การจำแนกคลื่นไฟฟ้าสมองด้วยวิธีการเรียนรู้ของเครื่อง ด้านอารมณ์ความประทับใจ ขณะอ่านคำภาษาไทยและฟังเสียงดิจิทัล

MACHINE LEARNING CLASSIFICATION OF EMOTIONAL VALENCE STATE FROM EEG DATA DURING COGNITIVE TASK: THAI WORD AND SOUND

JAKKARIN CHINSUWAN

Burapha University

2022

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จักรรินทร์ ชินสุวรรณ

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MACHINE LEARNING CLASSIFICATION OF EMOTIONAL VALENCE STATE FROM EEG DATA DURING COGNITIVE TASK: THAI WORD AND SOUND

JAKKARIN CHINSUWAN

A THESIS SUBMITTED IN PARTIAL FULFILLMENT OF
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The thesis of Jakkarin Chinsuwan has been approved by the examining committee to be partial fulfillment of the requirements for the Master Degree of Research and Statistics in Cognitive Science of Burapha University.

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In previous classification studies, supervised learning and unsupervised learning were reported as the foremost classifiers, both with very high accuracy. However, only a few studies have compared the performance of these classifiers by using the human brain waves created during seeing and listening to affective Thai words and sounds. The purposes of this study were 1) to compare the emotional valence during the Independent Component Analysis (ICA) and Principal Component Analysis (PCA) data pre-processing stage by using unsupervised machine learning classification, 2) to compare the emotional valence by using supervised machine learning algorithms in terms of the accuracy among five algorithms (kNN, RF, DT, SVM and DT), and 3) to find the brain regions that can most accurately classify emotional valence by using machine learning. This research used the secondary EEG data, examining brainwave data from 85 participants, aged 20-24 years old. The results were as follows: 1). In the comparison of two pre-processing algorithms, the ICA method was overall better than the PCA method. 2). When using 70% of the dataset for training and 30% for prediction: among the five supervised learning classifiers, the Naïve Bayes (NB) produced the highest overall accuracy of 67.64% followed by the kNN, 64.70%, the DT 61.76%, the SVM 58.82% and the RF 58.82%. 3). This study implicated the dorsolateral prefrontal cortex (F3, F4, FZ) as the brain region that performed the best clustering result of 70.67 % of the “Positive” and “Negative” emotional valence.

These findings may shed light on the application of EEG data to classify human emotion. Furthermore, the most practical algorithm for predicting human emotion, as found here, may also benefit the relevant fields for guiding EEG data analyses.

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Jakkarin Chinsuwan

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CHAPTER 1
INTRODUCTION

Statements and significance of the problems

In recent years, machine learning and deep learning have been widely used in different areas. Machine learning is a subject that evolved from the study of pattern recognition and computational learning theory in artificial intelligence. The research areas that machine learning and profound learning benefit include computational intelligence, computer vision, natural language processing, recommender system, graphical models, robotics and cognitive science, etc.

In cognitive science, "Emotion is central to the quality and range of everyday human experience from perception and attention to learning and decision-making, ‘an event' is perceived, evaluated, and acted upon once its ‘value' has been established as desirable or otherwise" (Dolan 2002). Emotions depict the impact that something as simple as sound can have on thoughts, memories, and how individuals live each day. Stated, "perception and cognition are directly influenced by information with the affective or motivational content." Thus, emotional experiences are viewed as a dynamic event rather than a passive event, which leads to emotional memory. Emotional memory is the storage of the event and the physiological changes that happen during that event (Todd & Thompson 2015).

Valence was presented here in the context of emotional responses to something. In everyday terms, we are using valence in a similar context to how people use the word emotion. As a term relating to emotional states, it was used in the same sense as pleasure, or displeasure would be, or happy/sad emotional states (Bradley & Lang, 1994). Valence can also be referred to as the natural attractiveness, or aversion of stimuli. This attractiveness or aversion was referred to as positive or negative valence. The term dyad or dyadic was used to refer to a one-on-one relationship. The texts used in this dissertation are being referred to as written stimuli. A stimulus was mostly a thing in the environment. The instrument being used in this study was the Self-Assessment Manikin (Bradley & Lang 1994). It measures participant's self-reports of valence, as well as arousal, and feelings of dominance. Arousal was used to mean states of excitement and calm. Dominance was used to mean feelings of being controlled or feelings of being in control. Therefore, this research aimed to study the machine learning algorithm to classify EEG emotional valence.

The study of EEG signals is not novel, and there are numerous applications in which EEG signals can help us understand and develop new sophisticated technology. Studies using EEGs have been used for biomedical applications as well as military applications; however, there is not a unique or set of patterns that allow us to understand the nature of EEG signals fully. In this research, the study of EEG signals is oriented towards the analysis and prediction of emotional valence activity in the brain. It is important to mention the fact that there are other ways to analyze and predict emotional valence; however, the objective of this thesis is to implement a digital signal processing algorithm to predict the initial states of emotional valence. To achieve the intended goal, bio-instrumentation hardware such as the EEG used to capture the analog EEG signals and software such as LabVIEW and R-Studio and MATLAB to process the EEG signals.

Machine learning has several categories. From the aspect of a phase of models, it consists of a training phase, validation phase, and testing phase. From the aspect of data with a label, it consists of supervised learning, unsupervised learning, semi-supervised learning, and reinforcement learning. From the aspect of probability and statistics, it consists of generative models and discriminative models. From the aspect of the number of models, it consists of a single model and ensemble model. There are three phases to find machine learning models.

The training phase is to use training data to fit the parameters of the model. It is usually to find the optimal or local optimal parameters with some learning rules. The validation phase is used to tune the parameters of a mode. Usually, it selects the optimal model and some hyper-parameters. The test phase is a normal working phase after the model is selected and the parameters are trained. It is to evaluate the performance of the model.

Supervised learning is the machine learning task to learn a model from labeled data. Classification and regression are the two main tasks. Classification is for the discrete labels, such as support vector machine (SVM), and convolutional neural networks (CNN). Regression is for continuous labels, such as linear regression.

Supervised learning required a lot of labeled datasets to train the network. However, there is no enough labeled dataset in the real world. Unsupervised learning is another machine learning task opposite to supervised learning. All the training data is unlabeled in unsupervised learning which clustering and dimension reduction are the two main tasks of unsupervised learning. Clustering is used to combine the data into several groups, such as K-means. Dimension Reduction is used to reduce the high-dimension data to low-dimension data, such as principal component analysis (PCA), and auto-encoder (AE). Semi-supervised learning is the combination of supervised learning, and unsupervised learning since only a part of the dataset has the label. Reinforcement learning is a machine learning task related to the environment. It concerns how the agent should take actions in an environment in order to maximize the cumulative reward or minimize the cumulative risk.

The current study focused on the use of supervised learning, specifically classification learning which the process starts by loading the independent and dependent data sets. This data contains multiple independent and dependent pairs. They were then pre-processing the data to extract certain features for learning. Afterward, it was sent to the classification learner to teach. After many cycles through many learners, the best one was selected as the ideal model. The purpose of this research was to test the feasibility of using machine learning to interpret brain signals in a fast and efficient way. The machine learning platform that was utilized in this research was the MATLAB classification learner. By literature review, five classification models of machine learning were chosen to use to predict emotional valence which are K-Nearest Neighbors (kNN), Random Forest (RF), Naïve Bayes (NB), Support Vector Machines (SVM), and Decision Tree (DT), respectively.

Objectives

1. To compare the emotional valence during the Independent Component Analysis (ICA) and Principal Component Analysis (PCA) data pre-processing stage by using unsupervised machine learning classification.

2. To compare the emotional valence by using supervised machine learning algorithms in terms of the accuracy among five algorithms (kNN, RF, DT, SVM and DT).

3. To find the brain regions that can most accurately classify emotional valence by using machine learning.

Conceptual Framework

This research investigated the human brainwaves, which were elicited during performing cognitive tasks and the brainwaves were elicited from seven brain regions, that is, Prefrontal cortex, Dorsolateral prefrontal cortex, Ventrolateral prefrontal, Frontal cortex, Temporal cortex, Parietal cortex and Occipital cortex as shown in figure 1

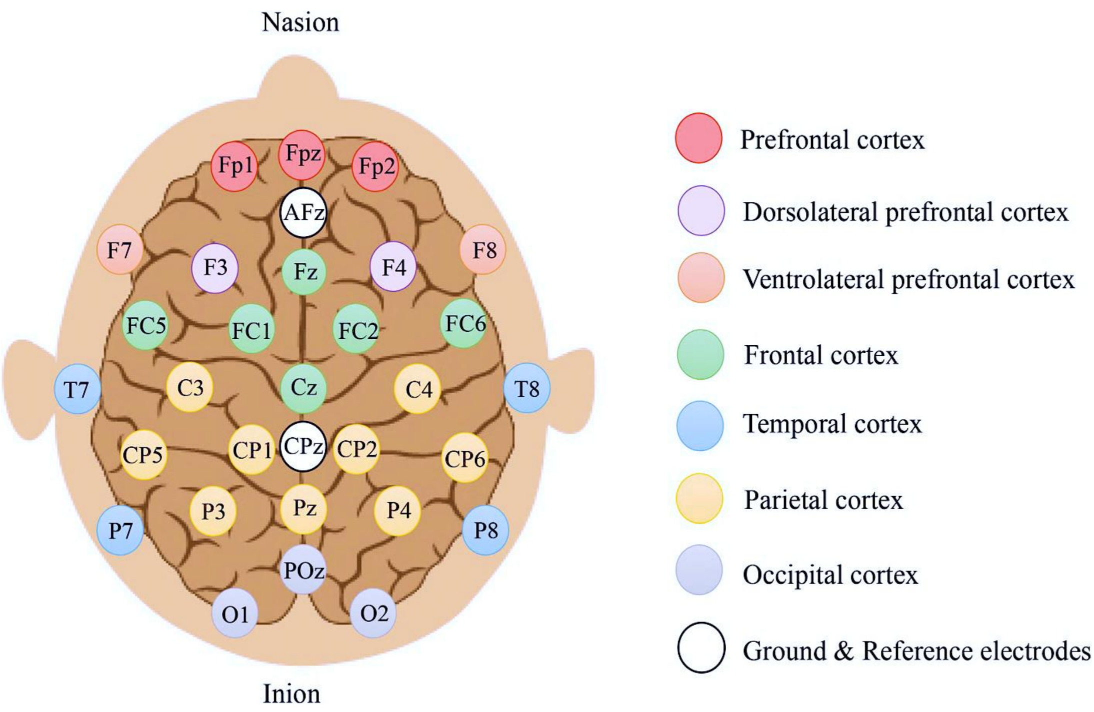


Figure 1 EEG brain locations

The mechanism of brain function after being stimulated by reading the Thai words will be perceived via the visual pathway starting from the cornea. Moreover, the cornea receives reflections from objects to the retina, then the signal will be transmitted on the optic chiasm through the optic nerves to the occipital lobe to verify that “What” are these words. Ventral occipital and temporal lobes check “Where / How”, then sent to the dorsal occipital and parietal lobes also pass the part of the brain and the thalamus via corpus callosum to frontal lobe (Kravitz et al., 2013; Mendoza-Halliday Torres & Martinez-Trujillo, 2014) then the data is transmitted to memory related areas. The Limbic system and hippocampus are responsible to review that I had ever known before, or new, then returning to the part of the orbitofrontal. cortex (OFC), medial prefrontal cortex (MPFC), ventromedial prefrontal cortex (VMPFC) posterior Superior temporal sulcus (pSTS), temporal poles and anterior cingulate cortex (ACC) to think, processing and evaluation of emotion that occur from seeing the Thai word. (Ahveninen et al., 2016; Kryklywy Macpherson Greening & Mitchell, 2013).

Listen to audio digital, the Mechanism of brain function after being stimulated by listening to audio digital — the sound transmits into the auditory pathway, which sounds to send data from the ear to the brain. The auditory nerve data from Cochlea forwarded to the Cochlear Nucleus by each stage of the transmission. Information about the sounds is processed by the neural network, such as Superior Olive would process about the location of the sound source. Lateral Lemniscus is Lam nerve fiber in the brain stem, send information about sound from Cochlear Nucleus to a new evident nerve in the brainstem and Inferior Colliculus on perception Pitch of the nerve fiber from Inferior Colliculus. Connected to the Medial Geniculate which is part of the thalamus in the brain by the thalamus was relayed. Station for information, sensory nerve fibers from the Medial Geniculate connected to Auditory Cortex which each step is data processing. The data will eventually reach the thalamus (Titus Revest & Shortland, 2010, pp. 220-240).

Look and listen to the Thai word and sound, observed emotional valence as the activation function of the brain. When the stimulus emotional are passed into the thalamus, then, the data is transmitted to the part of the brain two parts is 1) cerebral cortex, which contributes to various emotions. 2) the hypothalamus and the autonomic nervous system, and will cause emotional and behavioral psychology (Baumeister & Bushman 2008 Santrock, 2003) working process of brain multisensory the behavior of that reaction time: RT. On the incentive stimulation with emphasis on the perception of information redundancy and (Redundant), the interaction between the functions of the receiver touch. The discovery that water has three the 1) sensory processing, 2) response-selection processing, and 3) motor execution processing (Giard & Peronnet, 1999).

According to the theory, process thinking When people interpret the meaning of the stimulus. In this research are the digital Thai words and sound emotional valence. People will recognize and interpret the incentive assessment incentive, which Lazarus (Lazarus, 1984), offered a cognitive appraisal is the theory that focuses on the process of process appraisal is 2 steps 1) the primary appraisal when individuals face stimuli and 2) analysis of the second appraisal is that people use wisdom, knowledge, and experience of assessment. By this research. Can measure the level of emotional response in impressed with three aspects 1) neutral 2) satisfied and 3) unsatisfied. From the score, behavior was self-assessment Self-Assessment Manikin (SAM) and to study the electric brain wave measured by the height of the wave (μV).

Moreover, the width of the wave or latency changes during a stimulus of the word reading and sound listening of the digital equipment. The concept of research was shown in figure 2

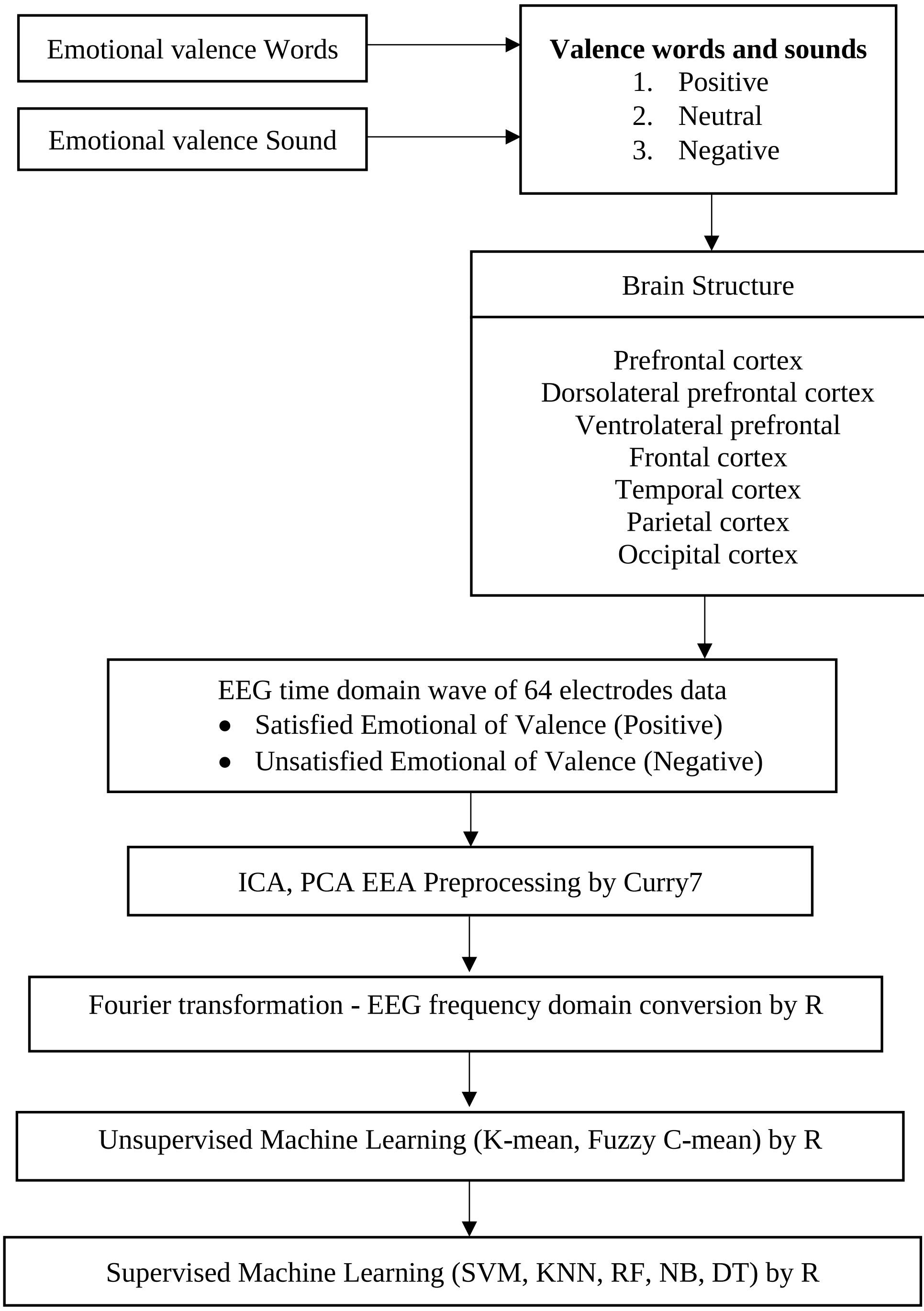


Figure 2 Concept of emotional valence machine learning research

After getting secondary emotional valence EEG data, we used Curry7 software to do two pre-processing methods which are independent component analysis ICA and Principal component analysis PCA method.

After finishing pre-processing data method, we used the Fast Fourier transformation algorithm on R-Studio to transform EEG time domain data to frequency domain data.

After finishing, Fast Fourier transformation process, we used 2 unsupervised machines learning algorithms: K-mean and Fuzzy C-mean on R-Studio.

After finishing, unsupervised machines learning algorithms process, we used 5 supervised Machines learning algorithms: K-Nearest Neighbors (KNN) Model, Random Forest (RF) Model, Naïve Bayes (NB) Model, Support Vector Machines (SVM) Model, Decision Tree (DT) Model on R-Studio.

Finally, it would be known, which brain surface area was the best predictor for emotional valence: Prefrontal cortex (FP1, FPZ, FP2), dorsolateral prefrontal cortex (F3, F4, FZ), ventrolateral prefrontal (F7, F8), frontal cortex (FC5, FC1, FZ, CZ, FC2, FC6) temporal cortex (T7, P7, T8, P8), parietal cortex (C3, CP5, CP1, P3, PZ, CP2, C4, P4, CP6), occipital cortex (O1, POZ, O2). Further, it would be known, which pre-processing was suitable for emotional valence. In addition, it would be known, which unsupervised machine learning were suitable for emotional valence classification and which supervised machine learning were suitable for emotional valence prediction.

Hypothesis

1. The first question of the current study was to build the machine learning model that could detect and classify emotional valence into positive and negative. In order to classify the emotions, different factors must be considered, which include participants, stimuli, the temporal window, and EEG features. Different EEG features were extracted from the EEG raw signal, and these features include time domain features, frequency domain features, and nonlinear features. Different words and sounds were used as stimuli in order to trigger different emotions. The expected outcome was the ability to classify two different types of emotions as positive and negative emotions. And the ICA data pre-processing method had a higher noisy EEG data reduction efficiency of emotional valence than the PCA data pre-processing method examined by using unsupervised machine learning classification.

2. In comparing among five models of supervised machine learning, which were K-Nearest Neighbors, Random Forest, Naïve Bayes, Support Vector Machines, and Decision Tree, The Support Vector Machine would have the highest correct percent of emotional valence prediction.

3. The Dorsolateral prefrontal was the best brain regions that could be used for the most accurately classify emotional valence by using machine learning algorithms.

Contribution to Knowledge

Several aspects of our work are useful for proving insights and theoretical hypotheses or/and being used in practical systems and real-world applications. Here is a summary of the contributions of our research:

1. Machine learning models.

This research studied several multimodal machine learning models in detail, used K-Nearest Neighbors, Random Forest, Naïve Bayes, Support Vector Machines, and Decision Tree to learn wave features for EEG emotional valence classification. These new knowledges generated could be beneficially use to develop EEG emotional classification program.

2. Sensors and datasets.

This research has explored beneficial types of sensors, each capturing one or more of the modalities used in our research. In other words, this research performed multimodal sensing and data processing for developing brain-computer interface applications.

The scope of the Study

The scope of digital sound and words, The Thai word and sound digital. It is a collection of words in Thai and digital audio of emotional valence. In the context of the Thai people. The specific words in Thai and digital audio of emotional valence divided into 1) satisfied 2) unsatisfied. This research use EEG secondary data which population was composed of healthy and undergraduate students, male and female, aged 20-24 years, who were studying at Burapha University, Chonburi in academic year of 2560. The specific details were shown as follows.

- Sex is male and female.
- The personality type is extravert and ambivert.
- The emotional valence includes: satisfied (Positive) and unsatisfied (Negative).
- An adult's EEG brain waves beginning, while looking and listening to digital audio Thai language emotional valence words being classified as two patterns:
    - Height or amplitude of EEG was measured in micro-Volts (μV).
    - Width or latency of EEG was measured in milliseconds (ms).
- Fast Fourier transformation was used to transform EEG data to frequency domains.

There were two EEG pre-processing methods:

1. Independent component analysis ICA
2. Principal component analysis PCA

There were two variables of unsupervised machine learning methods:

1. K-mean
2. Fuzzy C-mean

There were five supervised machine learning models:

1. K-Nearest Neighbors (KNN) Model
2. Random Forest (RF) Model
3. Naïve Bayes (NB) Model
4. Support Vector Machines (SVM) Model
5. Decision Tree (DT) Model

There were two variables of unsupervised machine learning methods:

1. Prefrontal cortex (FP1, FPZ, FP2)
2. Dorsolateral prefrontal cortex (F3, F4, FZ)
3. Ventrolateral prefrontal (F7, F8)
4. Frontal cortex (FC5, FC1, FZ, CZ, FC2, FC6)
5. Temporal cortex (T7, P7, T8, P8)
6. Parietal cortex (C3, CP5, CP1, P3, PZ, CP2, C4, P4, CP6)

7. Occipital cortex (O1, POZ, O2)

Definition of Terms

1. Emotional valence is an emotion state, means the intrinsic attractiveness/"good"-ness (positive valence) or averseness/"bad"-ness (negative valence) of an event, object, or situation.

2. Independent component analysis (ICA) is a pre-processing method that can be applied to any set of random variables to find a linear transform that maximizes the statistical independence of the output components.

3. Principal component analysis (PCA) is a pre-processing method that find a linear transformation of the data that maximizes the variance of the transformed data.

4. Machine learning is the study and development of algorithms that can learn and make predictions form a set of data.

5. Unsupervised machine learning is a machine learning technique in which the users do not need to supervise the model. Instead, it allows the model to work on its own to discover patterns and information that was previously undetected. It mainly deals with the unlabelled data.

6. K-mean is a method of vector quantization, originally from signal processing, that aims to partition n observations into k clusters in which each observation belongs to the cluster with the nearest mean, serving as a prototype of the cluster.

7. Fuzzy C-mean is one of the unsupervised machine learning which a form of clustering in which each data point can belong to more than one cluster.

8. Supervised machine learning is the machine learning task of learning a function that maps an input to an output based on example input-output pairs. It infers a function from labeled training data consisting of a set of training examples.

9. K-nearest Neighbors algorithm (k-NN) is one of the supervised machine learning with a non-parametric method used for classification and regression.

10. Decision tree (DT) is one of the supervised machine learning with decision tree as a predictive model, represented observations in the branches, represented the conclusions about the item's target value in the leaves. It is one of the predictive modeling approaches used in statistics, data mining and machine learning.

11. Random forests (RF) or random decision forests is one of the supervised machine learning with an ensemble learning method for classification, regression and other tasks that operate by constructing a multitude of decision trees.

12. Naive Bayes (NB) classifiers are one of the supervised machine learning with family of simple "probabilistic classifiers" based on applying Bayes' theorem with strong (naive) independence assumptions between the features.

13. Support-Vector Machines (SVM, also support-vector networks) are supervised learning models with associated learning algorithms that analyze data used for classification and regression analysis.

14. Electroencephalogram (EEG) is an electrophysiological monitoring technique for recording and interpreting electrical activity in the brain by attaching the electrodes are placed on the surface of the skull.

CHAPTER 2
LITERATURE REVIEW

This study was divided into six sections, that is, (i) concepts and theories of emotion and related studies, (ii) concepts and theories of emotional valence and related studies, (iii) audio, vision and related studies, (iv) electroencephalogram and related studies, (v) ICA and PCA processes and related studies, and (vi) machine learning and related studies.

Part 1 Concepts and theories of emotion and related studies

- Theories of Emotion
- The meaning of emotion
- The importance of emotion
- Concepts and theories of emotion
- Research related to emotion

Part 2 Concepts and theories of emotional valence and related studies

Part 3 Audio, vision, and related studies

Part 4 Electroencephalogram and related studies

- EEG Signals
- Electrodes Placement
- EEG Frequency
- EEG Signal Analysis
- Artifact/Noise removal
- The history of electroencephalography
- Comparison of EEG waves

Part 5 ICA and PCA processes and related studies

- Advantages of ICA
- The Fast Fourier Transform (FFT)

Part 6 Machine learning and related studies

Part 1 Concepts and theories of emotion and related studies

Emotion is a construct that everyone knows and can recognize but for which there is not one clear definition. It has been generally agreed, though, that there is a physiological response that accompanies emotion. In an emotional situation the body reacts, the heart flutters, pounds, and drops, palms sweat, muscles tense and relax, faces flush, smile, and frown (Bradley, 2000). These physical and behavioral changes are experienced subjectively and can be used to differentiate one emotion from another. An individual experiences these physiological and behavioral changes subjectively by noticing, for example, when their heart beats faster, or their breathing pattern changes in a situation. The physiological and behavioral changes that we experience ourselves we also notice in others and make assumptions based on these visible physiological states about others' emotional state.

The emotional response to external stimuli is generated automatically by the individual and is evident through their physiological and behavioral reactions. These physiological responses vary with the type of situation; that is, there is not a universal physiological response to all external stimuli (Lang, 1994). In particular, responding may be described or characterized as occurring in two dimensions. An evoked response may have either a positive (pleasant) or a negative (unpleasant) valence and occurs with a high or low level of arousal (Lang, Bradley, & Cuthbert, 1990). Thus, as the stimulus is interpreted and represented in the brain, it evokes physiological responses and biases the organism towards certain behaviors. In this way, an emotion may be considered, functionally and adaptively, to be a response disposition.

Lang and Bradley (Bradley, 2000; Lang, 1994) theorized that pleasure and arousal are the two fundamental dimensions that together makeup emotion. It has been observed in both animal and human motivational behavior that social situations elicit approach behavior, and unpleasant situations elicit withdrawal behavior. The world appears to be categorized by the valance of the flying experience, and the extent to which an event promotes (pleasant) or threatens (unpleasant) the individual. Said another way, life can be organized into the behavior of withdrawal versus approach evaluations of each situation. This suggests that this is a foundational characteristic in human (and nonhuman) emotions (Bradley, 2000).

1.1 Theories of Emotion

Theories of emotion fall into two broad categories: cognitive theories that view emotions as the result of cognitive appraisals (e.g., James-Lange theory, Cannon-Bard theory) and theories that are more biologically-oriented, viewing emotions and cognitions as having separate, but related, neural systems (Borod,1992). This latter category of theories is most relevant to neuropsychological theories of emotion (Borod, 1992).

1.2 The meaning of emotion

Emotion is a condition of change of body and mind due to the interaction between stimuli and organic. Moreover, it shows the dialog that according to the situation. The result comes from the interaction with the environment — the perception through the sensory nervous system. Moreover, there may be a hormone involved. A recognition of this often through affecting the thinking process and come. Which involves conscious experience. The physical response, both inside and outside. The tendency to support or curb the behavior has been motivation and cause different emotions such as happiness, sadness, greed, anger, depression. Depressed, etc., which will lead to good mental health, positive emotion the negative emotional make mental health deterioration affect body debilitating, unhappy life (Oraphan Leaboontawatchai, 2013, pp. 251-252; Dworetzky, 1991, p. 317). Health information of the corresponding article (Supa), business (Wattana, 2016) says, "hundreds of diseases comes from emotion. The role of the emotional impact of various diseases including cancer. A medical report, it was found that the patient 100 people with mental stress society was to 76 people. In cancer patients, and found that the first symptoms of cancer often appeared stressful condition variance. Severe emotional before 62.5 percent.

Emotion can occur from stimuli in nervous system stimulation through touch. The human five consists of the eye (picture) the tongue (taste) nose (smell) ear (voice) and body (touch) the researcher many of you. Each rate in perceptual awareness, many of the stimuli in unequal by sensory stimulation of sight as recognition that matters. Cause the perception which affects the change in behavior. Moreover, the physiological changes will vary according to the mood of the feelings of the individual. (Thawatchai Sripornngam, Seri, & Somporn Suwanee, 2015).

Although most people will understand well that emotion is. However, if everyone agreed precise meaning would be ambiguous because of a complex phenomenon. The dog. You basically what psychologists use is a feeling that consists of a physiological reaction. Perception, interpretation of the person and behavior expression. Scientists who study the emotion agreed that the element of emotion the main component 3 elements. With each other.

1. Physiological responses, such as changes in heart rate. The change in blood pressure.

2. Feelings such as happiness, sadness, and surprise.

3. Behavior expressed, such as facial expression or action, etc., and with the meaning of emotion has several meanings difficult to the enemy. The article only literally only depending on the WHO definition. If a cognitive theory has focused on the definition of thinking, evaluation, while. The ergonomic office will focus on in the ergonomic. The students will focus on the engineering behavior of emotional behavior. Because of this, there is the meaning of spiritual knowledge. Feel it enough to conclude as follows.

The Royal Academy (2013, p. 78) meaning of emotion. Emotion is a psychological feeling condition change according to internal, external stimuli are divided into two types is 1) positive mood cause happiness, such as love and 2) negative feelings, emotions cause suffering, anger, and envy.

Araya Piyagul (2013, pp. 48-53) suggested that emotions, mean the changes in the different elements, including elements of the body (awake body, such as the heart beats faster. Rapid pulse) elements of wisdom (of feeling or cognitive process such as perception. Interpretation thinking) the feelings. The affection of feelings (such as angry, like. Satisfaction/dissatisfaction) like elements and behavior (behavioral expression, such as the expression, gestures, their hands tightly. Get up run) by this change occurred in response to the environment. A person experiences.

Cushion Janpetch and Viroj Jedsdaluck (2016, pp. 125-135) indicated that the meaning of emotion is the emotion caused by stimuli can influences, and has both positive and negative emotions, emotions, such as satisfaction and feeling not fulfilled. Human behavior is under the control of emotion, which is different to different people - moreover, the mood as a stimulant to various activities.

Santrock (2003, p. 456) explained that emotion means which can be connected with feelings of awake in the physiology, such as Tachycardia with experience in hard condition, such as thinking of in love with someone, and the expression of behavior, such as smiling or grimace.

Scherer (2005, p. 695) explained that emotion is involved complex consists of the main elements that include the cognitive process. (Cognition) Neurophysiology of (Neurophysiology) motivation (Motivation) expression (Motor Expression) and inner feelings (Subjective. Feeling). Whitfield, Dube, Felitti, and Anda (2005, p. 798) discussed the meaning and emotion as a result of the model response associated with the mechanism. Changes in the total body that is a form of physical response is different and it can cause different moods. Besides, Gross, and Thompson (2007, pp. 498-499) suggested the emotion that feels change due to changes in the body. That means there will be changes in the body, such as heart rate, heart - the rise of blood pressure. An increase in the amount of blood sugar was a sense of emotion according to the changes.

Kulviwat et al. (2007, pp. 1059-1084) suggested that the mood in which sense various conditions of emotional. Behavior occurs from learning. Alternatively, by the incentive and lead to different behaviors, emotional reactions that occur from within is not constant. Change all the time, and that is what cannot touch clearly. It can be observed from the behavioral responses to show up.

Hamann (2012, pp. 458-466) suggested that emotions are given in the form of change. The impact caused by the temporary state feeling situation with feelings and involved. The multitasking system includes physiology and brain activity, behavior and the resulting from the situation of dominant Affectively related to coordination. Pattern system, including physiology, brain function, behavior and experience care. These changes will affect the response to adjust. Management and behavior, such as approach or avoidance. Important related to differences between perceived between the perception of emotion and experience emotions.

Moors et al. (2013, p. 169) suggested that the emotional feelings that do not know the background causes of emotional feelings. Nonspecific and specific to a particular stimulus especially. Emotional feelings this background on the human mind each person very much due to the ability of memory and decision making various including attitude and opinion of the individual.

Michel (2013, p. 7) provided the definition that the mood was designated as a series of reactions and actions with the exchange between individuals. In the process of continuous status in each emotion meaning itself. Each has each different mood. When things do not improve, according to the need, anxiety, fear, sadness, knowledge. Feelings of guilt, shame, jealousy, but when things right is happy and proud or love.

Pekrun and Linnenbrink-Garcia (2014, p. 1) defined emotional dimensions of learning that the mood is combined experience in educational management. That is, measuring tools for the evaluation of learning and personality development.

Garrett (2015, p. 201) suggested emotional means to increase or decrease in the physiological activities to stimulate the feeling of people. Moreover, emotional behavior or expression.

Coppin and Sander (2016, p. 3) suggested meaning of emotion from a synthesis of literature that the mood is a two-step process events fast the clump. With 1) mechanism of sensual related 2) causing emotional response many, such as the trend action. Automatic response expression and emotion.

Zhang Kong and Li (2017, pp. 1116-1125) suggested meaning of emotion, mood, feeling unable to control in which part or all of the SA. Can be in control, is 1) perception and understanding of the emotions 2) to get emotional 3) the ability to participate in behavior. It is aimed at the target. Moreover, ignore the inappropriate behavior when the mood is negative, and 4) access strategy. Effective control. Disorders of emotion are one of the essential characteristics of the disorder of emotional things. From the definition above, concluded that the emotion refers to a psychological state resulting from the response that has been stimulated by stimuli such as images or sound, through the sensory system and the process of perception and interpretation. Lead to a change in behavior.

1.3 The importance of emotion

The mood is imperative to live several possibilities. Emotions make life taste, whether happy or sad, that is to say, a mood is a machine. The measure of mental health is medium to others to understand the state identity of the person. Essential for healthy living in terms of both happiness and suffering. The survival of the people by the important per person (Chaweewan Sattayatam, 2009, pp. 152-153) as follows.

1. Emotion is fundamental to the personality, and daily life is very much like.

2. Satisfaction gained from curiosity. To help human knowledge and understanding of things.

3. Cheerful make good mental health. Happy. To reduce emotional stress.

4. Fear will cause caution cautious not careless.

5. Goethe to help people to overcome obstacles. Therefore, people succeed in life.

6. Emotional energy for human assembly of various missions to achieve, such as business in the industry to be the failure. BAC used creatively. Cause the benefit of humanity as the distinguished statesmen, poets, musicians, and artists who signed as well as the life of a person.

7. Emotions make human life with aesthetics. The motivation to do activities and encourage individuals actively at work. Influence on the adaptation of individuals to society and the environment. These will affect the adjustment and essential to human personality.

8. Mood media make people understand each other because that person knows the feeling of another person.

9. Emotions make life battle ready to increase the power to live in the fight against the crisis event materials to life — a survival.

The emotions are also crucial for coexistence in the society. The emotional functions are the medium of communication between themselves and others as a feeling and thoughts, which has both. Good and bad received. The effect of emotion is going to be the mood created by the people. The energy increase can work more than usual. Hope to live. As well as the persistent trying to overcome a variety of obstacles. The effects of emotion will occur when the emotion cannot break that. Car control, affect the body and mind until they cause the symptoms of the disease (Lupton, 1998, pp. 39-43).

1.4 Concepts and theories of emotion

Darwinian theories (1871), proposed the emotions of humans by Darwin explains that human behavior is the result of evolution. Tested and proven by studying the expression of the emotions in man and animals. The instinctive like animals. Received and transmitted through the genetic three folds. 1) expression was a small unrelated 2) features a more specific limit. The action and 3) bias towards emotional one. Darwin concluded that emotions are the without refined or primitive and related sequel from the past. In terms of both the evolution of humanity and the uniqueness of each. This theory proposes that the emotions associated with physiological reactions are a physiological process that is crucial made body action and response. The organ in the body. Which is to change the body first and then get feedback of changes occurred.

Theory of Oz's bell, (Ausubel 1970). Australia's bell explained. Expression and interaction of emotion four steps as follows.

1. Interpretative Phase is perceived events. There. The demand arrangement means and how we perceive ourselves.

2. Preparatory Reactive Phase is the stage between emotions and body get prepared answering model. Any of the emotions.

3. Consummatory Reactive Phase is a step the body and nervous system know the emotional aspects arising due to the nervous system and organs that the movement to work to the emotional response occurred.

4. Reflective Reactive Phase is the step body and external processing emotional state response reaction according to the form of abroad. Experience, which was influenced by the raised a person's personality. Theory of Cannon-Bard (1927), Cannon - Bach explained. Emotion caused by the brain process with high. The stimulus will cause the experience of emotions and in response to internal organs by birth — changes in physiology up simultaneously.

5. Contemporary Model of Emotion, this theory focuses on the effect of cognitive appraisal which evaluates is the interpretation of the individual to stimulate that anything. Color or evil threatened or support. Related or not related, etc., depending on the stimulus evaluation behavior. Facial expressions, gestures, and emotional feelings, which the behavior expression. To add a sense of emotion. Emotional

feelings influence assessment by affecting the stimulus, behavior, expression, and feeling as well. The feeling. The act will change when each element of emotional interaction with others (Strongman, 2003, pp. 66-67).

6. Schachter-Singer Theory (1962) Stanley Schacher and Jerome Singer presented the Two-Factor Theory of Emotion. The emotional concept factor is composed of 1) of awake in Physiology (Physiological Arousal) which will react physically the same conditions emotions. Such as when angry or afraid of a physiological reaction, such as heart rate, goosebumps, iris and shortness of breath. Frequency is appropriate reactions. There will determine the intensity of emotions and 2) excitement and cognitive appraisal (Cognitive Labeling or Cognitive. Appraisal) which are different in each emotion. This is because the intellectual factors specify the types of emotions, like when I see a snake. Part of the cognitive situation that the mood is fear, meanwhile, will eventually physiological reactions, such as the heart beats. , breathe and how often, and determine the intensity of fear increased. Explain the theory and the sector - singer. Mistake if alert conditions occur, such as a person may drink drinks with caffeine. Unconsciously cannot be assessed that the lather that happened from what? When faced with a situation that upset, this process is called transfer excitement (Excitation Transfer) is a condition excited from the place. Situation one (drink caffeine). Transfer to other situations (Moody). The research of Dutton and Aron (1974) is part of the research that supports the theory. Sat) - singer. The experiments provide women with the personality attractiveness one. The young man was asked to interview Walk across the bridge task compared to the interview in the same manner as a young man. Walking across the bridge is safe. The result showed that young man was walking across the bridge that horrible scored the original image testing technique of creating (Thematic Apperception. Test: TAT) than a man walks across the bridge is safe. Which explains of awake from fear. Will cause incorrect assessment is interested in the girl the interviewer. Which can explain the theory summary? The evaluation theory.

7. Emotional Appraisal Theory of Emotion in 1960, Richard Lazarus has a theory connection between cognition and motivation of emotions. The basic beliefs. The mood is the result of the evaluation of cognitive appraisal. Emotion caused by

intention. Appraisal theory is the theory that focuses on the emotional process appraisal by individuals and environment relationships all the time.

8. Moreover, friendship. A response to each other. Using the incentive based on perception and interpretation of the person through the process of thought (Cognitive Process) which evaluation. The situation or incentive, causing the emotions are two steps are as follows. Evaluation of the first.

8.1 Primary Appraisal is an assessment that events that face now are a challenge or threat status if the challenge is. Benefits and has resulted in progress, but if a threat may cause harmful waste or appropriate style. Results in a negative way, which needs to be evaluated in step 2 next.

8.2 Secondary Appraisal is the use of intelligence. The knowledge and experience to evaluate alternatives. In the removal of a dangerous thing. Assess whether the evaluation steps one right or not. Includes an assessment of consequences. If the solution is low, but the definite threat if the solution in a negative way considered a threat level allowed.

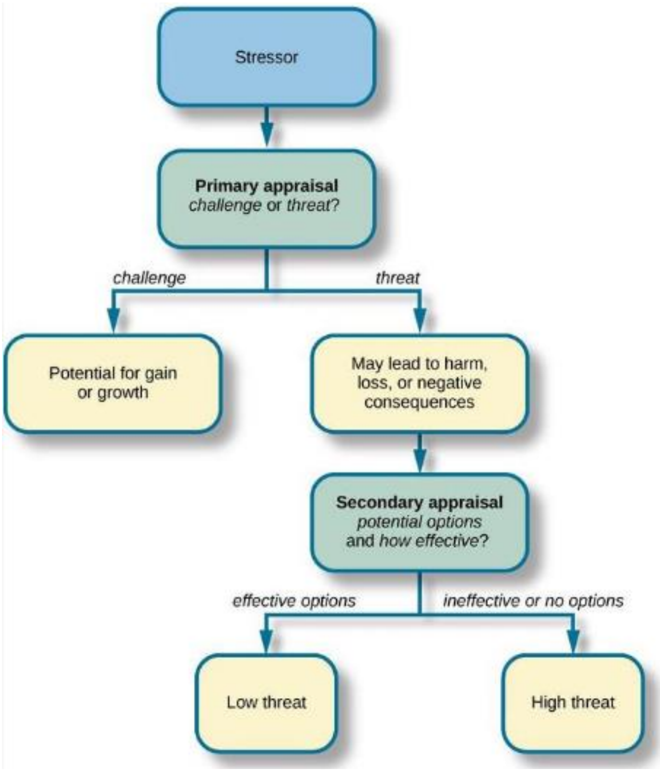


Figure 3 Appraisal Theory of Emotion (Hume, 2012, p. 262)

Emotion, a study on emotion appears the concept is very different. A review of the literature in psychology. To lead a proposal about the basic concepts. Breaking into the emotions. (Schr ö der 2001 pp. 561-564) Which has the technique? The breakdown of emotion, such as Multidimensional Scaling Semantic Differential techniques, and many other agents make the researchers. Others can summarize and present basic human emotions into 3 in the emotional breakdown outside, starts from the natural characteristics of tea. Consciousness and the expression of key features consistent with emotional concepts were a great feature, or bad features stimulate or relax the canal, and features powerful or weak. Better to remember the only culture in each emotion with plenty of various kinds. The study on the basic emotions of scholars Researchers interested in learning about emotions and past (Mehrabian, 1996, pp. 261-292; Schlosberg, 1954, pp. 81-88; Smith & Ellsworth,1985,pp. 813-838; Yik Russell & Barrett, 1999, pp. 600-619) has reviewed the literature on aspects of mood by references from the development of foreign, and can be summarized and classified the emotions in this research into 3 aspects.

1. Emotional valence caused by activated by stimuli. Then the recognition process and interpretation. It is impressive. The satisfaction that occurs within the mind of the individual can be divided into three styles is 1) characteristics do not satisfy the negative emotions (Negative. Valence) or called emotional dissatisfaction (Unsatisfied), such as bad, sad, sad depression 2) relaxed (Neutral). Moreover, the 3) the satisfaction, positive emotion (Positive Valence) or called emotional satisfaction (Satisfied) such as happy, impressive, pride.

2. Emotional arousal caused by activated by stimuli. Then the recognition process and interpretation. Cause emotional responses the feeling can be divided into three styles is 1) looks calm (Calm), such as peace, sometimes happy relieved. 2) looks relaxed (Neutral) and 3) looks excited (Excited) such as exciting, fun, energetic, cheerful.

3. Emotional dominance caused by the influence of the environment on the emotions of the individual. Affecting the ability to control emotions or not. A powerful or power. Emotional fear or fear of the environment. (Bradley & Lang, 1994, pp. 49-59; Mehrabian, 1996, pp. 261-292; Osgood & Colloquium, 1966, pp. 1-30; Russell & Mehrabian, 1977, pp. 273-294) which means that if emotions play an

important role in control Have the power, and do not be afraid, but if the mood not strong enough to fear, powerful, and cannot control feelings towards that Dominance is not. Relations are occurring inside of a person. However, the relationship is formed between the person and the environment (people, events or objects, etc.). Influence arising from activation by stimuli and meet a three style is 1) the emotional domination? Command management, not afraid to get a touch, touch (Control) 2) the mood relaxed (Neutral) and 3) emotional aspects are less than the power Water control, do not fear. Fear (Uncontrol), such as fear, panic, no mechanical trade, the dread. Much, do not be afraid, and use a gauge mood. Self-Assessment Manikin (SAM) of Bradley and Lang (1994, pp. 49-59).

1.5 Research related to emotion

Domes et al. (2010) studied the reaction between males and females on the photo negative feelings by image look. The volunteers to look at pictures and to rate pictures after a brain scan revealed no difference between sex in emotional perception abroad. Awake, but found that the brain of a female, the amygdala Right Temporal Pole Dorsolateral Prefrontal Cortex Left Middle and Temporal. Gyrus has to work than males, but some studies showed that the brains of males than females work on emotional stimuli negative feelings. Such as Schienle Schafer Stark, Walter and Vaitl (2005) to study the reaction between males and females on the photo disgusting and scary. The results showed that even if the female is an emotional perception of a grim picture image negative and alertness was higher than the male. However, when the volunteers looked at the pictures were attacked by humans or animals' brains of males and the Amygdala Left Fusiform Gyrus has worked more than females.

VästfjäLL (2012) studied Emotional Reactions to Sounds without Meaning. This research analyzed the relationship between the emotional reaction to sound means nothing (noise mixed - Tone and. Noise Complexes) and indicators of objectivity (voice Objective Sound Descriptors) experiment 2 times show that the leading dimension of emotion is the emotional state and activation related to perceived intensity and perceived: high-frequency content. The results can be used as a criterion for respectively designed. Induction of emotional voice. The use of sound smiley in the product. The research on voice recognition from the environment.

Soares et al. (2013) studied Affective Auditory Stimuli: Adaptation of The International Affective Digitized Sounds (IADS-2). For European Portuguese stimuli on mood: sound? The series of stimuli universal audio IADS-2 into Portugal in the European context. This research will lead to offering value norms, many of the excellent series motive them. A universal context IADS-2 into Portugal in Europe (Bradley & Lang 2007) is a standard database of sounds that occur naturally 167 sounds with applied research on emotion widely. These sounds are estimated by undergraduate students who speak Portuguese native 300 people in the emotional dimension three dimensions is satisfaction. Power (Valence) arousal (Arousal) and control (Dominance) using a self-assessment (Self-Assessment Manikin - SAM) the purpose of this study. There are three reasons 1) to develop a series of stimuli with sound standard and get the estimation of the norm (Normative), for use with the population to seconds. The research of Portugal in Europe and all the researchers in general 2) to investigate the differences in gender. Culture and from the estimated (Ratings) various dimensions of emotional stimuli between the sound of the standard value context of Portugal in Europe (EP). Context and American (Bradley & Lang, 2007) to standard context, Spain (Fernández-Abascal et al., 2008, pp. 104-113; Redondo et al., 2008, pp. 784-790) and 3) to promote research in the process of sound on mood in the country, Portugal in Europe were pointed out. Series universal audio stimuli IADS-2 database digital audio is a useful and accurate for the research on emotion in the context of the program. Portugal in Europe that can compare the results with the research at the international level, the other using the same sound database. After. Make a standard different from the set of stimuli IADS-2 universal audio in the context of Portugal in Europe.

Choi et al. (2015) studied Development of an Auditory Emotion Recognition Function Using Psychoacoustic Parameters Based. On the International Affective Digitized Sounds study. For the development of emotion from voice recognition, which may determine the emotion from the voice in our daily life. Selection. A voice from the sound stimuli conveys universal digital International Affective Digitized Sounds (IADS-2), which is the base of information noise standards aimed at stimulating. Mood and the quality of the four the wastes, i.e., 1) loudness 2) sharpness 3) roughness. 4) strength. Fluctuation Strength in the use of adjectives indicates mood (Emotion gauge Adjective Scale) test, university students 140 cases. To measure the basic three emotions (happiness, sadness, and negative feelings). The study each sound to predict the underlying emotions of each sound has accuracy in analysis of each sound. The overall percentage of 88.9 from experimental data to check the accuracy of each sound. Intercept parameter in both four from incentive 46 sound. Collected from the database again in one package. The errors in the audio function. Each sound. The results show the verified each sound overall percentage of 63.04 discovered that. In daily life, resulting in an emotional voice is singing. Moreover, music can bring to the human voice with the machine.

Aluja (2015) studied the effects of personality and anxiety. Moreover, impulsiveness on emotions the samples were students of psychology. University of Lausanne 847 people in the Swiss Nursery Land 428 men, 175 women, 253 men, mean age 24.17 years and a Spaniard of 419 men, 131 women, 288 men, mean age 21.65 years, the tools used. The trial is an image from a photo that conveys the emotion. (International Affective Picture System: IAP) It is divided by 60 to give a visual emotional valence. A stimulating minimum of 12 images that give an emotional valence that has spurred the 12 images that give an emotional valence that has spurred the 12 images that make no sense-emotional valence has stimulated low 12 images provided. Not impressed with the 12-provoking images and to feel relaxed 12 images in 60 image projection using a projector. Under each image gauge the emotions and the emotional valences of the awake. For example, to rate each photo. The study indicated that the sample was female with high anxiety to give the visual emotional valence that is not high. Moreover, samples the female A hasty to give the emotional valence that a high.

Aydin, Kaya, and Gular (2016) studied EEG. The pattern of an emotional valence. Moreover, awake Start experimenting by giving volunteers a total of 32 people view video clips that feel different, whether it is a fun, sad, happy, relaxed 40 clip from the Database for Emotion Analysis Using Physiological Signals: DEAP already selected 4. the clip features the highly impressive. High alert The impressive high Low awareness Low emotional valence High alert The impressive high Low awareness While the volunteers watch a video. The researchers recorded electrical brain waves. The electrode terminals 32 of the EEG data of a sample of 2, 8, 12 and

28 were analyzed. The study indicated that The four samples while watching video clips with an impressive low is higher than the EEG. Watch the video on a high and impressive while watching clips of the four characteristic gamma waves appear to be the most obvious.

Chai Lou Long and Yuan (2016) studied differences between gender and personality from seeing the images from the IAPs samples are undergraduate students. The 68 people. Everyone dominant right hand. No symptoms of mental disorders or ever receiving psychiatric treatment. The sample will do a screening personality. They are using a screening test, personality five elements. Then, they were divided into four groups, males with personality revealed. Males with type a personality, the other ambivert females with personality revealed — moreover, females with personality ambivert tool used in this study. Image sense is not impressed by IAPs Chinese Affective and Picture System (APS) was 120 images are divided into an image with characteristics still. " On 40 images. The image looks not impressed with 40 images.

Moreover, the image characteristic is not impressed with the inhibition of emotional 40 images. The study showed that the score image not impressed both are below the median of the scores on the part of the score of the inhibition of the emotional level of each group were not significantly different — the Wave. Diving at the 500-2,000 milliseconds, found that the electric brain wave of samples of each group was not different, but the effects of two slip slow 2,000-3,000 milliseconds. Found that males with type a personality, the other ambivert. Characteristics of electric brain wave, while watching the not impressed higher while watching the is not impressed with emotional inhibition. One effect of the slow wave that 3,000 – 4,000 milliseconds found that males have a personality type, the other ambivert have the characteristics of electric brain wave, while watching them. Impressed by the higher, while watching the images look is not impressed with the inhibition of emotions.

Pınar, Kübra, Tubanur, and Bahar (2017) studied the brain of Delete in response to emotion, the 33 people (female 17 people. The man 14 people) to look at the picture looks impressive ten pictures. Look not impressed ten images, and the relaxed ten images showed that the brightness of the image, the color of the image and background scenes of images affect the mood and behavior of groups, for example.

However, I found that the not impressed even with the brightness of the image found the response of Delta low.

Espuny (2018) studied electric brain waves associated with words that trigger the emotions impressed and awake. To see the process of the language. By studying the electric brain wave when reading the words impressed. While controlling the excitement. Moreover, check the effect of the different. Participants need to treat the two parts, which are 1) read aloud each word, written with black on white, and 2) named color or ink. Write down the result of the study shows that the main impact caused by emotional valence, regardless of work to do. There is no relationship between mood and impressed with the work to do. Most of the negative words and will affect the mood the most impressive, and EEG was Early Posterior Negativity (EPN) and Late. Positive Complex (LPC).

About the research related to emotion. The difference between gender and personality, perception, emotion, this may be due to Learning experience the situation or event experience. The female is sensitive to the perceived negative feelings or was not impressed than men. Moreover, the people personality publicly associated with emotion the impressive or positive.

Part 2 Concepts and theories of emotional valence and researches related

Valence, as used in psychology, especially in discussing emotions, means the intrinsic attractiveness/"good"-ness (positive valence) or averseness/"bad"-ness (negative valence) of an event, object, or situation. The term also characterizes and categorizes specific emotions. For example, emotions popularly referred to as "negative," such as anger and fear, have negative valence. Joy has a positive valence. Positively valenced emotions are evoked by positively valenced events, objects, or situations. The term is also used to describe the hedonic tone of feelings, affect, certain behaviors (for example, approach and avoidance), goal attainment or nonattainment, and conformity with or violation of norms. Ambivalence can be viewed as a conflict between positive and negative valence-carriers. Theorists taking a valence-based approach to studying effect, judgment, and choice posit that emotions with the same valence (e.g., anger and fear or pride and surprise) produce a similar influence on judgments and choices. Stress is a negative valence, and the opposite of this is pleasure or happiness. Stress can mean all unpleasant emotions.

The PAD emotional state model is a psychological model developed by Albert Mehrabian and James A. Russell (1974 and after) to describe and measure emotional states. PAD uses three numerical dimensions, Pleasure, Arousal and Dominance to represent all emotions. Its initial use was in a theory of environmental psychology, the core idea being that physical environments influence people through their emotional impact. It was subsequently used by Peter Lang and colleagues to propose a physiological theory of emotion. It was also used by James A. Russell to develop a theory of emotional episodes (relatively brief emotionally charged events). The PA part of PAD was developed into a circumplex model of emotion experience, and those two dimensions were termed "core affect." The D part of PAD was re-conceptualized as part of the appraisal process in an emotional episode (a cold cognitive assessment of the situation eliciting the emotion). A more fully developed version of this approach is termed the psychological construction theory of emotion. The PAD (Pleasure, Arousal, Dominance) model has been used to study nonverbal communication such as body language in psychology. It has also been applied to consumer marketing and the construction of animated characters that express emotions in virtual worlds.

Neuropsychological theories of emotion emerged mainly out of the study of hemispheric specialization, which grew out of phrenology (Harris, 1999). Researchers have long been interested in understanding the functions of the two hemispheres (Harris, 1999). Early research in this area focused primarily on the observation of cognitive functions among individuals with damage to specific regions of the brain. As early as 1865, Paul Broca proposed that the left hemisphere (LH) mediated language production; shortly after that, in 1874, John Hughlings-Jackson proposed that the right hemisphere (RH) mediated visual-spatial processing (Harris, 1999). Subsequent research among right-handed individuals provided support for these early theories while also expanding upon them (Borod, 1992). For example, Carl Wernicke discovered that not only was the LH involved in language production but language comprehension as well (Harris, 1999). Observations of patients with damage to the

RH led Hughlings-Jackson and Luys to hypothesize that the RH was involved in irrational and emotional functions (Harris, 1999). More recently, LH strategies have been described as analytic and linear, involving logical reasoning—the basis of which is language—whereas RH strategies have been described as holistic and spatial, involving perceptual insight (Borod, 1992; Harris, 1999; Robertson & Lamb, 1991). These ideas about hemispheric asymmetries for cognitive functions have been supported by empirical research; however, the hemispheric asymmetries for emotional functions remain unclear (Borod, 1992).

Neuropsychological research has produced four major theories regarding the neural correlates of emotion processing (i.e., expression and perception): the right hemisphere (RH), approach-withdrawal, valence-arousal, and behavioral activation system-behavioral inhibition system (BAS-BIS) models. The RH model, founded upon early experimental and clinical studies, proposes that all emotions, regardless of their valence, are processed preferentially by RH systems (Borod, 1992; Lang et al., 1990). Later experimental and clinical research suggested that both RH and LH prefrontal systems play a role in emotion processing, with LH prefrontal systems biased toward the processing of approach-related tendencies and emotions and RH prefrontal systems biased toward the processing of withdrawal-related tendencies and emotions (Davidson, 1992). This model became known as the approach-withdrawal model (Demaree, Everheart, Youngstrom, & Harrison, 2005). Recently, the approach-withdrawal model has mainly been incorporated into the valence-arousal model.

The valence-arousal model of emotion proposes that RH prefrontal systems are biased toward negative valences, RH parietal systems are biased toward arousal, and LH prefrontal systems are biased toward positive valences (Heller, Nitschke, & Lindsay, 1997). More recent research in the literature on the neuropsychology of emotion has integrated elements of the prior three models with Gray and McNaughton’s (2000) revised reinforcement sensitivity theory (RST) to produce the behavioral activation- behavioral inhibition (BAS-BIS) model, which makes similar predictions as the approach-withdrawal model, but links LH frontal systems with a behavioral activation system (BAS) and RH frontal systems with a behavioral inhibition system (BIS) rather than with approach and withdrawal tendencies and emotions, respectively.

The use of EEG Data for the classification of mental state the EEG is one of the most useful tools in clinical neurophysiology. EEGs are voltage measurements of the scalp, representing the sum of synchronous postsynaptic potentials arising from broad cerebral cortical areas and can be used for the identification of cerebral injuries or disorders (Epstein, 2012). Research also shows that EEG data can be used to recognize other more subtle mental states. Although a vast variety of applications are described, the literature does not involve signal analysis of EEG data is correctly used to measure attentiveness to short training videos. Nevertheless, the full cross-sections of published applications that have been researched have laid the foundation for the current research to be successful through refinement of the signal processing and pattern recognition techniques.

Alertness or Vigilance Alertness and vigilance mental states are well studied about EEG data correlation. The published research of (MacLean, Arnell, & Cote, 2012) shows how EEG data from participants who are resting can later be used to predict how well they can perform during fast-paced target identification using "attentional blink" measures (Goldfine et al., 2011). Demonstrated that EEG analysis can reveal awareness in brain-injured patients who are otherwise unable to communicate, but who are asked to imagine motor and spatial navigation tasks mentally. There has been researching on using EEG to detect when someone is no longer alert enough to safely operate a vehicle or maintain display vigilance (Wilson and Bracewell 2002). Another example (Jung et al., 1997) used EEG data to predict alertness as measured by lapses in auditory and visual sonar detection by trained Navy participants. Human experts can also look at features extracted from EEG data and tell if the participant is alert versus asleep or valence, as in the case of (Subasi et al., 2005) where trained neurologists looked at the EEG recordings, and then picked which EEG sequences clearly indicated alert, valence, or sleepy states of the subject.

Mental and Physical Activity More detailed classification of mental activity through EEG has been researched (Khare, et al. 2009) including differentiation between relaxed, imagining moving the right hand, watching a figure being rotated (imagining it as well), trivial multiplication (i.e., 2x3), and nontrivial multiplication (i.e., 49x78). Other mental tasks can be classified using EEG data (Palaniappan, 2006) to determine the mental activity of participants from a series of mental tasks including geometric figure rotation, multiplication, writing a letter to a friend, visual counting, and resting.

Emotional or Affective State EEG data has been used to classify the emotion of the user (Chakraborty et al., 2009) as compared to their facial expression when watching emotion inducing movies, where 50 participants were shown 60 audio-visual clips, covering a range of six different emotions (anxiety, disgust (anger), fear, happiness, sadness, and relaxation). Similarly, in Khosrowabadi et al. (2010)'s participants are presented with pictures and music to elicit four basic emotions of calm, happy, sad and fear, and they are also questioned using a self-assessment manikin as to the emotion they felt. The emotion is mapped onto a Valence-Arousal emotion plane, and EEG data is then measured to see if emotion can be detected. In Murugappan (2011) EEG data are related to emotional state by using five videos intended to elicit emotions (disgust, happy, fear, surprise and neutral) as selected by a college student panel from 115 international standard emotional clips. Separate participants wear EEG devices, and the data is used to identify the emotion elicited by the video clips. In a more recent study, Uusberg et al. (2013) examined how certain frequencies like the Alpha band (discussed below) of EEG activity may be more related to the active emotional state than earlier thought. Uusberg et al. (2013) Shows that the alpha band is present in varying amounts depending on the effective stimulus (pictures from the International Affective Picture System). It was found that the prevalence of details in the picture affected the Alpha band, and as such cannot be discounted when comparing useful stimulation results. Also, it was found that aversive (powerfully unpleasant) images generated high Alpha power, compared to rest and other images. Some studies try to use EEG data to detect less dynamic mental states such as personality, or pathologies such as mental disorders. In one study (Lee et al., 2010) children between the age of 10 and 13 years with Attention Deficit Hyperactivity Disorder (ADHD) were assessed for mental retardation using the Korean.

