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EEG-Based Emotion Classification: A Biologically Informed Channel Selection Approach

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Abstract: In the domain of neuroscience, electroencephalography (EEG) holds a pivotal role in determining the inner workings of the human brain, offering real-time insights into cognitive processes, emotions, and neurological disorders. While numerous EEG channels are available in a typical EEG brain-computer interface, selecting the optimal subset for emotion classification poses a significant challenge. Conventional channel selection methods overlook the biological relevance of specific brain lobes in emotional processing, leading to a lack of contextual specificity. This paper introduces a novel approach, by using a biologically informed channel selection approach in the EEG signals. The brain is segmented into various groups and sub-groups and the ability of the channels associated with those groups is determined using time and frequency domain features. The ability of each of these groups and sub-groups to attain higher performance is determined through the accuracy outcomes driven by the support vector machines (SVM). The ability of the selected channels in making accurate classification has been determined using a deep learning model in determining valence and arousal classes, and making a comparison with the selected channels-led classification methods. The approach is validated using the DEAP dataset, demonstrating its potential to enhance EEG-based emotion classification accuracy and efficiency. This innovative methodology offers a promising avenue for future EEG research, allowing customization based on the specific emotions under study, psychological intervention, and streamlining the setup process while maintaining the highest levels of accuracy, reaching an average of 95.7% for intra-subject and 94.65% for cross-subject emotion classification.

Keywords: Brain area, Emotion recognition, Cross-subject, Weighting, EEG, Channel selection.

1. Introduction

In modern times, the domain of neuroscience has undergone many transformations and expansions enabling medical practitioners to extract relevant information related to emotions, anomalies, and other mental states [1, 2]. In doing so, Electroencephalography (EEG) is a widely used non-invasive technique that allows medical practitioners to gain insight into the inner workings of the human brain [3]. EEG allows inferring the real-time activities taking place in the brain under a precise temporal resolution and a higher degree of precision [4, 5]. This permits medical practitioners to probe into the mental processes associated with cognitive activities, emotions, and other neurological disorders. The advancements made in the domain of EEG by making use of suitable machine learning methods, and signal processing tools have further harnessed their power in making real-time diagnosing, and inferring anomalies during their inception activating a whole new domain called brain computer interfacing (BCIs) [6, 7]. EEG systems have been designed to meet research and clinical needs, and thus are available in various configurations and forms. The number of electrodes and their positions play a key role in capturing the desired information from the brain. In typical EEG systems, the electrodes in the form of an array or a cap are strategically placed across various areas of the scalp. Internationally, the standard systems involve the use of 10-20 electrodes that are positioned across various locations of the scalp and are represented by a combination of letters and numbers (e.g. Fp1, T5, etc.) depending upon the specific region they belong to [8–10]. In other systems used for research and clinical purposes, the number of electrodes (or channels) can range from tens to hundreds as well, since the employment of a higher number of channels can allow capturing the details with fine spatial resolution, enabling researchers to infer even the subtle brain activities and patterns. While individual channels capture the electrical localized neural information, the collaboration of multiple channels can offer holistic picture activities taking place in different parts of the cerebral cortex [10, 11]. Therefore, such a combination of the individual and collaborative EEG channels helps capture various processes in local and global brain regions under different spatial scales.

The use of a 32-channel EEG system is another commonly used standard typically for research purposes and is available in resources like PhysioNet, etc [12]. Such a system poses several challenges in the context of emotion classification where the selection of the optimal subset of channels is non-trivial for making the desired analysis. Using a higher number of channels despite offering finer spatial information can lead to increased data dimensionality and risk of overfitting. Thus, it is imperative to maintain the right balance between the density of the channels and their computational feasibility. Moreover, the EEG possesses inherent limitations of spatial resolution compared to other neuroimaging methods like fMRI [13]. Such spatial resolutions make it challenging to target the specific brain regions of the cerebral cortex associated with emotion under complex interactions between the brain areas. Furthermore, the emotions are also simultaneously distributed across various cortical regions, while also having a bias towards one of these regions. Thus, having a lack of one-to-one mapping between emotion and cortical areas makes the interpretation of EEG data and its classification more challenging [14, 15]. The individual variability in emotion processing and the dynamic nature of emotions further pose challenges in the selection of the right set of channels of the cortical regions.

In EEG-based emotion recognition tasks, channel selection is a critical step to optimize the use of available EEG channels while minimizing noise and irrelevant information. Several channel selection methods are employed, including statistical techniques like t-tests or ANOVA to identify channels with significant differences in signal characteristics during specific emotional conditions [16]. Spatial filtering methods like principal component analysis (PCA) [17] or independent component analysis (ICA) [18] help extract relevant spatial patterns from EEG data. Feature selection algorithms such as recursive feature elimination (RFE) [19] and mutual information rank channels based on their contribution to classification tasks [20], [21]. Forward and backward selection methods iteratively add or remove channels to enhance classification performance. Expert knowledge allows domain experts to manually select channels based on a prior understanding of brain regions associated with emotions. Information theory, filter banks, hybrid approaches, and cross-validation techniques are also utilized for effective channel selection. Additionally, methods like Relief [22] and ReliefF fall under the category of feature selection algorithms and can be employed to identify informative EEG channels in emotion recognition tasks. These methods focus on selecting relevant features (in this context, EEG channels) for classification tasks by evaluating the importance of each feature (channel) based on their ability to discriminate between different classes (emotional states). Other methods in this category for EEG-based emotion recognition include chi-squared statistics, information gain, and fisher score, among others [23]. These methods assess the discriminatory power of EEG channels and select those that contribute the most to the classification of emotional states.

