Brain Computer Interface: Deep Learning Approach to Predict Human Emotion Recognition

Carmelo Ardito*, Ilaria Bortone†, Tommaso Colafiglio*, Tommaso Di Noia*,
Eugenio Di Sciascio*, Domenico Lofù*†, Fedelucio Narducci*, Rodolfo Sardone§ and Paolo Sorino*.

* *Dept. of Electrical and Information Engineering (DEI), Politecnico di Bari, Bari (Italy),*
e-mail: {name.surname}@poliba.it

† *Innovation, Marketing & Technology (IMT Lab), Exprivia SpA, Molfetta (Italy),*
e-mail: {name.surname}@exprivia.com

§ *Data Sciences and Innovation N.I of Gastroenterology "S. de Bellis", Castellana Grotte (Italy),*
e-mail: {name.surname}@irccsdebellis.it

***Abstract*—Brain-Computer Interfaces allow controlling machines through signals coming from Electroencephalography (EEG) analysis. Nowadays, there are several cheap electroencephalographs available on the market that guarantee good quality EEG signals. A very interesting approach in this area is related to detecting the emotional states of a user through the analysis of her EEG signal. In our study, we tried to detect the emotional polarity (Valence), the state of emotional excitement (Arousal), and the level of emotion control (Dominance). Through metric interpolation and Russell's circumplex model, it is possible to characterize and define the current emotional state of the user who wears the device. Our study presents a prototype of an EEG-based emotion recognizer that provides the user's emotional state exploitable as bio-feedback.**

***Index Terms*—Electroencephalographic, Deep Learning, Emotion Recognition, Bio-Feedback.**

I. Introduction

Artificial intelligence (AI) is a research domain that has been bringing significant scientific results in several fields in recent years [1]–[5]. In particular, affective computing is a subfield of AI [6], which includes automatic emotion recognition. The availability of cheap devices to capture brain signals as input to systems that decipher the relationship between emotions and electroencephalographic (EEG) changes has accelerated research. EEG-based brain-computer interfaces are the name given to these devices (BCI).

EEG is a technique for studying electrical signals in the brain. It is used in data analysis techniques such as time series and frequency series analysis. Ion current flows through the neurons of the brain causing voltage changes. This electrical activity is spontaneous and is recorded over time by several scalp electrodes to produce an EEG signal [7]. Traditionally, EEG signals are often recorded on the scalp; however, there are also iEEG signals [8] that are recorded inside the brain.

In this work, we focus on using Deep Learning (DL) to analyze the traditional scalp EEG signal, as better results have been obtained in recent years. In the work [9], the authors highlight the advantages of using EEG for brain activity analysis over other approaches: low cost, tolerance to the subject's movement, and no radiation exposure. On the other hand, some disadvantages of using EEG are low spatial resolution and low signal-to-noise ratio.

EEG signals are primarily used to diagnose and treat various brain disorders, including epilepsy, tremor, concussions, strokes, and sleep disorders. Machine learning (ML) as an analysis method has been used in recent EEG applications. ML Methods for automated EEG analysis have attracted great interest, especially in clinical diagnostics. For example, ML enables the automation of the process of EEG-based sleep stages [10] and neurological diagnosis of specific diseases such as Alzheimer's disease [11], autism spectrum disorders [12], depression [13], or general EEG pathology [14], [15]. Several factors contribute to the interest in automatic clinical EEG diagnosis.

In our paper, we present a prototype regression-based emotion recognition system that can detect the user's emotional state in a bio-feedback mode. It can be used in clinical trials for neuromotor rehabilitation or psychological therapies.

II. Rationale and Background

The automatic recognition of emotions is one of the most significant challenges for many application areas today: from the automotive industry, which is used for autonomous driving, to industry to support decision-making processes, to robotics to realize empathic interactions. The best way to detect human emotions is to process videos and images captured by a camera without distortions from interfering technologies, such as some wearable technologies (e.g., helmets, wristbands) or distributed sensors. There have been several attempts to achieve this goal in an automated way, and most use convolutional neural networks. Numerous studies have been conducted to analyse facial expression recognition, as it is of practical importance in social robotics, medicine, driver fatigue monitoring, and many other human interaction systems [16]–[19].

