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Subject-Independent Emotion Recognition System from EEG Signals Using Continuous Wavelet Transform and Alexnet

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نظام تمييز الانفعالات غير معتمد على الافراد من الإشارات الدماغية باستخدام التحويل المويجي المستمر ونموذج ألكس نت

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Abstract:
This study proposes a deep learning-based method for recognizing human emotions from Electroencephalogram (EEG) signals. To enhance the representation of EEG data, Continuous Wavelet Transform (CWT) has been employed to convert EEG signals into time-frequency images (scalograms). Alexnet model has been utilized for building subject-independent emotion classification system. The proposed approach was built as 2-stage recognition system; one for arousal and the other for valence. Data were imported from EEG AMIGOS dataset which includes four emotions; Calm, Fear, Happy, and Sad. The evaluation results have demonstrated a superior performance compared to the state-of-the-art methods in subject-Independent emotion recognition system from EEG signals, achieving average accuracy of 65.75% and 67.75% for arousal and valence respectively.

Keywords: EEG, Emotion Recognition, Wavelet Transform.

الملخص
تقترح هذه الدراسة طريقة تعتمد على التعلم العميق للتعرف على المشاعر البشرية من إشارات تخطيط كهربية الدماغ (EEG). لتعزيز تمثيل بيانات تخطيط كهربية الدماغ، تم استخدام التحويل المويجي المستمر (CWT) لتحويل إشارات تخطيط كهربية الدماغ إلى صور في نطاق الزمن-التردد (Scalogram). تم استخدام نموذج شبكة Alexnet لبناء نظام تصنيف المشاعر غير المعتمد على الافراد. تم بناء النظام المقترح على مرحلتين؛ واحدة لتمييز للإثارة والأخرى للتكافؤ. تم استيراد البيانات من مجموعة بيانات EEG AMIGOS التي تتضمن أربعة مشاعر؛ الهدوء والخوف والسعادة والحزن. أظهرت نتائج التقييم أداءً متفوقًا مقارنة بالطرق الحديثة في نظام التعرف على المشاعر غير المعتمد على الافراد من إشارات تخطيط كهربية الدماغ، حيث حقق متوسط دقة بلغ 65.75٪ و67.75٪ للإثارة والتكافؤ على التوالي.

الكلمات المفتاحية: تخطيط كهربية الدماغ، التعرف على المشاعر، التحويل المويجي المستمر.

Introduction

Emotion constitutes a fundamental aspect of human cognition, exerting a profound influence on behavior, social interactions, and overall well-being. Emotions are complex mental states composed of various cognitive processes. Accurate emotion recognition is a necessary requirement for interpersonal communication. The goal of emotion recognition is to improve brain-computer interface so that the computer can use emotional information to make sense of the world. Different methods have been used to estimate an individual's emotional states from a variety of indications, such as behavioral characteristics, tone of voice, facial expressions, or from physiological signals, such as pulse rate, electrocardiogram (ECG), electroencephalogram (EEG). The EEG-based approach is one of the most researched techniques in the field of emotion recognition since the detection device is portable, affordable, has a high temporal resolution, and has a tolerable spatial resolution. In addition to these features, EEG-based emotion recognition is more accurate and dependable since it can deliver more advanced and extensive information in a non-invasive manner [1]. Recently, affective computing has been recognized as one of the central area of interest in human-computer interaction (HCI). Affective computing offers computers the ability to observe, interpret, and generate affective traits. The Brain Computer Interface (BCI) system is therefore a very effective communication technology that reads brain signals from different areas of the brain and translates them into commands that can be used for controlling computer applications. Understanding and accurately classifying emotions has long been a challenging task because they are subjective and complex constructs. However, advances in neuroscience and machine learning techniques offer promising opportunities to explore new avenues for emotion analysis. Technological advancements, incorporating other recognition techniques, utilizing machine learning algorithms, and refining data analysis methods are all potential solutions. Building diverse datasets and involving human experts to validate results and curate data are also crucial. By employing more sophisticated signal processing and analyzing features linked to temporal EEG dynamics, it may increase the sensitivity of emotion identification by utilizing more advanced data processing and examining characteristics related to temporal EEG dynamics. These methods could lead to a more precise, broadly applicable system that can manage different situations [2].

