Analysis of Emotions through the Use of Physiological Signals

Konstantinos Sakkas*, Alexandra Tsogka*, Athanasios Gkimitzoudis*, Nikolaos Giannakeas*, Katerina D. Tzimourta*†, Markos Tsipouras†, Euripidis Glavas*, Alexandros T. Tzallas*

* Department of Informatics and Telecommunication, University of Ioannina, Arta, Greece
†Dept. of Electrical & Computer Engineering, University of Western Macedonia, Kozani, Greece
ksakkas@uoi.gr, alexandratsogka01@gmail.com, nasosgimi@gmail.com, giannakeas@uoi.gr, ktzimourta@uoi.gr, mtsipouras@uowm.gr, eglavas@uoi.gr, tzallas@uoi.gr

***Abstract*— Emotion is a psychosomatic process that is caused either by a conscious or non-conscious perception of an object or a situation whereas, the result of that process is depicted either by the expression of the face, or physically, or with a combination of the above. An important mechanism playing a significant role in the recognition of emotions is the encephalogram, which enables us to detect significant signals of the brain. The methodology developed aims to the identification of basic emotions by using an electroencephalogram through an experimental process where participants were asked to evaluate the experiment according to the valence, arousal and dominance of each emotion inflicted on them by videos they were subjected to watching. Through the experimental process, a vector of characteristics is analyzed for each of the electrodes of the electroencephalogram and for a series of videos. The training of a model and classification of algorithms were the key to finding the best methods in terms of sensitivity, accuracy, and specification of our data.**

***Keywords*— Emotion, Electroencephalogram, Brain, Machine learning, Classification algorithms**

I. Introduction

The brain constitutes the most important part of the human central neural system. Brain signals are caused by the electrical charge transfer between neurons as well as from the potential difference caused during this transfer.[1] Brain signals are recorded through electroencephalographic (EEG) devices. In these devices several electrodes are placed in specific parts of the brain with a scope to receiving signals [2]. Lately, several commercial wearable EEG recording devices have been developed for lifestyle monitoring that are also light-weight and in many cases affordable for daily use.

Emotions are a psychosomatic process caused by a conscious or non-conscious perception of an object or a condition, which is closely related to the stimulation of system's nervous through the chemical changes that occur, while the result of this action is depicted either by facial expressions or verbally, or physically, or a combination of them.

Emotions have become a research focus for scientists for decades, developing several theories such as the theory of Paul Ekman [3] who acknowledges in his theory seven different emotions which are anger, disgust, fear, happiness, sadness, and surprise. The cycle of emotions according to this theory is presented in figure 1.

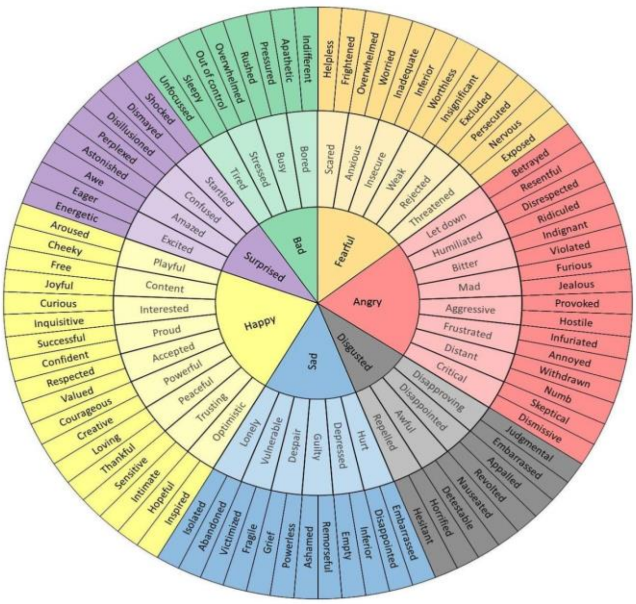

Fig. 1. The cycle of emotions according to Paul Ekman

Another theory is developed by Robert Plutchik [4], claiming that the basic emotions are eight, coming in opposite pairs and different colors. According to the theory, the darker the color the more intense is the emotion and, mixing the basic colors, second and third level emotions can arise. Figure 2 displays an imaginary cycle of emotions based this theory.

