= 21:
Negative (3.0)
|   |   |   |   |   |   |   |   |   |   Attention level > 21:
Positive (4.0)
|   |   |   |   |   |   |   |   Attention level > 23: Positive
(8.0)
|   |   |   |   |   |   Attention level > 24: Positive (14.0)
|   |   |   |   Attention level > 26: Positive (67.0/2.0)
|   |   |   Meditation level > 60: Positive (291.0)
```

```
Attention level > 30
|   Meditation level <= 40
|   |   Attention level <= 43
|   |   |   Meditation level <= 37: Negative (182.0)
|   |   |   Meditation level > 37
|   |   |   |   Attention level <= 40: Negative (38.0)
|   |   |   |   Attention level > 40
|   |   |   |   |   Attention level <= 41
|   |   |   |   |   |   Meditation level <= 38: Negative (2.0)
|   |   |   |   |   |   Meditation level > 38: Positive (4.0)
|   |   |   |   |   Attention level > 41: Positive (5.0)
|   |   Attention level > 43
|   |   |   Meditation level <= 35
|   |   |   |   Attention level <= 53
|   |   |   |   |   Meditation level <= 30
|   |   |   |   |   |   Attention level <= 51: Negative (65.0)
|   |   |   |   |   |   Attention level > 51
|   |   |   |   |   |   |   Meditation level <= 27: Negative (7.0)
|   |   |   |   |   |   |   Meditation level > 27: Positive (2.0)
|   |   |   |   |   Meditation level > 30
|   |   |   |   |   |   Attention level <= 44: Negative (20.0)
|   |   |   |   |   |   Attention level > 44: Positive (33.0)
|   |   |   |   Attention level > 53
|   |   |   |   |   Meditation level <= 24
|   |   |   |   |   |   Attention level <= 60: Negative (8.0)
|   |   |   |   |   |   Attention level > 60
|   |   |   |   |   |   |   Meditation level <= 10: Negative (6.0)
|   |   |   |   |   |   |   Meditation level > 10: Positive (12.0)
|   |   |   |   |   Meditation level > 24: Positive (54.0)
|   |   |   Meditation level > 35: Positive (113.0)
|   Meditation level > 40
|   |   Meditation level <= 44
|   |   |   Attention level <= 35: Negative (21.0)
|   |   |   Attention level > 35
|   |   |   |   Attention level <= 38
|   |   |   |   |   Meditation level <= 41: Negative (4.0)
|   |   |   |   |   Meditation level > 41
|   |   |   |   |   |   Meditation level <= 43
|   |   |   |   |   |   |   Attention level <= 37: Negative (2.0)
|   |   |   |   |   |   |   Attention level > 37: Positive (8.0)
|   |   |   |   |   |   Meditation level > 43: Positive (26.0)
|   |   |   |   Attention level > 38: Positive (181.0)
|   |   Meditation level > 44: Positive (2403.0)

Number of Leaves  :     39

Size of the tree :      77


Time taken to build model: 0.16 seconds

=== Stratified cross-validation ===
=== Summary ===

Correctly Classified Instances        4312               99.5383 %
Incorrectly Classified Instances        20                0.4617 %
Kappa statistic                          0.9875
Mean absolute error                      0.0053
Root mean squared error                  0.0649
```

```
Relative absolute error                  1.4212 %
Root relative squared error             15.0592 %
Coverage of cases (0.95 level)          99.6768 %
Mean rel. region size (0.95 level)      50.1385 %
Total Number of Instances             4332

=== Detailed Accuracy By Class ===

               TP Rate   FP Rate   Precision   Recall  F-Measure
ROC Area  Class
                 0.998     0.011      0.996     0.998     0.997
1         Positive
                 0.989     0.002      0.992     0.989     0.991
1         Negative
Weighted Avg.    0.995     0.009      0.995     0.995     0.995
1

=== Confusion Matrix ===

    a    b   <-- classified as
 3257    8 |    a = Positive
   12 1055 |    b = Negative
```

B. NAÏVE BAYES

```
=== Run information ===

Scheme:       WEKA.classifiers.bayes.NaiveBayes
Relation:     All Dataset
Instances:    4332
Attributes:   3
              Attention level
              Meditation level
              Emotion
Test mode:    10-fold cross-validation