Most presently available state-of-the-art EEG-based emotion recognition algorithms are subject-dependent, meaning that data used for training the system and data used for testing it are from the same subject and this implies that the system is customized for only one user. On the other hand, considerable emotion recognition systems must be subject -Independent, that means the system must be able to recognize the emotions regardless it has trained on subject’s data or not. The accuracy of such systems is still low and needs a high potential to be improved. In order to develop a valuable EEG-based emotion classification system, this research objectives to develop a subject-independent emotion recognition system by using a pre-trained convolution neural network (CNN) model known as “Alexnet”.

Literature review

Emotion is a fundamental aspect of human nature and affects a wide range of daily activities, such as learning, communication, and interaction. Therefore, a robust work has been conducted for emotions recognition from several aspects of physiological and psychological states. Emotions have been recognized from Blood Volume Pressure (BVP), ElectroEncephaloGram (EEG), and ElectroOculoGram (EOG), facial expressions and speech [3]. In recent years, many studies have been conducted to obtain informative properties from EEG signals for the purposes of emotion recognition.

Ismael et al. [4] proposed a method based on a two-stage majority voting for classifying emotions from EEG signals. In the first step, signal noise was removed with low-pass filters, and then rhythm extraction performed with a band-pass filter. The rhythms were then determined according to fractal dimension-based and wavelet-based entropy properties. Emotions have been classified by k-Nearest Neighbor (k-NN) with accuracy of 86.3% and 85% in two binary classifications; valence and arousal respectively.

Salama et al. [5] proposed a three-dimensional CNN-based method for multichannel EEG based emotion detection using DEAP dataset. Their findings revealed a recognition accuracy of 88.44% for valence and 88.49% for. In a study by Alakus et al. [6], the researchers introduced EEG based data for emotion detection. They formed a dataset containing EEG signals from four different computer games played by 28 different subjects. In their experimental studies, the Support Vector Machine (SVM) classifier achieved 73% and 71.64% success in detecting positive and negative emotions, respectively. Muzaffer Aslan [7], proposed a method to detect ‘Positive’ and ‘Negative’ emotions from GAMEEMO dataset of EEG. EEG signals were converted into (scalogram) images by using Continuous Wavelet Transform (CWT), Then, feature extraction was performed from EEG images with a pre-trained Google Net. Finally, k-Nearest Neighbor (k-NN), Support Vector Machine (SVM), and Extreme Learning Machine (ELM) algorithms were used for emotion classification. The comprehensive experimental results show that the proposed method achieved emotions classification accuracies of 98.78%, 98.53%, and 98.41% by SVM, k-NN, and ELM classifiers respectively. Bazgir et al. in [8] used valence-arousal model to classify four emotional states based on high or low. They applied Wavelet transform on EEG signals from DEAP dataset while they used SVM, KNN, and ANN as classifiers and they reported an average accuracy as 91.1% for valence and 91.3% for arousal. Yu Liu, et al. in [9] proposed an effective multi-level features guided capsule network (MLF-CapsNet) for multi-channel EEG-based emotion recognition which can simultaneously extract features from the raw EEG signals and determine the emotional states. Their approach was applied on DREAMER dataset and yields average accuracy of 94.59% and 95.26% for valence and arousal, respectively. Dewangan et al. in [10] conducted analysis for emotion recognition from SEED-IV EEG dataset using cubic SVM and fine Gaussian SVM. They reported that their models had achieved average subject-independent accuracy of 78.46% and 83.7% for cubic SVM and fine Gaussian SVM respectively. More recent, Bagherzadeh et al. in [11] used wavelet transform and ResNet-18 for happy and sad emotion recognition from four EEG datasets. Their study results subject-independent emotion recognition average accuracy of 75%, 76.66%, 78.12%, and 81.25% for the SEED-FRA, SEED-IV, SEED-V, and SEED-GER databases, respectively.