A more recent theory was proposed by W. Gerrod Parrott in 2001, who states that by analyzing deeper emotions in the form of a tree, more than 100 emotions can arise [5].

Recently, automated processing of EEG recordings goes beyond the analysis of neurological conditions such as epilepsy [6] or dementia[7]. EEG-based emotion analysis utilizing complex signal processing techniques and novel machine learning approaches has become a great field of research and innovation. Quantitative features extracted from EEG signals acquired from clinical or wearable EEG recording devices are used to capture the differences between emotional states.

We acknowledge the support of this work by the project "Immersive Virtual, Augmented and Mixed Reality Center Of Epirus" (MIS 5047221) which is implemented under the Action "Reinforcement of the Research and Innovation Infrastructure", funded by the Operational Programme "Competitiveness, Entrepreneurship and Innovation" (NSRF 2014-2020) and co-financed by Greece and the European Union (European Regional Development Fund).

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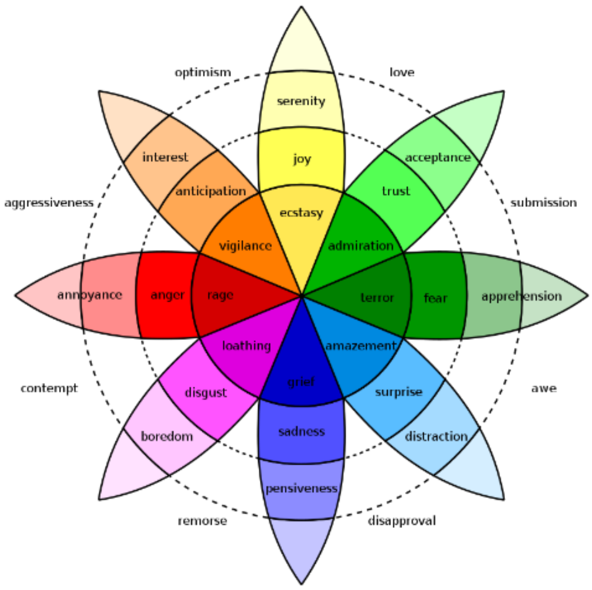

Fig. 2. Robert Plutchik's theory of emotions

Based on the literature review, most recent studies use different methods to recognize emotions. Some of them are Variational Mode Decomposition (VMD), Deep Neural Network, eye-tracking, short-term memory, Machine learning, recognize emotion etc. Regarding metrics, an approach was observed in related metrics such as Valence, Arousal, Dominance, Liking/Disliking, Negative, Neutral and Positive emotions.

In conclusion, from all the studies analyzed, common approaches emerge regarding the extracted feature vector as well as the classification model. The most common features calculated from the EEG signal ξ shown in the studies are [8][9]

- Energy $E_{\xi} = \sum_{-\infty}^{\infty} |\xi(t)|^2$
- The average price $\mu_{\xi} = \frac{1}{T} \sum_{t=1}^{T} \xi(t)^{\mathrm{T}}$
- The standard deviation $\sigma_{\xi} = \sqrt{\frac{1}{T} \sum_{t=1}^{T} (\xi(t) - \mu_{\xi})^2}$
- The 1st derivative $\delta_{\xi} = \frac{1}{T-1} \sum_{t=1}^{T-1} |\xi(t+1) - \xi(t)|$
- The Normalized 1st derivative $\underline{\delta} = \frac{\delta_{\xi}}{\sigma_{\xi}}$
- The 2nd derivative $\gamma_{\xi} = \frac{1}{T-2} \sum_{t=1}^{T-2} |\xi(\tau+2) - \xi(t)|$
- Normalized 2nd derivative $\underline{\gamma} = \frac{\gamma_{\xi}}{\sigma_{\xi}}$

The above are indicative characteristics of a wide range of frequency and statistical characteristics extracted from the EEG in studies using the DEAP Database [10] for control and validation of their methodology [11][12]. Table I briefly presents the characteristics calculated in each methodology as well as the results of these methods.