Educational Development Institute's Wechsler Intelligence Scale for Children. Afterward, EEG data was collected. Participants were asked to relax, count, and perform mental tasks. The EEG data was used to recognize if the child had only ADHD, or also had mental retardation. One research paper (Ito et al., 2010) demonstrated the ability to determine the personality of participants by using EEG measurements. In the study above, EEG data were collected while participants listened to music segments which they later rated as "Matches Mood," "Does not match the mood," and "Borderline" (Ito et al., 2010). Separately, the personality score of the participant is known from a 50-question exam (rating the person in the five areas of "Critical parent," "Nurturing parent," "Adult," "Free Child," and "Adapted Child.") The authors then compared the false-detection accuracy of the EEG classification system of "mood matching" to the personality trait of the participant, and claim that that false-detection may be related to the person's personality (Ito et al., 2010).

Even before the widespread use of EEG, there was an interest in the physiological and anatomical structure of the human brain with relation to purchasing decision making. Termed "Neuromarketing" in the seminal book of the same name (Renvoise & Morin 2007) the authors foreshadowed modern medical signal analysis techniques applied to market studies. Neuromarketing research includes such trials as De Vico Fallani et al. (2008) where EEG data is used to predict whether a short advertisement video clip embedded within a television documentary will be remembered or not several days after viewing. EEG data has been used in some aspects of the education field. For example, (RebolledoMendez et al., (2009) researchers described using EEG data while a student is taking an examination. In this case, participants interact with a computerized avatar that asks multiple choice questions. EEG attention rating from 0 to 100 is correlated with speed/accuracy of response and user self-described attentiveness levels. There was no student education or training provided – only assessment - the questions were targeted at Computer Science, and participants all were majors in computer science (and so should have been familiar with the answers to the questions). In another research experiment (Crowley et al., 2010) participants wearing an EEG cap were asked to do an increasingly stressful (faster) Stroop Test.

A Stroop test is an intentionally cognitively demanding task that asks the participant to name the displayed color of a different display word. For example, the participant is presented with the word "red," but it is colored in a green font. Subsequently, people will unintentionally say "red" instead of the correct response which is "green." During each trial, the speed was increased, while EEG was used to register "dips in meditation" which suggests lower relaxedness. The same research paper describes using the Tower of Hanoi problem (stacking different sized disks) was given to participants three times in a row – the researchers explain that this problem appears difficult to solve, but once a participant learns the stacking algorithm it becomes easier to solve (Crowley et al., 2010). EEG data was able to show trends in lowered assessment stress. Another research example that correlates educational assessment exercise stress to EEG data is (Mostow, Chang, & Nelson 2011) where easy and hard "reading for meaning" tasks assigned and EEG data compared for adults and children. Another research study (Berka et al., 2004) correlates EEG data to mental states including alertness (simulation defending against incoming enemy planes), cognitive task (response rate in identifying the number "5" out of digits presented), and memory (recognizing memorized images). Somewhat related to the current research, EEG data can also be used for the detection of physical activity (not just mental activity). In Nagashino et al. (2002) EEG is used to discriminate whether a participant in a relaxed state has their eyes open or closed, and in (Selvan & Srinivasan 1999) EEG data includes ocular artifacts [electrical signals from the muscles used to move the eyeball] where in this case the goal is the removal of those artifacts (adaptive noise canceller).

To conclude the review of related work on the use of EEG data to determine the mental state, prior research describes a wide variety of applications for this electrical engineering biometric measurement. These include measurement of dynamic mental activity such as alertness, type of mental task, the memory of a television commercial and emotional state, as well as more static mental aspects such as pathology [mental retardation, and ADHD] and even possibly personality. The review of related work did not find published research suggesting that signal analysis of EEG data has been used to measure attentiveness to short training videos. Nevertheless, the vast variety of applications described in the literature have paved the way for this research to refine the signal analysis and pattern matching methods to extend the use of EEG to this new application.

Part 3 Audio, vision, and researches related

Viinikainen, Katsyri, and Sams (2012) presented at the voice recognition process of the human brain. (Representation of Perceived Sound Valence in the Human Brain) Emotional perception impressed with sensory stimulation influences the processes in the tissue. Cortical parts (Various Cortical) and there is reliable evidence that the structure Subcortical. A negative emotional valence of the positive emotional valence is different. They tested how the brain works. When samples A sound actuator in a different mood, perception, emotional valence (not impressed, very impressed inaction) samples of 17 healthy people were. Selection tool (3 Tesla) while listening to the Sound Library Digital emotion (IADS 2) in the form of finished (Block Design Paradigm) the quadratic waveforms U-Shaped relationships between variables impressed. Oxygen levels in the blood. The concentration of the signal in the middle of the brain. Brain to perceive sound and music gala signals mild stimulant found in nature.

Moreover, the signal will increase when stimulated. A strong emotional valence Stimulate or no emotional valence at all. The study supports research that the critical factor in the functioning of the nervous system, the emotional side. Moreover, extending the approach that is the hallmark. This increases both a positive emotional valence and a negative emotional valence.

Soares et al. (2013) studied Affective Auditory Stimuli: Adaptation of The International Affective Digitized Sounds (IADS-2). For European Portuguese stimuli on mood: sound? The series of stimuli universal audio IADS-2 into Portugal in the European context. This research will lead to offering value norms, many of the excellent series motive them. A universal IADS-2 (Bradley & Lang 2007a context, to Portugal in Europe (EP) IADS-2 is database standard sounds occur naturally 167 sounds. Application research on emotion widely. These voices will be about values. The undergraduate students that speak Portuguese native 300 people in the emotional dimension three dimensions. 1) valence) 2) arousal and 3) dominance using a self-assessment the purpose of this study Manikin-SAM) There are three reasons 1) to develop a series of stimuli with sound standard and get normative, for use with the population to seconds. The research of Portugal in Europe and all the researchers in general 2) to investigate the differences in gender. Culture and from the estimated ratings. Various dimensions of emotional stimuli between the sound of standard Portuguese context in Europe (EP) and American context (Bradley & Lang, 2007a). With the standard context of Spain (Fernández-Abascal et al., 2008, pp. 104-113; Redondo et al., 2008, pp. 784-790) and 3) to promote research in the process of the sound on mood in the country. Portugal country in Europe, research findings indicate that the series of stimuli IADS-2 is a universal audio sound database digital useful and accurate. Research on emotion in Portugal and Europe that can compare the results with the educational research at the international level, the other choice. Using a database to sound the same. After the various norms from the set of stimuli IADS-2 universal audio in the context of Portugal in Europe.

Anderson White-Schwoch Choi and Kraus (2014) has some research on the perception of hearing. Training in the elderly group benefits short-term training with efficiency - an improvement of knowledge. The model of the sensory and elderly group gets the attention of people. The assumptions for example 8 weeks of hearing, according to training knowledge to reduce the potential for understanding the highest and maximum variance in the response of the nervous system. To say the voice and has been expanding in still images. The speed of processing, speech rate, perceived sound and short-term memory. See old while earlier studies demonstrate. Short-Term Plasticity in the elderly group to consider the long-term treatment of the training evaluation and training. Treatment of some of the perceived hearing the researcher invited participants from education, training earlier. To come back for the test track for six months. After completing the training, it was found that the improvement in response to the peak period to say the sound and the speed of processing gain. The treatment but participants do not heal, speech noise. To restore the memory, the study of factors which are essential in training to maintain the natural includes training practice. According to schedule, the need in the meeting sponsor. After completing the training.

Choi et al. (2015) study Development of an Auditory Emotion Recognition Function Using Psychoacoustic Parameters Based. On the International Affective Digitized Sounds for the development of emotion from voice recognition, which may determine the emotion from the voice in the environment in daily life. Our selection of sound from the sound stimuli conveys universal digital International Affective

Digitized Sounds (IADS-2). The audio database standards aimed at stimulating the mood and the quality of the audio, including 4 1) loudness 2) sharpness 3) roughness and 4) fluctuation strength using the gauge indicates emotion adjective scale to test students 140 cases to measure basic emotions three sides (happiness, melancholy, and negative feelings). The study each sound to predict the underlying emotions of each accuracy in the analysis of each sound. The overall percentage of 88.9 from experimental data. To check the accuracy of each sound. Intercept parameter in both four from incentive 46 sound. Collected from the database again in one package. The errors in function, each sound. The results show the confirmation of each sound overall percentage of 63.04 searches. They have found that the sound in daily life, resulting in emotional also singing. Moreover, music can bring to the human voice with the machine.

Nolden, Rigoulot, Jolicoeur, and Harmony (2017) research effects of expertise. The music on brain function movements. In response to sound with emotions. Emotions can be transmitted through a variety of channels in the form of sound whether it is the voiced no language or words. Also, recent studies have shown that the skill type sounds one. It might affect the processing noise on emotion in voice types others because this research found that A musician can process music.

Moreover, the music is more effective than ordinary people - however, the relationship with nervous of mixing these waves. Particular time is not compatible with the wave, so. This research focuses on the analysis of neural data emotional TAE. Many different functions of type sound.

Moreover, the expertise of the participants in experimental brain electric wave from the meter EEG from the sample is not a musical 20 people and musicians 17 were given and recorded by them to listen (voice and sound invention) and music, electric wave brain up while doing activities with a wave. The frequency Theta Alpha Beta Gamma is to measure and analyze the composition free Independent Component Analysis (ICA) was used to identify the essential elements of the work of Each frequency brain differences found in the frequency and Theta Alpha due to meet a music and speech sound bigger. DIT and later in the Beta frequency due to different speech processing. Besides, also, are used more and more in the brain - Frontal Alpha frequency, for example, a musician than not a musician.

Moreover, the interaction between the Expertise and emotional characteristics of sound in the frontal lobe Alpha frequency. Reflection on the expertise of the musicians in the perception of emotions in the broadcast music. Which seems to be talking about the emotional expression that conveys humanity according to the effect of the skill areas. The music and sound effects in the past. From a literature review about the sound and hearing, voices and the related research will find that Mechanical sound wave vibration of the object when the object vibration will cause. The compression and expansion of the sound wave and right transfer, such as air to the ears travel through matter in a gas state of these, but cannot travel through a vacuum. When the vibration to ears. It will be converted to a pulse nervous, which will be sent to the brain. We recognize and classify different sounds. Types of audios, divided by what the sound three styles are the noise, continuous and impact or impulse noise. The hearing, it was found that when a sound wave through the outer ear impacts the tympanic membrane. The vibration of the eardrum is based on the frequency of the sound waves. Then going to shake the 3 pieces in the middle ear ossicles the oscillations of the ossicles, this will help pass the sound waves to the inner ear, but also help amplify the signal waves (15-20 times) the pressure canal Relationship of liquid and snuggle up of vibration of the basilar resulting stereocilia (Stereocilia) which is smaller on the hair cells. With the noise, Ben approached Chi no cilium (Kinocilium), which is a large single hair the ion channels that nonspecific opened, the potassium ion in the water.

Enzo Li drive, which has a high concentration was published into the cells get sound is the receiving side sun (Depolarization) shall be induced calcium channel, which is the base of getting sound out? Calcium ion diffusion into the cell. The secretion of neurotransmitters. This will stimulate the nerve endings of nerve impulse nerve cochlea (Cochlear Nerve) and transmission line monitor PAIR 8 (Vestibulo-Cochlear Nerve) to the brain areas that sound in the cerebral cortex to act her interpretation of sound quality - hearing process variations. The sound waves into nerve impulses, this is called Mechanoelectrical. Transduction, because of this, most research has focused on the effects of using sound affect emotions. Includes some research on the perception of healing benefits.

The training in the elderly. Short term training is effective in improving knowledge. The model of the sensory and elderly group gets the attention of people. The researchers will study to study the trends affecting mood. This is highlighted in the nervous system.

Viinikaninen et al. (2010) studied emotion the emotional valence of university students in Helsinki. 17 healthy participants aged 21-26 years with normal eyesight. The experiment looked at the pictures feel the emotional valence of 270 images from the image communication system in Emotions (International Affective Picture System: IAP) divides the image into 30 series, every nine images, then watch image for 1000 milliseconds between the picture will change a black screen 1900 milliseconds between each image sets, to stay 6.5 seconds data record. With the machine fMRI after collecting machine fMRI and 3-10 days. The back all images again by viewing the image. 2 seconds. Active to rate each image gauge with emotions (SAM) results from the data recording FMRI found that the part of the brain that is working during the image. The emotional valence included Ventromedial, Prefrontal Cortex Dorsomedial Prefrontal Cortex Anterior Cingulate Cortex, Amygdala Lateral Sulcus, Insula Ventrolateral, Prefrontal Cortex, and Dorsolateral Prefrontal Cortex.

Winkler, Mihajlovic, and Tsoneva (2010) studied of emotion in the emotional valence of the electric brain wave. The sample is 9nine people between the ages of 23-27 years normal eyesight. The instruments used in the study are the images of the system image meaningful emotional feelings (International. Affective Picture System: IAP) where 48 images by image impressed the 48 images and images that do not impress the 16. Start the experiment samples. Open eyes. Two minutes, close eyes 2 minutes, then a blank). The center of the screen for 3 seconds, then the projection for 6 seconds. Alternately, save electric waves as the brain. See the image after the data record. The sample image that looks impressive. Moreover, the image characteristic is not impressed; however, the comment that Frontal EEG Asymmetry does not suit the emotions. An emotional valence.

Gerdes et al. (2010) investigated the emotional valence. From the samples are college students, 17. The experiment looked at the pictures feel the impressed both three styles is 1) image. Over much of 20 images 2) the relaxed, the 20 images and 3) picture that does not impress the 20 images from the imaging system means that the ah. Emotion feeling (International Affective Picture System: IAP) experiment with the samples. Look at the picture plus central monitor for 2000 milliseconds. Then there is a picture taken from the system image meaningful emotional feelings (International Affective Picture System: IAP) for 500 milliseconds. Then the image plus 1000 milliseconds times. The study found that it will cause an electric brain wave relative to the incident of the brain - the Parietal time 250 milliseconds.

Domes et al. (2010) studied the reaction between male and female on the photo negative feelings by image look. The volunteers to look at pictures and to rate pictures after a brain scan; the results showed that no significant difference between genders in the perception of emotions in both. Emotional valence. Awake, but found that the brain of a female, the amygdala Right Temporal Pole Dorsolateral Prefrontal Cortex Left Middle and Temporal. Gyrus has to work than a male.

Aluja (2015) studied of personality anxiety and impetuosity. On the emotion students. Students in psychology at the University of Lausanne number 847, divided into Switzerland 428. The people were 175. Female 253 people, the average age of 24.17 years and is a Spaniard 419 people were male, female 131 288 people, the average age 21.65 years. Tool. Used in the experiments is a picture from the International Affective Picture System: IAP was 60 images that are divided into image gives the emotional valence with low stimulation 12 images. The image gives the emotional valence of high stimulation 12 images. The image gives the emotional valence of high stimulation 12 images. Image sense is not impressed with low stimulation 12 images. Image sense is not impressed with high stimulation 12 images. Moreover, to feel relaxed. 12 image projection. The 60 images using the projector Under each picture has a gauge the emotional valence and the emotional awareness. To make a sample to rate each image. The results showed that the female who had high anxiety to rate pictures. Not highly impressed and samples are female. The rash will rate the images give the emotional valence is high.

Aydin, Kaya, and Gular (2016) studied electric brain waves from the form of emotional valence and the other dealing. Start the experiment from the volunteer. To the 32 people watch the video to feel different, whether it is fun, sad, happy, relaxed, the number of people 40 clips from Database. For Emotion Analysis using Physiological

Signals: DEAP and selecting the remaining four clips. With the appearance of high, high alertness emotional valence high awareness is low. The emotional valence is low, high alert and emotional valence, alertness, during the high low video. The researcher recorded the electric brain wave by using 32 electrode polarity — the data of the electric brain wave, which 2 8 12 28, and analyzing data. The study results showed that the whole four people. While watching a video with a deep emotional valence will have higher brain electric wave When viewing the video with high emotional valence while watching the video and both four styles. Appears the wave gamma most clearly.

Chai Lou Long and Yuan (2016) studied differences between gender and personality from seeing the images from the IAPs samples are undergraduate students. The 68 people the tools used in the study. Image sense is not impressed by IAPs Chinese Affective, and Picture System (APS) was 120 images are divided into an image with characteristics still. " On 40 images. The image looks not impressed with 40 images. Moreover, the image characteristic is not impressed with the inhibition of emotional 40 images. The result indicated that the score image not impressed both 2, lower. Median scores on the part of the score level emotion of the inhibition of each group were not significantly different. The waves slowly. The 500-2 000 milliseconds, found that the electric brain wave of samples of each group is different but the result of the slow wave, that 2 000-3 000 milliseconds, found that males with type a personality ambivert. Characteristics of electric brain wave, while watching the not impressed higher while watching the is not impressed with emotional inhibition. One effect of the slow wave that 3 000-4 000 milliseconds found that males have a personality type, the other ambivert have the characteristics of electric brain wave, while watching them. Impressed by the higher, while watching the images look is not impressed with the inhibition of emotions.

Pınar, Kübra, Tubanur, and Bahar (2017) studied the brain responses of Delta in the mood. The subjects in the study, 33 men (women 17, men 14) to view the picture looks impressive ten shots, and the dormant ten photos showed that the brightness of the color of the image and the background of the image result. The mood and behavior of the sample are not to be impressed with the brightness of the images. This can be stimulated by light energy in a limited range. The mechanism of the brain when stimulated by emotional valence messages on the emotional valence. It starts from the visible text into visual sensory pathways (Visual Pathway) on the retina, which is the image in both eyes, when the excitation light image Receiver turns light into nerve signals from the retina to the optic nerve. When it comes to the cross (Optic Chiasm) nerves from the retina to the nose (Nasal Half) to cross to the opposite side to combine with nerves from the retina to the temporal (Temporal Half) of the eye, the other side as a corridor, the optic nerve (Optic Tract) and to interface with nerve cells 3rd Lateral geniculate Nucleus (LGN) of the thalamus. Geniculocalcarine Fiber to the fibers that spread to the brain occipital lobe Visual Cortex (Brodmann Area 17). It will then be sent to the Association Area 18, 19 to interpret the image that is portrayed as anything. This interpretation is based on their experience. The optic nerve sends signals to the brain occipital primary Striate Cortex been seen as translating a visual image into a real headset. This sends a signal to the Visual Association Area (Brodmann Area 18, 19) at the top, above the first (Extra Striate Cortex) This means that the vision that shaped the look.

Moreover, then sends the data to the back of the wave underside of the temporal lobe and sent to the back of the wavy embossed middle temporal lobe in Brodmann Area 20 and 21 parts of the brain are working during the viewing to give. The emotional valence is that the Ventromedial Prefrontal Cortex, dorsomedial Prefrontal Cortex, Anterior Cingulate Cortex, Amygdala, Lateral Sulcus, Insula,. Male image brightness and color of the background to affect mood and behavior. The brain is the vital organs in the processing and expression of emotion education emotion from anatomical characteristics of the brain to study power. From the critical two parts, namely, the limbic system (Limbic System) and the frontal lobe (Prefrontal Cortex).

The limbic system is responsible for regulating the function of the central nervous system, and the part of the brain Amygdala in response to stimuli, the part of the brain Amygdala. Moreover, the Hypothalamus centered in the expression of the emotion. The area of the brain Amygdala perceived fear from the study of the Pavlow found that when brain surgery and Amygdala. Make feel trick - the cows, or from similar view images happy faces. Face made me feel afraid. It is found that in the area of the brain Amygdala will work. When looking at the face images to feel fear on the part of the Amygdala was destroyed when the image face to feel fear, there would be no love Feeling scared, but research at a later time, it was found that the Amygdala will work when other feelings, such as when a feeling of trust (Said. Et al., 2009) or feeling, attractive (Windton et al., 2007, pp. 195-206; Liang et al., 2010, pp, 2912-2919). In addition to the Amygdala with such emotions. Also, the emotion impressed in. The study was designed by one pole is emotionally positive or negative emotions, but no study simultaneously.

After the study of emotions in the emotional valence both polarity area of the brain and Amygdala (Paton et al., 2006, pp. 865-870).The limbic system. Besides Amygdala, also found that the perception of emotion in the emotional valence from the brain, the Cingulate Cortex The brain in this area is divided into three parts, a front Cingulate (Anterior Cortex-ACC) global (Middle Cingulate Cortex) and the back. (Posterior Cingulate Cortex-PCC) By Anterior Cingulate Cortex to study about the assessment of the emotion. Emotional perception of the experience. Study the mood of happiness (Murphy et al., 2003, pp. 769-780), and Posterior Cingulate Cortex (PCC) found that studies both from what urge to negative emotions. Compared with the stimuli to feel relaxed (Maddock et al., 2003, pp. 30-41).

Prefrontal Cortex is the right decision, tact, and the ability to restrain and control of emotion. In addition to the part of the limbic system of the brain areas associated with emotion the emotional valence, there is a part of the Prefrontal Cortex. A study by evaluating the emotion. Emotional perception of the experience. Which is often used as stimuli trigger to study (Posner et al., 2005; Goldin et al., 2008) the study found that the part of the brain associated with sense. The negative is the brains in the Ventromedial Prefrontal Cortex (Grimm et al., 2006; Quirk & Beer 2006; Urry et al., 2006; Etkin et al., 2011) the part of the brain Dorsolateral Prefrontal Cortex (Leon-Carrion et al., 2007; Hare et al., 2009; Berkman, & Lieberman, 2010) and the part of the brain that correlate with a positive feeling is the brains in the Ventrolateral Prefrontal Cortex (Lotze et al., 2006; Lee & Siegal. 2009; Northoff et al., 2009). Education the emotional valence of various stimuli.

1. Music: Study on emotion the emotional valence by using music to the music each time for about 1 minute. All the music to feel confident and negative. The music for the negative feelings often associated with brain function in the

Parahippocampal Gyrus Posterior Cingulate and Cortex. On the part of the music to feel positive. Be related to the brain function area and the Orbitofrontal Cortex Medial Subcallosal Cingulate Cortex.

2. Olfaction: A study on the emotional valence smell. The study of single polarity is a fragrance or odor alone with the mix at the sniffing the trick - organic aromatic odor and study. The fragrance is associated with the brain function area, Orbitofrontal Cortex the stench is related to the work of the brain, the Posterior Orbitofrontal Cortex Anterior Cingulate, and the Cortex Insula.

3. Gustation: Study on emotion the emotional valence from tasting the food will taste delicious food flavor compared with middle or other food does not taste good. Compared with the food flavor., which found that tasting the delicious food is related to brain function, the Insua Amygdala Hypothalamus Orbitofrontal Cortex Anterior, and Cingulate. Cortex and tasting the food is not delicious have a brain function in the same area.

4. Visual Domain Study of emotion the emotional valence of looking at pictures from most studies system pictures their meaning in the mood. Experience feelings (International Affective Picture System: IAP). However, many countries have built up the collection. To fit the context of culture such as China, Brazil, polish, which looking images. That gives the emotional valence that is related to the brain function area Orbitomedial Prefrontal Cortex Dorsomedial Prefrontal Cortex, Medial Parietal Cortex Insula part and looking at not impressed is associated with brain function and Ventrolateral Prefrontal Cortex.

5. Verbal/ Sentence Stimuli: Study on Incentive popular feeling in the emotional valence one is a word or a sentence (Lewis et al., 2007; Posner et al., 2009, pp. 25-42) the study found that the words or sentences that make sense weights associated with brain function and Orbitofrontal Cortex Insula Anterior Cingulate, Cortex words or sentences and to feel positive - related to the brain function area and Dorsolateral Prefrontal Cortex Medial Prefrontal Cortex.

6. Facial Expression: A face stimuli in the study. Often focus on the study of the perception of emotion. Evaluation and emotion. The study found that the face images to negative emotions. Related to brain function, the Parietal Cortex Anterior Cingulate Cortex Interior Frontal and Cortex the face images to feel positive

relationships. The work of the brain and the Fusiform Gyrus Occipitotemporal Cortex (Gerber et al., 2008, p. 175).

7. Movies/ Video Clips: The film or video has been widely popular in the study of emotions the emotional valence by a motion picture Walk or short video clips from time to time 1-5 minutes. The look and to rate or recorded brain activity. The study found that the film or canal Slip the video to negative feelings associated with brain function and Medial Prefrontal Cortex Interior Frontal Gyrus Posterior, Cingulate Cortex Amygdala Thalamus, and the film or video to feel a positive relationship with the look. Medial, Prefrontal Cortex Dorsomedial Prefrontal, and Cortex Hippocampus Thalamus (Goldin et al., 2005, pp. 4636-4643).

Part 4 Electroencephalogram and researches related

Electroencephalography signals, like speech signals, are the product of a physiological process that unfolds in time. For instance, it shows the temporal evolution of a seizure in one EEG channel and its respective spectrogram. In this sense, machine learning approaches that treat the observations in the data as independent and identically distributed (i.i.d.) would not successfully exploit the sequential nature of the data (Bishop, 2011). Modeling the temporal evolution of the frequency spectrum of an EEG signal suggests HMMs would be a promising baseline approach for classifying abnormal EEGs. In this chapter, we introduce a variety of favorite machine learning techniques that are capable of modeling this evolution. The theoretical explanations presented here follow that in Duda et al. (2001), Rabiner (1989), and Bishop (2011).

4.1 EEG Signals

EEG is the electrical activity measurement in the brain. The first measure for EEG was recorded by Has Berger in 1924 using a galvanometer. Based on the internal brain behavior or external stimulus, EEG varies in amplitude and frequency of the wave. The system contains an EEG headset, and this thesis used "NeuroSky Mindwave Mobile" which is using Bluetooth connection to transfer the EEG signal. The EEG receiver records and receives the EEG signal coming from an EEG headset which is written in Python. I used the Wukong framework to deploy WuClass for the EEG, and WuClass for a controller on Intel Edison and Raspberry Pi.

4.2 Electrodes Placement

There are different system placements of electrodes on the scalp. There is the 10/20 system which has 21 electrodes, the system 10/10 system which has 81 electrodes, and the 10/5 system which has 300 electrodes. This thesis discusses the 10/20 system because clinics and research mostly use it. The 10/20 System, The numbers 10 and 20 in the 10/20 system, refer to the distance between adjacent electrodes, which is 10% or 20% of the total front back or right-left distance of the skull. The 10/20 system has in total of 21 electrodes. There are two landmarks to positioning the EEG electrodes, the nation which is the area between the eyes above the nose bridge, and the union which is the skull lowest point from the back of the head.

4.3 EEG Frequency

4.3.1 Delta band (1 - 4 Hz)

The slowest and l Delta waves primarily exist between 1Hz and 4Hz. They are also known as deep sleep waves since they are most prevalent when the human body is in a state of deep meditation or relaxation as well as deep sleep. During this period of waves, the body is undergoing a process of healing and regeneration from the previous day's activities.

4.3.2 Theta band (4 - 7 Hz)

Theta waves are mostly generated around 4Hz to the 7Hz range. These waves are associated with light meditation as well as sleep. When an increasing number of theta waves are generated, the brain is in a " dream-mode" state. In this state, humans experience the Rapid Eye Movement (REM) sleep. Studies report that the frontal theta waves are correlated with information processing, learning, and memory recall.

4.3.3 Alpha band (8 - 12 Hz)

Alpha waves exist mostly at range 8Hz to 12Hz. The Alpha waves are known as the deep relaxation waves; they depict the resting state of the brain. These waves are dominant during a period of daydreaming or meditation. Alpha waves effect imagination, visualization, learning, memory, and concentration. Studies also report that alpha waves are correlated with reflecting sensory, motor and memory functions.

4.3.4 Beta band (12 - 25 Hz)

Beta waves exist mostly at 12Hz to 25Hz. These waves are associated with a person's consciousness and alertness. These waves are most prevalent when we are wide awake or alert, engaged in some form of mental activity such as problem-solving or decision making.

4.3.5 Gamma band (> 25 Hz)

Gamma waves are the fastest and along with beta waves, are most prevalent when the person is alert and awake. These waves are associated with cognition, information processing, attention span, and memory. It is speculated that the gamma waves can also denote a person's 'higher virtues,' altruism, love, and spiritual emergence.

4.4 EEG Signal Analysis

The preprocessing EEG signal is a weak signal and needs to be amplified in order to be brought to a suitable range for preprocessing.

4.5 Artifact/Noise removal

EEG signals often captured unwanted signals either coming from physiological artifacts and non-physiological artifacts. Physical artifacts such as muscle movement artifacts know as Electromyography (EMG), and eye movement artifacts are called Electrooculography artifacts (EOG). Also, other artifacts come from the cardiac activity known as Electrocardiogram (ECG). Non-physiological artifacts come from interferences from electrical equipment and cables in the surrounding environment. Standard filters such as high pass filter are used to remove low frequency, and low pass filter to remove high frequency from EEG signals. Also, other advanced filters are used such as Finite impulse response (FIR), Infinite impulse response (IIR), Principal Components Analysis (PCA), Independent Component Analysis (ICA), and Empirical Mode Decompositions (EMD). This phase of preprocessing the EEG signal aims to increase the signal to noise ration and enhance the quality of EEG information in the signal.

Segmentation. Due to the nature of the EEG signal which is a non-stationary signal, its values can vary from one point to another. Segmentation of the EEG signal can allow searching for a sequence. Also, segmentation is essential in order to apply feature extraction and classification. Segmentation of EEG can be varied from one second to several minutes based on the desired application.

4.6 The history of electroencephalography

The beginning of electroencephalography started in 1875 by British physiologist Richard Carton studied the properties of the electric potential generated by the brain in vivo. The single-pole type electrode placed on the cerebral cortex (Cerebral Cortex) and skull. Then measure the voltage generated by the dynamometer. (Galvanometer), he found that the voltage is increased, while the animal is asleep.

Moreover, it is reduced to disappear after the animal died. Then later he published this work. To the public for the first time after 15 years later, a physiologist's Polish name Adolf Beck has discovered the potential arising from the operation of the cerebral cortex (Cerebral Cortex) of dogs and rabbits, with a variation of voltage regular. In 1902, with the invention of the electric heart monitor.

Ein Beethoven (Einthoven Electrocardiograph) has many scientists who have tried to apply the tool used in the study of EEG. Until the year 1914 Napolean Cybulski and Jalenska Macieszyna to record EEG while dogs have seizures have been successful later has developed a device that allows electrical signals caused by small amounts of work. EEG records the brain can be even better. For electroencephalography in humans in the year 1924 Hans Berger psychiatrist. The Germans had a dynamometer type Ein Beethoven (Einthoven String Galvanometer) recorded electrical brain waves for the first time. By recording the EEG in his son.

That alpha waves (Alpha Rhythm) were the first person he found this wave is gone. When the patient's eyes or use the concentration calculation. The results of such studies are of fundamental importance in the investigation - moreover, the interpretation of EEG today. EEG recorders currently have developed more progressive. Computer systems are used to monitor and analyze EEG resolution. Precisely than in the past However, the result still requires a specialist. The diagnosis is more accurate.

Luo et al. (2016) studied the brain waves associated with human face events while viewing a sample of 23 men, eight women and 15 men every right to use his right hand. With normal vision, no medical history of mental illness. The samples were divided into three groups with a positive personality. The group has a negative personality and a healthy personality. The instrument is the face of the Chinese Facial Affective Picture System (CFAPS) faces 12 men and 12 women, and all images are deleted my ear off. Began to experiment using a sample image of a cross screen for 500 milliseconds, 300 milliseconds blank faces 2,000 milliseconds, 300 milliseconds blank screen and the screen to select the images that you see a man or a woman. When you tap the screen to be another busy one. 000 milliseconds study results appear. The group has a personality; it would appear EEG associated with the event, N170 and Early Posterior Negativity (ESPN) than those with personality, confident and healthy part of the slow waves (Late Positive Potential: LPP) of the group. Positive personality Is higher than those with a negative personality and conventional. So, when we put the metal to touch the skull of a man, we can signal recording electrical brain waves are moving up and down. As a general move the measurement unit of cycles per second. The electricity generated by the neurons much more. Also, the closed position to an electrical signal that can be recorded even with strength. Alternatively, a very large the electrodes used to record EEG. Recorded from the scalp area is smaller than the voltage at the wall Bhosle recorded approximately 100-1,000 times.

EEG can be determined by the nature and methods of signal types such as Electronic Entertainment News Palomar gram. (Electroencephalogram: EEG) electronic manual on holograms. (Electrooculogram: EOG) electron microscopy Mio gram. (Electromyogram: EMG) signals or magnesium master's South End Palomar gram. (Magnetoencephalogram: MEG) The signal used to study. Electricity can be measured by EEG type.

Electroencephalogram The electrical signals measured by EEG, the measurement method is called. Electronic Concepcion led the graphene (Electroencephalography) as a way to measure electrical signals from the scalp. Alternatively, from the surface of the brain inside the skull. The signs will be closely linked to the brain. Alternatively, nerves in the measurement signal from the scalp to measure voltage in millivolts (Millivolt) signal analysis takes experts.

Along with laboratory equipment that can measure up to date. The methods used to measure brain waves. The waves Electrical brain wave frequency will be studied about the activities of the human body - the kind of EEG frequencies.

Event-Related Potential: or commonly referred to as ERP is an electrocardiogram. The measurement of EEG. Electroencephalography or brain-wave machine. Magnetoencephalography (MEG) used for neurological studies. (Neuroscience) Neuroscience Cognitive (Cognitive Neuroscience) Physiology (Physiological) the senses (Sensory) Perception (Perception), intellectual (Cognition) and information processing of the brain (Brain Processing Information) ERP is a measure of activity. Electrical brain by placing electrodes on the scalp. EEG signals from the nerves of the brain simultaneously, or tens of thousands of cells. They are working together to stimulate activity. Brain (Event) devices and storage of electrical brain signals associated with the event. The details are as follows Storage EEG signals.

How to store electrical brain wave signals, the first step is to use a device called a polarized signal. Detects electrical signals from the scalp of a joint trial. Such a measure is a multi-polar both the patches (Plate) and a cap covering the head (Cap) if using caps. The measure multiple terminals the hat is made of multiple measurement capacities. Electrical signals from the electrodes to measure a very low voltage in millivolts. It amplifies the signal before the amplifier specifically called amplifier which has protective properties. Eliminating noise and amplifier frequency The EEG well Then converted into a digital signal. With digital digitizer and the digital signal is recorded by the computer.

To further use. Digital signal transmission between computers and digital Sir kidneys are separate electrical circuits. To prevent electricity from flowing back to the computer terminal to measure brain electrical signals. This could be dangerous for users. The form of electrical signals measured by electrodes measuring the brain. In general, the measurement electrodes (Electrode Plate) to detect EEG signals. There are two ways embedded within (Invasive) medical service. To check for or diagnose disorders. Brain function and an external patch (Noninvasive), which can be done quickly and without damaging the current measurement terminals of a hat to cover your head. This makes work more enjoyable. In this research, using hats to cover their heads. due to safety no risk of potential injury from electrical current.

Identify the location of the signal on the head. Each part of the brain is responsible for or associated with the activities of the body is different, so if you choose a location that is not appropriate to give a signal that there are elements that do not want more than what components to use.

The frequency of EEG can be measured. Because digital signals to be amplified by the first amplifier. If poorly designed amplifiers may result in the loss of a particular frequency. The noise may insert foreign objects into electrical signals the brain waves recorded.

Interference caused by electronic devices. Alternatively, the terminal is not. Effective and did not clean the scalp before installing a dipole. If the terminal is passive (Passive), a measure that has no polarity signal by itself. This noise May reduce the quality of the signal measured 4.1.6 Sampling Rate (Sampling Rate) is used to convert electrical signals from analog signals. To a digital signal (Digitization) if the sampling frequency is low. Will result in the loss of high-frequency signals. Due to the frequency of EEG can be used to analyze the range 0.5 to 100 Hz or will be in the 0.5 to 30 Hz, typically.

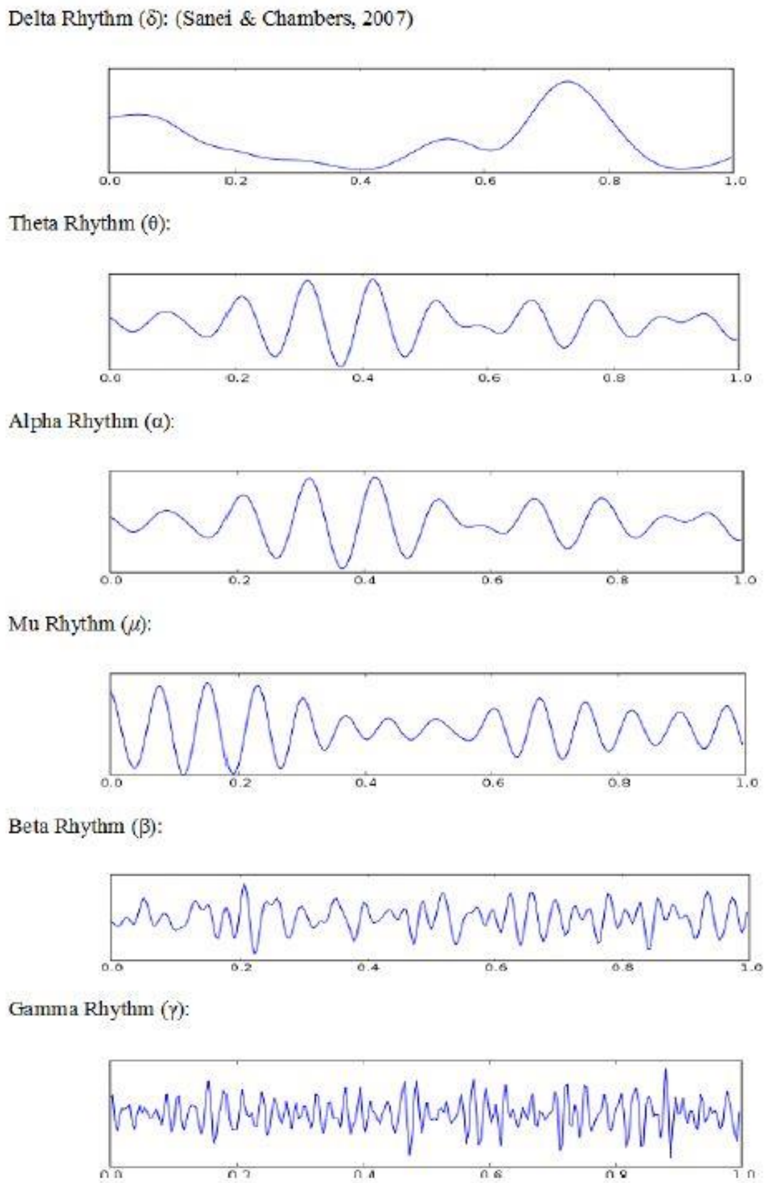


Figure 4 EEG frequency domain wave

4.7 Comparison of EEG waves

Low frequencies (typically 0.1 to 1 Hz), and high frequencies (typically 60 to 70 Hz) are filtered out to remove any artifacts that may occur from the eye, cardiac, or muscle activity. Where the electrodes, or pads, are placed are also crucial in EEG. The placement effects where on the surface on the brain activity is being recorded.

This is important since the functionality of the cerebrum, the most significant part of the human brain, is sectioned.

Four sections of the Cerebral Cortex. The image has been edited to remove the blue background from The Cerebrum, and the cortex is associated with higher brain function. The four sections are the frontal lobe, parietal lobe, occipital lobe, and temporal lobe. Each lobe is associated with different functions. The frontal lobe is associated with reasoning, planning, parts of speech, movement, emotions, and problem-solving. The parietal lobe is associated with movement, orientation, recognition, and perception of stimuli. The occipital lobe is associated with visual processing. The temporal lobe is associated with perception and recognition of auditory stimuli, memory, and speech.

Scalp EEG locations can be defined using the modified combinatorial nomenclature (MCN), which is a higher resolution version of the international 10-20 system. From the 10-20 system. These double letters AF, FC, CP, PO, FT, and TP, stand for the areas in between the letters mentioned above, with AF standing for the area between F and Fp. The number subscripts represent the distance away from the center, with the subscript "Z" representing zero. Odd and even numbers represent the left and right side respectively. The larger the number, the further away that location is away from zero. As shown in figure 5.

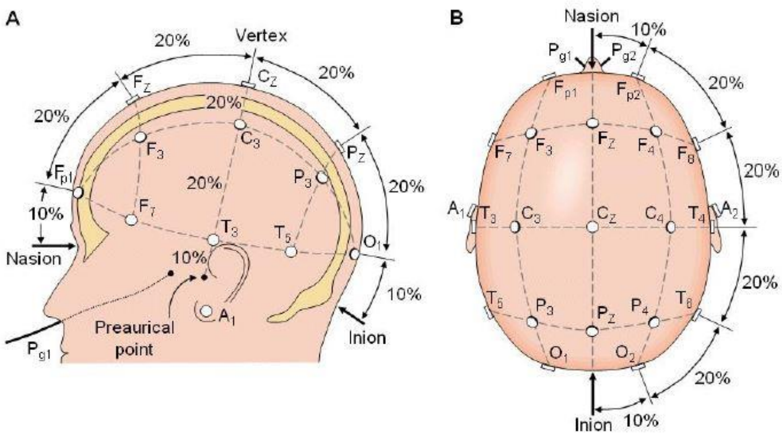


Figure 5 The EEG locations as international 10-20 system

The Affective Norms for Thai Words (Thai-ANW) Bank System means the stock system of Thai words in a meaningful way. The emotions that development in the form of web applications. Collect English words meaningful emotional feelings through quality inspection. As the emotional valence categories were divided into two styles is 1) satisfied and 2) unsatisfied is the Thai word that conveys emotional feelings through the selection criteria. Moreover, through the analysis of the quality of the content validity of Thai words that convey feelings, but each, and discrimination. To make the reliability of the Thai word on each category, emotion, systematic quality standard and reliable to use it as a scientific measurement tool.

Emotional Valence Thai Words mean the Thai word system, word norms of emotion. The Thai word in the category of emotional valence of the samples with age 18-36 years average two aspects.

1. Thai word characteristics satisfaction. The average between the 4.51-9.00.

2. Thai word looks unhappy. The average between the 1.00-4.50.

The inventory system, digital voice emotional feelings in the context of society (The Thai Affective Digitized Sounds Bank System in Thai Society). The low sound system collects an inventory system, a digital voice that conveys the emotion of Thais by the store. You. The computer industry developed in the AFL model web applications. Collecting, digital voice passed the quality inspection. Used to collect something as categories. Break out along the dimensions of emotion in the context of Thai society. Dimensions emotional valence can be divided into two styles is 1) satisfied and 2) unsatisfied is the dimension of the feelings of the digital voice quality standard. It is a collection of digital sound, and reliable features cover all the dimensions of emotion. The feeling in the context of society. A digital voice through the selection criteria, and a simple.

Gender refers to the biological characteristics of individuals. Divided into male and female. Gender identity is not only the division of male and female anatomy, physiology alone. However, to be determined by the social and cultural designation for women - men. The relationship between gender stereotypes and the identity of the female change over time. Emotional female emotions through facial expressions. Alternatively, communication This is a personality by the personality theory of five elements and Costa's applications. The Show Extraversion includes Extravert an Ambivert.

Extraversion means people are friendly. Intimacy with others quickly. Social likes to show leadership. Vigorous activity To Thrill Cheerful and mingle with friends Inclined to associate many friends. Show straightforward design Which is measured by a survey of personality are five elements to the Thai (NEO Personality Inventory 3; NEO-PI-3 Thai Version) by using the concept of Costa and Mc Cray (Costa & McCrae, 1992)

Ambiversion refers to a person's sobriety. Like an activity, I do not hustle behind. I kept feeling the expression I want excitement. The survey measured personality to the five elements of Thai (NEO Personality Inventory 3; NEO-PI-3 Thai Version) by using the concept of (Costa & McCrae, 1992).

EEG Event-Related Brain Potentials: ERPs refers to changes in the electrical potential of the EEG changes associated with events occurring after the stimuli appear (Sensory Stimuli) compared to the Baseline. In this study refers to the change of the EEG occurred while Thai a word and hear the digital emotional valence. The amplitude of the EEG and the latency of EEG.

Amplitude means the width of the electric wave brain (Latency) refers to the process of the brain function of the sign. Since the initial stimulus (0 milliseconds) did not change. Of voltage and time with the highest voltage level (Peak) while looking at the Thai word and digital sound, emotional valence. The width of the electric wave brain, in milliseconds (MS).

N100 or N1 sound (Auditory) means the electric brain wave associated with the adverse event at a time 90-200 milliseconds. Is the electric wave brain resulting from the perception of their sense of sight in the eye? Evident that the brain area Occipital Lobe, followed by the brain parietal lobe, brain mastoid temporal lobe and found in the brain at the frontal lobe.

P200 or P2 mean brain electric wave associated with the decisive event. The height of the wave appears at the time 100-250 milliseconds. Involves processing a variety of Cognitive, such as perception, attention, memory, and the language, both in the visual and audio by commonly used in experiments by the audit target stimuli and not qualify for and leading meaning (Target / non-Target) to choose to meet the right within the time limit.

N600 mean electric wave brain related to adverse events at a time 500-800 milliseconds. Associated with language processing is a work of the brain and the neuro-linguistic system of stimuli that is both visual and auditory words show a response to the Grammatical, that is to say, the wave N600 related work on processing of phrase. Alternatively, of the phrase interpretation of stimuli is a phrase or word by the whole picture that appears on the screen of the computer or sound headphones.

Young Adults means the Burapha university students at the undergraduate level between the ages of 20-24 years development of emotion. In the adult, is the ability of individuals to control the consistency of the mood and behavior. Increase the potential for coping with stress. Withstand disappointment and solve correctly. By thinking, reasoning, understanding ourselves. To create motivation in work and life.to place the terminals electrical measurements. Placing electrodes measure the electrical system by placing electrodes 10-20 as American Standard (American EEG Society) is the distance between the place where the bones (Bony Landmarks) to create a table. 10-20% of the intersection length of each line to be measured based on electrode placement. The standard for determining the position measurement signal (The Ten-Twenty System, The International 10-20 System of Electrode Placement) is the place to locate the electrodes. Electroencephalography to measure the head. Then divided into 10% and 20% (as measured at each phase by 100%), the 10-20 position represents an electrode measuring points each. Was scheduled to put on the breaks contrasting with 10% or 20% of the measured distance of each line on the head (Cacioppo, Tassinary, & Berntson, 2007, p. 61). Work on the bones that are in part.

1. The union is embossed on the bone at the center back of the head.
2. Nation the groove between the position above the nose, the forehead.
3. Preauricular Point is hollow bones in front of the ear, near the upper edge of Tragus each section are the characters used. The points are as follows:

- F (Frontal Lobe) is the brain.
- FP (Frontal Lobe) is the brain forehead.
- T (temporal Lobe) is the brain, the temporal.
- C (central Lobe) is the central brain.

- P (parietal Lobe) is part of the brain on.
- O (occipital Lobe) is the brain at the end. Swimming.

How to measure the distance to place the electrodes. Follow these steps:

Step 1: Measure the distance from Nasion to Union term lead to dividing the ten measured up Fpz and Oz, which will not stick electrode position this term break from Fpz to Oz, and then set the center line of the Cz. Half-Term breaks such as Fz and Pz.

Step 2: Measure the distance from Preauricular Point 2 next to last stage midway along the Step 1 cut a Cz take long to Division 5, measured from the center of the two sides of the intersection C3 C4 T3 T4 respectively.

Step 3 measuring head circumference through. The Oz Fpz T3 T4 led head circumference divided by 20 (5% Distance) to measure out Fpz an Fp1 and Fp2 and measuring head circumference divided by 10 (10% Distance) to measure the intersection F7 T3 t5 O1 F8 T4 T6. O2 by each terminal away 10% of the head circumference.

Step 4: Measure the distance from Fp1 to 01 through C3 and find the midpoint of Fp1 the C3 line of F3 and from C3 to 01 is a line of P3 a streak of F4, C4 SAME.

Step 5: Measure the distance from F7 too. F8 through the F3 Fz F4 to F7 and F8 is the half-term break of repeat F4 P3 P4 for the location of the line of t5 Pz T6 respectively A1 A2 electrodes are positioned on the left and right ear. If a wound cannot be determined precisely where not. The electrodes positioned close to the EEG Meter.

EEG monitoring (EEG) currently has two types. Wave Detection Electrical brain traditional (Conventional EEG) is used electroencephalography on Continuous paper recording. So monitoring of EEG signals using computers to record and display (Digital EEG), which are critical components of the EEG monitoring.

Connect the electrical box (Input Box Electrode Board or Head Box) is. The box is connected to the electrodes to measure the electrical tool EEG. Originally designed as an electrical current into the female connector type safety. The female electrodes buried deep in order not to be exposed. Jack usually arranged in a square-shaped head, or a name in a box on 10-20 May Impedance measurements are often combined with the Digital EEG machine for a contract extension and codec Analog to Digital in the box.

Channel Selector (Input Selector Switches) A switch that connects the signal from the measuring electrode to the amplifier for each channel (Channel), with each channel amplifier, is a bipolar electrode, called Grid 1. and Grid 2, the channel will allow users to choose whether to use the terminals are not connected to the Grid 1 or 2 channels freely also have the option to sign the (Master Switch) is used as a connector terminal. Fire the form displays Montage desired, using rotation or a single press. No part of the Digital Channel Selector using welding electrodes, each measuring signal to Grid 1 of each amplifier channel. The software then used to calculate the change in the pattern display standard signal generator. (Calibration) Function signal generator. To test the performance of the amplifier. Filters the signal and display. The different signals and different sizes in test.

Amplifier serves two purposes EEG signals were scrambled out. Moreover, the wave power amplifier.

Air filter (Filters) serves attenuation at frequencies corresponding to the specified due to the EEG average. Frequencies in the range of 1-30 Hz, except Spike Sharp Wave or a higher frequency. Understanding in this matter Can explain the choice of air filter for filtering signals can be generated by using electrical signals to the fact that the Analog Filter to create a computer program to filter the signal is converted into a signal called Digital Filter.

Display (Pen Writing Unit) is a signal recording EEG recorded continuously on paper that is commonly used Oscillography Pen figures are assembled from a pen attached to the coil in a magnetic field. (Galvanometer) Stylus pen to draw such a coiled spring back to its midpoint. When an electrical signal passes through the coil, the pen is moved up and down a motion made pens with ink in the pen tube. Write down on paper the continuous waveform recording Oscillography Pen can also be used to display other heat sensitive paper (Thermal Paper) Inkjet Printer and display a paper printout sheet using Laser Printer etc.

Analog to Digital Conversion, Monitoring EEG currently developing from traditional systems to the application of computer records and displays EEG. The critical difference of the traditional Digital EEG and EEG machines (Analog EEG)

Digital EEG is used to record electrical signals from each electrode measured simultaneously. By comparison with the same reference point. Then the signal format display (Montage) needed later so it can adjust the display size. (Sensitivity), Montage, Filters were assayed after easy thing to take into account the signal from Analog to Digital Conversion Rate is the measurement signal (Sampling Rate) must be done at least twice the maximum frequency. It enables to make the display maintains the original image signal correctly if the signal display is distorted to such a frequency lower than the reality. The phenomenon is called Aliasing.

Similarly, when Sampling Rate high enough to signal the correct value Dwell Time normal EEG were randomized at 200 Hz. The Dwell Time = 5 ms resolution of the measured signal values (Bit Number) in practice requires that there be at least two random signal power 12 = 4096 levels over the appropriate signal. Expanded range of electrical signals to the transducer (Input Voltage Range) can be no loss of signal. The display of the signal in Digital EEG used in the calculation, To create wave patterns of the emotional valence that the research needs (Montage Reformatting) due Digital EEG keeps the signal in the form of a Grid of each expansion slot connected to the electrical measurements the same position (Common Electrode Reference) so it can. Display as the desired format without limitation (Cacioppo, Tassinary, & Berntson, 2007, pp. 61-63).

Electrical brain wave patterns associated with the event. (Event-Related Potential: ERP) Patterns of electrical brain waves associated with the event. Determined by the height of the wave (Amplitude) and the time (Latency) by the height of the wave is positive. Instead, with a "P" at the height of the wave is negative. By the symbol "N" on the time axis is measured in milliseconds. The mean time from the start with the activation of the stimulus until the appearance of waves. The nature of EEG patterns associated with the event are as follows. (Luck & Kappenman, 2011, pp. 3-12)

1. P100 wave or EEG P1 is Event-Related Potential: ERP measurement of EEG. Electroencephalography (EEG) waves Positive The height of waves appears at 65-100 milliseconds related to cognitive processing. The visibility induced by stimuli of light as flashes of white light show clearly that the brain to pay attention to stimuli that trigger indicates the brain has the automatic recognition of stimuli is a light at the

earliest time of 65 milliseconds, the occipital Lobe or Brodmann area (BA) Work 17-18-19 (Lee. et al., 2010) Sound waves N100 or N1 (Auditory) N100 EEG is associated with an adverse event (Negative) at 80-120 milliseconds caused by stimulation of sound stimulation. EEG is the result of voice recognition is evident that the temporal lobe frontal lobe and parietal lobe and find the right brain than left. In clinical applications of N100 test abnormalities hearing. If you do not appear motivated by sound waves. Indicates that the person has trouble hearing or symptoms Dyslexia, which affects their ability to learn the language and use it to test a coma. The N100 also used to test hearing in Type Mismatch Negativity. (MMN) the study, the presence of a switch, while the N100 - not to stimuli (Go-no Go task) that is a sign of sound (Daltrozzo et al., 2007).

2. N100 wave or N1 ERP wave imaging (the Visual) N100 EEG is associated with an adverse event (Negative) at 150-200 milliseconds induced by stimulation of visible light is flashing at the time. 150-170 ms If the images appear to pop wave at 170-200 milliseconds, the brain waves caused by the perception of the senses of sight to the eyes. Clearly shown that the brain area backend (Occipital Lobe), followed by parietal lobe temporal lobe and found some in the frontal lobes (Frontal Lobe) use in the clinical spectrum N100 images at 150-170 ms.

3. The N170 wave EEG associated with the event. (Event-Related Potential: ERP) Negative (Negative) The height of waves appears at a pulse width of 150-200 milliseconds, the time involved in visual perception a person's face by the recognition. Photo people's eyes Evident when compared to stimuli other than a person's face, such as flowers picture house nature if present stimuli that a person's face is visible wave N170 showed the work the brain in Occipital Lobe minor. It is part of the medium, occipital-temporal and Frontal Lobe and found in the brain on the right side than the left. (Freeman, Ambady, & Holcomb, 2010; Luck &. Kappenman, 2011, pp. 115-118)

4. The P200 wave or P2

The P200 Event-Related Potential: ERP, actual the height of waves appears at 160-275 milliseconds associated with the processing of a variety of cognitive such as the perception, attention, memory, and the language in terms of image and sound used in the trial. The sample check provocation was the target and non-target, offering another rapid paradigm Oddball to test for attention, memory and excellent response by offering incentive target and non-target stimuli. It is a disturbance to sample select the correct response within the time limit.

5. N200 wave or N2

N200 EEG is Event-Related Potential: ERP Negative 200-350 milliseconds, the time involved in processing a wide range of intellectuals, such as the Executive brain Function and working memory the perception. Attention memory, and the language in both picture and sound. You can check the stimuli of different Mismatch Negativity (MMN) on target and non-target and Go / No-Go Task offering alternating rapid paradigm Oddball to test your memory and attention responses by offering incentive target or a Novelty on non-target stimuli. It is a disturbance to sample select the correct response. For example, if the stimulus is an image showing a sample image A response by pressing the right appears, press B left.

6. P300 wave or the P3

P300 EEG is associated with the event. (Event-Related Potential: ERP), positive (Positive) appear clearly at the height of the wave at 250-550 milliseconds associated with the processing of a variety. The cognitive function of the such as thinking, Decision Making, Evaluation, Problem Solving and classification. Categorization Wave P3 consists of the P300 wave P3a and P3b as the first wave, the second wave of P300.P3a EEG is associated with the event. At the moment 250-350 milliseconds associated with brain function in cognitive processes while working memory, decision Making, evaluation. Categorization attention and determining whether it is new or old (Novelty) P3a wave shows a clear brain. Most parts (Frontal Lobe) by Prefrontal addition, there appears little brain (Parietal Lobe) and the brain (its Temporal Lobe) P3b EEG is associated with the event. The summit is the second wave of P300.250-550 milliseconds at a time associated with brain function in cognitive processes (Cognitive Process) while working with memory (Working Memory) and retrieved from long term memory (Long-Term Memory) of. The thought process In its decision (Decision Making) assessment (Evaluation) classification. (Categorization) Solutions (Problem Solving) waves appear to P3b clear work area of the brain part (Frontal Lobe) with midbrain (Parietal Lobe), and the brain (Temporal Lobe) demonstrated interoperability. Between cognitive processes (Cognitive Process) process memory (Memory Process). (Lee et al., 2010; Luck & Kappenman, 2011, pp. 159-163)

7. N400 wave

The N400 EEG is Event-Related Potential: ERP Negative. The height of the waves in the negative at 280-500 milliseconds involved in processing a wide range of language as a function of the brain and nervous system. Neuro-linguistic of stimuli as Visual and Auditory Words shows the response of the brain to a Novelty Words or Unexpected Words of stimuli that sentence is the word. It can be presented either visual or audio.

8. P600 wave

P600 was associated with the EEG. (Event-Related Potential: ERP), positive (Positive) 500-650 milliseconds, the time involved in processing language (Language) as a function of the brain and nervous system of the language. (Neuro-linguistic) Of stimuli as saying. Audio-visual (Visual and Auditory Words) shows the response of the brain to grammar (Grammatical) or clause (Syntactic) said that a P600-related brain function in processing a sentence (Sentence Processing) and. Processing phrase (phrase processing) response of the brain to the new clause (Novelty Sentence) sentence unexpected (unexpected Sentence) or have a conflict of sentences. (Disagreement) alternatively, the interpretation of the phrase. (Interpretation) Of the stimuli as saying by sentence or phrase can offer the kind of image displayed on the computer screen. Alternatively, audio headphones.

Network analysis linking the brain (Brain Functional Connectivity Network analysis) network analysis is linking brain function. As part of the study area. What parts of the brain are active when given stimuli Moreover, the nature or form of work as any. Working as a network between the area or not. The network analysis linked to data from a waveform analysis (Data Analysis), which analyzed data from the waveform. Most have a matrix adjacent (Adjacency Matrix), then analyzed the network analysis is based on graph theory. Moreover, the graph data structure in the past. Measuring network linking brain function. There are various ways to calculate (Rubinov & Sporns, 2010) but the main index is enough to characterize. Also, the type of network This will include: (steam & Reijneveld, 2007)

1. The number of points or nodes in the network (Set of Nodes in a Network (N) and Size (n) or as a measure of network size (Size of Network) area of the brain. however, like all measuring points. Each point will work together as a network. This is linked to two types of work associated with the (Directed), and the link is no direction (Undirected) network size can be calculated from the adjacent matrix (Adjacency Matrix).

2. The amount of the connection and distribution (Degree (k) and Degree Distribution) measurements to determine the density of the network (Density of Network) index showing the distribution of the connection (Degree) between the points of consideration. another point Which is the average number of connected lines. If the index is high, then. A network linking brain size.

3. Network Infrastructure (Local Structure of Network) is a measure of character. The combination of the node as a network. The combination of a neighboring node, however. Can be measured by the coefficient of consolidation (Clustering Coefficient) coefficient group will be between 0-1 shows that the closer one is a combination of node similarly high. Make the network more efficient and the characteristics of the connection (Characteristic Path Length), indicating the nature of the connection between the node and the neighboring nodes. That is the long term or how much. If the features of the shortened links that link to a similar.

4. Network type (Type of Network) is a measure of the presence of complex networks (Complex Network) by the appearance of a link. also, uncontrolled The graph shows the theoretical model. The linking of networks of brain function by comparing the pattern of the network in a manner that is gathered, distributed among three types of normal network (Regular Network) looks at all the nodes are linked together coefficient.

5. Integration and feature line linking the pair higher. Network random (Random Network) as opposed to the regular network. The node will be randomized to link the coefficient makes integration. Moreover, it features a line linking the pair lower. Small World Network (Small-World Network) uses the concept of social networking by people in the group, or someone close will have the chance to know more people that are close together. It means Everyone in that group to know each other. I also had the opportunity to know people who are far apart on other groups as

well. A Small World The small world network integration coefficient is high. That is flexible and if there is a link feature means that network performance. Small world networks can be calculated in comparison to random networks.

6. EEG Network is linking the brain associated with emotional valence. EEG studies Network is linking the brain associated with emotional valence. There is an extensive education the details are as follows: Rozenkrants and Polich (2008) studied EEG events associated with the emotion of making things look. By studying the different levels of activation in response to stimuli in the emotional dimension of the image and emotional valence of alertness. Moreover, gender differences in the sample consisted of 32 students, 16 males, and 16 females, who used a photo from an image that conveyed the emotion. (International Affective Picture System: IAP), a picture that gives the emotional valence that there is less stimulation. Pictures give a highly stimulating emotional valence. The feeling was not impressed with the low stimulation. The feeling was not impressed with the stimulus measures 9x12 cm high projected on the screen. Set away from a sample of 75 cm each projection image takes 1,000 milliseconds between the eyes with a blank screen 2. 000 ms measuring EEG. The electrode terminals 21 Fz Cz Pz Fp1 / 2 F3 / 4 F7 / 8 C3 / 4 T7 / 8 P3 / 7 P7 / 8 O1 / 2 reference electrodes to the ear and forehead. The study indicated that Comparing photos in the emotion of Arousal level has stimulated a lot with little stimulation. Forms EEG that are characterized by high-rise (Larger Amplitude) different elements of a wave ERP is the peak second (N2) peak, the third largest positive value (P3) slow waves (Early Slow. wave) and slow-wave components (late slow wave components) in the image dimensions in emotion Valence Overall, no significant change compared between the different stimulation. Moreover, compare the results between the sexes were found. The stimulus has spurred the difference. Comparing photos in the emotion of Arousal level has stimulated a lot with little stimulation. Forms EEG that are characterized by high-rise (Larger Amplitude) different elements of a wave ERP is the peak second (N2) peak, the third largest positive value (P3) slow waves (Early Slow. wave) and slow-wave components (late slow wave components) in the image dimensions in emotion Valence Overall, no significant change compared between the different stimulation. Moreover, compare the results between the sexes were found. The stimulus has spurred the difference.

