Frontiers in Health Informatics
ISSN-Online: 2676-7104
2024; Vol 13: Issue 3

www.healthinformaticsjournal.com
Open Access

Localization and Classification of Human Emotions using Deep Neural Network

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Cite this paper as: Sweeti, Tejaswini S, Sumathy Y S, Ranveer Kumar, V S Saathwika, Akriti Santra, P Rithwik Reddy (2024) Localization and Classification of Human Emotions using Deep Neural Network. *Frontiers in Health Informatics*, 13(3), 139-148.

Abstract

Emotions are basic part of human living and they reflect the diverse aspects of human behavior. The way a person responds to certain situations, is very essential to study the emotional development. This paper discusses the difference between the activation of two brain lobes when subject is exposed to High Arousal Positive Valence (HAPV) emotions like Excited, Happy and Low Arousal Negative Valence (LANV) emotions like sad, bored. DEAP dataset is used to compare HAPV and LANV. Localization and Dipole fitting of most contributing Independent components is performed. Results suggest that Right lobe shows higher activation level for HAPV state while left lobe shows higher activation level for LANV. These emotions are further classified using deep neural network. Result suggests an average accuracy of 86.5%.

Keywords: *Arousal emotion, Valence emotion, Independent Components, Localization, Classification*

Introduction

One of the body's most intricate organs, the human brain is essential in controlling every physical function, including thoughts, movements, emotions, and senses. It comprises other cells including glial cells, astrocytes, and billions of neurons, which communicate with one another by electrochemical impulses. The brain is split into many zones or regions. These areas are divided into layers and sub regions, each of which serves a particular purpose. For instance, the cerebral cortex, the cerebrum's outermost layer, is further split into a number of regions that are in charge of processing sensory data and regulating movement, language, and memory. The midbrain, pons, and medulla are some of the components that make up the brainstem; each is responsible for controlling a different automatic bodily function.

The limbic system is in charge of controlling emotions, drive, and memory. The two structures found in this area namely, parahippocampal gyrus and the cingulate gyrus controls motivation, emotion, and judgements.

Overall, many brain regions cooperate to control and coordinate a variety of body tasks, from basic reflexes to intricate mental processes. Understanding of brain physiology and the mechanisms underlying various neurological and psychiatric illnesses requires knowledge of the function of each zone and how they interact.

Emotions can affect various aspects of life be it personal life or health. Various studies are mentioned in literature where different aspects of emotions are study by utilizing different computational approaches like EEG signal processing [1], speech signal processing and facial feature analysis in common. Studies shows that emotions can affect the feeding behaviour of subjects and it can be observed using EEG signals[2]. There are different approaches devised over the years to detect and analyse emotions. Speech signal analysis is one such method where spectra of signal is analysed [3] . Cumulative energy feature demonstrates significant contribution in emotion analysis using speech signal. Some advanced features like multiscale information analysis are employed which suggest the domination of high frequency oscillations for emotion detection [4]. Speech signal is analysed using spectral flatness feature that represents mixing of high frequency noise in voiced frames. Results show significant difference in three emotions[5]. Heart rate variability in different spectral bands is utilised to analyse emotions. Observations suggested that respiratory frequency and mean heart rate indicates difference in different emotions [6].

EEG records the electrical activity of the brain and by localizing activities; we can identify specific brain areas and neural networks involved in emotional processing. This can help us better understand the neural correlates of emotions and how they are regulated by the brain. By detecting changes in brain activity associated with different emotional states, computers can adapt their responses and provide more personalized interactions with users. Localization of emotions can be a valuable approach for understanding emotional processing in the brain, diagnosing emotional disorders, developing effective emotional regulation strategies, and improving human-computer interaction. Different machine learning algorithms are tested to classify high/ low arousal and positive/negative valence emotions following 2D model of emotions[7][8]. Such algorithms display good classification performance. Recently, Deep neural networks like convolution neural networks are largely applied in emotion classification due to their high feature extraction capability [9]. Such networks displays high classification accuracy upto 97.06% [10][11][12]. Recent feature extraction method based on Granger causality (GC) brain network is proposed. This method incorporates cross-frequency of EEG signals across two hemispheres and accuracy of 84.911% is reported [13]. Localization of human emotion is significant because emotions are believed to be processed and regulated by specific regions of the brain. Identifying the role of specific brain regions in emotional processing can aid in diagnosing and treating emotional disorders such as anxiety and depression. To help the observer detect the emotion of the person who cannot express the real emotion through itself, the best example of this case is the detection of the emotion of a baby and physically challenged people [14].

