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HUMAN EMOTION CLASSIFICATION FROM ELECTROENCEPHALOGRAM SIGNAL USING FEATURE EXTRACTION METHODS AND DEEP LEARNING

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Abstract. *Electroencephalogram (EEG) signals have an important role in identifying real human feelings or emotions to develop a Brain-Computer Interface (BCI) system. Emotion recognition systems can be applied to medical care and entertainment to overcome mental illness to relieve negative emotions to reduce suicide attempts. This study proposes a deep learning-based EEG human emotion classification system and applies different feature extraction methods. In the proposed system, 2-second segments of EEG are decomposed using Discrete Wavelet Transform (DWT) and Fast Fourier Transform (FFT) to obtain several sub-signals and extract their features. A Convolutional Neural Network (CNN) and Deep Neural Network (DNN) are trained and validated using these features to classify two different levels of arousal and valence. The system was evaluated and achieved the best performance for arousal and valence with 96.84% and 97.18% average accuracy, respectively. The results show that the use of data augmentation and feature extraction methods plays an important role in deep learning-based EEG human emotion classification systems and provides excellent performance. In addition, determining the number of channels can affect the performance of the classification system.*
Keywords: EEG, Emotion recognition, Affective state, DWT, FFT, CNN, DNN, DEAP dataset

1. **Introduction.** Emotional states relate to various kinds of human feelings, thoughts, and behaviors that affect the ability to act rationally, such as decision making, perception, and human intelligence. Emotion recognition helps cope with mental illness and is also important in various applications such as BCI, medical care, and entertainment. Therefore, emotion recognition studies using emotional signals enhance the BCI system as an effective subject for clinical applications and human social interactions [1]. Emotion recognition can help provide appropriate therapy to relieve a person's negative emotions to avoid attempting suicide. According to the World Health Organization (WHO), suicide was the second-highest death rate among those aged 15-29 in 2016 [2] and 1.4% of deaths in the world were caused by suicide in 2017 [3]. Researchers believe that the state of the brain can change according to human emotions or feelings so that EEG is suitable for detecting human emotions [4]. EEG has the advantage of having high speed in getting brain signals, non-invasive, meaning that it does not need to open the scalp, and does not cause pain to the subject so that EEG can detect real human emotions [5].

Over the years, numerous data preprocessing, feature extraction, and feature selection methods applied to classifying human emotions based on EEG signals have been proposed, including Empirical Mode Decomposition (EMD) [6], Surface Laplacian (SL) Filtering [7], DWT with "db4" wavelet function [7,8], FFT [9] and minimum-Redundancy-Maximum-Relevance (mRMR) [10]. Then the features obtained are Absolute Logarithmic

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REE (ALREE) [7], Power Spectral Density (PSD) [11-14], Power Asymmetry [11,12], Covariate shift adaptation of PCA [14], Frontal Asymmetry [9], statistical features [8,10,15] and energy features [6,8] used for classification with machine learning and deep learning. The modified Kohonen neural network that has been used for the classification of human emotions such as angry, happy, relax, and sad gave the best performance of human emotion classification compared to previous studies [15]. According to [15], different classifiers and feature sets can be used to improve system performance. Recent studies have used deep learning classification methods which can provide better classification performance than using machine learning. Deep learning and neural networks have an extraordinary ability to solve problems in image recognition, speech recognition, and natural language processing [14] which could effectively mirror the emotional affective states of subjects. Although deep learning already has feature extraction where the reduced feature set can then summarize most of the information contained in the original feature set, feature extraction methods such as DWT and FFT can be applied to analyzing the EEG signal in detail and locally enabling improved classification performance. In addition, the different combinations of the number and location of channel usage can also make it possible to improve classification performance.

This study aims to provide academic contribution by adding feature extraction methods such as DWT and FFT even though deep learning already has feature extraction. In addition, different feature sets and different combinations of the number and location of channel usage used in this study are expected to improve the classification performance of previous studies. In summary, the proposed method is to use DWT db4 with various levels and FFT as feature extraction to get statistical features and Power Spectral Intensity (PSI) features. Then, the obtained features are used as input to deep learning models such as CNN and DNN to classify two different levels of arousal and valence. Finally, performance comparisons will be made against several experiments based on the number of channels used, feature extraction methods, and deep learning models.

