Emotion Recognition from DEAP Dataset Using SVM Classifier

Sachin[1], Deepak Kumar[2]

[1] Department of Electronics & Communication Engineering, Om institute of technology and management, Hisar- 125001, Haryana, India; sachin.svk93@gmail.com.

[2] Department of Electronics & Communication Engineering, Om institute of technology and management, Hisar- 125001, Haryana, India; ergargdeepak@gmail.com.

Abstract: Emotion recognition has become critical for facilitating and enhancing human-computer interaction. Despite the critical role emotions play in human communication, the majority of existing human-computer interaction systems are incapable of recognising and interpreting user emotions. Internal physiological signs such as heart rate, breathing, and brain activity may be used to detect emotions. Physiological cues, particularly brain impulses, are regarded more trustworthy for emotion detection. Numerous academics and businesses have shown an interest in deciphering user intents through brain signals during the past few years. The most often utilised method for monitoring brain activity is electroencephalography (EEG). The EEG monitors the brain's electrical activity using electrodes implanted on the scalp. It provides great temporal resolution without posing any hazards, and it is very inexpensive. Several commercial EEG devices have been developed over the past several decades, and these devices are much simpler to set up and operate than laboratory-based EEG equipment.

Recognizing emotions from brain signals is not a simple job, since emotion representation is complex and gender dependent. The majority of prior research had poor accuracy in recognizing emotions, and some of them created a model for each user individually or for a subset of users. The purpose of this study is to enhance emotion identification by analyzing brain signals collected by EEG equipment and classifying male and female emotions. To decrease noise in EEG signals, many stages must be performed: reference, segmentation, band pass filtering, and denoising using wavelet transform. From the noise-free data, EEG frequency bands are isolated and five characteristics are computed to provide the feature vector for the classifier. Finally, we utilise an SVM classifier to identify the user emotion associated with the retrieved feature vector. The experimental findings established the suggested model's superiority and resilience in comparison to previous research that utilised the same dataset. The suggested model demonstrated a greater degree of accuracy (99.02%) when compared to the findings of previous research.

Keyword: Classifier, SVM, Machine Learning, EEG.

1.Introduction

Emotion recognition is the process of identifying human emotion. Giving computers the ability to recognize and express human emotions will enhance their performance in assisting humans. Many fields will be affected by enhancing the ability of computers to recognize emotions, such as, social media, multimedia auto-tagging, computer-assisted learning, entertainment and healthcare [1]. As example of benefits that obtained from enhancement of emotion recognition: the ability of attaching our real emotion with a Facebook post, the ability to auto-tag a YouTube video with the user emotion which will give better search results, the ability to skip boring contents of a lecture while providing computer-assisted learning courses, a strong impact in making videogames industry, and the ability to recognize the emotion of patients that have disabilities and can't express their health status [2].

Emotion refers to the changes in the psychological and physical state as a response to internal or external stimulus event. However, there is no widespread consensus on the definition of emotion. Not just that, but also there is an overlapping among the concepts of emotion, feeling and mood [3]. Affective state is more general term that is used by many researchers interchangeably with emotional state, and it can include the concepts of emotion, mood, etc.

One of the important issues in that research area is how to represent emotions. Although there are many defined models for emotion representation, there is no global agreement on what model must be used [4]. Most defined models for emotion representation fall under one of two major approaches, the simplest one is to use distinct words for each emotion, and the other one is to represent emotions through multi-dimensions scales [5]. The following subsections discuss those two approaches.

Emotions are expressed in a variety of non-verbal ways, including facial expressions, vocal intonation, and bodily movement. Internal physiological signals such as heart rate, skin conductance, and respiration, as well as Galvanic Skin Response (GSR), Electroencephalography (EEG), Positron Emission Tomography (PET), Magnetoencephalography (MEG), and functional Magnetic Resonance Imaging (MRI) can all be used to observe emotions (fMRI). Methods based on physiological signals, particularly those from the Central Nervous System (CNS), such as EEG, MEG, PET, and fMRI, are regarded more trustworthy than other methods [6].

The brain controls the majority of the body's other organs; typically, the brain sends messages to organs through nerves instructing the muscles to contract; for example, nerves transmit many electrical impulses to various muscles in the hand, enabling a person to move his hand with great accuracy [7]. User intents can be anticipated by monitoring and analysing brain signals. Brain-Computer Interface (BCI) is an area of study that is concerned with understanding user intentions based on brain activity monitoring [8]. It is very beneficial for individuals with severe motor impairments and may be the only way to communicate with patients who have lost all motor control in the Complete Locked-In State (CLIS).

The brain is the most enigmatic organ in the human body. It is in charge of the majority of other organs. It is in charge of our actions, conduct, and, of course, our emotions. The cerebrum, the brainstem, and the cerebellum comprise the human brain [9]. The cerebrum is the brain's biggest structure, and it is split into two cerebral hemispheres by a groove. Each cerebral hemisphere is composed of a grey matter layer called the cerebral cortex and a white matter layer. Each hemisphere's cerebral cortex is usually split into four regions or lobes, each called after one of the four skull bones that protect it: the frontal lobe, the temporal lobe, the parietal lobe, and the occipital lobe. Each region corresponds to a distinct function [10]. The many components of the human brain are shown in Figure 1.