TABLE I. THE CHARACTERISTICS STUDIED IN THE STUDIES EXAMINED

Authors	**Year**	**EEG characteristics**	**Results**
Rui Li et al.	2022	θ, α, β, γ, all	ACC 84.44% Valence 65.70% Arousal 64.22%
Parthana Sarma et al.	2021	62 channel from SEED, 32 channel from DEAP	ACC 95.85% Valence 82.21% Arousal 86.03%
Divya Garg et al.	2020	Multi-channel EEG signal	Valence 92.19% (2-Class) Arousal 61.23% (2-Class)
Liu and Sourina	2013	δ,θ,α,β,γ,FD,diff. asym of statist.	Accuracy 53.7% using 4 electrodes
Reuderink et al.	2013	Diff. asym of α(1-64Hz)	Condition Valence Arousal Dominance
Rozgic et al.	2013	θ,slow α,α,β,γ,differential asymmetries	Elastoviscoplastic materialmodel
Hadjidimitriou and Hadjileontiadis	2012	TF analysis of β(13-30Hz),γ(30-49Hz) with rest norm	Accuracy of 49.4%
Konstantinidis et al.	2012	Multichannel complexity D2	Arousal Gender
Liu and Sourina	2012	β/α ratio, β	Accuracy 73.64% to 75.17%
Brown et al.	2011	Max, kurtosis, peak of asym	Accuracy 48%

In the proposed methodology, the emotional state of individuals is studied, as it is captured by EEG recordings and by metrics related to the intensity of emotion, such as arousal and valence [13] - [21].

A. *Arousal and Valence*

Two terms that preoccupy emotion experts are Valence and Arousal. These two terms are often misinterpreted, so it is wise to make a distinction between them.

Arousal and Valence are terms used to describe the excitement or calmness of an emotion, respectively. Positive or negative emotional occurrences are analyzed by Valence. Our reptile brain is where arousal first begins. It causes the fight-or-flight reaction, which helped us survive [15].

From terms such as Valence and Arousal emerge combinations of these (high arousal – low valence, high arousal – high valence, low arousal – low valence, low arousal – high valence) and corresponding emotions as illustrated in the Figure 3.

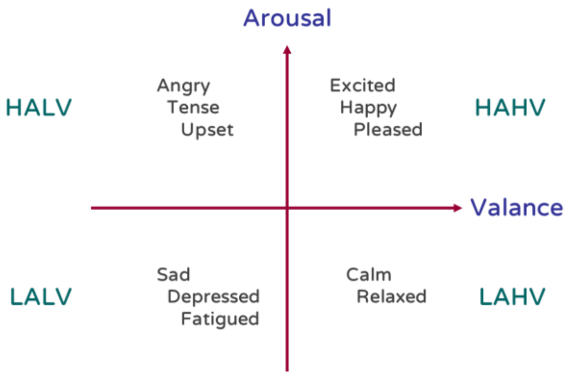

Fig. 3. Valence and Arousal combination

II. Methodology

A. *DEAP database*

For the emotional's state analysis, the DEAP database was used [16] which consists of EEG recordings and peripheral signals of **32 people**. The recordings were collected during music videos where participants were subjected to watching.

To elicit various emotions, diverse visual cues were utilised in music videos. Initially, **120 videos** were selected. Accordingly, a 1-minute segment was then determined based on the participants' preferences to constitute the visual stimulus. Finally, a subjective evaluation experiment was performed, so that the final selected stimuli were narrowed down to 40. The participants evaluated each video in terms of **valence, arousal, familiarity, liking, and dominance** selecting the most appropriate video for each individual.