Methodology

This section discusses the methodology followed as shown in figure 1.

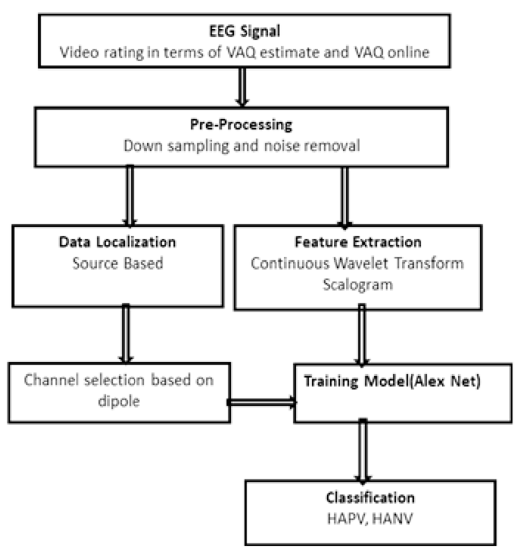


Fig. 1. Methodology

2.1 EEG Signal

EEG signals from the popular DEAP dataset are used. 32 EEG channels data from 16 males and 16 women, ranging in age from 17 to 37, are included in this collection from two different cities in Geneva and Twente, 32 individuals watched music videos while having their EEG channels captured. Individuals used the Self-Assessment Manikin (SAM) to evaluate each recording on a measure of 1 to 9 based on the notions of valence and arousal. A group of online participants also gave their ratings for this video which was called VAQ online (Valence Arousal quadrant). There are four quadrants of emotions as per 2D model of emotion as shown in figure 2.

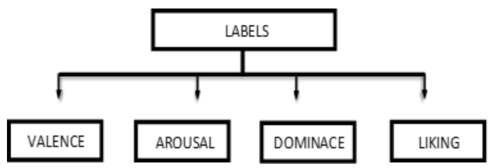


Fig. 2. Four Quadrants of Emotion

Present data is divided into two classes:

- Class A: High Arousal Positive Valence (Excited, Happy), HAPV
- Class B: Low Arousal Negative Valence (Sad, Bored), LANV

Originally, the raw EEG data each video was for 63 seconds. First 3 seconds data is discarded assuming no emotional labeling during first few seconds. Discarded data is considered as baseline recording.

2.2 Localization and Dipole Fitting

EEG-based localization of emotions is frequently employed in combination with other techniques to better understand brain activity. EEG data can be integrated with structural imaging methods like MRI (magnetic resonance imaging) to develop customized brain models that will enhance localization. This can help more to precisely pinpoint the parts of the brain responsible for processing emotions.

Independent Component Analysis (ICA)

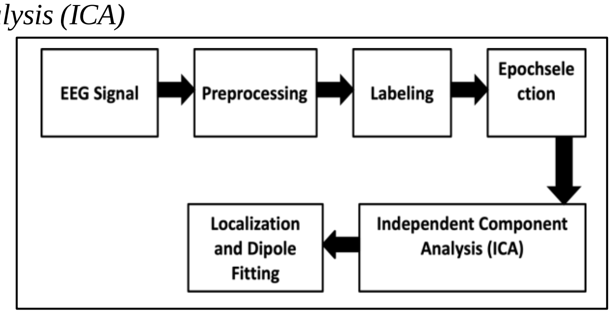


Fig. 3. Localization and Dipole fitting procedure

Figure 3 shows the localization and dipole fitting procedure. It is assumed that EEG is a non-Gaussian signal and linear combination of independent components. ICAis used to separate EEG signal into its independent components.

