Original Article

An Emotion Recognition Embedded System using a Lightweight Deep Learning Model

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Abstract

Background: Diagnosing emotional states would improve human-computer interaction (HCI) systems to be more effective in practice. Correlations between Electroencephalography (EEG) signals and emotions have been shown in various research; therefore, EEG signal-based methods are the most accurate and informative. **Methods:** In this study, three Convolutional Neural Network (CNN) models, EEGNet, ShallowConvNet and DeepConvNet, which are appropriate for processing EEG signals, are applied to diagnose emotions. We use baseline removal preprocessing to improve classification accuracy. Each network is assessed in two setting ways: subject-dependent and subject-independent. We improve the selected CNN model to be lightweight and implementable on a Raspberry Pi processor. The emotional states are recognized for every three-second epoch of received signals on the embedded system, which can be applied in real-time usage in practice. **Results:** Average classification accuracies of 99.10% in the valence and 99.20% in the arousal for subject-dependent and 90.76% in the valence and 90.94% in the arousal for subject independent were achieved on the well-known DEAP dataset. **Conclusion:** Comparison of the results with the related works shows that a highly accurate and implementable model has been achieved for practice.

Keywords: *Convolutional neural network, electroencephalography, embedded system, emotion recognition*

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Introduction

Nowadays, human–computer interaction (HCI) systems are a big part of human lives. It seems that such interactions need to have the same social and natural principles as the human-to-human interactions. In many related applications, emotional information is required to have more effective systems. For example, in some diseases, understanding the emotions of patients affects the therapy manner. Some patients, for example, those with autism disorder, could not express their emotions. Therefore, the ability to understand the users' emotions is of interest.[1] In the recent research, the lack of emotional information in HCI has been considered. To improve such ability in HCI systems, machines need to understand and interpret the emotions of humans. The aim is to have adaptive and personalized means of emotion recognition which needs research in different fields of science, for example, artificial intelligence, psychology, computer science, and neuroscience.[2]

Humans may have different emotions such as happiness, sadness, joy, and satisfaction. In the literature, various models have been proposed for emotion states.[3] One of the most popular is Russell's 2D circumplex model, which defines emotions as a two-dimensional space of valence and arousal. The term "Valence" indicates the level of pleasure, and "Arousal" indicates the level of excitation.[4] Although in Russell's model and some studies, for example,[5] the emotions have been regarded as continuous variables, in most related works, they have been regarded as discrete states.

Emotions can be recognized from speech, behavior, motion, facial expression, or physiological signals. Physiological data used for this purpose are electrocardiography (ECG), heart rate variability, electroencephalography (EEG), facial recognition, forehead biosignal, speech recognition, skin temperature (SKT), blood volume pulse, and respiration (RSP).[6-10]

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In Zhang *et al.*'s study,[11] RSP signals were studied to recognize emotions. The model was developed using the DEAP dataset[12] and the Augsburg University dataset. In some studies, galvanic skin response (GSR) signals are used for emotion recognition. For example, in Ayata *et al.*'s study,[13] valence and arousal were categorized using GSR. In Villarejo *et al.*'s study,[8] GSR was used to build a stress sensor. In Domínguez-Jiménez *et al.*'s study,[14] information about heart rate as well as GSR was considered to recognize three target emotions. In some works, ECG signals were decoded to detect the emotional states. For example, a deep neural network (DNN) in Keren *et al.*'s study[15] and a scattering wavelet algorithm in Sepúlveda *et al.*'s study[16] were employed to detect emotion from ECG signals.

To improve the accuracy (ACC) of emotion recognition, some studies use both physical signs and physiological signals. In Tarnowski *et al.*'s study,[17] an experiment was designed with 22 subjects using a movie as the stimulus; meanwhile GSR and EEG signals of each subject were extracted and processed. Frequency domain features were extracted, and two classifiers, support vector machine (SVM) and K-Nearest Neighbors (KNN), were implemented. In Goshvarpour *et al.*'s study,[18] ECG and GSR signals were used to recognize emotions. An experiment was designed with 11 subjects, and the stimulus was a music clip. Features were extracted using Wavelet and Discrete Cosine Transforms. After reducing the dimension of the features, principal component analysis was used to detect the four classes of valence and arousal plane. The results of this paper showed that the ACC using ECG features is more than those of GSR. Facial expression data, ECG, SKT and conductance, breathing signal, mouth length, and pupil size were used in Tan *et al.*'s study[19] to recognize the emotions by enhanced neural networks.