Comparing photos in the emotion of Arousal level has stimulated a lot with little stimulation. Forms EEG that are characterized by high-rise (Larger Amplitude) different elements of a wave ERP is the peak second (N2) peak, the third largest positive value (P3) slow waves (Early Slow. wave) and slow-wave components (late slow wave components) in the image dimensions in emotion Valence Overall, no significant change compared between the different stimulation. Moreover, compare the results between the sexes were found. The stimulus has spurred the difference. (Late Slow Wave Components) in the image dimensions in emotion Valence Overall, no significant change compared between the different stimulation. Moreover, compare the results between the sexes were found. The stimulus has spurred the difference. (Late Slow Wave Components) in the image dimensions in emotion Valence Overall, no significant change compared between the different stimulation. Also, compare the results

Dennis and Hajack (2009) studied the EEG slow wave. From image processing to express emotion. The sample consisted of 20 children aged between 5-10 years was used as a picture from the picture that conveyed the emotion. (International Affective Picture System: IAP) of the 30 images as the emotional valence and images that give a sense of cool experiment by projecting images found on the computer screen 19-inch drop from the sample is 24 inches from the image plus (. +), the screen for 5 minutes, then project the image from a system image that conveyed the emotion. (International Affective Picture System: IAP) 2,000 ms, followed by a visual narrative alternate between 5-7 seconds through the 30 recorded EEG. The electrode terminals 64, the study found. There was a positive response at the right occipital lobe brain. Sidelobe brain regions (Occipital-Parietal) and the height of waves in the range 500-1,500 millisecond when the picture was not impressed

Zhang, Liu, Ding, and Zhou (2012) studied the analytical theory of the connection between the work of EEG recognition in music. The sample of university students Siteia Xiamen 20 right-handed average age of 22.55 years recorded in the EEG of 64 positions by the participants were listening to music with three conditions. Namely a silence for 2 minutes sound appears for 40 seconds. Moreover, listen to the disturbing findings show that 40 seconds. The perception of music there is a link between the higher phase. The clustering coefficient, the more valuable while listening to music. By changing the physical structure shown in the perception of music. The network links the brain represents the connection to work effectively. Between the sexes were found. The stimulus has spurred the difference.

Leite Carvalho Galdo-Alvarez and Alves (2012) to study brain electric waves associated with the events from the emotional valence. The University of 15 is all the people a healthy good right hand, vision, and hearing. No history of head injury or treatment of psychotic symptoms, no use of drugs within four weeks before. The experiment, and in the day of the experiment do not drink alcohol or beverage that caffeine and smoking tool used is the image from dat. The information system image emotion International (International Affective Picture System: IAPS) was 125 images by is the emotional valence that it surprised 50 images. Style not impressed 50 images.

Moreover, to feel relaxed 25 images projecting from the computer screen size. Nineteen inches, the distance 1.5 meters, each image is projected for 5,000 milliseconds; the study found that the brain wave time 200-250 milliseconds. To rise while the powerful and Not impressed when comparing the images to feel relaxed, such as one with the electric brain wave appears in the time 700-750 milliseconds to higher while watching the impressive and not impressed Compared to the image to feel relaxed.

Wu Zhang Ding and Zhou (2013) studied of music network of brain functions, analysis of the network. The university students in China, the number of 16 people are male, female 8 8 people with age between 22.55 years. There are no abnormalities). Hear or training about the song, not a record with EEG 64 position. The trials the subjects received advice on listening to music by choosing to unfamiliar and psychic. The voice acoustic which sounds, each with a period 40 seconds and respectively arranged by speakers the 2. Behind the distance two is light. Three ringing at 60 dB the results indicated that the link function of the net increase in brain waves on the alpha two between the perception of the Eden the current study was supported women about the effect of the music in the network check.

Citron, Weekes, and, Ferstl (2013) studied emotional valence. The alert by looking at the words. The students were 31. 15Fifteen men and women 16 people between the ages of 19-36 years, mean age 24 years dominant right hand - Moreover, words that have no meaning to mingle. Each set of 10 words by different experiment 6 series, when fully 3 set eyes, then another three the rest. Advanced record data with the recorder electric wave brain. The study found that appear high waves while watching the words with the relaxed, more than once look at words make sense? Positive and LPC SSP also found to appear high wave ESPN while watching the words to feelings. The positive and negative more than words to feel relaxed. normal eyesight. The tool used is the word of 150 words from the English Lexicon Project are both nouns, verbs and vocabulary words you were three styles is the word feeling relaxed and positive negative and 150 people as words that have no meaning, from the ARC Nonword Database trials by each group. A hit at the keyboard, then. Blank screen, 1,000 MS and images, close your eyes 700 milliseconds. Each set consists of words with meaning.

Kwon et al. (2013) studied electric brain waves from a look at the picture on the valence emotion of a sample 28 man as male and female 15 people 13 people. The tools used are the images from the International Affective Picture System: IAP. The 60 images by image give the emotional valence. The pictures were not impressed, and the visual feeling relaxed, conducted by the group. For example, sit comfortably. The room with adequate lighting and temperature properly. Start baht middle screen for 500 milliseconds. Then as the picture 2 emotional valence, blank screen 2,000 milliseconds. 2,500-4,500 milliseconds, divide the image four series, every 15 pictures. The eyes. Between each image series. Save data with completely with electrodes 32 polarities. The result suggests that there will be high waves after the projection image to light. Three were impressed enough for 200-400 milliseconds. However, when the projection that does not impress will be high when the time 100-500 milliseconds.

Syrjanen and Wiens (2013) Studied emotional valence ERP comparison between man and women. The samples Psychology students at Stockholm University, 34 were men, 17 were used as a medium of International Affective Picture System: IAP 150 by a picture that looks very impressive 50 not impressive collection of 50 photographs and images that give a sense of calm, a total of 50 images projected on a screen size of 21 inches away from the group. For example, 80 cm divided into six sets of 25 images of the samples from the initial image of a cross at 1,500-1,800 milliseconds of viewing media images of one emotion. Five hundred milliseconds using an EEG recorder with 128 electrodes to record data. The results of the study appear in the male height of EEG when viewing an image that looks impressive on the above image is not impressed. There was no difference in the wave of the female.

Wang et al. (2013) studied the emotions of watching the characters as names and nouns sample of students, 22 were male and 13 females, aged 9.19-24 years, mean age 21.5 years, skillfully used his right hand with normal vision using Chinese as the primary language. Moreover, it has no medical history of mental illness. The instrument is called the 303 and 350 words on behalf of the Chinese Web site. People divided into two packs of 151 and 152 share a noun into two packs of 175 words, then give the volunteers were 60 names and nouns. Selected names and nouns scored more than 3.4 points from the gauges seven segmented into words or names of people who felt positive, negative or indifferent to people's names in packs of 38 names and nouns in packs of 40. The experiments were sitting in a comfortable chair. Projector white letters on a black background. The font size 48 from the viewing screen, black 300 milliseconds from the projected value of 1,000 milliseconds for the third time. 000 milliseconds to press 1, 2, 3, the nature of emotions, positive and negative, passive data logger with EEG electrodes with 64 terminals study results appear. Waves at N1 (900-1,000 milliseconds after the word appeared on the screen) from view by a noun to a very high view of the noun -that negative feeling High waves P2 (170-250 milliseconds) of the names and nouns in every aspect.

Syrjanen and Wiens (2013) did a study comparing the EEG associated with the event by watching Wyczesany, Ferdek, and Grzybowski (2014) studied the connection function of the cerebral cortex, which is associated with the emotional valence of an emotional state. The sample consisted of 32 women with an average age of 20.8 years, all right-handed: no neurological or psychiatric disorders and no history of drug use. EEG recorded with the number 64 position to attend the trial in silence for 30 seconds to see a positive emotion aside, and negative research results appear. There are three main areas where the network is changing the mood to impress. The front part of the fuselage near the right temple. These structures play a role in the network connection. Feelings and emotional states are different.

Jiang et at al. (2014) studied the brain activity of the words in a sentence. The sample of students from Liaoning Normal University in China between the ages of 22-26 years with an average age of 23. 7-year-old was a regular sight. No history of head injury Or untreated mental disorder. Do not use drugs. Not in any treatment will be applied to measure EEG and used as an adjective That feels impressive 30 words and adjectives that looks at least 30 words from a database Chinese Affective Words System and choose the adjective five words to use in practice sentences using adjectives 65 words in each sentence. Then convert the sentence into a sentence by adding the word "not" in front of the adjective. From the experimental samples sit comfortably in a well-lit room. To ride away from the computer screen projector 1m red cross on a computer screen for 300 milliseconds 5 Projection adjectives individual words takes 300 milliseconds, then release clause. Each sentence is 800 milliseconds, for example, press to select a sentence that feels positively. Alternatively, feeling negative Stay for a short time between sentence and sentence for every 20 samples at sight. It takes 45-60 minutes in the trial record by recording electrical brain waves with electrodes 128 terminals study found. The sample will respond to the sentence to less impressed. Slower than the sentence that gives the emotional valence of high. In the EEG waves related to events that are highly screened N50 or 15-58 seconds after the sentence was impressed. Moreover, they will wave again at the N400 or 290-470 milliseconds after the screening sentence or a sentence of less impressed. The waves are high or N50 15-58 seconds after the projector sentence impressed. Moreover, they will wave again at the N400 or 290-470 milliseconds after the screening sentence or a sentence of less impressed. The waves are high or N50 15-58 seconds after the projector sentence impressed. Moreover, they will wave again at the N400 or 290-470 milliseconds after the screening sentence or a sentence of less impressed.

Luo et al. (2014) studied the brain waves associated with the event (Event-Related Potential: ERP) while viewing images that convey emotional valences. The nature of the images was not impressed. The sample of undergraduate psychology in China, consisting of 34 males, 17 females and 17 males aged 19-23 years, mean age 21.3 years, all healthy, right-handed or hand-eye fix, for normal vision. There was no reported history of mental illness. All participants signed an informed consent form.

Moreover, they receive compensation for trial. The Academic Board of the University approved the trial. The experiment is based on the ethical standards of the Declaration of Helsinki. The stimuli using a system of International Affective Picture System: IAP 3 categories: 1) images that look. Not impressed by the high level such as individual images are being beaten so severely that he almost died 2) images that look like photographs were not impressed with moderate personality, that is sad. Sorrow or grief, and 3) a neutral nature, such as portraits, everyday activities are typically stimuli. Each category has 34 overall by 102 randomly presented. Appears centered on the computer screen. A place away from the eyes of his subjects 60 cm before the recording offered a preview of 24 shots (Condition 8 photos) to volunteer familiar with the experiments carried out electroencephalography using electrodes 32, the 10-20 system ERP recordings before stimulation 200 ms. to 1,500 ms. Results showed that. Females will have a height of EEG (Amplitude) high, while the image does not look impressive at a high level in the period 350-750 milliseconds (LPP 350), both male and female, will be a function of wavelength. High electrical brain While watching the picture looks moderately impressed. Moreover, the neutral image that is not impressed by the high level of brain activity in the part of the Frontal Central Parietal over time 160-200 ms (N2).

Omigie et al. (2014) studied the brain waves associated with the event. From listening to feel impressed by a study on a sample of 10 men, three women, and seven men, average age 34 and 85 years used a clip of music by 80 percent as a piano or organ; each clip took 1,800 milliseconds. To listen to a clip of 12 seconds in packs of 40 clips recorded with EEG recorder. The study found that the brain appears to clear the area and the Amygdala Orbitofrontal Cortex Auditory Cortex and high waves when listening to a clip that gives an emotional valence that lasts 200-600 milliseconds, but when listening to an audio clip that will not impress. Wave height range is 100-400 milliseconds and two milliseconds, 800-1300.

Choi et al. (2015) study on the introduction of a series of digital audio stimuli that convey universal emotions. The adjustment in the context of Korea. By comparing the crossover culture. Moreover, analyzing the nuances of emotional response to the audio system, digital emoticon. International between the American and Korean people. Research shows that the emotional valence and emotional arousal is different. The Korean people to express themselves emotionally in dimension. Less positive emotional valence by dimension greater awareness. Compared to the United States The influence of no difference. Compare and analyze interactions between sex and gender.

Fruhholz, Trost, and Kotz (2016) studied the emotional tone of the views of the network. Neural processing of emotional tone. The sound is an essential part of the natural environment and the social cause, shape and influence behavior in a variety of species. In terms of processing by the brain, the nervous system and brain Subcortical selected a network that supports voice, sense of hearing. In this paper, artificial neural networks, helping to decode emotional meaning. The nervous system is affecting different for a specific mood. A neural network combined audio decoder impressed by the role. Complete work to define a specific node in the neural network together also highlights the importance of brain networks that extend out over the central nervous system and the ear is involved in processing sound with sense.

Luo et al. (2016) studied the electrocardiogram associated with a second event while viewing faces. The sample consisted of 23 men, eight women and 15 men every right to use his right hand. With normal vision, no medical history of mental illness. The samples were divided into three groups: 1) group with a positive personality, 2) a negative personality and 3) a healthy personality. The instrument is the face of the Chinese Facial Affective Picture System (CFAPS) faces 12 men and 12 women, and all images are deleted my ear off. Began to experiment using a sample image of a cross screen for 500 milliseconds, 300 milliseconds blank faces 2,000 milliseconds, 300 milliseconds blank screen and the screen to select the images that you see a man or a woman. Pressing select will be Blank screen 1,000 milliseconds, the study found. The group has a negative personality EEG is displayed relative to the N170 and the Early Posterior Negativity (EPN) higher than those who have personality and positive part of the usual slow waves (Late Positive Potential: LPP) of a personality. Favorable than those with a negative personality and conventional. The Interaction Between Gender and Found No Book & Difference.

Fruhholz And Staib (2017) studied the neural circuitry of the processing of sound. Mood disorders This study is a disorder in clinical practice. By decoding the meaning of Emotional information from the brain to the nerves. This behavior

Adaptation in natural and social contexts. The human voice (such as speech and non-speech) with an expression of disgust, feeling as exciting or satisfying our behavior, which sometimes lacks balance. In the process, feel good. These may come from a lack of balance disorders of neural networks in the brain from a recent study in patients with psychiatric and neurological disorders in psychiatric patients. The central nervous system the role of independent work and different for audio processing with emotion.

Mijalkov et al. (2017) studied the program BRAPH (Brain Analysis using Graph Theory) program, a network analysis linking brain function. The study projected images of the brain is a complex network of large works based on the interaction between the various areas in recent years. The education network linking brain function has been studied extensively by pitching the concept of graph theory. Which represents the brain of a node (Node) that is connected by a link (Edges) to display this brain area. The link can be used. To assess the critical reflection of the physical structure. (Topological) By developing a software-based network analyzer to link brain function on MATLAB programs for network analysis linking brain activity data from four primary sources: 1) the projected image. Electromagnetic waves (MRI) 2) imaging with magnetic resonance (FMR) 3) imaging tomography (PET) and 4) to measure brain waves. Electroencephalogram (EEG).

Romain Vincent, Yi-Fang Hsua, and Florian Waszak (2017) studied the EEG associated with the event now view all 44 images from Affective International Set (IAPS) (Lang, Bradley, & Cuthbert, 2008) is an adult oriented. Delete Adult and positive image for the positive. Moreover, children's negative Compare potentials associated with events (ERPs) were as a result. EEG events associated with the N400.

In conclusion, EEG studies related to events in analyzing the emotional valence that there were many researchers have used the technique. EEG studies related to the event (Event-Related Potential: ERP) to study brain function. By using visual stimuli from images, words, and sounds that convey the emotion. (International Affective Picture System: IAP) Randomly presented on a computer screen. Since the diameter of 17-21 inches away from the eyes of the volunteers 70-80-150 centimeter positioning the electrode system by the standards of American (American EEGSociety) used a 10-20 electrode terminals Electrode number from 16-32. -64 to 128 terminals filter (Filters) in the range of 0.5-35 Hz. Impedances configured to start recording less than five kilohms ERP before stimulation from 100-200 milliseconds, 400-5000 milliseconds after the stimulus. The study focused on the period of 250-350 milliseconds (P300) of the high EEG (Amplitude).

The research involved a network linking the brain conclusion. Many researchers focus on network analysis linking brain function by guest Co-trial activities. To view links and density in a cluster of brain nodes (Nodes), which can analyze the network linking the brain with which BPH a program. The primary step is to do three steps: 1) determining the position or area of the brain that measures 2) Import data for analysis and 3) chart analysis.

Part 5 ICA and PCA processes and researches related

The application of ICA in the analysis of electrophysiological data is based primarily upon two assumptions (Delorme & Makeig 2004). First, it is assumed that EEG data recorded at multiple scalp sensors are linear sums of temporally independent components arising from spatially fixed, distinct, or overlapping brain or extra-brain networks. If the sources within the brain are not temporally stable, ICA will not reveal the actual brain activity. Second, it is assumed that the spatial spread of electric current from sources by means of volume conduction does not involve significant time delay. The spreading time of brain waves is considered zero and the linear addition is immediate, so that mixtures and sources correspond temporally.

A report by Makeig (Makeig et al.1997) indicated that different brain activities and noises could be separated as separate components by ICA. ERPs in 11 normal adults were recorded from 13 different scalp channels in an auditory vigilance test. An additional channel was placed near the eyes measuring Electrooculargraphy (EOG). The channels were bipolar diagonally placed on the scalp, with a sampling rate at 312.5 Hz and frequency pass band of 0.1 - 100 Hz. Participants were instructed to press a button when they heard a weak noise-burst within a continuous noise embedded with a click-train of 39 Hz. Data for each participant in the detected and undetected conditions were averaged respectively into 1-second data sets (1 second is the length of a trial in this experiment). The responses of detected and undetected conditions contained the standard auditory response peaks N l, P2 and N2. A total of fourteen independent components were identified by applying ICA simultaneously on two 1-second data sets. The largest ten components accounted for 97% of the response variance and all components had peaks within 50-500 ms latency range. Among the ten components, three were found only in detected condition; while three others existed only in the undetected condition. One component occurred in both conditions and additional three others were related to the 39 Hz click-train presented throughout the experiment at 1/8 of the EEG sampling rate. The remaining four components accounted for a mere 3% of the total variance and each had a complex topographic structure. These appeared to be activities from weak brain signals and extra brain sources. The largest ten components were robust across subjects and within trials. The correlation between components among difference subjects was very high, .90 or higher in some cases. This experiment showed that ICA was sensitive to small differences between response types.

Given the presumed ability to separate independent signals, ICA was then used to remove eye noise. Jung et al. (2000) conducted a visual selection task using a sample of 28 normal adults and 22 clinical patients who were unable to inhibit blink during the task. The clinical patient consisted of 10 high-functioning autistic and 12 brain lesion subjects.

EEG data was recorded from 31 scalp electrodes, with 29 placed on the scalp, one below the right eye and one (VEOG) at the left outer canthus (HEOG). All channels were referred to the right mastoid and digitized at 256Hz. In the 2-hour visual spatial selection attention task, subjects were instructed to maintain fixation on a central cross and to press the response button as soon as they saw a filled circle replacing the cross. ICA decomposition was performed on 1-second data epochs from 500 to 700 trials for each of 28 normal controls and 22 clinical subjects. Only trials in which the subject pressed the response button within 200-1000 ms were analyzed. All target epochs were decomposed simultaneously. The ICA decomposition identified 31 components.

Blink-related components were identified in a sequential manner. ICA activations were first compared with the original EEG data to find out if the times of activations corresponded to the times of appearances of blinks. Blinks were defined as brief, large monopolar potentials in EEG data. Components whose activation corresponded with blinks were marked as blink-related candidate components. In a subsequent step, scalp maps for each candidate component were plotted. If the ICA component exhibited concentrated activations around the eye region, it was said to blink-related.

To find eye blink-related components, single-trial EEG records were also separately analyzed at each electrode site. Then, the averaged EEG data at each site was compared with the ICA components. A search was made for ICA components whose time course changed systematically with the stimulus locations. These were marked as ICA candidate components sensitive to eye-induced artifacts. Finally, a verification of the candidate eye movement was made by plotting scalp maps.

After identifying components related to eye blinks and eye movements, Jung, et al. showed that the components identified as containing eye noise did not contain brain signals. The original brain waves were classified into three categories: little, moderately and heavily contaminated. They hypothesized that if only noise was removed, brain waves with minimal contamination should change little after ICA correction; whereas, the heavily contaminated ones would exhibit a significant change. Data before and after ICA correction confirmed this hypothesis.

Using the same data, Jung et al. (2001) did a further detailed analysis concluding that ICA components did in fact represent differentially artifacts, stimulus-locked, response-locked, and background ERP signals. They used the same methods that they had earlier used to locate and remove eye blink and eye movements. Categorization of the remaining components was done with what they referred to as single trial activations. In this, trials were not averaged together, but were connected serially. Single trial activations for each component were then plotted in one picture. The amplitudes of activations were represented by a color spectrum. Each trial was represented as a solid line with multiple colors. All trials were horizontally stacked, so that changes of activations could be viewed clearly by looking at the color change across time (vertically) or across trials (horizontally). For some components, the activities changed immediately after stimulus onset; for others, the activations occurred after subjects responded to stimuli; and for still others, changes observed were not associated with stimuli or responses. Taken along with the noise components removed earlier, these results suggested that ICA was able to separate stimulus-locked, response-locked, and non-event-related brain activities into separate components. This could not have been accomplished had ICA been applied in the traditional manner; i.e., after data averaging. Finally, they showed that components related to eye blinks, eye movements, temporal muscle activity, alpha activities, and event-evoked potentials were similar across subjects, thereby suggesting that ICA was constant and reliable.

PCA and ICA are sometimes carried together in data analysis. Due to their dissimilar principals, PCA and ICA have totally different purposes. On one hand, by applying PCA, one obtains orthogonal components and the order of variance which shows how important those components are in the data. We choose, generally arbitrarily, the components/factors that carry the most variance and disregard the rest because the remaining components add little to the total variance.

On the other hand, the order of variance does not really matter in ICA. What matters is the characteristic of individual components: whether they represent noise or signal. ICA retains brain signal and removes noise, even though some noise may account for a large variance. Figure 2 shows that PCA and ICA have similar expressions; however, they differ greatly in both their mathematics and representations. PCA assumes that data follow a Gaussian distribution while ICA fits data to a super-Gaussian distribution (Hyvarinen, Karhunen, & Oja, 2001).

PCA seeks for maxima variance, while ICA seeks for maximal kurtosis. In summary, ICA components were demonstrated to represent simpler brain signals than the original data and represent the different varieties of signals, including eye blinks, eye movements, stimulus-locked, response-locked and non-phase locked activations. It was possible with ICA to study the subtle difference between two slightly different brain conditions. The separating ability of ICA enables it to remove eye noise and even muscle noise from the original data without removing the stimulus locked data. ICA was compared with many other methods such as PCA and regression, and was reported to be better than these in separating noise from signal. The advantages and disadvantages of ICA were summarized as following (Jung et al., 2000).

5.1 Advantages of ICA

5.1.1 ICA requires no knowledge of signals; decomposition is based on the characteristics of the data.

5.1.2 ICA does not delete trials but only noise components within trials. It attempts to preserve as much of the data as possible.

5.1.3 ICA can preserve data from all scalp channels, including frontal and periocular sites. Those sites are usually regarded reference channels in regression method and cannot be further processed in regression research.

5.1.4 ICA can be important in single-trial analysis of ERP data. Single trial analysis is of value in investigating trial to trial variation, but because of high noise, single trials are rarely studied. By applying ICA to ERP data, noise could be removed on each single trial providing information about trial-to-trial variation and perhaps a better average.

Independent Component Analysis (ICA) is a technique that decomposes the data into statistically independent components. PCA uses second order statistic of data, i.e., covariance to find the uncorrelated components. ICA uses higher order statistics to find statistically independent components. ICA is defined as an optimization problem to minimize mutual information between the source components using higher order statistics to measure non-Gaussanity. The central limit theorem states that sum of a large number of independent processes tends toward a Gaussian distribution. Therefore, if Y is assumed to be a set of truly independent channels, X must follow a Gaussian distribution. ICA computes the spatial weight matrix W such that it maximizes the non-Gaussianity of Y. There are many algorithms that use different metrics like minimization of mutual information or maximum likelihood estimation to compute statistically independent components. (Comon, 1994)

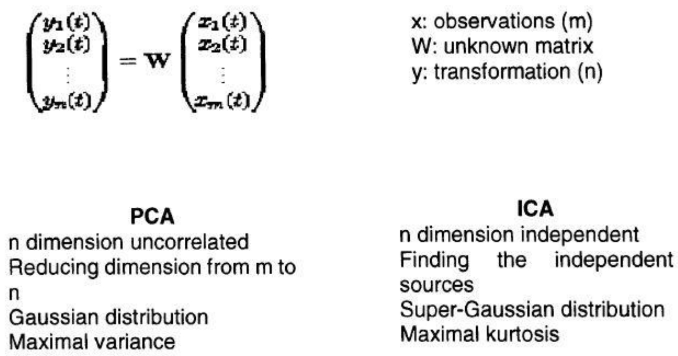


Figure 6 Comparison of PCA and ICA, they have similar formula, but they differ a lot in principles, characteristics and usages

5.2 The Fast Fourier Transform (FFT)

It is one of the most popular digital signal processing (DSP) techniques for converting the one domain signal to another domain signal such as time to a frequency domain and vice versa, by using two methodologies called DFT (Discrete Fourier Transform) and Inverse DFT (E Oran Brigham 1988). Sample conversion is presented in Figure 7.

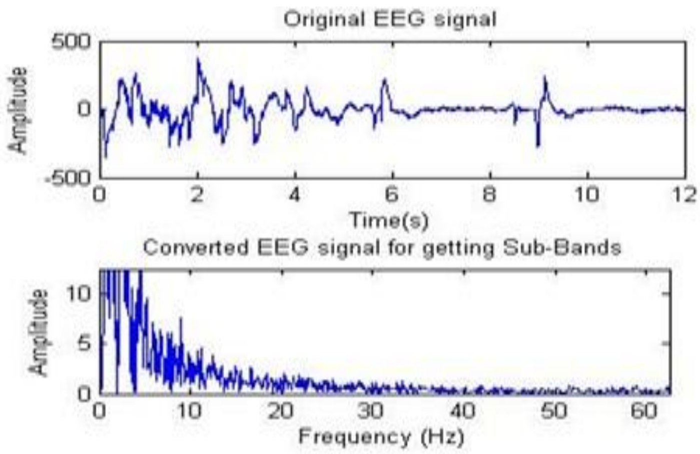


Figure 7 Raw EEG data (first graph) with time domain and Frequency domain EEG data (second graph)

For performing this process, we have some predefined functions in the Matlab, such as "fft" and "ifft" (Mathuranathan 2013). This technique allows for the separation and studies of the dif- ferent EEG frequencies for analyzing the EEG signal. FFT technique breaks down the signal into small components (follows the divide and conquer rule). To extracting the EEG sub-bands, the FFT decomposes the EEG signal into sins and cosines waves of different frequencies (Wojciech 2014). FFT is easy to use, and computing time is low because it reduces the number of computations from N2 to N log2 N. Here N is the size of a problem; for our EEG signal, we consider it as several samples (Pierre and Martin 1990). FFT for continuous-time signal x(t) is X (f) is shown in below equation.

$$X(f) = \int_{\infty}^{-\infty} x(t)e^{-j2\pi ft}dt$$

The FFT is not only limited to extract the EEG sub-bands. It is also useful for extracting statistical features like power spectral density, spectral centroid, spectral energy, etc. (M Murugappan, Subbulakshmia and Celestin, et al 2014). The simple FFT is limited to the stationary signals because FFT only analyzes the continuous signal with uniform frequency. For non-stationary signals, FT provides Short-time Fourier Transform (STFT, also called Gabor Transform) with an approximated window to decompose the signal into piece-wise stationery. It is a time-frequency representation of the time-based EEG signal. An indication of STFT is similar to the FFT. Here, the only difference is an extra win- dowing function ω(t) and whose positions are translated in time by τ.

$$STFT(f,\tau) = \int_{\infty}^{-\infty} x(t)\omega(t-\tau)e^{-j2\pi ft}dt$$

Digital Filter is frequently used and executed in relation- ships with the recurrence relations that describe in what way the output signal is linked to the input signal, for example,

$$y[n] = \frac{1}{a_0}(b_0x[n]+b_1x[n-1]\ldots b_px[n-p]-a_1y[n-1]-a_2y[n-2]-\ldots-a_Qy[n-Q])$$

Here P and bi are feed-forward filter order & coefficients. Q and ai is the feedback filter order & coefficients, x[n] and y[n] are input and output signal respectively. Without Filters concept of digital signal processing, many fragments of EEG would be incomprehensible. The utilization of Filters can influence the EEG motion in ways that range from the unpretentious to the emotional. The principal advantage of filters is that they can clean the EEG to make it simpler to understand. The frequencies of all mind electrical action of intrigue exist in a specific data transfer capacity called bandwidth. EEG filters are set up with the goal that one filter rejects the larger part of the high-frequency action, and another filter rejects the lion's share of low-frequency movement. The scope of frequencies between these undesirable high and low frequencies permitted to go through the filter setup is alluded to as the band-pass. Digital filter has two models such as FIR and IIR for filtering EEG signal into various bands.

Part 6 Machine learning and researches related

For Machine Learning algorithms to do this, on common processors with limited parallelism, would be computationally prohibitive. For this reason, the transformation algorithm is used to convert similar signals, differing only by shift, to be made similar. So mostly, instead of creating a machine learning system which can recognize signals shifted by every increment of time possible, one can merely convolve the EEG signal EEG(t) with a transformation signal Trans(t) as in Equation 5 or cross-correlate the signal as in Equation 6 (these are equivalent in the aforementioned examples since the transformation signal is symmetrical/even) with a sine wave or a wavelet and present the resulting magnitude data to the machine learning algorithm.

In this way, it is possible to remove information that is not important to the classification algorithm at hand. The next section will continue the discussion of discarding unnecessary data, in the form of dimensionality reduction.

Dimensionality Reduction and Optimal Feature Extraction As discussed in the previous section, the EEG signal has been transformed into a more convenient form, from the time domain into the frequency/phase domain of the Fourier transform or the scale/shift domain of the wavelet transform. In that discussion, it was also noted that some dimensionality reduction took place.

Dimensionality reduction is essential for several reasons. First, it dramatically reduces computation time for the machine learning algorithms that follow. Second, it helps to avoid the "curse of dimensionality" (discussed further in the next section) which causes over-fitting of training data reducing the generality of the resultant machine learning algorithm. Finally, dimensionality reduction is a means of looking only at the data which is common across many participants and is relevant or common to all those instances in identifying the feature of importance (such as attentiveness), hence for feature extraction. Dimensionality reduction is typical in many machine learning implementations and may include application specific methods, such as banding or Principal Component Analysis (PCA).

PCA is a common dimensionality reduction method that requires samples of data (training data), and once the transformation matrix is calculated, it must accompany the classifier so it can be applied to all new incoming data. PCA does not use any information about the desired workings of the machine learning algorithm, nor the application in question. PCA searches for directions in the data that have the most considerable variance and subsequently project the data onto it. (Welling, 2012) Another method similar to PCA which seeks to address the classification issue at hand is Fischer Discriminant analysis. Fischer Discriminant analysis seeks to add to PCA, using classification information in the calculation of an optimal linear separation of the data. The Fischer Discriminant seeks to find a long separation of the data that maximizes the ratio of scattering of interclass data divided by the ratio of scattering of intraclass data. (Welling, 2012) It is therefore theoretically possible to use the Fischer Discriminant formula (the ratio of inter-class scatter over intra class scatter) as the algorithm with which to compare feature extraction methodologies.

One example in the literature is (S. Lee, B. Abibullaev and W.-S. Kang, et al. 2010) where a number of wavelet transforms were used and visually compared the fifth level decomposition coefficients of Bior3.1, Sym7, Db4, and Coif5; although an analytic (numerically on its own) comparison was not provided, the paper did compare the feature extraction method in terms of overall system performance. Also notable is the work is done in (Murugappan 2011) which compared feature extraction methods, mainly as part of how they performed as part of the overall system. This paper is important because it discusses an interesting hypothesis of the importance of non-linearity. (Murugappan 2011) notices that the "Entropy" metric seems to be one of the better ones to use and the authors go on to hypothesize that this is because of it.

"Captures the nonlinearity of the EEG signals over different emotions [better] than other statistical features." Without a complete understanding of the physical brain neuron-firing mechanisms related to when someone is attentive towards a short training video, it would be difficult to make any definitive conclusions as to why the direct comparison of feature extraction methods might not reveal the one that will work best in the classifier.

Nevertheless, it is well understood that the ANN classifier does allow non-linear pattern recognition. It could be that the ANN can solve this pattern recognition problem because it can handle non-linear combinations of input data. Therefore, a purely linear comparison of feature extraction methods might not find the one method that contains the data needed to solve the classification problem the best. If indeed, linear methods of comparing feature extraction methods are not revealing the best method for feature extraction, then this may imply that common linear methods for dimensionality reduction may be flawed. For example, PCA is frequently used to reduce a large feature vector down to a smaller dimensionality, such as in (Khare et al., 2009; Chakraborty et al., 2009) PCA makes assumptions about the ability to find an optimal matrix that is multiplied by the input data. This linear operation, similar to the category using Fischer Discriminant, is by definition taking a linear combination of the entire set of data to create a reduced set of data (discarding information).

Similarly, the banding methods described in the previous section use linear combinations of adjacent frequency power values to combine them into a single band power value. If an engineer is looking to reduce the amount of data while minimally impacting classification accuracy, these linear methods may not offer the best solution. It may instead be those linear methods of dimensionality reduction do not yield the best classification accuracy.

In conclusion, dimensionality reduction is essential to speed computation, help the machine learning algorithm avoid over-fitting, and extract a subset of the features that are important for the application. Another purpose of dimensionality reduction is to help increase the generalizing abilities of the solution by removing those features that distinguish between participants rather than their mental state. The literature describes several methods of dimensionality reduction including using power (throwing away phase information), grouping frequencies into bands, PCA (Khare et al., 2009; Chakraborty et al., 2009), and converting wavelet coefficients into statistical measures such as entropy and standard deviation (Murugappan, 2011).

Machine Learning Classification Algorithms of Biometric Data Even though researchers may have good examples of the data they are looking for, and even though they can extract numerical features from those examples, researchers must also still implement a classification algorithm. Classification algorithms are used to classify the observed signal being a member of one or more categories. (Rumelhart, Widrow, & Lehr 1994) Artificial Neural Networks (ANN) have been successfully deployed to perform such tasks as detecting ... sleepiness (Sandberg et al., 2010) (Hayashi et al., 2005), and basic statistical analysis tasks such as primary feature classification (Li &Tufts 1997). Other classification algorithms described in the literature include k Nearest Neighbor (NN) and Support Vector Machines (SVM).

The algorithm used in research. One machine learning algorithm is kNN. kNN is supported in the literature and consists of selecting some number k of nearest vectors (using Euclidean distance) from the set of manually classified vectors. The classification of these k vectors is examined, and the most popular classification wins. This method has some variations, mostly designed to overcome limitations when the vectors contain many dimensions or less relevant dimensions whose scale is large compared to the other dimensions, thereby giving an excessive non-relevant contribution to the distance measures.

SVM is an algorithm that, like a single layer ANN, can be used to find a line, plane, or hyperplane that separates the two classes of vectors with as much distance between the vectors and the separator as possible. If the vectors cannot be linearly separated, then SVM attempts to calculate a non-linear transformation (a kernel function) that maps the vectors into a domain where they can be linearly separated (a domain with more dimensions).

Random Forest is a machine learning algorithm based on classification trees. A classification tree is constructed by looking at each dimension of the vectors and seeing if it can be used to split the data. This continues until, a final classification is made (at the leaf of the tree) and several algorithms exist to optimize the creation and pruning (i.e., optimization) of the classification trees. Random Forest takes this one step farther and creates many decision trees (skipping the pruning step), based on randomly selected ensembles of vectors from the original data set (including, sometimes, repeats of the data, sometimes called bootstrap ensembles).

Genetic Algorithms are a machine learning method that mimics the natural selection of life-based on chromosomes. Each solution has a mother and father, from which it gets a set of chromosomes. The fitness of the offspring is determined (classification error is one possible measure), and only the fittest are selected to have the next generation of offspring. In this way, a large number of chromosomes (vector dimension values) can be winnowed out to find the best combination to classify the data set. Some examples from the literature include (Ito et al., 2010) which used a weighting of individual features (biased Euclidean distance) generated by a competitive "real-coded genetic algorithm" which seeks to genetically find a weighting to maximize the Euclidean distance between vectors from different classes then kNN was used. In (Ito et al. 2010) the result was the selection from one of three choices for classification which were "Matches Mood," "Does not match the mood," and "Borderline" (or other). In (Khosrowabadi et al., 2010) researchers documented that they tried kNN and SVM, with the latter performing a bit better. (Murugappan, 2011) Described the use of kNN with 2 to 8 values for k tried. It seems the best results are with 64 electrodes, sym8 DWT (although not much difference), and Entropy as the parameter used and k=6 for the kNN classification algorithm. (Mostow, Chang and Nelson 2011) Discussed trained binary logistic regression classifiers to estimate the probability of easy or hard based on EEG data. The researchers specifically describe their testing across users (leaving out one user) and across samples for one user (leaving out one sample). Also described were some methods used to deal with the disparity in some examples (many more easy examples, many more hypothetical word examples) which can plague both ANN and kNN classification methods.

Finally, De Vico Fallani (2008) did not use a classifier and simply graphed average efficiency measures for each band, Theta, Alpha, Beta, Gamma - showing more efficiency for forgotten videos. This implies a human classification by visual examination of the graphs. Also, Lisetti and Nasoz (2004) experimented with three different supervised learning algorithms including k nearest neighbor (kNN), Discriminant function analysis (DFA), and Marquardt backpropagation algorithm (MBP) for ANN. MBP seemed to do best, and the addition of the feature extraction (min, max, etc…) also slightly improved performance. So to conclude the review of related work on automated pattern recognition (machine learning) of biometric data, classification algorithms require personal supervised training (such as ANN, SVM, and Random Forests) and human supervised selection of exemplary feature vectors for each category (such as for kNN). Once this is done, an unsupervised automated algorithm can recognize the pattern, and suitably classify the biometric data.

Nonparametric Models: k-Nearest Neighbor (kNN) and Random Forest (RF)

Before starting to discuss the specific modeling of sequential data with HMMs and deep learning, it is essential to consider two classic non-parametric techniques that we used for an exploratory study of the subject: k-Nearest Neighbor (kNN) (Duda et al., 2003) and Random Forest (RF) (Breiman, 2001). These techniques are both well understood and have been widely adopted in different areas of pattern recognition (Keysers et al., 2007; Chu et al., 2015). Despite their antiquity, these models are still useful for pattern recognition problems in which the distributions that generate the data are difficult to model.

One of the oldest and simplest pattern recognition algorithms is kNN. When combined with other techniques such as neural networks or prior knowledge, however, models that rely on kNN can achieve competitive results (Weinberger & Saul, 2009; Belongie et al., 2002). Explained merely, kNN classifies a given data sample by considering the k-nearest neighboring samples and selecting the label that predominates in the considered window. Traditionally, in the absence of prior knowledge about the data, a simple Euclidean distance measure between the input vectors is used to calculate the distances between data samples, but the distance metrics are often adapted to the task being solved. Some systems, such as (Chopra et al., 2005), additionally learn a similarity metric from the data, which significantly improves the classification performance. Another well-known machine learning technique that is still being successfully used for a variety of problems, such as gene selection and classification (Díaz-Uriarte, 2006), is RF. RFs are different from standard trees in that the nodes are split using a random set of samples selected explicitly at that node, rather than the best split among all variables. By the RF algorithm presented by Breiman (2001), an ensemble of trees is formed in order to produce a class prediction. A final classification decision is then made through the consideration of a majority vote yielded by each ensemble of trees. RFs are an excellent choice for a baseline system because they are robust to overfitting and perform well across a wide range of applications. Some of the preliminary studies in our work rely on standard kNN and RF techniques to evaluate the strange EEG problem before considering HMMs and Deep learning approaches.

CHAPTER 3
RESEARCH METHODOLOGY

This chapter outlines the methodological framework and it composes of five main parts, namely (i) research methodology, (ii) data pre-processing by ICA and PCA methods, (iii).

Part 1 Research methodology

Part 2 Data pre-processing by ICA and PCA methods

Part 3 Fourier transformation to change the data to frequency domain

Part 4 Data clustering by two unsupervised machine learning models

Part 5 Training and validation by five supervised machine learning models

Part 1 Research methodology

This research used the secondary data of Dr. Phatcha Chaiyasung. The data was collected as the following processes. Participants start projecting definite (+) black on white background in the middle of the screen (Fixation Point) for 500 milliseconds on a black screen 6,000 milliseconds. Then open up the Thai digital emotional valence words and sounds at the same time with duration 6,000 milliseconds. Then it will appear Self-Assessment Manikin (SAM), 3,000 milliseconds to score him/herself. After that, the computer shows a white background for 1,000 milliseconds, then participants start the loop again until finish 14 words and sound task as shown in the figure 8.

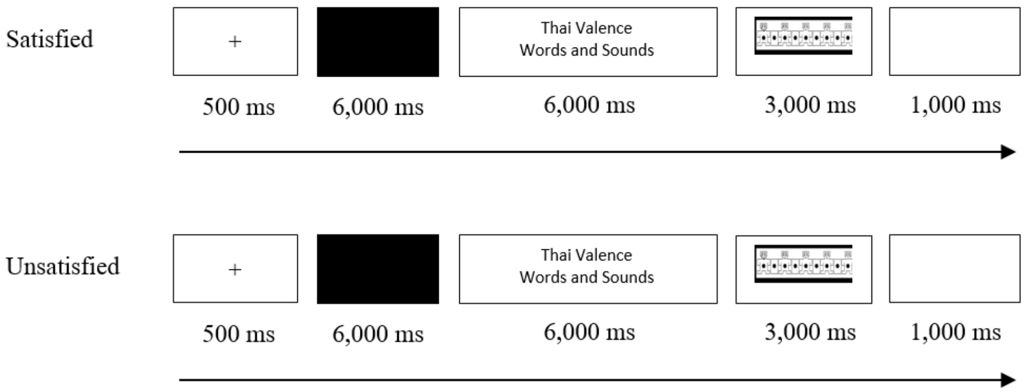


Figure 8 The process of collecting emotional valence EEG data of Thai word and sound task

Eighty-four healthy, right-handed subjects (42 males and 42 females) participated in this study. Their ages ranged from 20 to 64 (). The participants were all Thai and lived in Thailand. All participants reported no history of neurological or psychiatric disorders. The ERP data were recorded during the experiment in a quiet, softly lit room. Participants were instructed to sit comfortably in a seat. The distance from their eyes to the screen was about 80 cm, and the horizontal and vertical angles of view were 5◦. Brain electrical activity was recorded with a Curry Neuroimaging Suite 7.0, United States. The cap electrode system reference standard 10-20 (Electro-Cap) 64 channels EEG and referenced to the front central midline electrode (FCz). the electrode impedances kept below 5 k Ohm. Using the G * power test, the effect size was 0.80, Alpha (α). 05 power (1 - β) of .95.

This research use Curry7 software to operate data pre-processing of independent component analysis (ICA) and Principal component analysis (PCA) as shown in figure 9.

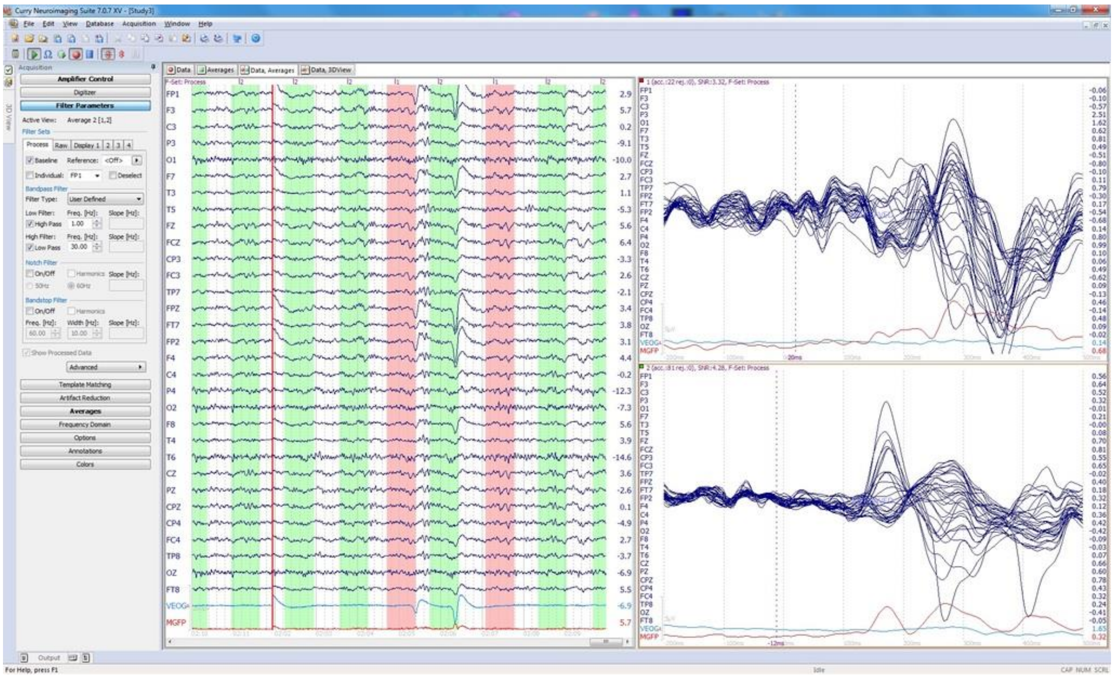


Figure 9 Curry7 EEG software

This research use R-Studio for Fast Fourier transformation process, data frame operations, unsupervised machine learning, supervised machine learning, plot graph and pictures as shown in figure 10.

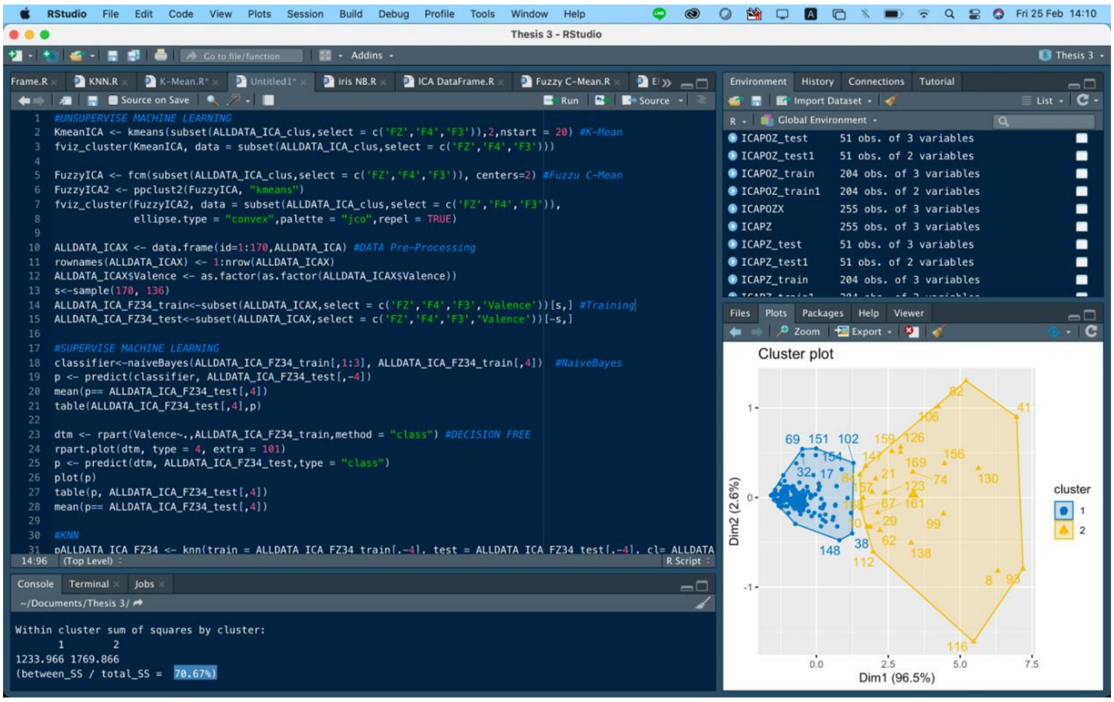


Figure 10 R-Studio software

Part 2 Data pre-processing by ICA and PCA methods

2.1 These are the R algorithm for declaring variables of ICA emotional valence EEG data of 85 participants by upload csv file format from document folder to R environment which exclude header and set row 1 as row name. the letter “A” behind define that it is the EEG data from “positive” emotional valence tasks.

```
ICA01A <- read.delim("/Users/jakkarinchinsuwan/Documents/Master Degree/ICA TEXT DATA/1_IA", header=FALSE, row.names=1)
ICA02A <- read.delim("/Users/jakkarinchinsuwan/Documents/Master Degree/ICA TEXT DATA/2_IA", header=FALSE, row.names=1)
ICA03A <- read.delim("/Users/jakkarinchinsuwan/Documents/Master Degree/ICA TEXT DATA/3_IA", header=FALSE, row.names=1)
.
.
.
ICA85A <- read.delim("/Users/jakkarinchinsuwan/Documents/Master Degree/ICA TEXT DATA/85_IA", header=FALSE, row.names=1)
```

2.2 These are the R algorithm for declaring variables of ICA emotional valence EEG data of 85 participants by upload csv file format from document folder to R environment which exclude header and set row 1 as row name. the letter “C” behind define that it is the EEG data from “negative” emotional valence tasks.

```
ICA01C <- read.delim("/Users/jakkarinchinsuwan/Documents/Master Degree/ICA TEXT DATA/1_IC", header=FALSE, row.names=1)
ICA02C <- read.delim("/Users/jakkarinchinsuwan/Documents/Master Degree/ICA TEXT DATA/2_IC", header=FALSE, row.names=1)
ICA03C <- read.delim("/Users/jakkarinchinsuwan/Documents/Master Degree/ICA TEXT DATA/3_IC", header=FALSE, row.names=1)
.
.
.
ICA85C <- read.delim("/Users/jakkarinchinsuwan/Documents/Master Degree/ICA TEXT DATA/85_IC", header=FALSE, row.names=1)
```

2.3 These are the R algorithm for declaring variables of PCA emotional valence EEG data of 85 participants by upload csv file format from document folder to R environment which exclude header and set row 1 as row name. the letter “A” behind define that it is the EEG data from “positive” emotional valence tasks.

```
PCA01A <- read.delim("/Users/jakkarinchinsuwan/Documents/Master Degree/PCA TEXT DATA/1_PA", header=FALSE, row.names=1)
PCA02A <- read.delim("/Users/jakkarinchinsuwan/Documents/Master Degree/PCA TEXT DATA/2_PA", header=FALSE, row.names=1)
PCA03A <- read.delim("/Users/jakkarinchinsuwan/Documents/Master Degree/PCA TEXT DATA/3_PA", header=FALSE, row.names=1)
…
PCA85A <- read.delim("/Users/jakkarinchinsuwan/Documents/Master Degree/PCA TEXT DATA/85_PA", header=FALSE, row.names=1)
```

2.4 These are the R algorithm for declaring variables of PCA emotional valence EEG data of 85 participants by upload csv file format from document folder to R environment which exclude header and set row 1 as row name. the letter “C” behind define that it is the EEG data from “negative” emotional valence tasks.

```
ICA01C <- read.delim("/Users/jakkarinchinsuwan/Documents/Master Degree/ICA TEXT DATA/1_IC", header=FALSE, row.names=1)
ICA02C <- read.delim("/Users/jakkarinchinsuwan/Documents/Master Degree/ICA TEXT DATA/2_IC", header=FALSE, row.names=1)
ICA03C <- read.delim("/Users/jakkarinchinsuwan/Documents/Master Degree/ICA TEXT DATA/3_IC", header=FALSE, row.names=1)
.
.
.
ICA85C <- read.delim("/Users/jakkarinchinsuwan/Documents/Master Degree/ICA TEXT DATA/85_IC", header=FALSE, row.names=1)
```

2.5 These are the R algorithm for dataframe operation of ICA emotional valence EEG data of 85 participants by deleting the row 1 and row 64, and deleting the column 6202. the letter “A” behind define that it is the EEG data from “positive” emotional valence tasks.

ICA01A <- ICA01A[-64,-6202] *ICA02A <- ICA02A[-64,-6202]* *ICA03A <- ICA03A[-64,-6202]* . . . *ICA85A <- ICA85A[-64,-6202]*	*ICA01A <- ICA01A[-1,]* *ICA02A <- ICA02A[-1,]* *ICA03A <- ICA03A[-1,]* . . . *ICA85A <- ICA85A[-1,]*

2.6 These are the R algorithm for dataframe operation of ICA emotional valence EEG data of 85 participants by deleting the row 1 and row 64, and deleting the column 6202. the letter "C" behind define that it is the EEG data from "negative" emotional valence tasks.

ICA01C <- ICA01C[-64,-6202] *ICA02C <- ICA02C[-64,-6202]* *ICA03C <- ICA03C[-64,-6202]* … *ICA85C <- ICA85C[-64,-6202]*	*ICA01C <- ICA01C[-1,]* *ICA02C <- ICA02C[-1,]* *ICA03C <- ICA03C[-1,]* … *ICA85C <- ICA85C[-1,]*

2.7 These are the R algorithm for dataframe operation of PCA emotional valence EEG data of 85 participants by deleting the row 1 and row 64, and deleting the column 6202. the letter "A" behind define that it is the EEG data from "positive" emotional valence tasks.

PCA01A <- PCA01A[-64,-6202] *PCA02A <- PCA02A[-64,-6202]* *PCA03A <- PCA03A[-64,-6202]* … *PCA85A <- PCA85A[-64,-6202]*	*PCA01A <- PCA01A[-1,]* *PCA02A <- PCA02A[-1,]* *PCA03A <- PCA03A[-1,]* … *PCA85A <- PCA85A[-1,]*

2.8 These are the R algorithm for dataframe operation of PCA emotional valence EEG data of 85 participants by deleting the row 1 and row 64, and deleting the column 6202. the letter "C" behind define that it is the EEG data from "negative" emotional valence tasks.

PCA01C <- PCA01C[-64,-6202] *PCA02C <- PCA02C[-64,-6202]* *PCA03C <- PCA03C[-64,-6202]* … *PCA85C <- PCA85C[-64,-6202]*	*PCA01C <- PCA01C[-1,]* *PCA02C <- PCA02C[-1,]* *PCA03C <- PCA03C[-1,]* … *PCA85C <- PCA85C[-1,]*

Part 3 Fourier transformation to change the data to frequency domain

The Fast Fourier Transform (FFT) is a way to reduce the complexity of the Fourier transform computation from O (n 2) to O (n log n), which is a dramatic improvement. The primary version of the FFT is one due to Cooley and Tukey. The basic idea of it is easy to see.

Suppose we have a time series y1,…,yn and we want to compute the complex Fourier coefficient z1. Going by the formula in the previous section, this would require computing

$$z_0 = \sum_{t=0}^{n-1} y_t,$$

which is simply proportional to the mean of the data. If the data have been de-meaned or de-trended then this will be zero. The next Fourier coefficient is then

$$\begin{aligned} z_1 &= \sum_{t=0}^{n-1} y_t \exp(-2\pi i \cdot 1 \cdot t/n) \\ &= y_0 \exp(-2\pi i \cdot 1 \cdot 0/n) + y_1 \exp(-2\pi i \cdot 1 \cdot 1/n) + y_2 \exp(-2\pi i \cdot 1 \cdot 2/n) + \cdots. \end{aligned}$$

Now suppose we want to compute the next coefficient z2. This requires computing

$$z_2 = y_0 \exp(-2\pi i \cdot 2 \cdot 0/n) + y_1 \exp(-2\pi i \cdot 2 \cdot 1/n) + \cdots$$

Notice how the exponential in the second term in the sum for z2 is the same as the exponential in the third term in the sum for z1. They are both equal to exp

(−2πi · 1 · 2/n). There is no need to compute this expoential quantity twice. We can simply compute it the first time, store it in memory, and then retrieve it when it is needed to compute z2 (assuming that retrieving from memory is faster than computing it from scratch.) One can think of the FFT algorithm as an elaborate bookkeeping algorithm that keeps track of these symmetries in computing the Fourier coefficients.