Observed data,

$$x= As \qquad (1)$$

Where, A is mixing matrix and s is independent source signal vector.

ICA aims to discover a linear transformation A of the data that yields a set of components, s which are statistically independent from each other. This algorithm tries to optimize and find unmixing matrix to obtain independent components. Resultant independent components represent various brain sources.

Dipole fitting

It is an inverse problem and performed to locate neural activity in the brain based on the independent components extracted from EEG data. It involves estimating the dipole sources of brain activity based on anatomical data from MRI scans. By using the spatial data from structural MRI scans, dipole fitting is done. MRI image is co-registered with independent components of EEG data. This further aligns the anatomical structure with the captured brain activity.

This works like an optimization problem where objective is to find dipole parameters to represent observed data.

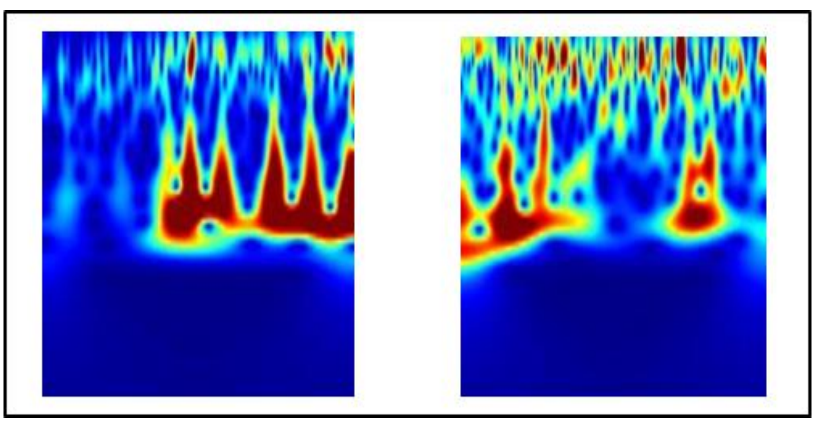
$$D = GM \qquad (2)$$

Where M represents dipole parameter and G is forward lead matrix.

Gradient decent Algorithm tries to find M to minimize$\|\|\|D - GM\|\|\|_2^2$ This results in estimate of dipole parameters for best of EEG data.

2.3 Feature Extraction

EEG signal is a one-dimensional data, which is measured with respect to the frequency. The EEG data is transformed into a two-dimensional image using continuous wavelet transform (CWT). CWT breaks down a signal into its time and frequency components. Continuous wavelet transform is a mathematical analysis tool that breaks down a signal into small, time-varying components, known as wavelets, which can be visualized as short bursts of energy or oscillations. This analysis provides information on the frequency and location of specific patterns within the data. The continuous wavelet transform facilitates to analyze and characterize features of the data that may not be easily detectable using other conventional analysis techniques as shown in figure 4.



(a) (b)

Fig 4. Continous wavelet transform (a) class A (b) class B

2.4 Classification

Basic convolutional, pooling, and Fully Connected (FC) layers make up CNN's robust hierarchy. Convolutional and pooling layers, however, extract and decrease features, respectively. Following that, classification is carried out in the Fully Connected layer.

A machine learning approach called transfer learning allows a model that has been trained for one task to be used for another. The goal is to use the information learned from training a model on one task to enhance the model's performance on other tasks. The pre-trained model is utilized as a starting point and is refined on a fresh dataset for a new task in transfer learning. Better model performance may result from this, which can also save time and resources. Transfer learning is frequently employed for different.machine learning applications, including natural language processing, and image recognition.