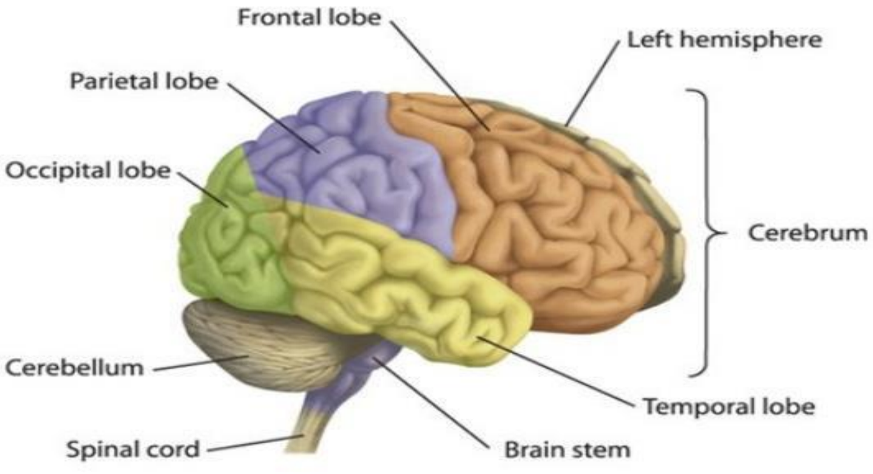

Figure 1. Human Brain

The Brain-Computer Interface (BCI) is a kind of communication technology that establishes a direct connection between the human brain and the computer without involving other bodily parts [11]. Historically, this technique was aimed at people with severe motor impairments, with the goal of improving their quality of life and lowering the expense of critical care. BCI is currently utilized not just by locked-in individuals, but also by non-locked-in individuals in a variety of areas like as entertainment and marketing. BCI has grown in popularity over the past two decades and lately attracted a large number of researchers [12].

2. Literature Survey

Emotion recognition using brain signals become a hot topic nowadays which attracts many researchers. Machine learning techniques are used intensively in this research area. The first issue that faces researches when applying machine learning techniques is using a large dataset with enough data. This dataset can serve as a benchmark to compare research results with each other [13].

One of the critical challenges in this field of study is amassing sufficient data for training and evaluating the model. Kolestra et al. developed the DEAP dataset (a Database for Emotion Analysis Using Physiological Signals) for emotion analysis [14]. The EEG, GSR, blood volume pressure, respiration amplitude, skin temperature, electrocardiogram (ECG), electromyogram (EMG), and electrooculogram (EOG) of 32 individuals were monitored while they saw 40 one-minute music video clips. Along with these physiological indications, a camera captured the faces of 32 individuals. A total of 1280 trials were made available for research. Following each trial, the subject was instructed to select his valence, arousal, dominance, and liking levels. Each scale's level may be adjusted between 1 and 9 [26]. EEG devices that were used in DEAP dataset have only 32 electrodes. Four electrodes are on the center, and the other 28 electrodes are on either the left or the right hemispheres, which forming 14 symmetrical pairs of electrodes.

2.1 Previous Work

This subsection presents a set of studies for EEG-based emotion recognition.
Kolestra et al., the DEAP dataset's creators, examined the relationship between EEG signal frequency and participant evaluations [15]. They used characteristics derived from EEG signals, peripheral physiological data, and multimedia content analysis modalities to achieve a single-trial classification for the scales of valence, arousal, and liking. Welch's technique was used to extract characteristics such as the spectral strength of the theta, slow alpha, alpha, beta, and gamma bands for each electrode in the EEG modality [26]. Additionally, the spectral power imbalance between all symmetrical pairs of electrodes was retrieved for the four bands alpha, beta, theta, and gamma. 216 characteristics were retrieved from EEG data in total.

For the feature selection step, Fisher's linear discriminant was employed with a threshold of 0.3. The three scales of valence, arousal, and liking were divided into two groups (low and high), and each of those three binary classification issues was solved using a Gaussian naive Bayes classifier. Due to the presence of imbalanced classes on certain measures, F1-scores were utilised in addition to accuracy to assess classification performance for each participant individually using a leave-one-out cross-validation method. The experiment revealed that the average accuracies for valence, arousal, and liking were 57.6 percent, 62.0 percent, and 55.4

percent, respectively, while the F1-scores were 56.3 percent, 58.3 percent, and 50.2 percent. The classification results obtained using EEG were marginally better than those obtained using random classification [16].

Matiko et al. developed a categorization method for positive and negative emotions that is based on fuzzy logic. Fuzzy rules are established in this study based on prior research demonstrating a significant connection between negative and positive emotions and activity of the human brain's right and left hemispheres [17]. For each symmetrical pair of electrodes, the alpha band was filtered using a finite impulse response filter with 127 filter coefficients, and four statistical characteristics were computed: mean, standard deviation, and mean of the absolute values of the first and second differences. Along with statistical characteristics, the alpha band's signal strength was calculated [18].

3. Methodology

Automated emotion detection using EEG data is a relatively new research area that is being actively investigated in the Affect Computing group. EEG signals are generated by the Central Nervous System (CNS) and directly reflect brain activity, which may overcome the difficulties associated with other physiological signals (such as the galvanic skin response) in the presence of undesired interferences caused by non-emotional, physical, or environmental changes. EEG signals gathered from several channels with correlated data may enable the development of a more accurate and robust emotion detection system. The goal of an automated EEG emotional signal processing system is to build a statistical model (supervised machine learning) based on the input training samples that can accurately predict the label of a testing sample given certain restrictions. Recently, as a result of advancements in electronics like as wearable sensors, high-fidelity, affordable, and unobtrusive EEG headsets have become widely available, with the potential to transform the current generation of impact computing applications.