Material and methods

DATASET

In this research AMIGOS dataset has been used, which was created by researchers from Queen Mary University of London, UK to study the relationship between affect, personality, and mood [12]. The dataset consists of multimodal recordings of participants and their responses to fragments of emotional videos. Participants took part in two experimental setups while watching long and short videos; individual scenario, and group scenario. While watching the videos, EEG and other measurements of participants have been recorded. The information from the individual–short videos scenario has been used, in which 40 participants (male = 27, female = 13, aged 21–40 years, mean age = 28.3 years) watched 16 videos (duration < 250 s). EEG data have been collected by 14-channel Emotive EPOC Neuroheadset at 128Hz sampling rate which were located due to 10-20 system. The 14 channels are AF3, AF4, F3, F4, F7, F8, FC5, FC6, T7, T8, P7, P8, O1 and O2.

EEG data were categorized into four groups in respect of the stimuli (video clips) that represent four kinds of emotion based on their evaluated valence and arousal; happy (high valence and high arousal), fear (low valence and high arousal), sad (low valence and low arousal), and calm (high valence and low arousal) [13]. The details of video clips that have been used as stimuli are shown by Table 1.

Table 1: Details of video clips used as stimuli.

Category	Excerpt's source	Video ID
Happy	Airplane	4
Fear	Silent Hill	30
Sad	Exorcist	19
Calm	August Rush	10

Data preprocessing

EEG signals are usually recorded with artifacts and environment noise. For better analysis and processing, EEG signals must be preprocessed for two main reasons; to remove noise and to select suitable frequency bands. The artifacts can be generated by eye blinking, muscle movements, heartbeat and other physiological activities while environmental noise can be picked up from 50/60 Hz AC interferences, electrode movements, mobile signals, or other technical resources. Therefore, EEG signals have been preprocessed by normalization and by applying (8-45 Hz) passband filter to remove noises and unwanted frequencies. Frequency band was determined to be from 8Hz to 45Hz as it the best reported frequency band for emotion recognition [13].

Converting EEG signals into images using sclaogram function “cwtfilterbank”

It has been suggested to use AlexNet model for recognizing emotions from EEG. AlexNet is a type of CNN which uses for image classification. Therefore, EEG signals should be converted into images. Scalogram technique is commonly used for converting signals into images by applying continuous wavelet transform. Signal processing in this research has been performed by using MATLAB® 2018 software which uses “cwtfilterbank” function for generating scalogram images from given signals based on its CWT coefficients. Four EEG signals; F3, C4, T7, and T8 have been selected for analysis. From each channel, A segment of 1000 samples has been taken to utilize the filter bank function since a signal with 1024 samples is intended to be used with the basic filter bank. Each scalogram was represented by the color map of the type jet with 128 colors. The four channels’ Scalograms are then converted into images, combined in one image, then the combined image has been resized to fit the size requirement of the input image of Alexnet model, which is 227x227 x3(RGB colors), and saved into folders corresponding to each class of emotions. Figure 1 shows the proposed system block diagram.