Transfer learning is a faster way to fine-tune a network. It is much easier than designing and training a network from scratch. Learned features can be transferred quickly to a new problem by applying a smaller set of training images. The AlexNet architecture consists of 5 convolutional layers, 3 pooling layers, and 3 fully connected layers.Last fully connected layer is replaced by a classification layer to classify emotions as shown in figure 5.

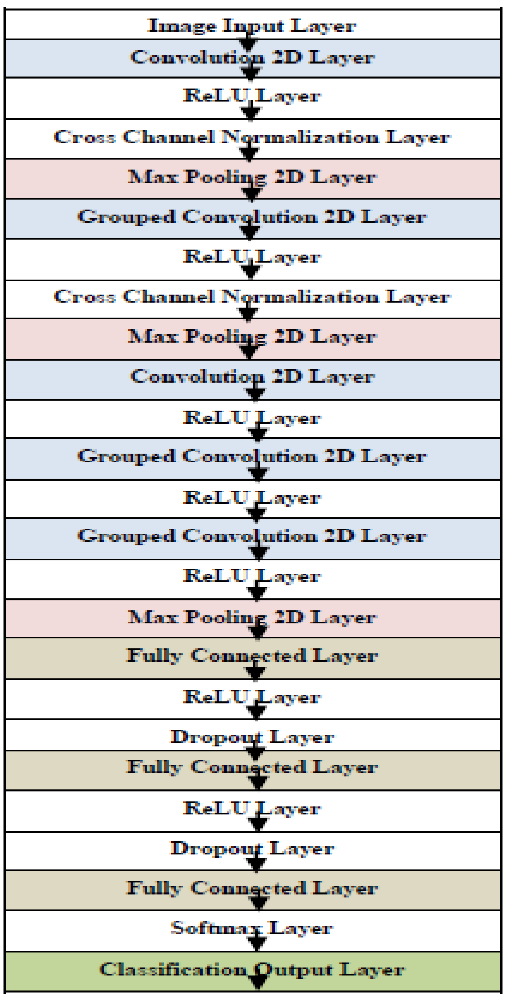


Fig 5. Layers of AlexNet

2.4.1 Performance evalation

Sensitivity: It is the probability of identifyinga positive instance correctly. It is calculated by dividing the number of true positive predictions by the sum of true positives and false negatives:

$$Sensitivity = \frac{TP}{(TP+FN)} \quad (3)$$

Specificity: A measure of specificity shows the percentage of true negatives (TN) that are correctly detected out of all the actual negatives. In binary classification issues, where the objective is to classify examples into one of two categories, commonly labelled as positive and negative, specificity is frequently used. It completes the idea of sensitivity (or recall), which gauges how many true positives out of all the positives are correctly identified. Specificity is calculated as the ratio of true negatives (TN) to the sum of true negatives and false positives (FP):

$$Specificity = \frac{TN}{(TN+FP)} \quad (4)$$

Accuracy: The accuracy of a classification model's predictions is measured as a whole. It is one of the most often-employed performance indicators for assessing a model's efficacy.

Mathematically, accuracy can be represented as:

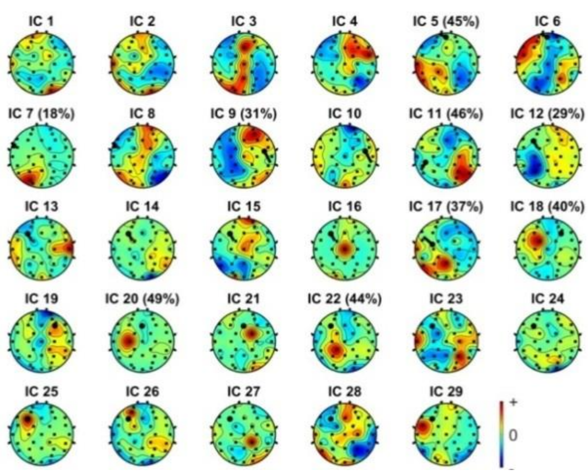
$$\text{Accuracy}=\frac{(TP+TN)}{(TP+FP+TN+FN)} \quad (5)$$