The DEAP dataset is used in this study, which is a database collecting a variety of physiological signs of emotions from a variety of individuals, both for negative and positive emotions [51]. Members listened to music recordings and rated each video on arousal, valence, resemblance/abhorrence, predominance, and commonality. EMG signals were collected while participants viewed the recordings. The test's stimuli were picked in stages: first, 120 initial improvements were chosen; next, a one-minute feature segment was resolved for each upgrade; and finally, 40 stimuli were chosen through an electronic abstract assessment test.

We recorded EEG signals from thirty-two scalp locations. The suggested methodology's basic block diagram is shown in Figure 2. The DEAP dataset contains data from forty channels, thirty-two of which are EEG channels and eight of which are not. To begin, we retrieved EEG data from the whole dataset. Following that, the EEG data were denoised and sub-frequency bands were separated from the raw data.

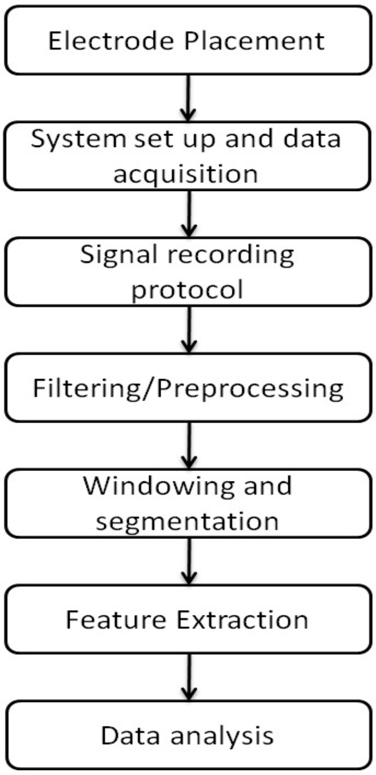

Figure 2. Block diagram

4. EEG Pre-processing

Electroencephalography (EEG) is a method used to capture the brain's electrical activity [19]. This activity is produced by synchronous neuron activity and is recorded using several electrodes lying on the scalp and spatially arranged according to a method called the 10-20 system [20]. EEG signals collected from the scalp are frequently contaminated by a variety of noises (i.e., thermal noise) and artefacts (electrode movement, electrophysiological potentials generated by muscle activities such as eye movements, biting, and chewing) that are continuous in time and have a very large amplitude. This results in low signal quality, which makes direct interpretation difficult and often impossible [21]. The purpose of the preprocessing phase in such a signal processing system is to remove noise and artefact interference, as well as to mitigate volume conduction interference from neighbouring neural networks [22]. Elimination of artefacts is critical for the robustness of any EEG emotion detection system. Numerous techniques for eliminating or minimising such interference have been described in the literature. Current artefact removal techniques, such as the digital band-pass filter, remove all frequency components above the cut-off frequency that may include critical information for detection, resulting in erroneous EEG signal interpretation [23].

5. Results and Discussion

The examination's objective is to ascertain the male and female subjects' emotional state. We need to ensure that the participant was in an eager state of disgust while examining the parts devoted to eliciting the emotion. When we recognise the individual is in an emotional state of disgust, we can make sense of the EEG signals and information. IBM SPSS Statistics 20 and MATLAB were used to analyse the data.

Each participant rates the video signals for valence and arousal on a scale of 0 to 9 in the DEAP dataset. The average of each video's valence and arousal values is computed and categorised as high-low valence-arousal. A topic with a valence value more than 5 is considered to have a high valence, whereas one with a valence value less than 5 is considered to have a low valence. Similarly, data is segmented according to level of arousal. Thus, four categories are defined for the valence data which are high valence male (HVM), low valence male (LVM), high valence female (HVF) and low valence female (LVF). Similarly, four categories are defined for the arousal data; high arousal alcoholic (HAA). Low arousal alcoholic (LAA), high arousal non-alcoholic (HANA) and low arousal non-alcoholic (LANA). The eight different classification accuracies are classified between these categories.

5.1 Statistical analysis

Five characteristics of the filtered EEG signal are quantified. Each feature was computed for the baseline EEG signal, the stimulus EEG signal associated with each mood, and the EEG signal associated with each window. The Wilcoxon test, MANOVA, and SVM classifier are used to evaluate the EEG data depending on mood. The p value was calculated in statistical tests, and its value determined whether the null hypothesis was accepted or rejected. The p-value indicates the chance of getting a test statistic that is at least as severe as the observed one, given that the null hypothesis is true. When the p-value is less than the significance threshold, e.g. 0.05, one often "rejects the null hypothesis." We used P values of 0.05, 0.01, and 0.001 as nominal levels of significance, high significance, and very high significance, respectively, to test the various hypotheses.

5.2 EEG baseline analysis

The neutral movie segments were utilized to determine the baseline value for the EEG signals. The thirty seconds immediately after the commencement of the neutral movie fragment were omitted in order to prevent carryover effects from the preceding movie fragment. We initially used the t-test to determine if similar baselines were produced for the thirty-two EEG channels. For the baseline data, all five characteristics were computed. To begin, we examined the data for the five characteristics. As anticipated, we discovered a statistically significant difference (p 0.05) in a variety of EEG characteristics across all thirty-two channels. Following that, statistical analysis were conducted between EEG channels. Then we determined if there was a statistically significant difference between the male and female groups. For the male group, substantial variations in baseline EEG signals across all channels were found. For the female group, similar findings are found. These findings were anticipated, given that similar amounts of baseline activity had previously been discovered for various individuals.

