Eustress and Distress Analysis Based on Neuro-Physiological Model of Affect

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Abstract: Researchers have focused on the negative effects of stress while its benefits have been relatively ignored. There has been limited studies to quantitatively understand the positive impact of stress. Although most of the studies were carried out by psychologist, in general, stress can be characterized by negative valence from the perspective of the affective state model (ASM). In fact, most recent psychological findings show that positive stress, also known as eustress, can improve motivation factor of an individual. In this paper we propose the use of electroencephalography (EEG) device to capture the brain's electrical activity in the frontal and central areas, in identifying positive (eustress) and negative (distress) stress. The distinctive brainwave patterns from the EEG device can be used to extract emotion/mood information of an individual and can be used to corelate the differing stress. The neurophysiological Model of affect (NPMoA) extracts the valence (V) and arousal (A) from the brainwave signals and corelate then to the psychological instruments for extracting eustress and distress. The Student Academic Stress Scale (SASS) will be used as the psychological instruments to extract eustress and distress. Preliminary results show the ability of using the EEG device to extract the brainwave pattern and to use in detecting stress based on the valence and arousal of the emotion. It is expected that NPMoA should be able to reveal correlation between positive emotions and eustress through the V and A. Such understanding can be extended to further analyze different stressors for academic stress and their effects on the brain signals.

Keywords: Eustress, Distress, Style, EEG, Student Academic Stress Scale, Affective Space Model

1. Introduction

Stress is a common response from various stressors that consists of physiological and psychological changes that may introduce illness and discomfort if recurrently experienced [1, 2]. It is viewed as an unavoidable part of life that has detrimental consequences such as chronic disease and loss of productivity. Selye [1] described stress by using three main components, namely; alarm, resistance, and exhaustion in a model coined as General Adaptation Syndrome (GAS). When an individual encounters threat or potential stressor, the alarm state is triggered. Typical physical reactions in this phase are the raise heart rates, goosebumps, increased adrenaline, and other symptoms that prepared the body for fight-or-flight reactions. If the stressor continues to exist, the individual is shifted to the resistance phase where coping mechanisms will be kicked in such as the strengthening of heart muscle and functions. This is a natural body defense and protection. However, if a longer stress situation persists than the body could cope; the individual normal function cannot be maintained. Such a situation is called the exhaustion phase. If an individual unable to cope with the pressure for such duration of time, the body may react in fatigue, burnout, depression, anxiety, and decreased stress tolerance. The physical effects of this stage also weaken the immune system and increase the risk of stress-related illnesses. Figure 1 shows percentage of Malaysian employees with depression symptoms from moderate to severe. Thus, it is obvious that teenagers between age 18 to 30 have high potential of depression which could be due to stress and need to be analyzed.

As a subset of stress, stress occurs as a consequence of the pressure to succeed and has been shown to afflict university students in particular because the workload usually involves time constraints [3]. Moreover, other academic stressors in university may come in the form of overwhelming course material, continuous evaluation, unclear assignments, and poor teacher-student relationships [4]. According to the Yerkes-Dodson Law [5], stress is likely to increase the task performance of an individual to a point, but then performance decreases gain with too much stress. Stress is also shown to act as a modulator of memory processes and human learning, thus having major implications in academics. When stress is closely related to course material, memory capacity, and information retention has been shown to improve, while the opposite happens when stress is unrelated to course material [6]. Children with learning disabilities (LD) may even be at a higher risk and easily affected by stress and anxiety. LD children seem to have a low self-concept, generally less socially accepted, high locus of external control, and more anxious than normal children [7, 8]. However, Santos et al. [7] reported that there are no statistical differences for stress signs between children with and without LD. Hence, in this paper, the focus is aimed at academic stress for university students.
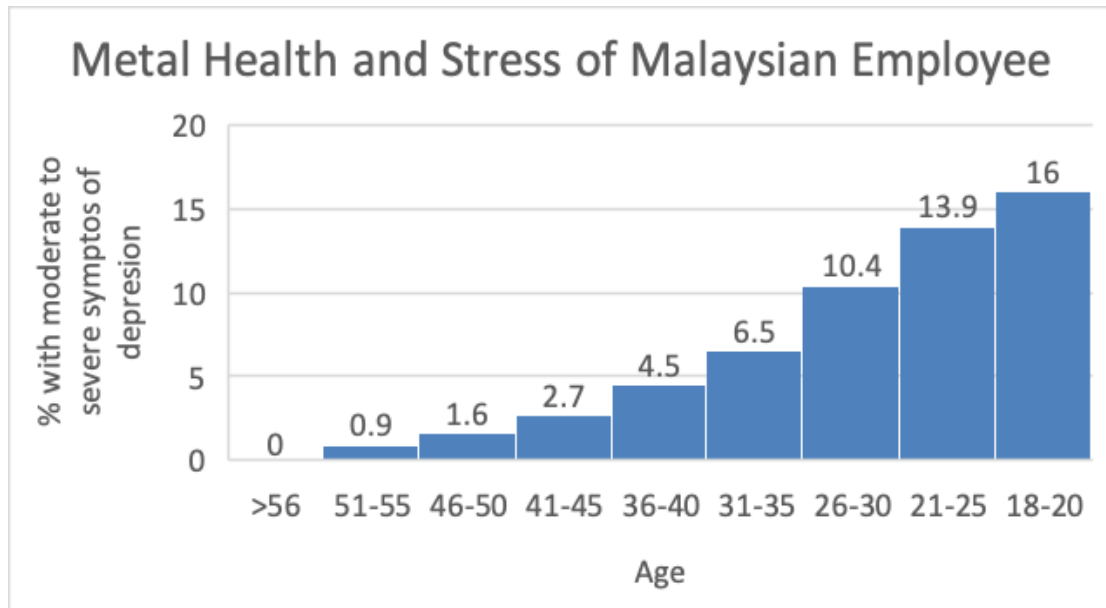
Figure 1. Mental Health and Stress of Malaysian Employees [37]