Although research on emotion recognition is very extensive, some methods are subject-based, and in some cases, an external reaction against a stimulus depends on the personality of the subjects. For example, if a subject decides to conceal his feeling, the performance of some methods would be affected. Overall, methods based on physiological signals are more reliable. As the brain is the source of human reactions to external stimuli, EEG signal-based methods are the most accurate and informative. Correlations between EEG signals and emotions have been shown in the research. The frontal scalp seems to store more emotional activation compared to other regions of the brain.[20] Furthermore, processing EEG signals has more advantages compared to some different techniques. Providing an immediate medical care with low cost and ease in use for patients who cannot respond or have any movement makes EEG signals favorable in detecting some diseases and emotional states.[21]

Research on emotion recognition using EEG signals is extensive. There are differences in the extracted features, categories, classifiers, and the number of used channels, datasets, and experiments. In Zhang *et al.*'s study,[22] EEG signals of only two channels were employed, and empirical mode decomposition (EMD) strategy and SVM classifier were used. Two neural models, convolutional neural network (CNN) and DNN, were employed in Tripathi *et al.*'s study[23] on the DEAP dataset. Results in 2-class and 3-class modes were compared. In some studies, to find the most critical features of EEG signals to recognize emotions, different categories of features have been considered. In Khateeb *et al.*'s study,[24] time, frequency, and wavelet domain features were extracted, and using SVM, nine classes of emotions were identified. In Moon *et al.*'s study,[25] the power spectrum and correlation between two electrodes were extracted and fed to a CNN for classification. In Gannouni *et al.*'s study,[26] multi-class emotion recognition was studied on the DEAP dataset. Considering nine emotion states, the authors achieved more ACC rate using quadratic discriminant classifier (QDC) and recurrent neural network (RNN).

In the literature, most deep learning algorithms achieved higher accuracies than machine learning ones. On the other hand, such algorithms are usually too complicated for practical implementation. In this paper, we aim to develop an emotion recognition model that is highly accurate and implementable on an embedded system using EEG signals. We use different state-of-the-art CNN models which are appropriate for decoding EEG signals and assess them to find the most accurate one in diagnosing the emotional states. Since the models did not need feature extraction and selection steps, the processing steps were reduced. We use baseline removal preprocessing to improve classification ACC. Each network is assessed in two setting ways: subject-dependent and subject-independent. Next, we improve the selected CNN model to be lightweight and implementable on a Raspberry Pi processor. Using EEG signals from the DEAP[12] dataset, we investigate the model while the processing is in progress on the embedded board. The emotional states are recognized for every 3-s epoch of received signals on the embedded system, which will be appropriate for real-time usage. The results show that this lightweight model could achieve high ACC in recognizing the emotions and will be applicable for implementation in practice.

The rest of this paper is organized as follows: the material and methods are explained in Section 2, the simulation results are presented in Section 3, the implementation of the model on the hardware is described in Section 4, and Section 5 concludes the paper.

Materials and Methods

In this study, a deep learning model is used to detect emotions using the DEAP dataset. The study is performed in both subject-dependent and subject-independent settings. We have included preprocessing in our technique to remove artifacts from EEG data. The baseline signal is removed, which improves the classification ACC significantly. Then, the data are segmented and finally passed to the convolutional network. EEGNet, EEG Shallow Convolutional Network (ShallowConvNet), and EEG Deep CNN (DeepConvNet) are carried out to recognize emotions in both subject-dependent and subject-independent settings. Finally, the ACC and F-score of the three convolutional networks are compared. We also implement the lightweight model of the emotion recognition process on an embedded system using a Raspberry Pi board. The steps applied in this paper are shown in Figure 1. These steps are described more precisely in the rest of the section.