3. Results

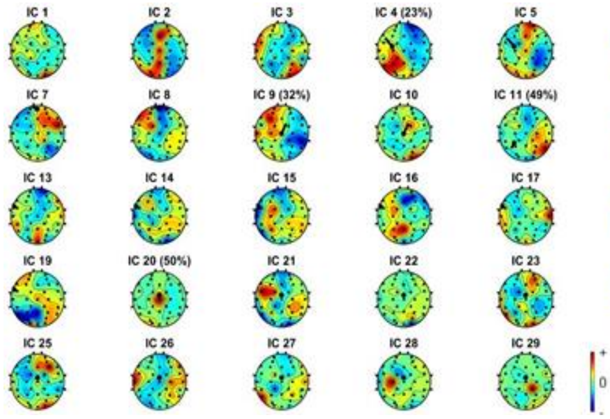
The analysis is performed using EEGLAB in MATLAB. Twenty-nine Independent components are extracted and analyzed.

3.1. Most contributing independent dipoles

Figure 6(a) shows that IC4, IC8, IC11 and IC13 are most contributing components for class A. Dipoles of these components directs to frontal lobe as shown in figure 7(a). Similarly, figure 6(b) shows that IC4, IC9 and IC12 are most contributing components for class B. Dipoles of these components directs to central lobe as shown in figure 7(b). These findings suggest the difference in neural activation for HAPV and LANV emotional states. Results are not displaying conclusive results as different other regions are also contributing to the activity.

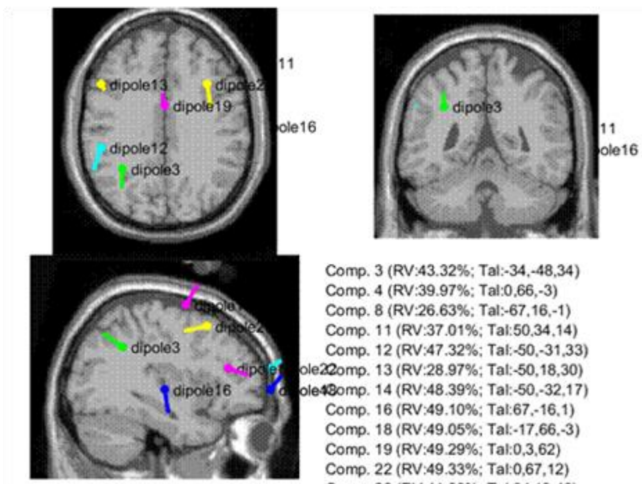


(a)

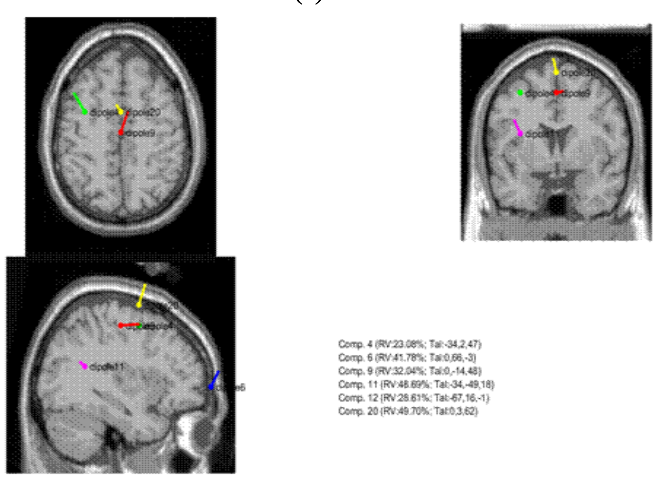


(b)

Fig. 6. Topoplots with Dipoles on Component maps for (a) Class A and (b) Class B



(a)