One of the key limitations of all of these existing channel selection approaches is their insensitivity toward analyzing the relevance of specific lobes of the brain to emotional states. The EEG electrode placement and distribution are administered by various areas on the scalp including the frontal lobe, temporal lobe, occipital lobe, and central and parietal lobe [10]. The frontal lobe (ventromedial prefrontal cortex) is known to be associated with emotion regulation and decision-making processes [24]. Thus its associations with stimuli, impulse control, and self-regulation of emotions are significant. Existing channel selection methods often do not prioritize frontal lobe channels specifically for capturing the regulatory aspects of emotions. This means that the selection may not adequately account for the prefrontal cortex's contributions to emotional processing and regulation. The temporal lobe (superior temporal sulcus) [25] is non-trivial in capturing the emotional cues from social stimuli in the form of facial expressions or voice prosody. Existing methods may not emphasize the importance of temporal lobe channels for capturing social and interpersonal aspects of emotional processing. While the occipital lobe [26] is primarily associated with visual processing, it is relevant for emotional states as it processes emotional content in visual stimuli. Emotional scenes, facial expressions, and other visual emotional cues are processed here. Traditional channel selection approaches may not prioritize occipital lobe channels for capturing emotional responses to visual stimuli. However, including them can enhance the understanding of how emotional information is extracted from the visual environment. The central lobe, particularly the central cortex [27] plays a role in motor control and sensorimotor integration. While not traditionally considered a primary center for emotional processing, it is involved in emotional responses related to body movements and action-related aspects of emotions. The parietal lobe, particularly contributes to aspects of spatial perception and attention. It can be involved in emotional processing, especially in tasks requiring attention to emotional stimuli or spatial aspects of emotional experiences.

By focusing on selecting specific lobes of the brain, rather than individual channels, researchers can explore the role of individual pre-segmented EEG electrode placement regions. This approach allows for the incorporation of the known relevance of specific lobes to emotional states, ensuring that channels within these regions are adequately considered when developing EEG-based emotion classification models. It provides a more biologically informed and comprehensive perspective on emotional processing and regulation. Aside from that, this may contribute to future research and knowledge regarding the intervention of specific brain regions in emotional disorders.

The focus of this paper lies in introducing an innovative approach to EEG-based emotion classification by shifting the focus from traditional channel selection methods to a feature-led classification strategy. Instead of selecting individual channels, this approach centers on the selection of specific lobes of the brain (along with their corresponding channels) known to be biologically relevant to emotional processing. This departure from convention represents an exploration and advancement in the field of EEG-based emotion recognition. By adopting this approach and exploring the potential benefits it offers, the paper opens up new avenues for EEG research. Upon attaining optimal performance, it could revolutionize the way researchers approach electrode placement in EEG experiments related to emotion recognition. Instead of using a one-size-fits-all approach for electrode positioning, researchers would have the opportunity to tailor electrode placement based on the specific type of emotion under investigation. This customization has the potential to significantly reduce both the effort required in electrode setup and the number of channels needed for accurate emotion classification. The paper utilizes the DEAP dataset, which includes classes of arousal (high and low) or arousal (high and low), to demonstrate the effectiveness of this approach. The dataset serves as a valuable resource for validating the proposed method and showcasing its potential benefits in improving EEG-based emotion classification accuracy. Thus the overall contribution of the paper is presented below:

i. The selection of channels is based on biologically informed brain regions. The EEG-distributed electrodes (channels) are segmented into groups and sub-groups based on biological and cognitive characterizations. The ability of channels in each of these groups/sub-groups to make accurate classifications of the cognitive tasks is analyzed using time and frequency domain features and SVM-led classification.
ii. The selected channels (corresponding to the groups/subgroups) have been subjected to deep classification in valence and arousal classes to determine their effectiveness in a comparative manner (relative to existing studies).
iii. Potential to revolutionize electrode placement strategies, allowing customization based on the type of emotion under study, thereby reducing setup efforts and channel requirements.

The rest of the paper has been structured as follows. Section 2 presents the related works that primarily make use of channel selection methods and deep learning architectures to make classifications. Section 3 presents the methodology adopted in this paper including the dataset employed and the details of the channel selection model and deep learning classifier. Section 4 presents the results and discussion, and section 5 concludes the study.