5.3 Comparison of baseline and stimuli data

The five features were calculated of the EEG activities for the emotional stimulus. The average of the each window for each activity was taken. The data were analyzed for the male and female groups. We tested baseline-to-trial changes of emotional activity for both groups and within the groups for each electrode, separately.

Firstly, the statistical difference between baseline and emotional stimuli EEG for each feature has been calculated. It was firstly tested for average value. The average of each electrode was calculated. When comparing the average amplitude between the baseline and emotion EEG using Wilcoxon test, we find a significant difference ($p < 0.05$). Within the male group, we also find a significant difference between the baseline and emotion for the average EEG amplitude of the high valence ($p = 0.017$), low valence ($p = 0.029$), high arousal ($p =0.015$) and low arousal ($p = 0.031$). For the female group, we also find a significant difference between the baseline and emotion for the average EEG amplitude of the high valence ($p = 0.023$), low valence ($p = 0.019$), high arousal ($p =0.033$) and low arousal ($p = 0.04$). It was expected that the emotional stimuli will be significantly different from the baseline EEG data since the emotional stimuli video produces changes in the brain waves. Similar results are obtained for the other four features; correlation, variance, kurtosis and skewness. The fact that the features are significantly different probably due to cross talk since these features lie in the vicinity of each other.

Multivariate analyses of variance (MANOVA) were conducted on electrode locations to determine how stimulus category impacted the activity of the EEG channels and if there were variations between groups in this regard. For the EEG, MANOVA analysis included one between-subjects factor group (with two groups) and one within-subjects factor emotion. For the FPz channel, we find a main effect of group ($L = 0.391$; $F = 10.31$; $p < 0.05$) and a main effect of emotion ($L = 0.44$; $F = 12.98$; $p < 0.05$). We find that for emotion there are significant differences for the all five features. For the AFz, we only find a main effect of emotion (L =

0.37; F = 19.43; $p < 0.05$). It was found for the all five features. Similar results are obtained for the other electrodes. We find that for emotion, there are significant differences in all features. For the emotion and group interaction also, five features shows the significant difference. We used Spearman Rank Order Correlation coefficients to calculate the correlations between the different EEG features and the emotions. We found significant correlations between the different EEG features and emotions.

5.4 Classification results

Five features are calculated of EEG signal for the emotional videos. The features are calculated for the high-low/valence-arousal of the male and female. The calculated features are arranged in eight datasets; high valence male (HVM), low valence male (LVM), high valence female (HVF), low valence female (LVF), high arousal male (HAM), low arousal male (LAM), high arousal female (HAF), and low arousal female (LAF). SVM classifier is used to classify the different categories of data. Classifier is used to classify the any two categories of dataset. For the classification process, one category is defined as '1' and other is defined as '2'. Five-fold cross validation process is used to classify the data. In five-fold process, the data is divided into five parts. Out of five parts, four parts (80% data) is used to train the classifier and fifth part is used to test the trained classifier. This process is repeated for each part of the dataset and at last, average of five accuracies were obtained. In this work, classification accuracies were calculated for the eight different categories of the data set. These categories are:

High and low valence

1. high valence male (HVM) and low valence male (LVM)
2. high valence female (HVF) and low valence female (LVF)

High and Low arousal

3. high arousal male (HAM) and low arousal male (LAM)
4. high arousal female (HAF) and low arousal female (LAF)

Alcoholic and Non-alcoholic

5. high valence male (HVM) and high valence female (HVF)
6. low valence male (LVM) and low valence female (LVF)
7. high arousal male (HAM) and high arousal female (HAF)
8. low arousal male (LAM) and low arousal female (LAF)

5.4.1 HVM and LVM

The classification was performed between high and low valence of the male. The feature vector was constructed using high valence male as category '1' and low valence male as category '2'. The classification accuracy varies from 64.16% to 65.31% in five-fold process. The achieved average classification is 64.87%. The results showed that the high valence is different from the low valence male. These classification accuracies are presented in Figure 3.

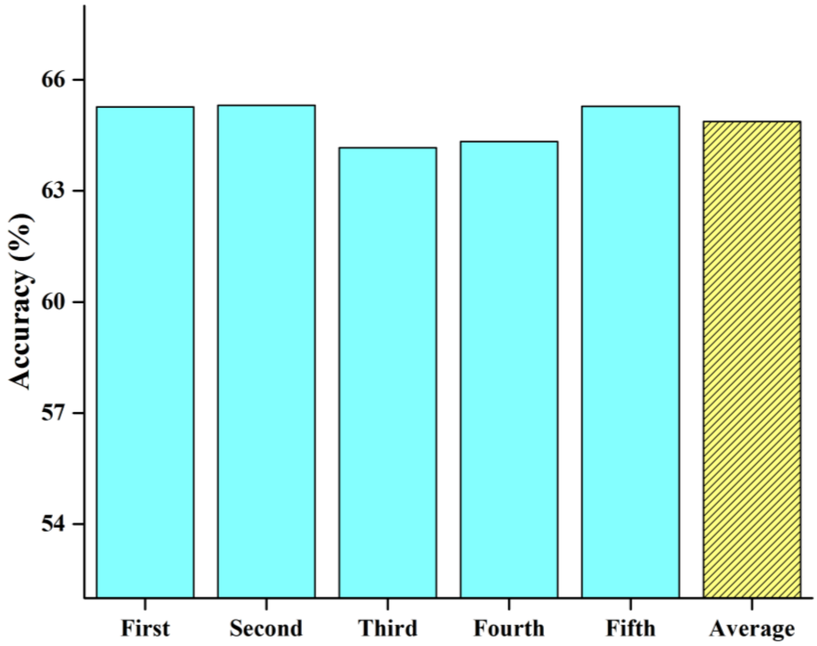

Figure 3. Classification accuracy for HVM and LVM

5.4.2 HVF and LVF

The classification was performed between high and low valence of the female. The feature vector was constructed using high valence female as category '1' and low valence female as category '2'. The classification accuracy varies from 55.02% to 55.89% in five-fold process. The achieved average classification is 55.55%. The results showed that the high valence is different from the low valence female. These classification accuracies are presented in Figure 4.