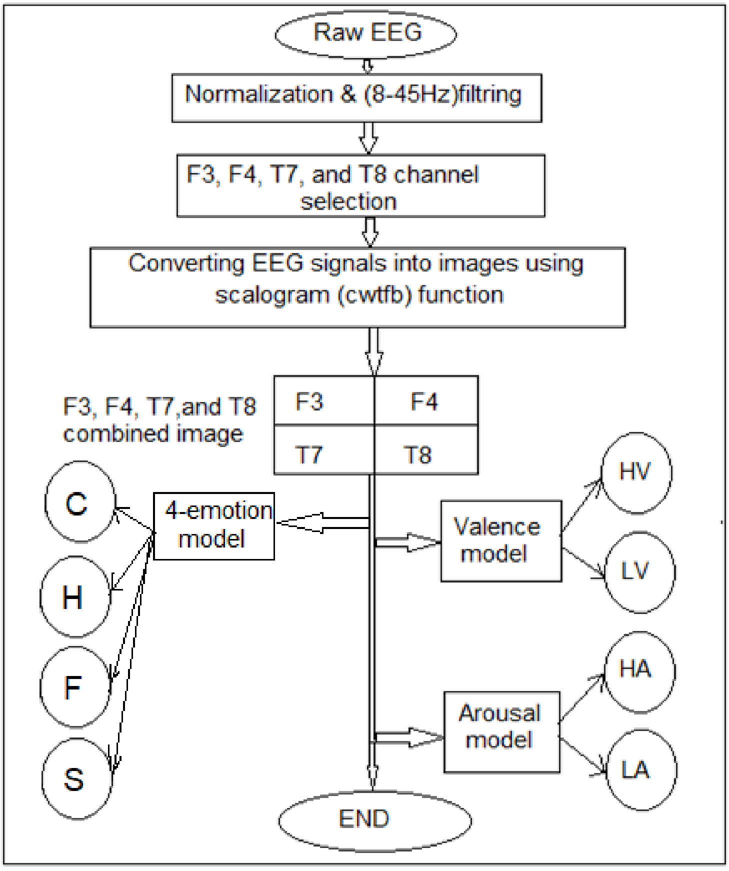

Figure 1: Block diagram of the system.

Image classification using AlexNet model

Alexnet is a fundamental, simple, and efficient Convolution Neural Network (CNN) architecture that was trained on more than a million images from the ImageNet database. It is primarily made up of cascaded stages, which include convolution layers, pooling layers, rectified linear unit (ReLU) layers, and fully connected layers. In particular, Alexnet as shown by figure 3.6 is constructed from composed of five convolutional layers; the first, second, third, and fourth layers, which are followed by the pooling layer and the three fully-connected layers in the fifth layer. By using the stochastic gradient descent (SGD) technique to optimize the whole cost function, the convolutional kernels for the Alexnet architecture are extracted during the back-propagation optimization process. Convolutional layers often use a sliding window model to operate on the input feature maps.

Generally, the pooling layers work on the convolved feature maps to aggregate the data within the specified neighborhood window using a max pooling operation or an average pooling operation. The convolutional layers act upon the input feature maps with the sliding convolutional kernels to generate the convolved feature maps. Figure 2 displays the pre-trained Alexnet network architecture [14].

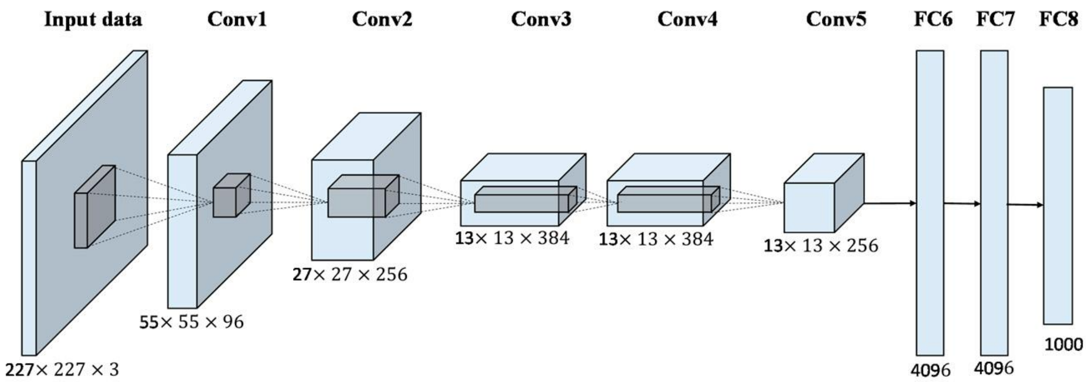

Figure 2: Alexnet model architecture.

Results and discussion

This section presents results of the system evaluation when it applied on data from the same dataset that were used for training and when it applied on new data that the system has not seen them before.

System evaluation using training dataset:

Dataset was split into training dataset, validation dataset, and test dataset. The training accuracy can be calculated after the system finishes its training. The system was evaluated using training dataset, with data size of images as 496, 484, 496, and 443 for calm, fear, happy, and sad respectively. Figure 3 illustrates the confusion matrix of classification results for training data.

	C	F	H	S
C	**475**	0	0	0
F	1	**460**	0	22
H	20	21	**496**	22
S	0	3	0	**399**

Figure 3: Confusion matrix of the system.

