Emotion Recognition Using Deep Learning From EEG Data: A preliminary study

Büşra Çorak, Fatih Mehmet YURT
Biyomedikal Mühendisliği Bölümü, İzmir Kâtip Çelebi Üniversitesi, İzmir, Türkiye
busracorak1404@outlook.com fatihyurt94@gmail.com

Onan Güren
Biomedical Engineering
Izmir Katip Celebi University
Izmir, Turkey
onan.guren@ikc.edu.tr

***Abstract*— In this study, a new deep neural network structure for emotion detection from EEG is presented. DEAP data set is used for testing the performance of the method. Convolutional neural network structure is implemented in Matlab and hyperparameters and the structural properties of the deep network are optimized empirically.**

***Keywords*—Emotion Recognition, EEG, Deep Learning, DEAP**

I. INTRODUCTION

Emotion detection is an important process and has a great potential for various areas such as neuroscience, brain-computer interface applications and neuromarketing [1]. Different type of data such as text, speech, facial expression, electroencephalogram EEG, ECG and galvanic skin response (GSR) have been used for emotion recognition. Among these data, EEG has gained special interest in the field of emotion recognition since it provides efficient information about human emotion state [2] and gives accurate results in the classification methods [3].

Emotion categorization is a key phenomenon in emotion classification problem. Generally, mapping of emotions into 2D or 3D space has been used. In 2D model, arousal-valence values are represented by each axis[4].

Classification approaches such as Support Vector Machine (SVM), k-nearest neighbor, naïve Bayes, neural networks, etc. have been implemented to detect emotions from EEG data. It has been reported that, SVM gives the highest accuracy results among these methods [5]. Recently, Deep Learning method have been introduced to emotion classification [6].

Deep Learning (DL) is a distinctive machine learning process in which features and classifiers are learned precisely from data. The deep learning terms comes from the architecture of the model. This model is established on a cascade of educable feature extractor modules. Deep Learning have accomplished admirable achievement in recognition works within a broad range of practices including images, videos, speech, and text. [7]. Convolutional Neural Network (CNNs) is the most representative supervised DL model and are inspired by the biological system of cat's visual cortex. They generally require huge amount of data set for training process and are usually used for image classification by finding patterns in images to recognize objects. Applications such as object recognition, computer vision, self-driving cars, and face recognition are made with the help of CNNs. Recently, it has been implemented in emotion recognition from EEG [8].

In this study, we report the primary results of our study which aims to predict emotions by implementing deep learning methods from EEG data. To be able compare the success of our study, we consider the data from DEAP database. In section I, less comprehensive literature review which covers studies use DEAP database is presented. In section II, we explain our deep network structure and the method used to resemble EEG as a picture. We give our results in section III.

I. LITERATURE REVIEW

In [9], Liu and Saurina discover real-time EEG-based emotion detection algorithm using Higuchi Fractal Dimension Spectrum. At this research they realize EEG as a nonlinear and multi-fractal signal, so the Fractal Dimension spectrum can understand the nonlinear properties of EEG in a more excellent manner using Support Vector Machines as the classifier. They have two datasets which are DEAP and their own dataset to test their method. Considering 8 emotions, they record the classification accuracy 53.7% in subject dependent classification of DEAP dataset.

In [10], Chung and Seong, by using Bayesian Classification method which is a type of learning algorithm, concentrate primarily on classification of DEAP data into category of Valence and Aurosal. They categorize the input data into Valence and Aurosal and both are graded as high-low and high-normal-low. For high-low classification, 66.6% and 66.4% accuracy is obtained, and 53.4% and 51.0% accuracy is achieved for high-normal-medium classification model.

In [11], Candra et al focus the significance of the window size on the EEG data of DEAP using SVMs and wavelet entropy. They achieve that a very large window can lead to an overload of information that causes the feature to interfere with other information. Likewise, if the time window is very short, the data about the feeling may not be sufficiently extracted. That's why they utilize common discrete wavelet transform coefficient to extract time frequency domain features. After tests, they finally report that the accuracy is 65.33% in aurosal classification with 310 seconds window length, and 65.13% valence accuracy with 312 seconds window length.

In [12], Sohaib et al have useful investigation about several classifiers for Emotion 19 Recognition, by using their own dataset that has 20 subjects instead of DEAP. It is for testing the data taken from International Affective Picture System (IAPS). Their application includes Support Vector Machine (SVM), Artificial Neural Network (ANN), Bayesian Network (BN), K-Nearest Neighbor (KNN) for classification process. And they realize that it is problematic to train a classifier with big number of subjects, such as 15. And they showed that over not that large subjects' data, such as 5, the emotions can be recognized with 77.78% accuracy by using KNN and SVM with certain features.

II. MATERIAL AND METHOD

A. Experimental Setup

In this experiment, DEAP (Dataset for Emotion Analysis using EEG, Physiological and Video Signals) is used. It includes the EEG and peripheral physiological signals of 32 participants when watching 40 one-minute music videos. It also contains participants' rate of each video in terms of the levels of arousal, valence, like/dislike, dominance, and familiarity [13].