Academic stress can be segregated into positive and negative stress. Lazarus [2] extended Salye [1] observation of stress into psychology and distinguished two types of stress, namely; eustress (positive stress) and distress (negative stress). Most researches on the impact of stress have focused on its negative effects while its positive side has relatively been ignored. Eustress is experienced when stress can produce positive outcomes that act as a source of challenge and opportunity. It is also associated with positive feelings and health benefits. On the contrary, distress is viewed as negative stress that is the source of harm and threat that has detrimental consequences such as chronic disease and loss of productivity [9]. For instance, sitting for a promotion interview may be perceived as eustress if the candidate is well prepared, motivated, and confident of his/her performance. Such feeling is not replicable if the candidate did not meet the minimum requirements or even cheating in his/her application. He or she may feel such exercise may harm his/herself image. Hence, the distress and eustress are very much defendant on the appraisal process. According to the Transactional Theory of Coping [10], the appraisal of a stressor generates emotions, which when perceived as a challenge or threat initiates coping strategies to manage that stressor or its resulting emotions [11]. The outcome of the coping processes alters the person-environment relationship, which is then re-appraised as having either a favorable, unfavorable, or unresolved outcome. A favorable resolution of stressful stimuli leads to positive emotions often characterized by a positive outlook on life, motivation, resilience, etc., while unfavorable or unresolved resolutions usually lead to negative consequences such as pessimism, high blood pressure, depression, etc. These negative outcomes provoke a person to consider other coping mechanisms [12, 13]

Stress evaluation is typically conducted using questionnaires and other clinical psychological assessment tools, such as Psychological Stress Measure (PSM) [14], revised Beck Depression Inventory (BDI-II) [15], Daily Life Experience Checklist (DLE) [16], Cohen Perceived Stress Scale [17], Daily Stress Inventory [18] and others. The PSM contained 49 items drawn from descriptors generated by focus groups on stress. It stresses on the biopsychosocial model of stress that includes environmental parameters and individual processes of perception and coping with stressors [14]. The BDI-II is an effective measure of depressed mood that has a 21-item format that allows participants to select a response from the present (0) to severe (3) [15]. The DLE [16] comprised of 78 items that represent work, leisure, family, financial and other domains. The participants need to rate the event desirability and meaningfulness of each experienced event. The Cohen Perceived Stress Scale (PSS) [17] is widely used for measuring individual perception of stress. It is commonly implemented in a 10-question form and measures the way respondents have found their lives unpredictable, uncontrollable, and overwhelming in the previous 14 days. The scale also includes several direct queries about current levels of experienced stress. Subsequently, the Daily Stress Inventory [18] is a 58-item questionnaire that asks about minor events occurring in the last 2-weeks. The questionnaires attempt to probe the impact of the experiences that may introduce stress to an individual