2. Related work

To further evaluate the contribution and effectiveness of our proposed model and to make a comparative analysis later, several EEG classification studies have been focused on that make use of one of the channel selection methods followed by a machine learning-based classification. The authors in [28] present a channel selection method introduced for motor imagery (MI) classification based on distinctive correlation coefficient values. It forms channel groups using strong correlations and computes the fisher score using filter-bank CSP (FBCSP). The results show a mean classification accuracy of 88.62%. In [29], emotion recognition using multi-channel EEG data from the DEAP database is explored. The study achieves average recognition accuracies of 72.03% and 71.7% using various EEG features and applies the ReliefF algorithm to select optimal combinations of 6 and 13 channels, paving the way for the development of portable emotion recognition devices. Authors in [30] introduce a channel selection method for EEG-based emotion recognition by employing normalized mutual information (NMI) to select an optimal subset of EEG channels, maintaining a high accuracy of 74.41% for valence and 73.64% for arousal on the DEAP database. The selected channels align with cortical areas associated with general emotion tasks, demonstrating the effectiveness of the approach.

In [31], the authors propose a channel selection method using stepwise discriminant analysis (SDA). The study employs EEG data from a public emotion dataset recorded with 62 EEG channels for three target emotions (positive, negative, and neutral). Differential entropy features from five frequency bands are extracted (delta, theta, alpha, beta, and gamma), and SDA selects optimal channels based on the Wilks Lambda score. The EEG features are then classified using linear discriminant analysis (LDA). Notably, the highest accuracy of 99.85% is achieved with 15 selected channels, demonstrating the reliability of alpha, beta, and gamma frequency bands for EEG emotion recognition. Authors in [32], incorporate the mRMR feature selection algorithm for channel selection and employ the extreme learning machine with kernel for classification. By employing this approach, channels have been reduced from 32 to 22 attaining a classification accuracy of 79.37%. [33] focuses on epileptic seizure prediction using EEG signals and patient-specific EEG channel selection methods based on permutation entropy (PE) values, integrating K nearest neighbors (KNNs) and a genetic algorithm (GA), and using SVM as the classifier. Results indicate that using patient-tailored channels significantly improves prediction rates, with an average accuracy increase of 10.58%, sensitivity increase of 23.57%, and specificity increase of 5.56% compared to SVM testing with all channels. [34] introduces a channel selection method based on dynamic channel relevance (DCR) scores for EEG signals in the BCI. It uses support vector machines (SVM) for classification and achieves superior accuracy (85.4%, 80.33%, and 85.20%) on three EEG datasets while reducing the number of channels and computation time compared to state-of-the-art methods. The authors in [35] employed a channel selection method utilizing a neuro-evolutionary algorithm (NEA) with modified particle swarm optimization (MPSO) and common spatial pattern feature extraction. They used a multi-layer perceptron neural network (MLP-NN) as the machine learning model, achieving an accuracy of 89.95% on their EEG dataset and 89.83% on the BCI competition IV ECoG dataset. The article in [36] focused on developing a model for emotion recognition from non-stationary EEG signals. The study employed ReliefF and neighborhood component analysis (NCA) for optimal electrode selection and used CNNs for feature extraction, achieving accuracy rates of 90.76% for valence, 92.92% for arousal, and 92.97% for dominance.

The techniques presented in this section possess certain limitations leading to a need for adopting a biologically informed channel selection approach as proposed in this study. The use of the filter-bank CSP-led approach makes use of predefined frequency bands that may fail to capture all the relevant information due to the static nature of the analysis. ReliefF method although being commonly used is sensitive to the distribution of the dataset. When the distribution is biased or associated with outliers, the technique may result in suboptimal results. The idea of using normalized mutual information (NMI) assumed an independent nature of the features. This may not be true for the channels which are biologically related. The use of a neuro-evolutional algorithm (NEA) requires a higher level of complexity especially for large datasets like those of EEG. This leads to extensive computations. mRMR-based feature selection method resides on a linear nature of the relationship establishment. The method may fail to capture non-linear relationships in the EEG channels, leading to limited effectiveness. The Patient-Specific EEG channel selection method may work well for the intra-subject case, yet its ability to work in cross-subject scenarios remains limited. The use of dynamic channel relevance (DCR) scores is sensitive to the temporal changes in the data. Any rapid changes in the time domain signals can lead to higher instability in outcomes. The HOLO-FM methods are complex due to the holographic mapping process making it difficult to analyse the biologically significant processes.

These studies and limitations have been treated as a benchmark to make a performance comparison with the proposed method later.

3. Materials and method

3.1 Datasets

The study makes use of an open-source DEAP dataset [37]. The data involves EEG and peripheral physiological signal recordings from 32 healthy participants aged between 19 and 37. EEG data was recorded using 32 active AgCl electrodes, following the international 10-20 system, with a sampling rate of 512 Hz. Additionally, 13 peripheral physiological signals were recorded. The experiment protocol included participants watching music videos and performing self-assessments for arousal, valence, liking, and dominance. It includes 120 videos, each lasting 1 minute, for affective highlight analysis. These videos were selected using last.fm affective tags and manual curation. Each video received 14 - 16 ratings on the scales of arousal, valence, and dominance, using a discrete scale ranging from 1 to 9. For the physiological experiment, 32 participants were involved, and 40 videos were selected from the online annotated dataset based on clear responses. Participants rated these videos on the scales of arousal, valence, dominance, liking (video preference), and familiarity (familiarity with the video). The EEG data was preprocessed, down-sampled to 256 Hz, and high-pass filtered at 2 Hz. Welch's method was used to extract frequency power in various bands (theta, alpha, beta, and gamma), and correlations between power changes and subjective ratings were computed. The dataset provides valuable information for studying the relationship between EEG signals and emotional responses.