=== Classifier model (full training set) ===

Naive Bayes Classifier

                       Class
Attribute           Positive Negative
                      (0.75)   (0.25)
=====================================
Attention level
  mean                49.5768  26.9025
  std. dev.           16.4311  12.2998
  weight sum             3265     1067
  precision             1.678    1.678

Meditation level
  mean                62.0552  39.7913
  std. dev.           14.7691   12.994
  weight sum             3265     1067
  precision            1.7069   1.7069



Time taken to build model: 0.04 seconds

=== Stratified cross-validation ===
=== Summary ===

Correctly Classified Instances        4159               96.0065 %
Incorrectly Classified Instances       173                3.9935 %
Kappa statistic                          0.8865
Mean absolute error                      0.1419
Root mean squared error                  0.2221
Relative absolute error                 38.22   %
Root relative squared error             51.5395 %
Coverage of cases (0.95 level)         100      %
Mean rel. region size (0.95 level)      76.1542 %
Total Number of Instances             4332

=== Detailed Accuracy By Class ===

               TP Rate   FP Rate   Precision   Recall  F-Measure
ROC Area  Class
                 0.999     0.158      0.951     0.999     0.974
0.992    Positive
```

```
                 0.842     0.001      0.996     0.842     0.912
0.992    Negative
Weighted Avg.    0.96      0.12       0.962     0.96      0.959
0.992

=== Confusion Matrix ===

    a    b   <-- classified as
 3261    4 |    a = Positive
  169  898 |    b = Negative
```

C. PRODUCTION RULES (PART)

```
=== Run information ===

Scheme:       WEKA.classifiers.rules.PART -M 2 -C 0.25 -Q 1
Relation:     All Dataset
Instances:    4332
Attributes:   3
              Attention level
              Meditation level
              Emotion
Test mode:    10-fold cross-validation

=== Classifier model (full training set) ===

PART decision list
------------------

Attention level > 30 AND
Meditation level > 40 AND
Meditation level > 44: Positive (2403.0)

Meditation level > 60 AND
Attention level > 17: Positive (291.0)

Attention level <= 40 AND
Meditation level <= 40: Negative (403.0)

Attention level <= 35 AND
Meditation level <= 51: Negative (315.0/1.0)

Attention level <= 23 AND
Meditation level <= 69 AND
Meditation level <= 57: Negative (88.0)

Meditation level > 30 AND
Attention level > 44: Positive (257.0)

Meditation level <= 37 AND
Attention level <= 53 AND
Meditation level <= 35 AND
Attention level <= 51: Negative (120.0)

Attention level > 26 AND
Meditation level > 37 AND
Meditation level > 43 AND
Attention level > 27: Positive (115.0)

Attention level > 26 AND
Meditation level > 21 AND
Attention level > 56: Positive (38.0)

Attention level <= 14 AND
Meditation level <= 69: Negative (56.0)

Meditation level > 37 AND
Attention level > 38 AND
Meditation level > 38: Positive (45.0)
```

```
Meditation level > 64 AND
Attention level > 10: Positive (33.0)

Meditation level <= 27 AND
Attention level <= 69 AND
Meditation level <= 17: Negative (9.0)

Attention level <= 21 AND
Meditation level <= 70: Negative (21.0)

Meditation level > 56 AND
Attention level > 1: Positive (36.0)

Attention level <= 26 AND
Meditation level <= 54: Negative (16.0)

Attention level > 24 AND
Meditation level <= 53 AND
Attention level > 37 AND
Meditation level <= 41 AND
Attention level > 41 AND
Meditation level > 37: Positive (11.0)

Attention level <= 61 AND
Meditation level > 24 AND
Attention level <= 53 AND
Meditation level <= 41 AND
Attention level <= 43: Negative (16.0)

Attention level > 24 AND
Meditation level > 27 AND
Attention level > 37: Positive (17.0)

Attention level <= 61 AND
Meditation level <= 53 AND
Attention level <= 53: Negative (10.0)

Attention level > 24 AND
Meditation level > 24: Positive (13.0)