3.1 These are the R algorithm for setting up Fast Fourier transformation EEG data by install R package names "gsignal".

```
#install.packages("gsignal")
library(gsignal)

fs <- 1000
nsecs <- 6
lx <- fs * nsecs
lx
t <- seq(0, nsecs, length.out =  lx)
t
```

3.2 These are the R algorithm for combinding dataframe of ICA of 84 samples. The letter "A" behind define that it is the EEG data from "positive" emotional valence tasks.

```
data_ICAA                                                                    =
c("ICA01A","ICA02A","ICA03A","ICA04A","ICA05A","ICA06A","ICA07A","ICA0
8A","ICA09A","ICA10A","ICA11A","ICA12A","ICA13A","ICA14A","ICA15A","IC
A16A","ICA17A","ICA18A","ICA19A","ICA20A","ICA21A","ICA22A","ICA23A","
ICA24A","ICA25A","ICA26A","ICA27A","ICA28A","ICA29A","ICA30A","ICA31A
","ICA32A","ICA33A","ICA34A","ICA35A","ICA36A","ICA37A","ICA38A","ICA3
9A","ICA40A","ICA41A","ICA42A","ICA43A","ICA44A","ICA45A","ICA46A","IC
A47A","ICA48A","ICA49A","ICA50A","ICA51A","ICA52A","ICA53A","ICA54A","
ICA55A","ICA56A","ICA57A","ICA58A","ICA59A","ICA60A","ICA61A","ICA62A
","ICA63A","ICA64A","ICA65A","ICA66A","ICA67A","ICA68A","ICA69A","ICA7
0A","ICA71A","ICA72A","ICA73A","ICA74A","ICA75A","ICA76A","ICA77A","IC
A78A","ICA79A","ICA80A","ICA81A","ICA82A","ICA83A","ICA84A","ICA85A")
```

3.3 These are the R algorithm of the loop of ICA dataframe of 84 samples to transform in to numeric class and transform into frequency domain by Fast Fourier transformation. And get the maximum power amplitude frequency by command “pwelch”. The letter “A” behind define that it is the EEG data from “positive” emotional valence tasks.

```
max1ICAA <- 1
for(i in 1:length(data_ICAA)) {
  x <- get(data_ICAA[i])
  x <- (x[1,102:6101])
  x <- as.numeric(as.data.frame(x))
  pw <- pwelch(x, window = lx, fs = fs, detrend = "none")
  max1ICAA[i] <- max(pw$spec)
}
max2ICAA <- 1
for(i in 1:length(data_ICAA)) {
  x <- get(data_ICAA[i])
  x <- (x[2,102:6101])
  x <- as.numeric(as.data.frame(x))
  pw <- pwelch(x, window = lx, fs = fs, detrend = "none")
  max2ICAA[i] <- max(pw$spec)
}
max3ICAA <- 1
for(i in 1:length(data_ICAA)) {
  x <- get(data_ICAA[i])
  x <- (x[3,102:6101])
  x <- as.numeric(as.data.frame(x))
  pw <- pwelch(x, window = lx, fs = fs, detrend = "none")
  max3ICAA[i] <- max(pw$spec)
}
```

3.4 These are the R algorithm for setting up Fast Fourier transformation EEG data.

```
fs <- 1000
nsecs <- 6
lx <- fs * nsecs
lx
t <- seq(0, nsecs, length.out =  lx)
t
```

3.5 These are the R algorithm for combinding dataframe of ICA of 84 samples. The letter “C” behind define that it is the EEG data from “negative” emotional valence tasks.

```
data_ICAC =
c("ICA01C","ICA02C","ICA03C","ICA04C","ICA05C","ICA06C","ICA07C","ICA08C","ICA09C","ICA10C","ICA11C","ICA12C","ICA13C","ICA14C","ICA15C","ICA16C","ICA17C","ICA18C","ICA19C","ICA20C","ICA21C","ICA22C","ICA23C","ICA24C","ICA25C","ICA26C","ICA27C","ICA28C","ICA29C","ICA30C","ICA31C","ICA32C","ICA33C","ICA34C","ICA35C","ICA36C","ICA37C","ICA38C","ICA39C","ICA40C","ICA41C","ICA42C","ICA43C","ICA44C","ICA45C","ICA46C","ICA47C","ICA48C","ICA49C","ICA50C","ICA51C","ICA52C","ICA53C","ICA54C","ICA55C","ICA56C","ICA57C","ICA58C","ICA59C","ICA60C","ICA61C","ICA62C","ICA63C","ICA64C","ICA65C","ICA66C","ICA67C","ICA68C","ICA69C","ICA70C","ICA71C","ICA72C","ICA73C","ICA74C","ICA75C","ICA76C","ICA77C","ICA78C","ICA79C","ICA80C","ICA81C","ICA82C","ICA83C","ICA84C","ICA85C")
```

3.6 These are the R algorithm of the loop of ICA dataframe of 84 samples to transform in to numeric class and transform into frequency domain by Fast Fourier transformation. And get the maximum power amplitude frequency by command “pwelch”. The letter “C” behind define that it is the EEG data from “negative” emotional valence tasks.

```
max1ICAC <- 1
for(i in 1:length(data_ICAC)) {
  x <- get(data_ICAC[i])
  x <- (x[1,102:6101])
  x <- as.numeric(as.data.frame(x))
  pw <- pwelch(x, window = lx, fs = fs, detrend = "none")
  max1ICAC[i] <- max(pw$spec)
}
max2ICAC <- 1
for(i in 1:length(data_ICAC)) {
  x <- get(data_ICAC[i])
  x <- (x[2,102:6101])
  x <- as.numeric(as.data.frame(x))
  pw <- pwelch(x, window = lx, fs = fs, detrend = "none")
  max2ICAC[i] <- max(pw$spec)
}
max3ICAC <- 1
for(i in 1:length(data_ICAC)) {
  x <- get(data_ICAC[i])
  x <- (x[3,102:6101])
  x <- as.numeric(as.data.frame(x))
  pw <- pwelch(x, window = lx, fs = fs, detrend = "none")
  max3ICAC[i] <- max(pw$spec)
}
.
.
.
max62ICAC <- 1
for(i in 1:length(data_ICAC)) {
  x <- get(data_ICAC[i])
  x <- (x[62,102:6101])
  x <- as.numeric(as.data.frame(x))
  pw <- pwelch(x, window = lx, fs = fs, detrend = "none")
  max62ICAC[i] <- max(pw$spec)
}
```

3.7 These are the R algorithm for combinding dataframe of PCA of 84 samples. The letter “A” behind define that it is the EEG data from “positive” emotional valence tasks.

```
data_PCAA =
c("PCA01A","PCA02A","PCA03A","PCA04A","PCA05A","PCA06A","PCA07A","PCA08A","PCA09A","PCA10A","PCA11A","PCA12A","PCA13A","PCA14A","PCA15A","PCA16A","PCA17A","PCA18A","PCA19A","PCA20A","PCA21A","PCA22A","PCA23A","PCA24A","PCA25A","PCA26A","PCA27A","PCA28A","PCA29A","PCA30A","PCA31A","PCA32A","PCA33A","PCA34A","PCA35A","PCA36A","PCA37A","PCA38A","PCA39A","PCA40A","PCA41A","PCA42A","PCA43A","PCA44A","PCA45A","PCA46A","PCA47A","PCA48A","PCA49A","PCA50A","PCA51A","PCA52A","PCA53A","PCA54A","PCA55A","PCA56A","PCA57A","PCA58A","PCA59A","PCA60A","PCA61A","PCA62A","PCA63A","PCA64A","PCA65A","PCA66A","PCA67A","PCA68A","PCA69A","PCA70A","PCA71A","PCA72A","PCA73A","PCA74A","PCA75A","PCA76A","PCA77A","PCA78A","PCA79A","PCA80A","PCA81A","PCA82A","PCA83A","PCA84A","PCA85A")
```

3.8 These are the R algorithm of the loop of PCA dataframe of 84 samples to transform in to numeric class and transform into frequency domain by Fast Fourier transformation. And get the maximum power amplitude frequency by command “pwelch”. The letter “A” behind define that it is the EEG data from “positive” emotional valence tasks.

```
max1PCAA <- 1
for(i in 1:length(data_PCAA)) {
  x <- get(data_PCAA[i])
  x <- (x[1,102:6101])
  x <- as.numeric(as.data.frame(x))
  pw <- pwelch(x, window = lx, fs = fs, detrend = "none")
  max1PCAA[i] <- max(pw$spec)
}
max2PCAA <- 1
for(i in 1:length(data_PCAA)) {
  x <- get(data_PCAA[i])
  x <- (x[2,102:6101])
  x <- as.numeric(as.data.frame(x))
  pw <- pwelch(x, window = lx, fs = fs, detrend = "none")
  max2PCAA[i] <- max(pw$spec)
}
max3PCAA <- 1
for(i in 1:length(data_PCAA)) {
  x <- get(data_PCAA[i])
```

```
  x <- (x[3,102:6101])
  x <- as.numeric(as.data.frame(x))
  pw <- pwelch(x, window = lx, fs = fs, detrend = "none")
  max3PCAA[i] <- max(pw$spec)
}
…
max62PCAA <- 1
for(i in 1:length(data_PCAA)) {
  x <- get(data_PCAA[i])
  x <- (x[62,102:6101])
  x <- as.numeric(as.data.frame(x))
  pw <- pwelch(x, window = lx, fs = fs, detrend = "none")
  max62PCAA[i] <- max(pw$spec)
}
```

3.9 These are the R algorithm for combinding dataframe of PCA of 84 samples. The letter “C” behind define that it is the EEG data from “negative” emotional valence tasks.

```
data_PCAC =
c("PCA01C","PCA02C","PCA03C","PCA04C","PCA05C","PCA06C","PCA07C",
"PCA08C","PCA09C","PCA10C","PCA11C","PCA12C","PCA13C","PCA14C","P
CA15C","PCA16C","PCA17C","PCA18C","PCA19C","PCA20C","PCA21C","PC
A22C","PCA23C","PCA24C","PCA25C","PCA26C","PCA27C","PCA28C","PCA2
9C","PCA30C","PCA31C","PCA32C","PCA33C","PCA34C","PCA35C","PCA36
C","PCA37C","PCA38C","PCA39C","PCA40C","PCA41C","PCA42C","PCA43C"
,"PCA44C","PCA45C","PCA46C","PCA47C","PCA48C","PCA49C","PCA50C","
PCA51C","PCA52C","PCA53C","PCA54C","PCA55C","PCA56C","PCA57C","P
CA58C","PCA59C","PCA60C","PCA61C","PCA62C","PCA63C","PCA64C","PC
A65C","PCA66C","PCA67C","PCA68C","PCA69C","PCA70C","PCA71C","PCA7
2C","PCA73C","PCA74C","PCA75C","PCA76C","PCA77C","PCA78C","PCA79
C","PCA80C","PCA81C","PCA82C","PCA83C","PCA84C","PCA85C")
```

3.10 These are the R algorithm of the loop of PCA dataframe of 84 samples to transform in to numeric class and transform into frequency domain by Fast Fourier transformation. And get the maximum power amplitude frequency by command “pwelch”. The letter “C” behind define that it is the EEG data from “negative” emotional valence tasks.

```
max1PCAC <- 1
for(i in 1:length(data_PCAC)) {
  x <- get(data_PCAC[i])
  x <- (x[1,102:6101])
  x <- as.numeric(as.data.frame(x))
  pw <- pwelch(x, window = lx, fs = fs, detrend = "none")
  max1PCAC[i] <- max(pw$spec)
}
max2PCAC <- 1
for(i in 1:length(data_PCAC)) {
  x <- get(data_PCAC[i])
  x <- (x[2,102:6101])
  x <- as.numeric(as.data.frame(x))
  pw <- pwelch(x, window = lx, fs = fs, detrend = "none")
  max2PCAC[i] <- max(pw$spec)
}
max3PCAC <- 1
for(i in 1:length(data_PCAC)) {
  x <- get(data_PCAC[i])
  x <- (x[3,102:6101])
  x <- as.numeric(as.data.frame(x))
  pw <- pwelch(x, window = lx, fs = fs, detrend = "none")
  max3PCAC[i] <- max(pw$spec)
}
…
max62PCAC <- 1
for(i in 1:length(data_PCAC)) {
  x <- get(data_PCAC[i])
  x <- (x[62,102:6101])
  x <- as.numeric(as.data.frame(x))
  pw <- pwelch(x, window = lx, fs = fs, detrend = "none")
  max62PCAC[i] <- max(pw$spec)
}
```

3.11 These are the R algorithm to combind row of max ICA frequency domain data. The letter “A” behind define that it is the EEG data from “positive” emotional valence tasks.

```
tALLDATA_ICAA <-
rbind(max1ICAA,max2ICAA,max3ICAA,max4ICAA,max5ICAA,max6ICAA,max7IC
AA,max8ICAA,max9ICAA,max10ICAA,max11ICAA,max12ICAA,max13ICAA,max1
4ICAA,max15ICAA,max16ICAA,max17ICAA,max18ICAA,max19ICAA,max20ICAA
,max21ICAA,max22ICAA,max23ICAA,max24ICAA,max25ICAA,max26ICAA,max2
7ICAA,max28ICAA,max29ICAA,max30ICAA,max31ICAA,max32ICAA,max33ICAA
,max34ICAA,max35ICAA,max36ICAA,max37ICAA,max38ICAA,max39ICAA,max4
0ICAA,max41ICAA,max42ICAA,max43ICAA,max44ICAA,max45ICAA,max46ICAA
,max47ICAA,max48ICAA,max49ICAA,max50ICAA,max51ICAA,max52ICAA,max5
3ICAA,max54ICAA,max55ICAA,max56ICAA,max57ICAA,max58ICAA,max59ICAA
,max60ICAA,max61ICAA,max62ICAA)
```

3.12 These are the R algorithm to combind row of max ICA frequency domain data. The letter “C” behind define that it is the EEG data from “negative” emotional valence tasks.

```
tALLDATA_ICAC <-
rbind(max1ICAC,max2ICAC,max3ICAC,max4ICAC,max5ICAC,max6ICAC,max7I
CAC,max8ICAC,max9ICAC,max10ICAC,max11ICAC,max12ICAC,max13ICAC,ma
x14ICAC,max15ICAC,max16ICAC,max17ICAC,max18ICAC,max19ICAC,max20IC
AC,max21ICAC,max22ICAC,max23ICAC,max24ICAC,max25ICAC,max26ICAC,m
ax27ICAC,max28ICAC,max29ICAC,max30ICAC,max31ICAC,max32ICAC,max33I
CAC,max34ICAC,max35ICAC,max36ICAC,max37ICAC,max38ICAC,max39ICAC,
max40ICAC,max41ICAC,max42ICAC,max43ICAC,max44ICAC,max45ICAC,max4
6ICAC,max47ICAC,max48ICAC,max49ICAC,max50ICAC,max51ICAC,max52ICA
C,max53ICAC,max54ICAC,max55ICAC,max56ICAC,max57ICAC,max58ICAC,ma
x59ICAC,max60ICAC,max61ICAC,max62ICAC)
```

3.13 These are the R algorithm to combind row of max PCA frequency domain data. The letter “A” behind define that it is the EEG data from “positive” emotional valence tasks.

```
tALLDATA_PCAA <-
rbind(max1PCAA,max2PCAA,max3PCAA,max4PCAA,max5PCAA,max6PCAA,max
7PCAA,max8PCAA,max9PCAA,max10PCAA,max11PCAA,max12PCAA,max13PC
AA,max14PCAA,max15PCAA,max16PCAA,max17PCAA,max18PCAA,max19PCA
A,max20PCAA,max21PCAA,max22PCAA,max23PCAA,max24PCAA,max25PCAA,
max26PCAA,max27PCAA,max28PCAA,max29PCAA,max30PCAA,max31PCAA,m
ax32PCAA,max33PCAA,max34PCAA,max35PCAA,max36PCAA,max37PCAA,max
38PCAA,max39PCAA,max40PCAA,max41PCAA,max42PCAA,max43PCAA,max44
PCAA,max45PCAA,max46PCAA,max47PCAA,max48PCAA,max49PCAA,max50P
CAA,max51PCAA,max52PCAA,max53PCAA,max54PCAA,max55PCAA,max56PCA
A,max57PCAA,max58PCAA,max59PCAA,max60PCAA,max61PCAA,max62PCAA)
```

3.14 These are the R algorithm to combind row of max PCA frequency domain data. The letter "C" behind define that it is the EEG data from "negative" emotional valence tasks.

```
tALLDATA_PCAC <-
rbind(max1PCAC,max2PCAC,max3PCAC,max4PCAC,max5PCAC,max6PCAC,ma
x7PCAC,max8PCAC,max9PCAC,max10PCAC,max11PCAC,max12PCAC,max13P
CAC,max14PCAC,max15PCAC,max16PCAC,max17PCAC,max18PCAC,max19PC
AC,max20PCAC,max21PCAC,max22PCAC,max23PCAC,max24PCAC,max25PCA
C,max26PCAC,max27PCAC,max28PCAC,max29PCAC,max30PCAC,max31PCAC
,max32PCAC,max33PCAC,max34PCAC,max35PCAC,max36PCAC,max37PCAC,
max38PCAC,max39PCAC,max40PCAC,max41PCAC,max42PCAC,max43PCAC,m
ax44PCAC,max45PCAC,max46PCAC,max47PCAC,max48PCAC,max49PCAC,ma
x50PCAC,max51PCAC,max52PCAC,max53PCAC,max54PCAC,max55PCAC,max
56PCAC,max57PCAC,max58PCAC,max59PCAC,max60PCAC,max61PCAC,max6
2PCAC)
```

3.15 These are the R algorithm to transpose 4 dataframes.

```
ALLDATA_ICAA <- t(tALLDATA_ICAA)
ALLDATA_ICAC <- t(tALLDATA_ICAC)
ALLDATA_PCAA <- t(tALLDATA_PCAA)
ALLDATA_PCAC <- t(tALLDATA_PCAC)
```

3.16 These are the R algorithm to change class array to data frame.

```
ALLDATA_ICAA <- as.data.frame(as.array(ALLDATA_ICAA))
ALLDATA_ICAC <- as.data.frame(as.array(ALLDATA_ICAC))
ALLDATA_PCAA <- as.data.frame(as.array(ALLDATA_PCAA))
ALLDATA_PCAC <- as.data.frame(as.array(ALLDATA_PCAC))
```

3.17 These are the R algorithm to trigger the valence type by adding the "Valence" column as the last column. And label "Positive" to A type dataframes and "Negative" to C type dataframes.

```
ALLDATA_ICAA$Valence <- 'Positive'
ALLDATA_ICAC$Valence <- 'Negative'
ALLDATA_PCAA$Valence <- 'Positive'
ALLDATA_PCAC$Valence <- 'Negative'
```

```
ALLDATA_ICAA
ALLDATA_ICAC
ALLDATA_PCAA
ALLDATA_PCAC
```

3.18 These are the R algorithm to delete the Valence column - (column 63) in order to use for unsupervised machine learning.

```
ALLDATA_ICAA_clus <- ALLDATA_ICAA[,-63]
ALLDATA_ICAC_clus <- ALLDATA_ICAC[,-63]
ALLDATA_PCAA_clus <- ALLDATA_PCAA[,-63]
ALLDATA_PCAC_clus <- ALLDATA_PCAC[,-63]
```

These are the R algorithm to name the column as 64 EEG electrode 10-20 positions to ALLDATA_ICAA_clus, ALLDATA_ICAC_clus, ALLDATA_PCAA_clus, ALLDATA_PCAC_clus.

```
colnames(ALLDATA_ICAA_clus) <-
c('FP1','FPZ','FP2','AF3','AF4','F7','F5','F3','F1','FZ','F2','F4','F6','F8','FT7','FC5'
,'FC3','FC1','FCZ','FC2','FC4','FC6','FT8','T7','C5','C3','C1','CZ','C2','C4','C6','T8'
,'M1','TP7','CP5','CP3','CP1','CPZ','CP2','CP4','CP6','TP8','M2','P7','P5','P3','P1','
PZ','P2','P4','P6','P8','PO7','PO5','PO3','POZ','PO4','PO6','PO8','O1','OZ','O2')
colnames(ALLDATA_ICAC_clus) <-
c('FP1','FPZ','FP2','AF3','AF4','F7','F5','F3','F1','FZ','F2','F4','F6','F8','FT7','FC5'
,'FC3','FC1','FCZ','FC2','FC4','FC6','FT8','T7','C5','C3','C1','CZ','C2','C4','C6','T8'
,'M1','TP7','CP5','CP3','CP1','CPZ','CP2','CP4','CP6','TP8','M2','P7','P5','P3','P1','
PZ','P2','P4','P6','P8','PO7','PO5','PO3','POZ','PO4','PO6','PO8','O1','OZ','O2')
colnames(ALLDATA_PCAA_clus) <-
c('FP1','FPZ','FP2','AF3','AF4','F7','F5','F3','F1','FZ','F2','F4','F6','F8','FT7','FC5'
,'FC3','FC1','FCZ','FC2','FC4','FC6','FT8','T7','C5','C3','C1','CZ','C2','C4','C6','T8'
,'M1','TP7','CP5','CP3','CP1','CPZ','CP2','CP4','CP6','TP8','M2','P7','P5','P3','P1','
PZ','P2','P4','P6','P8','PO7','PO5','PO3','POZ','PO4','PO6','PO8','O1','OZ','O2')
colnames(ALLDATA_PCAC_clus) <-
c('FP1','FPZ','FP2','AF3','AF4','F7','F5','F3','F1','FZ','F2','F4','F6','F8','FT7','FC5'
,'FC3','FC1','FCZ','FC2','FC4','FC6','FT8','T7','C5','C3','C1','CZ','C2','C4','C6','T8'
,'M1','TP7','CP5','CP3','CP1','CPZ','CP2','CP4','CP6','TP8','M2','P7','P5','P3','P1','
PZ','P2','P4','P6','P8','PO7','PO5','PO3','POZ','PO4','PO6','PO8','O1','OZ','O2')
```

3.19 These are the R algorithm to combind “Positive” and “Negative” data together.

```
ALLDATA_ICA_clus <- rbind(ALLDATA_ICAA_clus,ALLDATA_ICAC_clus)
ALLDATA_PCA_clus <- rbind(ALLDATA_PCAA_clus,ALLDATA_PCAC_clus)
```

3.20 These are the R algorithm to name the column as 64 EEG electrode 10-20 positions to ALLDATA_ICAA, ALLDATA_ICAC, ALLDATA_PCAA, ALLDATA_PCAC.

```
colnames(ALLDATA_ICAA) <-
c('FP1','FPZ','FP2','AF3','AF4','F7','F5','F3','F1','FZ','F2','F4','F6','F8','FT7','FC5'
,'FC3','FC1','FCZ','FC2','FC4','FC6','FT8','T7','C5','C3','C1','CZ','C2','C4','C6','T8'
,'M1','TP7','CP5','CP3','CP1','CPZ','CP2','CP4','CP6','TP8','M2','P7','P5','P3','P1','
PZ','P2','P4','P6','P8','PO7','PO5','PO3','POZ','PO4','PO6','PO8','O1','OZ','O2','Va
lence')
```

```
colnames(ALLDATA_ICAC) <-
c('FP1','FPZ','FP2','AF3','AF4','F7','F5','F3','F1','FZ','F2','F4','F6','F8','FT7','FC5'
,'FC3','FC1','FCZ','FC2','FC4','FC6','FT8','T7','C5','C3','C1','CZ','C2','C4','C6','T8'
,'M1','TP7','CP5','CP3','CP1','CPZ','CP2','CP4','CP6','TP8','M2','P7','P5','P3','P1','
PZ','P2','P4','P6','P8','PO7','PO5','PO3','POZ','PO4','PO6','PO8','O1','OZ','O2','Va
lence')
colnames(ALLDATA_PCAA) <-
c('FP1','FPZ','FP2','AF3','AF4','F7','F5','F3','F1','FZ','F2','F4','F6','F8','FT7','FC5'
,'FC3','FC1','FCZ','FC2','FC4','FC6','FT8','T7','C5','C3','C1','CZ','C2','C4','C6','T8'
,'M1','TP7','CP5','CP3','CP1','CPZ','CP2','CP4','CP6','TP8','M2','P7','P5','P3','P1','
PZ','P2','P4','P6','P8','PO7','PO5','PO3','POZ','PO4','PO6','PO8','O1','OZ','O2','Va
lence')
colnames(ALLDATA_PCAC) <-
c('FP1','FPZ','FP2','AF3','AF4','F7','F5','F3','F1','FZ','F2','F4','F6','F8','FT7','FC5'
,'FC3','FC1','FCZ','FC2','FC4','FC6','FT8','T7','C5','C3','C1','CZ','C2','C4','C6','T8'
,'M1','TP7','CP5','CP3','CP1','CPZ','CP2','CP4','CP6','TP8','M2','P7','P5','P3','P1','
PZ','P2','P4','P6','P8','PO7','PO5','PO3','POZ','PO4','PO6','PO8','O1','OZ','O2','Va
lence')
```

3.21 These are the R algorithm to combind “Positive” and “Negative” data together.

```
ALLDATA_ICA <- rbind(ALLDATA_ICAA,ALLDATA_ICAC)
ALLDATA_PCA <- rbind(ALLDATA_PCAA,ALLDATA_PCAC)
```

3.22 These are the R algorithm to check the class of 4 data frames.

```
class(ALLDATA_ICAA)
class(ALLDATA_ICAC)
class(ALLDATA_PCAA)
class(ALLDATA_PCAC)
```

3.23 These are the R algorithm for combinding dataframe of ICA of 84 samples preparing for the plot loop operation.

```
data_names =
c("ICA01A","ICA02A","ICA03A","ICA04A","ICA05A","ICA06A","ICA07A","ICA0
8A","ICA09A","ICA10A","ICA11A","ICA12A","ICA13A","ICA14A","ICA15A","IC
A16A","ICA17A","ICA18A","ICA19A","ICA20A","ICA21A","ICA22A","ICA23A","
ICA24A","ICA25A","ICA26A","ICA27A","ICA28A","ICA29A","ICA30A","ICA31A
","ICA32A","ICA33A","ICA34A","ICA35A","ICA36A","ICA37A","ICA38A","ICA3
9A","ICA40A","ICA41A","ICA42A","ICA43A","ICA44A","ICA45A","ICA46A","IC
A47A","ICA48A","ICA49A","ICA50A","ICA51A","ICA52A","ICA53A","ICA54A","
ICA55A","ICA56A","ICA57A","ICA58A","ICA59A","ICA60A","ICA61A","ICA62A
","ICA63A","ICA64A","ICA65A","ICA66A","ICA67A","ICA68A","ICA69A","ICA7
0A","ICA71A","ICA72A","ICA73A","ICA74A","ICA75A","ICA76A","ICA77A","IC
A78A","ICA79A","ICA80A","ICA81A","ICA82A","ICA83A","ICA84A","ICA85A")
```

3.24 These are the R algorithm of plot loop operation of both ICA and PCA of both time domain and frequency domain emotional valence data.

```
for(i in 1:length(data_names)) {
  x <- get(data_names[i])
  x <- (x[1,102:6101])
  x <- as.numeric(as.data.frame(x))
  png(filename = paste0(data_names[i],"_time",".png"))
  plot(t,x , type = "l", xlab = "Time (s)", ylab = "", main = "ICA ICA Original FP1
signal")
  #class(x)
  dev.off()
  pw <- pwelch(x, window = lx, fs = fs, detrend = "none")
  png(filename = paste0(data_names[i],"_Hz",".png"))
  plot(pw, xlim = c(0, 20), main = "FP1 Frequency Domain estimate using FFT")
  print(max(pw$spec))
  max1ICA <- max(pw$spec)
  dev.off()
}
```

Part 4 Data clustering by two unsupervised machine learning models

After we finish the data transformation and data frame operations, then it is the unsupervised machine learning processing which we run both K-mean amd Fuzzy C-mean to ICA and PCA of 7 brain surface regions Prefrontal cortex (FP1, FPZ, FP2), Dorsolateral prefrontal cortex (F3, F4, FZ), Ventrolateral prefrontal (F7, F8), Frontal cortex (FC5, FC1, FZ, CZ, FC2, FC6), Temporal cortex (T7, P7, T8, P8), Parietal cortex (C3, CP5, CP1, P3, PZ, CP2, C4, P4, CP6), Occipital cortex (O1, POZ, O2).

4.1 K-Mean emotional valence ICA can run by these R-Studio algorithm.

4.1.1 Prefrontal cortex (FP1, FPZ, FP2)

```
#Prefrontal cortex (FP1, FPZ, FP2)
KmeanICA <- kmeans(subset(ALLDATA_ICA_clus,select = c('FP1','FPZ','FP2')),2,nstart
= 5)
KmeanICA
viz_cluster(KmeanICA, data = subset(ALLDATA_ICA_clus,select = c('FP1','FPZ','FP2')))
```

4.1.2 Dorsolateral prefrontal cortex (F3, F4, FZ)

```
KmeanICA <- kmeans(subset(ALLDATA_ICA_clus,select = c('F3', 'F4', 'FZ')),2,nstart =
5)
KmeanICA
fviz_cluster(KmeanICA, data = subset(ALLDATA_ICA_clus,select = c('F3', 'F4', 'FZ')))
```

4.1.3 Ventrolateral prefrontal (F7, F8)

```
KmeanICA <- kmeans(subset(ALLDATA_ICA_clus,select = c('F7', 'F8')),2,nstart = 5)
KmeanICA
fviz_cluster(KmeanICA, data = subset(ALLDATA_ICA_clus,select = c('F7', 'F8')))
```

4.1.4 Frontal cortex (FC5, FC1, FZ, CZ, FC2, FC6)

```
KmeanICA <- kmeans(subset(ALLDATA_ICA_clus,select = c('FC5', 'FC1', 'FZ',
'CZ', 'FC2', 'FC6')),2,nstart = 5)
KmeanICA
fviz_cluster(KmeanICA, data = subset(ALLDATA_ICA_clus,select = c('FC5', 'FC1',
'FZ', 'CZ', 'FC2', 'FC6')))
```

4.1.5 Temporal cortex (T7, P7, T8, P8)

```
KmeanICA <- kmeans(subset(ALLDATA_ICA_clus,select = c('T7', 'P7', 'T8', 'P8')),2,nstart
= 5)
KmeanICA
fviz_cluster(KmeanICA, data = subset(ALLDATA_ICA_clus,select = c('T7', 'P7', 'T8', 'P8')))
```

4.1.6 Parietal cortex (C3, CP5, CP1, P3, PZ, CP2, C4, P4, CP6)

```
KmeanICA <- kmeans(subset(ALLDATA_ICA_clus,select = c('C3', 'CP5', 'CP1',
'P3', 'PZ', 'CP2', 'C4', 'P4', 'CP6')),2,nstart = 5)
KmeanICA
fviz_cluster(KmeanICA, data = subset(ALLDATA_ICA_clus,select = c('C3', 'CP5',
'CP1', 'P3', 'PZ', 'CP2', 'C4', 'P4', 'CP6')))
```

4.1.7 Occipital cortex (O1, POZ, O2)

```
KmeanICA <- kmeans(subset(ALLDATA_ICA_clus,select = c('O1', 'POZ', 'O2')),2,nstart =
5)
KmeanICA
fviz_cluster(KmeanICA, data = subset(ALLDATA_ICA_clus,select = c('O1', 'POZ', 'O2')))
```

4.2 K-Mean emotional valence PCA can run by these R-Studio algorithm.

4.2.1 Prefrontal cortex (FP1, FPZ, FP2)

```
KmeanICA <- kmeans(subset(ALLDATA_PCA_clus,select = c('FP1','FPZ','FP2')),2,nstart
= 5)
KmeanICA
fviz_cluster(KmeanICA, data = subset(ALLDATA_PCA_clus,select = c('FP1','FPZ','FP2')))
```

4.2.2 Dorsolateral prefrontal cortex (F3, F4, FZ)

```
KmeanICA <- kmeans(subset(ALLDATA_PCA_clus,select = c('F3', 'F4', 'FZ')),2,nstart =
5)
KmeanICA
fviz_cluster(KmeanICA, data = subset(ALLDATA_PCA_clus,select = c('F3', 'F4', 'FZ')))
```

4.2.3 Ventrolateral prefrontal (F7, F8)

```
KmeanICA <- kmeans(subset(ALLDATA_PCA_clus,select = c('F7', 'F8')),2,nstart = 5)
KmeanICA
fviz_cluster(KmeanICA, data = subset(ALLDATA_PCA_clus,select = c('F7', 'F8')))
```

4.2.4 Frontal cortex (FC5, FC1, FZ, CZ, FC2, FC6)

```
KmeanICA <- kmeans(subset(ALLDATA_PCA_clus,select = c('FC5', 'FC1', 'FZ',
'CZ', 'FC2', 'FC6')),2,nstart = 5)
KmeanICA
fviz_cluster(KmeanICA, data = subset(ALLDATA_PCA_clus,select = c('FC5', 'FC1',
'FZ', 'CZ', 'FC2', 'FC6')))
```

4.2.5 Temporal cortex (T7, P7, T8, P8)

```
KmeanICA <- kmeans(subset(ALLDATA_PCA_clus,select = c('T7', 'P7', 'T8', 'P8')),2,
nstart = 5)
KmeanICA
fviz_cluster(KmeanICA, data = subset(ALLDATA_PCA_clus,select = c('T7', 'P7',
'T8', 'P8')))
```

4.2.6 Parietal cortex (C3, CP5, CP1, P3, PZ, CP2, C4, P4, CP6)

```
KmeanICA <- kmeans(subset(ALLDATA_PCA_clus,select = c('C3', 'CP5', 'CP1',
'P3', 'PZ', 'CP2', 'C4', 'P4', 'CP6')),2,nstart = 5)
KmeanICA
fviz_cluster(KmeanICA, data = subset(ALLDATA_PCA_clus,select = c('C3', 'CP5',
'CP1', 'P3', 'PZ', 'CP2', 'C4', 'P4', 'CP6')))
```

4.2.7 Occipital cortex (O1, POZ, O2)

```
KmeanICA <- kmeans(subset(ALLDATA_PCA_clus,select = c('O1', 'POZ', 'O2')),2,nstart
= 5)
KmeanICA
fviz_cluster(KmeanICA, data = subset(ALLDATA_PCA_clus,select = c('O1', 'POZ', 'O2')))
```

4.3 Fuzzy C-Mean emotional valence ICA can run by these R-Studio algorithm.

4.3.1 Prefrontal cortex (FP1, FPZ, FP2)

```
FuzzyICA <- fcm(subset(ALLDATA_ICA_clus,select = c('FP1','FPZ','FP2')), centers=2)
FuzzyICA
summary(FuzzyICA)
FuzzyICA2 <- ppclust2(FuzzyICA, "fanny")
viz_cluster(FuzzyICA2, data = subset(ALLDATA_ICA_clus,select = c('FP1','FPZ','FP2')),
ellipse.type = "convex",palette = "jco",repel = TRUE)
```

4.3.2 Dorsolateral prefrontal cortex (F3, F4, FZ)

```
FuzzyICA <- fcm(subset(ALLDATA_ICA_clus,select = c('F3', 'F4', 'FZ')), centers=2)
FuzzyICA
summary(FuzzyICA)
FuzzyICA2 <- ppclust2(FuzzyICA, "fanny")
fviz_cluster(FuzzyICA2, data = subset(ALLDATA_ICA_clus,select = c('F3', 'F4',
'FZ')),ellipse.type = "convex",palette = "jco",repel = TRUE)
```

4.3.3 Ventrolateral prefrontal (F7, F8)

```
FuzzyICA <- fcm(subset(ALLDATA_ICA_clus,select = c('F7', 'F8')), centers=2)
FuzzyICA
summary(FuzzyICA)
FuzzyICA2 <- ppclust2(FuzzyICA, "fanny")
fviz_cluster(FuzzyICA2, data = subset(ALLDATA_ICA_clus,select = c('F7', 'F8')),
ellipse.type = "convex",palette = "jco",repel = TRUE)
```

4.3.4 Frontal cortex (FC5, FC1, FZ, CZ, FC2, FC6)

```
FuzzyICA <- fcm(subset(ALLDATA_ICA_clus,select = c('FC5', 'FC1', 'FZ', 'CZ',
'FC2', 'FC6')), centers=2)
FuzzyICA
summary(FuzzyICA)
FuzzyICA2 <- ppclust2(FuzzyICA, "fanny")
fviz_cluster(FuzzyICA2, data = subset(ALLDATA_ICA_clus,select = c('FC5', 'FC1',
'FZ', 'CZ', 'FC2', 'FC6')),ellipse.type = "convex",palette = "jco",repel = TRUE)
```

4.3.5 Temporal cortex (T7, P7, T8, P8)

```
FuzzyICA <- fcm(subset(ALLDATA_ICA_clus,select = c('T7', 'P7', 'T8', 'P8')), centers=2)
FuzzyICA
summary(FuzzyICA)
FuzzyICA2 <- ppclust2(FuzzyICA, "fanny")
fviz_cluster(FuzzyICA2, data = subset(ALLDATA_ICA_clus,select = c('T7', 'P7', 'T8', 'P8')),ellipse.type = "convex",palette = "jco",repel = TRUE)
```


4.3.6 Parietal cortex (C3, CP5, CP1, P3, PZ, CP2, C4, P4, CP6)

```
FuzzyICA <- fcm(subset(ALLDATA_ICA_clus,select = c('C3', 'CP5', 'CP1', 'P3', 'PZ', 'CP2', 'C4', 'P4', 'CP6')), centers=2)
FuzzyICA
summary(FuzzyICA)
FuzzyICA2 <- ppclust2(FuzzyICA, "fanny")
fviz_cluster(FuzzyICA2, data = subset(ALLDATA_ICA_clus,select = c('C3', 'CP5', 'CP1', 'P3', 'PZ', 'CP2', 'C4', 'P4', 'CP6')),ellipse.type = "convex",palette = "jco",repel = TRUE)
```

4.3.7 Occipital cortex (O1, POZ, O2)

```
FuzzyICA <- fcm(subset(ALLDATA_ICA_clus,select = c('O1', 'POZ', 'O2')), centers=2)
FuzzyICA
summary(FuzzyICA)
FuzzyICA2 <- ppclust2(FuzzyICA, "fanny")
fviz_cluster(FuzzyICA2, data = subset(ALLDATA_ICA_clus,select = c('O1', 'POZ', 'O2')),ellipse.type = "convex",palette = "jco",repel = TRUE)
```

4.4 Fuzzy C-Mean emotional valence PCA can run by these R-Studio algorithm.

4.4.1 Prefrontal cortex (FP1, FPZ, FP2)

```
FuzzyICA <- fcm(subset(ALLDATA_PCA_clus,select = c('FP1','FPZ','FP2')),
 centers=2)
FuzzyICA
summary(FuzzyICA)
FuzzyICA2 <- ppclust2(FuzzyICA, "fanny")
fviz_cluster(FuzzyICA2, data = subset(ALLDATA_PCA_clus,select = c('FP1','FPZ','FP2')),
             ellipse.type = "convex",
             palette = "jco",
             repel = TRUE)
```

4.4.2 Dorsolateral prefrontal cortex (F3, F4, FZ)

```
FuzzyICA <- fcm(subset(ALLDATA_PCA_clus,select = c('F3', 'F4', 'FZ')), centers
=2)
FuzzyICA
summary(FuzzyICA)
FuzzyICA2 <- ppclust2(FuzzyICA, "fanny")
fviz_cluster(FuzzyICA2, data = subset(ALLDATA_PCA_clus,select = c('F3', 'F4',
'FZ')), ellipse.type = "convex",palette = "jco",repel = TRUE)
```

4.4.3 Ventrolateral prefrontal (F7, F8)

```
FuzzyICA <- fcm(subset(ALLDATA_PCA_clus,select = c('F7', 'F8')), centers=2)
FuzzyICA
summary(FuzzyICA)
FuzzyICA2 <- ppclust2(FuzzyICA, "fanny")
fviz_cluster(FuzzyICA2, data = subset(ALLDATA_PCA_clus,select = c('F7', 'F8')),
ellipse.type = "convex",palette = "jco",repel = TRUE)
```

4.4.4 Frontal cortex (FC5, FC1, FZ, CZ, FC2, FC6)

```
FuzzyICA <- fcm(subset(ALLDATA_PCA_clus,select = c('FC5', 'FC1', 'FZ', 'CZ',
'FC2', 'FC6')), centers=2)
FuzzyICA
summary(FuzzyICA)
FuzzyICA2 <- ppclust2(FuzzyICA, "fanny")
fviz_cluster(FuzzyICA2, data = subset(ALLDATA_PCA_clus,select = c('FC5', 'FC1',
'FZ', 'CZ', 'FC2', 'FC6')), ellipse.type = "convex",palette = "jco",repel = TRUE)
```

4.4.5 Temporal cortex (T7, P7, T8, P8)

```
FuzzyICA <- fcm(subset(ALLDATA_PCA_clus,select = c('T7', 'P7', 'T8', 'P8')), centers=2)
FuzzyICA
summary(FuzzyICA)
FuzzyICA2 <- ppclust2(FuzzyICA, "fanny")
fviz_cluster(FuzzyICA2, data = subset(ALLDATA_PCA_clus,select = c('T7', 'P7', 'T8', 'P8')), ellipse.type = "convex",palette = "jco",repel = TRUE)
```

4.4.6 Parietal cortex (C3, CP5, CP1, P3, PZ, CP2, C4, P4, CP6)

```
FuzzyICA <- fcm(subset(ALLDATA_PCA_clus,select = c('C3', 'CP5', 'CP1', 'P3', 'PZ', 'CP2', 'C4', 'P4', 'CP6')), centers=2)
FuzzyICA
summary(FuzzyICA)
FuzzyICA2 <- ppclust2(FuzzyICA, "fanny")
fviz_cluster(FuzzyICA2, data = subset(ALLDATA_PCA_clus,select = c('C3', 'CP5', 'CP1', 'P3', 'PZ', 'CP2', 'C4', 'P4', 'CP6')), ellipse.type = "convex",palette = "jco",repel = TRUE)
```

4.4.7 Occipital cortex (O1, POZ, O2)

```
FuzzyICA <- fcm(subset(ALLDATA_PCA_clus,select = c('O1', 'POZ', 'O2')), centers =2)
FuzzyICA
summary(FuzzyICA)
FuzzyICA2 <- ppclust2(FuzzyICA, "fanny")
fviz_cluster(FuzzyICA2, data = subset(ALLDATA_PCA_clus,select = c('O1', 'POZ', 'O2')), ellipse.type = "convex",palette = "jco",repel = TRUE)
```

Part 5 Training and validation by five supervised machine learning

After we know that Dorsolateral prefrontal cortex (F3, F4, FZ) is the best brain region for unsupervised machine learning algorithms for this research, then we do the 5 supervised machine learning methods. We train 70% of data and validate 30% of data for prediction.

5.1 K-Nearest Neighbors (kNN) of ICA of emotional valence of Dorsolateral prefrontal cortex (F3, F4, FZ) EEG data.

```
#install.packages("class")
library(class)
#install.packages("gmodels")
library(gmodels)

ALLDATA_ICAX <- data.frame(id=1:170,ALLDATA_ICA)
rownames(ALLDATA_ICAX) <- 1:nrow(ALLDATA_ICAX)
ALLDATA_ICAX
ALLDATA_ICAX$Valence <- as.factor(as.factor(ALLDATA_ICAX$Valence))
class(ALLDATA_ICAX$Valence)
s<-sample(170, 136)
ALLDATA_ICA_FZ34_train<-subset(ALLDATA_ICAX,select = c('FZ','F4','F3',
'Valence'))[s,]
ALLDATA_ICA_FZ34_test<-subset(ALLDATA_ICAX,select = c('FZ','F4','F3',
'Valence'))[-s,]

pALLDATA_ICA_FZ34 <- knn(train = ALLDATA_ICA_FZ34_train[,-4], test =
ALLDATA_ICA_FZ34_test[,-4], cl= ALLDATA_ICA_FZ34_train$Valence,k =
3,prob=TRUE)
pALLDATA_ICA_FZ34
mean(ALLDATA_ICA_FZ34_test[,4]==p)
CrossTable(x = ALLDATA_ICA_FZ34_test$Valence, y = p ,prop.chisq=FALSE)
plot(pALLDATA_ICA_FZ34)
mean(ALLDATA_ICA_FZ34_test[,4]==p)
```

5.2 Random Forest (RF) of ICA of emotional valence of Dorsolateral prefrontal cortex (F3, F4, FZ) EEG data.

```
#install.packages("randomForest")
library(randomForest)

ALLDATA_ICAX <- data.frame(id=1:170,ALLDATA_ICA)
rownames(ALLDATA_ICAX) <- 1:nrow(ALLDATA_ICAX)
ALLDATA_ICAX

ALLDATA_ICAX$Valence <- as.factor(as.factor(ALLDATA_ICAX$Valence))
```

```
class(ALLDATA_ICAX$Valence)

s<-sample(170, 136)
ALLDATA_ICA_FZ34_train<-subset(ALLDATA_ICAX,select =
c('FZ','F4','F3','Valence'))[s,]
ALLDATA_ICA_FZ34_test<-subset(ALLDATA_ICAX,select =
c('FZ','F4','F3','Valence'))[-s,]

rfm <- randomForest(Valence~.,ALLDATA_ICA_FZ34_train)
p <- predict(rfm, ALLDATA_ICA_FZ34_test)
table(ALLDATA_ICA_FZ34_test[,4],p)
mean(ALLDATA_ICA_FZ34_test[,4]==p)
importance(rfm)
getTree(rfm,500,labelVar=TRUE)
p
```

5.3 Naïve Bayes (NB) of ICA of emotional valence of Dorsolateral prefrontal cortex (F3, F4, FZ) EEG data.

```
library(e1071)
ALLDATA_ICAX <- data.frame(id=1:170,ALLDATA_ICA)
rownames(ALLDATA_ICAX) <- 1:nrow(ALLDATA_ICAX)
ALLDATA_ICAX
ALLDATA_ICAX$Valence <- as.factor(as.factor(ALLDATA_ICAX$Valence))
class(ALLDATA_ICAX$Valence)
s<-sample(170, 136)
ALLDATA_ICA_FZ34_train<-subset(ALLDATA_ICAX,select = c('FZ','F4','F3',
'Valence'))[s,]
ALLDATA_ICA_FZ34_test<-subset(ALLDATA_ICAX,select = c('FZ','F4','F3',
'Valence'))[-s,]

classifier<-naiveBayes(ALLDATA_ICA_FZ34_train[,1:3],
ALLDATA_ICA_FZ34_train[,4])
classifier
p <- predict(classifier, ALLDATA_ICA_FZ34_test[,-4])
p
mean(p== ALLDATA_ICA_FZ34_test[,4])
table(ALLDATA_ICA_FZ34_test[,4],p)
```

5.4 Support Vector Machines (SVM) of ICA of emotional valence of Dorsolateral prefrontal cortex (F3, F4, FZ) EEG data.

```
library("e1071")
ALLDATA_ICAX <- data.frame(id=1:170,ALLDATA_ICA)
rownames(ALLDATA_ICAX) <- 1:nrow(ALLDATA_ICAX)
ALLDATA_ICAX
ALLDATA_ICAX$Valence <- as.factor(ALLDATA_ICAX$Valence)
class(ALLDATA_ICAX$Valence)
s<-sample(170, 136)
col<-c("FZ","F4","F3","Valence")
ALLDATA_ICA_FZ34_train<-subset(ALLDATA_ICAX,select = c('FZ','F4','F3',
'Valence'))[s,col]
ALLDATA_ICA_FZ34_test<-subset(ALLDATA_ICAX,select = c('FZ','F4','F3',
'Valence'))[-s,col]
col
svmfit <- svm(Valence ~., data = ALLDATA_ICA_FZ34_train, kernel = "linear",
cost = 0.1, scale = FALSE)
print(svmfit)
plot(svmfit, ALLDATA_ICA_FZ34_train[,4])
p <- predict(svmfit, ALLDATA_ICA_FZ34_test[,4], type="class")
plot(p)
p
mean(p== ALLDATA_ICA_FZ34_test[,4])
table(ALLDATA_ICA_FZ34_test[,4],p)
```

5.5 Decision Tree (DT) of ICA of emotional valence of Dorsolateral prefrontal cortex (F3, F4, FZ) EEG data.

```
library(rpart)
library(rpart.plot)

ALLDATA_ICAX <- data.frame(id=1:170,ALLDATA_ICA)
rownames(ALLDATA_ICAX) <- 1:nrow(ALLDATA_ICAX)
ALLDATA_ICAX
ALLDATA_ICAX$Valence <- as.factor(as.factor(ALLDATA_ICAX$Valence))
class(ALLDATA_ICAX$Valence)
s<-sample(170, 136)
ALLDATA_ICA_FZ34_train<-subset(ALLDATA_ICAX,select = c('FZ','F4','F3',
'Valence'))[s,]
```

```
ALLDATA_ICA_FZ34_test<-subset(ALLDATA_ICAX,select = c('FZ','F4','F3',
'Valence'))[-s,]

dtm <- rpart(Valence~.,ALLDATA_ICA_FZ34_train,method = "class")
rpart.plot(dtm, type = 4, extra = 101)
p <- predict(dtm, ALLDATA_ICA_FZ34_test,type = "class")
table(ALLDATA_ICA_FZ34_test[,4],p)
p
plot(p)

table(p, ALLDATA_ICA_FZ34_test[,4])
mean(p== ALLDATA_ICA_FZ34_test[,4])
```

5.6 K-Nearest Neighbors (kNN) of PCA of emotional valence of Dorsolateral prefrontal cortex (F3, F4, FZ) EEG data.

```
#install.packages("class")
library(class)
#install.packages("gmodels")
library(gmodels)

ALLDATA_PCAX <- data.frame(id=1:170,ALLDATA_PCA)
rownames(ALLDATA_PCAX) <- 1:nrow(ALLDATA_PCAX)
ALLDATA_PCAX
ALLDATA_PCAX$Valence <- as.factor(as.factor(ALLDATA_PCAX$Valence))
class(ALLDATA_PCAX$Valence)
s<-sample(170, 136)
ALLDATA_PCA_FZ34_train<-subset(ALLDATA_PCAX,select = c('FZ','F4','F3',
'Valence'))[s,]
ALLDATA_PCA_FZ34_test<-subset(ALLDATA_PCAX,select = c('FZ','F4','F3',
'Valence'))[-s,]

pALLDATA_PCA_FZ34 <- knn(train = ALLDATA_PCA_FZ34_train[,-4], test =
ALLDATA_PCA_FZ34_test[,-4], cl= ALLDATA_PCA_FZ34_train$Valence,k =
3,prob=TRUE)
pALLDATA_PCA_FZ34
mean(ALLDATA_PCA_FZ34_test[,4]==p)
CrossTable(x = ALLDATA_PCA_FZ34_test$Valence, y = p ,prop.chisq=FALSE)
plot(pALLDATA_PCA_FZ34)
mean(ALLDATA_PCA_FZ34_test[,4]==p)
```

5.7 Random Forest (RF) of PCA of emotional valence of Dorsolateral prefrontal cortex (F3, F4, FZ) EEG data.

```
#install.packages("randomForest")
library(randomForest)

ALLDATA_PCAX <- data.frame(id=1:170,ALLDATA_PCA)
rownames(ALLDATA_PCAX) <- 1:nrow(ALLDATA_PCAX)
ALLDATA_PCAX

ALLDATA_PCAX$Valence <- as.factor(as.factor(ALLDATA_PCAX$Valence))
class(ALLDATA_PCAX$Valence)

s<-sample(170, 136)
ALLDATA_PCA_FZ34_train<-subset(ALLDATA_PCAX,select = c('FZ','F4','F3',
'Valence'))[s,]
ALLDATA_PCA_FZ34_test<-subset(ALLDATA_PCAX,select = c('FZ','F4','F3',
'Valence'))[-s,]

rfm <- randomForest(Valence~.,ALLDATA_PCA_FZ34_train)
p <- predict(rfm, ALLDATA_PCA_FZ34_test)
table(ALLDATA_PCA_FZ34_test[,4],p)
mean(ALLDATA_PCA_FZ34_test[,4]==p)
importance(rfm)
getTree(rfm,500,labelVar=TRUE)
p
```

5.8 Naïve Bayes (NB) of PCA of emotional valence of Dorsolateral prefrontal cortex (F3, F4, FZ) EEG data.

```
library(e1071)
ALLDATA_PCAX <- data.frame(id=1:170,ALLDATA_PCA)
rownames(ALLDATA_PCAX) <- 1:nrow(ALLDATA_PCAX)
ALLDATA_PCAX
ALLDATA_PCAX$Valence <- as.factor(as.factor(ALLDATA_PCAX$Valence))
class(ALLDATA_PCAX$Valence)
s<-sample(170, 136)
ALLDATA_PCA_FZ34_train<-subset(ALLDATA_PCAX,select = c('FZ','F4','F3',
'Valence'))[s,]
```

```
ALLDATA_PCA_FZ34_test<-subset(ALLDATA_PCAX,select = c('FZ','F4','F3',
'Valence'))[-s,]

classifier<-naiveBayes(ALLDATA_PCA_FZ34_train[,1:3],
ALLDATA_PCA_FZ34_train[,4])
classifier
p <- predict(classifier, ALLDATA_PCA_FZ34_test[,-4])
p
mean(p== ALLDATA_PCA_FZ34_test[,4])
table(ALLDATA_PCA_FZ34_test[,4],p)
```


5.9 Support Vector Machines (SVM) of PCA of emotional valence of Dorsolateral prefrontal cortex (F3, F4, FZ) EEG data.

```
library("e1071")
ALLDATA_PCAX <- data.frame(id=1:170,ALLDATA_PCA)
rownames(ALLDATA_PCAX) <- 1:nrow(ALLDATA_PCAX)
ALLDATA_PCAX
ALLDATA_PCAX$Valence <- as.factor(ALLDATA_PCAX$Valence)
class(ALLDATA_PCAX$Valence)

s<-sample(170, 136)
col<-c("FZ","F4","F3","Valence")
ALLDATA_PCA_FZ34_train<-subset(ALLDATA_PCAX,select = c('FZ','F4','F3',
'Valence'))[s,col]
ALLDATA_PCA_FZ34_test<-subset(ALLDATA_PCAX,select = c('FZ','F4','F3',
'Valence'))[-s,col]
col
svmfit <- svm(Valence ~., data = ALLDATA_PCA_FZ34_train, kernel = "linear",
cost = 0.1, scale = FALSE)
print(svmfit)
plot(svmfit, ALLDATA_PCA_FZ34_train[,4])
p <- predict(svmfit, ALLDATA_PCA_FZ34_test[,4], type="class")
plot(p)
p
mean(p== ALLDATA_PCA_FZ34_test[,4])
table(ALLDATA_PCA_FZ34_test[,4],p)
```

5.10 Decision Tree (DT) of PCA of emotional valence of Dorsolateral prefrontal cortex (F3, F4, FZ) EEG data.

```
library(rpart)
library(rpart.plot)

ALLDATA_PCAX <- data.frame(id=1:170,ALLDATA_PCA)
rownames(ALLDATA_PCAX) <- 1:nrow(ALLDATA_PCAX)
ALLDATA_PCAX
ALLDATA_PCAX$Valence <- as.factor(as.factor(ALLDATA_PCAX$Valence))
class(ALLDATA_PCAX$Valence)
s<-sample(170, 136)
ALLDATA_PCA_FZ34_train<-subset(ALLDATA_PCAX,select = c('FZ','F4','F3',
'Valence'))[s,]
ALLDATA_PCA_FZ34_test<-subset(ALLDATA_PCAX,select = c('FZ','F4','F3',
'Valence'))[-s,]

dtm <- rpart(Valence~.,ALLDATA_PCA_FZ34_train,method = "class")
rpart.plot(dtm, type = 4, extra = 101)
p <- predict(dtm, ALLDATA_PCA_FZ34_test,type = "class")
table(ALLDATA_PCA_FZ34_test[,4],p)
p
plot(p)

table(p, ALLDATA_PCA_FZ34_test[,4])
mean(p== ALLDATA_PCA_FZ34_test[,4])
```

CHAPTER 4
RESEARCH METHODOLOGY

This chapter present the main findings of the current study. The four main parts of this chapter are shown as follows:

Part 1 Descriptive statistics

Part 2 Emotional valence unsupervised machine learning results

Part 3 Emotional valence supervised machine learning results

Part 4 The Brain regions influence emotional valence machine learning

Part 1 Descriptive statistics

After we run the pre-processing and Fast Fourier transformation algorithm, we get the new data with the descriptive statistic as table below, consist of the minimum value, the 1st quarter, median, mean, the 3rd quarter and the maximum value.

1.1 Summary of frequency domain of the positive and negative emotional valence ICA data of 85 samples.

Table 1 Summary of frequency domain of the positive and negative emotional valence ICA data of 85 samples

FP1	FPZ	FP2	AF3
Min. : 0.4865	Min. : 0.6321	Min. : 0.5952	Min. : 0.2883
1st Qu.: 3.0830	1st Qu.: 3.0578	1st Qu.: 3.1602	1st Qu.: 2.3076
Median : 10.1756	Median : 9.2524	Median : 8.2205	Median : 4.6416
Mean : 15.1378	Mean : 15.1504	Mean : 14.0806	Mean : 8.0560
3rd Qu.: 18.0778	3rd Qu.: 18.7435	3rd Qu.: 17.1742	3rd Qu.: 8.8938
Max. :129.1569	Max. :143.1576	Max. :127.6476	Max. :59.4010

Table 1 Summary of frequency domain of the positive and negative emotional valence ICA data of 85 samples

AF4	F7	F5	F3
Min. : 0.2348	Min. : 0.1605	Min. : 0.1668	Min. : 0.1844
1st Qu.: 2.3365	1st Qu.: 1.4140	1st Qu.: 1.4846	1st Qu.: 1.6387
Median : 4.4738	Median : 2.9169	Median : 2.6387	Median : 2.6735
Mean : 7.1810	Mean : 4.7347	Mean : 4.5673	Mean : 4.3918
3rd Qu.: 8.6859	3rd Qu.: 4.9582	3rd Qu.: 5.2962	3rd Qu.: 4.9589
Max. :53.4897	Max. :37.6665	Max. :33.4441	Max. :26.7327
F1	**FZ**	**F2**	**F4**
Min. : 0.174	Min. : 0.2544	Min. : 0.1625	Min. : 0.1223
1st Qu.: 1.512	1st Qu.: 1.5849	1st Qu.: 1.4384	1st Qu.: 1.4116
Median : 2.755	Median : 2.6917	Median : 2.5727	Median : 2.5787
Mean : 4.285	Mean : 4.1880	Mean : 4.0624	Mean : 3.9458
3rd Qu.: 4.958	3rd Qu.: 5.0094	3rd Qu.: 4.9585	3rd Qu.: 4.6988
Max. :22.714	Max. :22.3767	Max. :23.0483	Max. :24.6325
F6	**F8**	**FT7**	**FC5**
Min. : 0.1277	Min. : 0.1111	Min. : 0.1146	Min. : 0.1283
1st Qu.: 1.3783	1st Qu.: 1.2786	1st Qu.: 0.8503	1st Qu.: 0.9402
Median : 2.5634	Median : 2.4324	Median : 1.4367	Median : 1.7170
Mean : 3.8706	Mean : 3.7966	Mean : 2.3009	Mean : 2.6215
3rd Qu.: 4.7743	3rd Qu.: 5.0008	3rd Qu.: 2.5455	3rd Qu.: 2.6778
Max. :25.4649	Max. :24.1792	Max. :15.9664	Max. :18.6172
FC3	**FC1**	**FCZ**	**FC2**
Min. : 0.1417	Min. : 0.1405	Min. : 0.3243	Min. : 0.1957
1st Qu.: 1.1300	1st Qu.: 1.2271	1st Qu.: 1.2108	1st Qu.: 1.1019
Median : 1.9475	Median : 2.1562	Median : 2.1052	Median : 2.0284
Mean : 2.8915	Mean : 3.1187	Mean : 3.2872	Mean : 3.0887
3rd Qu.: 3.1207	3rd Qu.: 3.5573	3rd Qu.: 3.8452	3rd Qu.: 3.5801
Max. :24.9777	Max. :27.1013	Max. :29.9507	Max. :34.3593

Table 1 Summary of frequency domain of the positive and negative emotional valence ICA data of 85 samples

FC4	FC6	FT8	T7
Min. : 0.1273	Min. : 0.1031	Min. : 0.08765	Min. : 0.09854
1st Qu.: 1.0610	1st Qu.: 0.9840	1st Qu.: 0.77520	1st Qu.: 0.52690
Median : 1.7591	Median : 1.5644	Median : 1.42428	Median : 0.90877
Mean : 2.7664	Mean : 2.5943	Mean : 2.24407	Mean : 1.67384
3rd Qu.: 3.1162	3rd Qu.: 2.6865	3rd Qu.: 2.68023	3rd Qu.: 1.85509
Max. :36.6127	Max. :30.1749	Max. :22.49354	Max. :15.43032
C5	**C3**	**C1**	**CZ**
Min. : 0.1293	Min. : 0.2501	Min. : 0.1940	Min. : 0.2585
1st Qu.: 0.7306	1st Qu.: 0.9446	1st Qu.: 0.9878	1st Qu.: 0.9488
Median : 1.3092	Median : 1.6299	Median : 1.7496	Median : 1.7552
Mean : 2.0491	Mean : 2.4519	Mean : 2.6031	Mean : 2.7475
3rd Qu.: 2.2583	3rd Qu.: 2.4785	3rd Qu.: 2.5950	3rd Qu.: 2.8691
Max. :20.9945	Max. :43.4156	Max. :55.6319	Max. :61.9201
C2	**C4**	**C6**	**T8**
Min. : 0.1504	Min. : 0.1384	Min. : 0.1348	Min. : 0.07924
1st Qu.: 0.8791	1st Qu.: 0.8258	1st Qu.: 0.7100	1st Qu.: 0.53375
Median : 1.6561	Median : 1.5060	Median : 1.3483	Median : 0.98633
Mean : 2.6473	Mean : 2.4668	Mean : 2.1978	Mean : 1.68904
3rd Qu.: 2.6153	3rd Qu.: 2.4228	3rd Qu.: 2.3630	3rd Qu.: 1.79148
Max. :69.8347	Max. :65.7620	Max. :50.6508	Max. :22.47389
M1	**TP7**	**CP5**	**CP3**
Min. : 0.02939	Min. : 0.1033	Min. : 0.1764	Min. : 0.1903
1st Qu.: 0.11760	1st Qu.: 0.4408	1st Qu.: 0.6257	1st Qu.: 0.7774
Median : 0.18450	Median : 0.8017	Median : 1.1032	Median : 1.2294
Mean : 0.62814	Mean : 1.4258	Mean : 1.8289	Mean : 2.2581
3rd Qu.: 0.35993	3rd Qu.: 1.5862	3rd Qu.: 1.8774	3rd Qu.: 2.0888
Max. :18.01423	Max. :18.1449	Max. :31.4837	Max. :72.1582

Table 1 Summary of frequency domain of the positive and negative emotional valence ICA data of 85 samples

CP1	**CPZ**	**CP2**	**CP4**
Min. : 0.1661	Min. : 0.1921	Min. : 0.1850	Min. : 0.1993
1st Qu.: 0.7876	1st Qu.: 0.7802	1st Qu.: 0.8944	1st Qu.: 0.8560
Median : 1.4136	Median : 1.4547	Median : 1.4283	Median : 1.3238
Mean : 2.4036	Mean : 2.6870	Mean : 2.5962	Mean : 2.4093
3rd Qu.: 2.1501	3rd Qu.: 2.3995	3rd Qu.: 2.2609	3rd Qu.: 1.9128
Max. :85.0007	Max. :113.9685	Max. :102.6124	Max. :90.8379
CP6	**TP8**	**M2**	**P7**
Min. : 0.1425	Min. : 0.09222	Min. : 0.02939	Min. : 0.1298
1st Qu.: 0.6687	1st Qu.: 0.47373	1st Qu.: 0.11760	1st Qu.: 0.4604
Median : 1.0711	Median : 0.79534	Median : 0.18450	Median : 0.7908
Mean : 2.0587	Mean : 1.62929	Mean : 0.62814	Mean : 1.4752
3rd Qu.: 1.7569	3rd Qu.: 1.59548	3rd Qu.: 0.35993	3rd Qu.: 1.5985
Max. :71.4873	Max. :34.58890	Max. :18.01423	Max. :18.7124
P5	**P3**	**P1**	**PZ**
Min. : 0.1651	Min. : 0.1414	Min. : 0.1834	Min. : 0.1300
1st Qu.: 0.5375	1st Qu.: 0.6625	1st Qu.: 0.6887	1st Qu.: 0.6769
Median : 1.0034	Median : 1.1196	Median : 1.2114	Median : 1.2592
Mean : 1.8209	Mean : 2.3407	Mean : 2.6098	Mean : 2.8769
3rd Qu.: 1.6271	3rd Qu.: 1.9264	3rd Qu.: 1.9972	3rd Qu.: 2.3914
Max. :48.7349	Max. :104.1401	Max. :124.4188	Max. :164.8966
P2	**P4**	**P6**	**P8**
Min. : 0.1710	Min. : 0.2160	Min. : 0.1530	Min. : 0.1366
1st Qu.: 0.6921	1st Qu.: 0.7388	1st Qu.: 0.6016	1st Qu.: 0.4289
Median : 1.1663	Median : 1.0503	Median : 0.9362	Median : 0.7901
Mean : 2.6252	Mean : 2.5768	Mean : 2.1999	Mean : 1.8268
3rd Qu.: 2.1937	3rd Qu.: 2.1135	3rd Qu.: 1.8227	3rd Qu.: 1.6714
Max. :133.2701	Max. :131.6252	Max. :90.3605	Max. :56.2079

Table 1 Summary of frequency domain of the positive and negative emotional valence ICA data of 85 samples

PO7	PO5	PO3	POZ
Min. : 0.1581	Min. : 0.1714	Min. : 0.1403	Min. : 0.1526
1st Qu.: 0.5045	1st Qu.: 0.5292	1st Qu.: 0.6218	1st Qu.: 0.6167
Median : 0.8939	Median : 0.9479	Median : 1.0191	Median : 1.0902
Mean : 1.6801	Mean : 1.9948	Mean : 2.2220	Mean : 2.7284
3rd Qu.: 1.7048	3rd Qu.: 1.8140	3rd Qu.: 1.9389	3rd Qu.: 2.1170
Max. :33.0573	Max. :63.4675	Max. :77.1812	Max. :153.4515
PO4	**PO6**	**PO8**	**O1**
Min. : 0.2111	Min. : 0.1784	Min. : 0.1330	Min. : 0.1115
1st Qu.: 0.6620	1st Qu.: 0.5376	1st Qu.: 0.4760	1st Qu.: 0.4559
Median : 1.0919	Median : 0.9558	Median : 0.9209	Median : 0.8883
Mean : 2.6610	Mean : 2.2984	Mean : 2.0201	Mean : 1.7488
3rd Qu.: 2.1769	3rd Qu.: 2.0008	3rd Qu.: 1.6807	3rd Qu.: 1.6996
Max. :126.1561	Max. :86.3911	Max. :72.5148	Max. :35.9708
OZ	**O2**	**Valence**	
Min. : 0.1203	Min. : 0.1088	Length:170	
1st Qu.: 0.4602	1st Qu.: 0.4502	Class :character	
Median : 0.8489	Median : 0.7655	Mode :character	
Mean : 1.7446	Mean : 1.7861		
3rd Qu.: 1.7969	3rd Qu.: 1.6270		
Max. :39.2000	Max. :47.4337		