According to researchers at the DEAP Database, the valence-arousal space corresponding to emotional states can be divided into four quadrants: LALV (low arousal - low valence), LAHV (low arousal - high valence), HALV (high arousal - low valence), HAHV (high arousal - high valence).

Participants in the experiment watched music videos and scored them on arousal, valence, and dominance at nine distinct levels.

Each participant watched several videos as they liked, while they could finish the rating at any time. The collection of videos was chosen at random. As a result, each video received roughly the same number of ratings (14-16 ratings per video). Additionally, it's made sure that participants ever watched the same film for second time.

The Self-Assessment Manikin (SAM) is a questionnaire that measures an emotional response. It was designed to measure three characteristics that relate to the strength / pleasure of the response, perceptual stimulation, and perceptions of control / dominance. These characteristics were identified as central to emotion, based on research by Lang and his associates [22]. In Figure 4 is being displayed a self-assessment card which is based on the SAM system.

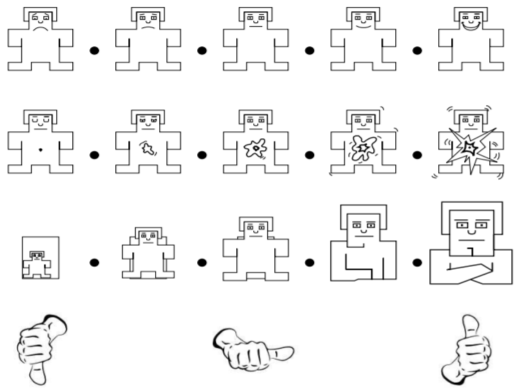

Fig. 4. Self-assessment card. Arousal SAM, Valence SAM, Dominance SAM, Liking

The final 40 videos from the base were chosen because all 120 videos received ratings from at least 14 volunteers each. A normalized arousal and valence score was derived for each X video by dividing the mean score by the standard deviation (E(x)/S). Then, the ten movies that were closest to the extreme corner of each quadrant in the normalized arousal / valence interval were chosen, creating a total of 40 videos that make up the DEAP Database.

B. *Experimental procedure*

The experiment involved **32 people, 16 men and 16 women**, with the age in range from 19 to 37 years (the average years is 26.9). Before the start of the experiment, each participant filled out a **questionnaire** and was informed about the experimental process. During the experiments, **48 channels** were recorded (32 EEG signals, 12 regional signals, 3 empty signals and 1 status signal).

TABLE II. EMOTION WHEEL

1.Pride	5.Relief	9.Sadness	13.Envy
2.Elation	6.Hope	10.Fear	14.Disgust
3.Joy	7.Interest	11.Shame	15.Contempt
4.Satisfaction	8.Surprise	12.Guilt	16.Anger

During the process of self-assessment, the participants rated the valence and arousal of each emotion provoked by the video they watched. The selection of emotions was made by a wheel of emotions (emotion wheel).

The measurement scale of arousal spectrum from calm / bored to stimulated / excited, whereas the scale of valence ranges from unhappy / sad to happy / joyful. The dominance metric ranged from submissive to dominant. The fourth scale was considered about whether the video was liked by each participant or not. Finally, there was the question of whether each of the participants had been aware of the popularity of the song.

C. Feature extraction

The DWT (Discrete Wavelet Transform) was used for the analysis of EEG signals. DWT is the most widespread Transformation in Wavelet Analysis. DWT is a Time-Frequency analysis transformation according to which the signal decomposes into high and low frequency coefficients, after displacement and scaling of a basal wavelet called the mother wavelet. Then the low frequency factor decomposes again at high and low frequencies in a process reminiscent of a tree path. The process is repeated until the signal is completely decomposed at the desired frequencies [23].

From the signals researched characteristics such as Accuracy, Sensitivity and Specificity were calculated with a percentage scale in each algorithm that was applied.