Dataset

In this study, the well-known DEAP dataset[12] is used, which includes the electroencephalogram and other peripheral physiological signals of 32 subjects aged between 19 and 37 while watching 40 1-min music videos as the stimuli. EEG signals of 32 channels are available in the DEAP dataset. The level of arousal and valence of the subjects' emotions after each experiment was assessed using Self-Assessment Manikin, with values from 1 to 9 for each dimension. The emotional states were presented in a two-dimensional valence-arousal model, in which the valence ranged from sad to joyful, and arousal ranged from bored to excited.[27] We segment each valence-arousal space into two parts. The values >5 are high valence/arousal, and those below 5 are low valence/arousal.

Preprocessing

In the DEAP dataset, EEG signals were recorded by the International Standard 10–20 Electrode Systems with a sampling rate of 512 Hz. In the preprocessing step, the signals were down-sampled to 128 Hz, and a band-pass

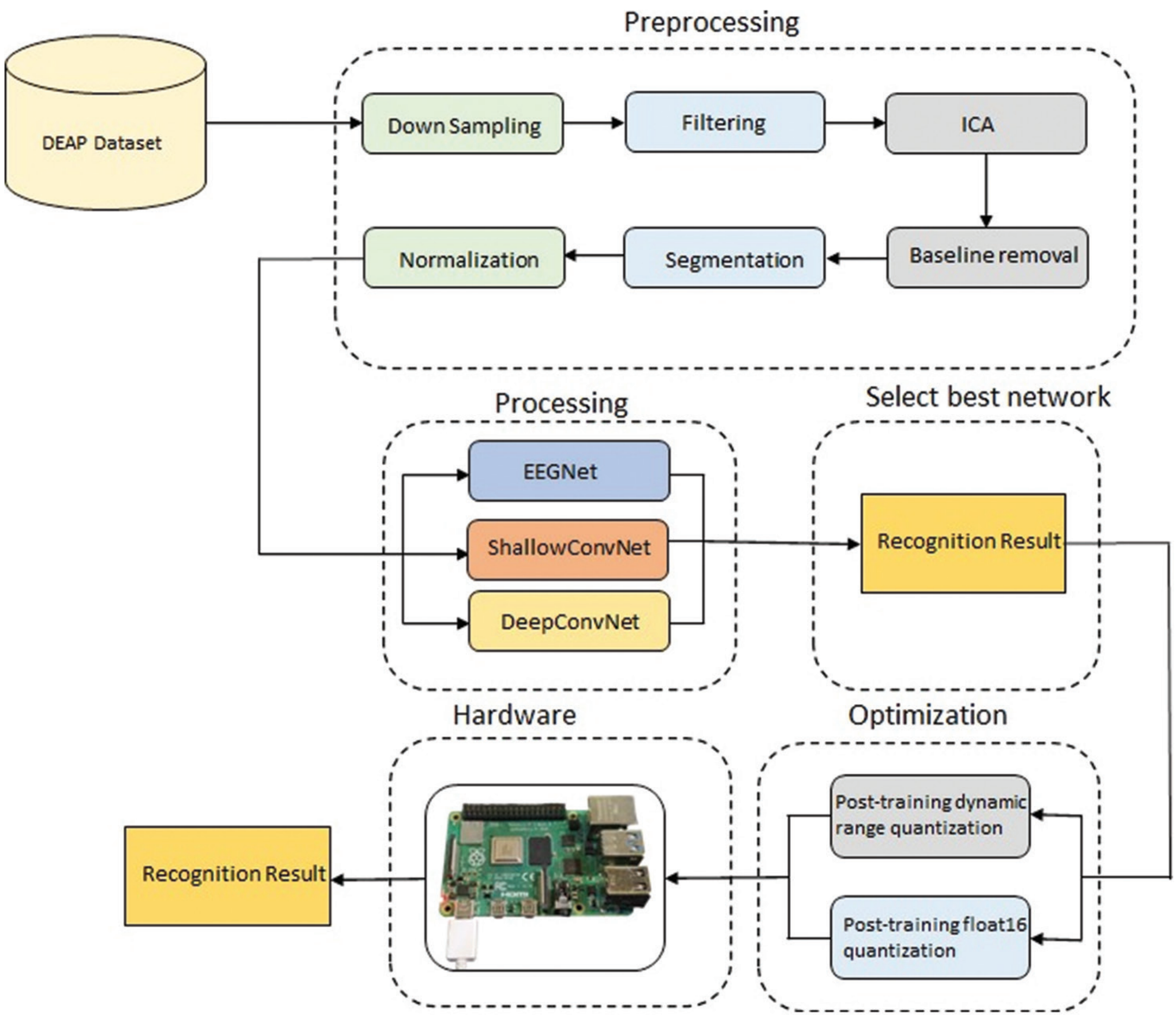

Figure 1: The workflow diagram applied in this paper

filter from 4.0 Hz to 45.0 Hz was applied to reduce electromyography and ECG effects from the signals. Eye movement artifacts and interferences of other sources were removed using blind source separation techniques like Independent Component Analysis (ICA).

The duration of each EEG signal in the DEAP dataset is 63 s, containing a 3-s pretrial baseline and 60 s of emotional information. The first 3-s pretrial signal, in which the video had not started playing, was repeated 20 times, to get a 60-s signal, and then, this signal was subtracted from the 60-s trial. Then, the pretrial times were removed from the signals. Next, each 60-s signal was segmented into 3-s epochs, and finally, Z-normalization was applied.

Processing