3.2 Brain areas weighting

The core idea of our model is to identify the brain areas and respective channels that can help us attain higher classification rates under the valence and arousal classes. To attain this, the study underwent numerous steps. Initially using a random split operation, a subset D_s of the EEG data D having N samples and M channels from across various subjects was extracted.

Each sample x_i in the selected EEG data has been segmented into consecutive 4-second windows W with a 1-second overlap, allowing for a comprehensive analysis of temporal aspects. On the windowed signals X_(i,j) (i is sample index, and j is window index), we employed a set of time and frequency domain-selected features, namely root mean square F^RMS, spectral centroid F^SC, spectral bandwidth F^SB, and spectral roll-off F^SR, as the foundation of our feature extraction process. These features have been chosen for their unique characteristics and potential benefits in the context of EEG-based emotion recognition. RMS captures the signal's magnitude, providing insight into the overall signal energy. Spectral centroid identifies the center of mass of the frequency spectrum, offering information about the dominant frequency in each window. Spectral bandwidth measures the spread of frequencies, reflecting the signal's variability. Finally, spectral roll-off helps differentiate between low and high-frequency content. The combination of these features enables us to capture both temporal and spectral aspects of EEG signals, enhancing our ability to discriminate emotional states with precision. The feature extraction method has been presented in Algorithm 1.

Algorithm 1: Features extraction approach

Inputs: $\boldsymbol{D_s},\ \boldsymbol{X_{i,j}}$

Outputs: Features $\boldsymbol{F}$

Process Starts:

1. **For** i, j in $X_{i,j}$ **do**
2. $\quad F_{i,j}^{RMS} \leftarrow \sqrt{\frac{1}{L}\sum_{l=1}^{L} X_{i,j}[l]^2}$
3. $\quad F_{i,j}^{SC} \leftarrow \frac{1}{L}\sum_{l=1}^{L} f[l].\left|X_{i,j}[l]\right|$
4. $\quad F_{i,j}^{SB} \leftarrow \sqrt{\frac{1}{L}\sum_{l=1}^{L}\left(f[l] - F_{i,j}^{SC}\right)^2 . \left|X_{i,j}[l]\right|}$
5. $\quad F_{i,j}^{SR} \leftarrow \sum_{l=1}^{L} X_{i,j}[l]$
6. **End For**
7. $F \leftarrow \{F^{RMS}, F^{SC}, F^{SB}, F^{SR}\}$

Here $f[l]$ represents the frequency at index l, $\sum_{l=1}^{L} X_{i,j}[l]$ represents P% of the total energy.

Following the extraction of features, the EEG channels were systematically grouped into specific channel categories G_1, G_2, and G_3, driven by the underlying organization of the human brain. This grouping strategy aligns with known anatomical and functional divisions of the brain, allowing for a more biologically meaningful analysis of EEG signals in the context of emotion recognition. In the first category, encompassing frontal, parietal, central, temporal, and occipital regions, channels including $\boldsymbol{G_1}$: *F3, F7, FC5, FC1, AF4, F4, F8, FC6, FC2, T7, CP1, P3, P7, Pz, CP6, CP2, P4, P8, Fp1, Fp2, AF3, AF4, C3, T7, Cz, C4, T8, P04, O1, Oz, PO4, and O2* were selected [38]. These channels collectively cover a wide array of brain areas associated with emotional processing. The second category, including frontal, parietal, temporal, and occipital regions, features channels include $\boldsymbol{G_2}$**:** *Fp1, Fp2, AF3, F3, F7, FC5,* *FC1, AF4, Fz, F4, F8, FC6, FC2, CP5, CP1, P3, P7, PO3, Pz, CP6, CP2, P4, P8, PO4, T7, T8, C3, Cz, C4, O1, O2, and Oz* [39]. These channels were chosen to provide insight into brain activity across multiple areas involved in emotional responses. Lastly, the third category distinguishes between left frontal, right frontal, left parietal-temporal-occipital (left pto), and right parietal-temporal-occipital (right pto) regions, utilizing channels such as $\boldsymbol{G_3}$: *Fp1, AF3, F3, F7, FC5, FC1, C3, Cz, Fz, F4, F8, FC6, FC2, AF4, Fp2, C4, O1, PO3, P7, P3, CP1, CP5, T7, Oz, O2, PO4, P8, P4, CP2, CP6, T8, and Pz* [39], [40]. This differentiation reflects the lateralization of certain emotional processes in the brain. Out of these primary channel groups, sub-groups G_{1s}, G_{2s}, G_{3s} were further created capturing the frontal, parietal, central, temporal, and occipital channels individually. By grouping channels in this manner, we aim to uncover the intricate neural dynamics associated with emotion recognition, enhancing our comprehension of emotional states from EEG signals.