At the same time, thanks to the incredible increase in chip processing capacity and increasingly well-designed network architectures, studies in various fields have begun to employ deep-learning methods that have achieved the accuracy of state-of-the-art recognition methods and far surpassed previous results [20], [21]. For the specific task of emotion recognition, the increasingly effective training data from facial expressions enabled the implementation of effective

Authors are listed in alphabetical order. Corresponding authors: Tommaso Colafiglio (tommaso.colafiglio@poliba.it) and Paolo Sorino (paolo.sorino@poliba.it).

deep learning architectures to handle complicated situations where emotions needed to be recognised in real-world scenarios [22].

Hazourli et al. [23] collected good quality data in challenging real-world scenarios that implicitly promote the transition of research from laboratory-controlled environments to everyday environments *in the wild*. Environmental conditions such as light, distance to the lens, etc., are not controllable in the latter. Essential visual and emotional analysis tools include Affectiva's Affdex, which allows us to determine a subject's emotional tendency by detecting Ekman and Keltner's primary emotions [24], and Microsoft's cognitive services on the Azure platform[1]. Using convolutional networks and recurrent neural networks, these tools can also see age, gender, and ethnicity. Although it is possible to hide emotions by wearing a *forced* facial expression, biological signals originating from the autonomic nervous system (ANS) cannot lie because they are involuntary [25]. In this sense, biosensors can detect a person's physiological status and determine the complete emotional state. With this detection, 24 biosignals, including heart rate variability (HRV), electrothermal activity (EDA), photoplethysmography (PPG), skin temperature (ST), and electroencephalographic signals (EEG), were collected and entered into the International Affective Picture System (IAPS) and the pictures and associated emotions are recorded [26]. Experiments with IAPS have shown that a collection of features can be derived from biological data, allowing classification between discrete emotion groups [27]. Various methods for analysing EEG signals have been used to extract technical features that significantly improve the model's predictive power.

Recent researches have led to the introduction of wearable systems and smartphone-based controls, reaching good precision (from 80% to 90%) in detecting emotional conditions in general [28].

III. Material and Methods

A. Device Description

In the domain of emotion recognition related to electroencephalographic signals, several studies based on multiple datasets and reference devices exist in the literature. We remember some of them, such as DEAP, Dreamer, and IDEA [29]–[31]. In this study, we focused on the Dreamer dataset [30] because it was made with a device that is easy to find and easy to use, such as the Emotive Epoc with 14 electrodes[2]. The device used has the following electrodes: AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4, plus two mastoid references, M1 and M2. In Fig. 1 we can observe the arrangement of the electrodes according to the standard configuration of the system 10-20 [32].

The sampling frequency of the device is 128Hz in output. One goal of our study is to further reduce the channels of the EEG signal acquisition device while continuing to obtain good predictive values. According to this goal, we used the Emotive - Insight 5[3] electrode device with its electrodes AF3, AF4, T7, T8, Pz with an output rate always at 128 Hz.

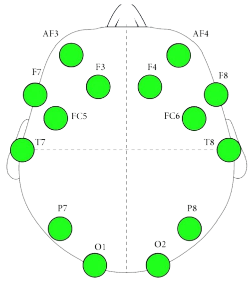

Fig. 1. Emotive Epochs 14 Channels.

The two devices share the same technical characteristics but have a different number of electrodes. Specifically, we only considered the electrodes related to the emotion, only AF3, AF4, T7, and T8 because the Pz is not shared. However, with only 4 electrodes, we found the possibility of obtaining good prediction results with our 1D Convolution Deep Learning model. In Fig. 2 are the electrodes of the Emotive Insight 5 device are shown according to the standard configuration 10-20.

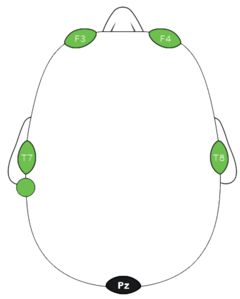

Fig. 2. Emotive Insight 5 electrodes.