After preprocessing, the signals are prepared to be processed. In this work, three networks, namely, EEGNet,[28] EEG ShallowConvNet,[29] and EEG DeepConvNet[29] were used for emotion recognition. For each network, two setting ways were conducted in learning: subject-dependent and subject-independent learning. In the subject-dependent setting, the model was trained, and parameters were extracted for each subject. In this method, we had 800 samples (40 experiments ×20 epochs with 3-s interval) for each subject. In the subject-independent, the model was trained for all subjects, and 32 × 800 samples were available. We adopted a 5-fold cross-validation for both methods.

The results of the test on the three networks and with the two mentioned methods were compared in terms of ACC of emotion recognition in arousal and valence. The best method was determined based on the results. In the following, we introduce the three used networks and the parameters set in this study.

ElectroencephalographyNet

EEGNet[28] is a compact convolutional network that can be applied in different brain-computer interface models, and can be trained using limited data. The structure of this network is shown in Table 1. The input of this network is as (C, T), in which C is the number of channels (in this study, C = 32) and T stands for time samples (in this study, T = 384 = 3 s × 128 Hz). Signals are passed from eight 2D convolutional filters. The output of this layer is EEG signals in eight frequency bands. Next, the signals are fed to DepthwiseConv2D as a special filter. To prevent overfitting, we use the dropout layer. Average polling is applied to reduce the size of features. After separable convolution, the last block is a softmax classifier with N units, where N is the number of classes set to 2 in this study. The model is trained using an Adam optimizer and a batch size of 64, learning rate of 0.01, and dropout rate of 0.5. We run the model 50 and 30 training iterations for subject-dependent and subject-independent methods, respectively.

Electroencephalography DeepConvNet

EEG DeepConvNet[29] is an EEG decoding DeepConvNet that is compatible with any type of feature. The structure of this network is shown in Table 2. This network contains five convolution layers and one dense softmax classifier. This model is trained with the same parameters mentioned in the EEGNet section.