The feature vector that resulted from the calculation of the above characteristics for each of the **32 electrodes** for the 40 projection videos consists of 1280 rows and 480 columns. Since the size of the characteristic vector is large and can mislead the training of the classification model, the technique's of PCA (**Principal Component Analysis)** was applied [24]. Based on PCA, data is displayed in a space in such a way as to maximize the dispersion of points and display the dataset in a smaller number of dimensions. In the end, the data is represented as a new dataset derived from the linear combination of the initials [25].

III. RESULTS AND DISCUSSION

The results of the methodology were derived from the training of the model and from classification algorithm tests.

A. Classification model training

A 4-class classification problem was used for the training and performance evaluation of the classification model. The values of arousal and valence, that characterize the emotional state of the participants were used to create 4 categories. Given that the participants were rating on a scale of 1 to 9 the degree of their reaction to the video they were watching (arousal) and the degree of intensity (valence) that the feeling caused by the video had, 4 distinct classes were classified:

- **high arousal – high valence** (HAHV): This category includes EEG characteristics corresponding to arousal and valence values greater than 4.5.
- **high arousal – low valence** (HALV): This category includes the EEG characteristics corresponding to an arousal value greater than 4.5 and a valence value of less than 4.5.
- **low arousal – high valence** (LAHV): This category includes EEG characteristics corresponding to an arousal value of less than 4.5 and a valence value greater than 4.5.
- **low arousal – low valence** (LALV): This category includes EEG characteristics corresponding to arousal and valence values of less than 4.5.

As a result, there was a problem of sorting 4 classes that were used as input to 6 classification algorithms which we analyze below in detail [26].

The training and control of the performance of each classifier was done with the cross-validation method and specifically with the **10-fold cross-validation**. This method is an iterative method in which the set of EEG characteristics is divided into 10 equal sections that are used as a training set and as a test set [27].

In the Table III below, we observe the methods of approach as well as the metrics that emerged in similar papers in comparison to our own method, we examine through classification algorithms the greatest accuracy we can have for the detection of emotional state by electroencephalographic signals [28] - [35].

TABLE III. METHOD AND METRICS FROM SIMILAR PAPERS

Year	**1st Author**	**Method Description**	**Metric**
2022	Pallavi Pandey	EEG signals utilizing the classifier Deep Neural Network and the feature extraction method VMD.	Valence, Arousal, Dominance and Liking/Disliking
2022	Siyu Zhu	Using eye-tracking (ET) and electroencephalograph (EEG) data	Valence, arousal, dominance, liking, and familiarity.
2022	Buket D. Barkana	EEG readings during the retention of short-term memories in various emotional states.	Neutral, negative, and positive emotions.
2022	Mohammad Shabbir Alam	Examining the use of machine learning to identify human	Joyful, cool, angry and

		attention and emotion based on EEG data	sad.
2022	Minchang Yu	Developing a new emotion EEG dataset, virtual reality (VR) (VREED)	Negative/ positive emotions
2014	You Yun Lee	Using EEG-based functional connectivity patterns to categorize various emotional states	Emotional states, neutral, positive, negative.
2022	Padhmashree V.	Emotion recognition relation with temporal frequency ditection of multivariate signals from EEG.	Arousal, Valence and dominance.
2022	Sara Bagherzadeh	EEG data can be used to identify emotional states using frequency effective connection maps and a transfer learning technique.	Calmness, surprise, fear, Anger, Sadness, excitement, disgust, happiness and amusement emotions.
2014	Shangfei Wang	EEG user data and video content combined for hybrid video emotional tagging	Valence and arousal

B. Testing sorting algorithms

For the validation of the proposed methodology, well-known classifiers were tested, which have been widely used in scientific papers that address the issue of emotional state analysis. Specifically, Decision Trees, Random Forests, Naïve Bayes, a MultiLayer Perceptron and Support Vector Machines were tested.