1.2 Summary of frequency domain of the positive and negative emotional valence PCA data of 85 samples.

Table 2 Summary of frequency domain of the positive and negative emotional valence PCA data of 85 samples

PO7	PO5	PO3	POZ
Min. : 0.4541	Min. : 0.6321	Min. : 0.5952	Min. : 0.2876
1st Qu.: 3.0758	1st Qu.: 3.0374	1st Qu.: 3.3040	1st Qu.: 2.1761
Median : 9.3445	Median : 8.5254	Median : 8.0439	Median : 4.6857
Mean : 14.7393	Mean : 14.7818	Mean : 13.6970	Mean : 7.8064
3rd Qu.: 18.1096	3rd Qu.: 17.8150	3rd Qu.: 16.6786	3rd Qu.: 8.6373
Max. :124.2407	Max. :137.2171	Max. :122.4244	Max. :57.1511
AF4	**F7**	**F5**	**F3**
Min. : 0.2372	Min. : 0.1646	Min. : 0.171	Min. : 0.1887
1st Qu.: 2.3067	1st Qu.: 1.2514	1st Qu.: 1.370	1st Qu.: 1.4568
Median : 4.1533	Median : 2.9346	Median : 2.642	Median : 2.5716
Mean : 6.8924	Mean : 4.6295	Mean : 4.447	Mean : 4.2525
3rd Qu.: 8.3145	3rd Qu.: 4.9184	3rd Qu.: 5.176	3rd Qu.: 4.8100
Max. :50.3474	Max. :36.2615	Max. :32.287	Max. :25.8452
F1	**FZ**	**F2**	**F4**
Min. : 0.178	Min. : 0.2483	Min. : 0.1583	Min. : 0.119
1st Qu.: 1.467	1st Qu.: 1.5922	1st Qu.: 1.3851	1st Qu.: 1.301
Median : 2.594	Median : 2.5581	Median : 2.4618	Median : 2.425
Mean : 4.128	Mean : 4.0687	Mean : 3.9406	Mean : 3.825
3rd Qu.: 4.941	3rd Qu.: 4.8587	3rd Qu.: 5.1573	3rd Qu.: 4.693
Max. :22.120	Max. :24.5981	Max. :23.2249	Max. :24.907

Table 2 Summary of frequency domain of the positive and negative emotional valence PCA data of 85 samples

F6	F8	FT7	FC5
Min. : 0.1098	Min. : 0.1021	Min. : 0.1096	Min. : 0.1303
1st Qu.: 1.3254	1st Qu.: 1.2388	1st Qu.: 0.7869	1st Qu.: 0.8811
Median : 2.3998	Median : 2.2714	Median : 1.3363	Median : 1.6591
Mean : 3.7580	Mean : 3.6894	Mean : 2.2547	Mean : 2.5362
3rd Qu.: 4.5836	3rd Qu.: 4.5724	3rd Qu.: 2.5381	3rd Qu.: 2.7109
Max. :26.2786	Max. :24.7588	Max. :14.6717	Max. :17.2083
FC3	**FC1**	**FCZ**	**FC2**
Min. : 0.144	Min. : 0.1396	Min. : 0.3235	Min. : 0.1934
1st Qu.: 1.000	1st Qu.: 1.2137	1st Qu.: 1.1846	1st Qu.: 1.1012
Median : 1.943	Median : 2.0792	Median : 1.9882	Median : 1.8733
Mean : 2.820	Mean : 3.0333	Mean : 3.1830	Mean : 3.0258
3rd Qu.: 3.231	3rd Qu.: 3.4872	3rd Qu.: 3.9200	3rd Qu.: 3.4891
Max. :25.008	Max. :27.1259	Max. :29.9779	Max. :34.3767
FC4	**FC6**	**FT8**	**T7**
Min. : 0.1399	Min. : 0.1117	Min. : 0.09489	Min. : 0.08697
1st Qu.: 1.0301	1st Qu.: 0.9719	1st Qu.: 0.75618	1st Qu.: 0.51945
Median : 1.7505	Median : 1.5033	Median : 1.34863	Median : 0.90583
Mean : 2.7106	Mean : 2.5394	Mean : 2.18172	Mean : 1.65443
3rd Qu.: 2.8733	3rd Qu.: 2.6694	3rd Qu.: 2.57100	3rd Qu.: 1.87302
Max. :36.6461	Max. :30.2025	Max. :21.51463	Max. :13.97105
C5	**C3**	**C1**	**CZ**
Min. : 0.1594	Min. : 0.2476	Min. : 0.2317	Min. : 0.2585
1st Qu.: 0.6720	1st Qu.: 0.9059	1st Qu.: 1.0110	1st Qu.: 0.9313
Median : 1.2567	Median : 1.6563	Median : 1.7269	Median : 1.6188
Mean : 2.0094	Mean : 2.4046	Mean : 2.5618	Mean : 2.6974
3rd Qu.: 2.1811	3rd Qu.: 2.4187	3rd Qu.: 2.5457	3rd Qu.: 2.8868

Table 2 Summary of frequency domain of the positive and negative emotional valence PCA data of 85 samples

C2	C4	C6	T8
Min. : 0.1495	Min. : 0.1367	Min. : 0.1358	Min. : 0.08679
1st Qu.: 0.9076	1st Qu.: 0.8187	1st Qu.: 0.7432	1st Qu.: 0.52827
Median : 1.6347	Median : 1.4560	Median : 1.3228	Median : 0.95007
Mean : 2.6126	Mean : 2.4239	Mean : 2.1592	Mean : 1.67435
3rd Qu.: 2.5654	3rd Qu.: 2.3671	3rd Qu.: 2.2526	3rd Qu.: 1.79696
Max. :69.8617	Max. :65.7997	Max. :50.6919	Max. :20.71084
M1	**TP7**	**CP5**	**CP3**
Min. : 0.03073	Min. : 0.1190	Min. : 0.172	Min. : 0.1779
1st Qu.: 0.12141	1st Qu.: 0.4342	1st Qu.: 0.647	1st Qu.: 0.7977
Median : 0.19139	Median : 0.8089	Median : 1.055	Median : 1.2514
Mean : 0.62950	Mean : 1.4111	Mean : 1.821	Mean : 2.2564
3rd Qu.: 0.36381	3rd Qu.: 1.7083	3rd Qu.: 1.850	3rd Qu.: 2.0547
Max. :15.92203	Max. :16.0653	Max. :31.508	Max. :72.1877
CP1	**CPZ**	**CP2**	**CP4**
Min. : 0.1661	Min. : 0.1921	Min. : 0.1850	Min. : 0.1934
1st Qu.: 0.7812	1st Qu.: 0.7726	1st Qu.: 0.9013	1st Qu.: 0.8340
Median : 1.4072	Median : 1.4758	Median : 1.4262	Median : 1.3196
Mean : 2.4066	Mean : 2.6675	Mean : 2.5885	Mean : 2.3960
3rd Qu.: 2.1726	3rd Qu.: 2.1963	3rd Qu.: 2.2367	3rd Qu.: 2.1586
Max. :85.0273	Max. :113.9890	Max. :102.6230	Max. :90.8754
CP6	**TP8**	**M2**	**P7**
Min. : 0.1476	Min. : 0.09869	Min. : 0.03073	Min. : 0.1295
1st Qu.: 0.6672	1st Qu.: 0.48012	1st Qu.: 0.12141	1st Qu.: 0.4516
Median : 1.0550	Median : 0.76704	Median : 0.19139	Median : 0.8090
Mean : 2.0421	Mean : 1.61616	Mean : 0.62950	Mean : 1.4906
3rd Qu.: 1.7957	3rd Qu.: 1.56752	3rd Qu.: 0.36381	3rd Qu.: 1.6598

Table 2 Summary of frequency domain of the positive and negative emotional valence PCA data of 85 samples

P5	P3	P1	PZ
Min. : 0.1521	Min. : 0.1414	Min. : 0.1768	Min. : 0.1300
1st Qu.: 0.5613	1st Qu.: 0.6462	1st Qu.: 0.6640	1st Qu.: 0.6567
Median : 0.9784	Median : 1.0921	Median : 1.2347	Median : 1.2497
Mean : 1.8294	Mean : 2.3577	Mean : 2.6341	Mean : 2.8965
3rd Qu.: 1.6935	3rd Qu.: 2.0107	3rd Qu.: 2.0570	3rd Qu.: 2.5056
Max. :48.7608	Max. :104.1675	Max. :124.4338	Max. :164.9088
P2	**P4**	**P6**	**P8**
Min. : 0.1710	Min. : 0.2160	Min. : 0.1722	Min. : 0.1365
1st Qu.: 0.7012	1st Qu.: 0.7485	1st Qu.: 0.6434	1st Qu.: 0.4612
Median : 1.2226	Median : 1.0936	Median : 0.9851	Median : 0.7859
Mean : 2.6366	Mean : 2.5945	Mean : 2.2061	Mean : 1.8159
3rd Qu.: 2.2541	3rd Qu.: 2.1676	3rd Qu.: 1.8426	3rd Qu.: 1.7215
Max. :133.2779	Max. :131.6680	Max. :90.4006	Max. :56.2343
PO7	**PO5**	**PO3**	**POZ**
Min. : 0.1535	Min. : 0.1715	Min. : 0.1403	Min. : 0.1460
1st Qu.: 0.5187	1st Qu.: 0.5520	1st Qu.: 0.6660	1st Qu.: 0.6255
Median : 0.9034	Median : 0.9362	Median : 1.0169	Median : 1.0748
Mean : 1.7045	Mean : 2.0241	Mean : 2.2635	Mean : 2.7506
3rd Qu.: 1.7438	3rd Qu.: 1.8045	3rd Qu.: 1.9808	3rd Qu.: 2.1792
Max. :33.0745	Max. :63.4912	Max. :77.2057	Max. :153.4572
PO4	**PO6**	**PO8**	**O1**
Min. : 0.1800	Min. : 0.1781	Min. : 0.1591	Min. : 0.1131
1st Qu.: 0.6548	1st Qu.: 0.5631	1st Qu.: 0.4711	1st Qu.: 0.4464
Median : 1.0920	Median : 0.9864	Median : 0.9358	Median : 0.9276
Mean : 2.6906	Mean : 2.3177	Mean : 2.0212	Mean : 1.7743
3rd Qu.: 2.1407	3rd Qu.: 2.0260	3rd Qu.: 1.6769	3rd Qu.: 1.7615

Table 2 Summary of frequency domain of the positive and negative emotional valence PCA data of 85 samples

OZ	O2	Valence
Min. : 0.1217	Min. : 0.1135	Length:170
1st Qu.: 0.4614	1st Qu.: 0.4321	Class :character
Median : 0.8383	Median : 0.7804	Mode :character
Mean : 1.7596	Mean : 1.7886	NA
3rd Qu.: 1.7864	3rd Qu.: 1.5959	NA
Max. :39.2080	Max. :47.4380	NA

1.3 Fourier Transformation Results

In order to run both unsupervised and unsupervised machine learning on emotional valence EEG data we have to transform time domain data in to frequency domain data. The pictures below are the example of frequency domain graph of both ICA and PCA of 1 example.

We calculate the max power value of frequency of each 64 EEG electrode: Prefrontal cortex (FP1, FPZ, FP2), Dorsolateral prefrontal cortex (F3, F4, FZ), Ventrolateral prefrontal (F7, F8), Frontal cortex (FC5, FC1, FZ, CZ, FC2, FC6), Temporal cortex (T7, P7, T8, P8), Parietal cortex (C3, CP5, CP1, P3, PZ, CP2, C4, P4, CP6), Occipital cortex (O1, POZ, O2) as shown in figures 11 to 72

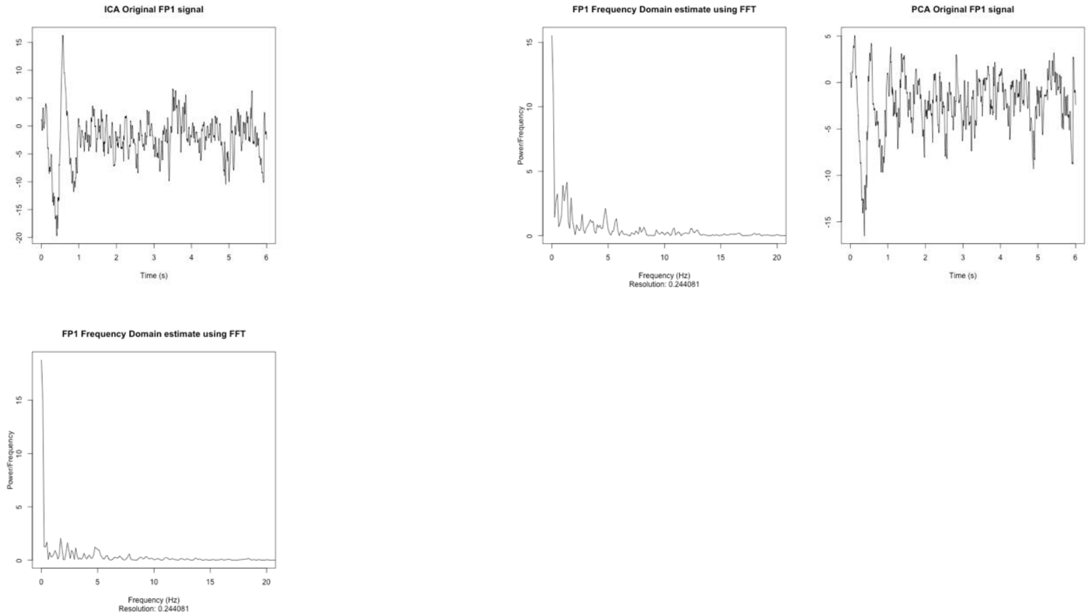


Figure 11 Show graph of time and frequency domain of ICA and PCA emotional valence. Max Power Frequency of ICA FP1 = 15.54241 and Max Power Frequency of PCA FP1 = 18.78346

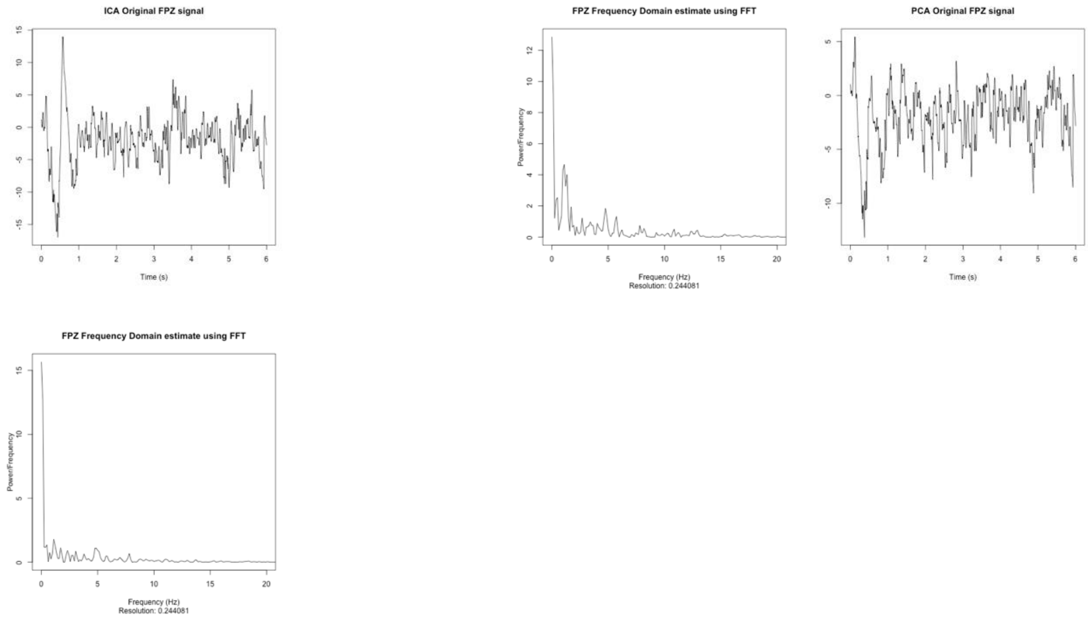


Figure 12 Show graph of time and frequency domain of ICA and PCA emotional valence. Max Power Frequency of ICA FPZ = 12.85753 and Max Power Frequency of PCA FPZ = 15.66601

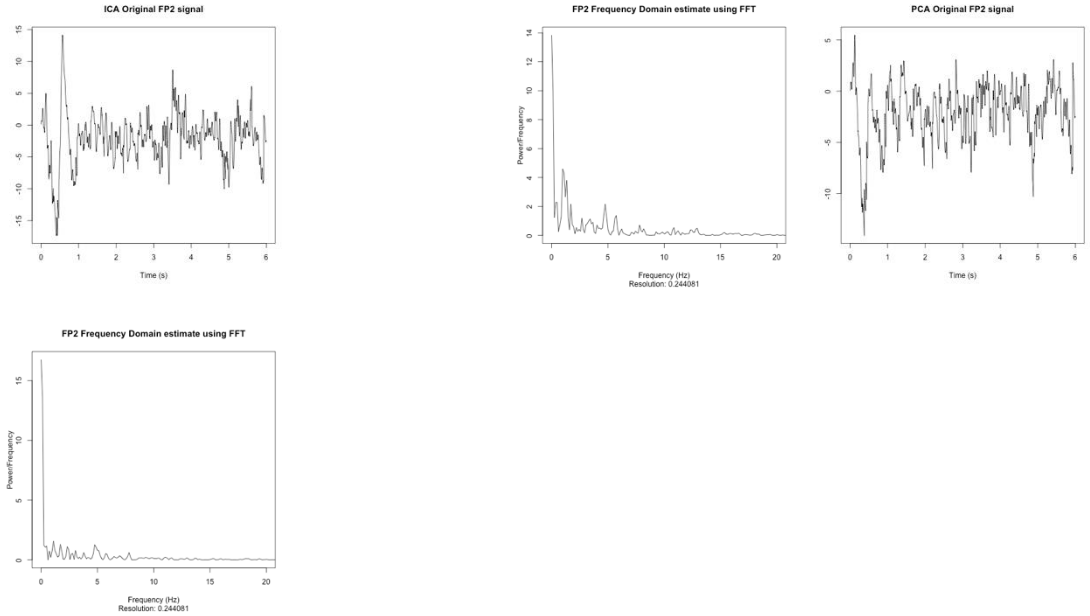


Figure 13 Show graph of time and frequency domain of ICA and PCA emotional valence. Max Power Frequency of ICA FP2 = 13.84152 and Max Power Frequency of PCA FP2 = 16.76552

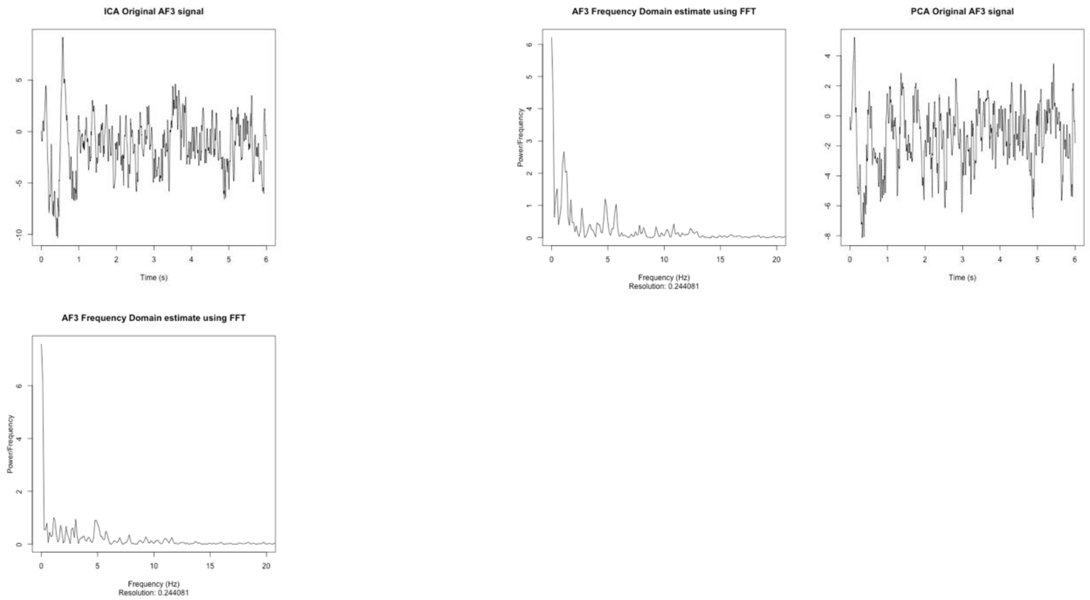


Figure 14 Show graph of time and frequency domain of ICA and PCA emotional valence. Max Power Frequency of ICA AF3 = 6.21596 and Max Power Frequency of PCA AF3 = 7.58324

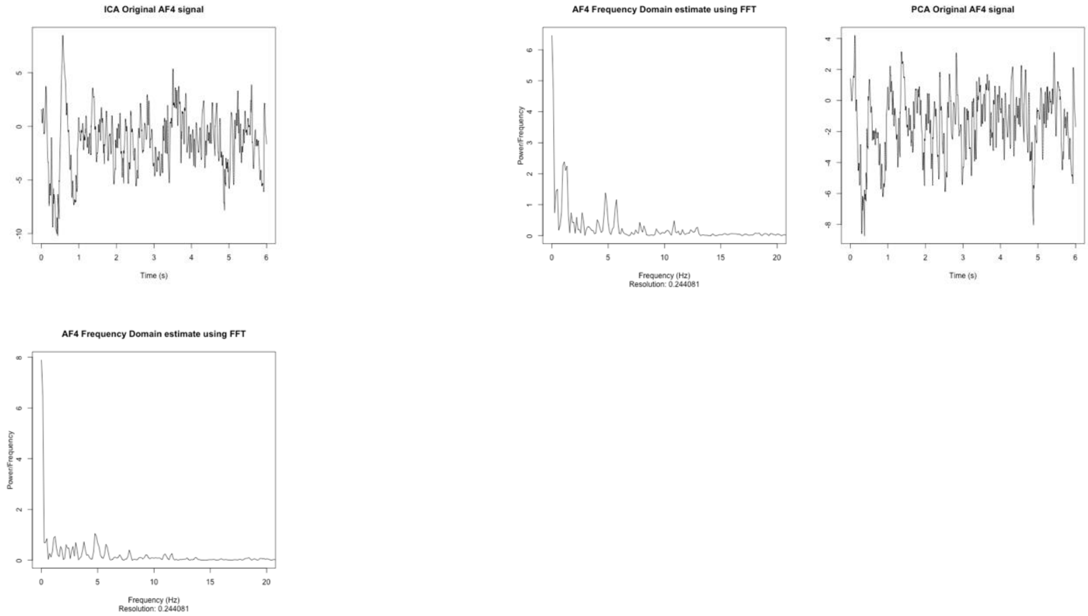


Figure 15 Show graph of time and frequency domain of ICA and PCA emotional valence. Max Power Frequency of ICA AF4 = 6.466457 and Max Power Frequency of PCA AF4 = 7.896089

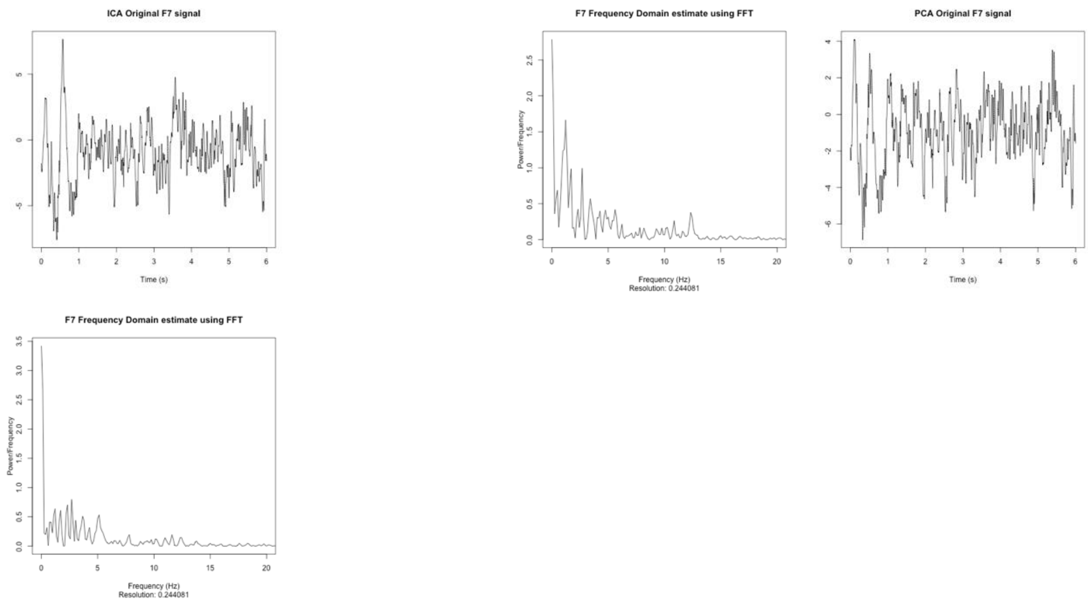


Figure 16 Show graph of time and frequency domain of ICA and PCA emotional valence. Max Power Frequency of ICA F7 = 2.786168 and Max Power Frequency of PCA F7 = 3.420115

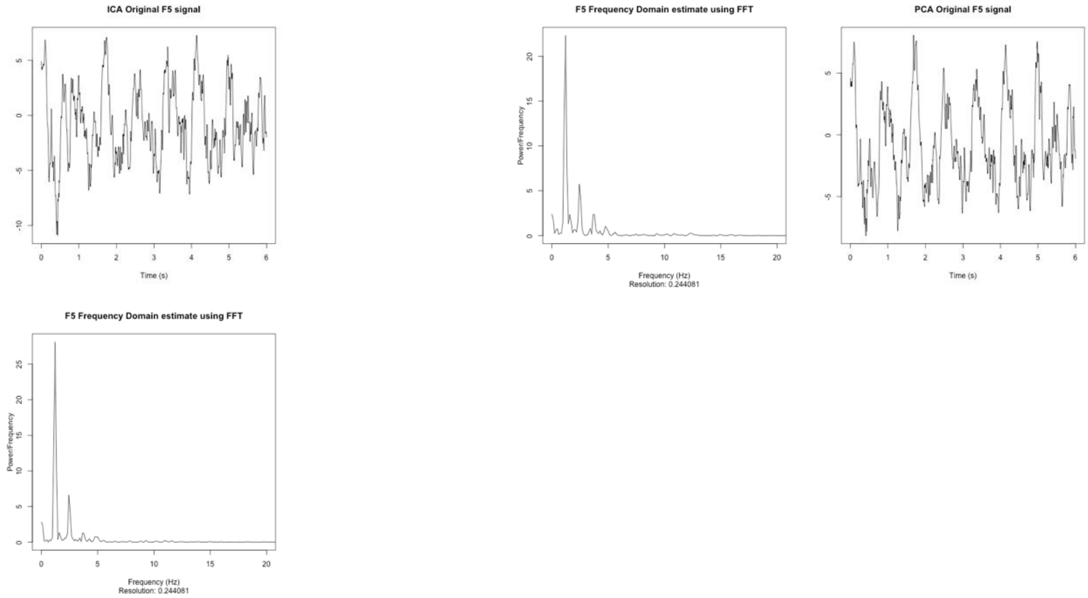


Figure 17 Show graph of time and frequency domain of ICA and PCA emotional valence. Max Power Frequency of ICA F5 = 22.32623 and Max Power Frequency of PCA F5 = 28.1328

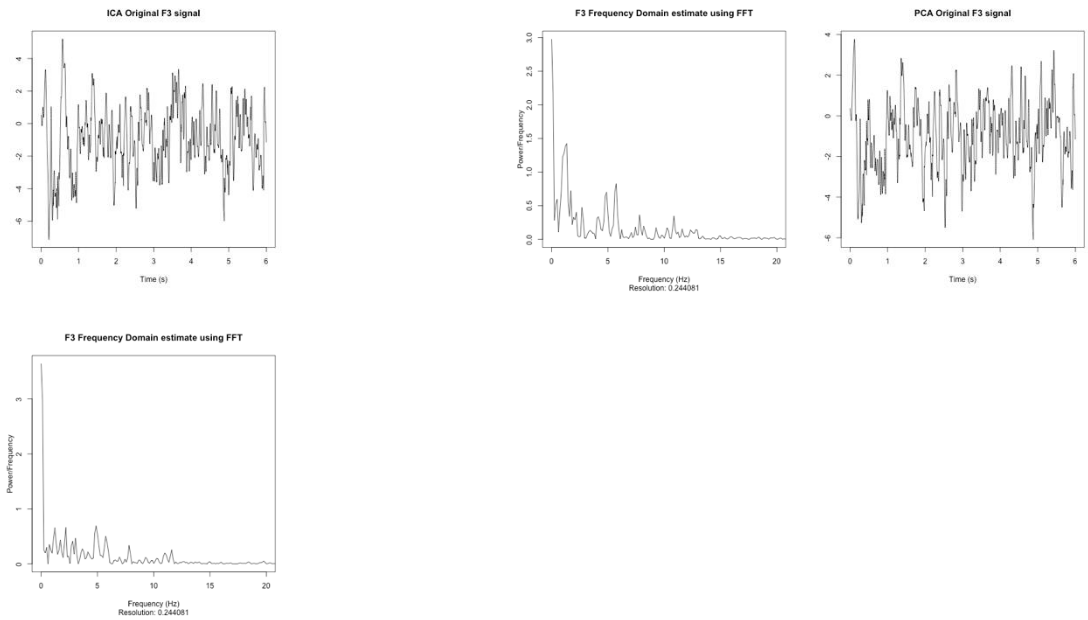


Figure 18 Show graph of time and frequency domain of ICA and PCA emotional valence. Max Power Frequency of ICA F3 = 2.977615 and Max Power Frequency of PCA F3 = 3.642902

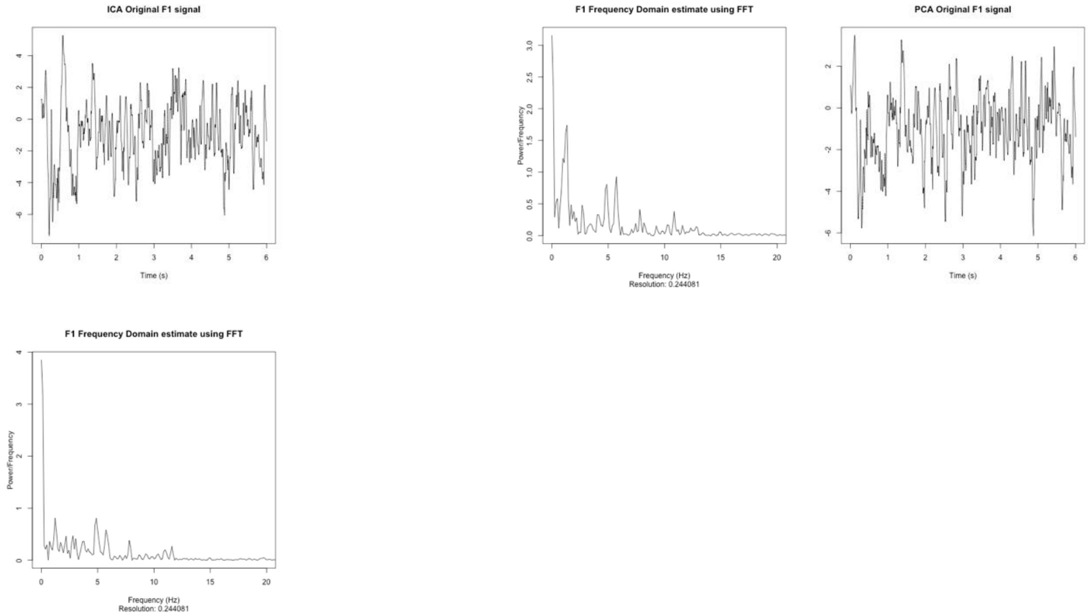


Figure 19 Show graph of time and frequency domain of ICA and PCA emotional valence. Max Power Frequency of ICA F1 = 3.156259 and Max Power Frequency of PCA F1 = 3.850023

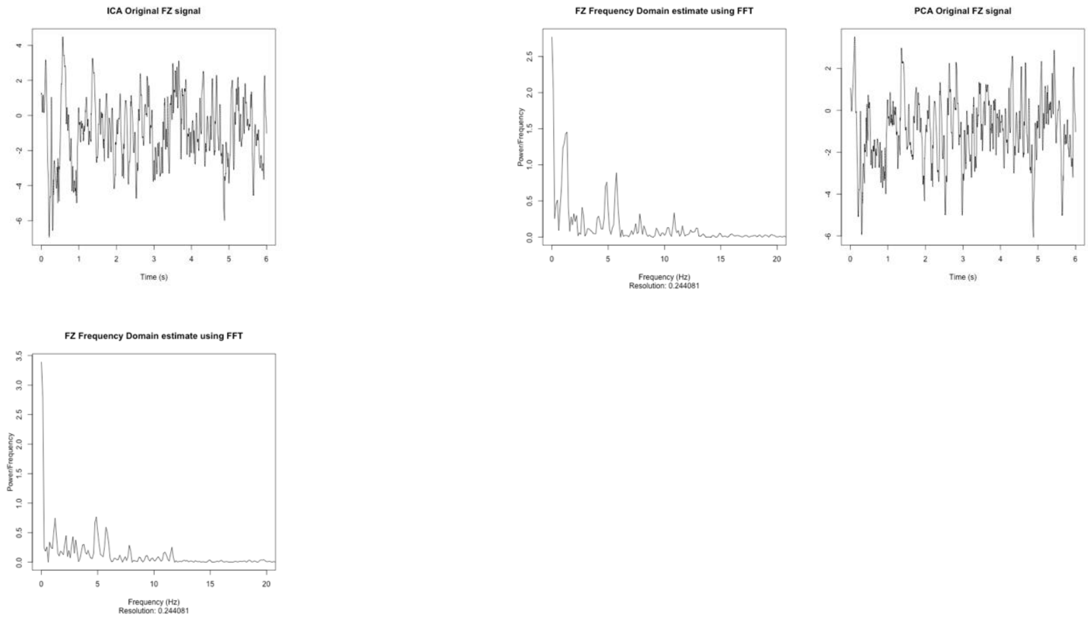


Figure 20 Show graph of time and frequency domain of ICA and PCA emotional valence. Max Power Frequency of ICA FZ = 2.771715 and Max Power Frequency of P CA FZ = 3.3934

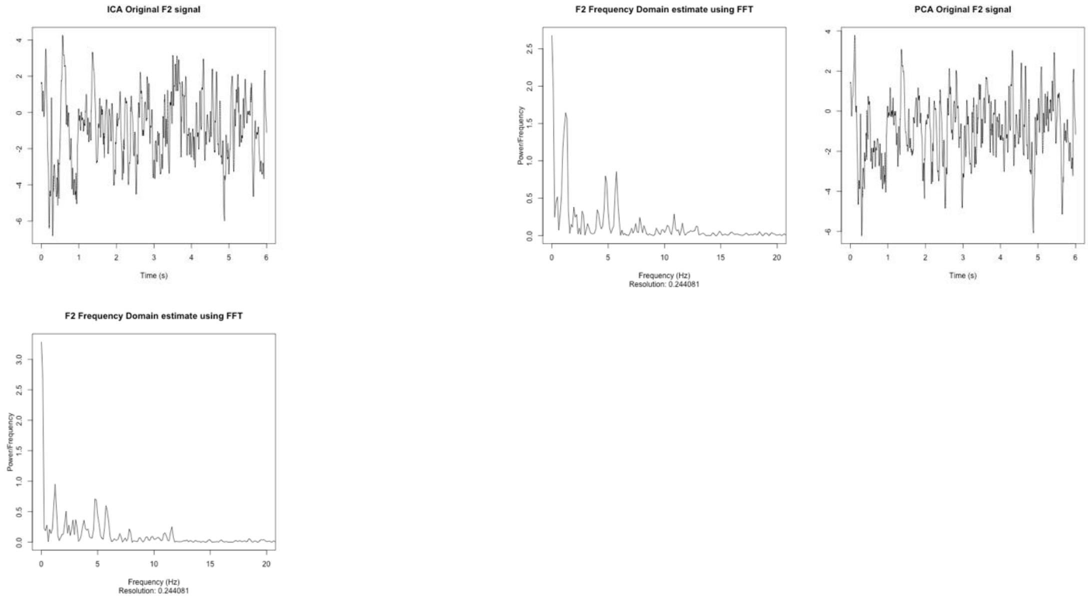


Figure 21 Show graph of time and frequency domain of ICA and PCA emotional valence. Max Power Frequency of ICA F2 = 2.678589 and Max Power Frequency of PCA F2 = 3.286887

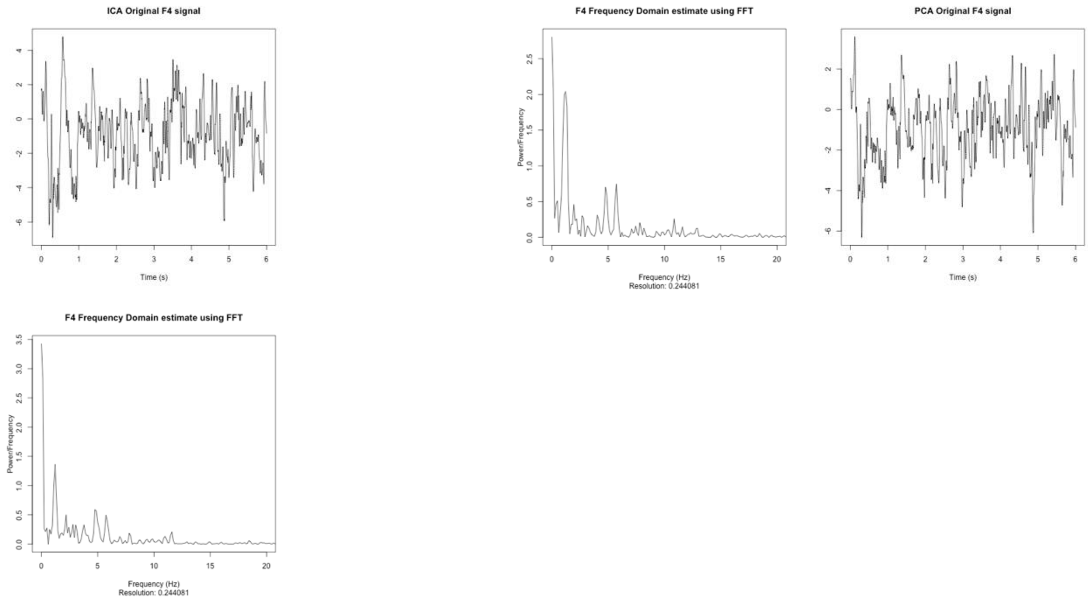


Figure 22 Show graph of time and frequency domain of ICA and PCA emotional valence. Max Power Frequency of ICA F4 = 2.805251 and Max Power Frequency of PCA F4 = 3.427059

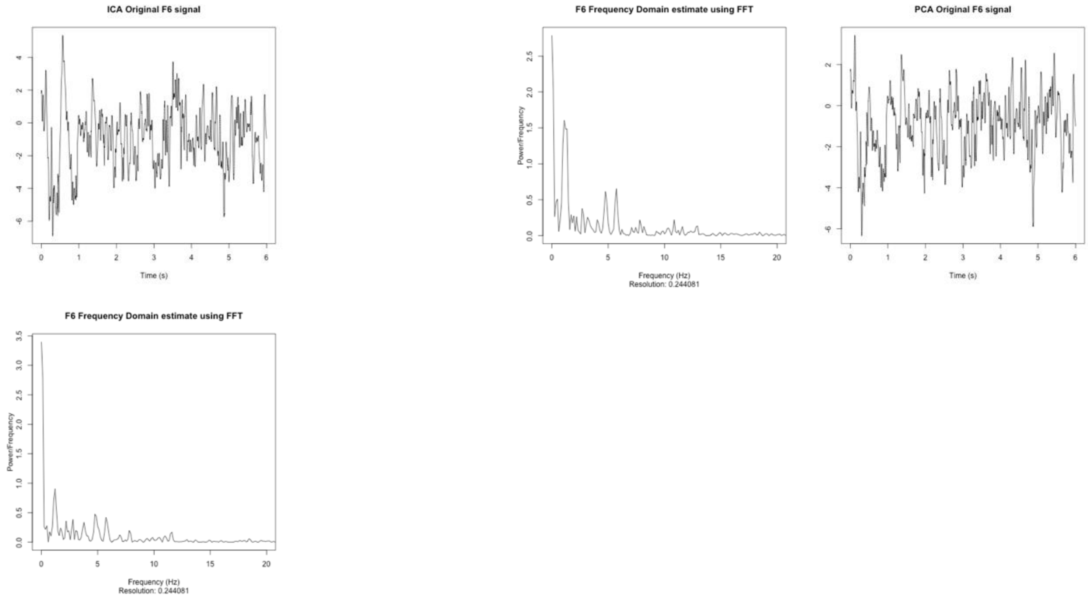


Figure 23 Show graph of time and frequency domain of ICA and PCA emotional valence. Max Power Frequency of ICA F6 = 2.788126 and Max Power Frequency of PCA F6 = 3.398327

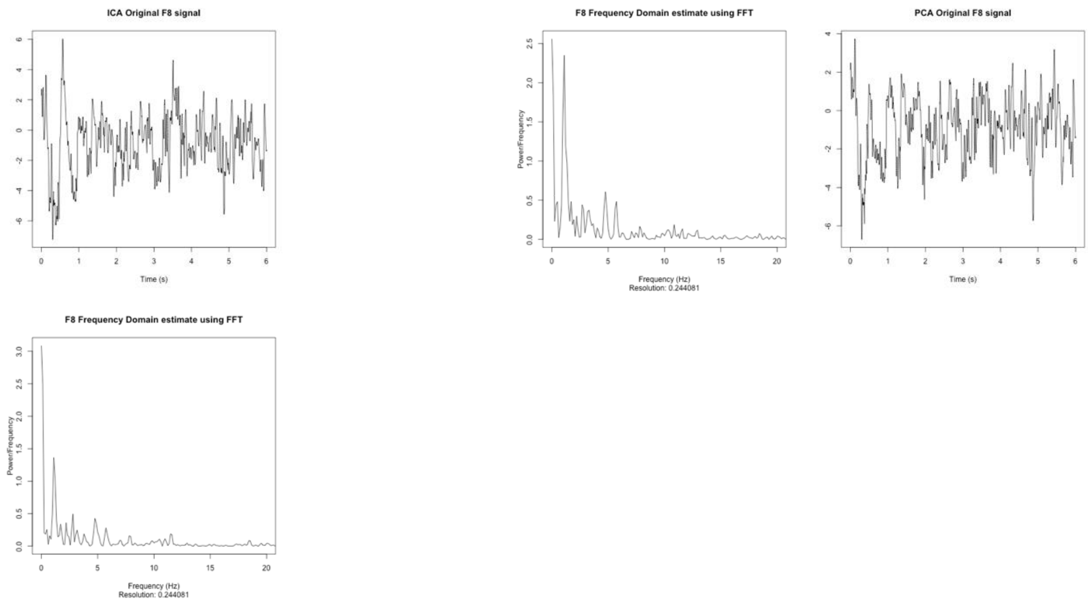


Figure 24 Show graph of time and frequency domain of ICA and PCA emotional valence. Max Power Frequency of ICA F8 = 2.559046 and Max Power Frequency of PCA F8 = 3.085356

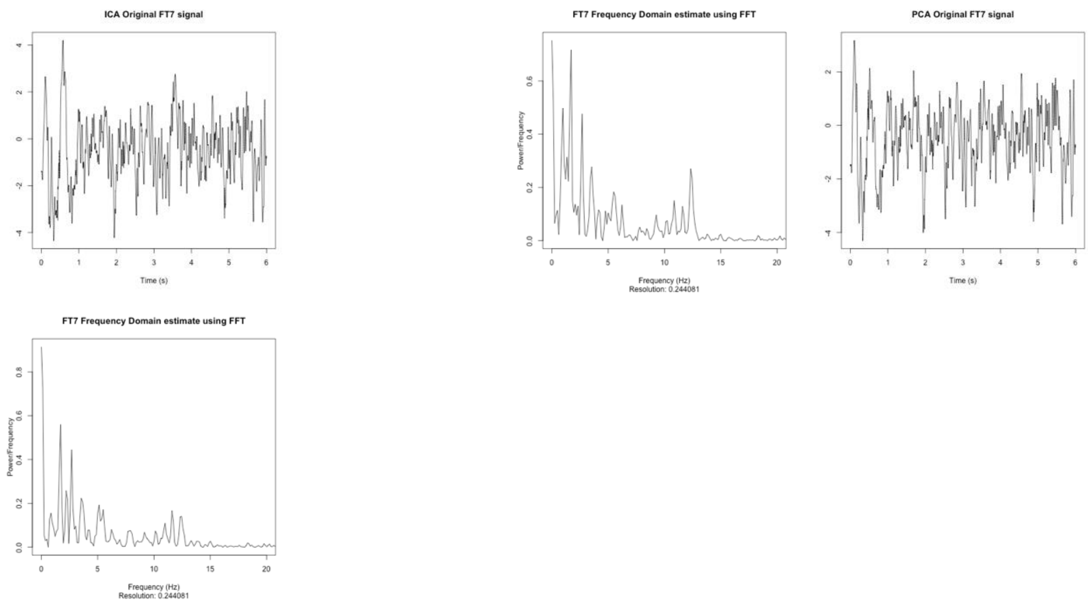


Figure 25 Show graph of time and frequency domain of ICA and PCA emotional valence. Max Power Frequency of ICA FT7 = 0.7523933 and Max Power Frequency of PCA FT7 = 0.914213

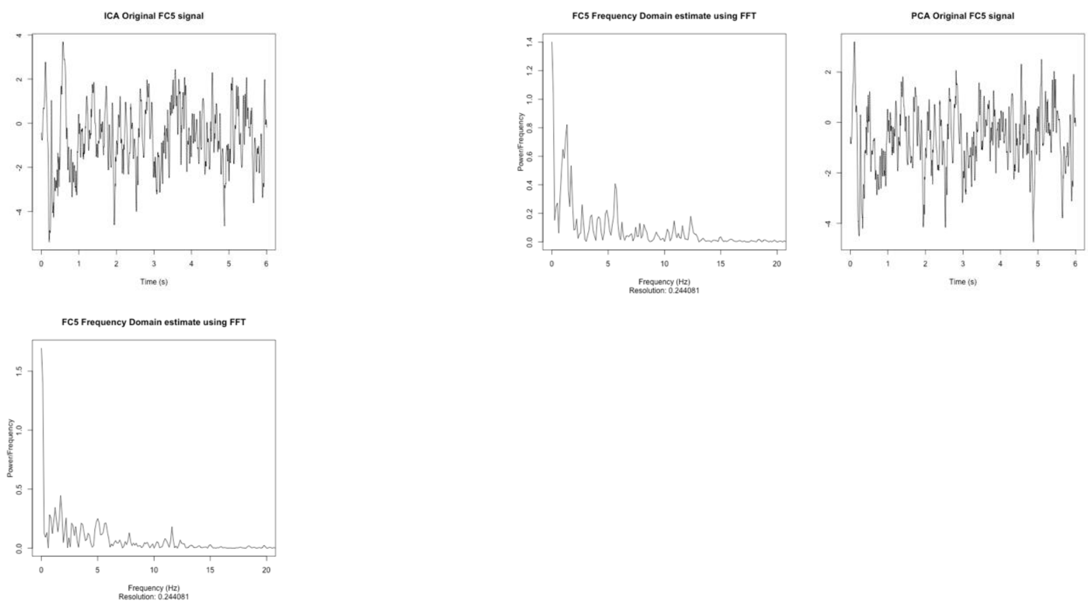


Figure 26 Show graph of time and frequency domain of ICA and PCA emotional valence. Max Power Frequency of ICA FC5 = 1.40169 and Max Power Frequency of PCA FC5 = 1.695358

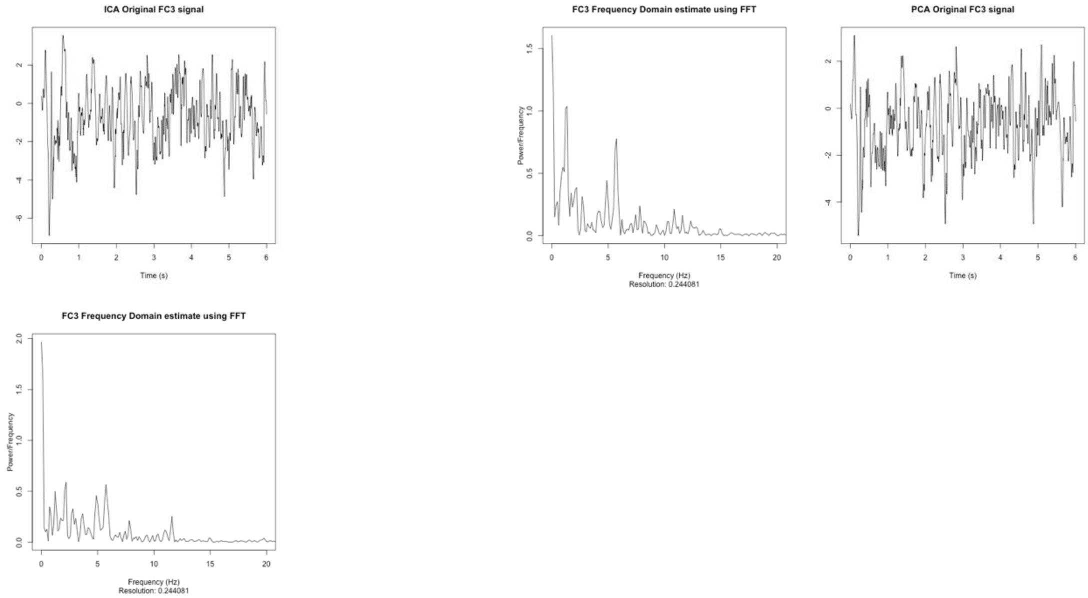


Figure 27 Show graph of time and frequency domain of ICA and PCA emotional valence. Max Power Frequency of ICA FC3 = 1.605456 and Max Power Frequency of PCA FC3 = 1.966838

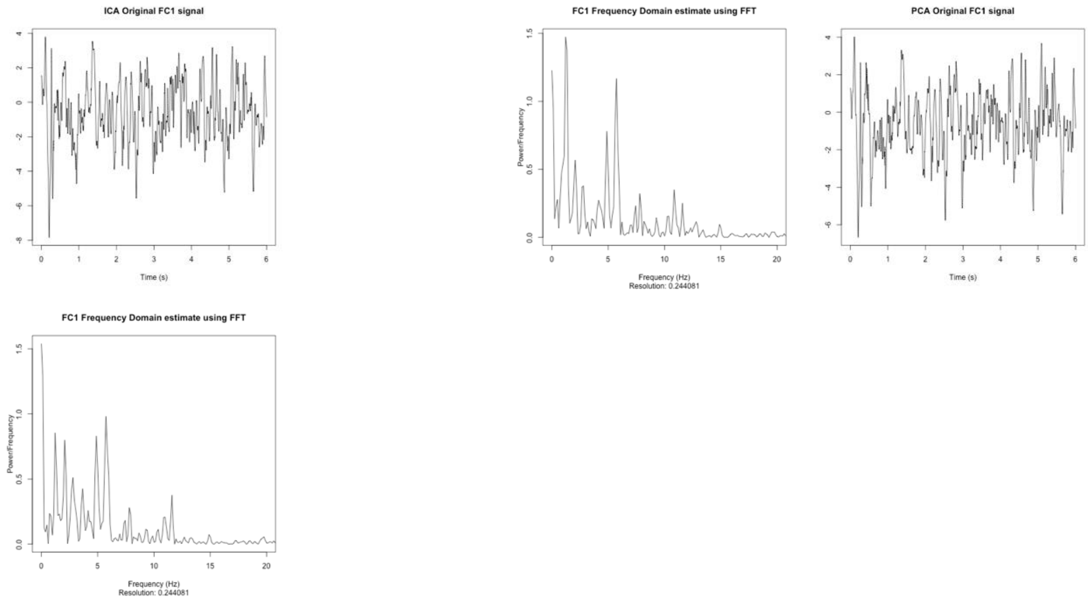


Figure 28 Show graph of time and frequency domain of ICA and PCA emotional valence. Max Power Frequency of ICA FC1 = 1.473292 and Max Power Frequency of PCA FC1 = 1.539454

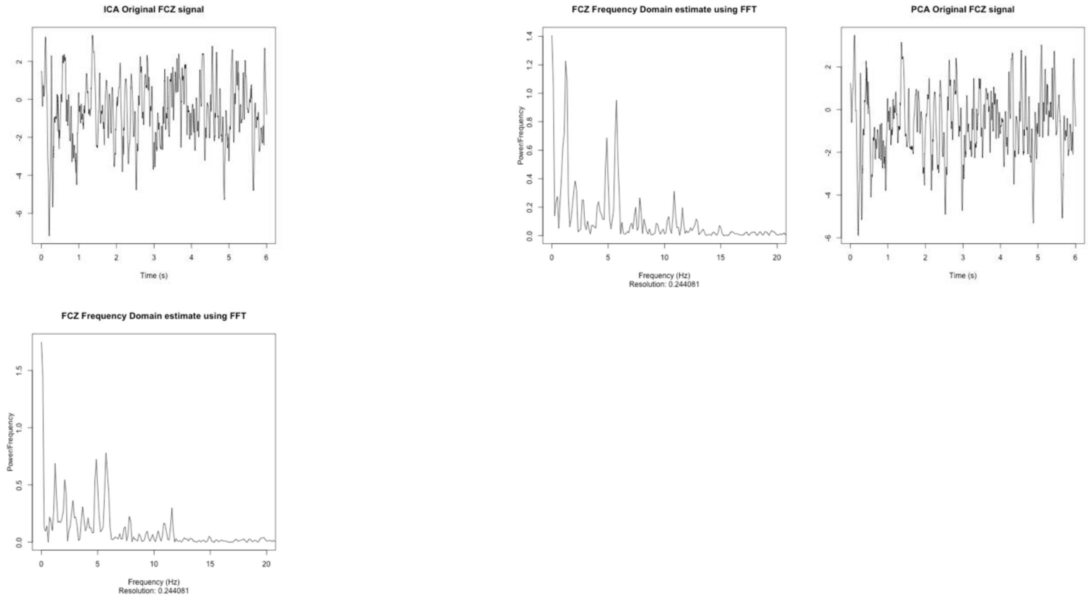


Figure 29 Show graph of time and frequency domain of ICA and PCA emotional valence. Max Power Frequency of ICA FCZ = 1.406679 and Max Power Frequency of PCA FCZ = 1.750489

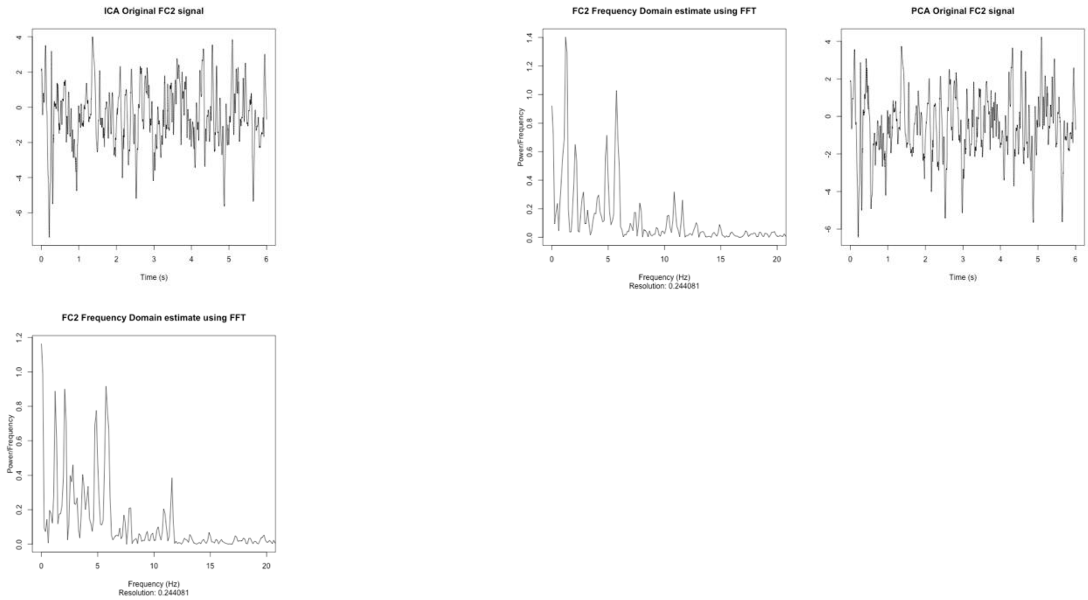


Figure 30 Show graph of time and frequency domain of ICA and PCA emotional valence. Max Power Frequency of ICA FC2 = 1.404092 and Max Power Frequency of PCA FC2 = 1.164625

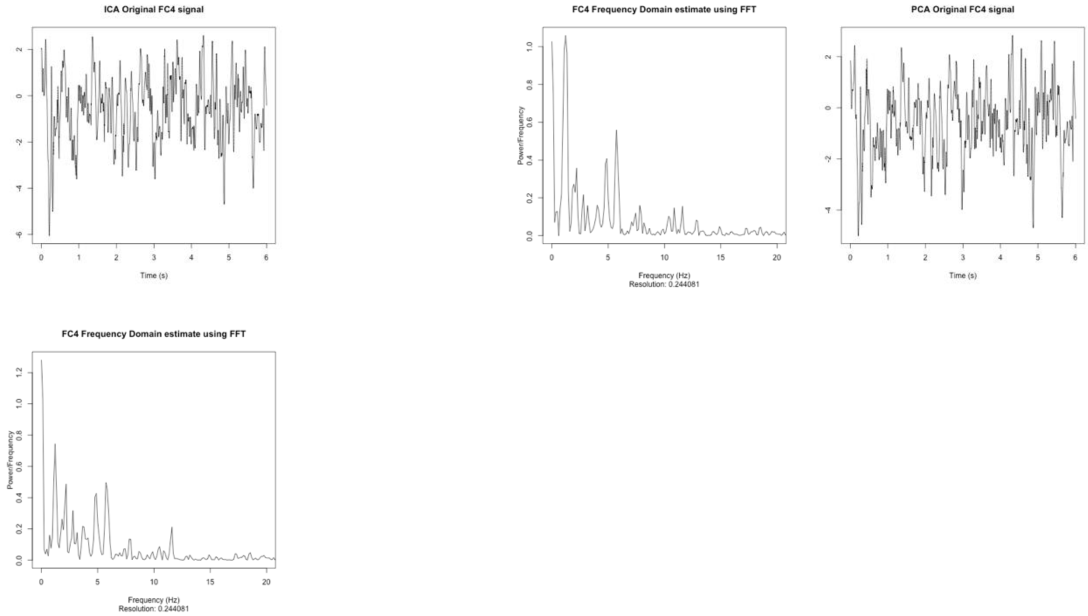


Figure 31 Show graph of time and frequency domain of ICA and PCA emotional valence. Max Power Frequency of ICA FC4 = 1.05967 and Max Power Frequency of PCA FC4 = 1.281508

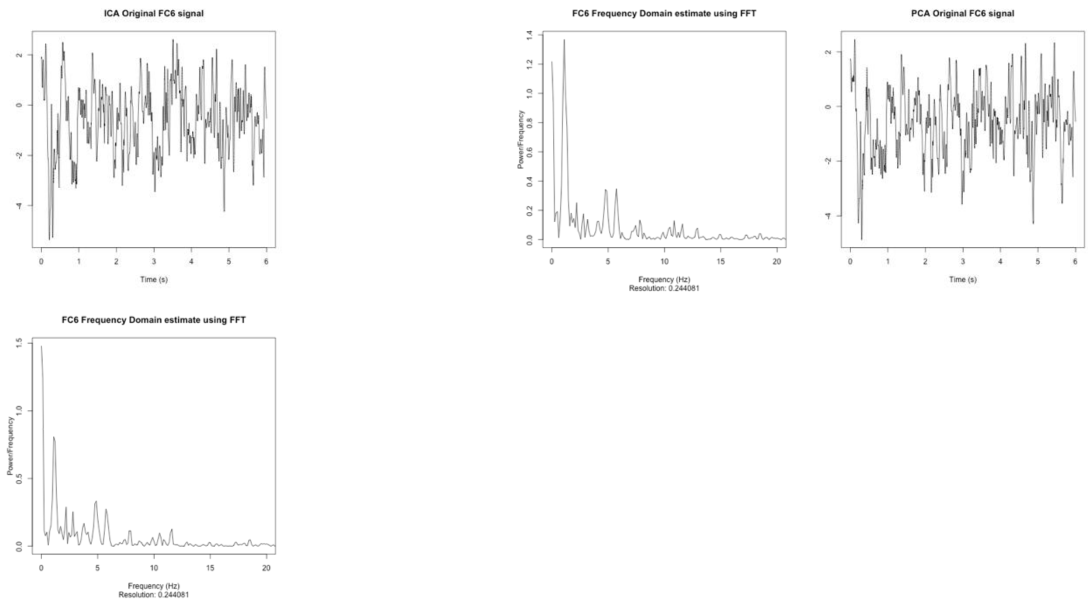


Figure 32 Show graph of time and frequency domain of ICA and PCA emotional valence. Max Power Frequency of ICA FC6 = 1.369617 and Max Power Frequency of PCA FC6 = 1.480242

