The challenges of emotion recognition methods based on electroencephalogram signals: a literature review

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ABSTRACT

Electroencephalogram (EEG) signals in recognizing emotions have several advantages. Still, the success of this study, however, is strongly influenced by: i) the distribution of the data used, ii) consider of differences in participant characteristics, and iii) consider the characteristics of the EEG signals. In response to these issues, this study will examine three important points that affect the success of emotion recognition packaged in several research questions: i) What factors need to be considered to generate and distribute EEG data?, ii) How can EEG signals be generated with consideration of differences in participant characteristics?, and iii) How do EEG signals with characteristics exist among its features for emotion recognition? The results, therefore, indicate some important challenges to be studied further in EEG signals-based emotion recognition research. These include i) determine robust methods for imbalanced EEG signals data, ii) determine the appropriate smoothing method to eliminate disturbances on the baseline signals, iii) determine the best baseline reduction methods to reduce the differences in the characteristics of the participants on the EEG signals, iv) determine the robust architecture of the capsule network method to overcome the loss of knowledge information and apply it in more diverse data set.

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1. INTRODUCTION

Emotions are interactions and behaviors of human psychology which play an important role in everyday human social interactions. They usually arise as a response to certain conditions or problems representing a certain target to be achieved [1]. Positive emotions have the ability to maintain a person's mental state and increase work efficiency. In contrast, negative emotions cause mental state disorders and the buildup, at the top of the day, also leads to depression. Moreover, emotions arise spontaneously amid physical and physiological changes associated with human organs and tissues such as the brain, heart, skin, blood flow, muscles, facial expressions, and voice [2]. It is, therefore, important to acknowledge human emotions in an effort to understand human psychological interactions and behavior. There are generally two major categories of emotion recognition methods which are: i) physical or external aspects of humans and

ii) physiological signals or internal aspects of humans. Meanwhile, the emotions expressed externally are usually deliberately hidden within the social environment [2]–[4]. These problems are mostly solved using the physiological signals from the central nervous system (CNS) via electroencephalogram (EEG) signals [5]. The EEG signals-based emotion recognition has several advantages such as: i) portability, low cost, and ease to line up [5], ii) rich spatial, temporal, and spectral data on human affective experiences which support the underlying neural mechanisms [6], [7], and iii) the occurrence of emotional reactions first in the human brain, especially within the subcortical, which means it is possible to directly reflect the changes in EEG signals in the human emotional condition [4], [6]. The EEG signals-supported emotion recognition studies have been widely applied within the 2 problem domains: medical and non-medical [8].

There has been rapid development of research on EEG signals-based recognition over the past five years in terms of data acquisition, data preprocessing, feature extraction, feature representation, and classification process [2], [7]–[11]. The success of this study, however, is strongly influenced by: i) distribution of the data used [9], ii) consider of differences in participant characteristics, such as personality traits, intellectual abilities, and gender in emotion reaction [12], [13], and iii) consider the characteristics of the EEG signals such as having a low frequency and containing spatial information on emotion recognition [14], [15]. In response to these issues, the research presented here will examine three important points that affect the success of emotion recognition packaged in several research questions: i) what factors need to be considered to generate and distribute EEG data to represent emotional reactions?, ii) how can EEG signals be generated with consideration of differences in participant characteristics?, and iii) how do EEG signals with characteristics exist among its features for emotion recognition? Therefore, the findings of this study are expected to be a reference for further research on emotion recognition based on EEG signals.

2. RESEARCH METHOD

This literature study was based on several articles retrieved from www.scopus.com, and the articles collected them through the two stages explained in the following subsections.

2.1. Selection stage

Several criteria based on the query were applied in the searching process in electronic databases, as shown in Figure 1. The retrieving process based on these queries results in 316 articles consisting of 171 conference papers and 145 journal articles.

2.2. Analysis stage

The next process is to analyze the articles obtained, and the process involved five stages: i) stage 1, focusing on the EEG signals and emotion recognition by checking the title and abstract, (ii) stage 2, checking the access of the articles, iii) stage 3, focusing on the three issues of the study by checking each article's introduction and methods, and iv) stage 4, Select the relevant article by checking the results and conclusion of each article. In Figure 2, the stages of selection and analysis of several articles are presented.