The brain weights have been attained by making use of SVM as a classification model. The feature channel groups have been passed through individual SVM models, and the corresponding weights of these channel groups have been recorded. This information helps in the selection of the desired brain regions that are suitable for the valence and arousal of emotional states. For each subgroup G_{1s}, G_{2s}, G_{3s} , SVM classification $X_{i,j}^{G_{is}}$ was determined. SVM is used to train classifiers C_{is} for each channel subgroup using the feature-labels pairs $F_{i,j}^{G_{is}}$ with an optimization goal determined as follows:

$$Cost\ Function = \ minimize \frac{1}{2}\|w\|^2 + C\sum_{j=1}^{W} \kappa_{i,j} \tag{1}$$

Subject to $y_{i,j}\left(w^T F_{i,j}^{G_i} + b\right) \geq 1 - \ \kappa_{i,j}, \kappa_{i,j} \geq 0, j = 1, 2, \dots, W$

Where w is the weight vector, C is the regularization parameter, $\kappa_{i,j}$ are slack variables, b is the bias term.

The outcomes of the model have been based on the accuracy scores.

3.3 EEG selected channels classification

Having successfully identified the potential brain regions and channels using the weighing methodology presented above, we have developed a deep learning simplified convolutional neural network (CNN) model on the selected channels. In doing so, the process of converting raw EEG data of the selected channels into two-dimensional (2D) spectrogram images was a crucial step in facilitating data visualization and classification. This transformation was achieved using the short time fourier transform (STFT), which is well-suited for converting data into time-frequency information. The STFT method offers a unique advantage by using color intensity levels to represent both temporal and spectral localization in the data. This transformation allowed us to capture the inherent spectral characteristics present in individual EEG channels. In this study, the temporal segments selected for analysis corresponded to the second half of each EEG signal, a method validated and widely used in prior research. The mathematical representation of the STFT transformation is provided by Eq. 2:

$$STFT\ \{x[n]\} = X(n, \omega) = \sum_{m=-\infty}^{\infty} x[m]w[n-m]e^{-j\omega m} \tag{2}$$

Where w[m] represents the time window used to extract the framed signal, $e^{(-j\omega m)}$ represents the frequency response of the windowed signal. By scaling the spectrograms, RGB pictures with dimensions of 224x224x3 were created.

The convolutional neural network (CNN) architecture employed for emotion classification was adapted from our previous work [41]. This architecture, known for its simplicity and a lower number of parameters compared to prior research, played a pivotal role in our study. The architecture, depicted in Fig. 1, utilized the rectified linear unit (ReLU) as the activation function, the Adam optimizer, 150 training epochs, a batch size of 16, and a learning rate of 1e-4, and has been taken from our previous published work presented in [40]. This CNN architecture was chosen for its effectiveness in classifying emotions based on the spectrogram images generated from EEG data.

This methodology enabled the extraction of relevant features from the EEG data, transforming it into a format conducive to emotion classification. The subsequent CNN-based classification process was built upon these 2D spectrogram images to achieve accurate emotion recognition.

4. Result and discussion

4.1 Brain areas weighting

In this section, we have presented and discussed the resulting outcomes from the groups and subgroups of channels as presented in the previous section. The accuracy has been used as a weighting

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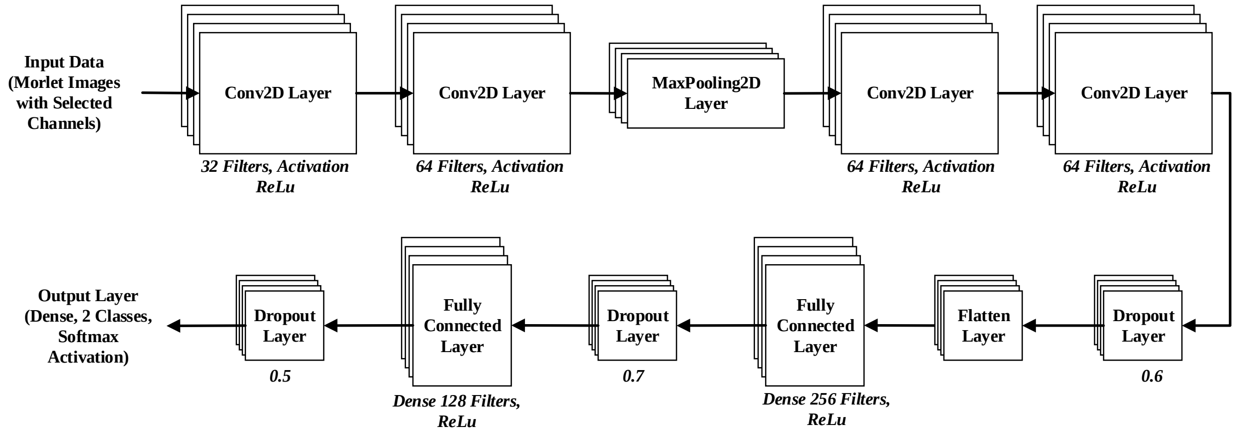

