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Development of Unified Neuro-Affective Classification Tool (UNACT)

Md Farhad Hossain[1], Hamwira Yaacob[2], Azlin Nordin[3]

[1,2,3]Department Computer Science, International Islamic University Malaysia, Jalan Gombak, 53100, Selangor, Malaysia

E-mail: [1]emamulfarhat@gmail.com

Abstract. Brain signals have been analysed to understand the affective state of different cognitive and mental conditions. For example, through the analysis, we can visualize the changes of emotion while driving, identify an autistic kid, understand the conditions that stimulate attention while studying, and many more, because emotion has a strong impact on cognitive processes in humans' activities. This can be done through a machine learning technique, which includes data acquisition, pre-processing, feature extraction, and training. However, no existing tool integrates all supervised machine learning processes for affective state classification, which makes the process tedious and time-consuming for an analyst by doing programming. Therefore, this project aims to develop a brain analysis tool, namely Unified Neuro-Affective Classification Tool (UNACT). It consists of 3 main functions including training, classifying, and analysis. In the study of affective state electroencephalogram (EEG) signals have used, which measures brain signals. UNACT uses the Butterworth Bandpass filter for EEG signal filtering, the Power Spectral Density method for feature extraction, and the Multi-layer perceptron (MLP) for emotion classification. This tool can be used by a non-technical person to perform affective-emotional state analysis without having programming knowledge.

1. Introduction

Emotions play a crucial role in our life. It helps us to think and behave. Emotion regulation includes a variety of psychological processes including attitude, personality, mood, and motivation. The emotional effect on the learning process has been found to have a positive or negative influence on cognitive abilities for storing and retrieving knowledge, processing information and motivational factors, among many others [1]. That's' why recent days, there are growing efforts for technical and scientific advances in neuroimaging to understand neural processes associated with brain functions for clinical evaluation. For this purpose, numerous experimental models and techniques have been proposed to understand the affective-emotional state from brain signals. This will be helpful in biomedical research, mainly for the treatment of psychological disorders.

Brain signal can be measured through EEG signals. The study of brain-computer interfaces (BCI) has shown that emotions can be measured through EEG emotional recognition systems [2]. EEG signals generate significant temporal resolutions compared to other instruments. Brain waves can be inputs to calculate valence and arousal. All EEG channels can capture the emotional experience.

Emotions are complex and progressive, as shown by the valence degree and the arousal strength [5]. One of the recognized models for quantifying emotion is the circumplex model [4]. This representation is known as the Affective Space Model (ASM). ASM places an emotion as a point on a two-dimensional plane: (i) valence (x axis) and (ii) arousal (y axis). The representation of the ASM is shown in Figure 2. In the study of affective-emotional profiling through EEG signals by applying a supervised machine learning technique, which includes data collection, pre-processing, extraction of features and modelling. EEG signals are recorded during emotion stimulation activities for the data collection process. Preprocess includes filtering signals for removing noise. After that feature extractions for performing the trained model.

There are many techniques and existing tools to analyze EEG signals. Although different techniques applied for emotion profiling, but no existing tool analyze EEG signals for emotion profiling. Analysts need to program each time for analysis, which makes time-consuming and tedious. It is also very difficult for the non-programmer analyst to perform emotion affective-emotional state analysis. Thus, this project aims to develop a brain analysis tool, namely Unified Neuro-Affective Classification Tool (UNACT). UNACT is an integrated analysis tool consisting of EEG signal processing, feature extraction, supervised machine learning for training and affective state classification from EEG signals. The preprocessing involves the filtering of EEG signals using the Butterworth bandpass method. Then, power spectral density (PSD) used for feature extraction. PSD is calculated by using a short-time Fourier transform to take the average spectral power. Multilayer perceptron (MLP) used to conduct emotional state classification from a collection of input traits derived from EEG signals. Classification of emotions is measured by the valence and arousal. The performance is described in an affective space model (ASM) with four quadrants.

2. Review of previous works

There are several contributions to emotion profiling using supervised machine learning techniques. In [5], the authors illustrated two-dimensional affective state distribution of the brain during emotion stimulation. EEG data recording involved 6 children. Photos taken from the Radboud Faces Database (RafD) for stimulation of emotions [6] for the basic emotions. Preprocessing involves noise filtering using a bandpass filtering. The theta and alpha bands were extracted for emotion classification. Kernel Density Estimation (KDE) used for feature extraction and a multilayer perceptron (MLP) algorithm for emotion classification. Their findings prove that all basic emotional states are well distributed throughout the respective quadrants in ASM where the classifier signifies the arousal and valence. The findings also showed the dynamics of emotional responses described by the arousal and valence.