Student academic stress is typically measured using different and more specific instruments. This is to tailor specifically to the stressors that impede the students' performance. Kohn and Frazer reported that final grades, excessive homework, term papers, examinations, and studying for examinations were the most significant

stressors among the identified 35 stressors [19]. Such notion is supported by other researchers that listed several factors, such as; course requirements; time management issues; financial burdens; interactions with faculty; personal goals; social activities; adjustment to the campus environment; and lack of support networks [20]. Kohn et al. [21] further introduced the Inventory of College Students' Recent Life Experiences (ICSRLE) questionnaire that comprised of 49-items that needed the participants to record their intensity of experiencing the event over the past month. The values are ranging from 1- not at all part of my life to 4 – very much part of my life over seven factor-based subscales, namely; developmental challenge, time pressure, academic alienation, romantic problems, assorted annoyances, general social mistreatment, and friendship problems. In more recent work, Stallman [22] developed the University Stress Scale that consists of a 21-items measure to provide an index of the intensity of an individual's stress experienced in the previous month. This is to gauge the severity of stress levels in the six factors of academic, equity, relationships, parenting, practical, and health.

Despite the high success rate reported with the questionnaire method, the participants sometimes are not being conscientious enough to record their assessment. For instance, the Daily Life Experience Checklist (DLE) [16] need the participants to record the stress level that the participants experienced within the last 24 hours while other tools such as the Beck Depression Inventory [15], Cohen Perceived Stress Scale (PSS) [17] and Daily Stress Inventory [18] questionnaires acquire the participants to rate on the minor events that occurred in the past 2 weeks that is consistent with the Diagnostic and Statistical Manual of Mental Disorders (DSM-IV). Moreover, participants have been found to report minor or positive events in response to questions designed to elicit negative and undesirable events [23]. Hence, to support the result from the questionnaire, many recent studies have succeeded in measuring stress through other types of physiological markers such as brain signals, blood pressure, or heart rate. These techniques were previously limited to laboratory environments, but technological advancement allows data to be collected ubiquitously and less obtrusive methods of stress assessment [24].

As academic stress is a major determinant of academic performance, more accurate prediction methods are needed to provide targeted prevention and intervention for it, as well as a greater focus on the utilization of its positive effects to bring about higher life satisfaction and productivity. In this paper, the potential of EEG in determining academic stress analysis is explored and investigated. Such an effort is to complement the Academic Stress Scale questionnaire that provides an alternative perspective from neurophysiological input of brain signals. The EEG is selected due to its ability to detect valence and arousal value and the signals are uninterrupted because it cannot be controlled by the participants. This paper is organized in the following manner. Section II discusses several related works in stress recognition using EEG to give some ideas on the state-of-the-art approaches. The proposed approach of academic stress analysis using EEG is outlined in Section III. As this work is still in its preliminary stage, a simplified discussion is provided before the paper concludes with a summary and future work in Section IV.

2. Related Work in Stress Recognition

Electroencephalography (EEG) is one such device that provides rich information about a subject's mental status by placing electrodes on the scalp to allow a non-intrusive analysis of the electrical activity in the brain [25, 26, 27]. As stress causes fluctuations in brainwave frequency components, EEG is especially suited for stress analysis.

Saeed et al. [28] studied long-term stress addressed using PSS labels and expert evaluation coupled with the EEG can be used for recognizing chronic stress without inducing stress using a stimulus to emulate stress in everyday life. Five different classifiers are used, such as; support vector machine (SVM), Naive Bayes (NB), K-nearest neighbor (KNN), Logistic Regression (LR), and Multi-Layer Perceptron (MLP) to classify 45 features extracted from the EEG signals. The experimental result shows that SVM and LR give the highest accuracy with a performance of 85.20%. Ahn et al. [29] used a combination of EEG and heart rate variability (HRV) responses to develop a wearable device that enables continuous monitoring of stress. Statistical analysis was used on the EEG and HRV parameters for feature extraction, while the Support Vector Machine (SVM) classifier was used for classification of stressors. It was reported that the classification performed obtained 90% sensitivity, 85% specificity, and 87.5% accuracy. A stressor such as music is also used to study short term stress. Asif et al. [30] used EEG signals to examine the effect of English and Urdu music tracks on human stress levels. Four classification algorithms were tested and findings showed that linear regression (LR) classification performed the best in identifying stress with a reported accuracy of 98.76% when participants were classified as stressed or non-stressed, and an accuracy of 95.06% when participants were classified as non-stressed, medium stressed or highly-stressed.