In our method, DEAP is loaded to the MATLAB which has EEG recordings from 40 channels. Then the number of channels is reduced to 18 due to prevent information pollution and gain time, so only more related channels remained. These channels are Fp1, AF3, F3, F7, FC5, FC1, C3, T7, Fp2, AF4, F4, F8, FC6, FC2, C4, T8, Fz 25 and Cz that shown in Figure 1.

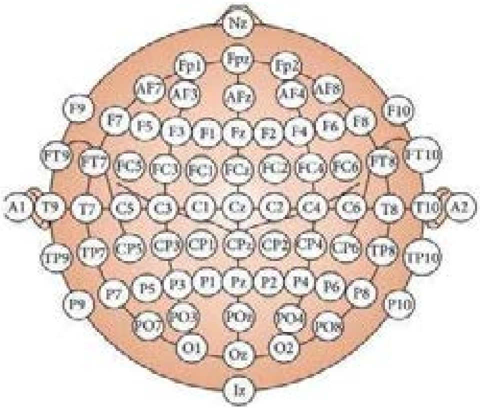

Figure.1. Selected EEG Channels

In DEAP, the experimental subjects' rates after the video scale between 1 and 9. For simplicity, we labeled these rates as 0 when the rate is smaller than 5 also equals to it, and 1 when subject's rate is greater than 5. To expand data, we divide each signals into epochs for every channel as shown in Figure 2. The amount of data used in each training and testing processes are arranged as 80% for training and 20% for testing.

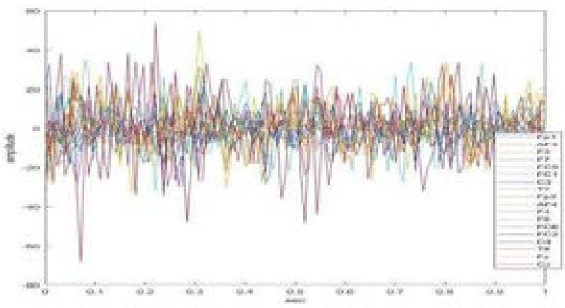

Figure.2. EEG signals for 4. Epoch with channel numbers

B. Methods

. To be able to apply DL methods, one dimensional EGG signal must be resembled as 2 dimensional signal. Several methods such as Short Time Fourier Transform (STFT), Continuous Wavelet Transform (CWT) and Hilbert-Huang Transform (HHT) provide to analyze the signal in time-frequency domain. As a result, time-frequency representation of an EGG signal can be interpreted as a picture of a brain signal. [14]

EEG signal is non-stationary and CWT succeeds to catch time-frequency disintegration of the signal at any time interval and any resolution degree[15]. In this method, the signal is represented by a mother wavelet and other wavelets are reproduced by scaling and converting the mother wavelet. Wavelet coefficient, which represents the relation between the wavelet function and the model of the waveform at that interval, evaluates the quantity of the wavelet at that resolution degree and position [16].

In our study, we combine the signals of 18 channel of 60 seconds as a sample and then we calculate CWT of each samples. In Figure3, time-frequency representation of a signal is given.

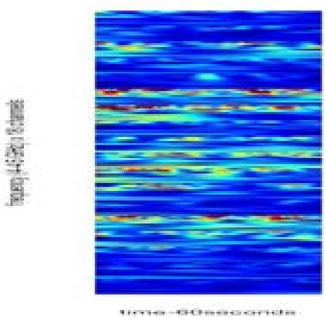

Figure.3. CWT of EEG signals from 18 channels

The structure of our deep network model implemented in Matlab was shown given in Figure 4. It has 3 convolution layers, 3 pooling layers, 1 fully connected layers and 1 Soft-Max layer. The imageinput is a 612x128x3 RGB image which is shown as in **Figure 3.** Each of 2-Dimensional convolutional layers have 36 filters with kernel size of 16x16 per filter. Each convolutional layer is followed by a batch normalization layer, a rectified linear unit (ReLU) layer and an average pooling layer with stride of 4 and pooling size of 1. In batch normalization layer, all input channels are standardized as a mini-batch. This layer is used to gain speed of training of CNNs [16]. Here, the activations of all channels are standardized by extracting the mini-batch mean and dividing by the mini-batch standard deviation, and then the inputs are changed to a learnable scalable parameters. By doing this, the network training becomes easier[17]. The ReLU layer is used for specifying operation for thresholds, as nonlinear activation layer. It does not change the size of initial elements. Softmax layer has two outputs.

Figure.4. CNN structure

III. RESULTS AND DISCUSSION

The training and testing processes are shown in Figure 5, For valence value, 55.63% accuracy is obtained. To reach that accuracy, we tried some changes on parameters such as number of epochs, mini-batch size, filter dimensions and numbers of each convolution layer, stride dimensions. For example when we have changed the mini-batch size from 128 to 64 with not changing other parameters, we got the 54.79% accuracy. Changing the number of epochs was not effective, the accuracy remained same. But at first our each convolutional layers was using 36 filters with 9x9 dimension, and the accuracy was 54.88%. When we have reduced the dimension of strides, accuracy was getting worse.