The rest of this paper is organized as follows: Section 2 lists literature and works related to the study; Section 3 elaborates the proposed system and methodology; Section 4 discusses the evaluation results; Section 5 concludes the study and offers suggestions for future works.

2. Literature Review and Related Works.

2.1. Emotion models. Most dimensional models combine arousal and valence. Valence refers to the level of "pleasure" associated with an emotion. These range from unpleasant (e.g., sad, and stressed) to pleasant (e.g., happy, and delighted). While arousal refers to the strength of the emotions experienced. This arousal occurs along a continuum and can range from inactive (e.g., disinterested, and bored) to active (e.g., alert, and excited) [16]. The emotional quadrant based on the valence and arousal models is shown in Figure 1.

2.2. Electroencephalogram (EEG). EEG is a recording of electrical signals derived from human brain signals. The electrical signal is generated naturally over a while and received by many channels or electrodes. EEG wave signals are classified into 5 wave types including delta (0.5-4 Hz), theta (4-8 Hz), alpha (8-13 Hz), beta (13-30 Hz), and gamma (30-40 Hz) which describe different emotional states [18]. Delta appears when someone is fast asleep. Delta signals can also indicate physical abnormalities in the brain. Theta appears in someone who is experiencing emotional stress, especially frustration or disappointment. Alpha is a relaxed state of mind. Beta is a brain wave that usually occurs when a person is actively thinking, actively concentrating, or focusing on solving a problem. Gamma is a brain wave that occurs when a person experiences very high mental activity, a state of extreme panic or fear in a state of full awareness.

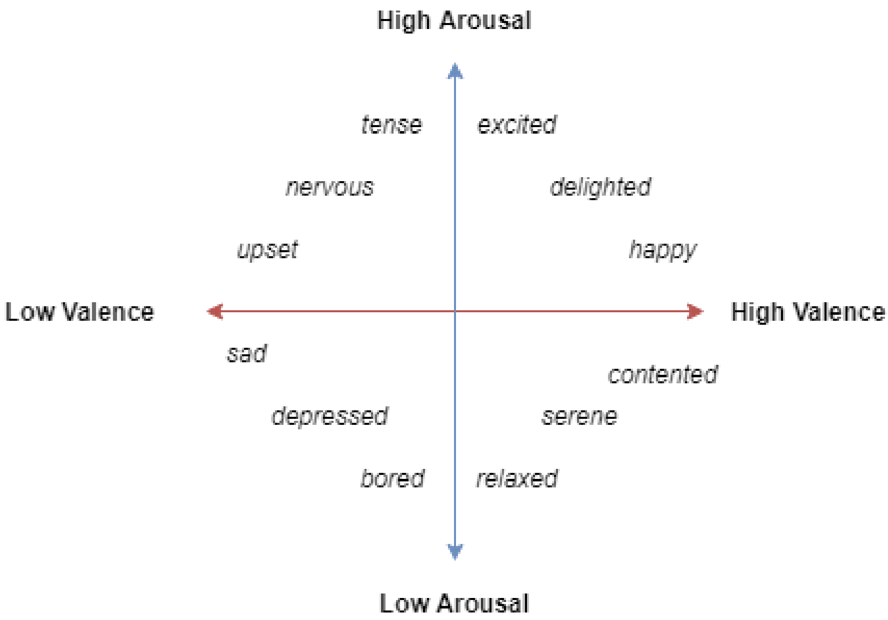

Figure 1. Quadrant of emotions based on arousal and valence [17]

2.3. **Discrete Wavelet Transform (DWT).** The ability to capture frequency information during brain activity is difficult to obtain [19]. For this problem, Wavelet Transform (WT) is used, which is considered as a technique that uses multi-resolution analysis that divides the signal into different frequency spectrums. In addition, WT combines the high and low-frequency spectrum. DWT is efficient due to the frequency filter bank, which is used to remove unwanted frequencies and decompose the signal into multiple levels [20]. The main characteristic of DWT is its resolution of frequency and time that leads to the optimal state for time-frequency resolution [21]. The process begins with the first signal that enters the band-pass filter. A band-pass filter is a combination of a High-band-Pass Filter (HPF) and a Low-band-Pass Filter (LPF) to obtain the desired result. This process is categorized as the first level, which includes two corresponding coefficients: one is Approximation (A) and the other is Detailed (D). In each run, the frequency resolution is doubled using a filter as it parses and reduces the time complexity in half. After getting those coefficients, then apply the statistical formulas to getting statistical features. Statistical features include Mean Absolute Value (MAV), Average Power (AVP), Standard Deviation (SD), Variance, Mean, Root Mean Square (RMS), and Skewness (Pearson's Coefficient).