Attention level <= 61: Negative (15.0/1.0)

: Positive (4.0)

Number of Rules  :     23


Time taken to build model: 0.23 seconds

=== Stratified cross-validation ===
=== Summary ===

Correctly Classified Instances        4314               99.5845 %
Incorrectly Classified Instances        18                0.4155 %
Kappa statistic                          0.9888
Mean absolute error                      0.0048
Root mean squared error                  0.0629
Relative absolute error                  1.2918 %
```

```
Root relative squared error              14.5965 %
Coverage of cases (0.95 level)           99.6537 %
Mean rel. region size (0.95 level)       50.1962 %
Total Number of Instances              4332

=== Detailed Accuracy By Class ===

               TP Rate   FP Rate   Precision   Recall  F-Measure
ROC Area  Class
                 0.998     0.01       0.997     0.998     0.997
0.999    Positive
                 0.99      0.002      0.993     0.99      0.992
0.999    Negative
Weighted Avg.    0.996     0.008      0.996     0.996     0.996
0.999

=== Confusion Matrix ===

    a    b   <-- classified as
 3258    7 |    a = Positive
   11 1056 |    b = Negative
```

APPENDIX E

MYEmotion: CODE FRAGMENTS

A. Preprocessing

```
%preprocessing script

filtered_data=raw_data;

%data filtering
filtered_data(filtered_data(:,1)<id_start,:)=[];  %remove id<id_start
filtered_data(filtered_data(:,1)>id_end,:)=[];    %remove id>id_start
filtered_data(filtered_data(:,2)==22,:)=[];       %remove type 22
filtered_data
filtered_data(filtered_data(:,3)==0,:)=[];        %remove data=0
(unvalid)


[row column]=size(filtered_data);          %calculate the total number
fo data after data filtering process
filtered_data(1,5)=0;                      %new column of time (column
5), starts with 0 reading


for i=2:row

    filtered_data(i,5)=(filtered_data(i,4)-filtered_data(i-
1,4))+filtered_data(i-1,5); %column 5=time sequence

end

a=filtered_data;
a(a(:,2)==5,:)=[]; %create new table of a (attention level)

b=filtered_data;
b(b(:,2)==4,:)=[]; %create new table of a (attention level)


data_mood(:,1)=a(:,5);
data_mood(:,2)=a(:,3);
data_mood(:,3)=b(:,3);
```

B. Baseline Set

```
baseline_emotion(i,4)=(baseline_emotion(i,2)+baseline_emotion(i,3))/2;

    if baseline_emotion(i,4)>40

        baseline_emotion(i,5)=1;

    else

        baseline_emotion(i,5)=0;