For more student stress analysis, EEG signals are captured during the examination and test-taking. Hafeez et al. [31] capture the brain signals' of the participant using the EEG to investigate the effect of stress on exam performance of students. To induce the short term stress, the participants are needed to adhere to a strict time constraint. Results showed a clear degradation in the performance of students when tested under time constraints that the power spectral density analysis showed 85% of students to be stressed in these circumstances. Subsequently, Zyma et al. [32] used the EEG brain signals to develop a database to assess stress based on the performance of participants while solving arithmetic problems of varying difficulty. Their findings show promising results in the analysis of brain activation regarding task difficulty. Hence, in this work, the performance of the participants solving arithmetic problems will be selected as a stressor to induce stress to the participants. To add to the urgency, a time constraint will also be added.

3. Research Methodology

In developing the proposed approach to study the academic stress using EEG, the theoretical framework based on the assumptions supported by works of literature are outlined. The overall theoretical framework is presented in Figure 2. Emotion is influenced by stress, either eustress or distress therefore there is a correlation between these two components [33]. Catanzaro [34] reported that individuals reporting more depressive symptoms performed more poorly on the exam. However, students with stronger negative mood regulation expectancies managed to be unaffected or even aided by experiencing anxiety. This may be hypothesized that eustress gives a positive impact on examination performance. Both stress and emotion can be measured using psychologists' instruments [21, 22] and neurophysiological input [25, 26, 27]. In this work, the brain signal is captured using the electroencephalogram (EEG). To cross-checked both results, statistical correlation analysis to model the relationship between emotion and stress are conducted [35].

3.1 Theoretical Framework

Based on the theoretical framework, the block diagram of the academic stress recognition system using EEG is proposed. There are two types of input collected, which are the psychological instrument data garnered from a well-established questionnaire and the neurophysiological input of the EEG. Before any data acquisition is done, the participants need to fill up the consent form. Only healthy participants, had no clinical manifestations of mental or cognitive impairment, verbal or non-verbal learning disabilities are eligible to enroll in the study. Exclusion criteria are the use of any influence of alcohol, drugs, and psychoactive medication and psychiatric or neurological complaints.

The participants are briefed on the objective and the flow of the experiment to give some mental preparation. The participants are asked to minimize movement to ensure the EEG signals captured are not distorted with movement artifacts. Once ready, the participants are asked to sit comfortably in front of a computer. The EEG device of 19 channels is used. The room has a controlled ambiance with minimal background noise and movement. The silver electrodes arrangement on the scalp is following the international standard of 10-20 EEG scheme with an impedance level of less than 2 Ohm. All electrodes are referenced to the interconnected ear reference electrodes.
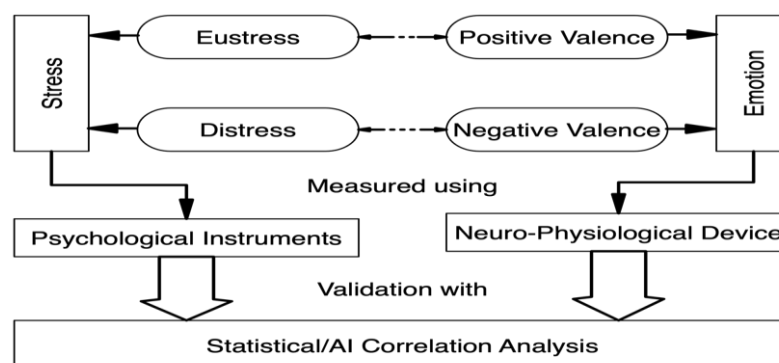

Figure 2. Theoretical framework for academic stress measurement

3.2 Stress Recognition Protocol

For initialization, the resting state of the participants is recorded. The participants are acquired to close their eyes for one minute and open their eyes for another minute. This is to get the baseline data of the participants' stress and emotion threshold. Then, stimuli are presented. In this work, two tests are conducted to measure emotion and academic stress.

For emotion elicitation, images from the International Affective Picture System (IAPS) dataset are selected to elicit 4 emotions of fear, happiness, sadness, and calm. This is to get the positive/negative threshold of the emotion primitives of valence and arousal. Valence is the effect of the emotion of either positive or negative whereas arousal is the value to activation that ranging from passive to active.

Each emotion stimuli are presented for a minute with 20 seconds gap. For academic stress elicitation, arithmetic tasks with varying degrees of complexity are given within a time constraint. The participants need to answer as many questions as possible within 5 minutes without any electronic aid such as a calculator. The total duration of the EEG recording is less than 15 minutes per person.