By calculating evaluation metrics, Table 2 shows the accuracy, F1-score, precision, sensitivity, and specificity of the system classification when it used for classifying four emotions. The system has achieved an average accuracy of 98% while it has achieved classification accuracy of each emotion as 98.9%, 97.6%, 96.7%, and 97.5% for calm, fear, happy and sad respectively.

Table 2: Evaluation of subject -Independent system.

Class ID	Accuracy (%)	F1-Score (%)	Precision (%)	Sensitivity (%)	Specificity (%)
Calm	98.9	97.8	95.7	100	98.5
Fear	97.6	95	95	95	98
Happy	96.7	94	100	88.7	100
Sad	97.5	94	90	99	97
Average	**98 %**				

System evaluation using new (test) dataset:

Although the system showed high potential for subject-dependent emotion recognition, the average accuracy of classification was 50% when the system has been used for classifying emotions using new data that the system has not seen them before. That means the system was not able to classify emotions from new data and was not valid for subject-independent emotion recognition. Therefore, the problem has not been solved yet and needs more work to solve.

Results of Valence/Arousal emotion recognition system

To solve the problem of subject-independent emotion recognition, valence/arousal model has been built which showed valuable potential in emotion recognition from testing data (data from new subject). The system classifies emotions based on Russel's two dimensional model; high or low arousal and high or low valence [15].

For arousal classification, the system has achieved validation accuracy of 83.57% and low validation loss less than 0.2 as illustrated by Figure 4

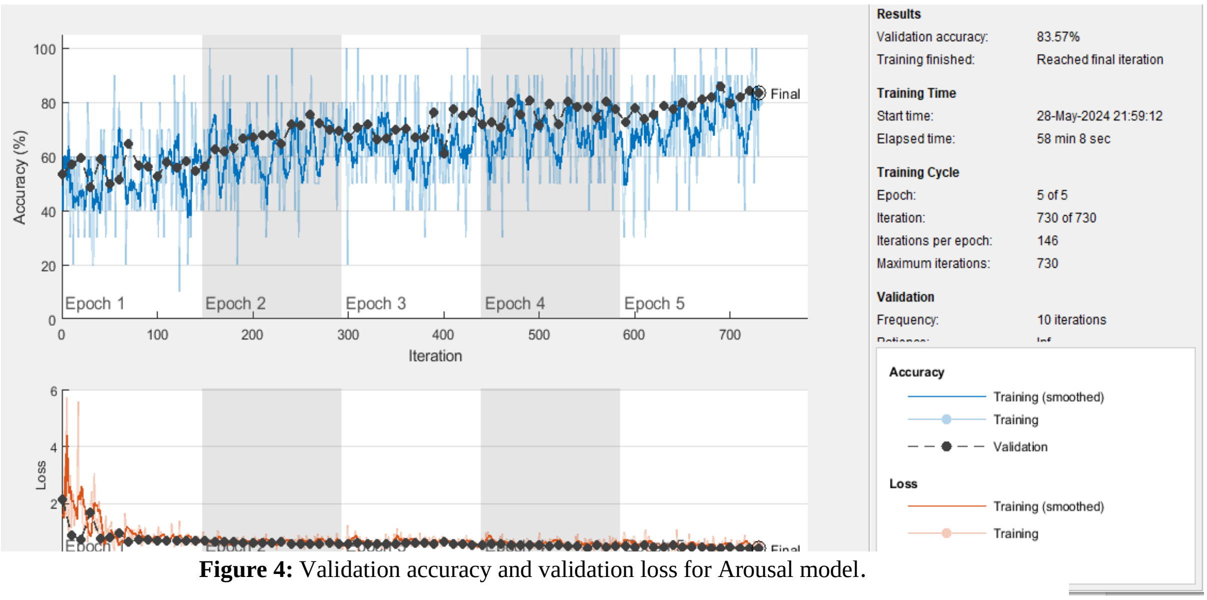

Figure 4: Validation accuracy and validation loss for Arousal model.

The system evaluation for arousal recognition has yielded the confusion matrix which explains the actual value of arousal and its system prediction as shown by Figure 5. The average classification accuracy of arousal was calculated from confusion matrix and was 97.44%.