Figure. 1 Simplified CNN architecture for the 2D EEG images classification

Table. 1 Brain areas weighting scores

Channel Groups	Channel Subgroups	Valence (%)	Arousal (%)
G1 [38]	***Frontal lobe*** F3, F7, FC5, FC1, AF4, F4, F8, FC6, FC2	64.4	66.3
	Parietal lobe T7, CP1, P3, P7, Pz, CP6, CP2, P4, P8	63.6	66.1
	Central lobe C3, T7, Cz, C4, T8	63.5	64.0
	Temporal lobe FP1, FP2, AF3, AF4	63	63.6
	Occipital lobe PO3, O1, Oz, PO4, O2	62.8	64.1
G2 [39]	***Frontal lobe*** Fp1, Fp2, AF3, F3, F7, FC5, FC1, AF4, Fz, F4, F8, FC6, and FC2	64.6	67.5
	Parietal lobe CP5, CP1, P3, P7, PO3, Pz, CP6, CP2, P4, P8, and PO4	63.9	66.3
	Temporal lobes T7, T8, C3, Cz, and C4	63.5	64.1
	Occipital lobes O1, O2, and Oz	62.6	63.7
G3[39], [40]	***Left Frontal*** Fp1, AF3, F3, F7, FC5, FC1, C3, Cz	63.6	66.3
	Right Frontal Fz, F4, F8, FC6, FC2, AF4, Fp2, C4	64	65.1
	Left parietal-temporal-occipital (left pto) O1, PO3, P7, P3, CP1, CP5, T7, Oz	64.5	66.0
	Right parietal- temporal-occipital (right pto) O2, PO4, P8, P4, CP2, CP6, T8, Pz	63.1	65.2

measure for the two groups of emotional states i.e. valence (low and high), and arousal (low and high), to develop a pragmatic link between the selection of channels group and the emotional states. Numerous Subgroups G_is have been created based on the subsiding lobes. The groups along with their weighted outcomes have been presented in Table 1.

In the analysis of channel subgroups based on valence and arousal accuracy rates, some subgroups exhibited higher performance, while others showed relatively lower accuracy. Among the best-performing regions, the Frontal Lobe subgroup comprising channels F3, F7, FC5, FC1, AF4, F4, F8, FC6, and FC2 demonstrated remarkable accuracy, achieving a valence accuracy of 64.4% and an arousal accuracy of 66.3%. This result suggests that these channels within the frontal lobe are particularly adept at capturing and predicting emotional responses. Similarly, the frontal, parietal, central, temporal, and

Table. 2 Dependent-subject 2D CNN-based classification outcomes

Groups	Channel Subgroups	BR Weight (%)	Weighting Order	Valence Accuracy (%)	Accuracy Order	BR Weight (%)	Weighting Order	Arousal Accuracy (%)	Accuracy Order
G1	***Frontal lobe*** F3, F7, FC5, FC1, AF4, F4, F8, FC6, FC2	64.4	1	92.7	1	66.3	1	92.4	1
	Parietal lobe T7, CP1, P3, P7, Pz, CP6, CP2, P4, P8	63.6	2	91.3	2	66.1	2	89.1	2
	Central lobe C3, T7, Cz, C4, T8	63.5	3	86.6	3	64,1	3	82	4
	Temporal lobe FP1, FP2, AF3, AF4	63	4	79.9	4	63,6	5	80.3	5
	Occipital lobe PO3, O1, Oz, PO4, O2	62.8	5	82.2	5	64	4	86.1	3
G2	***Frontal lobe*** Fp1, Fp2, AF3, F3, F7, FC5, FC1, AF4, Fz, F4, F8, FC6, and FC2	64.6	1	95.7	1	67.5	1	95.7	1
	Parietal lobe CP5, CP1, P3, P7, PO3, Pz, CP6, CP2, P4, P8, and PO4	63.9	2	94	2	66.3	2	95	2
	Temporal lobes T7, T8, C3, Cz, and C4	63.5	3	75.3	3	64.1	3	80.5	3
	Occipital lobes O1, O2, and Oz	62.6	4	72.7	4	63.7	4	66.4	4
G3	***Left Frontal*** Fp1, AF3, F3, F7, FC5, FC1, C3, Cz	63.6	3	91.3	2	66.3	1	88.4	4
	Right Frontal Fz, F4, F8, FC6, FC2, AF4, Fp2, C4	64	2	91.1	3	65.1	4	89.2	1
	Left parietal-temporal-occipital (left pto) O1, PO3, P7, P3, CP1, CP5, T7, Oz	64.5	1	92.7	1	66	2	88.6	2
	Right parietal- temporal-occipital (right pto) O2, PO4, P8, P4, CP2, CP6, T8, Pz	63.1	4	90.5	4	65.2	3	88.4	2