Then, the paper [7] compares the results of emotion profiling on original interrupted and adjusted EEG signals by casting using a supervised machine learning technique. The signals collected for 64 channels using A.N.T. EegoSport by following the international standard 10-20 EEG location of the electrode [8]. Power spectral density applied for feature extraction. A short-time Fourier transform used to take the average spectral power to calculate PSD. Emotion classification involved a multilayer perceptron (MLP) algorithm. Classification of emotions calculated on the basis of valence and arousal. The findings are shown in the Affective Space Model. This paper proved that the proposed technique is useful for emotion profiling using interrupted EEG signals because the accuracy increased in both situations with the total variant segments from 1 to 19 segments with 400 seconds of EEG collection.

Additionally, in [9] illustrated, multiple approaches for EEG signal collection during emotion stimulation, then various features extraction strategies and classification models for affective-emotional profiling. Furthermore, besides the discussed papers over the past few years a various new EEG signal processing methods proposal increasing for affective-emotional state analysis. In order to support the proposed approaches, new tools are needed to enable the comprehensive analysis of EEG data for affective state analysis using more sophisticated experimental designs. However, there are several EEG signal processing tools. The most widely used tool is EEGLAB [10] which was introduced in 2001. EEGLAB is an integrated graphical user panel and a script-based command-line tool [11]. It was implemented in MATLAB. Since EEGLAB is a collection of MATLAB functions, it needs MATLAB runtime and some understanding of MATLAB data structures. Reprogramming systems are not easy to use in EEGLAB. Its' features include (i) structure of events and functions to import, edit, and manipulate, (ii) degradation of electroencephalographic data by independent component analysis (ICA),

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(iii) adaptability ready for anyone with multi-levels of sophisticated programming, (iv) enable any user to produce and modify plug-in functionality that appear automatically in the EEGLAB menu windows [11].

The NFT (Neuroelectromagnetic Forward Head Modeling Toolbox) [12] is accessible as an EEGLAB plug-in through the EEGLAB graphical interface [10]. The NFT software handles almost all of the functions required to produce a practical head model from magnetic resonance (MR) and/or measured EEG sensor coordinate, and provide advanced boundary element method (BEM) and finite element method (FEM) solvers to estimate the projected scalp fields for a given range of possible brain source areas, thereby estimating the EEG modeling solutions [12]. The following measures are performed by NFT: (i) segmentation of MR images, (ii) high-quality head models, (iii) deforming the template header model, (iv) electrode locations registration with the mesh of the head and (v) an effective and efficient forward-looking approach to the dilemma.

The SIFT (Source Information Flow Toolbox) is a toolbox for visualization and modeling data flow between EEG data points and is likely to be divided (immediately) into the full independent process using ICA. Currently, the toolbox consists of four main phases, (i) preprocessing, (ii) fitting of the model and estimating of connectivity, (iii) statistical analysis, and (iv) visualization. An important aspect of SIFT is that it focuses on predicting and visualizing an efficient multivariate connection within the source domain but also between scalp electrodes impulses. SIFT can help to locate temporary, network topology events that connect static element processes spatially [10].

The ERICA (Experimental Real-Time Interactive Control and Analysis) architecture is based on a particular data processing and real-time multiple synchronization infrastructures called DataRiver developed from the ADAPT data collection and stimulation control system. [13]. The key technology driving ERICA growth is the advancement of data acquisition through mobile brain imaging (MoBI) and methods of analysis [14] – simultaneous analysis of what the brain does, what the brain feels, and what the brain regulates while performing naturally inspired acts in ordinary 3-D activities. Another tool known as BCILAB [10] is a platform for the development of Brain-Computer Interfaces. Since data stream integration and pre-processing results have been achieved inside the ERICA framework, BCILAB is the open-source MATLAB toolkit and the EEGLAB plug-in can be used to support brain-computer interface analysis and, more generally, to develop, learn, use and test real-time prediction model that operates on the signal.