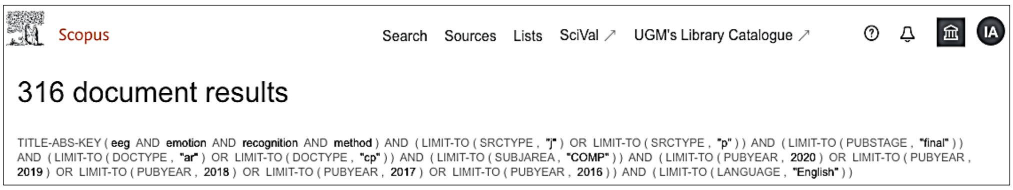

Figure 1. The query for searching articles

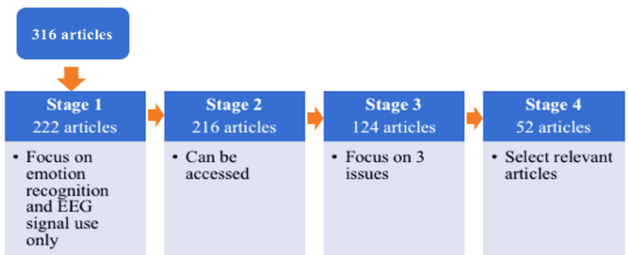

Figure 2. Selection and analysis stages of articles

Based on the analysis stage, 52 relevant articles were obtained as references in this study. Apart from the 52 articles obtained from searching the Scopus database, this study also uses several additional articles totaling 37 articles to enrich the research study. So, this study uses 89 articles. The distribution of articles is based on three research questions (RQ) in this study are represented in Table 1. In distributing articles on each RQ, article redundancy can occur because each article answers more than one RQ.

Table 1. Analysis of the articles

No	Research questions	Selected articles
1	RQ 1	25 articles
2	RQ 2	27 articles
3	RQ 3	44 articles
	Total	96 articles

3. RESULTS AND DISCUSSION

This study reviewed several issues associated with EEG signals-based emotional recognition, which can use for further research.

3.1. RQ 1: What factors need to be considered to generate and distribute EEG data to represent emotional reactions?

Several factors are taken into consideration in generating the EEG dataset for emotion recognition, including [11]:

a) Stimulus media: The literature studies showed several categories of stimuli to evoke emotions such as audio [16], [17], visual, and audio-visual media [14] as well as others including the ambient assisted living (AAL) technology [18], a combination of music, video, and game stimuli [19], mobile learning application [20], augmented reality (AR) [21], virtual reality (VR) [22], [23], and tactile enhanced multimedia (TEM) [24].

b) Proper stimuli presentation setup [11]. Several factors influencing the presentation of a stimulus, including the monitor screen size, lighting, viewing angles. Viewing distance and each of them is represented in the (1):

$$\hat{y} = -14 + 70x_1 + 2x_2 - 0.0015x_2^2 + 0.46x_3^2 \tag{1}$$

where, $\hat{y}$ is the prediction of the preferred viewing distance *(millimeters)*, x_1 represents the TV monitor size *(inches)*, x_2 represents the illumination value in the room *(lux)*, while x_3 represents the viewing angle (*degrees* °).

c) Standardization of experimental protocols [11]. The stimulus presentation in experimental design is an important factor influencing the type of emotion it evokes. Therefore, the general implementation protocol to extract emotions is explained in Figure 3.

Pre-stimuli (in minutes/seconds)			Stimuli (in minutes/seconds)	Post-stimuli (in minutes/seconds)
R	C	W	S	M

Figure 3. Experimental design [11]

where, *R* is a relaxation time or blank screen condition, *C* is a countdown frame, *W* is a white cross-presentation/baseline/normal state, *S* is a presented stimulus, and *M* is a self-assessment manikin (SAM)/rest time assessment.