occipital lobes subgroup, which included channels such as Fp1, Fp2, AF3, F3, F7, FC5, FC1, AF4, Fz, F4, F8, FC6, and FC2, displayed exceptional performance. This subgroup achieved a high valence accuracy of 64.6% and an impressive arousal accuracy of 67.5%, highlighting its effectiveness in emotion prediction. Additionally, the Left parietal-temporal-occipital (left) subgroup, composed of channels O1, PO3, P7, P3, CP1, CP5, T7, and Oz, demonstrated strong valence accuracy (64.5%) and good arousal accuracy (66%), further underscoring the relevance of these channels in emotional state recognition. On the other hand, the analysis revealed some regions with lower performance. The occipital lobe subgroup, encompassing channels PO3, O1, Oz, PO4, and O2, exhibited relatively lower valence accuracy at 62.8% and arousal accuracy of 64.1%. Similarly, the occipital lobes subgroup, represented by channels O1, O2, and Oz, showed modest valence accuracy (62.6%) and arousal accuracy (63.7). Furthermore, the right parietal- temporal-occipital (right) subgroup, which included channels O2, PO4, P8, P4, CP2, CP6, T8, and Pz, displayed a valence accuracy of 63.1% and an arousal accuracy of 65.2%, indicating room for improvement in emotional state recognition within this region. Thus, specific channel subgroups, particularly those within the frontal and

Table 3. Cross-subject 2D CNN-based classification outcomes

Groups	Channel Subgroups	BR Weight (%)	Weighting Order	Valence Accuracy (%)	Accuracy Order	BR Weight (%)	Weighting Order	Arousal Accuracy (%)	Accuracy Order
G1	***Frontal lobe*** F3, F7, FC5, FC1, AF4, F4, F8, FC6, FC2	64.4	1	92.1	1	66	2	91	2
	Parietal lobe T7, CP1, P3, P7, Pz, CP6, CP2, P4, P8	63.6	2	91.4	2	66.1	1	91.7	1
	Central lobe C3, T7, Cz, C4, T8	63.5	3	83.9	3	64.1	3	82.8	3
	Temporal lobe FP1, FP2, AF3, AF4	63	4	82	4	63.6	5	79.6	5
	Occipital lobe PO3, O1, Oz, PO4, O2	62.8	5	80.5	5	64	4	80.3	4
G2	***Frontal lobe*** Fp1, Fp2, AF3, F3, F7, FC5, FC1, Fp2, AF4, Fz, F4, F8, FC6, and FC2	64.6	1	95	1	67.5	1	94.3	1
	Parietal lobe CP5, CP1, P3, P7, PO3, Pz, CP6, CP2, P4, P8, and PO4	63.9	2	93.6	2	66.3	2	92.7	2
	Temporal lobes T7, T8, C3, Cz, and C4	63.5	3	83.7	3	64.1	3	79.3	3
	Occipital lobes O1, O2, and Oz	62.6	4	67.5	4	63.7	4	68.1	4
G3	***Left Frontal*** Fp1, AF3, F3, F7, FC5, FC1, C3, Cz	63.6	3	89.6	4	66.3	2	88	4
	Right Frontal Fz, F4, F8, FC6, FC2, AF4, Fp2, C4	64	2	90.6	2	65.1	4	89.2	3
	Left parietal-temporal-occipital (left pto) O1, PO3, P7, P3, CP1, CP5, T7, Oz	64.5	1	91.2	1	66	1	92	1
	Right parietal- temporal-occipital (right pto) O2, PO4, P8, P4, CP2, CP6, T8, Pz	63.1	4	90.3	3	65.2	3	91.1	2

Left parietal-temporal-occipital (left pto), showcased superior performance in accurately predicting valence and arousal while selecting occipital and Right parietal- temporal-occipital (right pto) subgroups exhibited room for enhancement. These findings contribute to the refinement of channel selection strategies for emotion recognition applications using EEG data.

4.2 Intra-subject classification using CNN

The intra-subject accuracy results presented in Table 2 provide valuable insights into the performance of different channel subgroups and their weighted positions. To assess the relationship between weighting order and classification accuracy, we can observe that in both valence and arousal prediction, the subgroup with the highest Brain Region (BR) weight achieved the highest accuracy. Specifically, the frontal, parietal, central, temporal, and occipital lobes subgroup secured the top weighting position with a BR weight of 64.6% and, correspondingly, achieved the highest valence accuracy of 95.7% and the highest arousal accuracy of 95.7%. This indicates a strong alignment between the weighting order and predictive accuracy. The second-best performance was observed in the Frontal Lobe subgroup, which had a BR weight of 64.4% and attained a valence accuracy of 92.7% and an arousal