The existing tools are strong at their performance and fast analysis. However, this platform-dependent tool requires technical knowledge and expert level understanding to perform analysis. Therefore, the existing tools are not integrated with machine learning techniques for emotion profiling. For this purpose, the UNACT has developed to support analysts without having technical support for affective state analysis. By reviewing several papers and existing tools the current version of UNACT implemented using the Butterworth Bandpass filter, Power Spectral Density feature extraction technique, Multilayer Perception (MLP) algorithm as an emotion classifier and affective space model (ASM) to represent findings from the supervised machine learning technique.

3. Theoretical support for UNACT

3.1. Emotion profiling

Emotions describe human nature because humans' activities determine by emotions. A person how mentally strong can be identified by his emotional experience. An individual's activities towards society also can determine through emotional experience. We can feel the emotions through emotional experience because emotions link to our thought, actions, and belief. Different emotions are responsible for different actions. Emotions help us to survive. Take the example of cooking food. while people cook for, they become very conscious about cutting vegetables to avoiding cut hair and avoid burning from fire. Another example could be watching a horror movie. Although we are sitting in a safe place, we try to make ourselves strong-minded, sometimes people feel like hiding and very focused to control our body movement. Besides these many individuals are weak emotionally, by means, they are scared easily and may lead to death. While people are driving, they become more conscious to avoid accidents. Somehow the drivers may feel sleepy and cause accidents. Emotions are important in critical thinking because they can influence people's learning progress. There are different opinions on the number of basic emotions in research, as in paper [15-16] discussed different research about basic emotions theory. However, UNACT is working with four basic emotions happy, sad, calm, and fear. The affective-emotional profiling technique through brain waves by applying a supervised machine learning technique that includes data acquisition, preprocessing, feature extraction, and training illustrated in Figure 1. Brain signals can measure using the EEG signal. The recent version of UNACT does not integrate data acquisition techniques.

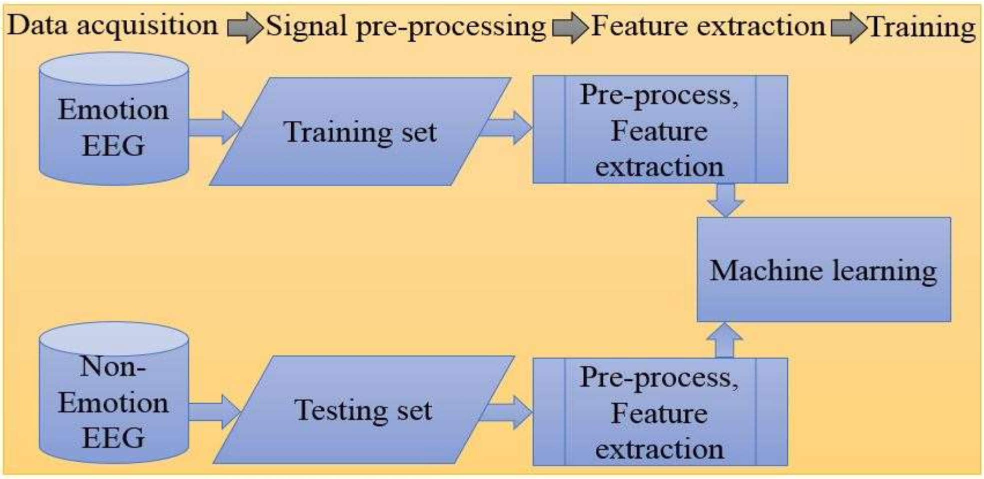

Figure 1. Emotion profiling

3.2. *Affective Space Model (ASM)*

Emotions are categorical, so every emotion is controlled by a distinct and autonomous neural [17]. Figure 2 illustrates Affective Space Model (ASM), it is a two-dimensional circumplex model of affect [4] to distinguish emotions by placing them in a dimension, focusing on individual assessment of specific emotional events.

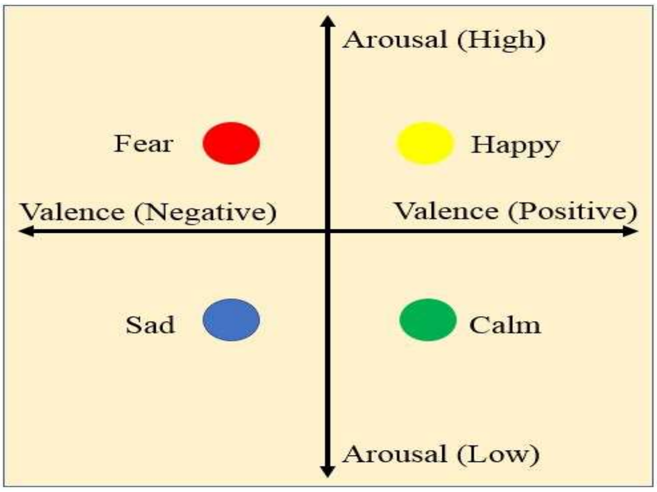

Figure 2. Affective Space Model (ASM)