B. Dataset Description

The Dreamer dataset is composed of EEG signals from 23 users during emotional induction. The emotional stimulation protocol was carried out using audio-video clips. 18 movie clips cataloged in nine basic emotions such as amusement, excitement, happiness, calmness, anger, disgust, fear, sadness, and surprise are used. Each user had to watch all the video clips of variable length between 65 and 393s. The self-assessment was given on a 5-point Likert scale for Valence, Arousal, and Dominance whenever the video clip ended. In order to perform this task, the participants fill out the Self-Assessment Manikin questionnaire at the end of each experiment [33]. In the dataset both the recordings without emotional elicitation (baseline) and the recordings during the emotion induction are collected. Finally, the authors of the study released the dataset in the Matlab format[4].

C. Preprocessing

One of the big problems with EEG signals is the strong presence of artifacts (noise) or faulty EEG channels that can seriously compromise the analysis of the data. An important part of our study is the development of an automated preprocessing step in order to create an easy-to-use routine for capturing EEG signals in real-time. The preprocessing

[1]https://azure.microsoft.com/en-au/services/cognitive-services/

[2]www.emotiv.com/epoc-x/

[3]https://www.emotiv.com/product/emotiv-insight-5-channel-mobile-brainwear/

[4]https://it.mathworks.com/products/matlab.html

flow is crucial as our prototype aims to provide a real-time detection system of the user's emotional spectrum. The same preprocessing system is also used for preprocessing the Dreamer dataset for deep learning model training. We verified the efficiency of the automated preprocessing technique by visually inspecting all EEG trials.

D. Steps of the preprocessing

- All the trials with related labels were selected, obtaining a total of 414 samples. Each trial is composed of signals coming from the EEG channels of the Emotive device and the corresponding values of Valence, Arousal, and Dominance.
- Once acquired all the trials, the first preprocessing step was to remove the Direct Current offset (DC offset) present in the raw data from the Emotive device. It has been used the script suggested by the helmet manufacturer[5].
- After the removal of the DC Offset, we move on making the data format compatible with the MNE [6] framework for adapting the skull electrode position according to the standard arrangement 10-20. In this way, the cap location was built in line with the electrodes of the device used in the study.
- The last 60 seconds are taken for each trial according to the study submitted directly by the authors of the dataset [30].
- The noise of commercial electric current are removed using a notch filter calibrated on the cutting frequency equal to 50hz.
- The whole trial was normalized in the 1-40Hz frequency range.
- From the continuous EEG signal, we have created epochs of length equal to 1 second.
- Before proceeding with the removal of ocular artifacts [34] through the Independent Component Analysis (ICA), all noisy epochs are removed controlling the deviation from the mean of the values for each channel, the amplitude of the epochs, the variance, and the distance from the mean.
- After that, ICA was applied for the identification of the components of the EEG signal. The AF3, AF4 reference electrodes are used as false EOG electrodes for the automatic recognition of components related to electro-oculographic artifacts (EOG). This operation allows us to automatically identify the artifact peaks related to the eye movements present in the signal.
- After removing EOG artifacts, a correction of the artifacts related to electromyographic patterns (EMG), ocular sacs, and any other artifact drifts is made through the Autoreject framework[7] with a particular setting of the hyperparameters. Specifically, a very high decimation threshold is applied.
- As a further step, the detection and interpolation of defective channels and epochs are done through the pyprep framework[8]. Epochs that exceed a certain noise threshold are, however, removed and not interpolated.
- As the last step, the continuous EEG signal is reconstructed by joining all the various epochs thus preprocessed. We add that some trials are removed if they do not pass one of these preprocessing phases, so after operation, the actual trials are 247.

[5]https://emotiv.gitbook.io/emotivpro-v3/notes-on-the-data/code-examples
[6]https://mne.tools/stable/index.html
[7]https://autoreject.github.io/stable/index.html

E. Training dataset

Once you get all the free trials from the artifacts, the dataset is built as follows:

1) Split into 4-second epochs of each continuous EEG trial.
2) All epochs are in overlap every 1280 samples. The new generated epochs have the same label as the originals.
3) For each epoch in overlap, five features are extracted related to the amplitudes of the bands Theta, Alpha, Beta1, Beta2, Beta3 with the framework neurokit2[9]. The Theta band is considered in the range 4-8Hz. The Alpha band in the range 8-13Hz, the Beta 1 in the 13-16 Hz, the Beta2 from 16-20Hz, and the Beta3 between 20-30Hz. In this modality, the dataset of 46,991 epochs with the relative labels of reference is created.