(b)

Fig.7. Localization of independent components for (a) Class A (b) Class B

3.2. Activation

There exist a relation between valence and arousal, and strength of this relation can help us understand different facets of emotional perception [15]. Studies performed in literature also display hemispheric symmetry. With positive high-arousal and negative low-arousal words, right insular cortex shows greater neural activation [16]. Following these observations, another comparison is performed over the two emotional states to compare neuronal activation of two hemispheres. The analysis displays difference in activation for the two emotions over left and right hemisphere as shown in figure 7(a) & (b). Interestingly, the Right lobe shows higher activation level for HAPV (exited, happy) state while left lobe shows higher activation level for LANV (sad, bored).

3.3. Classification

Features are extracted for two classes with respect to brain regions of importance. These features are converted into scalogram to generate the input images for deep neural network. The deep network takes the input at input layer and gives output across the classification layer. Results display an average accuracy of 86.85%. Figure 8 gives the summary of subject wise classification results over parameters such as accuracy, sensitivity and specificity.

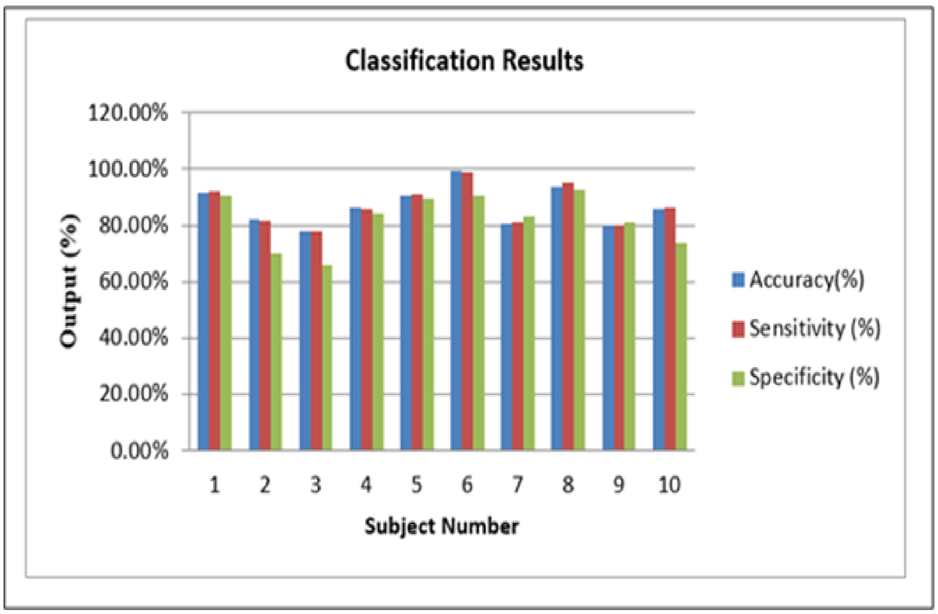


Fig. 8. Classification Results using AlexNet

4. Conclusion

Emotions are integral part of a human being. Understanding of emotions can uncover various aspect of human existence. This research is done to understand the emotional processing process of brain. This work focuses on the localization of neural activity during High Activation Positive Valence state and Low Activation Negative Valence state corresponding to happy/exited and sad/boring. Results show the contribution of different brain region including frontal, parietal- occipital and temporal for respective emotional states. Major outcome of work is that for HAPV state right lobe activates more and for LANV state left lobe activates. This theory needs to be verified with further analysis and cross-spectrum studies. Along with it, deep neural network is employed to classify emotions. Resultant classification accuracy of 86.5% suggests a descent performance by Alexnet. This network can be further tested and applied in real-time classification of emotions.

Acknowledge

Authors would like to thank Queen Mary University of London for providing DEAP dataset. We would also like to acknowledge Ramaiah Institute of Technology, Bengaluru for continuous support.

Conflicts of interest

The authors declare no conflicts of interest.

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