2.4. **Fast Fourier Transform (FFT).** FFT is an algorithm for calculating discrete Fourier transform and its inverse [9]. FFT converts data in the time domain to the frequency domain and vice versa. The FFT method works recursively by dividing the original vector into two parts, calculating the FFT of each part, and then combining them. One of the features that can be obtained from FFT is PSI by using the "bin_power" function from the PyEEG library [22].

2.5. **Related works.** Most studies, such as [6-8,10-13], apply the feature extraction method and use a machine learning classifier such as K-Nearest Neighbor (KNN), Naive Bayes, and Support Vector Machine (SVM). There are only a few studies that use deep learning classifiers such as [9,14,15]. Each study has a different purpose of detecting emotions, based on different emotional classes (e.g., happy, and sad) and levels of arousal and valence (e.g., low, and high). Each study uses a different number of subjects and channels. Although [7] achieved 83.26% average accuracy in classifying five emotion classes (disgust, happy, surprise, fear, and neutral) by using DWT+KNN and 62 channels, they have not used a standardized dataset based on electrode placement and EEG data collection methods. They recruit students to be research subjects. Recently, most studies using the DEAP dataset were collected by [11]. The recent study whose detection is similar to our study is [6] that detects two different levels of emotion based on the dimensions of arousal and valence. They used the first difference of time series (IMF1), the first difference of phase, and the normalized energy features and then classified using SVM and achieved 69.10% and 71.99% average accuracy for valence and arousal, respectively using 8 channels. However, the disadvantage of the SVM method is that high-dimensional data requires high computerization capabilities to train the model and requires complex feature engineering. Unlike SVM, the deep learning method such as CNN is very suitable for high-dimensional data because CNN can take advantage of natural signals such as local connections, shared weights, pooling, and uses multiple layers which makes it possible to train high-dimensional data using minimum computational capabilities. In the most recent study, [15] detects four classes of emotions (angry, happy, relaxed, and sad) that achieved 87% average accuracy by using Modified Kohonen Neural Network I and statistical features which is better than the previous studies. However, a Kohonen Neural Network can also be called a self-organized map which is a single layer, unsupervised, feed forward artificial neural network which only uses one hidden layer. The use of deep learning with a large number of hidden layers such as DNN and CNN can improve the transmission and processing of information between layers, making it possible to increase the precision and versatility of the number of features and improve prediction accuracy.

3. **Proposed System and Methodology.** This study proposes combining feature extraction methods such as DWT and FFT with deep learning for the classification of two different levels of arousal and valence. Figure 2 displays the substantial flow of the proposed system. Initially, the number of subjects and channels that will be used in the experiment is determined, and then an effective window size of 2-second was used to process data augmentation to increase the amount of EEG data. Then, feature extraction methods such as DWT or FFT are applied to decomposing signals, and calculations are performed to obtain statistical or power features, respectively. All feature vectors are subsequently preprocessed and resampled into training and testing sets. CNN and DNN are trained and validated by utilizing the training set. This CNN and DNN are used to predict the labels of every feature vector within the testing set. The predicted labels are compared with the actual ones to compute several performance metrics for evaluation purposes. Meanwhile, the methodology to develop the system can be divided into five core stages.