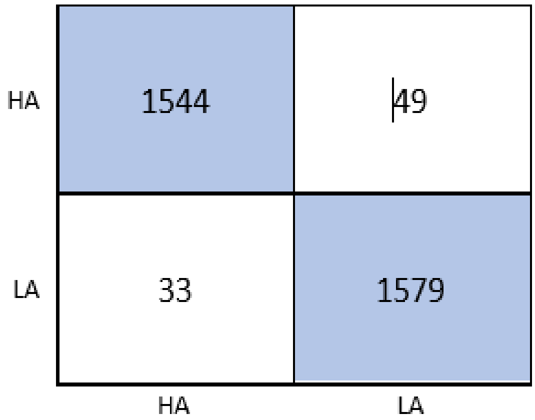

Figure 5: Confusion matrix for Arousal model.

For valence classification, the system has achieved validation accuracy of 80% and validation loss of 0.4 as illustrated in figure 6.

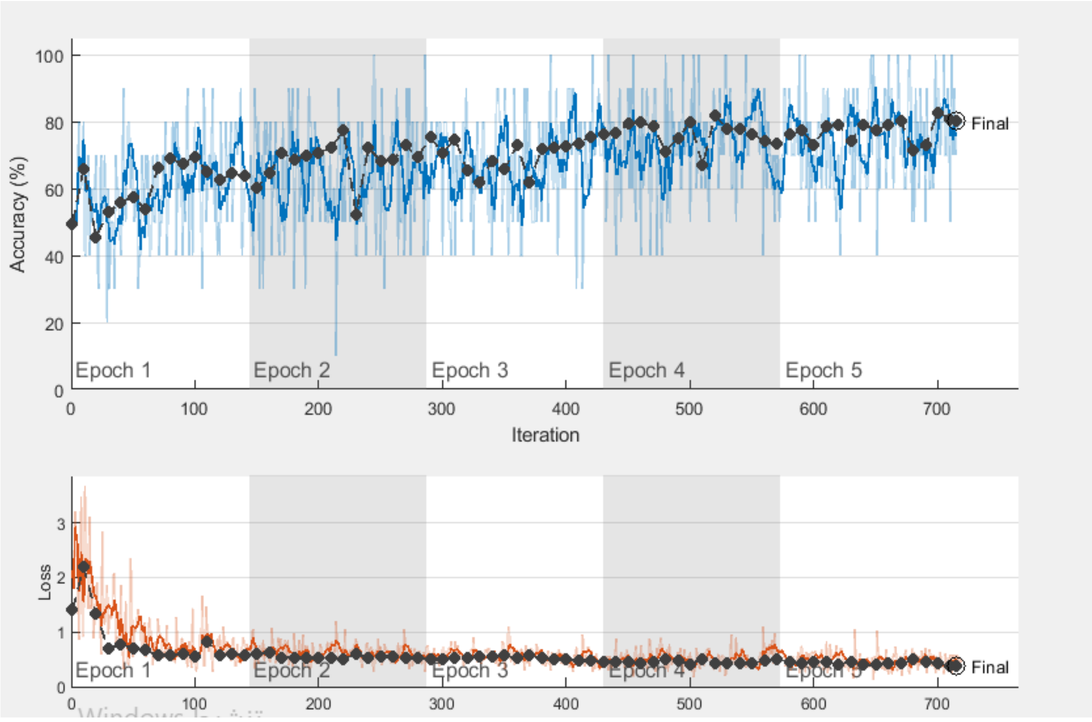

Figure 6 : The validation and loss accuracies for valance model.

The system evaluation for valence recognition has yielded the confusion matrix which explains the actual value of arousal and its system prediction as shown by **Figure 7**. The average classification accuracy of arousal was calculated from confusion matrix and was 99.64%.