Several studies have provided publicly available emotional datasets that other researchers can use, such as: DEAP [25], ASCERTAIN [26], GAMEEMO [27], DREAMER [28], MPED [29], SAFE [30], AMIGOS [31], MAHNOB-HCI [32], and SEED-IV [33]. Although some datasets are publicly available, these datasets may have an unbalanced distribution of data. The performance of the emotion recognition method depends on the data balance. Several studies that used public datasets such as DEAP were observed to have a high imbalance of emotional data. It was discovered that only respondents 16, 28, 30, and 31 had balanced data for the arousal emotion label out of the 32 analyzed, while 10, 14, 15, 22, and 32 had for emotional valence label [34]. There are several oversampling methods for data imbalance problems, such as adaptive synthetic sampling approach for imbalanced learning (ADASYN) [34], a novel fitness function, g-score genetic programming (GGP) [35], and synthetic minority oversampling technique (SMOTE) [36], [37]. However, most of the existing oversampling methods still found overlapping data in the final results, making it difficult to determine the decision limit for each class. The radius-SMOTE method can overcome this problem. This method emphasizes the initial selection approach by generating synthetic data based on the safe radius distance. However, the radius-SMOTE method has limitations in detecting noise in the data boundary area [38]. Therefore, the challenge for future studies is to determine robust methods for imbalanced EEG signals data.

3.2. RQ 2: How can an EEG signal be generated with consideration of differences in participant characteristics?

The participants' emotional reactions in EEG signals are strongly influenced by the different characteristics of participants, such as personality traits, intellectual abilities, and gender [9], [12]. The different characteristics of these participants can produce unique EEG signals patterns. Several studies have examined the use of baseline EEG signals to consider the different participant characteristics on experimental signals [39], [40]. It is important to note that the baseline EEG signals represent a calm state before a stimulus medium is given [25], [28], [31], [41], [42]. The steps of the baseline approach are cutting all the C channels in the baseline signals into several N segments with length L, and each segment is averaged to obtain the $BaseMean$ value using the (2). Furthermore, the baseline reduction process on the EEG test signal is carried out by subtracting the value of the EEG test signal from the baseline EEG signal value using the (3).

$$BaseMean = \frac{\sum_{i=1}^{N} BaseSignal_i}{N} \tag{2}$$

$$Clean\_EEG_j = Trial\_EEG_j - BaseMean \tag{3}$$

The $Clean\_EEG_j$ signals are an EEG signal that represents a subjective emotional reaction according to a given media stimulus. Several baseline reduction methods are applicable to characterize signals data, such as the difference, relative difference, and fractional difference methods. However, they have been observed to be effective with only black tea aroma data [43]. However, the tea aroma has similar characteristics to the EEG signals data, such as containing a lot of noise and weak frequency intensity. Therefore, it is a challenge for future research to test the three baseline reduction methods suitable for use in EEG signals data.

The baseline signals approach has increased emotion recognition accuracy compared to without using the EEG baseline signals approach [40], [44], [45]. This approach also significantly increases the accuracy of recognizing 2 classes of emotions (arousal and valence) and 4 classes of emotions (high arousal positive valence; high arousal negative valence; low arousal negative valence; and low arousal positive valence) [46]. Other studies have also been proposed a correlation approach to determine the baseline signals that has a high correlation with the stimulus medium [47]. This approach can overcome cross-subject emotion recognition. Although the baseline EEG signals approach has produced high accuracy, this approach is strongly influenced by the quality of the baseline EEG signals [9]. Recording the baseline EEG signals that are free from external, internal, and disturbances originating from the participants' emotional reactions isn't easy to do even though the participants are in a calm state [39], [48], [49]. This disturbance causes the baseline EEG signals to be unable to characterize the differences in participant characteristics found in the EEG signals. There are several methods applicable to eliminate disturbance/artifacts in the EEG signals, including regression [50], wavelet transform [51], and blind source separation (BSS), which further include other techniques such as independent component analysis (ICA) usually applied for electrooculography (EOG) artifacts [5], [29] and eye blinking [52]. This ICA also has the ability to remove artifacts using statistical independence between EEG and artifacts [10]. Another method is the principal component analysis (PCA) used to analyze EEG intervals not contaminated artifacts by extracting eigenvalues and eigenvectors corresponding to the clean EEG signals [45]. Meanwhile, the signals mixed with the eye blink are usually decomposed into a series of intrinsic mode functions (IMFs) [2]. Most artifacts removal algorithms offer good performance, but this method only focuses on detecting and removing specific artifacts such as EOG, ECG, and EMG [50].