TABLE IV. ACCURACY (ACC), SENSITIVITY (SENS) AND SPECIALTY(SPEC) RESULTS

	ACC (%)	**SENS (%)**	**SPEC (%)**
Decision Tree	70.23	70,30	70,20
Random Forests	78.59	84,00	78,60
Naïve Bayes	49.37	50,47	49,42
Multilayer Perceptron	63.12	62,80	63,10
Support Vector Machines	61.40	60,70	61,41
k-Nearest Neighbors	73.36	73,65	73,48

From the table we observe that the random forests algorithm has a higher percentage of accuracy for all three methods (Accuracy, Sensitivity and Specificity), while the **kNN algorithm** follows directly after that.

IV. CONCLUSIONS

The present paper studies the emotional state of individuals, as it is captured by EEG recordings and by metrics related to the intensity of emotion, such as arousal and valence.

More specifically, the study used EEG recordings of 32 healthy participants, 16 from them are men and other 16 are women, with ages between 19 and 37 years (average 26.9 years). For the experiment, sensors for the peripheral signals as well as the electrodes for the electroencephalogram, were individually placed on the participants. The subject recorded their emotional state after each film using the predetermined measures of dominance, valence, arousal, familiarity, and liking.

The proposed methodology for EEG-based emotional analysis is based on the Discrete Wavelet Transformation, which is the most widespread Transformation in Wavelet Analysis. Utilizing the WEKA OA software, the suggested model's performance was evaluated in this situation using machine learning techniques such Random Forests, MLP, Naive Bayes, SVM, Decision Trees and kNN. The classification model was tested in the **LALV/ LAHV/ HALV/ HAHV** categorization problem that separates the following 4 classes:

I. HIGH AROUSAL – HIGH VALENCE

II. HIGH AROUSAL – LOW VALENCE

III. LOW AROUSAL – HIGH VALENCE

IV. LOW AROUSAL – LOW VALENCE

The best classification results were obtained using the Random Forests algorithm in terms of Accuracy (78.59%), Sensitivity (84.00%) and Classification Specialty (78.60%).

A psycho physiological process, emotion is frequently linked to feeling, character, personality, and motivation. It is set off by the perception of a thing or circumstance, whether conscious or unconscious. Human communication places a high value on emotions, which can be communicated vocally through emotional dialect or nonverbally through the use of factors like voice volume, gestures, and facial expressions. Human communication is greatly influenced by emotions, which can be represented vocally through emotional dialect or nonverbally through gestures, facial expressions, and voice inflection changes. In other words, they do not have the ability to recognize the human emotional state, nor to use information from it to perform the appropriate actions.

The aim is to find the emotional elements through human-computer interaction systems and to synthesize emotional response. In the future we could test additional machine learning algorithms to validate the reliability of our experiment, as well as different features. In addition, a future extension of the present dissertation could be considered as the application of the classification model, with appropriate modifications to the points, to real data that we will have collected from people who will wear an electroencephalogram recorder, as well as the addition of an experiment with virtual reality devices to compare the results.

REFERENCES

[1] W. T. Sullivan, "Outward Searchers: SETI Pioneers . Scientists Talk about Their Search for Extraterrestrial Intelligence. DAVID W. SWIFT. University of Arizona Press, Tucson, 1990. xiv, 436 pp., illus. $35," Science (1979), vol. 250, no. 4978, pp. 303–303, Oct. 1990, doi: 10.1126/science.250.4978.303-a.

[2] V. L. Towle et al., "The spatial location of EEG electrodes: locating the best-fitting sphere relative to cortical anatomy," Electroencephalography and Clinical Neurophysiology, vol. 86, no. 1, pp. 1–6, Jan. 1993, doi: 10.1016/0013-4694(93)90061-Y.

[3] D. K. P Ekman, "Universal facial expressions of emotion," California mental health research digest, 1970.

[4] R. Plutchik, "A psychoevolutionary theory of emotions," Social Science Information, vol. 21, no. 4–5, pp. 529–553, Jul. 1982, doi: 10.1177/053901882021004003.

[5] C. Darwin, The expression of the emotions in man and animals. 2002.