    end
```

```
end
```

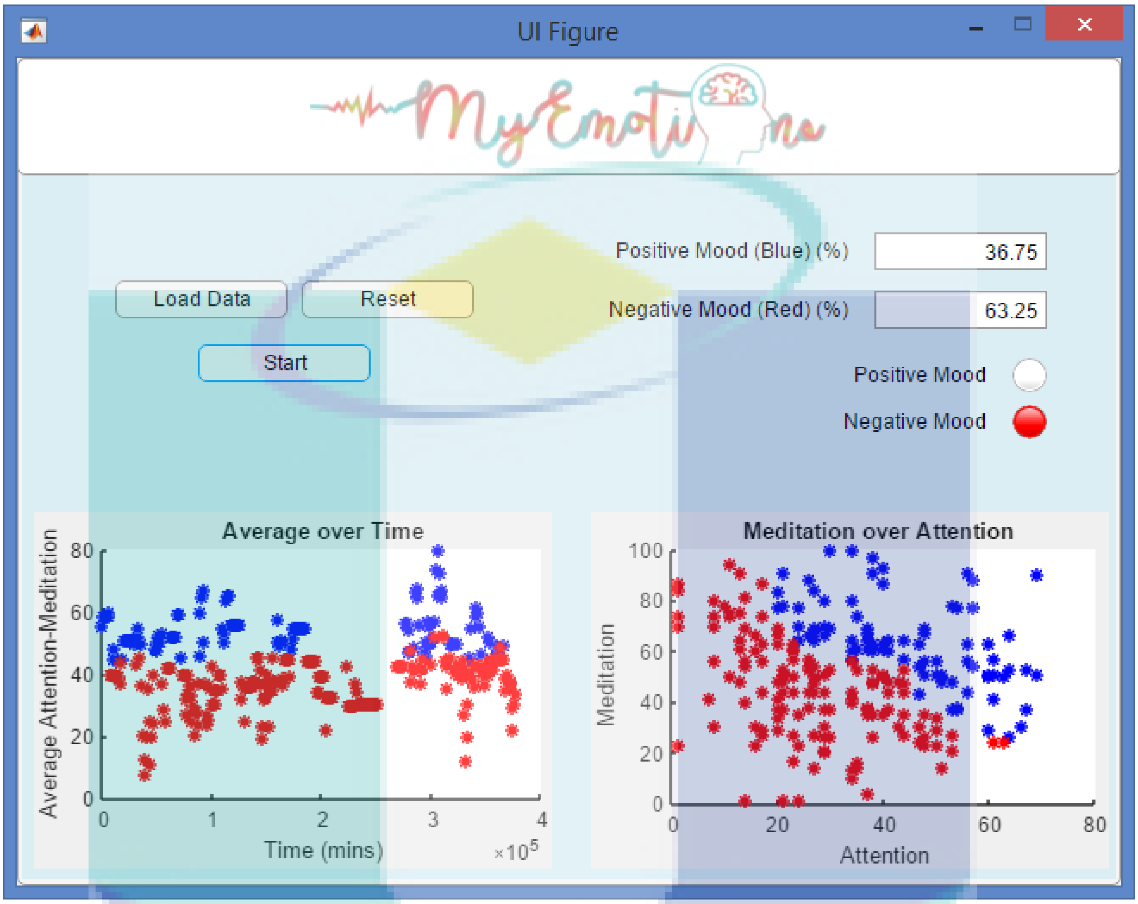
C. **Prediction (production rules) Set**

```
%---------------------positive--------------------

    if rule_based_emotion(i,2)>30 && rule_based_emotion(i,3)>40
        rule_based_emotion(i,5)=1;
    end
    if rule_based_emotion(i,2)>17 && rule_based_emotion(i,3)>60
        rule_based_emotion(i,5)=1;
    end
    if rule_based_emotion(i,2)>43 && rule_based_emotion(i,3)>35
        rule_based_emotion(i,5)=1;
    end
    if rule_based_emotion(i,2)>26 && rule_based_emotion(i,3)>37
        rule_based_emotion(i,5)=1;
    end
     if rule_based_emotion(i,2)>53 && rule_based_emotion(i,3)>24
        rule_based_emotion(i,5)=1;
    end
    %--------------------negative--------------------
    if rule_based_emotion(i,2)<=40 && rule_based_emotion(i,3)<=40
        rule_based_emotion(i,5)=0;
    end
    if rule_based_emotion(i,2)<=35 && rule_based_emotion(i,3)<=51
        rule_based_emotion(i,5)=0;
    end
    if rule_based_emotion(i,2)<=23 && rule_based_emotion(i,3)<=69
        rule_based_emotion(i,5)=0;
```

```
    end
    if rule_based_emotion(i,2)<=44 && rule_based_emotion(i,3)<=56
        rule_based_emotion(i,5)=0;
    end