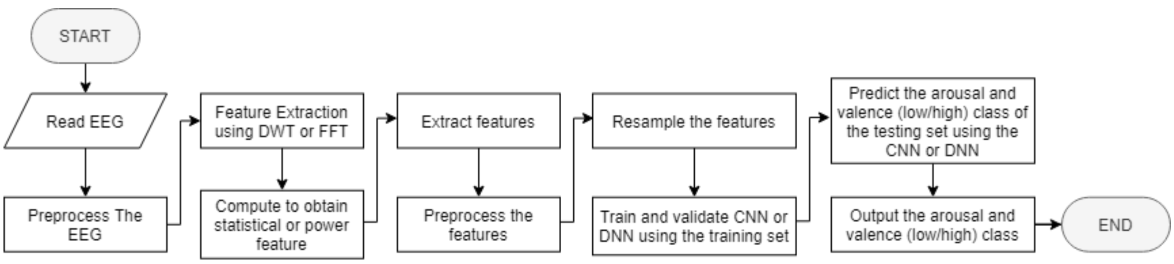

FIGURE 2. A flowchart summarizing the proposed system

3.1. **Dataset collection.** In this study, data was collected from the DEAP dataset website (http://www.eecs.qmul.ac.uk/mmv/datasets/deap/download.html) [11]. The DEAP dataset contains recordings of EEG data from 32 participants using 32 channels, which was performed when participants watched 40 music videos. When they watched the music video, participants were asked to rate the level of arousal and valence using the Self-Assessment Manikin (SAM) which is a technique to measure the level of arousal and valence of a person [23]. This study mapped the scales 1-9 into two levels of each state of valence and arousal according to the SAM rating. The valence scale of 1-5 is mapped to negative, and 6-9 to positive, respectively. The arousal scale of 1-5 is mapped to passive, and 6-9 to active. In this study, four subjects were selected: s01, s02, s03, and s04. Then, several channels were selected: 32 channels, 5 channels (Fz, AF3, F3, AF4, and F4) [9], and 4 channels (Fp1, Fp2, F3, and F4) [8].

3.2. **Dataset preprocessing.** Preprocessed DEAP dataset [11] is used in this study which the process consists of the following: The data were downsampled to 128 Hz; EOG artifacts were removed; A bandpass frequency filter from 4.0-45.0 Hz was applied; The data was averaged to the common reference; The EEG channels were reordered so that they all followed the Geneva order as above; The data was segmented into 60-second trials and a 3-second pre-trial baseline removed; Finally, the trials were reordered from presentation order to video (Experiment_id) order. Each participant file contains two arrays, namely data and labels shown in Table 1. In this study, only arousal and valence labels were used.

Table 1. Contents of each participant file

Array name	**Array shape**	**Array contents**
data	$40 \times 40 \times 8064$	video/trial $\times$ channel $\times$ data
labels	40×4	video/trial $\times$ label (valence, arousal, dominance, liking)

Then to increase the amount of data, data augmentation is applied by using an effective window size of 2 seconds for the data augmentation process. Slice raw data for 2 seconds, at 0.125-second intervals from each channel. Every 0.125 seconds update once. The process of data augmentation is shown in Figure 3.