Table 4. Performance comparison with related works in channel selection

Article	Channel Selection Method	Classification Method	Accuracy	Dataset	Description
[28]	Filter-bank CSP (FBCSP)	mean	88.6 %	BCI datasets, BCI competition III dataset IVa and BCI competition IV dataset I	motor imagery (MI) activities
[29]	ReliefF algorithm	Various EEG features	72 %	DEAP datasets	Emotion Recognition
[30]	Normalized mutual information (NMI)	Not specified	74.4 %	DEAP datasets	Emotion Recognition
[35]	Neuro-evolutionary Algorithm (NEA)	Perceptron Neural Network (MPL-NN)	89.95%	BCI competition IV	motor imagery (MI) activities
[32]	mRMR feature selection algorithm	Extreme Learning Machine with Kernel	79.3 %	DEAP datasets	Emotion Recognition
[33]	Patient-specific EEG channel selection (PE values)	K nearest neighbors (KNNs), Genetic Algorithm (GA), SVM	average 92.42%	CHB-MIT Scalp EEG Database	epileptic seizures
[34]	Dynamic Channel Relevance (DCR) scores	SVM	85.4%, 80.33%, 85.20%	(BCI Competition IV-2008 - IIA, BCI Competition IV-dataset 1, BCI competition III - dataset IVa)	motor imagery (MI) activities
[36]	R-HOLO-FM	CNN	88.19%	DEAP datasets	Emotion Recognition
[36]	N-HOLO-FM	CNN	88.31%	DEAP datasets	Emotion Recognition
[42]	Brain areas: frontal lobe	CNN	61%, 58%	DEAP datasets	Emotion Recognition
[39]	Brain areas: frontal lobe	LSTM	62.53%, 67.37%,	DEAP datasets	Emotion Recognition
Proposed Model	Weighted BR channel selection	Simplified CNN architecture	95.7 % dependent subject 94.65 % cross-subject	DEAP datasets	Emotion Recognition

accuracy of 92.4%. The Parietal, Central Lobes subgroup, with a BR weight of 63.6%, ranked third in weighting order, achieving a valence accuracy of 91.3% and an arousal accuracy of 89.1%.

These results emphasize the importance of considering channel subgroups and their corresponding weights when optimizing EEG-based emotion recognition models. The findings suggest that specific channel subgroups, particularly those encompassing multiple brain regions, can significantly enhance the accuracy of emotion prediction, holding promise for applications in affective computing and human-computer interaction.

4.3 Cross-subject classification using CNN

The cross-subject analysis of weighted BR subgroups, presented in Table 3, reveals interesting patterns in valence and arousal accuracy. To assess the impact of weighting orders on accuracy, we first examine the subgroups with the highest BR weights and their corresponding performance. In terms of valence accuracy, the frontal, parietal, temporal, and occipital lobes subgroup, which held the top weighting position with a BR weight of 64.6% and 67.5%, achieved the highest accuracy at 95% of valence. This demonstrates the consistency of high performance in valence prediction when this subgroup is given a higher weight. Notably, the frontal lobe in the G1 group, ranking second in weighting order with a BR weight of 64.4%, secured the second-highest valence accuracy at 92.1%. This suggests a close alignment between weighting order and valence accuracy. For arousal accuracy, the subgroup frontal, parietal, temporal, and occipital lobes also demonstrated its effectiveness by securing the top weighting position with a BR weight of 67.5% and achieving the highest arousal accuracy of 94.3%. This subgroup consistently outperformed others in both valence and arousal accuracy, emphasizing its significance in cross-subject emotion recognition.

The results across different subgroups underscore the importance of weighting strategies in optimizing emotion recognition models. In the cross-subject scenario, certain subgroups consistently outperform others, offering valuable insights into the selection of relevant channels and their impact on prediction accuracy. The highest overall accuracy in both valence and arousal prediction was achieved by the frontal, parietal, temporal, and occipital lobes subgroup, demonstrating its robustness in capturing emotional responses across different subjects.

4.4 Performance comparison

The performance of the proposed model has been compared with the existing studies to determine its effectiveness. The articles explored in the related works section have been summarized in Table 4 along with the outcomes of the proposed model.

5. Conclusion

The study has introduced a novel approach to EEG-based emotion classification, emphasizing the importance of selecting specific brain lobes known to be biologically relevant to emotional processing. By departing from traditional channel selection methods and focusing on the entire brain lobe, this approach has the potential to revolutionize the field of EEG research. It offers a more comprehensive and biologically informed perspective on emotion recognition, leading to more accurate and efficient classification. The study analyzed the channel's distribution into three main Groups and subgroups. By determining the highest-scored channels, the deep learning model has been employed to analyze the accuracy in the valence and arousal classes. The use of the DEAP dataset has demonstrated the effectiveness of this approach, highlighting its potential to improve emotion classification accuracy. It accuracy found in the case of intra-subject is 95.7 %, while in the case of cross-subject is 94.65 %. This is significantly higher compared to the 89.95 % previously attained using the Neuro-evolutionary algorithm (NEA) channel selection method. In addition, this research outperforms numerous other studies in terms of channel selection across different domains in Table 4.

The study opens up opportunities for customized electrode placement based on the type of emotion under investigation, reducing setup efforts, and channel requirements. Overall, this innovative method represents a significant step forward in the quest for precise and effective EEG-based emotion classification. It promises to enhance our understanding of emotional processing and regulation, contributing to advancements in the field of neuroscience and clinical applications in emotional intervention.

Conflicts of interest

The authors declare that they have no potential conflict of interest.

Author contributions

Conceptualization, Lia Farokhah and Riyanarto Sarno; methodology, All Authors; software, Lia Farokhah; validation, Chastine Fatichah; writing—original draft preparation, All authors; writing—review and supervision, Riyanarto sarno and Chastine Fatichah.

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