5.4.3 HAM and LAM

The classification was performed between high and low arousal of the male. The feature vector was constructed using high arousal male as category '1' and low arousal male as category '2'. The classification accuracy varies from 65.48% to 66.20% in five-fold process. The achieved average classification is 65.94%. The results showed that the high arousal is different from the low arousal male. These classification accuracies are presented in Figure 5.

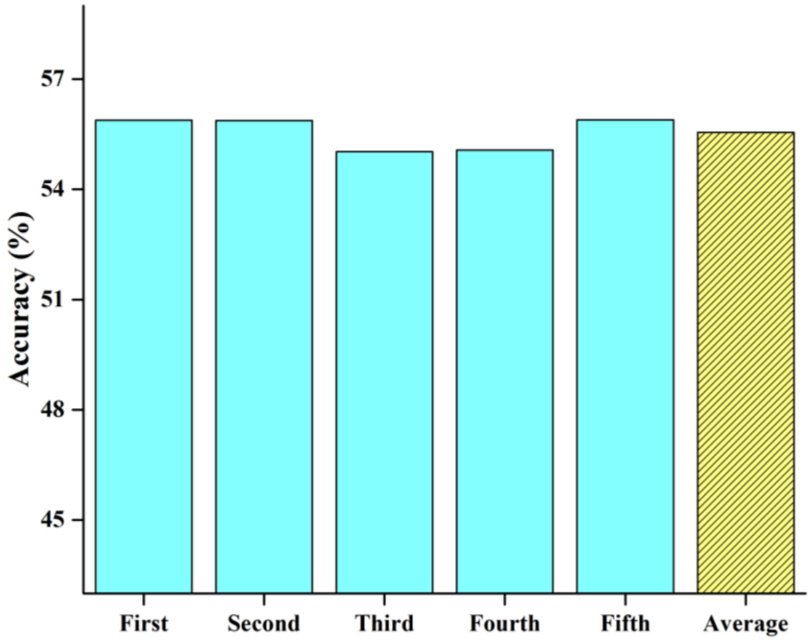

Figure 4. Classification accuracy for HVF and LVF

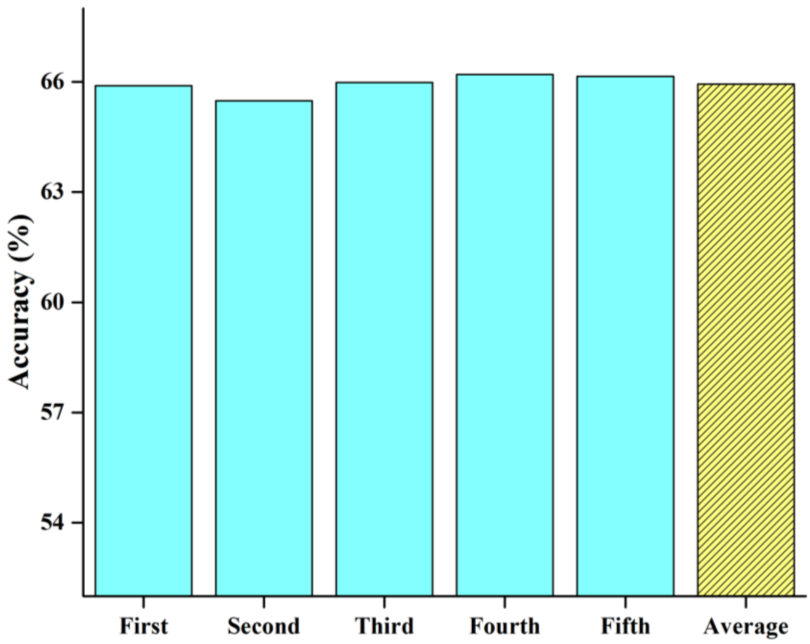

Figure 5. Classification accuracy for HAM and LAM

5.4.4 HAF and LAF

The classification was performed between high and low arousal of the female. The feature vector was constructed using high arousal female as category '1' and low arousal female as category '2'. The classification accuracy varies from 61.96% to 62.94% in five-fold process. The achieved average classification is 62.50%. The results showed that the high arousal is different from the low arousal female. These classification accuracies are presented in Figure 6.