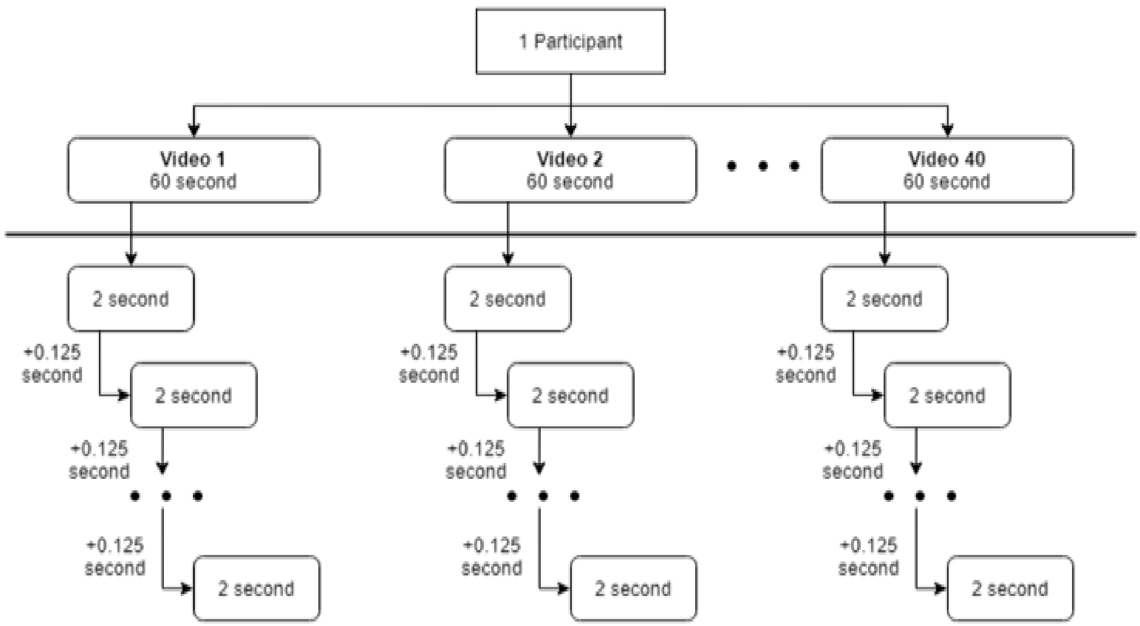

Figure 3. Block diagram of the data augmentation process

3.3. **Feature extraction.** Each EEG segment was subjected to the feature extraction stage. Initially, every 2-second segment of EEG was decomposed using DWT or FFT, producing several wave signals including delta, theta, alpha, beta, and gamma. DWT with the mother wavelet "db4" with levels 3, 4, and 5 were used. The feature extraction

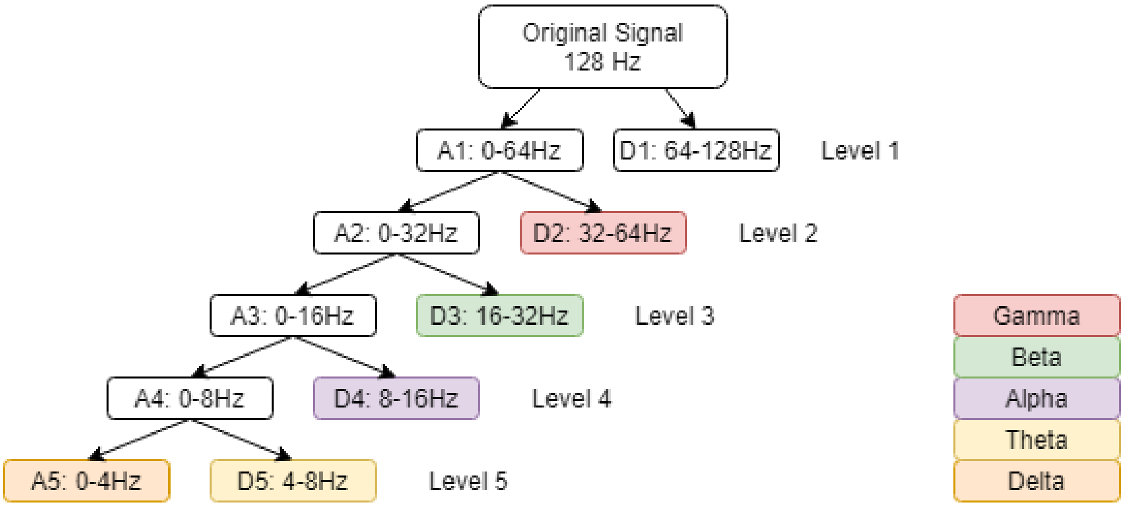

Figure 4. A flowchart showing the DWT process (levels 1-5)

process with DWT is shown in Figure 4. DWT db4 level 5 decomposed the EEG signal into several wave signals: D1 (64-128 Hz), D2 (32-64 Hz), D3 (16-32 Hz), D4 (8-16 Hz), D5 (4-8 Hz), and A5 (0-4 Hz). While in the FFT feature extraction method, the EEG signal was decomposed into several wave signals: theta (4-8 Hz), alpha (8-12 Hz), low beta (12-16 Hz), high beta (16-25 Hz), and gamma (25-45 Hz).

After the implementation of DWT, the coefficients were calculated using statistical function formulas so that several statistical features will be obtained: MAV, AVP, SD, Variance, Mean, RMS, and Skewness. Meanwhile, in the FFT process, the "bin_power" function is used to get the PSI features of each sub-signal. Finally, the features are combined to form a feature vector so that it becomes a feature set. The statistical and power feature sets were obtained from the DWT and FFT processes, respectively.