Another method that applies to eliminate external and internal interference on the EEG signals is the smoothing method [53], and the following are several smoothing methods, including mean filter, median filter, Savitzky-Golay filter, discrete Kalman filter, the Gaussian filter, and kernel density estimation kernel [54]. The process of smoothing the EEG data signals can smooth the fluctuations of the EEG signals and avoid the outlier EEG signals [55], [56]. Therefore, the next research challenge is determining the appropriate smoothing method to eliminate external or internal disturbances and emotional reactions in the baseline EEG signals and to study the best baseline reduction methods to consider the differences in the characteristics of the participants on the trial signals.

3.3. How do EEG signals with characteristics exist among its features for emotion recognition?

EEG signals have several important characteristics that need to be considered in emotion recognition, such as low frequency and spatial information. Several studies have identified some of these characteristics in feature extraction, feature representation, and the classification process [2], [7]–[11].

3.3.1. Feature extraction

This is usually used to obtain features relevant to the emotional state of the EEG signals, and the process is grouped into 3 as [8], [29]:

a) Time domain feature. This is based on the time domain of a signal, and some of it has been reviewed in previous studies, such as the mobility, complexity, and activity using Hjorth parameters [57], fractal dimension using the Higuchi method [58], [59], event-related potentials (ERP) features [60], and statistical feature [61].
b) Frequency domain feature. This is based on the frequency domain of a signal, and several features have been reviewed in previous studies such as power spectral density (PSD) [62], band power using wavelet transform [59], [63], mel-frequency cepstral coefficients (MFCCs) technique [64], and differential entropy (DE) [14], [15], [40], [65], [66].
c) Time-frequency domain feature. This is based on the time-frequency domain of a signal, and some examples reviewed in previous studies include short-time fourier transform (STFT) [67], discrete wavelet transform (DWT) Features [58], and Combination of statistical and fast Fourier transform (FFT) methods [68].

The differential entropy (DE) method has, however, been discovered to have the ability to distinguish high energy and low energy patterns from EEG frequencies [14] and also to characterize spatial information from EEG signals [15]. The features generated from the DE method are the most accurate and stable in emotion recognition compared to several others such as autoregressive parameters, fractal dimension, power spectral density (PSD), differential asymmetry (DASM), rational asymmetry (RASM), asymmetry (ASM), differential caudality (DCAU), wavelet features, and sample entropy [40], [65], [66]. The DE formula usually used to characterize an EEG signal is defined as (4) [40].

$$h(X) = \int_{X}^{\infty} f(X)\, log\big(f(x)\big)dx \tag{4}$$

Where, X is a random variable and f(x) is the probability density function of X. Meanwhile, the DE of the series X obeying the Gauss distribution N (μ, δ^2) is expressed as (5):

$$h(X) = \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi\delta^2}}\, e^{\frac{(x-\,\mu)^2}{2\delta^2}} \log\left(\frac{1}{\sqrt{2\pi\delta^2}} e^{-\frac{(x-\,\mu)^2}{2\delta^2}}\right) dx \quad = \frac{1}{2}\log(2\pi\delta^2) \tag{5}$$

for a given frequency band i, the DE is defined as (6):

$$h_i(\mathrm{X}) = \frac{1}{2}\log(2\pi e\delta^2) \tag{6}$$

where, e is Euler’s constant (2.71828), δ^2 the variance of the signal, and h_i represents the DE of the corresponding EEG signals in the frequency band.

3.3.2. Feature representation

It is important to determine the appropriate method to represent the features of the EEG signals due to their spatial information characteristics. Some of the representation methods used in previous studies include the multiband feature matrix (MFM) [62], 2D mesh [69], maximal information coefficient (MIC) [70], and 3D cube [40]. The 3D Cube method can maintain spatial information between channels as well as frequency bands, including theta, alpha, beta, and gamma. It is based on the channel representation of the international system 10-20 mapped into a 9x9 matrix [40]. The 3D cube representation also inspires computer vision through three basic colors, including red, green, and blue (RGB). These RGB color channels have a value range of 0 to 255 which indicates the intensity of the color in each channel. The DE features are represented in a 3D cube, as indicated in the processes in Figure 4.