The raw data of the EEG signals are then pre-processed to reduce noise and artifacts. The first 2 seconds of the signals are removed as the participants usually take to get ready for the given stimuli. A signal normalization using the Elliptical filter is conducted before the signals are segregated into its distinctive brainwave frequencies; delta, theta, alpha, beta, and gamma respectively at each electrode. Relevant features are then extracted. In this work, Mel Frequency Cepstral Coefficient is proposed. This is because such feature extraction managed to yield comparative performance in previous works [25, 26, 36].

To classify the labeled classes, four machine learning methods are used, namely Multi-Layer Perceptron, Support Vector Machine, Naïve Bayes, and Decision Tree classifiers. This is to give a comparative analysis of the performance of the different types of classification methods. The performance indicator used in this study focuses on accuracy that can be measured from the number of correctly classified instances over a total number of instances in the recorded data. The 80-20 rule of training and testing data arrangement of a 5-fold cross-validation technique is applied to get the generalization of the classification result.
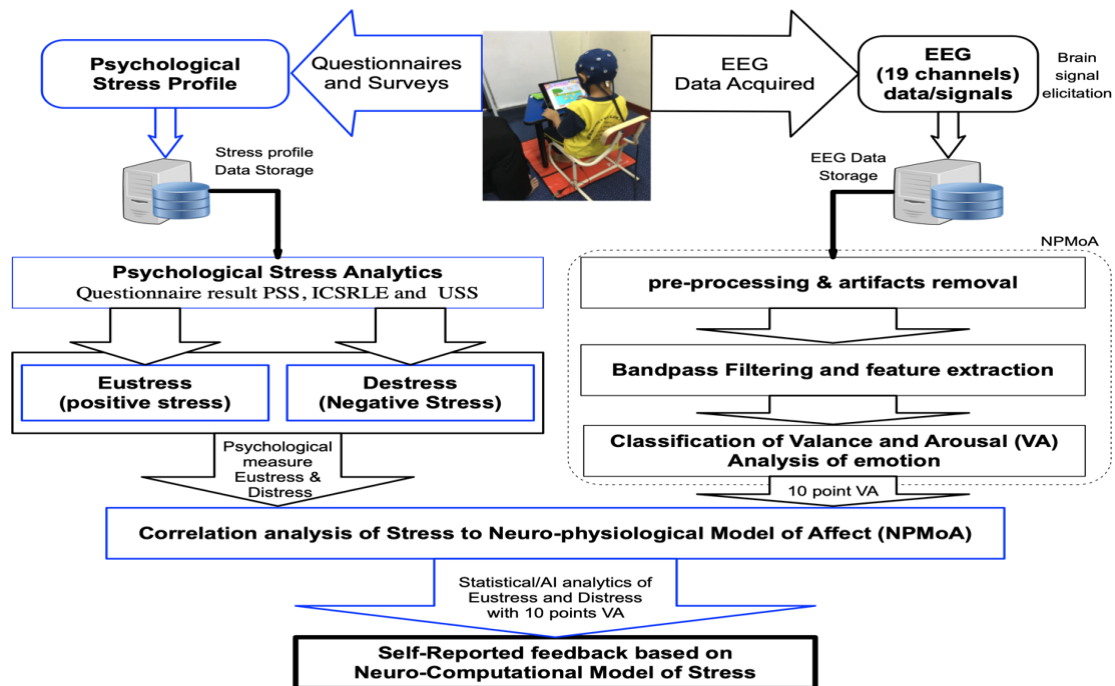

Figure 3. Academic Stress recognition system based on Neuro-Physiological Model of Affect (NPMoA) using

EEG

After EEG signal acquisition, the participants are asked to fill the Cohen's Perceived Stress Scale (PSS), Inventory of College Students' Recent Life Experiences (ICSRLE), and University Stress Scale (USS) to give insight from the psychologists' perspective. Based on the questionnaire scores, the psychologist groups the participants in either a stress or control group. Once both questionnaires and EEG test results are yielded, a

statistical correlation analysis is conducted to measure the relationship between positive and negative emotion to eustress and distress. Figure 3 illustrates the simplified box diagram for the proposed academic stress recognition system using the EEG signals. Figure 4 shows a preliminary After EEG signal acquisition, the participants are asked to fill the Cohen's Perceived Stress Scale (PSS), Inventory of College Students' Recent Life Experiences (ICSRLE), and University Stress Scale (USS) to give insight from the psychologists' perspective. Based on the questionnaire scores, the psychologist groups the participants in either a stress or control group. Once both questionnaires and EEG test results are yielded, a statistical correlation analysis is conducted to measure the relationship between positive and negative emotion to eustress and distress. Figure 3 illustrates the block diagram for the proposed academic stress recognition system using the EEG signals.