IV. CONCLUSION

As a conclusion, our accuracy is not enough for a good detection system but our researches continue. We claimed that adding more layers to the presented network and using many effective filters and activation functions will improve accuracy rate of the system.

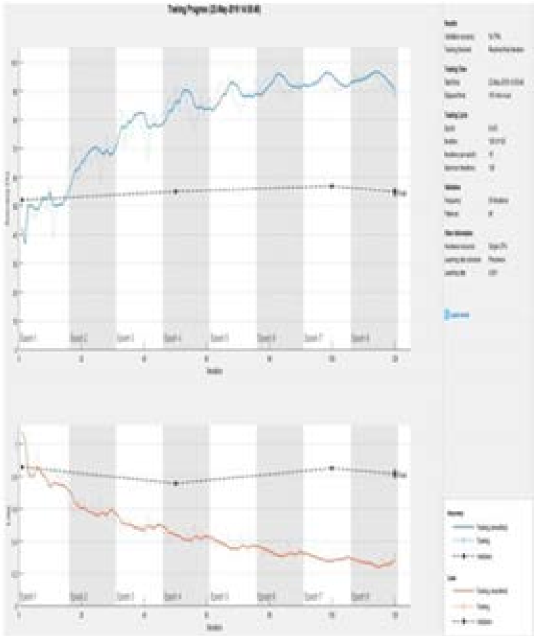

Figure.5. The training process of trial

REFERENCES

[1] S. Jerritta, M. Murugappan, R. Nagarajan and K. Wan, "Physiological signals based human emotion Recognition: a review," *2011 IEEE 7th International Colloquium on Signal Processing and its Applications*, Penang, 2011, pp. 410-415.

[2] Y. F. Chen, Y. L. Cui, and S. X. Wang, ''Review of emotion recogni- tion technology based on physiological signals,'' System Simul. Technol., vol. 13, no. 1, pp. 1–5, Sep. 2017.

[3] J. Li, G. Z. Liu, and J. Gao, ''Emotion classification based on EEG signal,'' J. Beijing Univ. Inf. Sci. Technol., vol. 32, no. 2, pp. 34–39, May 2017tures,'' Comput. Eng. Appl., vol. 54, no. 17, pp. 116–121, Jul. 2008.

[4] Verma, G. K., & Tiwary, U. S. (2017). Affect representation and recognition in 3D continuous valence–arousal–dominance space. *Multimedia Tools and Applications*, *76*(2).

[5] Fernández-Varela, I., Hernández-Pereira, E., Álvarez-Estévez, D., & Moret-Bonillo, V. (2017). Combining machine learning models for the automatic detection of EEG arousals. *Neurocomputing*, *268*, 100–108

[6] Jirayucharoensak, S., Pan-Ngum, S., & Israsena, P. (2014). EEG-based emotion recognition using deep learning network with principal component based covariate shift adaptation, (2014)..

[7] Lecun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *Nature*, *521*(7553), 436–444.

[8] Cheng, C., Wei, X., & Jian, Z. (2018). Emotion recognition algorithm based on convolution neural network. *Proceedings of the 2017 12th International Conference on Intelligent Systems and Knowledge Engineering, ISKE 2017*, *2018-Janua*, 1–5.

[9] Liu, Yisi, and Olga Sourina. "EEG-based subject-dependent emotion recognition algorithm using fractal dimension." Systems, Man and Cybernetics (SMC), 2014 IEEE International Conference on. IEEE, (2014)

[10] Chung, Seong Youb, and Hyun Joong Yoon. "Affective classification using Bayesian classifier and supervised learning." Control, Automation and Systems (ICCAS), 2012 12th International Conference on. IEEE, (2012).

[11] Candra, Henry, et al. "Investigation of window size in classification of EEG-emotion signal with wavelet entropy and support vector machine."Engineering in Medicine and Biology Society (EMBC),

2015 37th Annual International Conference of the IEEE. IEEE, (2015).

[12] Sohaib, Ahmad Tauseef, et al. "Evaluating classifiers for emotion recognition using EEG." Foundations of Augmented Cognition. Springer Berlin Heidelberg, (2013). 492- 501

[13] 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, 2011..

[14] P., H., G., P., M., M. T., & D., C. (2008). Comparative analysis of spectral approaches to feature extraction for EEG-based motor imagery classification. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, *16*(4), 317–326.

[15] H. U. Amin *et al.*, "Feature extraction and classification for EEG signals using wavelet transform and machine learning techniques," *Australasian physical & engineering sciences in medicine,* vol. 38, no. 1, pp. 139-149, 2015.

[16] J. Tong *et al.*, "EEG-based emotion recognition using nonlinear feature," in *2017 IEEE 8th International Conference on Awareness Science and Technology (iCAST)*, 2017: IEEE, pp. 55-59.

[17] T. Song, W. Zheng, P. Song, and Z. Cui, "EEG Emotion Recognition Using Dynamical Graph Convolutional Neural Networks," *IEEE Transactions on Affective Computing,* pp. 1-1, 2018, doi: 10.1109/TAFFC.2018.2817622.