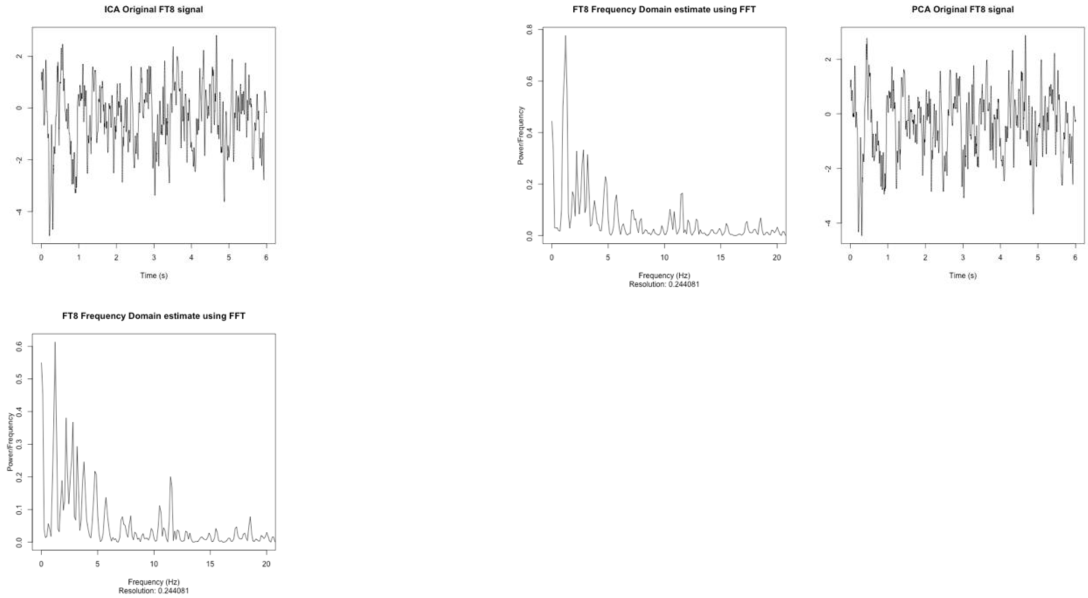


Figure 33 Show graph of time and frequency domain of ICA and PCA emotional valence. Max Power Frequency of ICA FT8 = 0.7771295 and Max Power Frequency of PCA FT8 = 0.6136762

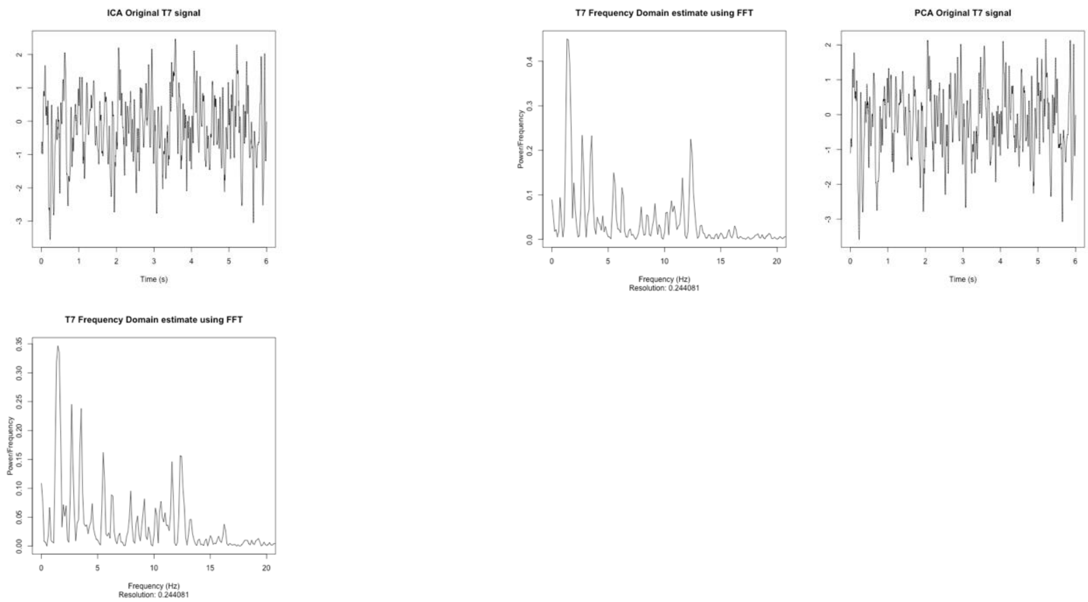


Figure 34 Show graph of time and frequency domain of ICA and PCA emotional valence. Max Power Frequency of ICA T7 = 0.4502006 and Max Power Frequency of PCA T7 = 0.3469118

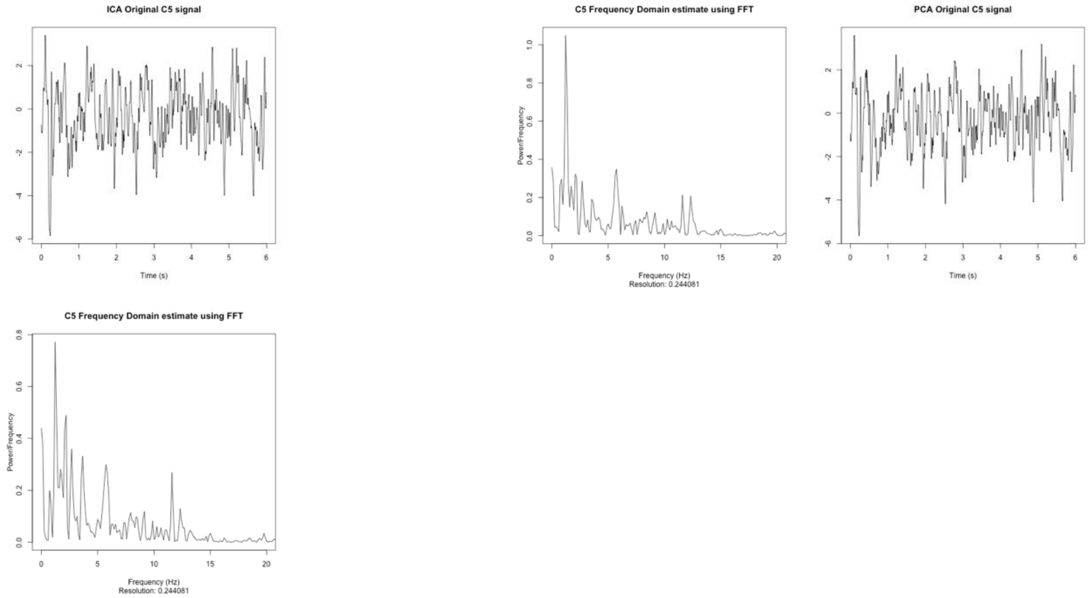


Figure 35 Show graph of time and frequency domain of ICA and PCA emotional valence. Max Power Frequency of ICA C5 = 1.049128 and Max Power Frequency of PCA C5 = 0.7717874

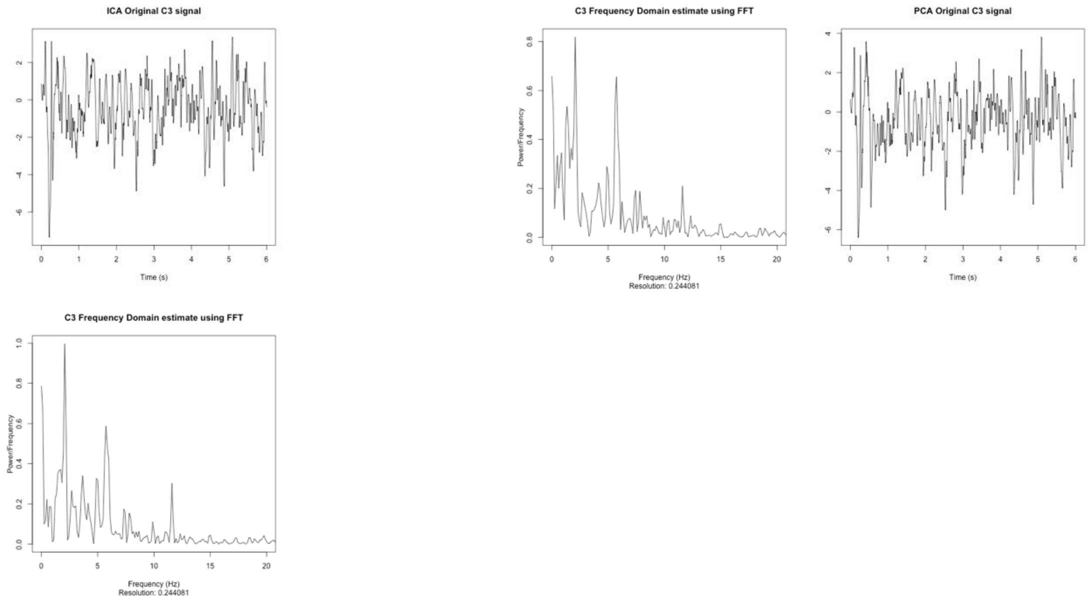


Figure 36 Show graph of time and frequency domain of ICA and PCA emotional valence. Max Power Frequency of ICA C3 = 0.819459 and Max Power Frequency of PCA C3 = 0.9975301

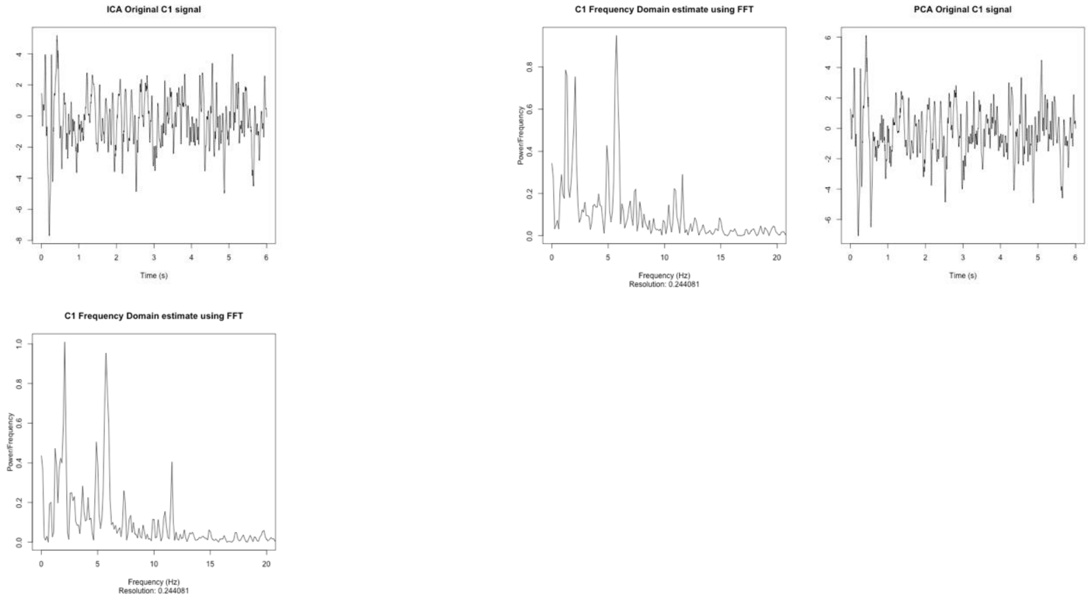


Figure 37 Show graph of time and frequency domain of ICA and PCA emotional valence. Max Power Frequency of ICA C1 = 0.9496677 and Max Power Frequency of PCA C1 = 1.010022

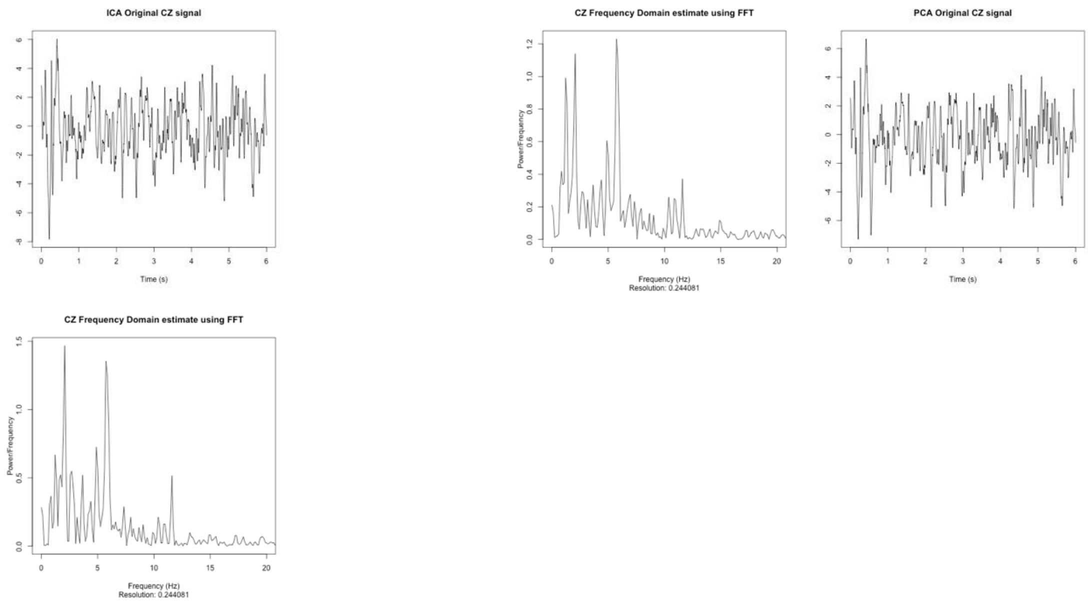


Figure 38 Show graph of time and frequency domain of ICA and PCA emotional valence. Max Power Frequency of ICA CZ = 1.230793 and Max Power Frequency of PCA CZ = 1.467825

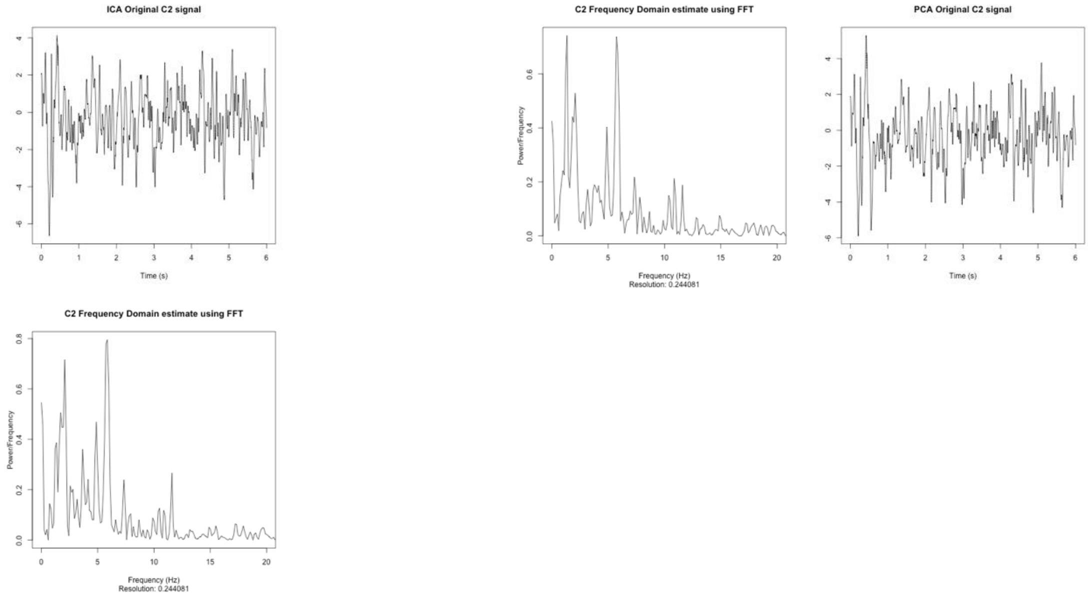


Figure 39 Show graph of time and frequency domain of ICA and PCA emotional valence. Max Power Frequency of ICA C2 = 0.74274 and Max Power Frequency of PCA C2 = 0.795451

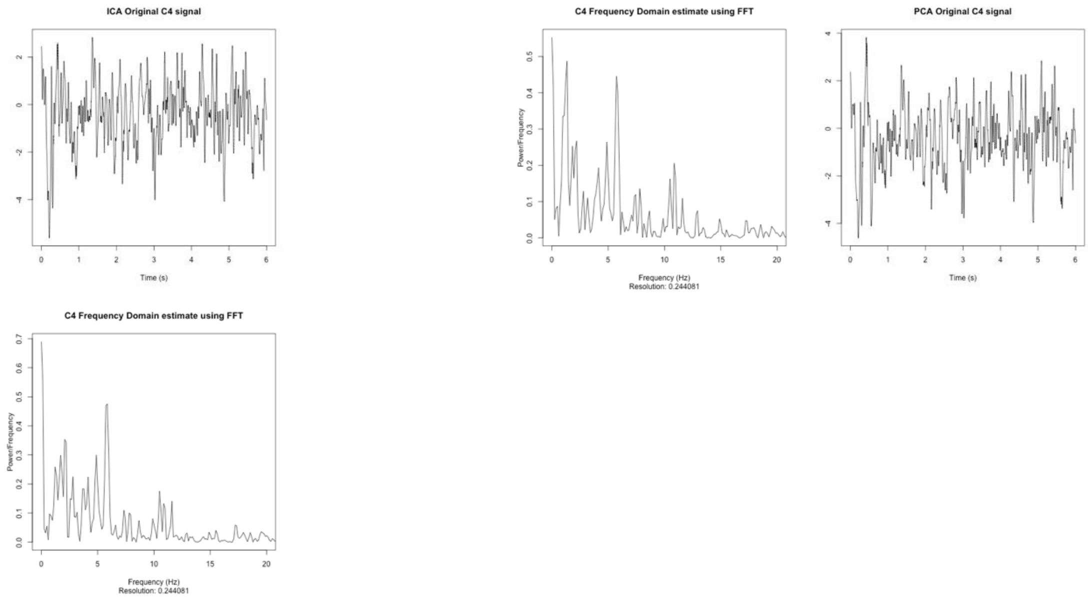


Figure 40 Show graph of time and frequency domain of ICA and PCA emotional valence. Max Power Frequency of ICA C4 = 0.55263 04and Max Power Frequency of PCA C4 = 0.6897003

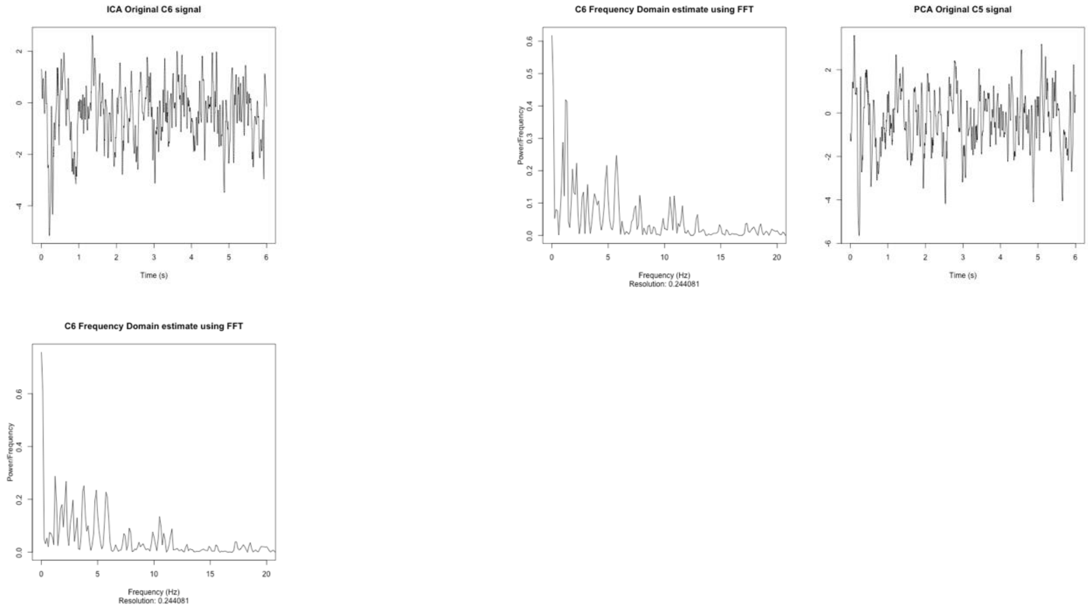


Figure 41 Show graph of time and frequency domain of ICA and PCA emotional valence. Max Power Frequency of ICA C6 = 0.617648 and Max Power Frequency of PCA C6 = 0.7577605

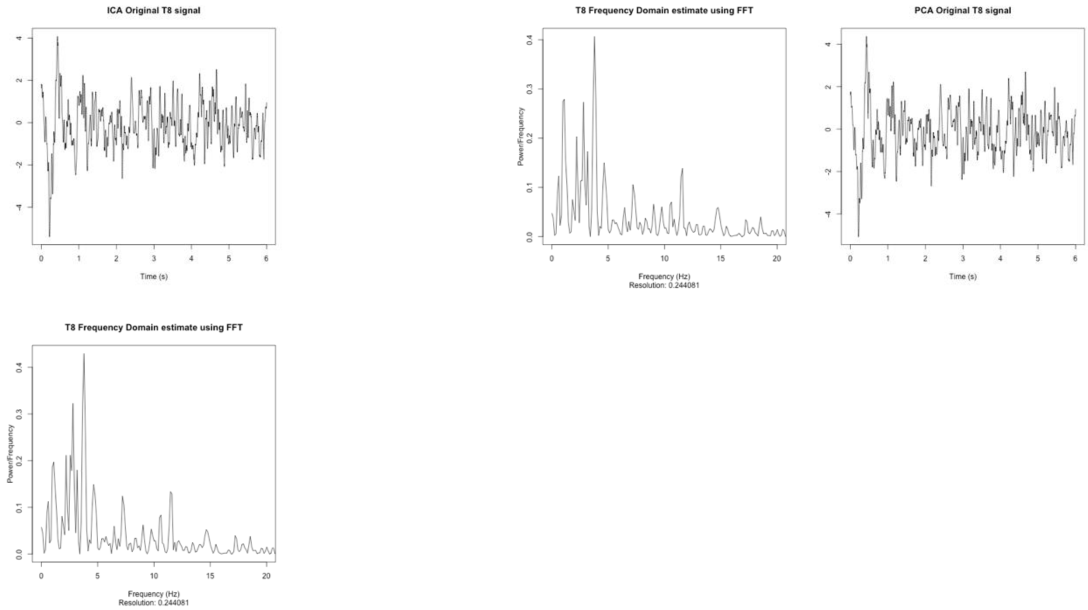


Figure 42 Show graph of time and frequency domain of ICA and PCA emotional valence. Max Power Frequency of ICA T8 = 0.4067026 and Max Power Frequency of PCA T8 = 0.429559

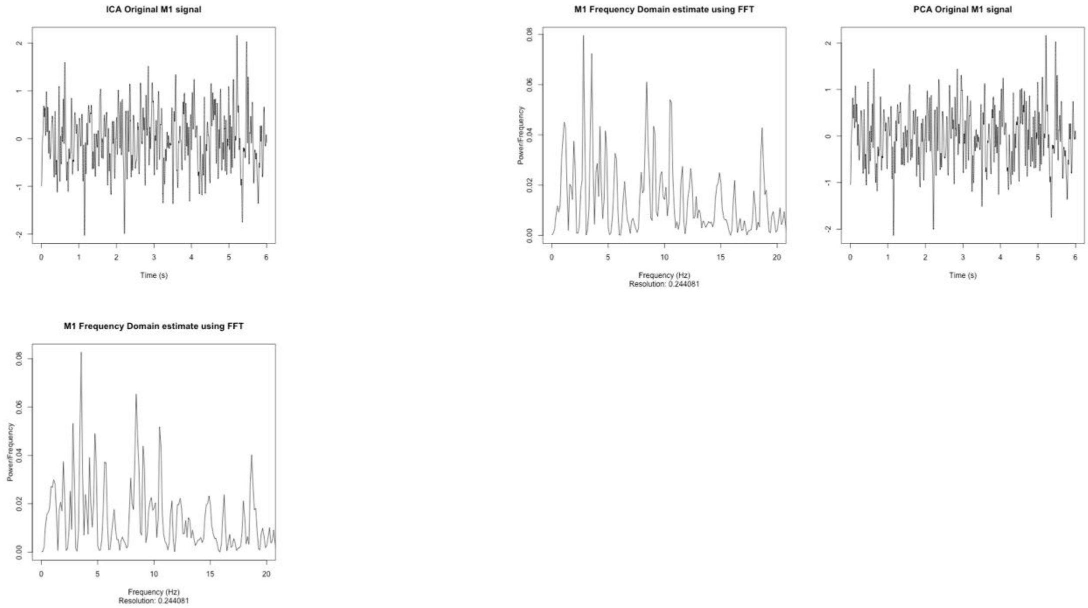


Figure 43 Show graph of time and frequency domain of ICA and PCA emotional valence. Max Power Frequency of ICA M1 = 0.07957361 and Max Power Frequency of PCA M1 = 0.08267037

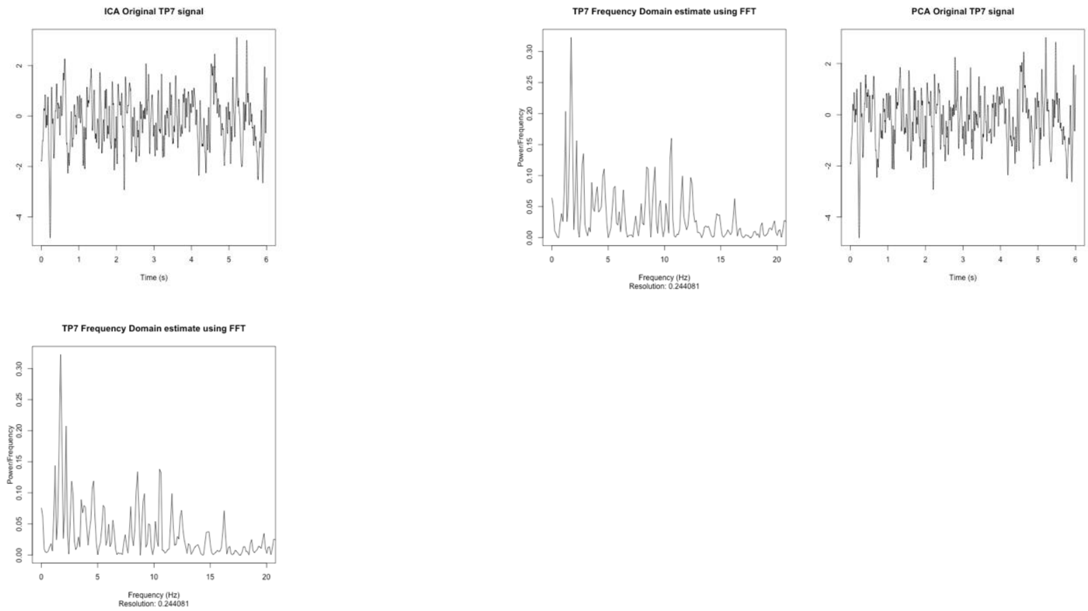


Figure 44 Show graph of time and frequency domain of ICA and PCA emotional valence. Max Power Frequency of ICA TP7 = 0.322671 and Max Power Frequency of PCA TP7 = 0.3225067

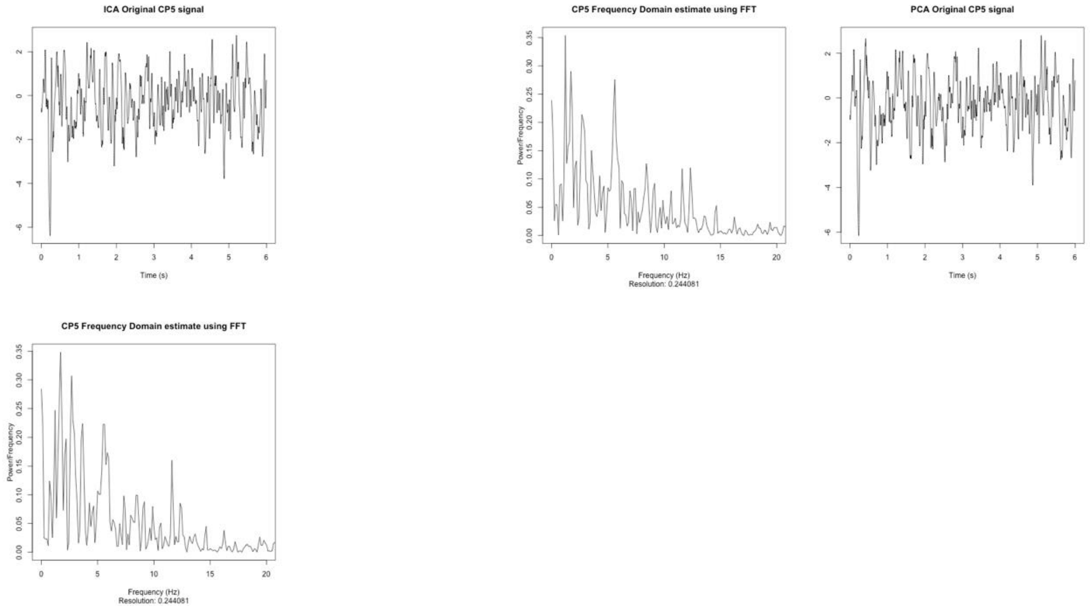


Figure 45 Show graph of time and frequency domain of ICA and PCA emotional valence. Max Power Frequency of ICA CP5 = 0.3540265 and Max Power Frequency of PCA CP5 = 0.3484302

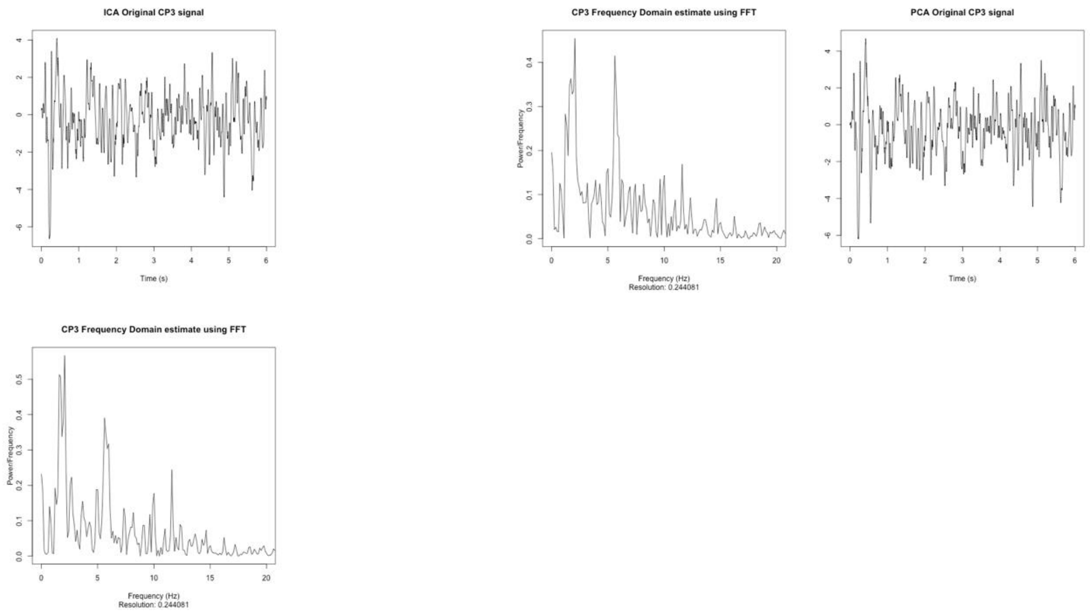


Figure 46 Show graph of time and frequency domain of ICA and PCA emotional valence. Max Power Frequency of ICA CP3 = 0.4544101 and Max Power Frequency of PCA CP3 = 0.5672764

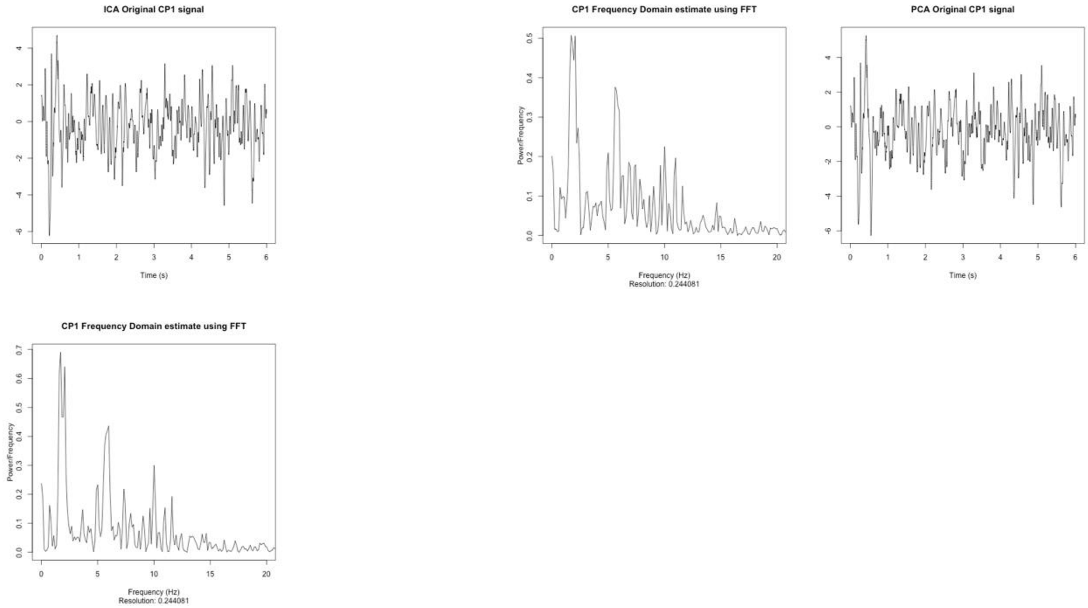


Figure 47 Show graph of time and frequency domain of ICA and PCA emotional valence. Max Power Frequency of ICA CP1 = 0.5071779 and Max Power Frequency of PCA CP1 = 0.6910813

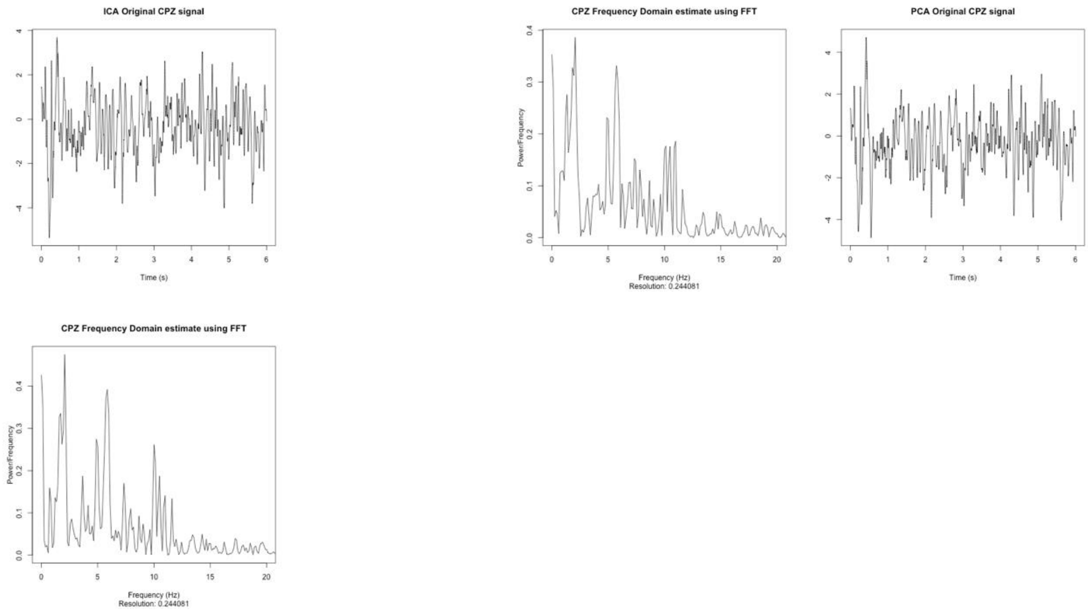


Figure 48 Show graph of time and frequency domain of ICA and PCA emotional valence. Max Power Frequency of ICA CPZ = 0.3859378 and Max Power Frequency of PCA CPZ = 0.4748336

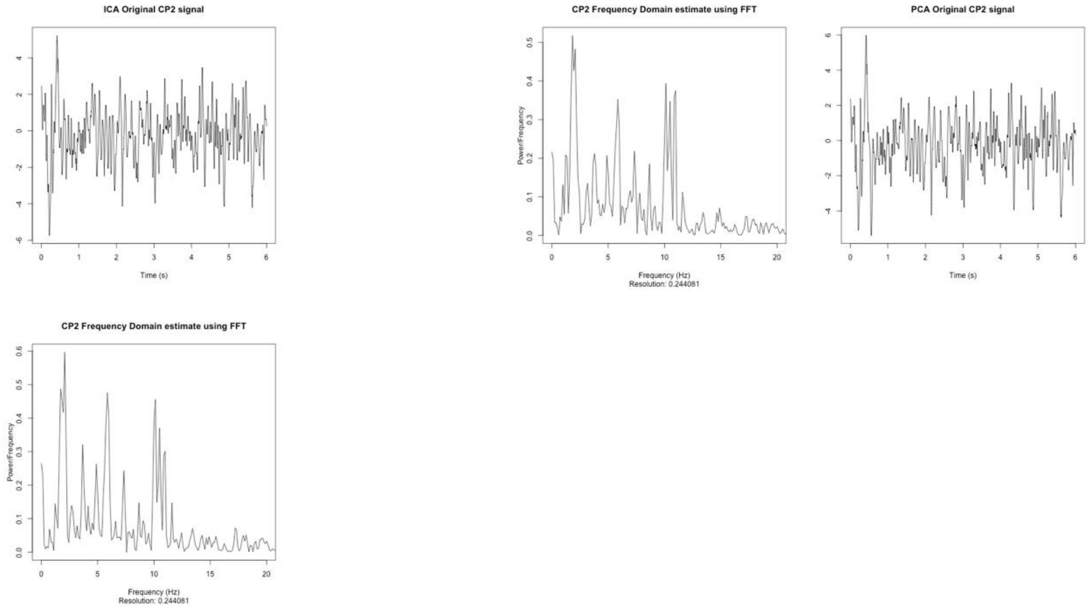


Figure 49 Show graph of time and frequency domain of ICA and PCA emotional valence. Max Power Frequency of ICA CP2 = 0.5179439 and Max Power Frequency of PCA CP2 = 0.5968724

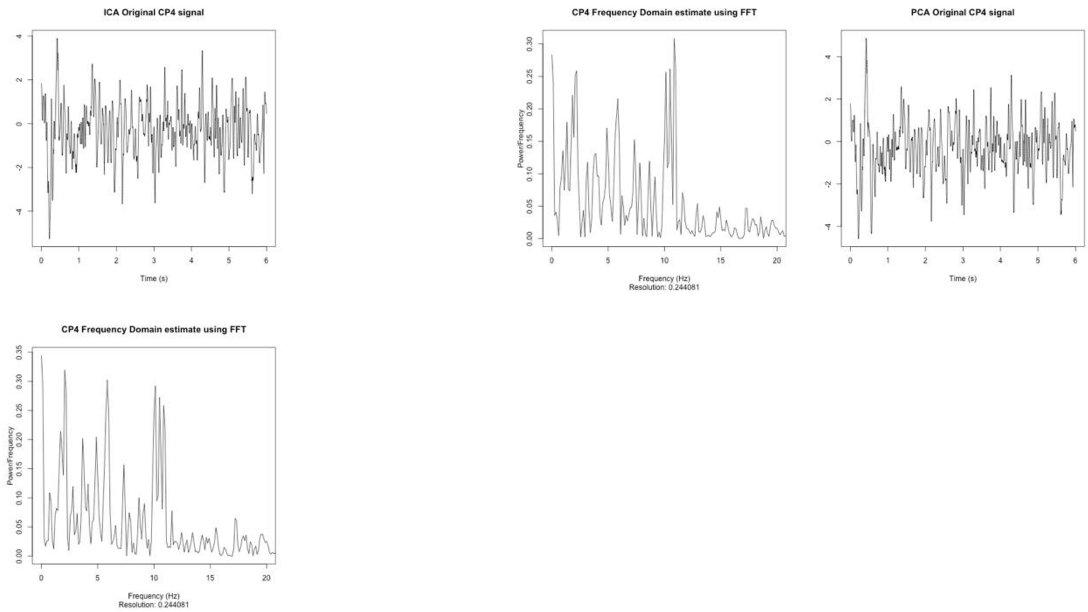


Figure 50 Show graph of time and frequency domain of ICA and PCA emotional valence. Max Power Frequency of ICA CP4 = 0.3085024 and Max Power Frequency of PCA CP4 = 0.3444564

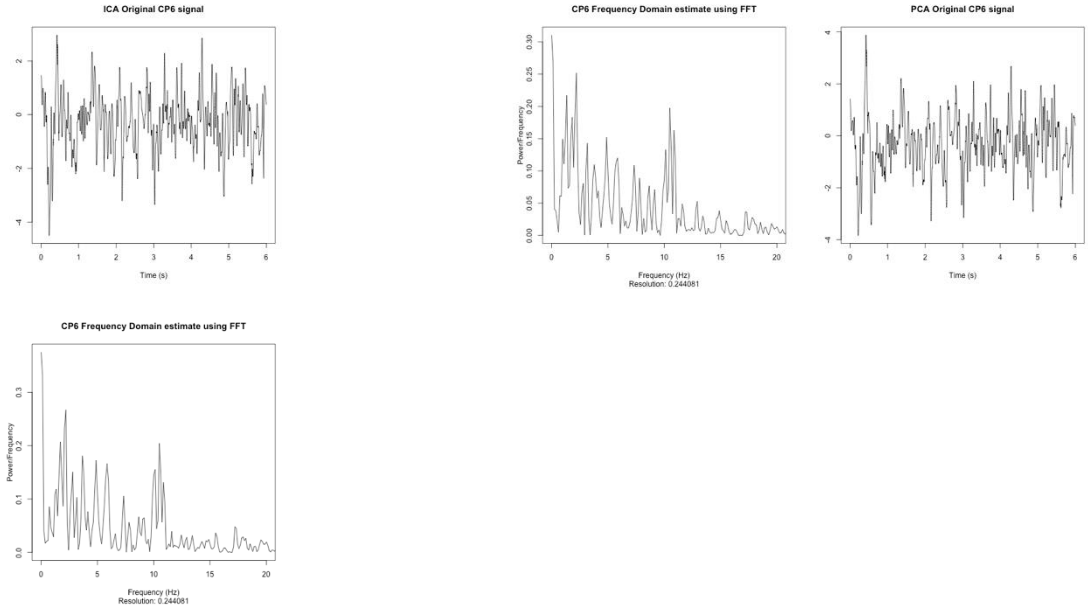


Figure 51 Show graph of time and frequency domain of ICA and PCA emotional valence. Max Power Frequency of ICA CP6 = 0.3104634 and Max Power Frequency of PCA CP6 = 0.3751994

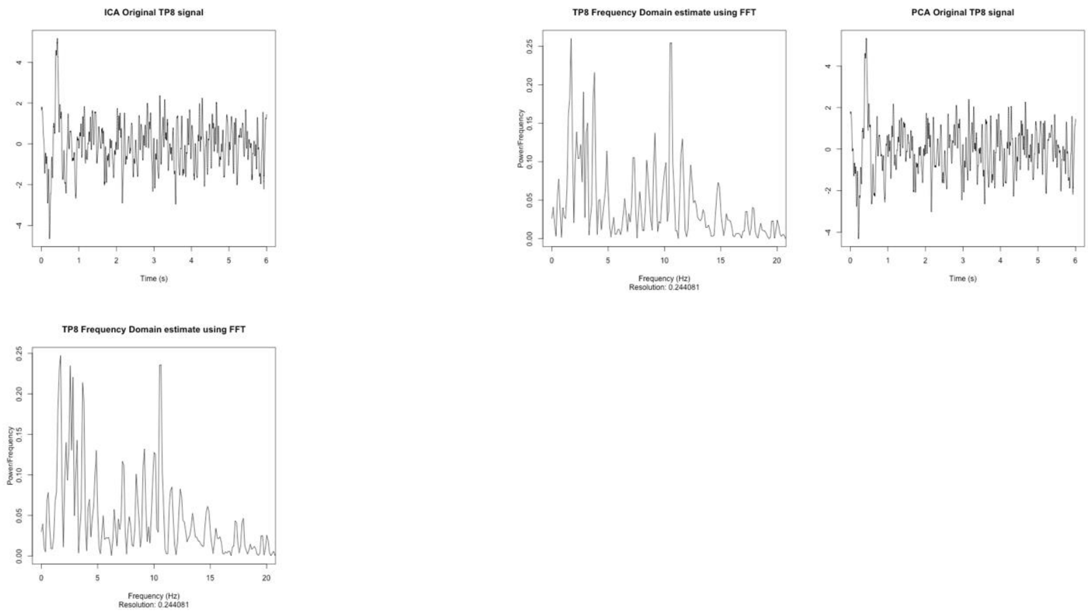


Figure 52 Show graph of time and frequency domain of ICA and PCA emotional valence. Max Power Frequency of ICA TP8 = 0.2602438 and Max Power Frequency of PCA TP8 = 0.2472832

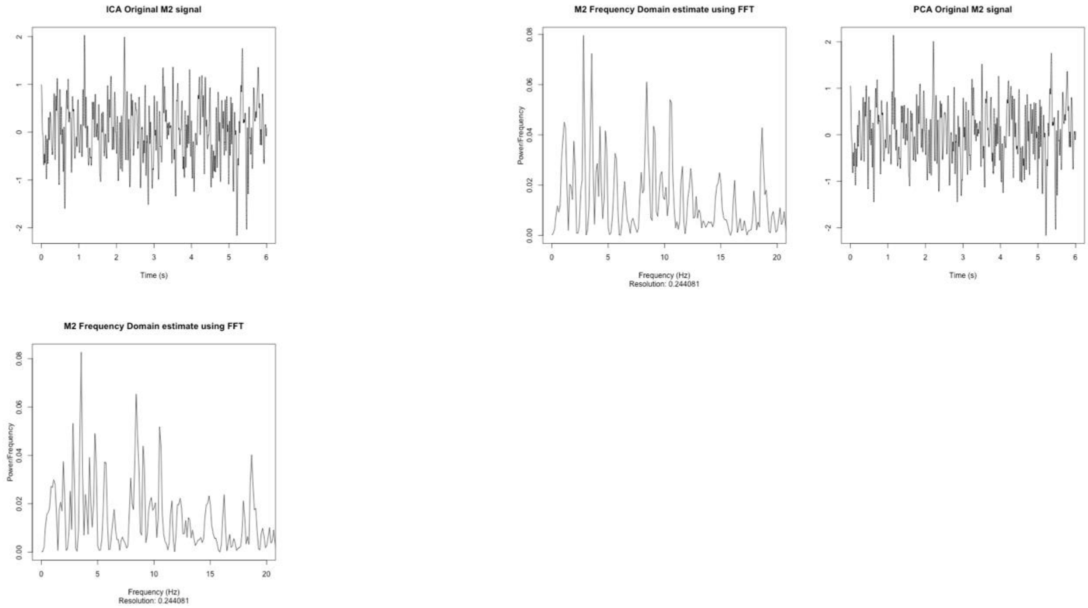


Figure 53 Show graph of time and frequency domain of ICA and PCA emotional valence. Max Power Frequency of ICA M2 = 0.07957361 and Max Power Frequency of PCA M2 = 0.08267037

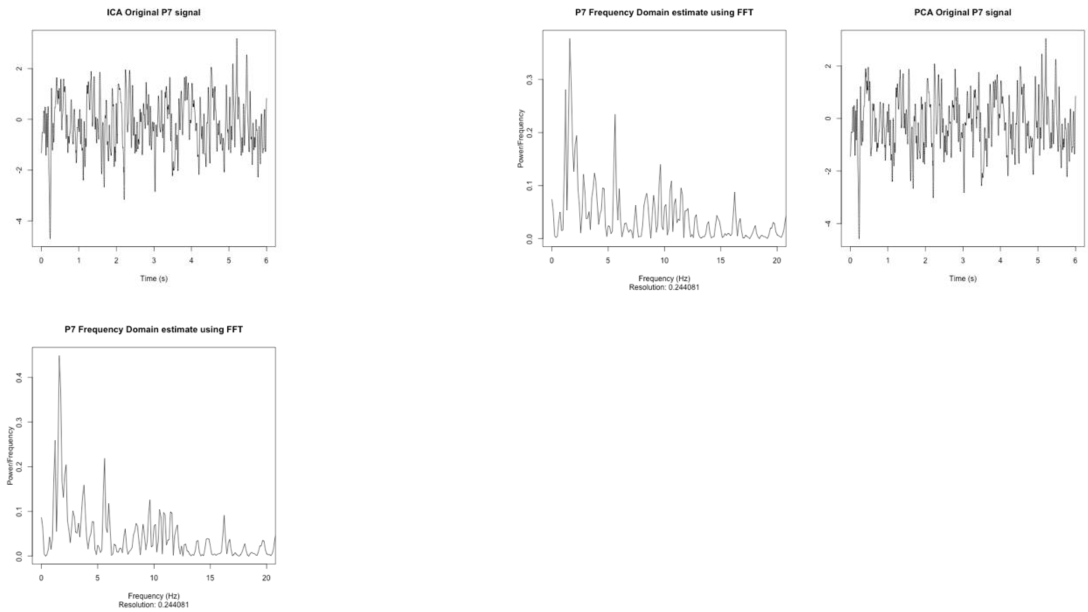


Figure 54 Show graph of time and frequency domain of ICA and PCA emotional valence. Max Power Frequency of ICA P7 = 0.3774214 and Max Power Frequency of PCA P7 = 0.4490379

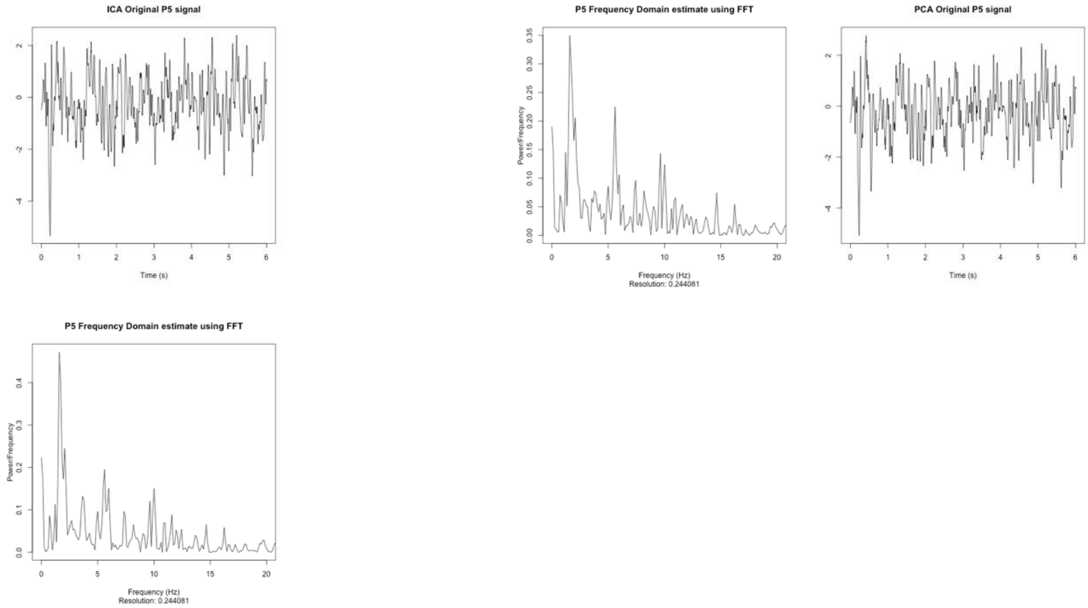


Figure 55 Show graph of time and frequency domain of ICA and PCA emotional valence. Max Power Frequency of ICA P5 = 0.3500315 and Max Power Frequency of PCA P5 = 0.4720573

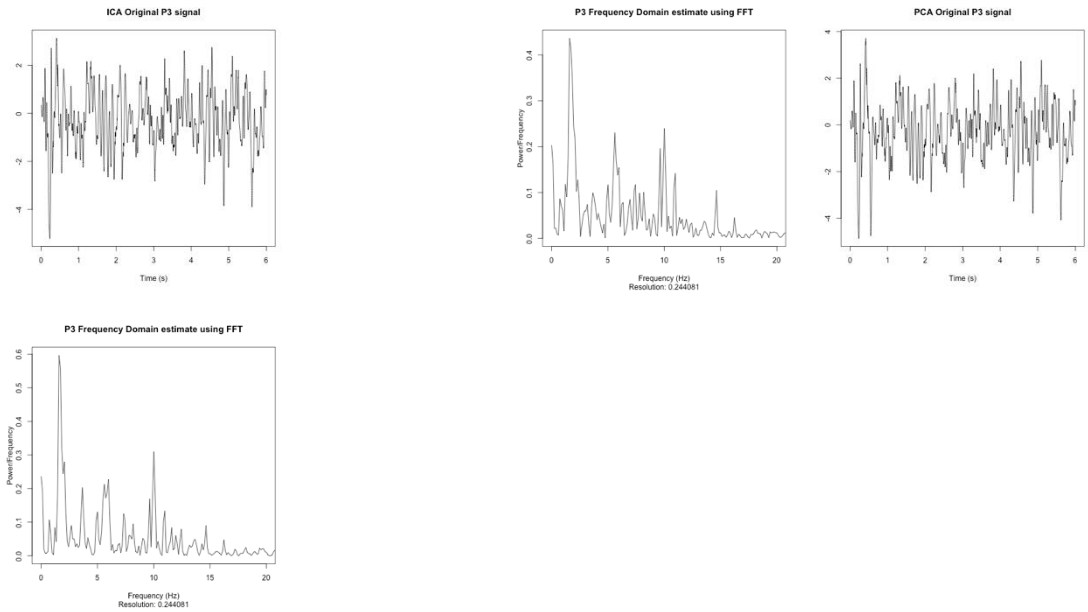


Figure 56 Show graph of time and frequency domain of ICA and PCA emotional valence. Max Power Frequency of ICA P3 = 0.4365789 and Max Power Frequency of PCA P3 = 0.5968814

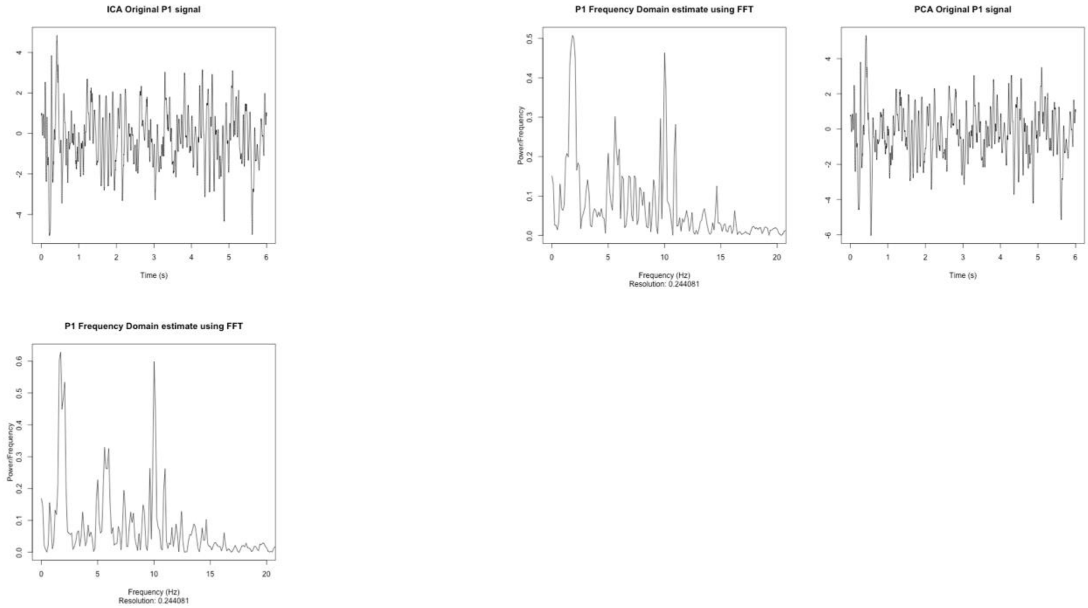


Figure 57 Show graph of time and frequency domain of ICA and PCA emotional valence. Max Power Frequency of ICA P1 = 0.5076769 and Max Power Frequency of PCA P1 = 0.6285759

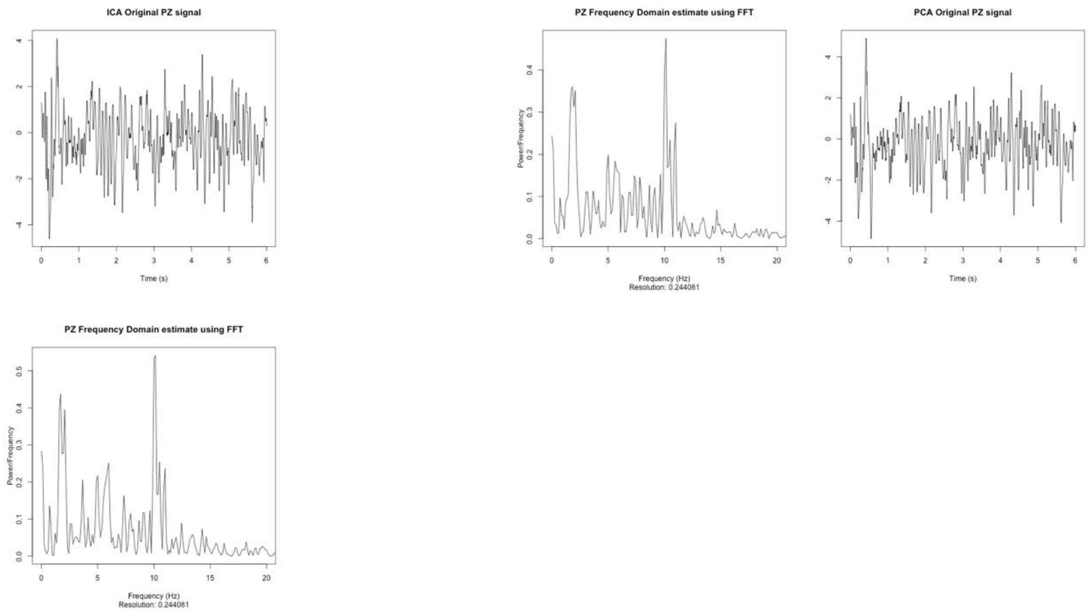


Figure 58 Show graph of time and frequency domain of ICA and PCA emotional valence. Max Power Frequency of ICA PZ = 0.4748745 and Max Power Frequency of PCA PZ = 0.5417212

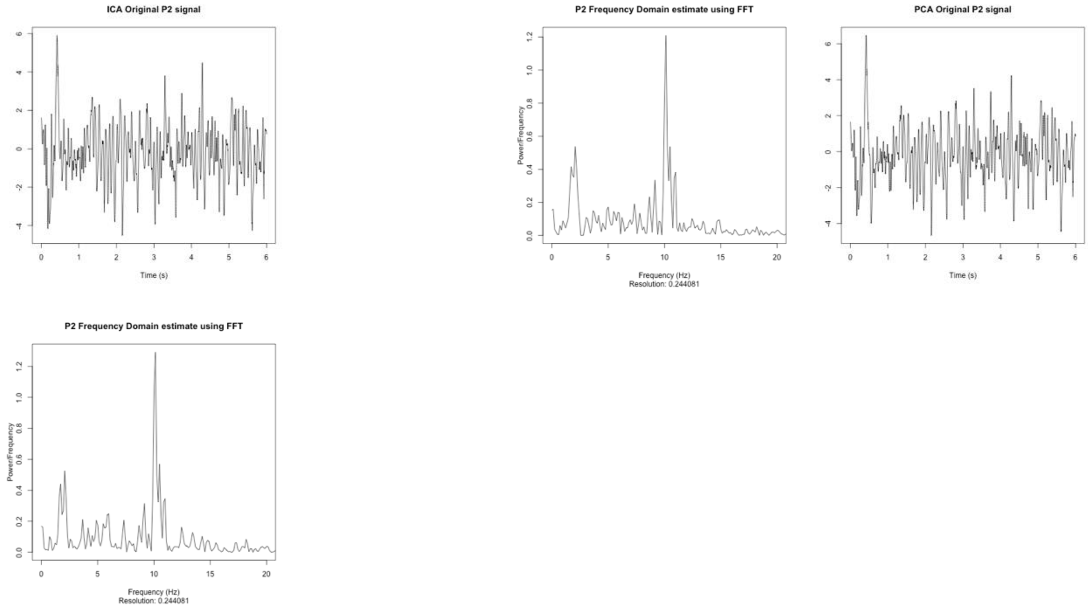


Figure 59 Show graph of time and frequency domain of ICA and PCA emotional valence. Max Power Frequency of ICA P2 = 1.209981 and Max Power Frequency of PCA P2 = 1.292249

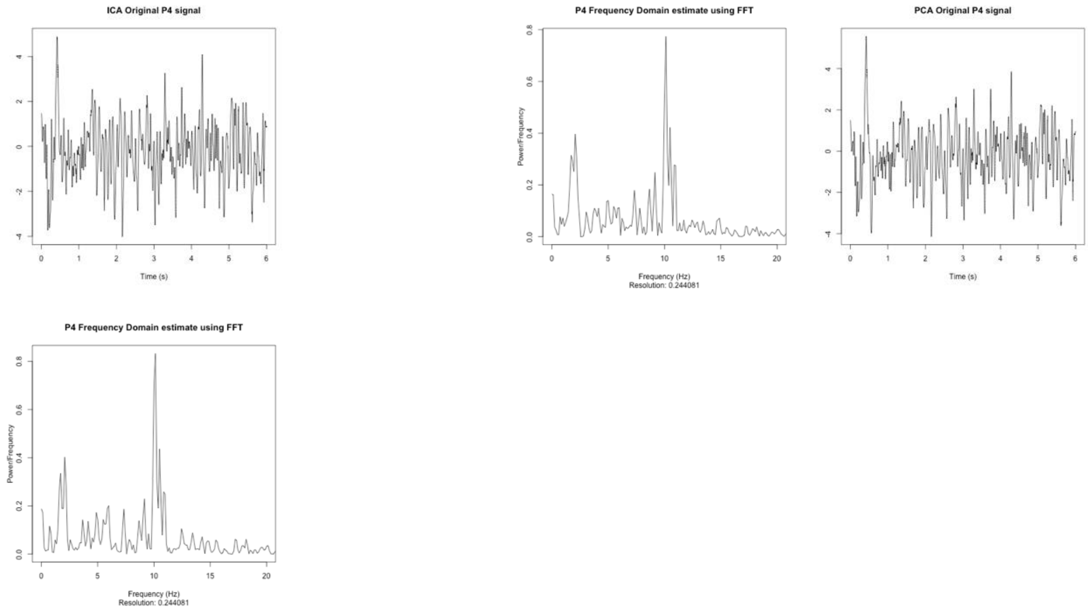


Figure 60 Show graph of time and frequency domain of ICA and PCA emotional valence. Max Power Frequency of ICA P4 = 0.7738545 and Max Power Frequency of PCA P4 = 0.8329052