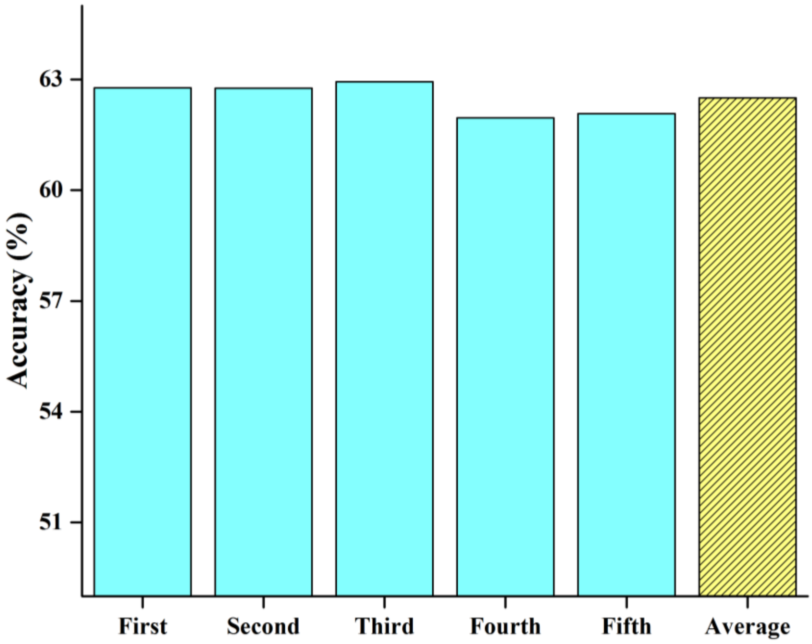

Figure 6. Classification accuracy for HAF and LAF

5.4.5 HVM and HVF

The classification was performed between high valence male and female. The feature vector was constructed using high valence male as category '1' and high valence female as category '2'. The classification accuracy varies from 98.63% to 99.40% in five-fold process. The achieved average classification is 99.02%. The results showed that the high valence male are different from the high valence female. These classification accuracies are presented in Figure 7.

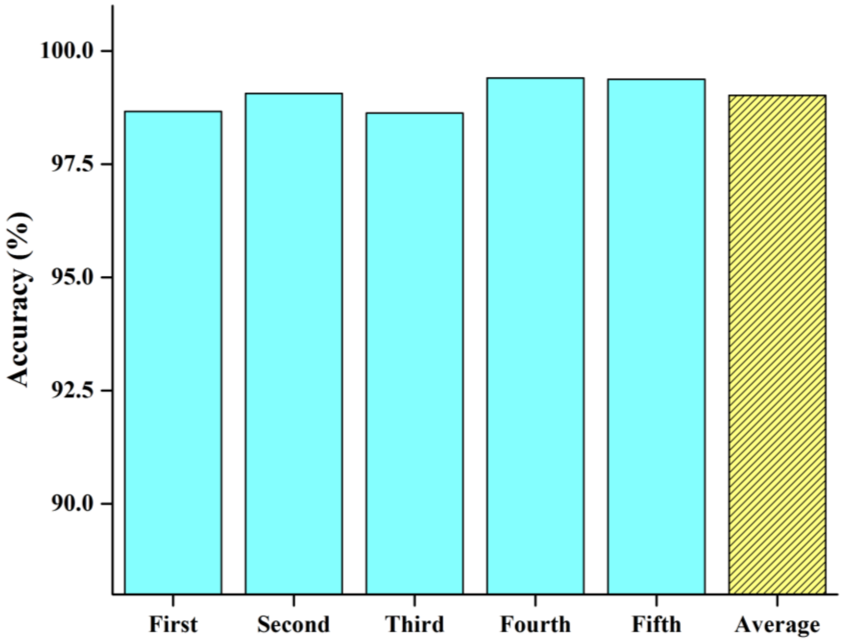

Figure 7. Classification accuracy for HVM and HVF

5.4.6 LVM and LVF

The classification was performed between low valence of the male and female. The feature vector was constructed using low valence male as category '1' and low valence female as category '2'. The classification accuracy varies from 97.80% to 98.71% in five-fold process. The achieved average classification is 98.32%. The results showed that the low valence male is different from the low valence female. These classification accuracies are presented in Figure 8.

5.4.7 HAM and HAF

The classification was performed between high arousal of male and female. The feature vector was constructed using high arousal male as category '1' and high arousal female as category '2'. The classification accuracy varies from 98.08% to 99.54% in five-fold process. The achieved average classification is 98.79%. The results showed that the high arousal male is different from the low arousal female. These classification accuracies are presented in Figure 9.