3.4. **Feature preprocessing and resampling.** The value of the valence and arousal labels ranges from 1-9, so it is necessary to process the label to make it suitable for binary classification. To distinguish between arousal and valence levels, values 1-5 are assigned a value of "0" which means low, and values 6-9 are assigned a value of "1" which means high. Then, the normalization process is needed to modify the values in the variables so that they can be measured on a common scale. The standard scaler has been used to normalize the features making each feature have a mean value of 0 and a variance of 1. The standard scaler removes the mean and scales to the unit variance. Normalized feature sets were resampled by splitting them into training and testing sets with a ratio of 80 against 20.

3.5. **Training and validation.** In this study, deep learning models such as CNN and DNN are used which use training sets to classify two different levels of arousal and valence. The CNN and DNN architectural models were inspired by [24] and [9], respectively. Then modify the deep learning architecture model to fit our experiments. Table 2 shows the hyperparameter values used in the experiment. Tables 3 and 4 show the architecture of the CNN and DNN models used in the experiment, respectively. While most values were determined according to best practices, adding additional layers such as dropout and pooling layer is the process of preventing overfitting and speeding up the learning process.

4. **Results and Discussion.** Deep learning received every feature vector within the testing set and predicted their corresponding labels. The predicted labels were compared with the actual ones to determine the number of true positives TP, false positives FP, false

Table 2. Hyperparameter values in the experiments

Hyperparameter	**Values**
batch_size	[32, 256] 32 batch size is only for experiments that do not use data augmentation and feature extraction methods (Raw EEG data).
epochs	[50]
optimizer	[adam] with default learning rate = 0.001
loss	[binary_crossentropy]
activation function	[relu, sigmoid]
validation_data	(x_test, y_test)
metrics	[accuracy]
input shape	Raw EEG data = (number of channels, 8064 data) DWT = number of channels ∗ (level + 1) ∗ 7 statistical features FFT = number of channels ∗ 5 bands ∗ 1 power feature

Table 3. CNN model architecture

#	**Layer**	**Details**
1	Conv1D	filter = 128, kernel_size = 15, padding = 'same', activation = 'relu'
2	Conv1D	filter = 128, kernel_size = 10, padding = 'same', activation = 'relu'
3	Conv1D	filter = 128, kernel_size = 5, padding = 'same', activation = 'relu'
4	MaxPooling1D	pool_size = 2, strides = 2
5	Flatten	
6	Dense	units = 64, activation = 'relu'
7	Dropout	drop rate = 0.2
8	Dense	units = 32, activation = 'relu'
9	Dropout	drop rate = 0.2
10	Dense	units = 16, activation = 'relu'
11	Dropout	drop rate = 0.2
12	Dense	units = 1, activation = 'sigmoid'

Table 4. DNN model architecture

#	**Layer**	**Details**
1	Dense	units = 2184, activation = 'relu'
2	GaussianNoise	stddev = 0.005
3	BatchNormalization	
4	Dropout	drop rate = 0.2
5	Dense	units = 1310, activation = 'relu'
6	GaussianNoise	stddev = 0.005
7	BatchNormalization	
8	Dropout	drop rate = 0.5
9	Dense	units = 786, activation = 'relu'
10	GaussianNoise	stddev = 0.005
11	BatchNormalization	
12	Dropout	drop rate = 0.5
13	Dense	units = 472, activation = 'relu'
14	GaussianNoise	stddev = 0.005
15	BatchNormalization	
16	Dropout	drop rate = 0.5
17	Dense	units = 1, activation = 'sigmoid'