ASM allows measuring emotions by mapping emotions on it, as illustrated in Figure 2. In [18] defined that the impact of arousal is the psychological-physiological state of being triggered and highly

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reactive to emotional responses. The physiological state involves high blood pressure and heart rate, among some other changes. The psychological state involves sensations of vigor, strength, and anxiety. Arousal is one dimension of emotion. To represent emotion in ASM needs another one dimension namely valence. Valence refers to positive or negative emotions. Positive emotions are joy, happiness, curiosity, interest, gratitude, excitement, and love. Whereas, negative emotions are like sadness, fear, anger, loneliness, jealousy, self-criticism. However, advanced neuroimaging technique uses brain waves to measure the values of arousal and valence. EEG tool allows measuring brain waves.

3.3. Electroencephalogram (EEG)

The electroencephalogram (EEG) is a neuroimaging tool to measure brain waves recorded by sensors on the scalp. It can capture electrical current when neurons are activated during brain activities. The EEG signals are high spatial resolution compared to other tools. EEG is known to be a secure and non-aggressive device [3][19]. The EEG sensor is an electrode placed on the top of the pericranium using a conductive gel. This helps to detect and direct the voltage to an amplifier. The electrodes are usually located in compliance with the international framework 10-20. The distance is specified between nasion, inion, and the latitude by the ten separations. The system faces an issue with ground circuit noise which is handled using differential amplifiers [21]. The brain waves measured in EEG are associated with the numerous oscillating sub-components and their subsequent breakdown. These are measured from peak value (between 0.5 v - 100 v amplitude). They are categorized as per their frequency, namely delta (0.5 Hz - 4 Hz), theta (4 Hz - 8 Hz), alpha (8 Hz - 13 Hz), beta (13 Hz - 30Hz) and gamma (> 30 Hz). However, theta and alpha bandwidths are commonly used to determine emotions [20-22].

3.4. Butterworth Bandpass Filter

The Butterworth filter is a signal processing filter to provide maximum flat frequency response in the pass-band. It is known as a maximally flat magnitude filter. The bandpass filter is used for wireless transmission and reception. It is used in a transmitter to limit the frequency of the output signal to the band assigned to the transmitter. This prohibits the transmitter to communicate with all other stations [23]. UNACT pre-processing involves filtering signals to remove noise and unnecessary artifacts. Bandpass filtering technique has been used to extract theta and alpha bands. Signal filtering involves a fifth-order Butterworth bandpass filter with a 4 Hz (lower frequency band) and a 13 Hz (upper-frequency band) cutoff frequency range.

3.5. Power Spectral Density

One of the most widely used feature extraction techniques is the power spectral density (PSD). The PSD is a measure of the power quality of the signal versus frequency. The power spectrum of the time series defines the power distribution to the signal frequency elements [24]. The Fourier analysis [25] defines that physical signals should be transformed into a variety of distinct frequencies or a frequency spectrum throughout a continuous range. As the signal energy is distributed across a limited interval of time, particularly when its total amount of energy is finite, the spectral energy density can be measured. The power spectral density applies to signals that have been existing for all time, or large enough over a time frame. Then, the PSD corresponds to the distribution of spectral energy that will be observed per unit time [24]. The power spectral density is used to describe the power of EEG signal components [26]. In UNACT, the PSD is used for the extraction of features. The PSD is calculated using the short-time Fourier transform (STFT) to take the average spectral power. The STFT is a Fourier-related transformation that used to evaluate the sinusoidal phase and frequency quality of the regional signal components as they travel over time [27].

3.6. Multi-layer perceptron (MLP)

Multilayer perceptron (MLP) is a feedforward artificial neural network (ANN). A single hidden layered MLP is known as the Vanilla neural network [28]. MLP uses a supervised machine learning approach known as back-propagation for instruction [29]. The MLP consists of a minimum three-node layer,

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namely an input layer (first layer), a hidden layer (second layer) and an output layer (third layer). The Input layer contains the same number of neurons and features. The second layer consists of a series of hidden layers, which is defined during the optimization process. MLP is being used for supervised machine learning, including emotion classification [5] [7] [30-33]. In UNACT, Multilayer perceptron (MLP) used to perform an emotional state classification based on the set of input features obtained from EEG signals. The classification of emotions is determined by the valence and the arousal.