F. Model Description

All the obtained features were initially split into train, validation, and test with the sklearn train_test_split library in proportion 80% for training and the remaining 20% for testing. The training dataset was then split into 75% for train and 25% for validation. After this operation, the normalization was performed with the MinMax scaler of sklearn [35]. The model used to make regression predictions is a 1D convolutional neural network (CNN) because it is useful in order to predict vectors of features at one size. The reference frameworks for the model are Keras [36] and Tensorflow [37]. The model consists of three convolutional layers, of which two to 128 neurons and a last to 64 neurons. A BatchNormalization was performed at the end of the first two layers of filters. Each layer was then condensed with the MaxPooling-1D in order to extract the most relevant correlation of engineered features. The kernel size is kept at 3, and the activation functions are Relu for convolutional layers. At the end of the convolutional layers, a Flatten operation is performed to create the input arrays for the next neural network. The neural network useful in order to predict regression values is a Fully Connected Layer composed of four layers, one of which is 128 neurons input, a second hidden at 128 neurons, and a third hidden layer at 32 neurons. The activation functions are relatively Tanh for the first two layers and Relu for the 32-neuron layer. Then a Dropout operation of 0.2 was performed in order to regularize learning to avoid overfitting. Finally, there is the last three neurons' output layer with linear output function useful for the purpose of the regression task. The three classes we want to predict are Valence, Arousal, and Dominance. During the learning, the mean_absolute_error was monitored as a loss function, and a callback was set to stop learning if the loss did not improve after ten iterations. (Patience = 10). The optimizer

[8]https://pypi.org/project/pyprep/0.2.1/
[9]https://neurokit2.readthedocs.io/en/latest/

chosen is the Adam algorithm [38]. We have to schematize the structure of the network as in Fig. 3.

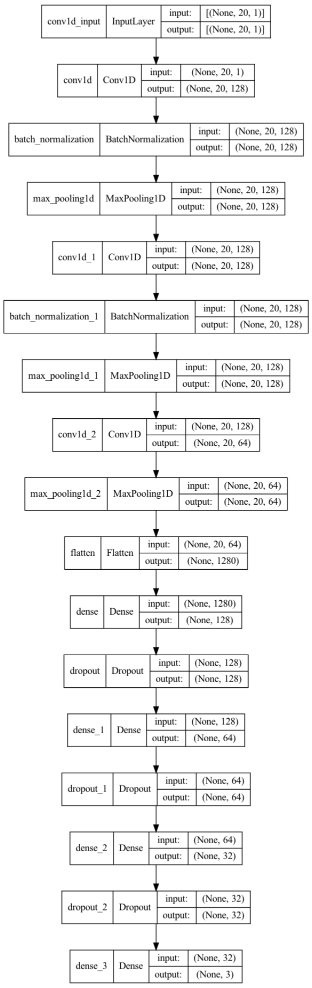

Fig. 3. Architecture of CNN-1D.

The main aim of our study is to provide an emotion recognition system that can provide real-time feedback on the user's emotional condition. In order to achieve this goal, the minimum length in terms of seconds was sought in relation to the greater level of accuracy of the R2 metric. In practice, the minimum time that maintains the levels of accuracy above 0.9% of R2 was sought, achieving periods not less than 4 seconds. In the same way, the optimal overlap coefficient was chosen to maintain the value of the metric R2 not less than 0.9%. This optimization of the hyperparameters was carried out experimentally to directly find the best solution that could avoid considering the eras of the EEG signal not too long but neither too short. Assuming to use epochs of 1-second length, or 128 samples, is not representative of an emotional state. Increasing the length of the epoch, the value R2 increases, but consequently, it creates a problem relative to the time of scan of the signal EEG during the acquisition in real-time.

IV. Results

The model thus trained achieves the following levels of predictive accuracy: R2 = 0.93 Mean Absolute Error = 0.08 Mean Absolute Percent Error = 0.07 All metrics are calculated with sklearn.metrics.

We can observe the distribution of errors in the following bar plots:

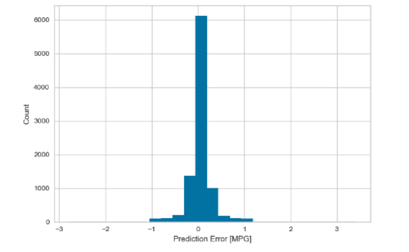

Fig. 4. Valence Error Distribution.