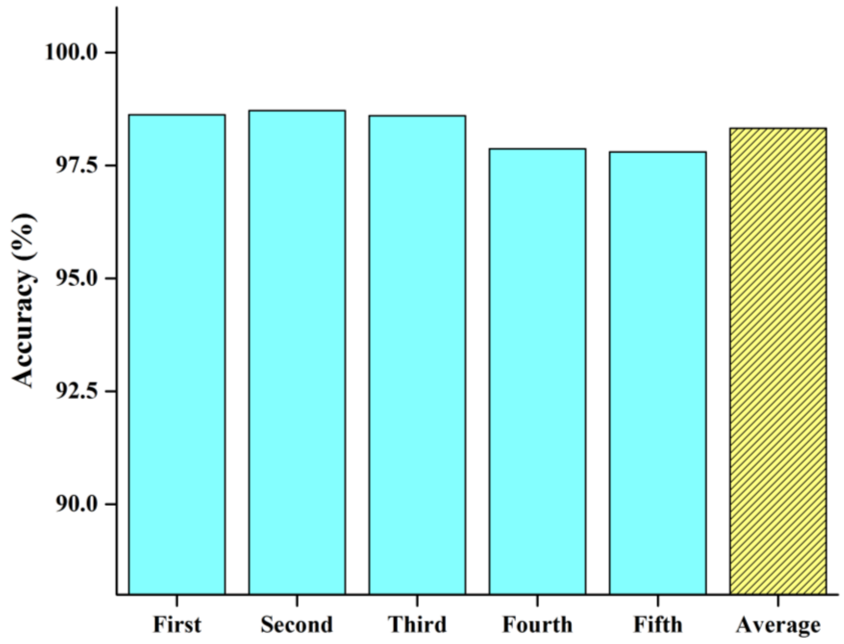

Figure 8. Classification accuracy for LVM and LVF

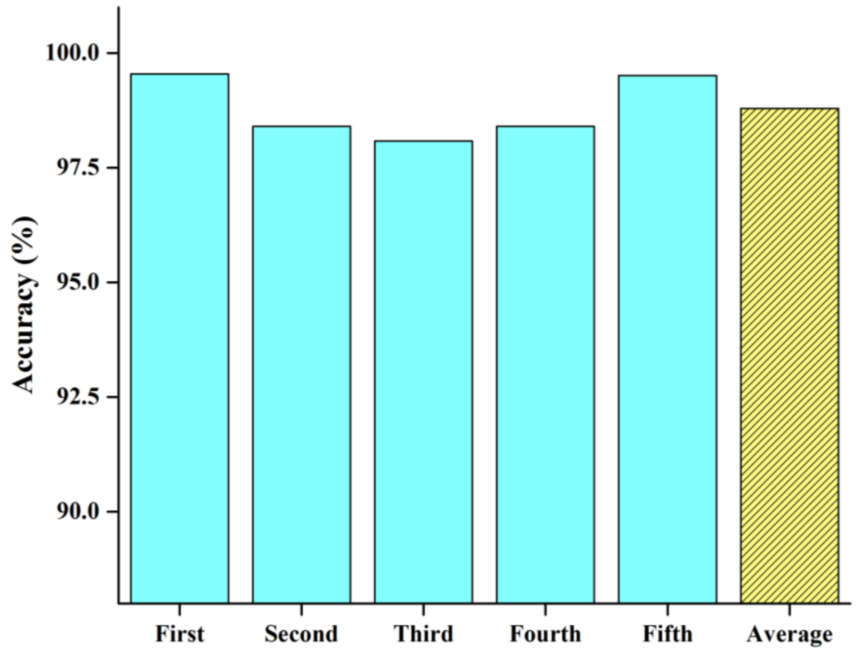

Figure 9. Classification accuracy for HAM and HAF

5.4.8 LAM and LAF

The classification was performed between low arousal of male and female. The feature vector was constructed using low arousal male as category '1' and low arousal female as category '2'. The classification accuracy varies from 97.57% to 98.18% in five-fold process. The achieved average classification is 98.05%. The results showed that the low arousal male is different from the low arousal female. These classification accuracies are presented in Figure 10.

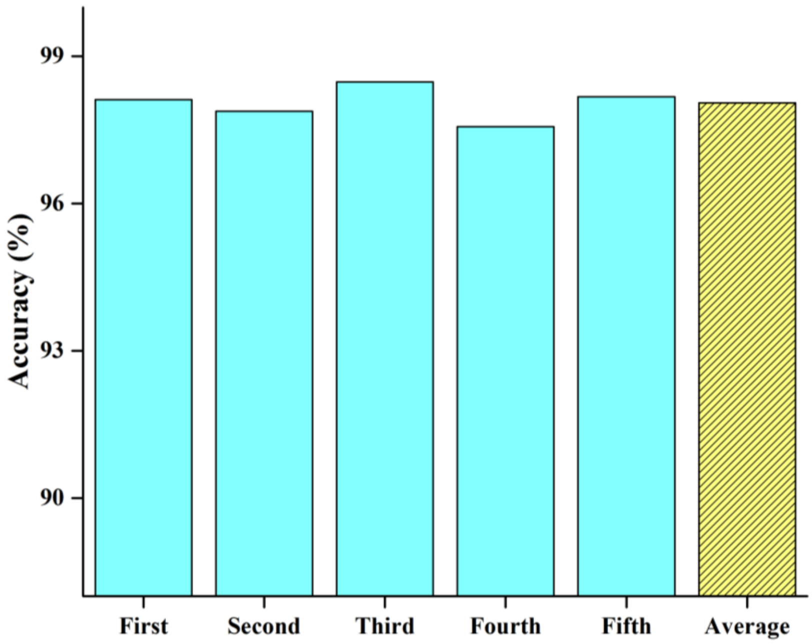

Figure 10. Classification accuracy for LAA and LANA

6. Conclusion

This thesis introduced a model for improving emotion recognition based on brain signals that recorded by EEG devices using SVM classifier. The proposed model cannot be constrained to specific users or specific groups of users, and it can become a convergence (trained) model for any new user, so no training or configuration steps are required before using it by new users. The proposed model was tested on a DEAP dataset with a relatively large number of participants. The emotional scales of valence and arousal in addition to male/female scale were targeted by the proposed model to be recognized. The experimental results showed that SVM classifier achieved high accuracy compared to previous studies. In case of the studies which applied the modern deep learning techniques, the proposed approach shows a distinguish competitor, since the proposed model achieved close results in terms of accuracy. The comparison with other studies confirms the superiority and robustness of the proposed model.