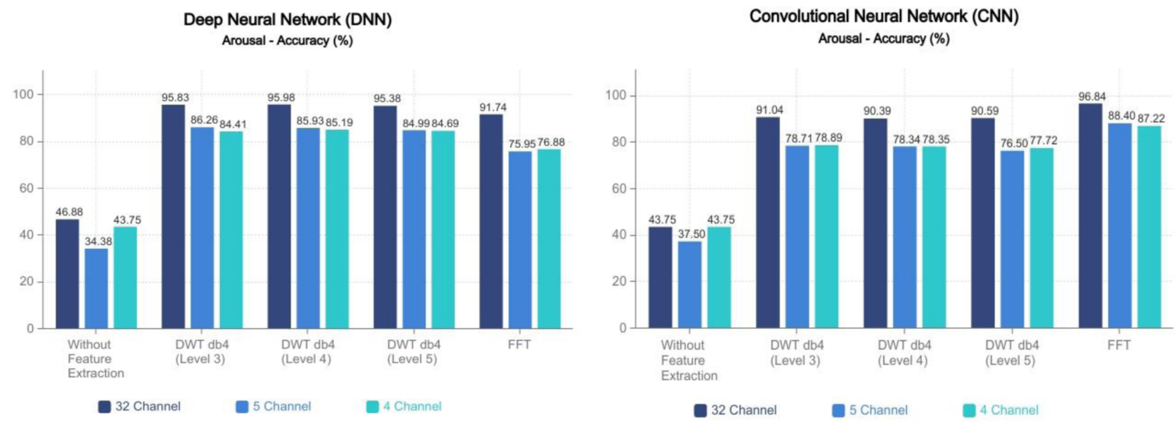

FIGURE 5. The average accuracy performance of arousal classification (%)

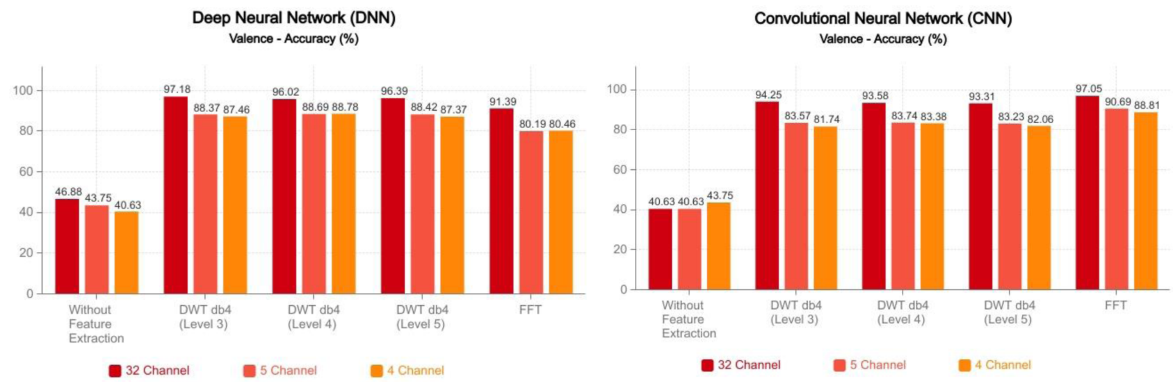

FIGURE 6. The average accuracy performance of valence classification (%)

TABLE 5. Best performance results based on the number of channels used

Label	Deep learning	Feature extraction	Number of channels	Precision (%)	Recall (%)	F1-Score (%)	Accuracy (%)
Arousal	**CNN**	**FFT**	**32**	**96.95**	**96.57**	**96.74**	**96.84**
Valence	**DNN**	**DWT db4 (level 3)**	**32**	**97.15**	**96.79**	**96.96**	**97.18**
Arousal	CNN	FFT	5	88.25	87.83	88.02	88.40
Valence	CNN	FFT	5	89.83	90.33	90.06	90.69
Arousal	CNN	FFT	4	86.95	86.73	86.83	87.22
Valence	CNN	FFT	4	87.76	88.54	88.11	88.81

negatives FN, and true negatives TN for every class. Based on these statistics, several performance metrics were computed: precision, recall, f1-score, and accuracy. Figures 5 and 6 summarize the system's classification performance, while Table 5 summarizes the best performance results for the classification of arousal and valence labels based on the number of channels used.