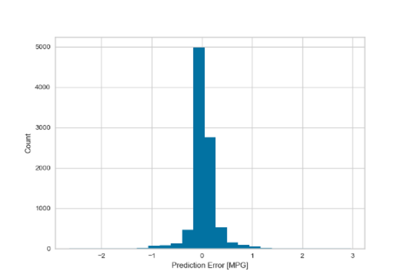

Fig. 5. Arousal Error Distribution.

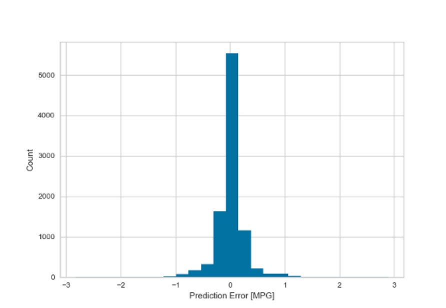

Fig. 6. Dominance Error Distribution.

Fig. 7 shows the course of the function of loss during the learning phase.

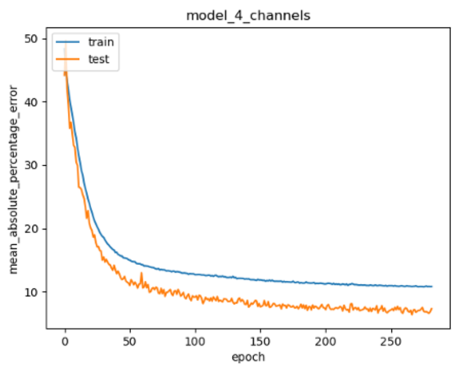

Fig. 7. Loss – Mean Absolute Percent Error.

Our emotion recognition system aims to recognize them in real-time, so it must provide continuous visual feedback of how the user's emotion varies in the domain of time. Fig. 8 shows the user interface

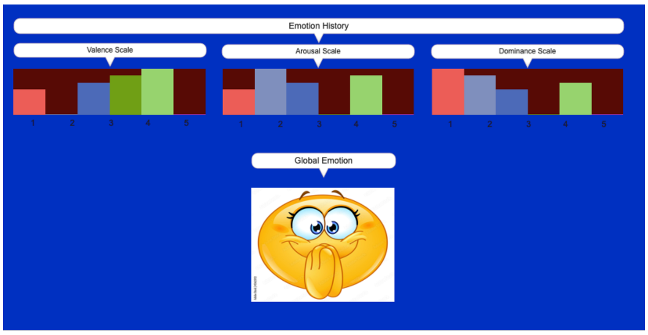

Fig. 8. User Interface.

The whole Front End is built in Max Msp[10], a software development environment mainly oriented to the development of applications in the domain of music but which offers great potential for the development of any stand-alone application. Fig.9. shows the full system architecture

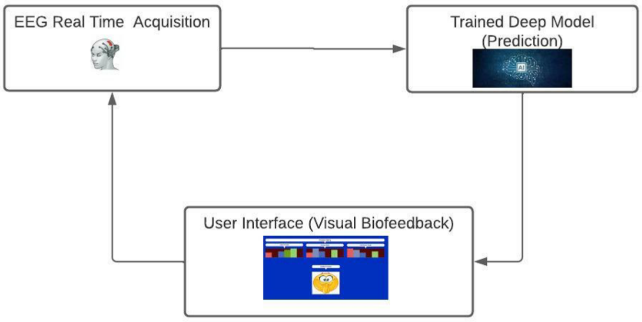

Fig. 9. System Architecture.

In Fig. 9 the user can continuously monitor their emotional state in order to be able to search, in real-time, to change it in the desired polarity. The steps necessary for the operation of the system are as follows: The user wears the device with the five electrodes. The EEG signal is sampled and preprocessed in real-time to make it conform to the subsequent analysis.