This thesis examined the possibility of using brainwaves to identify emotion. It has aided the area of emotional computing by increasing our knowledge of the relationship between affective states and Central Nervous System signals, as well as the feasibility of using this relationship in system design. The thesis demonstrated that EEG signals are appropriate for detecting the effects of gender via the use of an SVM classifier. Additionally, it offered quantitative support for the affective-related claims made from a human psychology viewpoint in terms of frontal asymmetry activity between the hemispheres while expressing various emotions.

References

[1] Picard, Rosalind W. “Affective Computing.” Technical report 321. MIT Media Laboratory Perceptual Computing Section, April 1995.

[2] Scherer, Klaus R. “What are emotions? And how can they be measured?” Social Science Information 44, no. 4, pp. 695–729, December 2005

[3] Soleymani, Mohammad, Sander Koelstra, Ioannis Patras, and Thierry Pun. “Continuous Emotion Detection in Response to Music ideos.” In IEEE International Conference on Automatic Face and Gesture Recognition and Workshops (FG 2011), pp. 803–808, IEEE, March 2011. 98

[4] Russell, James A. “Culture and the categorization of emotions.” Psychological Bulletin 110, no. 3, pp. 426–450, 1991.

[5] Ekman, Paul, Wallace . Friesen, Maureen O’Sullivan, Anthony Chan, Irene Diacoyanni-Tarlatzis, Karl Heider, Rainer Krause, William Ayhan LeCompte, Tom Pitcairn, Pio E. Ricci-Bitti, Klaus Scherer, Masatoshi Tomita, and Athanase Tzavaras. “Universals and Cultural Differences in the Judgments of Facial Expressions of Emotion.” Journal of personality and social psychology 53, no. 4, pp. 712–717, October 1987.

[6] Mehrabian, Albert. “Pleasure-arousal-dominance: A general framework for describing and measuring individual differences in Temperament.” Current Psychology 14, no. 4, pp. 261–292, December 1996.

[7] Fontaine, Johnny R.J., Klaus R. Scherer, Etienne B. Roesch, and Phoebe C. Ellsworth. “The World of Emotions is not Two-Dimensional.” Psychological Science 18, no. 12, pp. 1050–1057, December 2007.

[8] Koelstra, Sander, Christian Mühl, Mohammad Soleymani, Jong-Seok Lee, Ashkan Yazdani, Touradj Ebrahimi, Thierry Pun, Anton Nijholt, and Ioannis Patras. “DEAP: A Database for Emotion Analysis Using Physiological Signals.” IEEE Transactions on Affective Computing 3, no. 1, pp. 18–31, January 2012.

[9] Petrantonakis, Panagiotis C., and eontios J. Hadjileontiadis. “Emotion Recognition from Brain Signals Using Hybrid Adaptive Filtering and Higher Order Crossings Analysis.” IEEE Transactions on Affective Computing 1, no. 2, pp. 81–97, August 2010.

[10] Nicolas-Alonso, Luis Fernando, and Jaime Gomez-Gil. “Brain Computer Interfaces, a Review.” Sensors 12, no. 2, pp. 1211–1279, January 2012.

[11] Rosdahl, Caroline Bunker, and Mary T. Kowalski. “Textbook of basic nursing.” Lippincott Williams & Wilkins, 2011.

[12] Hans, S. and Ghosh, S.(2020), "Position analysis of brushless direct current motor using robust fixed order H-infinity controller", Assembly Automation, Vol. 40 No. 2, pp. 211-218.

[13] S. Hans,S. Gupta Algorithm for Signature Verification Systems National conference on Signal & Image Processing(NCSIP-2012), Sri sai Aditya Institute Of Science & Technology.

[14] S. Hans, S. Gupta Preprocessing Algorithm for Offline signature System" National Conference on Recent Trends in Engineering & science (NCRTES- 2012), Prestige Institute of Engineering & science, Indore.

[15] S. Hans, An Algorithm for Speed Calculation of a Moving Object For visual Servoing Systems International Conference on VLSI, Communication and Networks (VCAN-2011), Institute of Engineering & Technology Alwar-2011.

[16] S. Hans & SG Ganguli (2012) Optimal adaptive Visual Servoing of Robot Manipulators

[17] S. Katyal, S. Raina and S. Hans. "A Energy Audit on Gujarat Solar Plant Charanka." International Journal for Scientific Research and Development 5.4 (2017): 2133- 2138.

[18] S. Hans (2018) A Review of Solar Energy And Energy Audit on Harsha Abacus Solar Plant: A Energy Audit on Gujarat Solar Plant Charanka.

[19] S. Hans, R. Walia ,Thapar Institute of Engineering and Technology, Patiala. "Optimal MPPT Control using Boost Converter for Power Management in PV- Diesel Remote Area ." Global Research and Development Journal For Engineering 45 2019: 24 - 31.

[20] S.Katyal, S.Raina and S. Hans. "A Brief Comparative Study of Solar Energy." International Journal for Scientific Research and Development 5.4 (2017): 2126-2132.

[21] S. Hans and S. Ghosh, "H-infinity controller based disturbance rejection in continuous stirred-tank reactor," Intelligent Automation & Soft Computing, vol. 31, no.1, pp. 29–41, 2022.

[22] S. Hans, S. Ghosh, S. Bhullar, A. Kataria, V. Karar et al., "Hybrid energy storage to control and optimize electric propulsion systems," Computers, Materials & Continua, vol. 71, no.3, pp. 6183–6200, 2022

[23] S. Hans, S. Ghosh, A. Kataria, V. Karar and S. Sharma, "Controller placement in software defined internet of things using optimization algorithm," Computers, Materials & Continua, vol. 70, no.3, pp. 5073–5089, 2022