[6] U. R. Acharya, S. Vinitha Sree, G. Swapna, R. J. Martis, and J. S. Suri, "Automated EEG analysis of epilepsy: A review," Knowledge-Based Systems, vol. 45, pp. 147–165, Jun. 2013, doi: 10.1016/j.knosys.2013.02.014.

[7] A. Miltiadous et al., "Alzheimer's Disease and Frontotemporal Dementia: A Robust Classification Method of EEG Signals and a Comparison of Validation Methods," Diagnostics, vol. 11, no. 8, p. 1437, Aug. 2021, doi: 10.3390/diagnostics11081437.

[8] K. Takahashi, "Remarks on emotion recognition from multi-modal bio-potential signals," in 2004 IEEE International Conference on Industrial Technology, 2004. IEEE ICIT '04., pp. 1138–1143. doi: 10.1109/ICIT.2004.1490720.

[9] X.-W. Wang, D. Nie, and B.-L. Lu, "EEG-Based Emotion Recognition Using Frequency Domain Features and Support Vector Machines," 2011, pp. 734–743. doi: 10.1007/978-3-642-24955-6_87.

[10] S. Koelstra et al., "DEAP: A Database for Emotion Analysis ;Using Physiological Signals," IEEE Transactions on Affective Computing, vol. 3, no. 1, pp. 18–31, Jan. 2012, doi: 10.1109/T-AFFC.2011.15.

[11] Y. Liu and O. Sourina, "Real-Time Fractal-Based Valence Level Recognition from EEG," 2013, pp. 101–120. doi: 10.1007/978-3-642-38803-3_6.

[12] M. Murugappan, N. Ramachandran, and Y. Sazali, "Classification of human emotion from EEG using discrete wavelet transform," Journal of Biomedical Science and Engineering, vol. 03, no. 04, pp. 390–396, 2010, doi: 10.4236/jbise.2010.34054.

[13] R. Li, C. Ren, X. Zhang, and B. Hu, "A novel ensemble learning method using multiple objective particle swarm optimization for subject-independent EEG-based emotion recognition," Computers in Biology and Medicine, vol. 140, p. 105080, Jan. 2022, doi: 10.1016/j.compbiomed.2021.105080.

[14] P. Sarma and S. Barma, "Emotion recognition by distinguishing appropriate EEG segments based on random matrix theory," Biomedical Signal Processing and Control, vol. 70, p. 102991, Sep. 2021, doi: 10.1016/j.bspc.2021.102991.

[15] D. Garg and G. K. Verma, "Emotion Recognition in Valence-Arousal Space from Multi-channel EEG data and Wavelet based Deep Learning Framework," Procedia Computer Science, vol. 171, pp. 857–867, 2020, doi: 10.1016/j.procs.2020.04.093.

[16] Y. Liu and O. Sourina, "EEG Databases for Emotion Recognition," in 2013 International Conference on Cyberworlds, Oct. 2013, pp. 302–309. doi: 10.1109/CW.2013.52.

[17] B. Reuderink, C. Mühl, and M. Poel, "Valence, arousal and dominance in the EEG during game play," International Journal of Autonomous and Adaptive Communications Systems, vol. 6, no. 1, p. 45, 2013, doi: 10.1504/IJAACS.2013.050691.

[18] M. Rozgić, R. Appel, and M. Stiemer, "Enhanced Identification of Process Parameters in Technological Forming," PAMM, vol. 13, no. 1, pp. 403–404, Dec. 2013, doi: 10.1002/pamm.201310197.

[19] S. K. Hadjidimitriou and L. J. Hadjileontiadis, "Toward an EEG-Based Recognition of Music Liking Using Time-Frequency Analysis," IEEE Transactions on Biomedical Engineering, vol. 59, no. 12, pp. 3498–3510, Dec. 2012, doi: 10.1109/TBME.2012.2217495.

[20] Y. Liu and O. Sourina, "EEG-based Dominance Level Recognition for Emotion-Enabled Interaction," in 2012 IEEE International Conference on Multimedia and Expo, Jul. 2012, pp. 1039–1044. doi: 10.1109/ICME.2012.20.