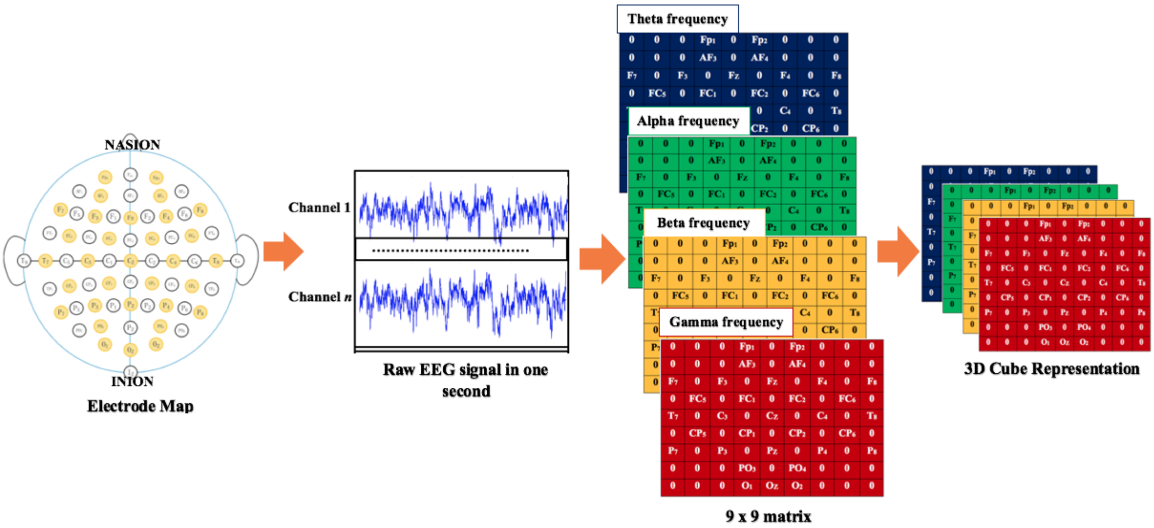

Figure 4. Feature representation based on 3D cube [40]

Based on Figure 4, every second, the EEG signals data generated from each EEG channel is decomposed into 4 frequency bands. Next, the feature extraction process is carried out for each frequency band. The feature value of each frequency band is then mapped into a 9x9 matrix so that it will produce 4 matrices. In the last stage, the 4 matrices are combined into a 3D cube [40]. The feature representation in the image is compared with the feature representation in the EEG signals in Table 2. The 3D cube-based feature representation has the ability to maintain spatial information between channels and also integrate between the frequency bands [40].

Table 2. Feature representation of images and EEG signals [40]

	Domain	
	Representation in computer vision	Representation in EEG signals
Term	Color image	EEG 3 cube
	Color channel (R, G, B)	Frequency band (θ, α, β, γ)
	Color Intensity	Differential entropy feature

3.3.3. Classification process

The classification is the main process of emotion recognition important to be studied in addition to the feature extraction and representation processes. There are, however, two approaches to the classification of emotion through EEG and these include the machine learning and neural network approaches.

a) Machine learning approach: Some of the methods usually applied include decision tree (DT) [71], naïve bayes (NB) [72], quadratic discriminant analysis (QDA) [73], k-nearest neighbors (kNN) [58], [74], [75], linear discriminant analysis (LDA) [14], relevance vector machines (RVM) [67], xtreme gradient boosting (XGBoost) [76], support vector machine (SVM) [77]–[79], AdaBoost [80], logistic regression via variable splitting and augmented lagrangian (LORSAL) [81], random forest (RF) [56], [82], and graph regularized extreme learning machine (GELM) [83].

b) Neural network approach: This method include artificial neural network (ANN) [61], [63], [84] deep belief networks [70], [85], convolutional neural network (CNN) [40], [46], [86], [87], long short-term memory (LSTM) [66], generative adversarial networks (GAN) [88], capsule network (CapsNet) [45], [62], and hybrid methods [4], [44], [69].