- The prediction of the values of Valence, Arousal, and Dominance on the EEG epochs that have passed the preprocessing flow, so we will get different prediction values in relation to the epochs analyzed. Remember that each epoch is 4 seconds.
- The prediction results are sent to the user interface, which in the back end performs the distribution of the received valence, arousal, and Dominance values. The distribution of these values is performed through a Spatial Model Encoding through the object ml.spatial[11] of Max MSP. The spatial encoder is a form of neural network that takes integer tokens and creates a vector that encodes the input sequence. The ml.spatial represents a form of "short-term memory" network where each vector element indicates the recursiveness of the various tokens. In this way, as you receive the input prediction data, you can see which classes are most present and which tend to decrease. The global emotion is instead calculated as the average of the various tokens in the time domain. For the assignment of the four emotional states, we refer to the circumflex model of Russel, which describes emotions as interpolation of the values of Valence and Arousal. Fig. 10 shows a schematization of the Russel model [39].

[10]https://cycling74.com/products/max
[11]https://cycling74.com/articles

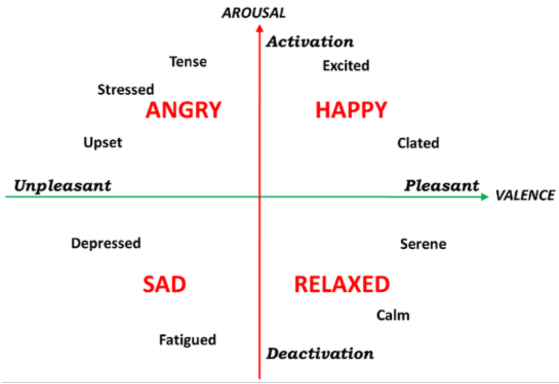

Fig. 10. The schematization of the Russel's Circumplex Emotion Model

In Table I, we observe the threshold for the allocation of the global emotional state.

TABLE I
GLOBAL EMOTION PARAMETER.

Valence	Arousal	Global Emotion
>2.5	>2.5	Happy
>2.5	<2.5	Relaxed
<2.5	<2.5	Sad
<2.5	>2.5	Angry

V. Discussion and Conclusion

In this study, we developed a prototype of emotional biofeedback based on EEG signals that can recognize human emotions. In particular, we have trained a deep neural network to classify valence, arousal, and dominance levels. From our point of view, classifying human emotions dynamically through the CNN-1D and the spatial encoder ml. spatial allows us to observe them better over time. From this perspective, we realized the possibility of observing the emotional history of a subject in real-time. This aspect makes our research original. The prototype could be used in epidemiological studies or screening. The purpose is to provide a real-time multimedia helpful stimulus as a feedback system for both the user and the clinician. The Convolutional Neural Network reached an R2 of 0.93, Mean Absolute Error = 0.08, and Mean Absolute Percent Error = 0.07. These results are very good according to the current state of research. However, the high metrics reached refer to a small population sample. Possible implementations could be aimed at validating this prototype on a more extensive test sample. In conclusion, these prototypes could be a good support tool in the clinical field and large-population studies.

ACKNOWLEDGMENT

This work was partial support of the projects: Italian P.O. Puglia FESR 2014 – 2020 (project code 6ESURE5) 'SECURE SAFE APULIA', Fincons CdP3, PASSPARTOUT, Servizi Locali 2.0, ERP4.0.

REFERENCES

[1] C. Ardito, F. Bellifemine, T. Di Noia, D. Lofu, and G. Mallardi, "A proposal of case-based approach to clinical pathway modeling support," in *2020 IEEE Conference on Evolving and Adaptive Intelligent Systems (EAIS)*. IEEE, 2020, pp. 1–6.

[2] C. Ardito, T. Di Noia, E. Di Sciascio, D. Lofú, G. Mallardi, C. Pomo, and F. Vitulano, "Towards a trustworthy patient home-care thanks to an edge-node infrastructure," in *International Conference on Human-Centred Software Engineering*. Springer, 2020, pp. 181–189.

[3] P. Boccadoro, V. Daniele, P. Di Gennaro, D. Lofù, and P. Tedeschi, "Water quality prediction on a sigfox-compliant iot device: The road ahead of waters," *Ad Hoc Networks*, vol. 126, p. 102749, 2022.

[4] E. Lella, A. Pazienza, D. Lofù, R. Anglani, and F. Vitulano, "An ensemble learning approach based on diffusion tensor imaging measures for alzheimer's disease classification," *Electronics*, vol. 10, no. 3, p. 249, 2021.