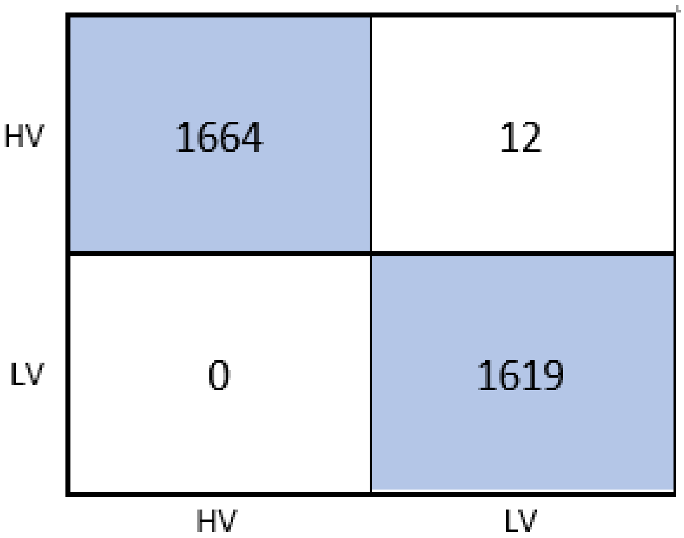

Figure 7: Confusion matrix for valance model.

By calculating system evaluation metrics, the valence model achieved better outcomes for all measurements comparing with the arousal model as shown by Figure 8, Obtaining 99.7% - 99.6% - 99% for accuracy, sensitivity, and precision, respectively.

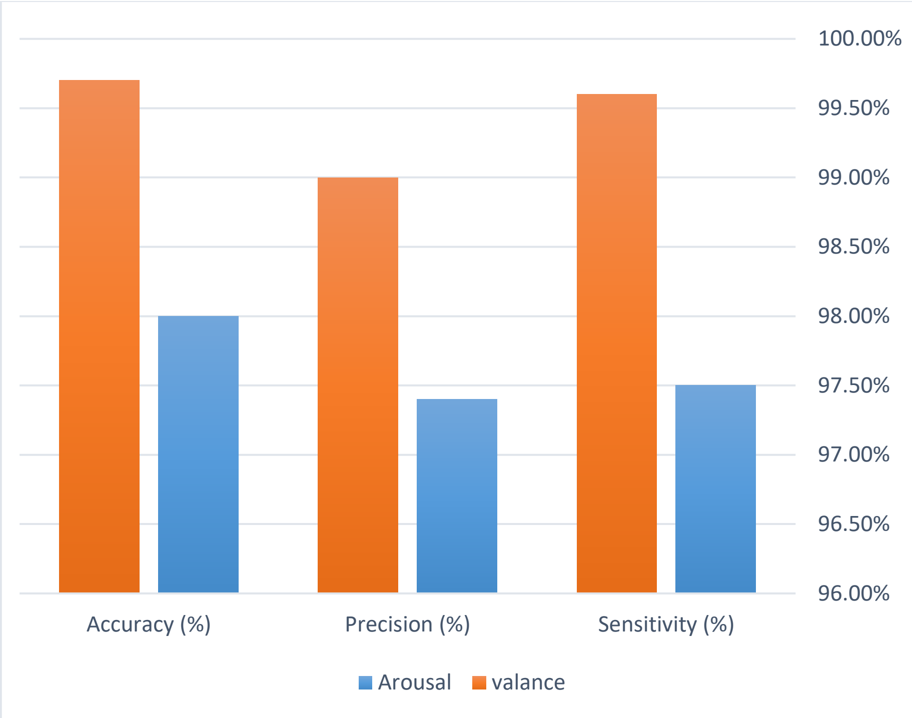

Figure 8: Evaluation metrics of Valance and Arousal models.

Test results of subject-Independent (Valance -Arousal) system

In this part, new data from ten individuals (subjects) have been tested using the proposed model to classify for emotions based on two-dimensional model; arousal and valence. Accuracy of classification are presented by Table 3.

Table 3: Test results of 10 subjects using Valance/Arousal model.