end
```

APPENDIX F

MYEmotion :GUI



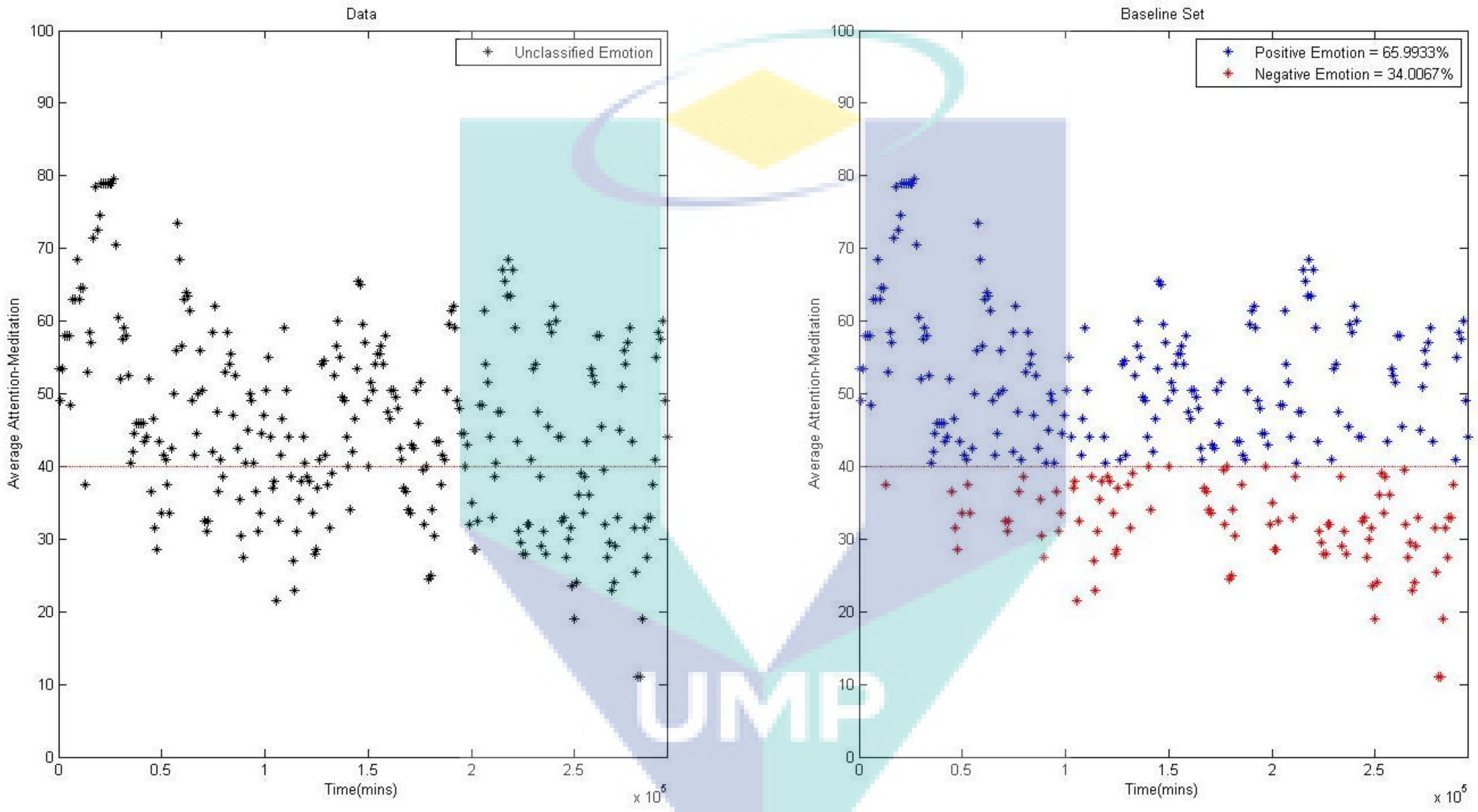


Figure 2 Respondent 1: Session 2 (Baseline set)

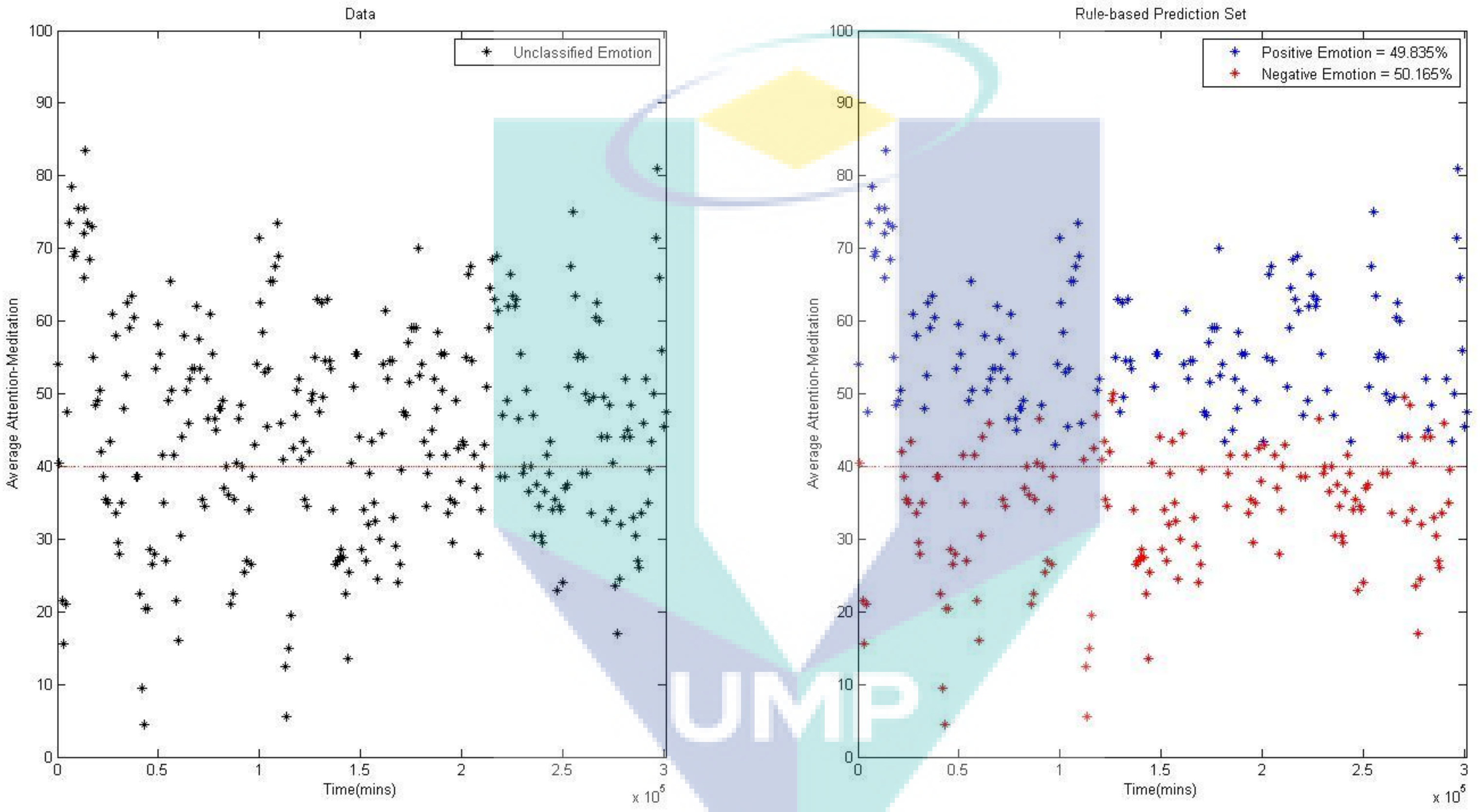


Figure 1 Respondent 1: Session 1 (Production rules prediction set)

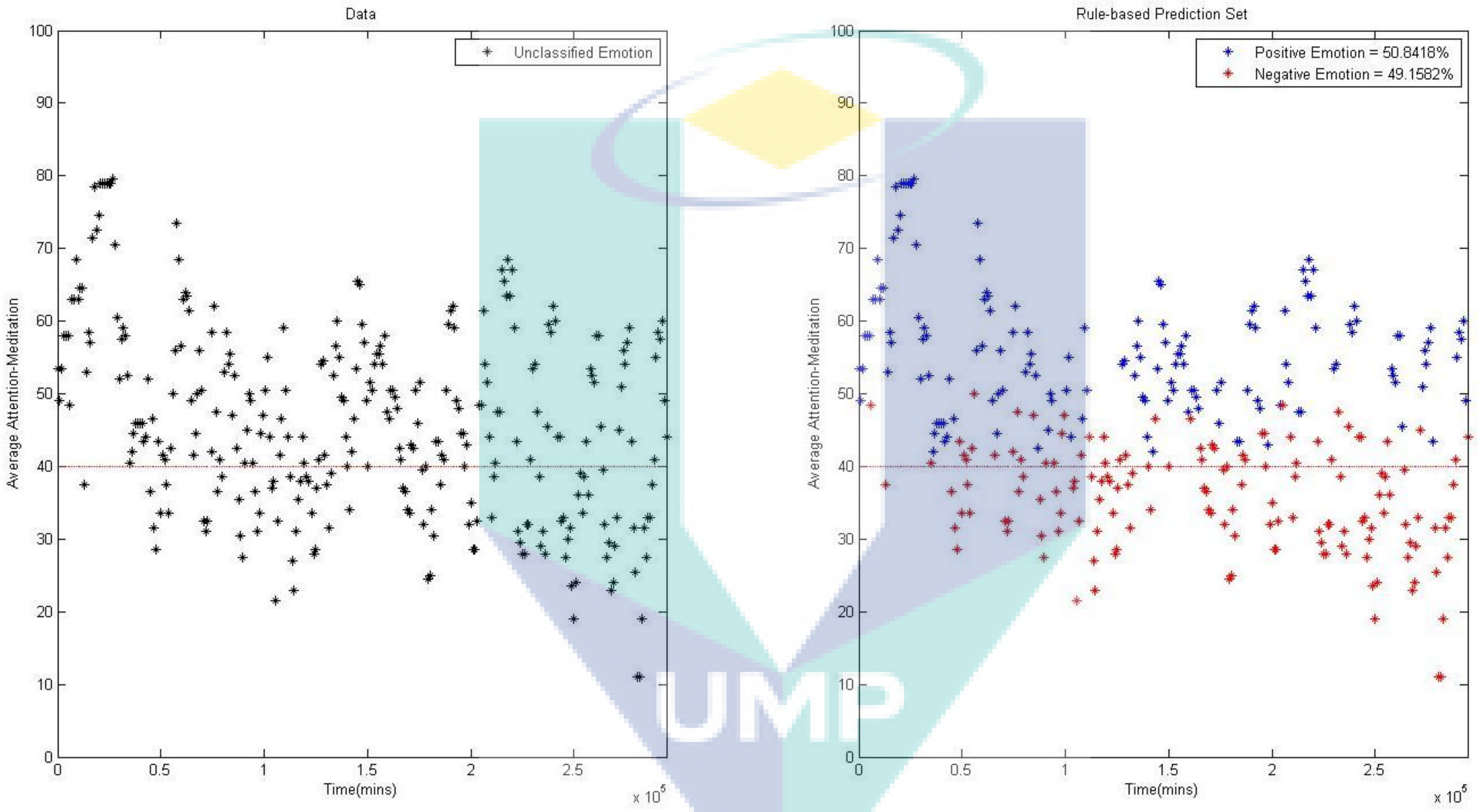


Figure 2 Respondent 1: Session 2 (Production rules prediction set)

LIST OF PUBLICATIONS

1) Mokhtar, R., Sharif, N., Ihsan, S. N., Zainuddin, A., and Mat, N. A. (2015). Assessing Attention and Meditation Levels in Learning Process using Brain Computer Interface. *Advance Science Letter*. (Accepted)

2) Sharif, N., Mokhtar, R., Ihsan, S. N., Zainuddin, A., and Mat, N. A. (2015). Capturing Data of Childrens' Concentration and Meditation Levels : How Learners ' Effort Influence the Academic Emotional Response Level. *Proceedings of the 2nd International Conference on Computational Science and Information Management*, pp. 48–53. (Unpublished)

3) Mokhtar, R., Sharif, N., Ihsan, S. N., Zainuddin, A., and Mat, N. A. (2015). Assessing Attention and Meditation Levels in Learning Process using Brain Computer Interface. *Proceedings of the 3rd International Conference on Computer, Communication and Control Technology*. (Unpublished)

4) Nurshafiqa Saffah, Mohd Sharif and Rahmah, Mokhtar and Siti Normaziah, Ihsan and Azlina, Zainuddin (2016) Learner's Positive and Negative Emotion Prediction using i-Emotion. *Proceeding of International Competition and Exhibition on Computing Innovation 2016* , pp. 271-281.. ISBN 978-967-2054-04-7