4. Unified Neuro-Affective Classification Tool (UNACT)

4.1. Methods

UNACT is an affective-emotion profiling tool using the collected EEG signal. UNACT has developed under Agile software development methodology as illustrated in Figure 3. Every single part of UNACT design, coding and testing have done right after completion. If there were any changes required in terms of design and development, then done immediately.

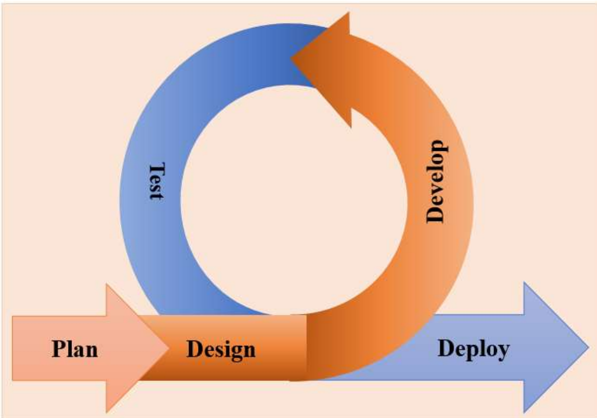

Figure 3. Agile methodology

The 4+1 [34] view model is designed to create a highly configurable UNACT architecture. This model includes a user view (Use case diagram), a logical view (Class diagram), a process view (Sequence diagram), a development view (Component diagram) and a physical view (Deployment diagram). Furthermore, the developed application possesses three modules includes (i) Modelling, (ii)Affective Classification and (iii) Analysis.

An important part of the system is the input and output design. UNACT only accepts the EEG data. Regarding training purposes, the collected EEG data should be in the sequence of Happy, Sad, Calm and Fear. Then, the data can be emotional or non-emotional EEG data to perform classification. Finally, the obtained data from the classification process should be used for analysis. UNACT produces the required output in every phase. In the modeling phase, the output is a trained valance, a trained arousal in the format of SAV. and emotion labeled data produced in CSV format. During the Classification phase, it produces only classified data in the format of CSV. Finally, the analysis part produces different required graphs (Arousal, Valence and Valence-Arousal) in the format of JPG.

UNACT integrated all supervised machine learning techniques for emotion profiling (described in section 3.1) except data acquisition (described in section 3.3) technique. Machine learning technique has been applied to the trained model, classify emotions and then visualize the classified emotions. Preprocessing purposes used the Butterworth bandpass filter technique (described in section 3.4) and used the Power Spectral Density (PSD) technique for the extraction of features. The Short-Time Fourier Transform used to take the average spectral power for PSD calculation (described in section 3.5). Then apply Multilayer perceptron (described in section 3.6) to conduct emotional state classification from a collection of input traits derived from EEG signals. Classification of emotions is measured by the valence and arousal (described in section 3.2). The performance is described in an affective space model (ASM) with four quadrants (described in section 3.2).

4.2. Tools
Python programming language has been used in the UNACT development. Python libraries used for system implementation. The libraries are NumPy, Pandas, SciPy, Sklearn, TkInter, and Matplotlib. However, NumPy, Pandas, SciPy, and Sklearn are used to applying machine learning technique. Matplotlib used for visualization, and TkInter used in the creation of user interfaces.