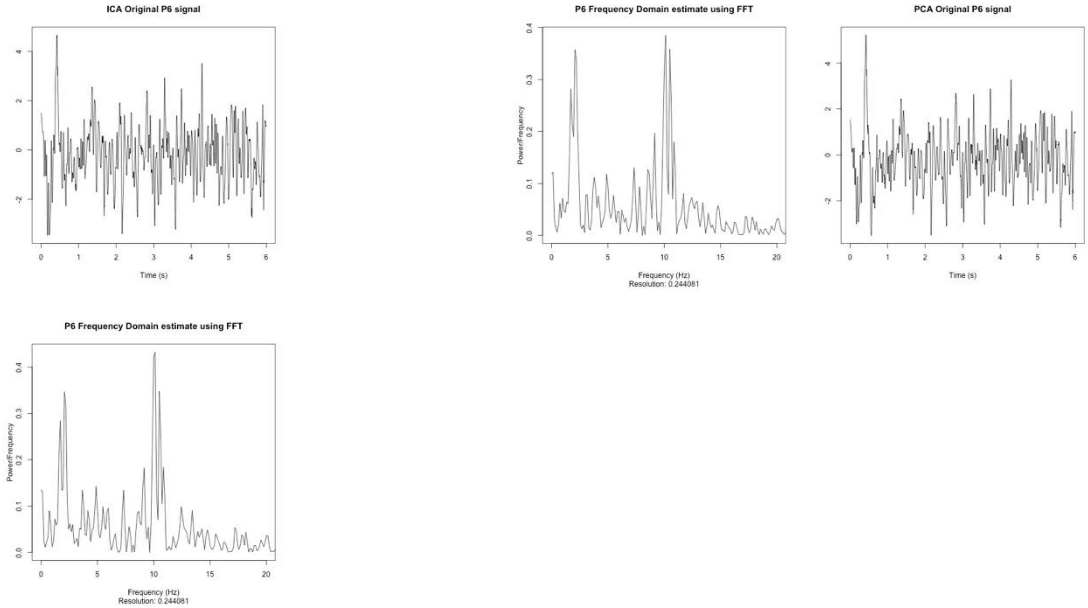


Figure 61 Show graph of time and frequency domain of ICA and PCA emotional valence. Max Power Frequency of ICA P6 = 0.3853468 and Max Power Frequency of PCA P6 = 0.4323366

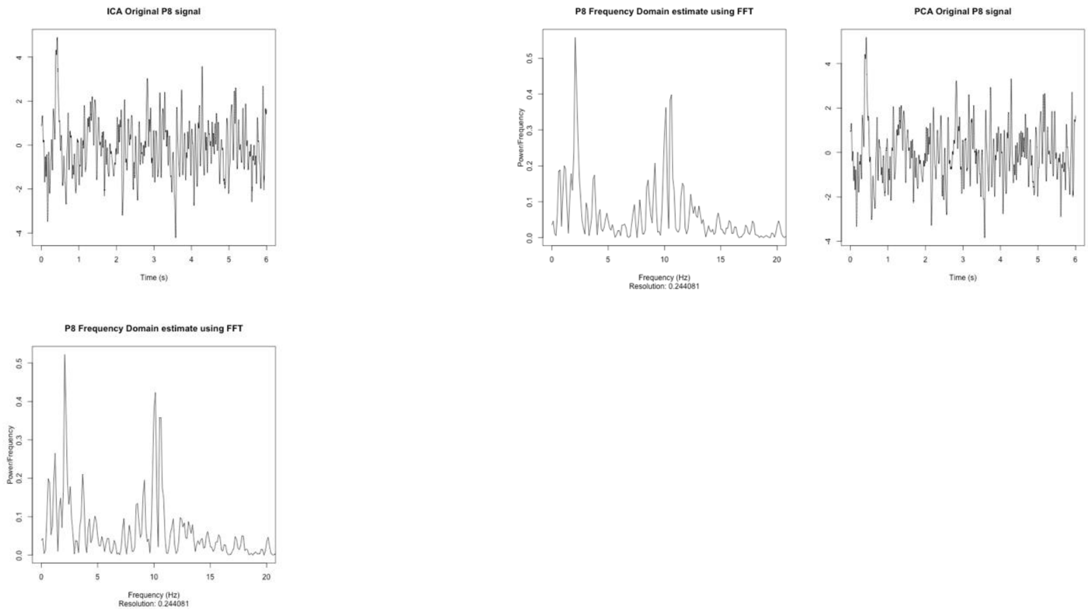


Figure 62 Show graph of time and frequency domain of ICA and PCA emotional valence. Max Power Frequency of ICA P8 = 0.5579805 and Max Power Frequency of PCA P8 = 0.5223744

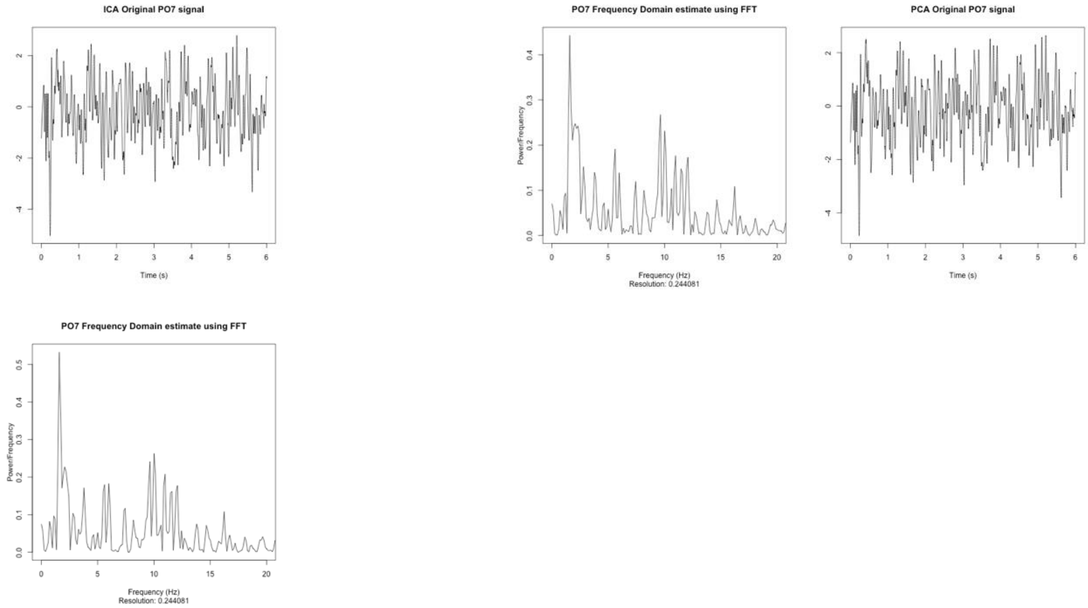


Figure 63 Show graph of time and frequency domain of ICA and PCA emotional valence. Max Power Frequency of ICA PO7 = 0.4429952 and Max Power Frequency of PCA PO7 = 0.5329527

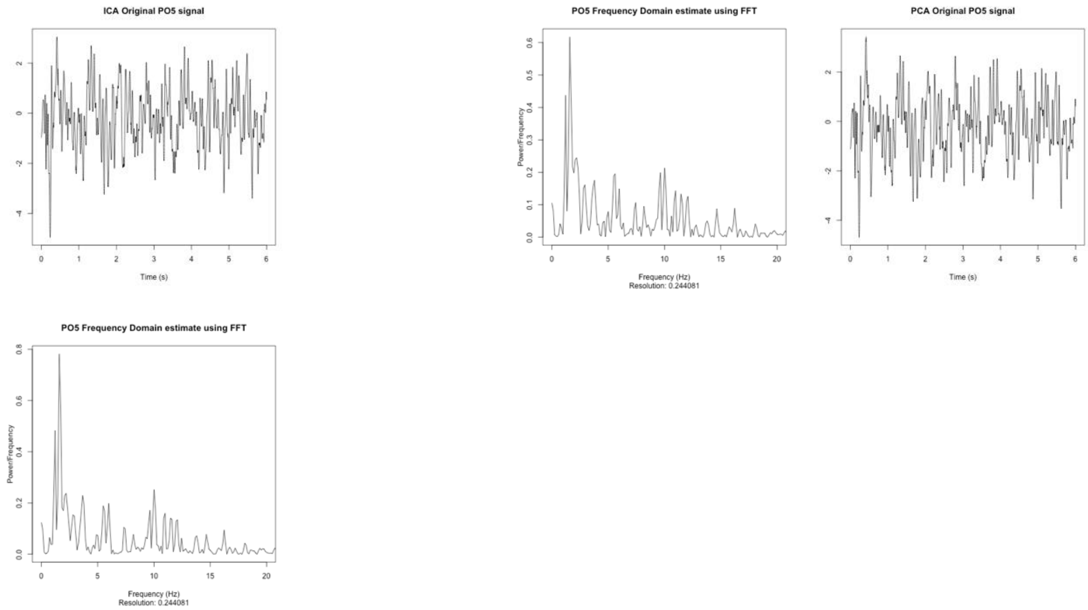


Figure 64 Show graph of time and frequency domain of ICA and PCA emotional valence. Max Power Frequency of ICA PO5 = 0.6172955 and Max Power Frequency of PCA PO5 = 0.7821178

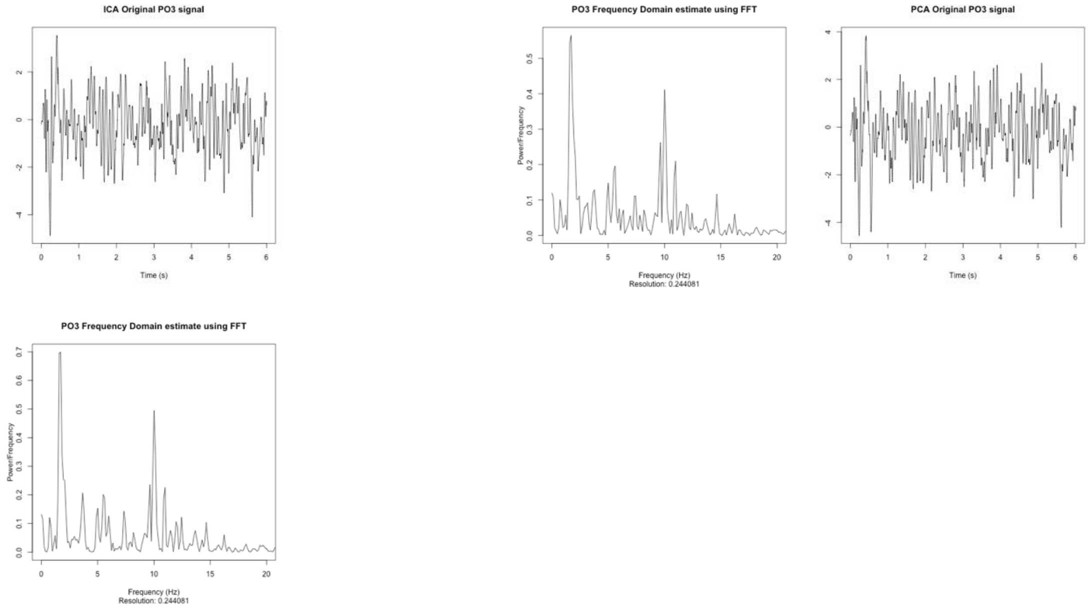


Figure 65 Show graph of time and frequency domain of ICA and PCA emotional valence. Max Power Frequency of ICA PO3 = 0.5649964 and Max Power Frequency of PCA PO3 = 0.6988402

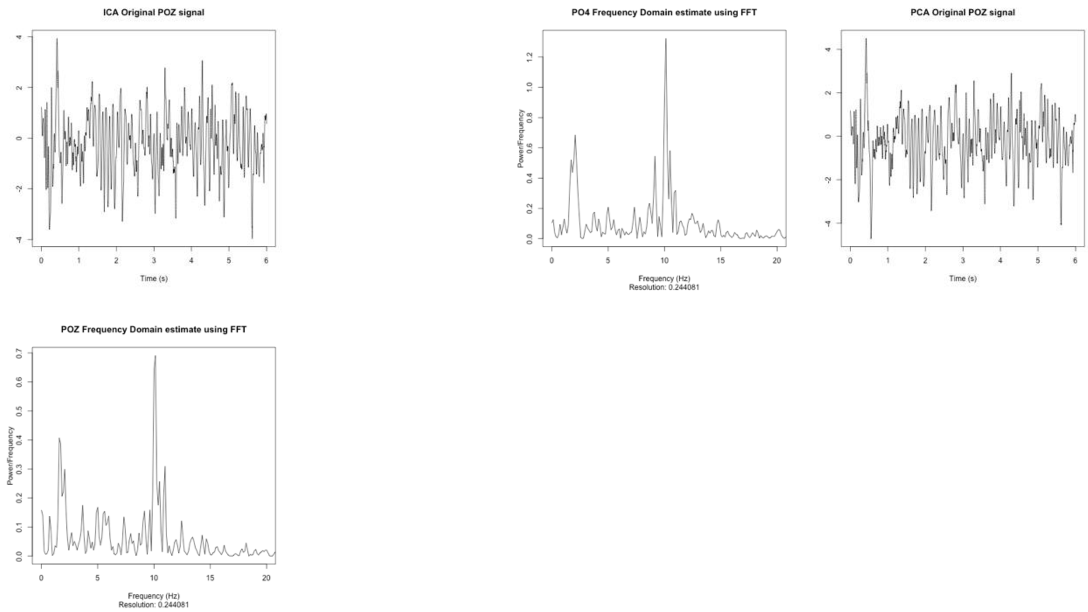


Figure 66 Show graph of time and frequency domain of ICA and PCA emotional valence. Max Power Frequency of ICA POZ = 0.6189004 and Max Power Frequency of PCA POZ = 0.6914237

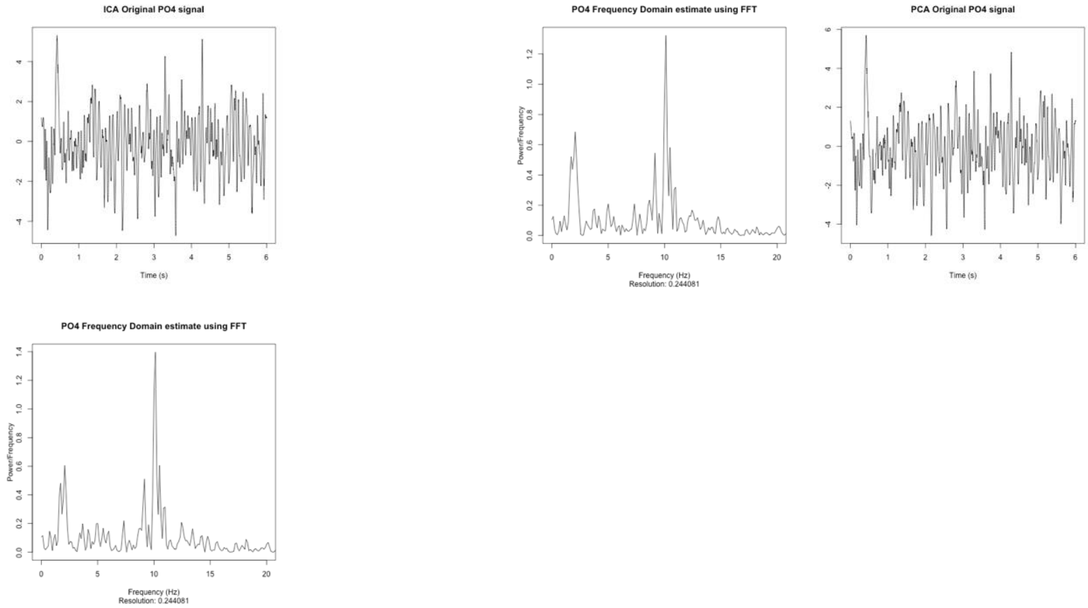


Figure 67 Show graph of time and frequency domain of ICA and PCA emotional valence. Max Power Frequency of ICA PO4 = 1.323039 and Max Power Frequency of PCA PO4 = 1.396633

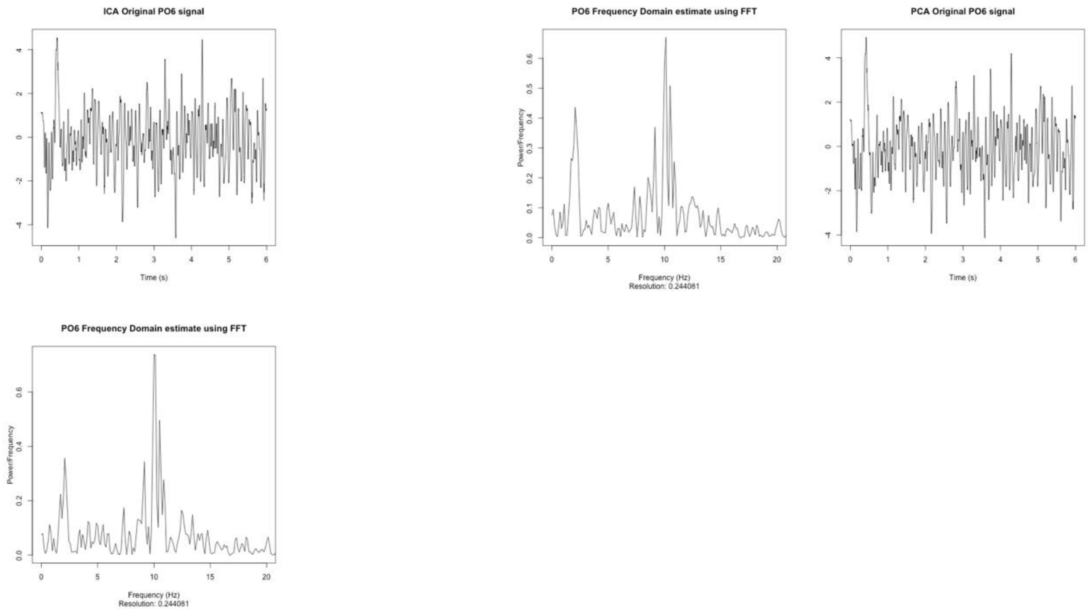


Figure 68 Show graph of time and frequency domain of ICA and PCA emotional valence. Max Power Frequency of ICA PO6 = 0.6705194 and Max Power Frequency of PCA PO6 = 0.7379805

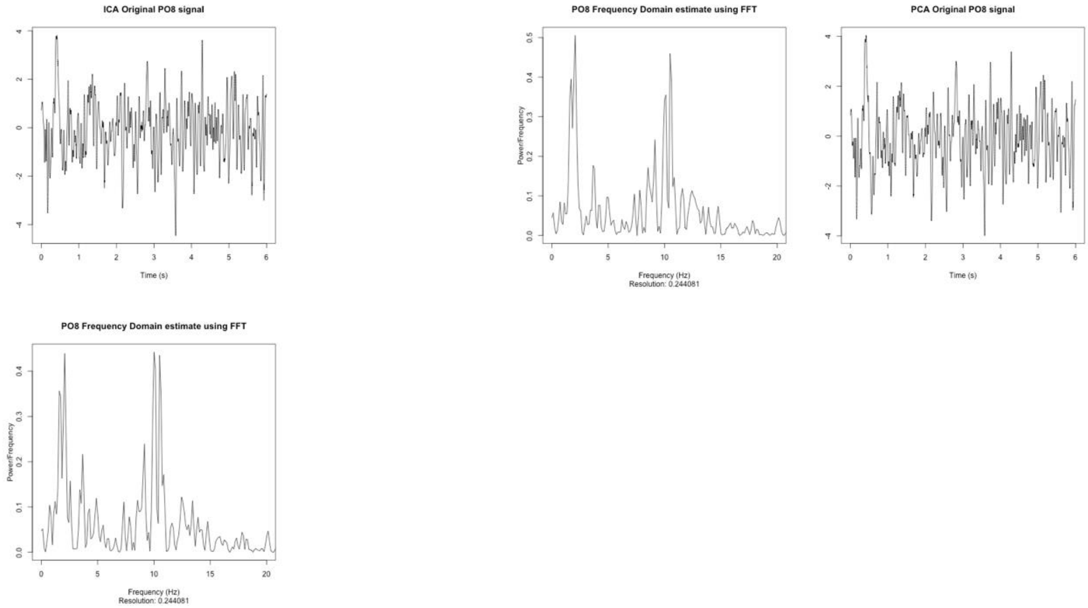


Figure 69 Show graph of time and frequency domain of ICA and PCA emotional valence. Max Power Frequency of ICA PO8 = 0.5054404 and Max Power Frequency of PCA PO8 = 0.4422149

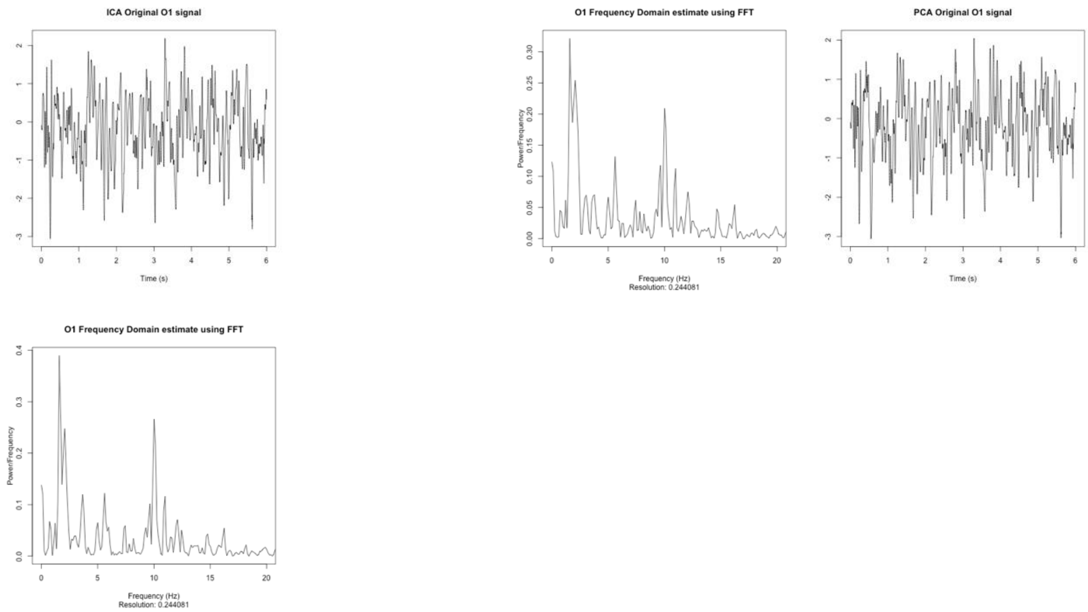


Figure 70 Show graph of time and frequency domain of ICA and PCA emotional valence. Max Power Frequency of ICA O1 = 0.3216134 and Max Power Frequency of PCA O1 = 0.3899792

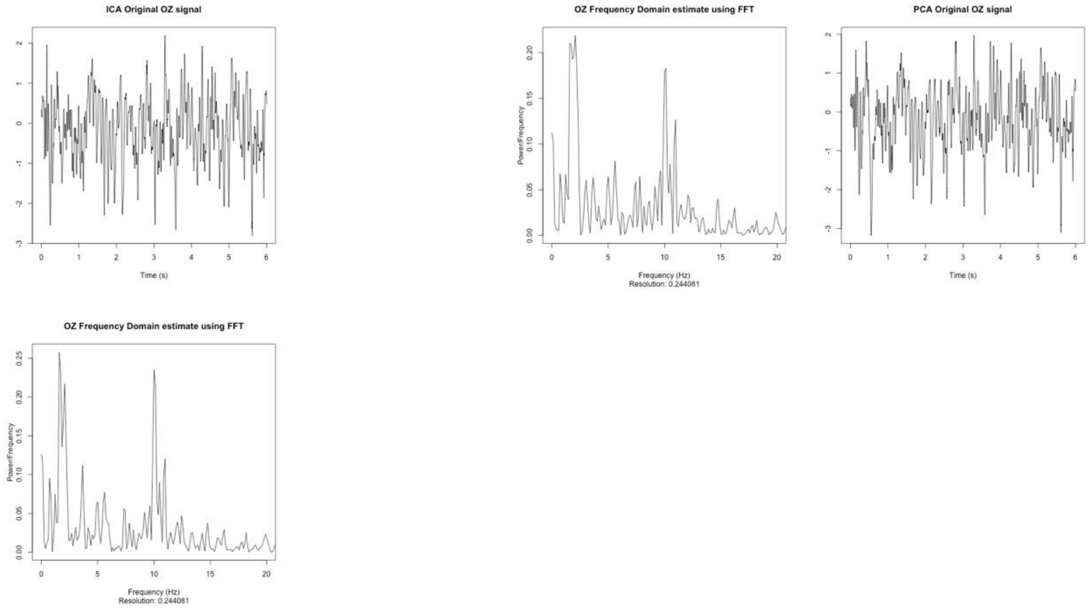


Figure 71 Show graph of time and frequency domain of ICA and PCA emotional valence. Max Power Frequency of ICA OZ = 0.2189855 and Max Power Frequency of PCA OZ = 0.2578516

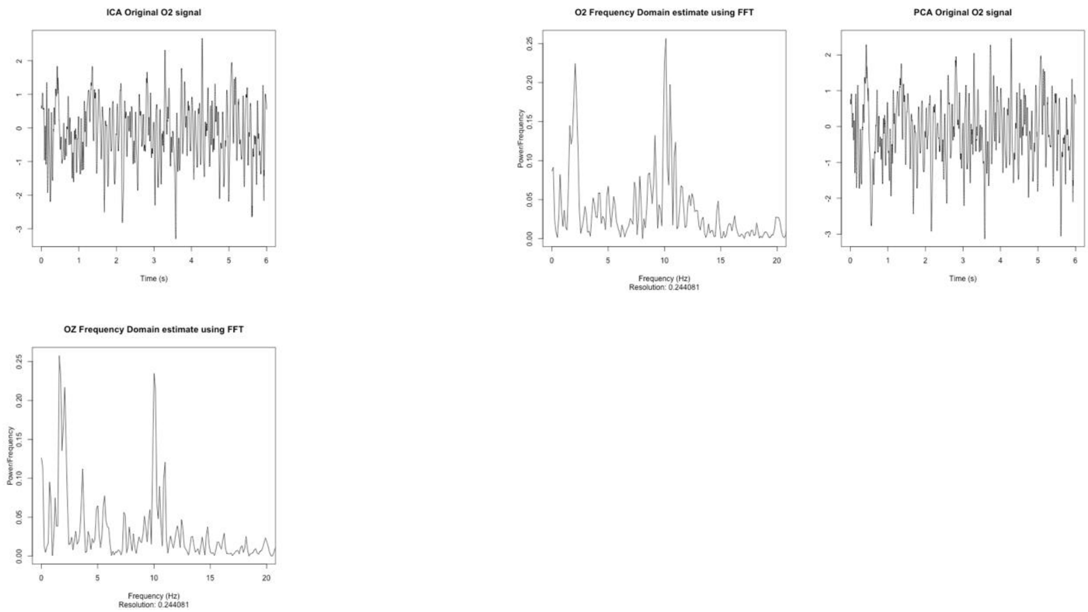


Figure 72 Show graph of time and frequency domain of ICA and PCA emotional valence. Max Power Frequency of ICA O2 = 0.2566512 and Max Power Frequency of PCA O2 = 0.3015992

Part 2 Emotional valence unsupervised machine learning results

2.1 After we transform emotional valenve EEG time domain data in to frequency domain data, we use K-mean unsupervised machine learning to classify negative and positive emotional valence of ICA pre-processing data of 7 brain surface regions as following Prefrontal cortex (FP1, FPZ, FP2), Dorsolateral prefrontal cortex (F3, F4, FZ), Ventrolateral prefrontal (F7, F8), Frontal cortex (FC5, FC1, FZ, CZ, FC2, FC6), Temporal cortex (T7, P7, T8, P8), Parietal cortex (C3, CP5, CP1, P3, PZ, CP2, C4, P4, CP6), Occipital cortex (O1, POZ, O2). and we get the clustering picture and result as shown in table 3

Table 3 K-Mean Algorithm ICA clustering results

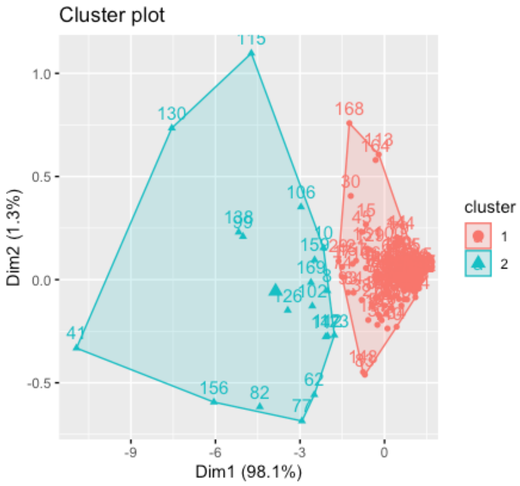
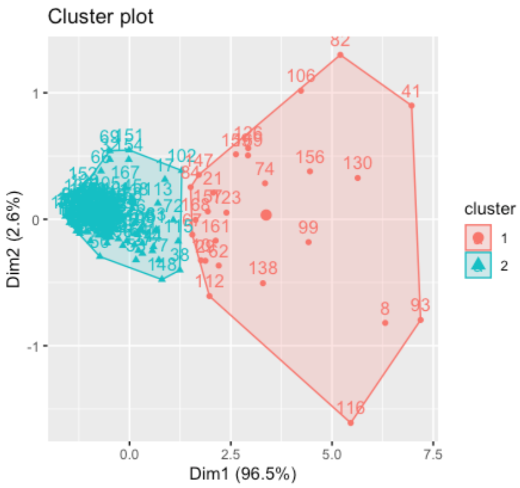
K-Mean Algorithm ICA	**Clustering results**
	Prefrontal cortex (FP1, FPZ, FP2) K-means clustering Within cluster sum of squares by cluster: (between_SS / total_SS = 63.0 %)
	Dorsolateral prefrontal cortex (F3, F4, FZ) K-means clustering Within cluster sum of squares by cluster: (between_SS / total_SS = 69.0 %)

Table 3 K-Mean Algorithm ICA clustering results

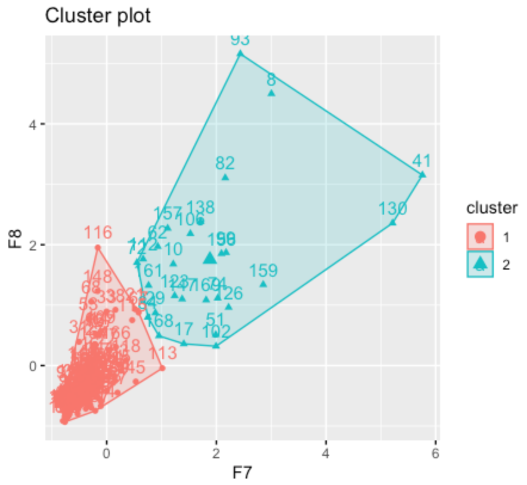
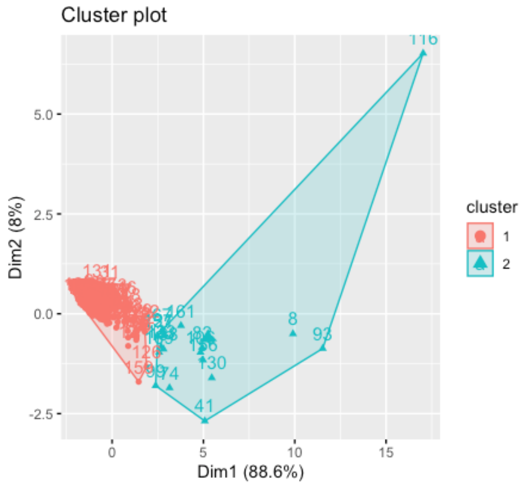
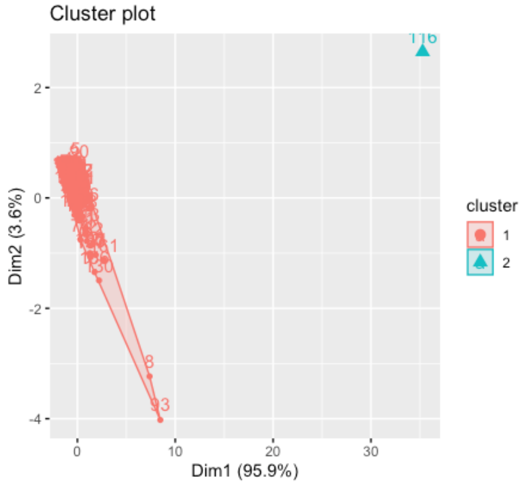
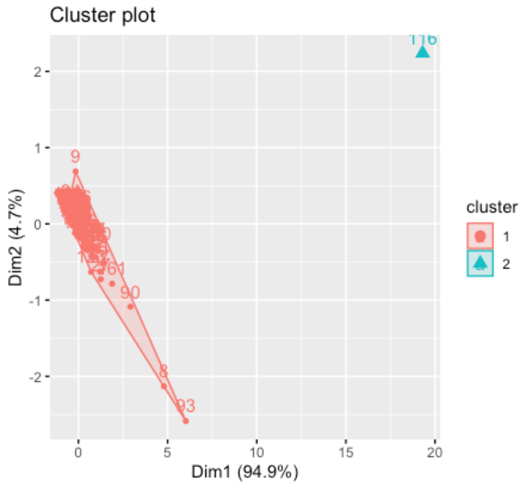
K-Mean Algorithm ICA	**Clustering results**
	Ventrolateral prefrontal (F7, F8) K-means clustering Within cluster sum of squares by cluster: (between_SS / total_SS = 64.5 %)
	Frontal cortex (FC5, FC1, FZ, CZ, FC2, FC6) K-means clustering Within cluster sum of squares by cluster: (between_SS / total_SS = 48.3 %)
	Temporal cortex (T7, P7, T8, P8) K-means clustering Within cluster sum of squares by cluster: (between_SS / total_SS = 66.5 %)

Table 3 K-Mean Algorithm ICA clustering results

K-Mean Algorithm ICA	Clustering results
	Parietal cortex (C3, CP5, CP1, P3, PZ, CP2, C4, P4, CP6) K-means clustering Within cluster sum of squares by cluster: (between_SS / total_SS = 91.1 %)
	Occipital cortex (O1, POZ, O2) K-means clustering Within cluster sum of squares by cluster: (between_SS / total_SS = 90.8 %)

2.2 After we transform emotional valenve EEG time domain data in to frequency domain data, we use K-mean unsupervised machine learning to classify negative and positive emotional valence of PCA pre-processing data of 7 brain surface regions as following Prefrontal cortex (FP1, FPZ, FP2), Dorsolateral prefrontal cortex (F3, F4, FZ), Ventrolateral prefrontal (F7, F8), Frontal cortex (FC5, FC1, FZ, CZ, FC2, FC6), Temporal cortex (T7, P7, T8, P8), Parietal cortex (C3, CP5, CP1, P3, PZ, CP2, C4, P4, CP6), Occipital cortex (O1, POZ, O2). and we get the clustering picture and result as shown in table 4

Table 4 K-Mean Algorithm PCA clustering results

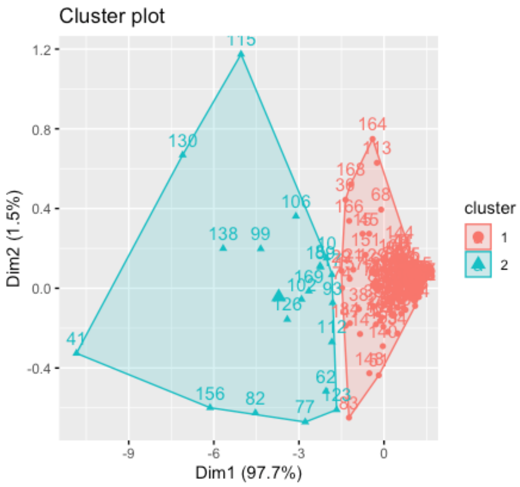
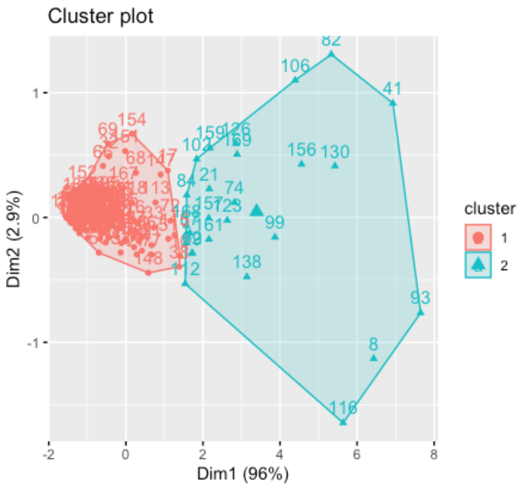
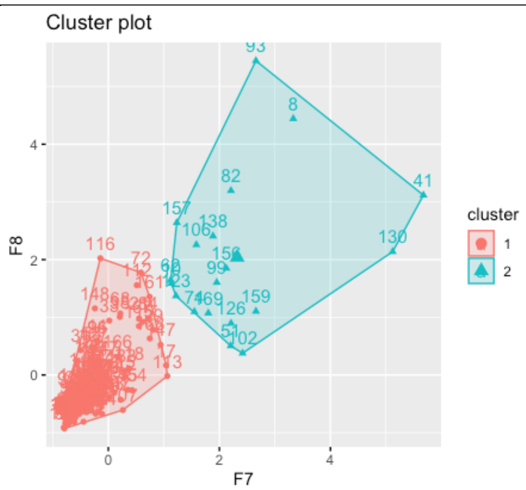
K-Mean Algorithm PCA	Clustering results
	Prefrontal cortex (FP1, FPZ, FP2) K-means clustering Within cluster sum of squares by cluster: (between_SS / total_SS = 61.5 %)
	Dorsolateral prefrontal cortex (F3, F4, FZ) K-means clustering Within cluster sum of squares by cluster: (between_SS / total_SS = 66.7 %)
	Ventrolateral prefrontal (F7, F8) K-means clustering Within cluster sum of squares by cluster: (between_SS / total_SS = 63.1 %)

Table 4 K-Mean Algorithm PCA clustering results

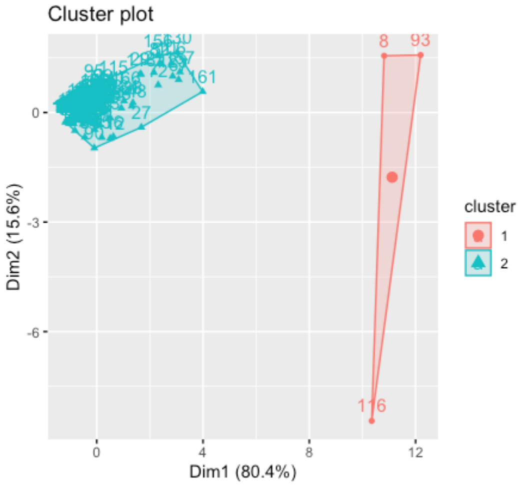
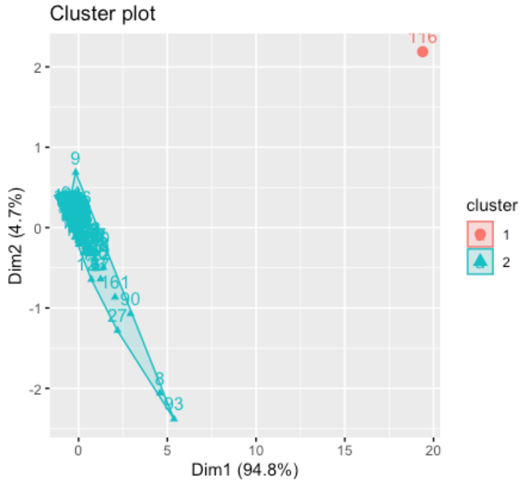
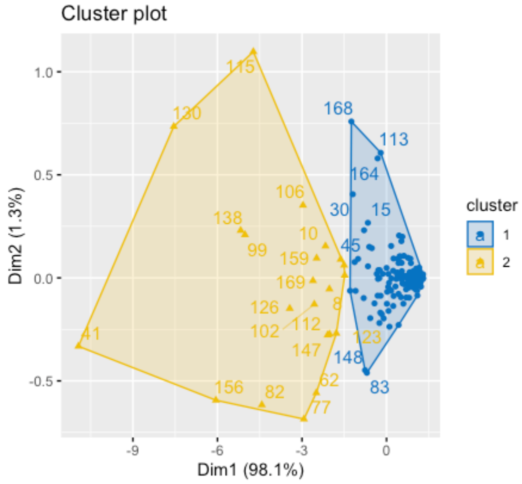
K-Mean Algorithm PCA	Clustering results
	Frontal cortex (FC5, FC1, FZ, CZ, FC2, FC6) K-means clustering Within cluster sum of squares by cluster: (between_SS / total_SS = 50.8 %)
	Temporal cortex (T7, P7, T8, P8) K-means clustering Within cluster sum of squares by cluster: (between_SS / total_SS = 63.4 %)
	Parietal cortex (C3, CP5, CP1, P3, PZ, CP2, C4, P4, CP6) K-means clustering Within cluster sum of squares by cluster: (between_SS / total_SS = 91.8 %)

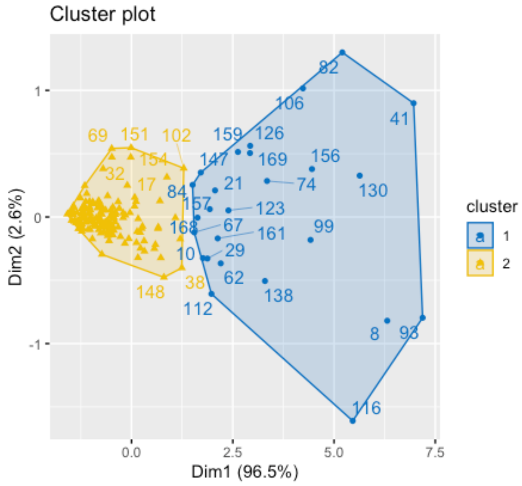
Table 4 K-Mean Algorithm PCA clustering results

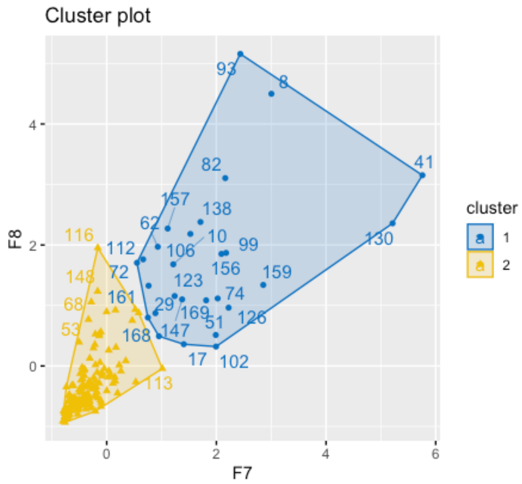
K-Mean Algorithm PCA	**Clustering results**
	Occipital cortex (O1, POZ, O2) K-means clustering Within cluster sum of squares by cluster: (between_SS / total_SS = 91.2 %)

2.3 After we transform emotional valenve EEG time domain data in to frequency domain data, we use Fuzzy C-mean unsupervised machine learning to classify negative and positive emotional valence of ICA pre-processing data of 7 brain surface regions as following Prefrontal cortex (FP1, FPZ, FP2), Dorsolateral prefrontal cortex (F3, F4, FZ), Ventrolateral prefrontal (F7, F8), Frontal cortex (FC5, FC1, FZ, CZ, FC2, FC6), Temporal cortex (T7, P7, T8, P8), Parietal cortex (C3, CP5, CP1, P3, PZ, CP2, C4, P4, CP6), Occipital cortex (O1, POZ, O2). and we get the clustering picture and result as shown in table 5

Table 5 Fuzzy C-Mean Algorithm ICA clustering results

<table>
<tr><th>Fuzzy C-Mean ICA Algorithm</th><th>Clustering results</th></tr>
<tr><td>
</td><td>Prefrontal cortex (FP1, FPZ, FP2)
Fuzzy C-means clustering

Within cluster sum of squares by cluster:
(between_SS / total_SS = 62.19%)</td></tr>
<tr><td>
</td><td>Dorsolateral prefrontal cortex (F3, F4, FZ)
Fuzzy C-means clustering

Within cluster sum of squares by cluster:
(between_SS / total_SS = 70.67%)</td></tr>
<tr><td>
</td><td>Ventrolateral prefrontal (F7, F8)
Fuzzy C-means clustering

Within cluster sum of squares by cluster:
(between_SS / total_SS = 63.68%)</td></tr>
</table>

Table 5 Fuzzy C-Mean Algorithm ICA clustering results

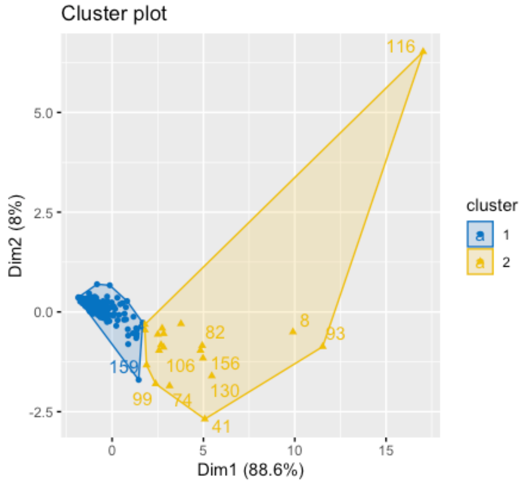
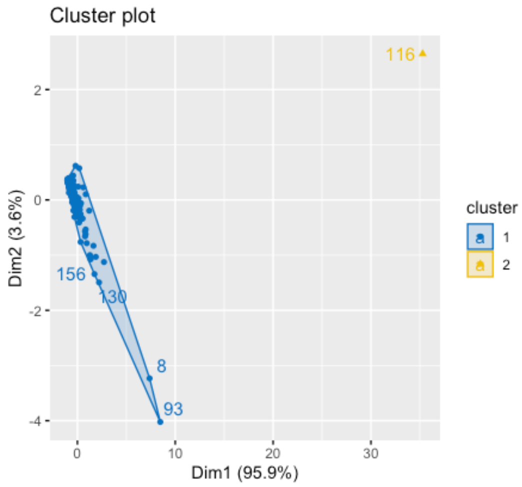
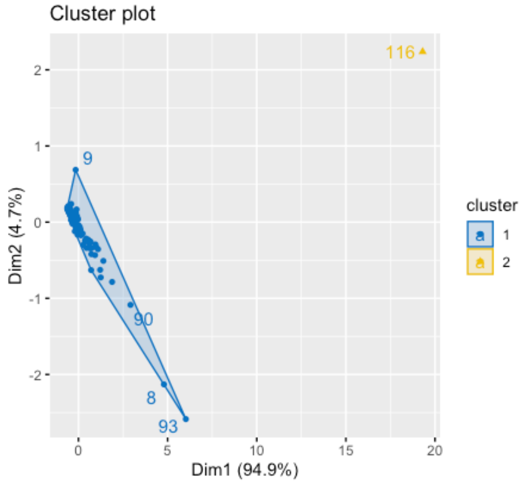
Fuzzy C-Mean ICA Algorithm	Clustering results
	Frontal cortex (FC5, FC1, FZ, CZ, FC2, FC6) Fuzzy C-means clustering Within cluster sum of squares by cluster: (between_SS / total_SS = 43.62%)
	Temporal cortex (T7, P7, T8, P8) Fuzzy C-means clustering Within cluster sum of squares by cluster: (between_SS / total_SS = 64.77%)
	Parietal cortex (C3, CP5, CP1, P3, PZ, CP2, C4, P4, CP6) Fuzzy C-means clustering Within cluster sum of squares by cluster: (between_SS / total_SS = 91.06%)

Table 5 Fuzzy C-Mean Algorithm ICA clustering results

Fuzzy C-Mean ICA Algorithm	**Clustering results**
	Occipital cortex (O1, POZ, O2) Fuzzy C-means clustering Within cluster sum of squares by cluster: (between_SS / total_SS = 90.77%)

2.4 After we transform emotional valenve EEG time domain data in to frequency domain data, we use Fuzzy C-mean unsupervised machine learning to classify negative and positive emotional valence of PCA pre-processing data of 7 brain surface regions as following Prefrontal cortex (FP1, FPZ, FP2), Dorsolateral prefrontal cortex (F3, F4, FZ), Ventrolateral prefrontal (F7, F8), Frontal cortex (FC5, FC1, FZ, CZ, FC2, FC6), Temporal cortex (T7, P7, T8, P8), Parietal cortex (C3, CP5, CP1, P3, PZ, CP2, C4, P4, CP6), Occipital cortex (O1, POZ, O2). and we get the clustering picture and result as shown in table 6

Table 6 Fuzzy C-Mean Algorithm PCA clustering results

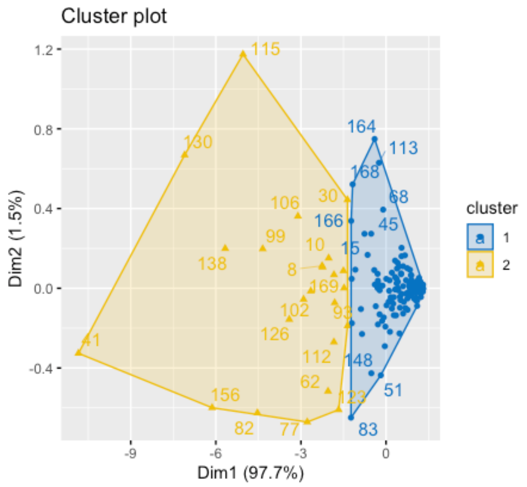
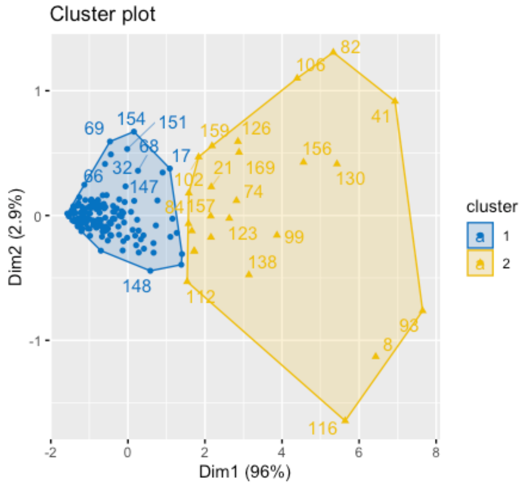
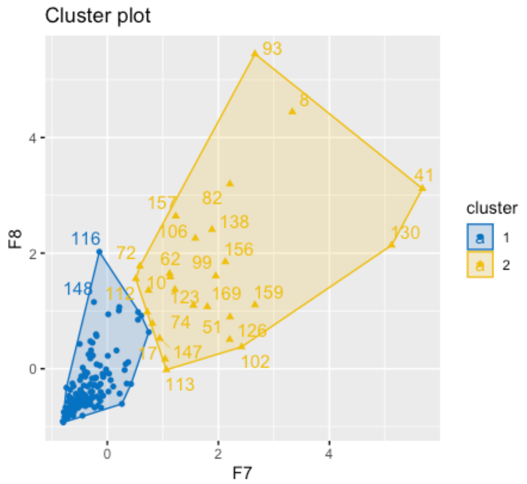
Fuzzy C-Mean PCA Algorithm	**Clustering results**
	Prefrontal cortex (FP1, FPZ, FP2) Fuzzy C-means clustering Within cluster sum of squares by cluster: (between_SS / total_SS = 61.1%)
	Dorsolateral prefrontal cortex (F3, F4, FZ) Fuzzy C-means clustering Within cluster sum of squares by cluster: (between_SS / total_SS = 67.61%)
	Ventrolateral prefrontal (F7, F8) Fuzzy C-means clustering Within cluster sum of squares by cluster: (between_SS / total_SS = 62.93%)

Table 6 Fuzzy C-Mean Algorithm PCA clustering results

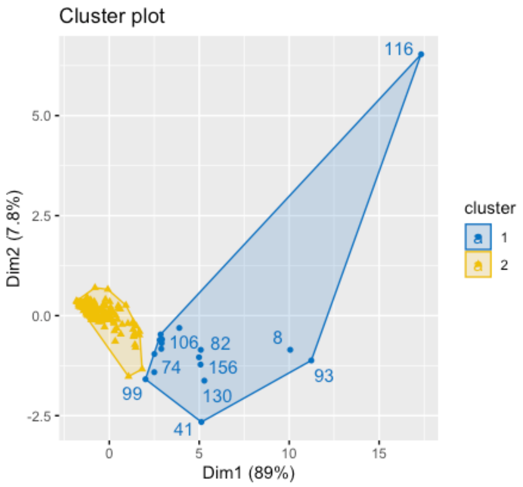
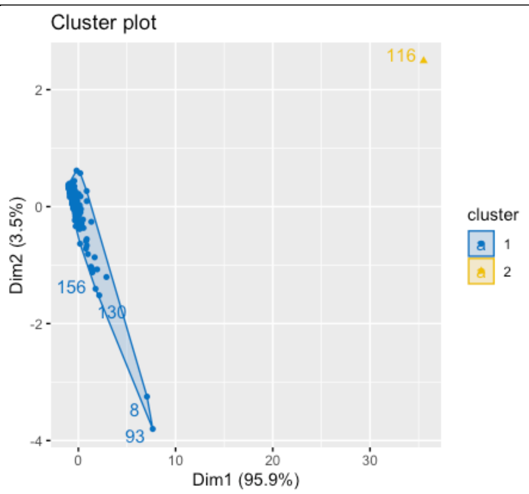
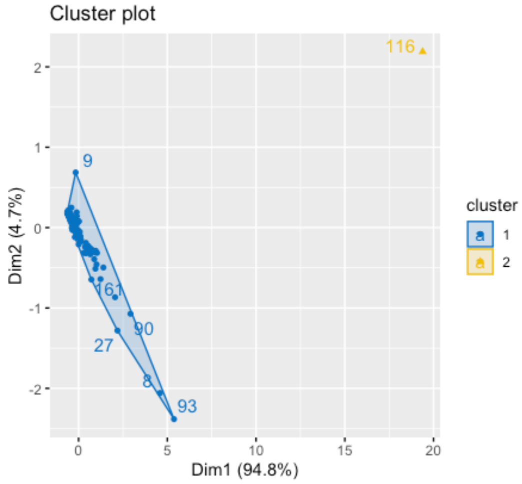
Fuzzy C-Mean PCA Algorithm	**Clustering results**
	Frontal cortex (FC5, FC1, FZ, CZ, FC2, FC6) Fuzzy C-means clustering Within cluster sum of squares by cluster: (between_SS / total_SS = 43.85%)
	Temporal cortex (T7, P7, T8, P8) Fuzzy C-means clustering Within cluster sum of squares by cluster: (between_SS / total_SS = 60.91%)
	Parietal cortex (C3, CP5, CP1, P3, PZ, CP2, C4, P4, CP6) Fuzzy C-means clustering Within cluster sum of squares by cluster: (between_SS / total_SS = 91.76%)

Table 6 Fuzzy C-Mean Algorithm PCA clustering results

Fuzzy C-Mean PCA Algorithm	**Clustering results**
	Occipital cortex (O1, POZ, O2) Fuzzy C-means clustering Within cluster sum of squares by cluster: (between_SS / total_SS = 91.14%)

Even though K-Mean Algorithm PCA of the Parietal cortex (C3, CP5, CP1, P3, PZ, CP2, C4, P4, CP6) clustering result is equal to 91.80 % is the highest percent clustering result but from the figure 4-3 to 4-6, we could conclude that Fuzzy C-Mean Algorithm ICA of the Dorsolateral prefrontal cortex (F3, F4, FZ) clustering result is equal to 70.67 % and Fuzzy C-Mean Algorithm PCA of the Dorsolateral prefrontal cortex (F3, F4, FZ) clustering result is equal to 67.61 % are the best clustering result.

Part 3 Emotional valence supervised machine learning results

After we finish unsupervised machine learning method, then we know that Dorsolateral prefrontal cortex is the best brain surface region for the emotional valence machine learning classification. Then we use the ICA of the Dorsolateral prefrontal cortex (F3, F4, FZ) and the PCA of the Dorsolateral prefrontal cortex (F3, F4, FZ) to run the 5 supervised machine learning.

3.1 K-Nearest Neighbors (kNN) of ICA of emotional valence of Dorsolateral prefrontal cortex (F3, F4, FZ) EEG data. The results are shown in figure 73 and 74.

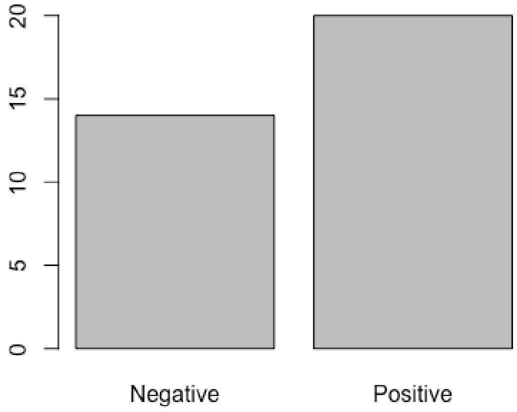


Figure 73 The K-Nearest Neighbors (kNN) of ICA of emotional valence of Dorsolateral prefrontal cortex (F3, F4, FZ) histogram chart

```
   Cell Contents
|-------------------------|
|                       N |
|           N / Row Total |
|           N / Col Total |
|         N / Table Total |
|-------------------------|


Total Observations in Table:  34


                              | p
ALLDATA_ICA_FZ34_test$Valence |  Negative |  Positive | Row Total |
------------------------------|-----------|-----------|-----------|
                     Negative |         2 |        13 |        15 |
                              |     0.133 |     0.867 |     0.441 |
                              |     0.667 |     0.419 |           |
                              |     0.059 |     0.382 |           |
------------------------------|-----------|-----------|-----------|
                     Positive |         1 |        18 |        19 |
                              |     0.053 |     0.947 |     0.559 |
                              |     0.333 |     0.581 |           |
                              |     0.029 |     0.529 |           |
------------------------------|-----------|-----------|-----------|
                 Column Total |         3 |        31 |        34 |
                              |     0.088 |     0.912 |           |
------------------------------|-----------|-----------|-----------|


> plot(pALLDATA_ICA_FZ34)
> mean(ALLDATA_ICA_FZ34_test[,4]==p)
[1] 0.5882353
>
```

Figure 74 The K-Nearest Neighbors (kNN) of ICA of emotional valence of Dorsolateral prefrontal cortex (F3, F4, FZ) has prediction accuracy = 58.82%

3.2 Random Forest (RF) of ICA of emotional valence of Dorsolateral prefrontal cortex (F3, F4, FZ) EEG data. The results are shown in figure 75.