[21] L. Brown, B. Grundlehner, and J. Penders, "Towards wireless emotional valence detection from EEG," in 2011 Annual International Conference of the IEEE Engineering in Medicine and Biology Society, Aug. 2011, pp. 2188–2191. doi: 10.1109/IEMBS.2011.6090412.

[22] T.-M. Bynion and M. T. Feldner, "Self-Assessment Manikin," in Encyclopedia of Personality and Individual Differences, Cham: Springer International Publishing, 2020, pp. 4654–4656. doi: 10.1007/978-3-319-24612-3_77.

[23] M. Murugappan, N. Ramachandran, and Y. Sazali, "Classification of human emotion from EEG using discrete wavelet transform," Journal of Biomedical Science and Engineering, vol. 03, no. 04, pp. 390–396, 2010, doi: 10.4236/jbise.2010.34054.

[24] A Wavelet Tour of Signal Processing. Elsevier, 2009. doi: 10.1016/B978-0-12-374370-1.X0001-8.

[25] K. D. Tzimourta et al., "A robust methodology for classification of epileptic seizures in EEG signals," Health and Technology, vol. 9, no. 2, pp. 135–142, Mar. 2019, doi: 10.1007/s12553-018-0265-z.

[26] P. Christodoulides et al., "Classification of EEG signals from young adults with dyslexia combining a Brain Computer Interface device and an Interactive Linguistic Software Tool," Biomedical Signal Processing and Control, vol. 76, p. 103646, Jul. 2022, doi: 10.1016/j.bspc.2022.103646.

[27] K. D. Tzimourta, L. G. Astrakas, M. G. Tsipouras, N. Giannakeas, A. T. Tzallas, and S. Konitsiotis, "Wavelet Based Classification of Epileptic Seizures in EEG Signals," in 2017 IEEE 30th International Symposium on Computer-Based Medical Systems (CBMS), Jun. 2017, pp. 35–39. doi: 10.1109/CBMS.2017.116.

[28] P. Pandey and K. R. Seeja, "A One-Dimensional CNN Model for Subject Independent Emotion Recognition Using EEG Signals," 2022, pp. 509–515. doi: 10.1007/978-981-16-2597-8_43.

[29] S. Zhu, J. Qi, J. Hu, and S. Hao, "A new approach for product evaluation based on integration of EEG and eye-tracking," Advanced Engineering Informatics, vol. 52, p. 101601, Apr. 2022, doi: 10.1016/j.aei.2022.101601.

[30] B. D. Barkana, Y. Ozkan, and J. A. Badara, "Analysis of working memory from EEG signals under different emotional states," Biomedical Signal Processing and Control, vol. 71, p. 103249, Jan. 2022, doi: 10.1016/j.bspc.2021.103249.

[31] M. Shabbir Alam, S. Zura A. Jalil, and K. Upreti, "Analyzing recognition of EEG based human attention and emotion using Machine learning," Materials Today: Proceedings, vol. 56, pp. 3349–3354, 2022, doi: 10.1016/j.matpr.2021.10.190.

[32] M. Yu, S. Xiao, F. Tian, and Y. Li, "Frontal-occipital network alterations while viewing 2D & 3D movies: a source-level EEG and graph theory approach," Biomedical Engineering / Biomedizinische Technik, vol. 67, no. 3, pp. 161–172, Jun. 2022, doi: 10.1515/bmt-2021-0300.

[33] Y.-Y. Lee and S. Hsieh, "Classifying Different Emotional States by Means of EEG-Based Functional Connectivity Patterns," PLoS ONE, vol. 9, no. 4, p. e95415, Apr. 2014, doi: 10.1371/journal.pone.0095415.

[34] P. V. and A. Bhattacharyya, "Human emotion recognition based on time–frequency analysis of multivariate EEG signal," Knowledge-Based Systems, vol. 238, p. 107867, Feb. 2022, doi: 10.1016/j.knosys.2021.107867.