4.3. User Interface
UNACT user interfaces are illustrated in Figure 4 including popup windows of the respective phase.

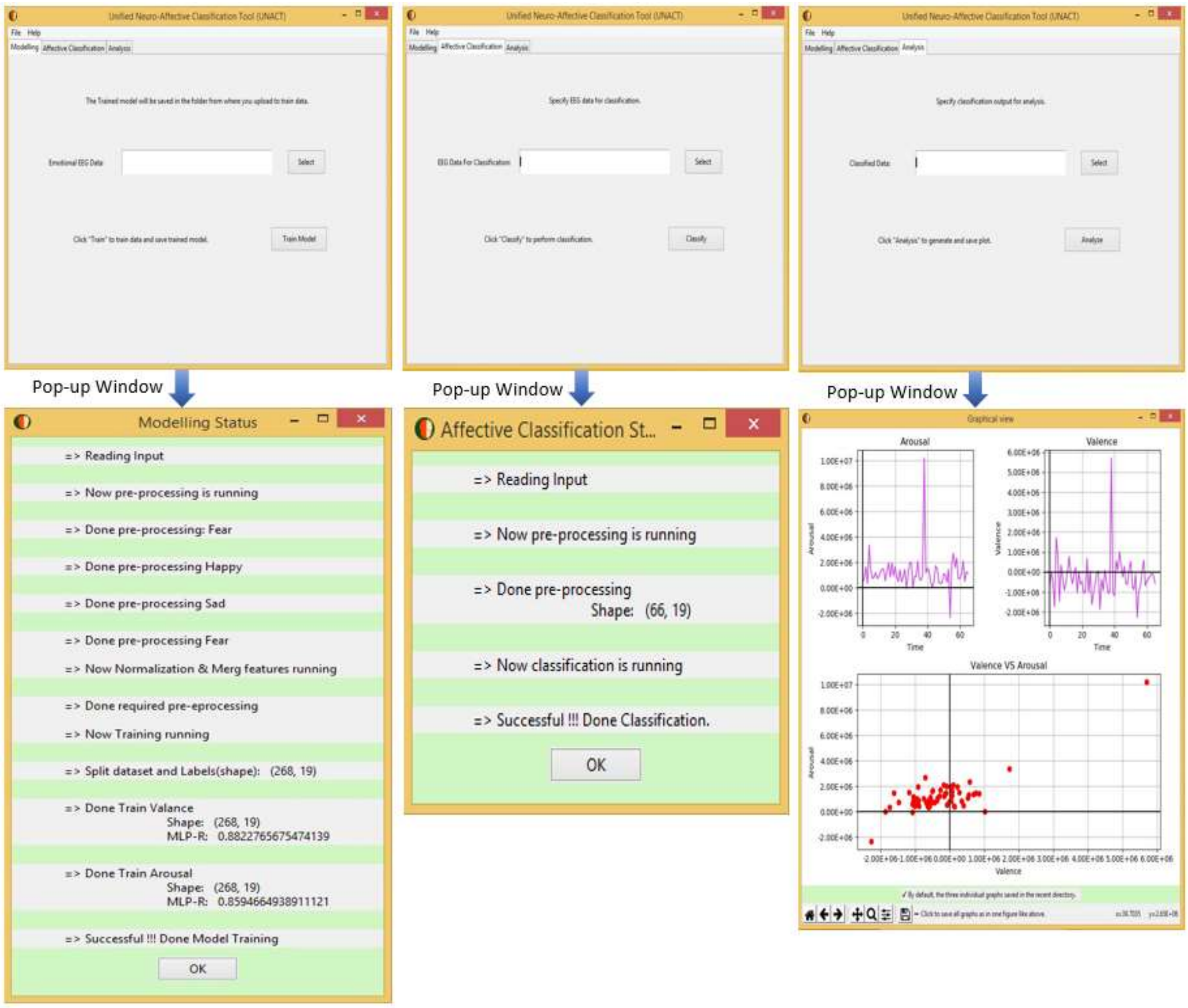

Figure 4. UNACT user-interface

5. UNACT Evaluation
The UNACT produces several outputs in different phase as mentioned bellow.

1. Modelling:
   - ✓ Trained arousal and Trained valence in the format of SAV.
   - ✓ Emotion labeled data in the CSV format.
2. Affective classification:

- ✓ Classified data in CSV format
3. Analysis:
   - ✓ Graph for arousal and valence in JPG format- depicted in Figure 5.
   - ✓ Graph for valence (x-axis) vs arousal (y-axis) in JPG format- depicted in Figure 5.