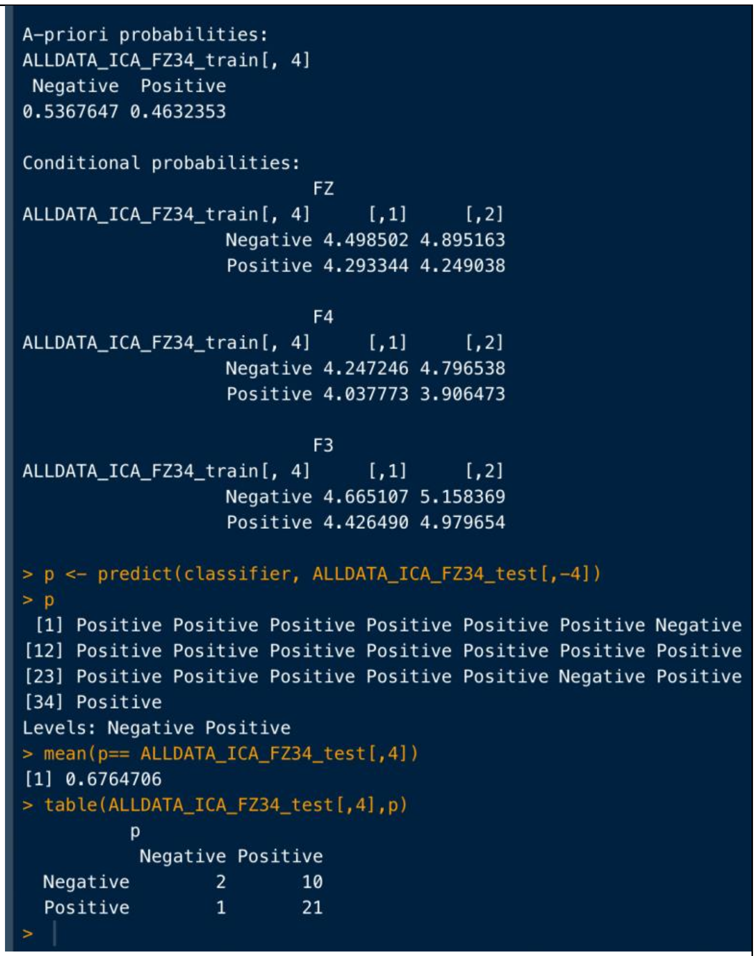
```
> rfm <- randomForest(Valence~.,ALLDATA_ICA_FZ34_train)
> p <- predict(rfm, ALLDATA_ICA_FZ34_test)
> table(ALLDATA_ICA_FZ34_test[,4],p)
          p
           Negative Positive
  Negative       10       10
  Positive        4       10
> mean(ALLDATA_ICA_FZ34_test[,4]==p)
[1] 0.5882353
> importance(rfm)
   MeanDecreaseGini
FZ         22.23768
F4         22.74149
F3         22.36557
> getTree(rfm,500,labelVar=TRUE)
```

Figure 75 Random Forest (RF) of ICA of emotional valence of Dorsolateral prefrontal cortex (F3, F4, FZ) EEG data has prediction accuracy = 58.82%

3.3 Naïve Bayes (NB) of ICA of emotional valence of Dorsolateral prefrontal cortex (F3, F4, FZ) EEG data. The results are shown in figure 76.

mean(p==
ALLDATA_ICA_FZ34
_test[,4])
0.6764706
table(ALLDATA_ICA_
FZ34_test[,4],p)

	Negative	Positive
Negative	2	10
Positive	1	21



```
A-priori probabilities:
ALLDATA_ICA_FZ34_train[, 4]
 Negative  Positive
0.5367647 0.4632353

Conditional probabilities:
                           FZ
ALLDATA_ICA_FZ34_train[, 4]     [,1]     [,2]
                   Negative 4.498502 4.895163
                   Positive 4.293344 4.249038

                           F4
ALLDATA_ICA_FZ34_train[, 4]     [,1]     [,2]
                   Negative 4.247246 4.796538
                   Positive 4.037773 3.906473

                           F3
ALLDATA_ICA_FZ34_train[, 4]     [,1]     [,2]
                   Negative 4.665107 5.158369
                   Positive 4.426490 4.979654

> p <- predict(classifier, ALLDATA_ICA_FZ34_test[,-4])
> p
 [1] Positive Positive Positive Positive Positive Positive Negative
[12] Positive Positive Positive Positive Positive Positive Positive
[23] Positive Positive Positive Positive Positive Negative Positive
[34] Positive
Levels: Negative Positive
> mean(p== ALLDATA_ICA_FZ34_test[,4])
[1] 0.6764706
> table(ALLDATA_ICA_FZ34_test[,4],p)
          p
           Negative Positive
  Negative        2       10
  Positive        1       21
>
```

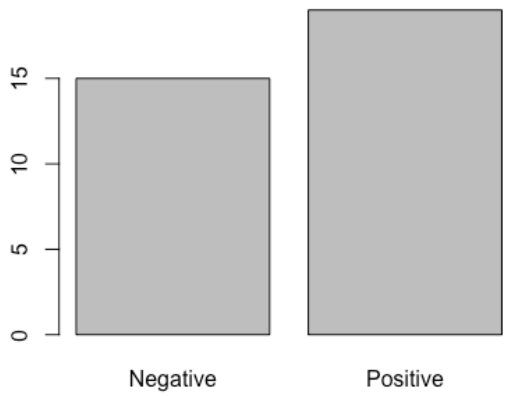
Figure 76 Naïve Bayes (NB) of ICA of emotional valence of Dorsolateral prefrontal cortex (F3, F4, FZ) EEG data has prediction accuracy = 67.64 %

3.4 Support Vector Machines (SVM) of ICA of emotional valence of Dorsolateral prefrontal cortex (F3, F4, FZ) EEG data. The results are shown in figure 77.

```
> mean(p== ALLDATA_ICA_FZ34_test[,4])
[1] 0.5882353
> table(ALLDATA_ICA_FZ34_test[,4],p)
          p
           Negative Positive
  Negative       10        8
  Positive        6       10
>
```


Figure 77 Support Vector Machines (SVM) of ICA of emotional valence of Dorsolateral prefrontal cortex (F3, F4, FZ) EEG data has prediction accuracy = 58.82%

3.5 Decision Tree (DT) of ICA of emotional valence of Dorsolateral prefrontal cortex (F3, F4, FZ) EEG data. The results are shown in figure 78.




```
> table(p, ALLDATA_ICA_FZ34_test[,4])

p           Negative Positive
  Negative        10        5
  Positive         8       11
> mean(p== ALLDATA_ICA_FZ34_test[,4])
[1] 0.6176471
>
```

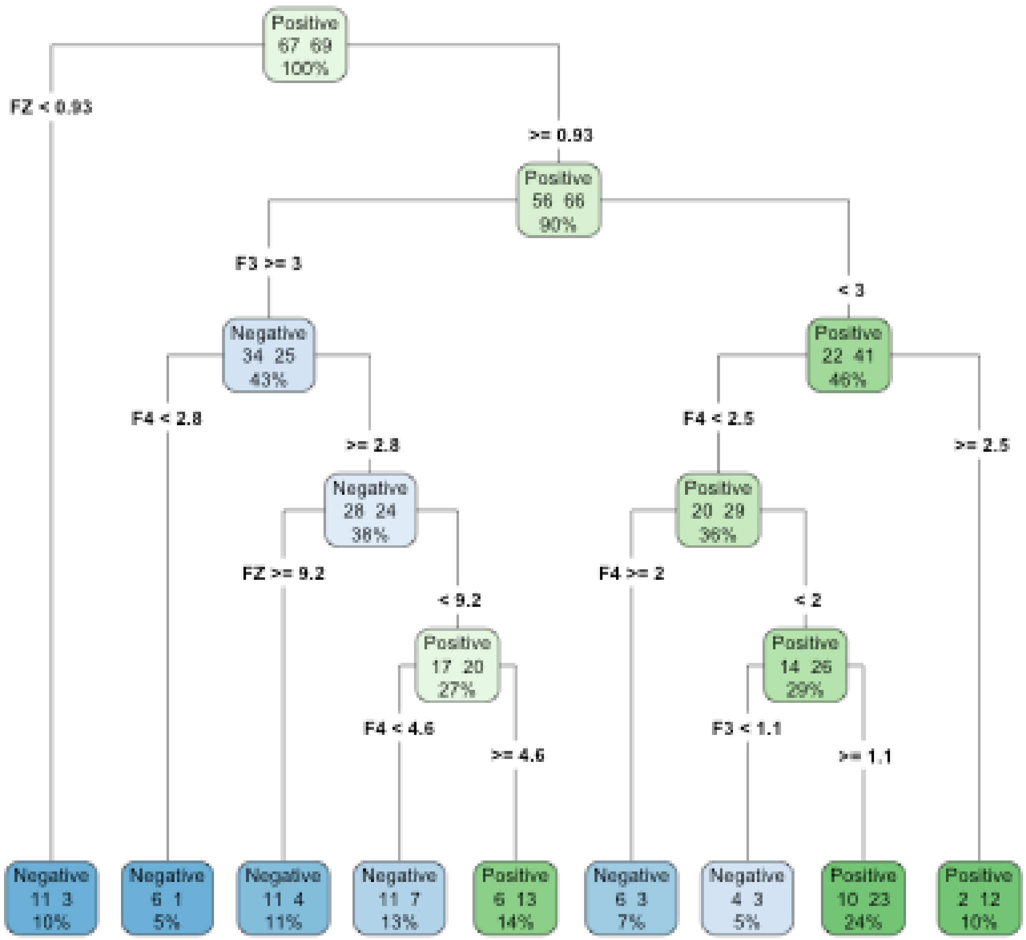


Figure 78 Decision Tree (DT) of ICA of emotional valence of Dorsolateral prefrontal cortex (F3, F4, FZ) EEG data has prediction accuracy = 61.76 %

3.6 K-Nearest Neighbors (kNN) of PCA of emotional valence of Dorsolateral prefrontal cortex (F3, F4, FZ) EEG data. The results are shown in figure 79 and 80.

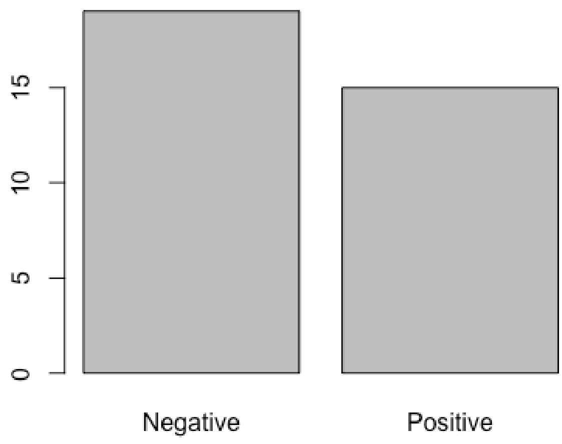


Figure 79 The K-Nearest Neighbors (kNN) of PCA of emotional valence of Dorsolateral prefrontal cortex (F3, F4, FZ) histogram chart

```
   Cell Contents
|-------------------------|
|                       N |
|           N / Row Total |
|           N / Col Total |
|         N / Table Total |
|-------------------------|


Total Observations in Table:  34


                             | p
ALLDATA_PCA_FZ34_test$Valence |  Negative |  Positive | Row Total |
-----------------------------|-----------|-----------|-----------|
                    Negative |         2 |        11 |        13 |
                             |     0.154 |     0.846 |     0.382 |
                             |     0.667 |     0.355 |           |
                             |     0.059 |     0.324 |           |
-----------------------------|-----------|-----------|-----------|
                    Positive |         1 |        20 |        21 |
                             |     0.048 |     0.952 |     0.618 |
                             |     0.333 |     0.645 |           |
                             |     0.029 |     0.588 |           |
-----------------------------|-----------|-----------|-----------|
                Column Total |         3 |        31 |        34 |
                             |     0.088 |     0.912 |           |
-----------------------------|-----------|-----------|-----------|


> plot(pALLDATA_PCA_FZ34)
> mean(ALLDATA_PCA_FZ34_test[,4]==p)
[1] 0.6470588
>
```

Figure 80 The K-Nearest Neighbors (kNN) of PCA of emotional valence of Dorsolateral prefrontal cortex (F3, F4, FZ) has prediction accuracy = 64.70 %

3.7 K Random Forest (RF) of PCA of emotional valence of Dorsolateral prefrontal cortex (F3, F4, FZ) EEG data. The results are shown in figure 81.

```
> rfm <- randomForest(Valence~.,ALLDATA_PCA_FZ34_train)
> p <- predict(rfm, ALLDATA_PCA_FZ34_test)
> table(ALLDATA_PCA_FZ34_test[,4],p)
          p
           Negative Positive
  Negative       10        9
  Positive        6        9
> mean(ALLDATA_PCA_FZ34_test[,4]==p)
[1] 0.5588235
> importance(rfm)
   MeanDecreaseGini
FZ         21.58895
F4         22.75844
F3         23.08503
> getTree(rfm,500,labelVar=TRUE)
```

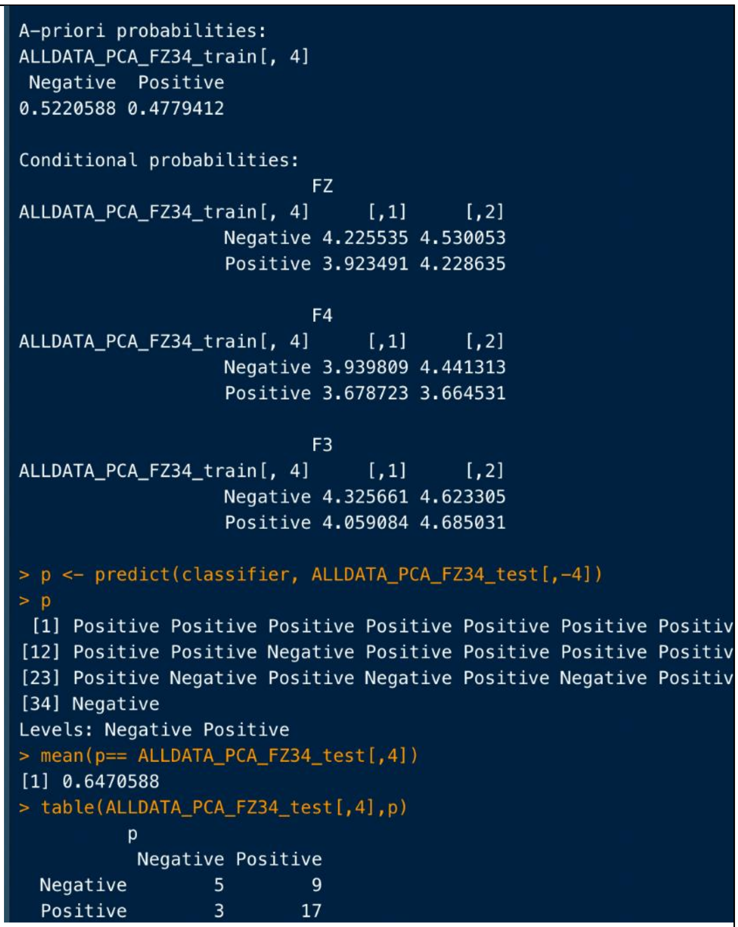
Figure 81 Random Forest (RF) of PCA of emotional valence of Dorsolateral prefrontal cortex (F3, F4, FZ) EEG data has prediction accuracy = 55.88 %

3.8 Naïve Bayes (NB) of PCA of emotional valence of Dorsolateral prefrontal cortex (F3, F4, FZ) EEG data. The results are shown in figure 82.

mean(p==ALLDATA_PCA_FZ34_test[,4])
0.6470588

table(ALLDATA_PCA_FZ34_test[,4],p)

	Negative	Positive
Negative	5	9
Positive	3	17



```
A-priori probabilities:
ALLDATA_PCA_FZ34_train[, 4]
 Negative  Positive
0.5220588 0.4779412

Conditional probabilities:
                           FZ
ALLDATA_PCA_FZ34_train[, 4]      [,1]      [,2]
                   Negative 4.225535 4.530053
                   Positive 3.923491 4.228635

                           F4
ALLDATA_PCA_FZ34_train[, 4]      [,1]      [,2]
                   Negative 3.939809 4.441313
                   Positive 3.678723 3.664531

                           F3
ALLDATA_PCA_FZ34_train[, 4]      [,1]      [,2]
                   Negative 4.325661 4.623305
                   Positive 4.059084 4.685031

> p <- predict(classifier, ALLDATA_PCA_FZ34_test[,-4])
> p
 [1] Positive Positive Positive Positive Positive Positive Positiv
[12] Positive Positive Negative Positive Positive Positive Positiv
[23] Positive Negative Positive Negative Positive Negative Positiv
[34] Negative
Levels: Negative Positive
> mean(p== ALLDATA_PCA_FZ34_test[,4])
[1] 0.6470588
> table(ALLDATA_PCA_FZ34_test[,4],p)
          p
           Negative Positive
  Negative        5        9
  Positive        3       17
```

Figure 82 Naïve Bayes (NB) of PCA of emotional valence of Dorsolateral prefrontal cortex (F3, F4, FZ) EEG data has prediction accuracy = 64.70 %

3.9 Support Vector Machines (SVM) of PCA of emotional valence of Dorsolateral prefrontal cortex (F3, F4, FZ) EEG data. The results are shown in figure 83.

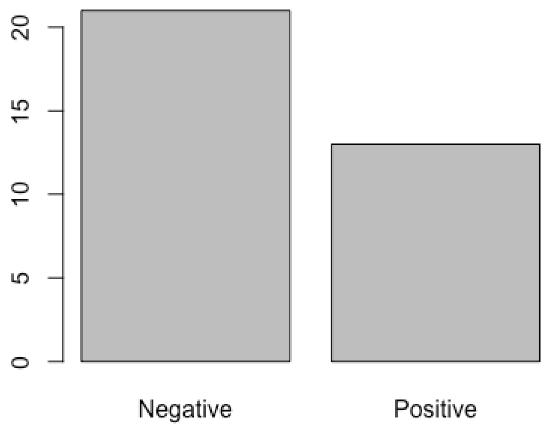
```
> mean(p== ALLDATA_PCA_FZ34_test[,4])
[1] 0.5588235
> table(ALLDATA_PCA_FZ34_test[,4],p)
          p
           Negative Positive
  Negative        8        7
  Positive        8       11
>
```

Figure 83 Support Vector Machines (SVM) of PCA of emotional valence of Dorsolateral prefrontal cortex (F3, F4, FZ) EEG data has prediction accuracy = 55.88 %

3.10 Decision Tree (DT) of PCA of emotional valence of Dorsolateral prefrontal cortex (F3, F4, FZ) EEG data. The results are shown in figure 84.

```
> table(p, ALLDATA_PCA_FZ34_test[,4])

p          Negative Positive
  Negative       14        7
  Positive        6        7
> mean(p== ALLDATA_PCA_FZ34_test[,4])
[1] 0.6176471
>
```



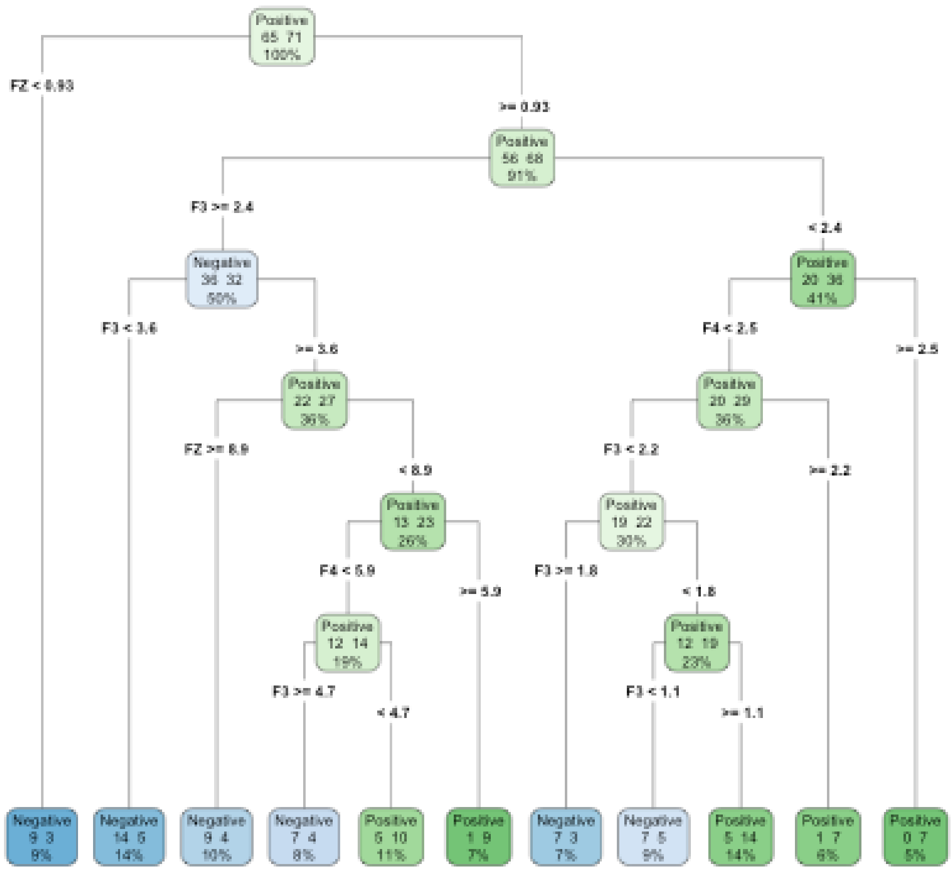


Figure 84 Decision Tree (DT) of PCA of emotional valence of Dorsolateral prefrontal cortex (F3, F4, FZ) EEG data has prediction accuracy = 61.76 %

In summary for the supervised machine learning, we could see the result of 5 methods as following.

1) The K-Nearest Neighbors (kNN) of ICA of emotional valence of Dorsolateral prefrontal cortex (F3, F4, FZ) has prediction accuracy = 58.82%.

2) The Random Forest (RF) of ICA of emotional valence of Dorsolateral prefrontal cortex (F3, F4, FZ) EEG data has prediction accuracy = 58.82%.

3) The Naïve Bayes (NB) of ICA of emotional valence of Dorsolateral prefrontal cortex (F3, F4, FZ) EEG data has prediction accuracy = 67.64 %.

4) The Support Vector Machines (SVM) of ICA of emotional valence of Dorsolateral prefrontal cortex (F3, F4, FZ) EEG data has prediction accuracy = 58.82%.

5) The Decision Tree (DT) of ICA of emotional valence of Dorsolateral prefrontal cortex (F3, F4, FZ) EEG data has prediction accuracy = 61.76 % as shown in figure 85.

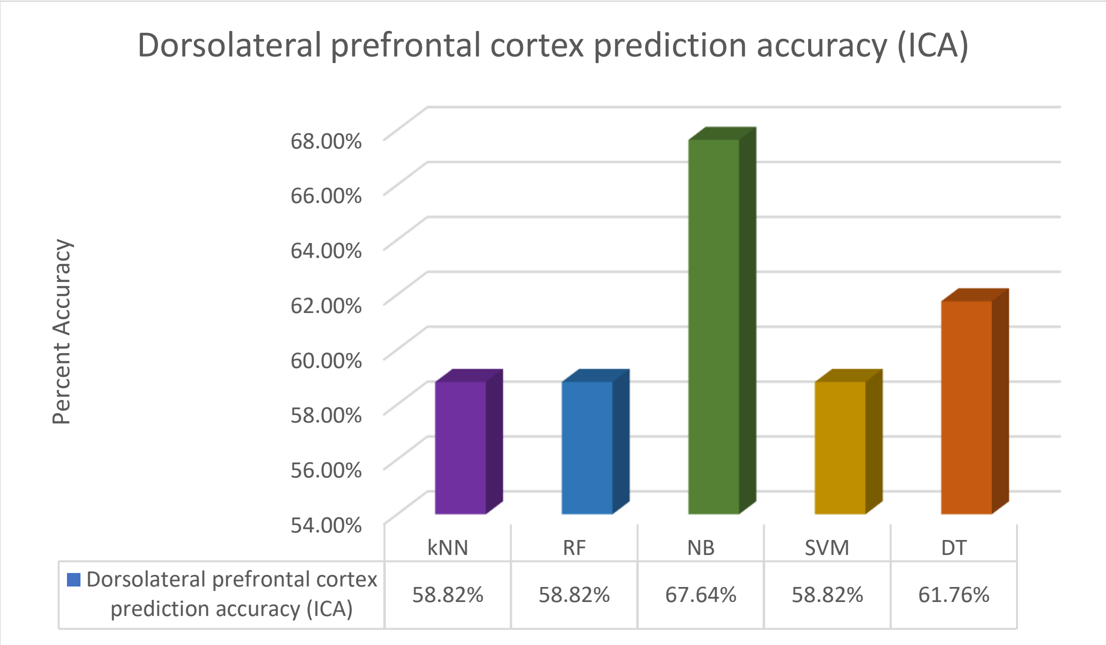


Figure 85 Dorsolateral prefrontal cortex supervised machine learning prediction accuracy (ICA)

In summary for the supervised machine learning.

1) The K-Nearest Neighbors (kNN) of PCA of emotional valence of Dorsolateral prefrontal cortex (F3, F4, FZ) has prediction accuracy = 64.70 %.

2) The Random Forest (RF) of PCA of emotional valence of Dorsolateral prefrontal cortex (F3, F4, FZ) EEG data has prediction accuracy = 55.88 %.

3) The Naïve Bayes (NB) of PCA of emotional valence of Dorsolateral prefrontal cortex (F3, F4, FZ) EEG data has prediction accuracy = 64.70 %.

4) The Support Vector Machines (SVM) of PCA of emotional valence of Dorsolateral prefrontal cortex (F3, F4, FZ) EEG data has prediction accuracy = 55.88 %.

5) The Decision Tree (DT) of PCA of emotional valence of Dorsolateral prefrontal cortex (F3, F4, FZ) EEG data has prediction accuracy = 61.76 % as shown in figure 86.

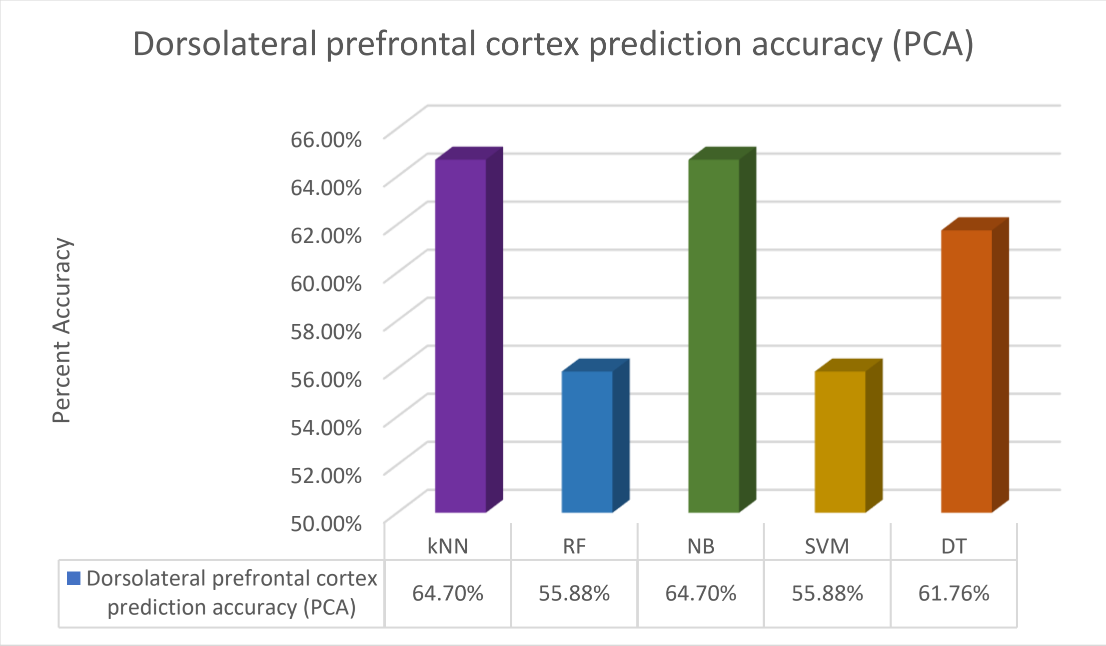


Figure 86 Dorsolateral prefrontal cortex supervised machine learning prediction accuracy (PCA)

The maximum prediction accuracy supervised machine learning method is The Naïve Bayes (NB) of ICA of emotional valence of Dorsolateral prefrontal cortex (F3, F4, FZ) EEG data has prediction accuracy = 67.64 %.

Part 4 The Brain regions influence emotional valence machine learning

4.1 For the unsupervised machine learning, we could see the result of 2 methods as following. K-Mean Algorithm ICA of the Prefrontal cortex (FP1, FPZ, FP2) clustering result is equal to 63.00%. K-Mean Algorithm ICA of the Dorsolateral prefrontal cortex (F3, F4, FZ) clustering result is equal to 69.00 %. K-Mean Algorithm ICA of the Ventrolateral prefrontal (F7, F8) clustering result is equal to 64.50 %. K-Mean Algorithm ICA of the Frontal cortex (FC5, FC1, FZ, CZ, FC2, FC6) clustering result is equal to 48.30 %. K-Mean Algorithm ICA of the Temporal cortex (T7, P7, T8, P8) clustering result is equal to 66.50 %. K-Mean Algorithm ICA of the Parietal cortex (C3, CP5, CP1, P3, PZ, CP2, C4, P4, CP6) clustering result is equal to 91.10 %. K-Mean Algorithm ICA of the Occipital cortex (O1, POZ, O2) clustering result is equal to 90.80 % as shown in figure 87.

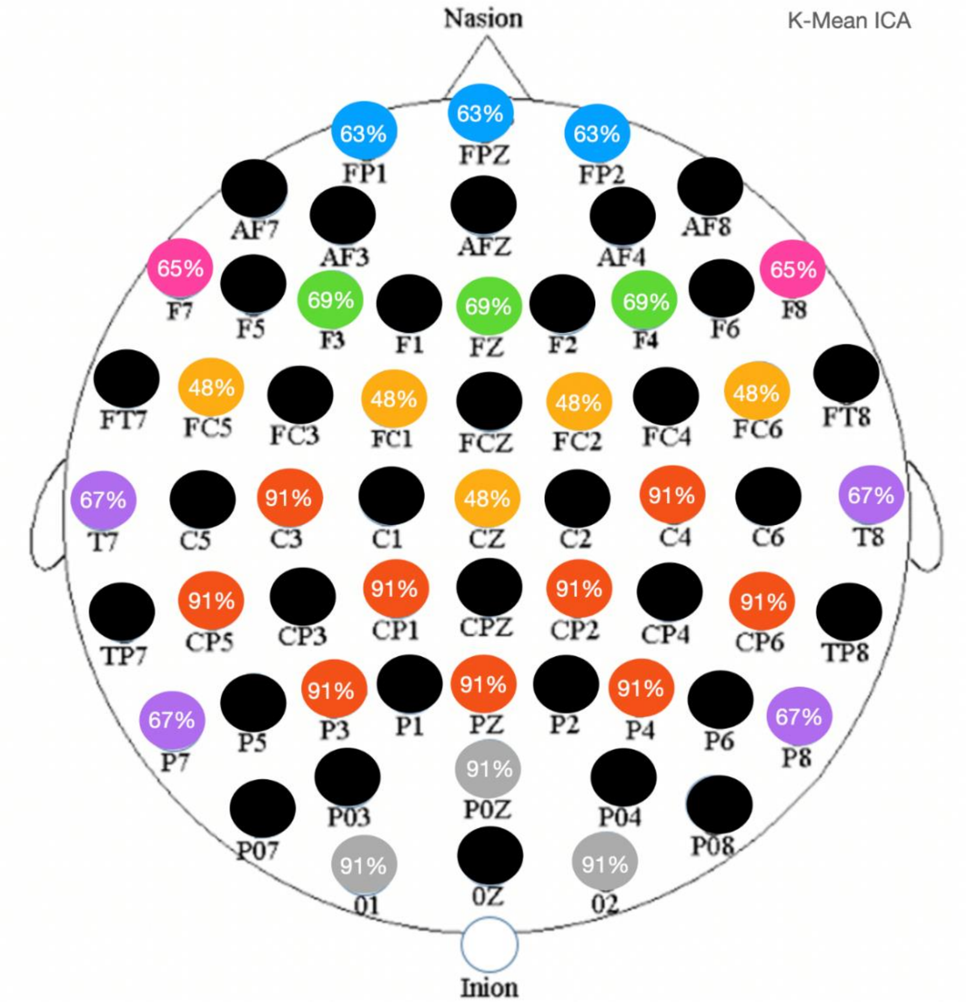


Figure 87 K-Mean ICA clustering results on brain regions

4.2 K-Mean Algorithm PCA of the Prefrontal cortex (FP1, FPZ, FP2) clustering result is equal to 61.50 %. K-Mean Algorithm PCA of the Dorsolateral prefrontal cortex (F3, F4, FZ) clustering result is equal to 66.70 %. K-Mean Algorithm PCA of the Ventrolateral prefrontal (F7, F8) clustering result is equal to 63.10 %. K-Mean Algorithm PCA of the Frontal cortex (FC5, FC1, FZ, CZ, FC2, FC6) clustering result is equal to 50.80 %. K-Mean Algorithm PCA of the Temporal cortex (T7, P7, T8, P8) clustering result is equal to 63.40 %. K-Mean Algorithm PCA of the Parietal cortex (C3, CP5, CP1, P3, PZ, CP2, C4, P4, CP6) clustering result is equal to 91.80 %. K-Mean Algorithm PCA of the Occipital cortex (O1, POZ, O2). clustering result is equal to 91.20 % as shown in figure 88.

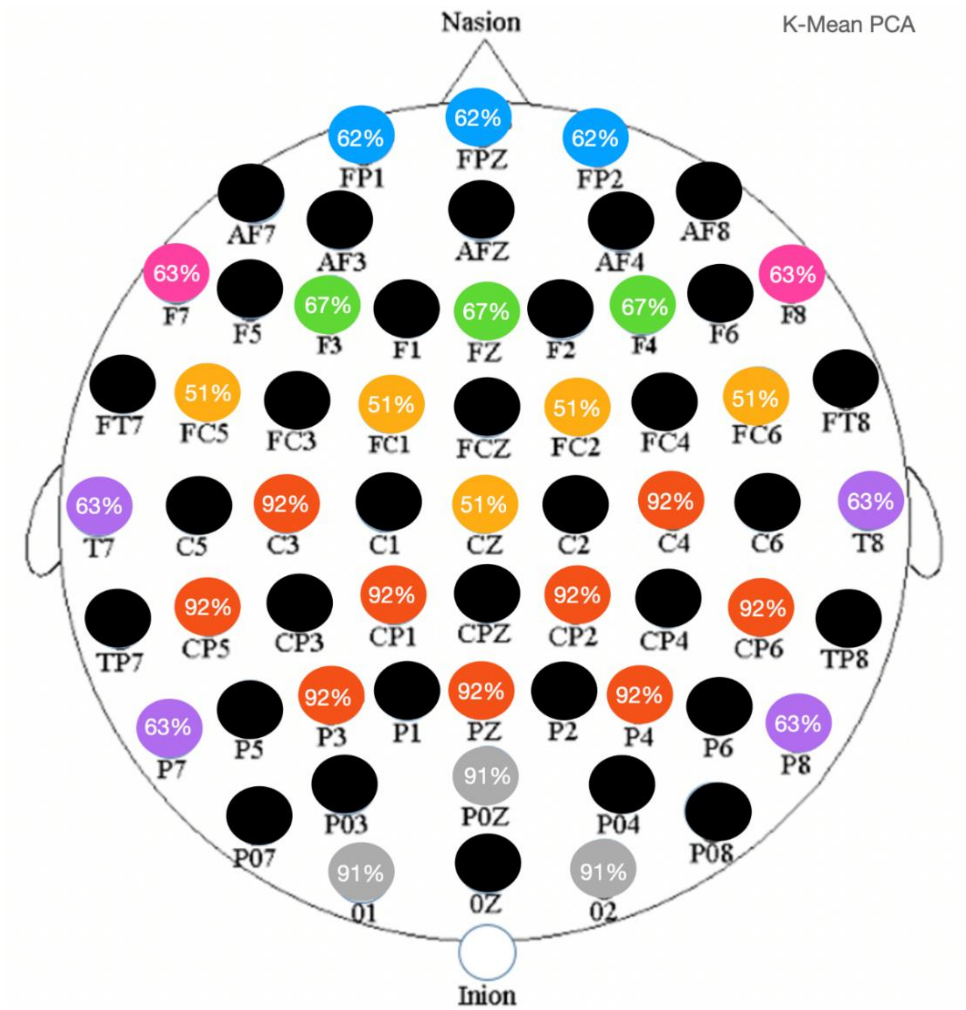


Figure 88 K-Mean PCA clustering results on brain regions

4.3 Fuzzy C-Mean Algorithm ICA of the Prefrontal cortex (FP1, FPZ, FP2) clustering result is equal to 62.19 %. Fuzzy C-Mean Algorithm ICA of the Dorsolateral prefrontal cortex (F3, F4, FZ) clustering result is equal to 70.67 %. Fuzzy C-Mean Algorithm ICA of the Ventrolateral prefrontal (F7, F8) clustering result is equal to 63.68 %. Fuzzy C-Mean Algorithm ICA of the Frontal cortex (FC5, FC1, FZ, CZ, FC2, FC6) clustering result is equal to 43.62 %. Fuzzy C-Mean Algorithm ICA of the

Temporal cortex (T7, P7, T8, P8) clustering result is equal to 64.77 %. Fuzzy C-Mean Algorithm ICA of the Parietal cortex (C3, CP5, CP1, P3, PZ, CP2, C4, P4, CP6) clustering result is equal to 91.06 %. Fuzzy C-Mean Algorithm ICA of the Occipital cortex (O1, POZ, O2) clustering result is equal to 90.77 % as shown in figure 89.

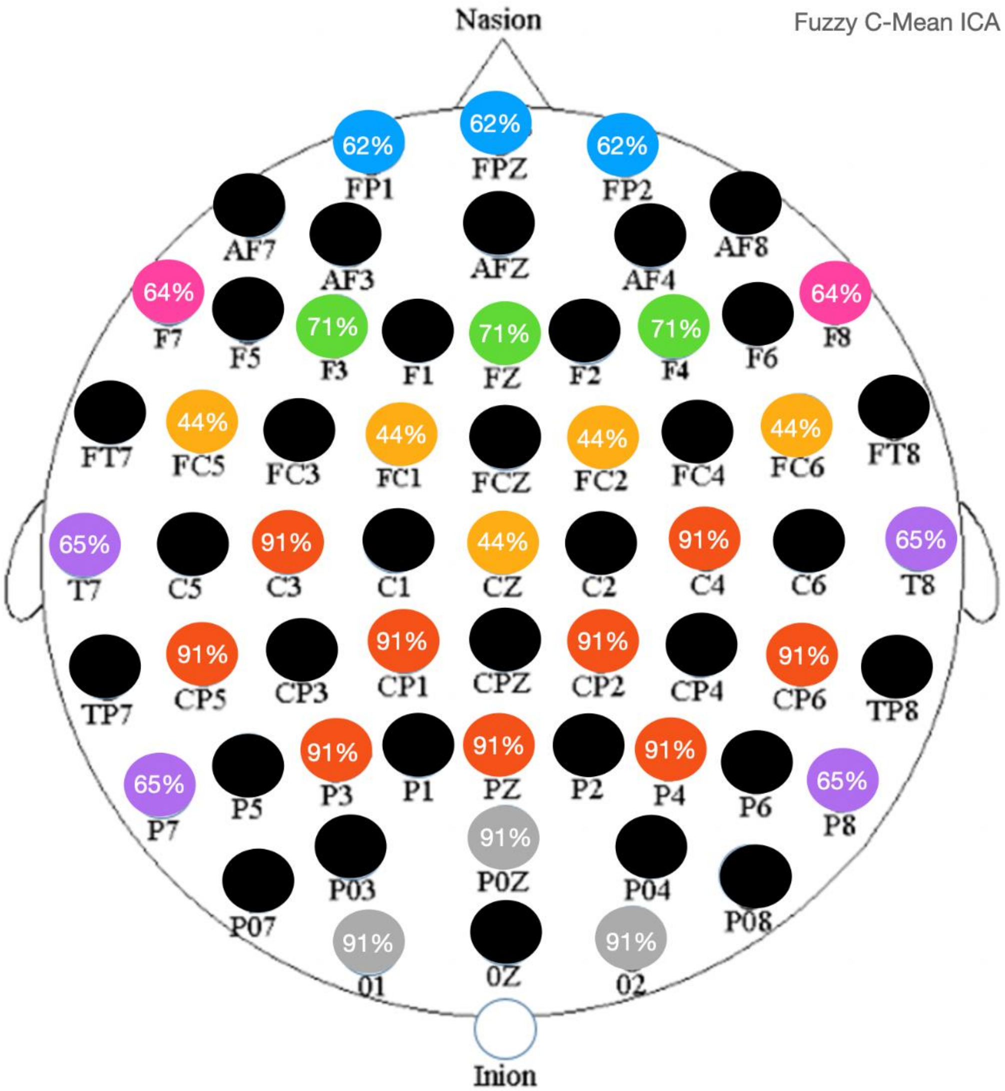


Figure 89 Fuzzy C-Mean ICA clustering results on brain regions

4.4 Fuzzy C-Mean Algorithm PCA of the Prefrontal cortex (FP1, FPZ, FP2) clustering result is equal to 61.10 %. Fuzzy C-Mean Algorithm PCA of the Dorsolateral prefrontal cortex (F3, F4, FZ) clustering result is equal to 67.61 %. Fuzzy C-Mean Algorithm PCA of the Ventrolateral prefrontal (F7, F8) clustering result is equal to

62.93 %. Fuzzy C-Mean Algorithm PCA of the Frontal cortex (FC5, FC1, FZ, CZ, FC2, FC6) clustering result is equal to 43.85 %. Fuzzy C-Mean Algorithm PCA of the Temporal cortex (T7, P7, T8, P8) clustering result is equal to 60.91 %. Fuzzy C-Mean Algorithm PCA of the Parietal cortex (C3, CP5, CP1, P3, PZ, CP2, C4, P4, CP6) clustering result is equal to 91.76 %. Fuzzy C-Mean Algorithm PCA of the Occipital cortex (O1, POZ, O2) clustering result is equal to 91.14 % as shown in figure 90.

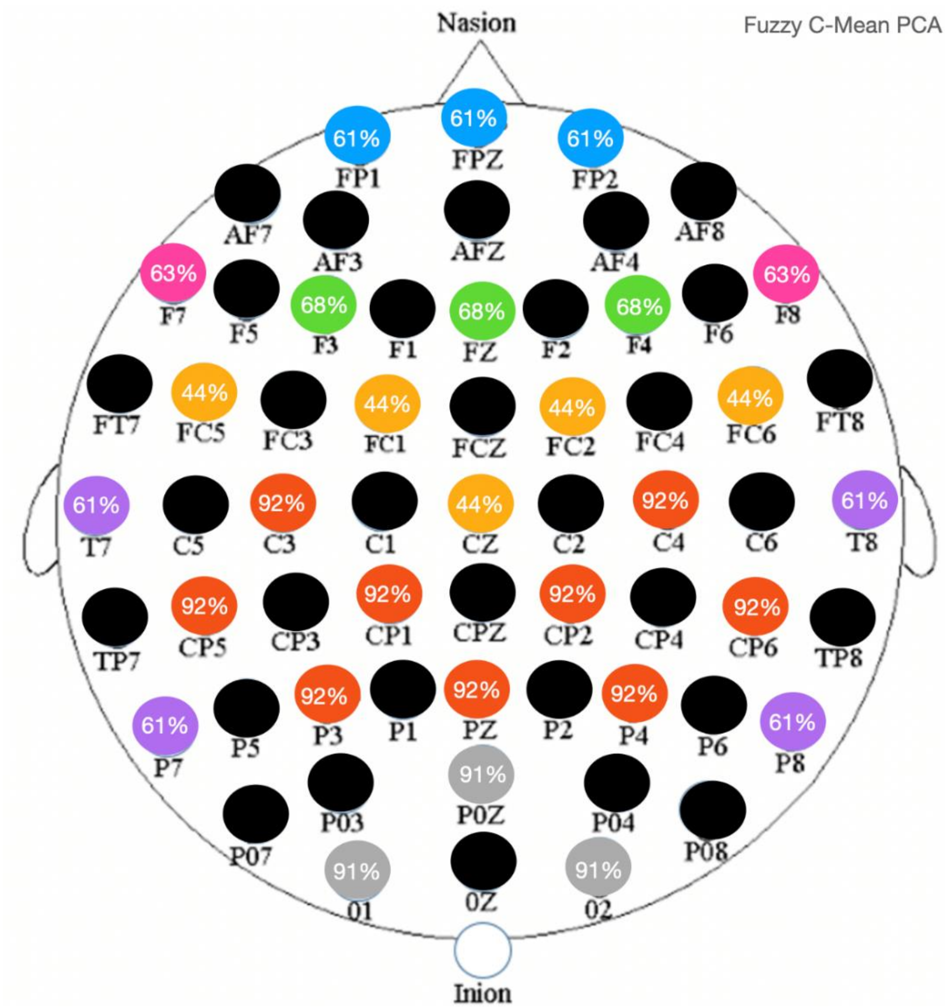


Figure 90 Fuzzy C-Mean PCA clustering results on brain regions

Even though K-Mean Algorithm PCA of the Parietal cortex (C3, CP5, CP1, P3, PZ, CP2, C4, P4, CP6) clustering result is equal to 91.80 % is the highest percent clustering result but from the figure 4-3 to 4-6, we could conclude that Fuzzy C-Mean Algorithm ICA of the Dorsolateral prefrontal cortex (F3, F4, FZ) clustering result is equal to 70.67 % and Fuzzy C-Mean Algorithm PCA of the Dorsolateral prefrontal cortex (F3, F4, FZ) clustering result is equal to 67.61 % are the best clustering result.

CHAPTER 5
DISCUSSION AND CONCLUSION

This chapter presents the interpretations of the main findings. Also, the limitations and suggestions for further studies are delineated. Finally, the conclusion of the current study is incorporated. The three main parts of this chapter are shown as follows:

Part 1 Discussion and cross-validation

Part 2 Limitations and suggestions for future research

Part 3 Conclusion

Part 1 Discussion and cross-validation

On the basis of our review of many published articles, various supervised machine learning has been widely applied in various tasks. Several metrics can affect the performance of classifiers, including different data sets, preprocessing techniques, and feature extraction methods. We presented an overview of feature extraction methods as part of our findings. We also introduced the publicly available R algorithms databases that have frequently been used for each task, and we directly analyzed the classification performance reported in relevant studies.

ICA is more powerful than PCA when using for emotional valence machine learning process, data-driven approach that has been used successfully to analyze simultaneous EEG frequency domain data.

	Advantages	Disadvantages
ICA	Computationally efficient High performance for ***large sizes data*** Decomposes signals into temporal independent.	Requires more computations for decomposition
PCA	A powerful tool for analyzing and for ***reducing*** the dimensionality of data	Assumes data linear and continuous.For complicated manifold PCA fails to process data

ICA is a powerful, data-driven approach that has been used successfully to analyze simultaneous EEG, and ERP data. It has been demonstrated time and again that integrations of the two modalities can be achieved at the source (statistical) level, as envisioned by the ICA. The overview provided here demonstrates the utility and diversity of the different existing approaches based on ICA for the analysis of brain imaging data. Multimodal integration via ICA is still under development.

Fuzzy C-Mean Clustering was smoother and better clustering than K-Mean clustering in all complex datasets containing the clusters dispersing in regular or irregular patterns.

Fuzzy C-Mean is an algorithm based on more iterative fuzzy calculations, so its performance was found to be comparatively higher than expected. Similar results have been reported by Panda et al. (2012) for the Iris, Wine and Lens datasets; by Jipkate and Gohokar (2012) for image segmentation; by Sivarathri and Govardhan (2014) for data on diabetes; and by Madhukumar and Santhiyakumari (2015) for brain MRI image data.

K-Mean Clustering seem to be faster than Fuzzy C-Mean clustering in most datasets containing the clusters dispersing in regular or irregular patterns. However, for the dorsolateral prefrontal cortex machine learning, Fuzzy C-Mean performs the better result. Fuzzy C-Mean is an algorithm based on more iterative fuzzy calculations, so its performance was found to be comparatively higher than expected. Similar results have been reported by Panda et al. (2012) for the Iris, Wine and Lens datasets; by Jipkate and Gohokar (2012) for image segmentation; by Ghosh and Dubey (2013) for the Iris dataset; by Bora and Gupta (2014) for the Iris dataset; by Sivarathri and Govardhan (2014) for data on diabetes; and by Madhukumar and Santhiyakumari (2015) for brain MRI image data.

One of the first things you learn about in applying machine learning is the importance of cross-validation: evaluating the performance of your model on a portion of your dataset separate from what you used to train your model. One way of doing this, is to holdout parts of the dataset when training your model, and estimate performance of the trained model using e.g the following approach: Fast Fourier transformation, ICA pre-processing, Fuzzy C-mean clustering and The Naïve Bayes supervised machine learning which use 70% of dataset for training and 30% for prediction.

The maximum prediction accuracy supervised machine learning method is The Naïve Bayes (NB) of ICA of emotional valence of Dorsolateral prefrontal cortex (F3, F4, FZ) EEG data has prediction accuracy = 67.64 %. Mustafa Sameer (2021) ROC Analysis of EEG Subbands for Epileptic Seizure Detection using Naïve Bayes Classifier the Naïve Bayes (NB) classifier has been used for performance evaluation of classifier. Among all subbands, gamma band alone shows a maximum AUC of 0.98 to classify between ictal and healthy class, while beta band shows a maximum AUC of 0.96 to differentiate between ictal and interictal class. Significance of this work is it shows the medical advantage of different subbands for the detection process. Noted, Mustafa's research predicted between normal people and epileptic seizure, so the percent accuracy would be high.

Cross-validation improves on this by letting you do this multiple times so you can see whether the test performance varies based on which samples you used to train / test. Although the results from this example case are actually very impressive when it comes to predicting emotional states from EEG recordings, there is still some way to go when it comes to more advanced applications. Also, the limited sample size of only two subjects during the experimental recordings raises the question of generalization to new individuals. Still, as an example case showing very promising results, it represents a good starting point for further investigations consistent with the concepts and theories the use of EEG Data for the Classification of Mental State the EEG is one of the most useful tools in clinical neurophysiology. EEGs are voltage measurements of the scalp, representing the sum of synchronous postsynaptic potentials arising from broad cerebral cortical areas and can be used for the identification of cerebral injuries or disorders (Epstein 2012). Research also shows that EEG data can be used to recognize other more subtle mental states. Although a vast variety of applications are described, the literature does not involve signal analysis of EEG data is correctly used to measure attentiveness to short training videos. Nevertheless, the full cross-sections of published applications that have been researched have laid the foundation for the current research to be successful through refinement of the signal processing and pattern recognition techniques.

Beside valence, the alertness or vigilance alertness and vigilance mental states are well studied about EEG data correlation. The published research of (MacLean, Arnell, & Cote 2012) shows how EEG data from participants who are resting can later be used to predict how well they can perform during fast-paced target identification using "attentional blink" measures. (Goldfine et al., 2011) Demonstrated that EEG analysis can reveal awareness in brain-injured patients who are otherwise unable to communicate, but who are asked to imagine motor and spatial navigation tasks mentally. There has been researching on using EEG to detect when someone is no longer alert enough to safely operate a vehicle or maintain display vigilance (Wilson & Bracewell 2002). Another example (Jung et al., 1997) used EEG data to predict alertness as measured by lapses in auditory and visual sonar detection by trained Navy participants. Human experts can also look at features extracted from EEG data and tell if the participant is alert versus asleep or valence, as in the case of (Subasi et al., 2005) where trained neurologists looked at the EEG recordings, and then picked which EEG sequences clearly indicated alert, valence, or sleepy states of the subject.

In summary, our results show that valence and emotional intensity play an important role in text comprehension and visual word and sound. Which are most active and show high prediction accuracy on Dorsolateral prefrontal cortex (F3, F4, FZ).

Armita Golkar (2012) Distinct contributions of the dorsolateral prefrontal and orbitofrontal cortex during emotion regulation confirmed that both the dorsolateral prefrontal cortex (DLPFC) and the lateral orbitofrontal cortex (OFC) contribute to emotion regulation through reappraisal. However, activity in the DLPFC was related to reappraisal independently of whether negative or neutral stimuli were reappraised, whereas the lateral OFC was uniquely related to reappraisal of negative stimuli. We suggest that relative to the lateral OFC, the DLPFC serves a more general role in emotion regulation, perhaps by reflecting the cognitive demand that is inherent to the regulation task.

Functions of Dorsolateral prefrontal cortex (DLPFC)

1. Executive Control Cognitive tasks recruit a "task activation ensemble" of frontal, parietal, and subcortical regions that can be subdivided into two distinct intrinsic connectivity networks (Seeley et al., 2007).

2. Theory of Mind (ToM) A comprehensive meta-analysis of studies on social cognition, including empathy and ToM, did not find particular task-related activations in the DLPFC (Schurz et al., 2021).

3. Mood Regulation The DLPFC seems also to be a superordinate control region for mood processing. As indicated by lesion-symptom mapping, it seems to be directly or indirectly involved in lesion-induced depression (Padmanabhan et al., 2019).

4. Conflict Management As a further function, the DLPFC is involved in conflict management regarding conflict detection, resolution, and adaptation (Oehrn et al., 2014).

5. Speaker–Listener Interaction Some fMRI experiments have investigated speaker–listener coupling during language processing. Regions involved in predictive and value-related processing including medial and dorsolateral prefrontal cortex (Stephens et al., 2010).

Part 2 Limitations and suggestions for future research

2.1 Limitations

2.1.1 This research use EEG data of participant whom have age between 20-24 years old.

2.1.2 This research studies on only negative and positive dimension of emotional valence.

2.1.3 The secondary data recorded 84 participants.

Many of the reviewed studies have compared the performance of different classifiers; SVM, and KNN were the most frequently used classifiers across all articles reviewed. Although model performance can be attributed to a variety of factors, our findings suggested that Naïve Bayes and KNN outperformed the other supervised ML classifiers. We also found that the Dorsolateral prefrontal cortex impressive performance in studies focused on Valence tasks when either ICA or PCA was used as a pre-processing method.

This systematic review provided recommendations for applying supervised machine learning and deep learning algorithms for the neural. decoding of EEG signals in various tasks and experimental protocols. Although each classification algorithm has its own strengths and limitations, these recommendations provide insight into the issues associated with the classification of EEG signals, which might be addressed in future research efforts in this field. Further in-depth studies combining the selection of feature extraction methods and types of classifiers are highly recommended.

This research uncovered new knowledge from a number of errors. The first time we ran the algorithm was not successful. But to be successful we have to run several times the first time. The first time we experienced failures, the cause of the data we were using was misaligned. Data frame alignment is very important in running a learning machine. We first ran Machine learning from time domain ERP data. We ran it several times and couldn't recognize it. We pulled up time domain specific brainwaves such as P200 and P600, or During the periods to make it stand still, the EEG could not be distinguished, the percentage prediction of the EEG was very low.

Subsequently, we took the time domain into frequency domain by Fast Fourier transformation method, and we used the mean waveform to analyze the emotional valence, but with no success. And later we switched to using the integral or sum of the EEG frequency domain but still no success.

In the last time the results were successful, we switched to the Fast Fourier transformation method and applied the maximum value of EEG frequency domain, this time we were successful and able to classify the EEG. of emotional valence and was able to predict machine learning EEG at an acceptable high percentage.

2.2 Suggestions for future research

2.2.1 Further in-depth studies should try the other extraction methods and types of classifiers are highly recommended.

2.2.2 Further study should try to apply other types of supervised machine learning and deep learning algorithms.

2.2.3 Further study should try to record of EEG signals in various tasks and experimental protocols.

2.2.4 Further study should try other programming language beside R, such as Python, JAVA, JavaScript, C++.

2.2.5 Further study should try to record of EEG signals on other emotions.

Part 3 Conclusion

Emotional valence machine learning conclusions. Following the above approach of feature extraction from the raw EEG data, we are left with a dataset containing 6,202 milliseconds of 85 sample with 64 electrode EEG node. For each row of the dataset, we have the corresponding target variable: '*Negative*' or '*Positive*'. Our goal then, is to train a machine learning model, based on this set of features, to successfully predict the corresponding mental state.

In this example case, I started out with ICA and PCA pre-processing algorithms as it is simple to set up and often works quite well without much hyperparameter tuning as evidence from literature reviews As a side-note: I try a unsupervised and supervised machine learning approach on the raw time-domain EEG and ERP data but it does not work, the percent result of clustering are very low and the percent prediction accuracy are very low too. Therefore, I convert EEG raw data to the frequency domain via Fast Fourier transformation. Since convolutions applied in the frequency-domain is intimately connected to the frequency characteristics of the signal through the convolution theorem, this might be a promising approach to increase the percent clustering and prediction accuracy results.

The results of this study are consistent with other studies on the emotional valence active part of the brain which Dorsolateral prefrontal cortex brain area is the regions that usually interact in serving different cognitive functions. On the other hand, this region is also involved in cognitive processing of emotions (valence, arousal and dominance) visual and sound stimuli.

3.1 Unsupervised machine learning conclusion

For the unsupervised machine learning, we could see the result of 2 methods as following. K-Mean Algorithm ICA of the Prefrontal cortex (FP1, FPZ, FP2) clustering result is equal to 63.00%. K-Mean Algorithm ICA of the Dorsolateral prefrontal cortex (F3, F4, FZ) clustering result is equal to 69.00 %. K-Mean Algorithm ICA of the Ventrolateral prefrontal (F7, F8) clustering result is equal to 64.50 %. K-Mean Algorithm ICA of the Frontal cortex (FC5, FC1, FZ, CZ, FC2, FC6) clustering result is equal to 48.30 %. K-Mean Algorithm ICA of the Temporal cortex (T7, P7, T8, P8) clustering result is equal to 66.50 %. K-Mean Algorithm ICA of the Parietal cortex (C3, CP5, CP1, P3, PZ, CP2, C4, P4, CP6) clustering result is equal to 91.10 %. K-Mean Algorithm ICA of the Occipital cortex (O1, POZ, O2) clustering result is equal to 90.80 %.

K-Mean Algorithm PCA of the Prefrontal cortex (FP1, FPZ, FP2) clustering result is equal to 61.50 %. K-Mean Algorithm PCA of the Dorsolateral prefrontal cortex (F3, F4, FZ) clustering result is equal to 66.70 %. K-Mean Algorithm PCA of the Ventrolateral prefrontal (F7, F8) clustering result is equal to 63.10 %. K-Mean Algorithm PCA of the Frontal cortex (FC5, FC1, FZ, CZ, FC2, FC6) clustering result is equal to 50.80 %. K-Mean Algorithm PCA of the Temporal cortex (T7, P7, T8, P8) clustering result is equal to 63.40 %. K-Mean Algorithm PCA of the Parietal cortex (C3, CP5, CP1, P3, PZ, CP2, C4, P4, CP6) clustering result is equal to 91.80 %. K-Mean Algorithm PCA of the Occipital cortex (O1, POZ, O2). clustering result is equal to 91.20 %.

Fuzzy C-Mean Algorithm ICA of the Prefrontal cortex (FP1, FPZ, FP2) clustering result is equal to 62.19 %. Fuzzy C-Mean Algorithm ICA of the Dorsolateral prefrontal cortex (F3, F4, FZ) clustering result is equal to 70.67 %. Fuzzy C-Mean Algorithm ICA of the Ventrolateral prefrontal (F7, F8) clustering result is equal to 63.68 %. Fuzzy C-Mean Algorithm ICA of the Frontal cortex (FC5, FC1, FZ, CZ, FC2, FC6) clustering result is equal to 43.62 %. Fuzzy C-Mean Algorithm ICA of the Temporal cortex (T7, P7, T8, P8) clustering result is equal to 64.77 %. Fuzzy C-Mean Algorithm ICA of the Parietal cortex (C3, CP5, CP1, P3, PZ, CP2, C4, P4, CP6) clustering result is equal to 91.06 %. Fuzzy C-Mean Algorithm ICA of the Occipital cortex (O1, POZ, O2) clustering result is equal to 90.77 %.

Fuzzy C-Mean Algorithm PCA of the Prefrontal cortex (FP1, FPZ, FP2) clustering result is equal to 61.10 %. Fuzzy C-Mean Algorithm PCA of the Dorsolateral prefrontal cortex (F3, F4, FZ) clustering result is equal to 67.61 %.

Fuzzy C-Mean Algorithm PCA of the Ventrolateral prefrontal (F7, F8) clustering result is equal to 62.93 %. Fuzzy C-Mean Algorithm PCA of the Frontal cortex (FC5, FC1, FZ, CZ, FC2, FC6) clustering result is equal to 43.85 %. Fuzzy C-Mean Algorithm PCA of the Temporal cortex (T7, P7, T8, P8) clustering result is equal to 60.91 %. Fuzzy C-Mean Algorithm PCA of the Parietal cortex (C3, CP5, CP1, P3, PZ, CP2, C4, P4, CP6) clustering result is equal to 91.76 %. Fuzzy C-Mean Algorithm PCA of the Occipital cortex (O1, POZ, O2) clustering result is equal to 91.14 %.

Even though K-Mean Algorithm PCA of the Parietal cortex (C3, CP5, CP1, P3, PZ, CP2, C4, P4, CP6) clustering result is equal to 91.80 % is the highest percent clustering result but from the figure 4-3 to 4-6, we could conclude that Fuzzy C-Mean Algorithm ICA of the Dorsolateral prefrontal cortex (F3, F4, FZ) clustering result is equal to 70.67 % and Fuzzy C-Mean Algorithm PCA of the Dorsolateral prefrontal cortex (F3, F4, FZ) clustering result is equal to 67.61 % are the best clustering result.

3.2 Supervised machine learning conclusion

For the supervised machine learning, we could see the result of 5 methods as following.

The K-Nearest Neighbors (kNN) of ICA of emotional valence of Dorsolateral prefrontal cortex (F3, F4, FZ) has prediction accuracy = 58.82%. The Random Forest (RF) of ICA of emotional valence of Dorsolateral prefrontal cortex (F3, F4, FZ) EEG data has prediction accuracy = 58.82%. The Naïve Bayes (NB) of ICA of emotional valence of Dorsolateral prefrontal cortex (F3, F4, FZ) EEG data has prediction accuracy = 67.64 %. The Support Vector Machines (SVM) of ICA of emotional valence of Dorsolateral prefrontal cortex (F3, F4, FZ) EEG data has prediction accuracy = 58.82%. The Decision Tree (DT) of ICA of emotional valence of Dorsolateral prefrontal cortex (F3, F4, FZ) EEG data has prediction accuracy = 61.76 %.

The K-Nearest Neighbors (kNN) of PCA of emotional valence of Dorsolateral prefrontal cortex (F3, F4, FZ) has prediction accuracy = 64.70 %. The Random Forest (RF) of PCA of emotional valence of Dorsolateral prefrontal cortex (F3, F4, FZ) EEG data has prediction accuracy = 55.88 %. The Naïve Bayes (NB) of PCA of emotional valence of Dorsolateral prefrontal cortex (F3, F4, FZ) EEG data has prediction accuracy = 64.70 %. The Support Vector Machines (SVM) of PCA of emotional valence of Dorsolateral prefrontal cortex (F3, F4, FZ) EEG data has prediction accuracy = 55.88 %. The Decision Tree (DT) of PCA of emotional valence of Dorsolateral prefrontal cortex (F3, F4, FZ) EEG data has prediction accuracy = 61.76 %.

The maximum prediction accuracy supervised machine learning method is The Naïve Bayes (NB) of ICA of emotional valence of Dorsolateral prefrontal cortex (F3, F4, FZ) EEG data has prediction accuracy = 67.64 %.

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