We have done many experiments to compare performance such as the number of channels used, feature extraction method, and deep learning model. The results show that the number of channels affects the performance of the classification system. The more channels used, the better the classification performance. A small number of channels turn out to get a good classification performance as well. Based on Figures 5 and 6, the application of data augmentation and feature extraction methods provides a better classification performance than directly using raw data. This can happen due to the implementation

Table 6. Comparison of various studies using DEAP dataset

Research	Details
[11]	**Features:** Power Spectral Density (PSD), Power Asymmetry; **Classifier:** Naïve Bayes; **Detect:** Two different levels of valence, arousal, and liking (low/high); **Result:** 57.0% for valence, 62.0% for arousal
[12]	**Features:** Power Spectral Density (PSD), Power Asymmetry; **Classifier:** Bayes; **Detect:** Two/three classes per dimension valence and arousal; **Result:** 53.4% for two classes, 51.0% for three classes
[13]	**Features:** Power Spectral Density (PSD); **Classifier:** Ontological Model; **Detect:** Two classes per dimension valence and arousal; **Result:** 75.19% for valence, 81.74% for arousal
[14]	**Features:** Power Spectral Density (PSD), Covariate shift adaptation of PCA; **Classifier:** DLN-50 with stacked autoencoder (SAE); **Detect:** Three different levels per dimension valence and arousal; **Result:** 53.42% for valence, 52.03% for arousal
[10]	**Features:** Statistical features, band power, Hjort parameters, fractal dimension; **Classifier:** Kernel; **Detect:** Three classes per dimension (valence and arousal); **Result:** 60.7% for valence, 62.33% for arousal
[8]	**Features:** Wavelet energy, wavelet entropy, modified energy, statistical features; **Classifier:** SVMs; **Detect:** Four classes of emotion (HVHA, HVLA, LVHA, LVLA); **Result:** 83.87%
[6]	**Features:** The first difference of time series (IMF1), the first difference of phase, the normalized energy; **Classifier:** SVM; **Detect:** Two different levels per dimension valence and arousal (low/high); **Result:** Accuracy 69.10% for valence and 71.99% for arousal, F1-Score 73.74% for valence and 77.69% for arousal
[9]	**Features:** PSD, Frontal Asymmetry; **Classifier:** DNN; **Detect:** Two classes per dimension valence and arousal; **Result:** Accuracy: 82.5%, Recall: 82.5%, Precision: 68.0%, Misclassification Rate: 17.5%
[15]	**Features:** mean, variance, standard deviation, skewness, kurtosis, mobility, complexity (statistical features); **Classifier:** Modified Kohonen Neural Network I; **Detect:** Four classes of emotion, i.e., Angry, Happy, Relax, and Sad; **Result:** 87.0%
Proposed method	**Features:** MAV, AVP, variance, SD, mean, RMS, Skewness, PSI; **Classifier:** CNN, DNN; **Detect:** Two different levels per dimension valence and arousal (low/high); **Result:** 97.18% for valence (DWT + DNN), 96.84% for arousal (FFT + CNN)

of data augmentation which increases the amount of data by dividing the data by the window size of 2 seconds. Then proceed with the application of the feature extraction method to analyze and extract important features from the window size of 2-seconds data. The CNN model turned out to be more suitable to be applied to FFT and the DNN model was more suitable to be applied to DWT.

The classification accuracy of our model was also compared to other previous studies that use similar approaches, where they used the same dataset but different classification techniques, features, and detections as shown in Table 6. The comparison shows that our proposed method exhibits very promising results when dealing with varying sizes of datasets and different detections of emotions. For example, the same number of different levels of valence and arousal, an improvement of 40.18% (valence) and 34.84% (arousal), and also 28.08% (valence) and 24.85% (arousal) was achieved with our proposed method when compared to [11] and [6], respectively.

5. **Conclusion and Future Works.** This study proposes a novel emotion classification system using CNN and DNN-based EEG combined with feature extraction methods such as DWT and FFT. The system can classify two different levels per dimension of arousal and valence to recognize a person's emotions. The method proposed in this study has a better performance compared to previous studies that have the same type of detection. The best performance was obtained for the classification of two different arousal and valence levels: 96.84% and 97.18% average accuracy; 96.74% and 96.96% average f1-score; 96.57% and 96.79% average recall; 96.95% and 97.15% average precision, respectively. The results show that the data augmentation and feature extraction methods get better performance results compared to directly using raw data to be classified in deep learning. In addition, the number of channels can affect classification performance. Future work of this research will improve the system by exploring the recent deep learning models, or using different feature extraction methods and feature sets. In addition, the use of the different datasets, numbers, and locations of channels can be applied to future work for the classification of human emotions.

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