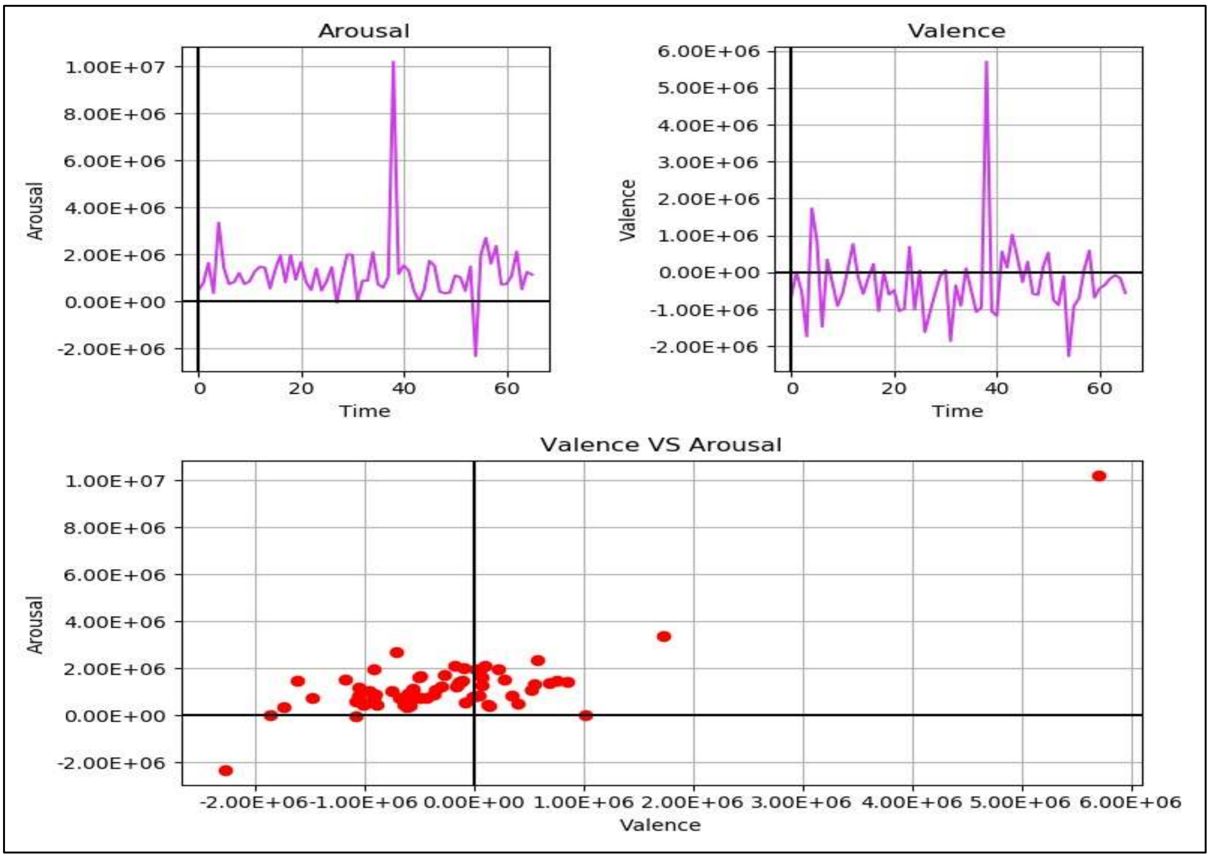

Figure 5. Graphical output from UNACT

The UNACT implementation has done under agile software development. The design, development (coding) and testing was repeated steps. While any block or part of the UNACT completed, it was tested. After the final product completion, the UNACT involved testing using EEG data (Collection process described in section 3.3). However, to compare the outcomes between the standard approach and the UNACT is used same Butterworth Bandpass filter, Power spectral density features, Multilayer perception algorithm. The output for valence classification accuracy is 88% and the arousal classification accuracy is 85%. The accuracy is slightly lower than a standard approach which was for valence is 89% and arousal is 88%. It may happen because of the PC power that the system utilizes for running the total process. The obtained results showed that UNACT is a real and reliable tool for the classification of emotions.

6. Conclusion

Emotion is a vital aspect of human behavior and attitude. Brain waves brain areas are known to be correlated with many cognitive and behavioral activities. Emotion can be used as a guide for those related activities. In order to analyze need tools which will save time and easy to use. UNACT is a tool that allows us to perform emotion profiling.

UNACT is user-friendly for non-technical persons. The user interface is simple, viable and easy-to-navigate for modeling, classification and analysis. Future work will focus on windowing and extension functionality for brain waves analysis using EEG signals including data acquisition technique, real-time EEG signal processing, multiple machine learning techniques to compare and get the best results. The UNACT aims to help in biomedical research because Neuro-Feedback therapy as an innovative procedure can help to recognize the basic emotional neuronal pathways by teaching the brain to regulate the actions of the brain and nervous system.

The result from UNACT Shows that it is a trustworthy tool to perform emotion profiling. However, future works will enhance UNACT as a self-analytic tool for the neurofeedback system.

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