M.TYPE	LA	HV	HA	LV	HA	HV	LA	LV	AVERAGE
S-ID	Calm		Fear		Happy		Sad		
S1	70%	62%	51%	54%	72%	69%	65%	57%	63%
S2	68%	74%	79%	67%	59%	96%	52%	51%	68%
S3	53%	55%	55%	59%	93%	94%	54%	71%	67%
S4	81%	62%	64%	51%	87%	58%	72%	65%	68%
S5	57%	75%	82%	83%	54%	71%	52%	93%	71%
S6	54%	53%	83%	79%	56%	100%	55%	52%	67%
S7	67%	53%	72%	81%	60%	100%	52%	51%	67%
S8	68%	78%	79%	63%	51%	80%	65%	50%	67%
S9	88%	60%	66%	58%	64%	58%	87%	64%	68%
S10	67%	79%	51%	58%	72%	64%	57%	65%	64%
Avg.	67%	65%	68%	65%	67%	79%	61%	62%	67%
	66%		66.5%		73%		61.5%		avg. **67%**

As can be seen from Table 3, the proposed system was able to classify four emotions; calm, fear, happy and sad with average accuracy of 66%, 66.5%, 73%, and 61.5% for calm, fear, happy, and sad respectively.

The effectiveness of the proposed model appears when it is used for classifying data from outside the training and validation groups. In comparison of the performance of our model with the state-of-the art emotion models, it can be observed that the suggested model has a higher score than others as illustrated by Table 4, recording emotion recognition accuracy of 65.75% and 67.75% for arousal and valance respectively.

Table 4: Test accuracy of proposed system and state-of-the-Art subject -Independent systems.

Article	Database	Classifier	Test Accuracy (%)
Li etal. 2018 [16]	DEAP dataset	SVM	59.06% positive &negative Emotions
Lan et al. 2019 [17]	DEAP dataset	Domain adaption technique	48.93% for three level Valance
Reyadoost and Soleimani,2018 [18]	DEAP dataset	CNN	Arousal 55.70% Valance 59.22%
W.-C. L. Lew et al. 2020 [19]	DEAP DATASET	Fully Connected Network (FCN)	Arousal 56.6% Valance 56.8%
Arjun*a, Aniket Singh Rajpoot 2022 [20]	DEAP DATASET	VGG-16	Arousal 56.3% Valance 52.5%
Dewangan et al. 2023 [10]	SEED-IV dataset	cubic SVM fine Gaussian SVM	78.46% 83.7%
Bagherzadeh et al. 2024 [11]	SEED-FRA SEED-IV SEED-V SEED-GER	ResNet-18	75% 76.66% 78.12% 81.25%
Proposed model	AMIGOS dataset	Alexnet	Arousal 65.75% Valance 67.75%

Discussion

Most published emotion recognition systems have reported a high accuracy in subject-dependent approaches. These systems use training, validation, and testing data from one subject (person). Due to individual differences in human information processing, there are also individual differences in their EEG signals. Therefore, subject-dependent systems cannot be generalized to recognize emotions for other subjects. To build a subject-independent emotion recognition system, data from different users must be used, so that the system can learn more features of emotion patterns instead of focusing on one subject's emotion patterns. Even though, EEGs are non-stationary signals and are contaminated with noise and artifacts as well as are low in signal-to-noise (SNR) ratio. Such issues led to use advanced approaches to increase the systems accuracy. This work proposes using continuous wavelet transform with AlexNet and AMIGOS dataset to build two subject-dependent emotion recognition systems:

In the first model, multiple class emotion recognition system was built and tested using same training data. The system has achieved an average accuracy of 98% while it has achieved classification accuracy of each emotion as 98.9%, 97.6%, 96.7%, and 97.5% for calm, fear, happy and sad respectively, as shown by Table 2 but has achieved low accuracy less than 50% when it was used for emotion recognition from new subject's data.

In the second model, arousal/valence emotion recognition system was built and it has been applied on data from 10 new subjects. The system average accuracy was 66%, 66.5%, 73%, and 61.5% for calm, fear, happy, and sad respectively as shown by Table 3.

Conclusion

This work aimed to develop a robust, subject-independent system for emotion recognition from EEG (brain) signals. To develop such system, EEG signals from AMIGOS dataset were imported and then converted into scalogram images using continuous wavelet transform function. 2-stage recognition system was designed for emotion classification based on 2-D (arousal/valence) emotion modeling; the first for high/low arousal and the other for high/low valence. AlexNet has been used as image classifier which showed a high potential of emotion recognition with accuracy of 65.75 and 67.75 for arousal and valence respectively. To further enhance the proposed emotion identification system, more training data is required for improving the overall training and testing accuracy that is essential for increasing the model's reliability.

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