[5] C. Ardito, T. D. Noia, E. D. Sciascio, D. Lofù, A. Pazienza, and F. Vitulano, "User feedback to improve the performance of a cyberattack detection artificial intelligence system in the e-health domain," in *IFIP Conference on Human-Computer Interaction*. Springer, 2021, pp. 295–299.

[6] R. W. Picard, "Affective computing for hci." in *HCI (1)*. Citeseer, 1999, pp. 829–833.

[7] J. D. Bronzino, *Biomedical Engineering Handbook 2*. Springer Science & Business Media, 2000, vol. 2.

[8] J. P. Lachaux, D. Rudrauf, and P. Kahane, "Intracranial eeg and human brain mapping," *Journal of Physiology-Paris*, vol. 97, no. 4-6, pp. 613–628, 2003.

[9] Y. Liu, Y. Ding, C. Li, J. Cheng, R. Song, F. Wan, and X. Chen, "Multi-channel eeg-based emotion recognition via a multi-level features guided capsule network," *Computers in Biology and Medicine*, vol. 123, p. 103927, 2020.

[10] S. Biswal, J. Kulas, H. Sun, B. Goparaju, M. B. Westover, M. T. Bianchi, and J. Sun, "Sleepnet: automated sleep staging system via deep learning," *arXiv preprint arXiv:1707.08262*, 2017.

[11] L. R. Gianotti, G. Künig, D. Lehmann, P. L. Faber, R. D. Pascual-Marqui, K. Kochi, and U. Schreiter-Gasser, "Correlation between disease severity and brain electric loreta tomography in alzheimer's disease," *Clinical Neurophysiology*, vol. 118, no. 1, pp. 186–196, 2007.

[12] L. Billeci, F. Sicca, K. Maharatna, F. Apicella, A. Narzisi, G. Campatelli, S. Calderoni, G. Pioggia, and F. Muratori, "On the application of quantitative eeg for characterizing autistic brain: a systematic review," *Frontiers in human neuroscience*, vol. 7, p. 442, 2013.

[13] X. Li, B. Hu, S. Sun, and H. Cai, "Eeg-based mild depressive detection using feature selection methods and classifiers," *Computer methods and programs in biomedicine*, vol. 136, pp. 151–161, 2016.

[14] Y. Roy, H. Banville, I. Albuquerque, A. Gramfort, T. H. Falk, and J. Faubert, "Deep learning-based electroencephalography analysis: a systematic review," *Journal of neural engineering*, vol. 16, no. 5, p. 051001, 2019.

[15] S. U. Amin, M. Alsulaiman, G. Muhammad, M. A. Bencherif, and M. S. Hossain, "Multilevel weighted feature fusion using convolutional neural networks for eeg motor imagery classification," *Ieee Access*, vol. 7, pp. 18 940–18 950, 2019.

[16] A. Rakshit, A. Konar, and A. K. Nagar, "A hybrid brain-computer interface for closed-loop position control of a robot arm," *IEEE/CAA Journal of Automatica Sinica*, vol. 7, no. 5, pp. 1344–1360, 2020.

[17] A. Dhall, "Emotiw 2019: Automatic emotion, engagement and cohesion prediction tasks," in *2019 International Conference on Multimodal Interaction*, 2019, pp. 546–550.

[18] C. Zhang and A. Eskandarian, "A survey and tutorial of eeg-based brain monitoring for driver state analysis," *arXiv preprint arXiv:2008.11226*, 2020.

[19] Y. Wang, S. Qiu, D. Li, C. Du, B.-L. Lu, and H. He, "Multi-modal domain adaptation variational autoencoder for eeg-based emotion recognition," *IEEE/CAA Journal of Automatica Sinica*, 2022.

[20] C. Szegedy, W. Liu, Y. Jia, P. Sermanet, S. Reed, D. Anguelov, D. Erhan, V. Vanhoucke, and A. Rabinovich, "Going deeper with convolutions," in *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2015, pp. 1–9.

[21] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," in *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2016, pp. 770–778.

[22] S. Li and W. Deng, "Deep facial expression recognition: A survey," *IEEE transactions on affective computing*, 2020.

[23] A. R. Hazourli, A. Djeghri, H. Salam, and A. Othmani, "Multi-facial patches aggregation network for facial expression recognition and facial regions contributions to emotion display," *Multimedia Tools and Applications*, vol. 80, no. 9, pp. 13 639–13 662, 2021.