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Figure 4 shows preliminary results using the EEG device to classify four different emotion based on different classification method. In this experiment we allow the participants to view four different emotion based on the international affective picture standards (IAPS) and their brainwave patterns were recorded using an 8 channel EEG device. Four different type of feature extraction methods, namely; cerbellum model articulation controller (CMAC), Kernel Density Estimate (KDE), Mel-Frequency Cepstral Coefficient (MFCC) and Power Spectral Desnsity (PSD) [38]. As can be seen with the combination of CMAC as feature extraction and using multi layer Perceptron (MLP) we can achieve more than 80% accuracy. This is important as emotion detection will be used in corelating eustress and distress to emotion detection using the EEG device based on the neuro-Physiological Model of Affect (NPMoA).
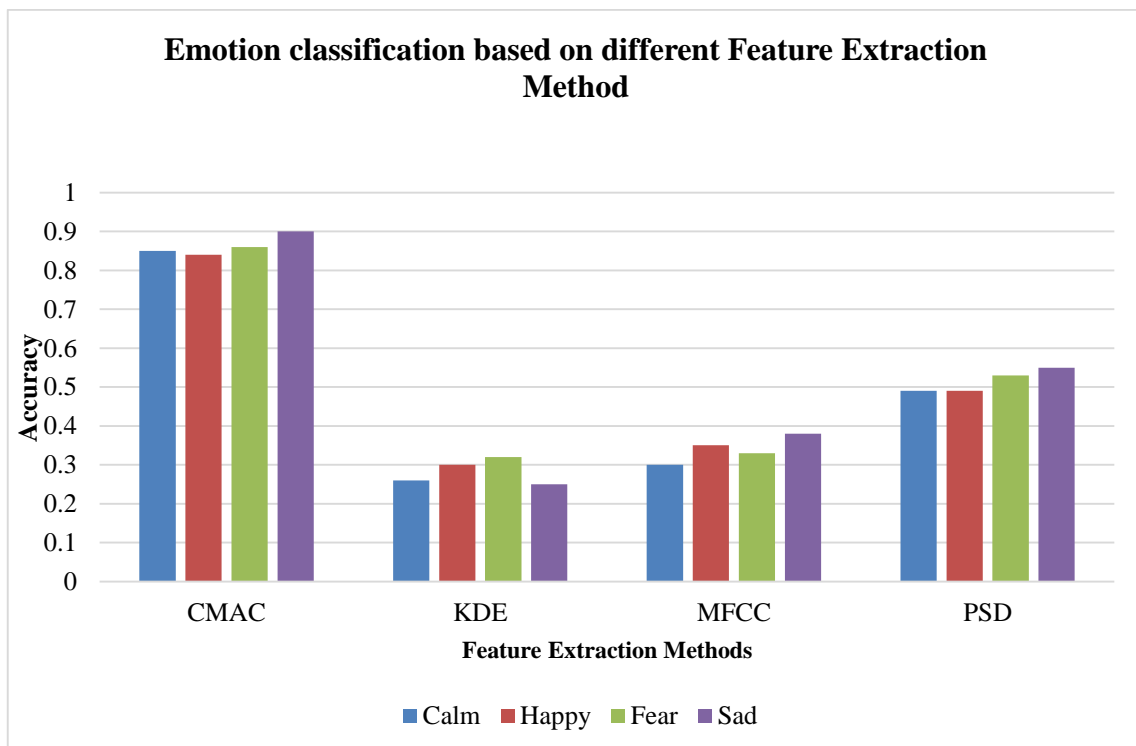

Figure 4. Emotion Classification using different Feature extraction method.

4. Conclusion and Future Work

Preliminary results show the ability of the EEG device based on the NPMoA to be able to detect the four-basic emotion accurately. Since the psychological findings relate emotion to eustress and distress, we can then corelate the brainwave pattern with the eustress and distress. The propose research can help students and faculty members to identify stress level so that stress can be handle in an optimum manner. Different emotion primitives of valence and arousal will then be used as benchmark to further improve the performance of the correlation. Since this work is still in its infancy stage, further work needs to be conducted in implementing the outlined methodology. It is hoped that such a system can be used to help counsellors to better understand the students' stress level with quantitative evidence.

5. Acknowledgment

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