Based on the articles obtained from the Scopus database from 2016-2020, CNN and SVM methods have been the most studied for emotion recognition based on EEG signals. In Figure 5, the distribution of several methods used for emotion recognition based on EEG signals is presented. Some deep learning methods, however, have superior accuracy compared to machine learning methods. The following summarizes the achievement of the highest accuracy of several deep learning methods in the classification of emotions based on EEG signals, as shown in Table 3.

Although the CNN method has slightly outperformed the capsule network method on the DREAMER dataset, however, the capsule network method has several advantages in recognizing emotions based on EEG signals, such as its ability to: (i) effectively characterize the spatial relationships between different features [89] and (ii) to be trained individually effective on a much smaller data scale compared to CNN [45]. Figure 6 shows the structure of the capsule network method generally consists of several parts, which include the following:

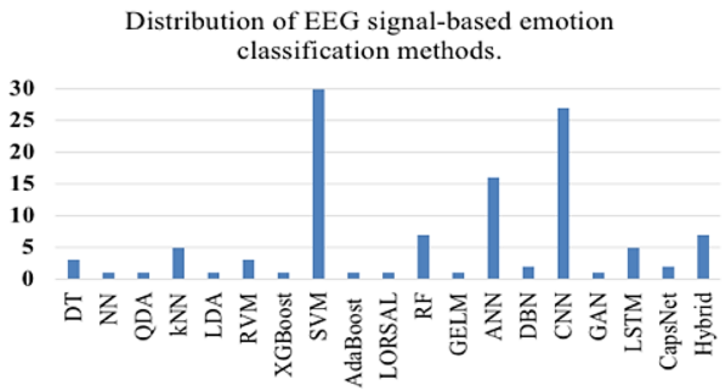

Figure 5. Distribution of EEG signals-based emotion classification method

Table 3. Comparison of the accuracy of deep learning methods

No	Methods	Emotion classes	DEAP dataset	DREAMER dataset	AMIGOS dataset
1	MLF Capsule Network [45]	2 emotional classes	97.97% for high/low valence; 98.31% for high/low arousal	94.59% for high/low valence; 95.26% for high/low arousal	-
2	RACNN [86]	2 emotional classes	96.65%; for high/low valence; 97.11% for high/low arousal	95.55% for high/low valence; 97.01% for high/low arousal	-
3	3D-CNN [46]	2 emotional classes	96.43% for high/low valence; 96.61% for high/low arousal	-	96.96% for high/low valence; 97.52% for high/low arousal
4	3D-CNN [46]	4 emotional classes	93.53% (high arousal and positive valence; high arousal and negative valence; low arousal and negative valence; and low arousal and positive valence)	-	95.95% (high arousal and positive valence; high arousal and negative valence; low arousal and negative valence; and low arousal and positive valence)

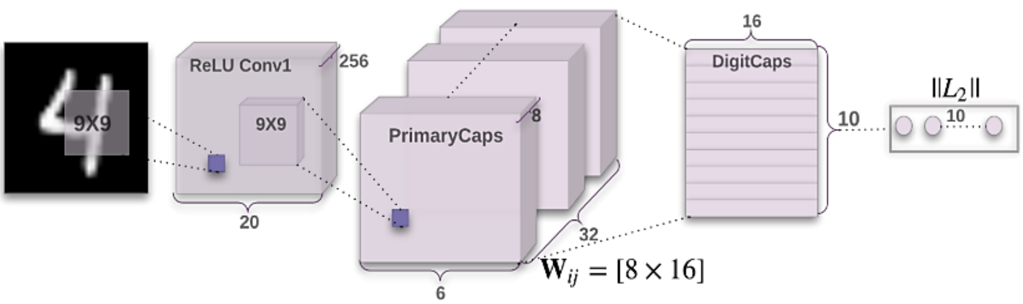

Figure 6. Capsule network architecture [89]

a) Convolutional section where convolution process is conducted on the input data matrix using the ReLU activation function to produce the feature map to be used as the data input for the PrimaryCaps.
b) PrimaryCaps section consists of four processes, including: i) convolution, ii) concatenate, iii) bottleneck, and iv) reshape. The reshaping process, however, generates the vector data u_i, which represents the input vector value of the lower capsule i).
c) DigitCaps section includes several processes, including the following:
- The *affine transformation* process aims to represent the spatial relationship between the sub-objects of the total objects at a higher layer. This is further used to predict the correlation of these sub-objects with objects at higher levels. The vector u_i and matrix $W_{i|j}$ are multiplied to produce vector $\hat{u}_{j|i}$, where *j* represents the index of each class output.