[24] P. Ekman and D. Keltner, "Universal facial expressions of emotion," *Segerstrale U, P. Molnar P, eds. Nonverbal communication: Where nature meets culture*, vol. 27, p. 46, 1997.

[25] M. Ménard, P. Richard, H. Hamdi, B. Daucé, and T. Yamaguchi, "Emotion recognition based on heart rate and skin conductance." in *PhyCS*, 2015, pp. 26–32.

[26] P. Lang and M. M. Bradley, "The international affective picture system (iaps) in the study of emotion and attention," *Handbook of emotion elicitation and assessment*, vol. 29, pp. 70–73, 2007.

[27] M. M. Bradley, M. Codispoti, B. N. Cuthbert, and P. J. Lang, "Emotion and motivation i: defensive and appetitive reactions in picture processing." *Emotion*, vol. 1, no. 3, p. 276, 2001.

[28] T. K. Hui and R. S. Sherratt, "Coverage of emotion recognition for common wearable biosensors," *Biosensors*, vol. 8, no. 2, p. 30, 2018.

[29] S. Koelstra, C. Muhl, M. Soleymani, J.-S. Lee, A. Yazdani, T. Ebrahimi, T. Pun, A. Nijholt, and I. Patras, "Deap: A database for emotion analysis; using physiological signals," *IEEE transactions on affective computing*, vol. 3, no. 1, pp. 18–31, 2011.

[30] S. Katsigiannis and N. Ramzan, "Dreamer: A database for emotion recognition through eeg and ecg signals from wireless low-cost off-the-shelf devices," *IEEE journal of biomedical and health informatics*, vol. 22, no. 1, pp. 98–107, 2017.

[31] V. M. Joshi and R. B. Ghongade, "Idea: Intellect database for emotion analysis using eeg signal," *Journal of King Saud University-Computer and Information Sciences*, 2020.

[32] A. Morley, L. Hill, and A. Kaditis, "10-20 system eeg placement," *European Respiratory Society, European Respiratory Society: Lausanne, Brussels and Sheffield*, 2016.

[33] M. M. Bradley and P. J. Lang, "Measuring emotion: the self-assessment manikin and the semantic differential," *Journal of behavior therapy and experimental psychiatry*, vol. 25, no. 1, pp. 49–59, 1994.

[34] O. G. Lins, T. W. Picton, P. Berg, and M. Scherg, "Ocular artifacts in eeg and event-related potentials i: Scalp topography," *Brain topography*, vol. 6, no. 1, pp. 51–63, 1993.

[35] F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot, and E. Duchesnay, "Scikit-learn: Machine learning in Python," *Journal of Machine Learning Research*, vol. 12, pp. 2825–2830, 2011.

[36] F. Chollet *et al.* (2015) Keras. [Online]. Available: https://github.com/fchollet/keras

[37] M. Abadi, A. Agarwal, P. Barham, E. Brevdo, Z. Chen, C. Citro, G. S. Corrado, A. Davis, J. Dean, M. Devin, S. Ghemawat, I. Goodfellow, A. Harp, G. Irving, M. Isard, Y. Jia, R. Jozefowicz, L. Kaiser, M. Kudlur, J. Levenberg, D. Mané, R. Monga, S. Moore, D. Murray, C. Olah, M. Schuster, J. Shlens, B. Steiner, I. Sutskever, K. Talwar, P. Tucker, V. Vanhoucke, V. Vasudevan, F. Viégas, O. Vinyals, P. Warden, M. Wattenberg, M. Wicke, Y. Yu, and X. Zheng, "TensorFlow: Large-scale machine learning on heterogeneous systems," 2015, software available from tensorflow.org.

[38] D. P. Kingma and J. Ba, "Adam: A method for stochastic optimization," *arXiv preprint arXiv:1412.6980*, 2014.

[39] H. Candra, M. Yuwono, A. Handojoseno, R. Chai, S. Su, and H. T. Nguyen, "Recognizing emotions from eeg subbands using wavelet analysis," in *2015 37th annual international conference of the IEEE engineering in medicine and biology society (EMBC)*. IEEE, 2015, pp. 6030–6033.