$$\hat{u}_{j|i} = W_{i|j} u_i \tag{7}$$

- The weighted sum process was conducted based on the multiplication of the C_{ij} with the input vector $\hat{u}_{j|i}$ to produce vector S_j.

$$S_j = \sum_i C_{ij} \hat{u}_{j|i} \tag{8}$$

The C_{ij} is determined using a *dynamic routing* algorithm that iterates several times to generate C_{ij} values (by default three times), as indicated in Table 4.

Table 4. Dynamic routing algorithm [89]

Dynamic routing algorithm
procedure ROUTING ($\hat{u}_{j\|i}$, *r*, *l*)
for all capsule *i* in layer *l* and capsule *j* in layer (*l* + 1): $b_{ij} \leftarrow 0$
for *r* iterations do
for all capsule *i* in layer *l*: $C_i \leftarrow$ SoftMax function (b_{ij})
for all capsule *j* in layer (*l* + 1): $S_j \leftarrow \sum_i C_{ij} \hat{u}_{j\|i}$
for all capsule *j* in layer (*l* + 1): $V_j \leftarrow$ squash function (S_j)
for all capsule *i* in layer *l* and capsule *j in layer* (*l*+1): $b_{ij} \leftarrow b_{ij} + \hat{u}_{j\|i}.V_j$
return V_j

The process aims to project several predictive vectors ($\hat{u}_{j|i}$) using the *coupling coefficients* (C_{ij}) in order to produce the *weighted sum* value (S_j).
- The squashing process generates an output vector v_j for each class at a higher level (*l*+1) and the maximum or highest value of v_j determines the predicted class level. The squashing function to obtain the probability value in each prediction class is, therefore, represented using the Formula (9).

$$V_j = \frac{\|S_j\|^2}{1 + \|S_j\|^2} \frac{S_j}{\|S_j\|} \tag{9}$$

d) The loss function calculation section was used to calculate the loss value based on the output and target values using the L2 regularization method.

$$L_e = T_e \max(0, m^+ - \|v_e\|)^2 + \lambda (1 - T_e) \max(0, \|v_e\| - m^-)^2 \tag{10}$$

T_e is equal to 1 if the emotion class matches the target at *e*, m^-=0.1 and m^+=0.9, and is the down-weighting of the loss function. By default, λ=0.5, and v_e represents the output vector of class *e*.

The capsule network method has several advantages over the others. Still, it allows the loss of knowledge information within the convolution process to work out feature maps and requires higher computation time than other deep learning methods [45]. This means the next research challenge is determining the acceptable architecture of the capsule network method to overcome the loss of knowledge information in the primary capsule. Moreover, it is also crucial to study the new architecture of the capsule network method to overcome the high computation time in the classification process. Considering that each emotion dataset has different characteristics, such as the number of channels used, the number of respondents, and the experimental strategy, for further research, it is also important to study the capsule network method in a more diverse data set and introduce 4 emotion classes. This study aims to obtain a more robust capsule network architecture on different datasets.

4. CONCLUSION

Although various studies have been conducted to overcome the three issues of emotion recognition based on EEG signals, there are several challenges to further study in the next research, include: i) determine robust methods for imbalanced EEG signals data, ii) determine the appropriate smoothing method to eliminate external or internal disturbances and emotional reactions in the baseline signals, iii) determine the best baseline reduction methods to consider the differences in the characteristics of the participants on the trial signals, and iv) determine the robust architecture of the capsule network method to overcome the loss of knowledge information and apply it in a more diverse data set. These challenges, in the future, are expected to produce robust models in emotion recognition based on EEG signals. This research study, however, has some limitations regarding the number of articles used. Therefore, further research needs to expand the scope of the emotion recognition domain, such as year, and topic.

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