Electroencephalography ShallowConvNet

EEG ShallowConvNet[29] has more shallow architecture than EEG DeepConvNet, and was designed to decode band power features of signals. The structure of this network is shown in Table 3. This model consists of a temporal and

Table 1: ElectroencephalographyNet network structure, K=32 is the kernel length, Nc is the number of channels, and *n* is the number of data points in the channels[28]

Layer	Number of filters	Kernel size	Padding	Output	Parameters
Input				(1, N_c, N)	
Conv2D	8	1×K	Same	(8, N_c, N)	K×8
BatchNorm2D				(8, N_c, N)	16
DepthwiseConv2D	16	N_c×1	Valid	(16,1, N)	N_c×16
BatchNorm2D				(16,1, N)	32
ELU activation				(16,1, N)	
AveragePooling2D		1×4	Valid	(16,1, N/4)	
Dropout				(16,1, N/4)	
SeparableConv2D	16	1×16	Same	(16,1, N/4)	512
BatchNorm2D				(16,1, N/4)	32
ELU activation				(16,1, N/4)	
AveragePooling2D		1×8	Valid	(16,1, N/32)	
Dropout				(16,1, N/32)	
Flatten				(16×N/32)	
Dense	384			(2)	
Softmax activation					

ELU - Exponential linear unit

then spatial convolutional layer, mean polling, and finally, classification layer. This model is trained with the same parameters mentioned in the EEGNet section.

Simulation Results

As explained in Section 2, in this study, EEG signals from the DEAP dataset were used for emotion detection on an embedded system. After preprocessing, baseline removal, and segmentation, the signals were fed to EEGNet, EEG DeepConvNet, and EEG ShallowConvNet using subject-dependent and subject-independent methods to recognize the emotional states. To evaluate the model, 5-fold cross-validation was used, and to compare the results, ACC and F-score[30] were utilized. The parameter is defined as:

$$\mathrm{ACC} = \frac{\mathrm{TP}+\mathrm{TN}}{\mathrm{TP}+\mathrm{TN}+\mathrm{FP}+\mathrm{FN}}, \quad (1)$$

in which, *TP* and *TN* are true classified cases (low arousal/negative valence named positive emotion and high arousal/positive valence named negative emotion), and *FN* and *FP* are false identified emotion ones.

The *F–score* parameter, which considers precision (*Pre*) and recall (*Rec*) rate, is as follows:

$$F-\mathrm{score} = \frac{2 * \mathrm{Rec} * \mathrm{Pre}}{\mathrm{Rec}+\mathrm{Pre}}, \quad (2)$$

in which, *Pre* and *Rec* are:

$$\mathrm{Pre} = \frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FP}}, \quad (3)$$

$$\mathrm{Rec} = \frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FN}}. \quad (4)$$

Table 4 compares the results of the three networks EEGNet, EEG DeepConvNet, and EEG ShallowConvNet in subject-independent method. As it turns out, the EEG ShallowConvNet model outperforms the other two models in the subject-independent method. We achieved the best accuracies of 90.76% for valence and 90.94% for arousal using the EEG ShallowConvNet model.

Table 5 shows the ACC and F-score results of the subject-dependent method for valence and arousal. The table shows that the best accuracies of 99.1% for valence and 99.2% for arousal using the EEG ShallowConvNet model were achieved. To see the detail of the results, the valence and arousal ACC acquired in this method are presented in Figures 2 and 3, respectively.

Table 2: Electroencephalography DeepConvNet structure[29]

Block	Layer	Activation	Padding	Filter	Size
1	Convolution	Linear	Valid	25	1,5
	Spatial filter	Linear	Valid	25	32,1
	Maximum polling				1,2
2	Convolution	Linear	valid	50	1,5
	Maximum polling				1,2
3	Convolution	Linear	valid	100	1,5
	Maximum polling				1,2
4	Convolution	Linear	valid	200	1,5
	Maximum polling				1,2
5	Classification	Softmax		2	

Table 3: Electroencephalography ShallowConvNet network structure[29]

Layer	Activation	Padding	Filter	Size
Convolution	Linear	Same	40	1,13
Spatial filter	Linear	Valid	40	32,1
Mean polling				Strides=(1,7)
Classification	Softmax		2	

Table 4: Classification results of the subject-independent method using electroencephalographyNet, electroencephalography ShallowConvNet, and electroencephalography DeepConvNet

Model	Arousal		Valence	
	Accuracy	*F*-score	Accuracy	*F*-score
EEGNet	75.91±1.41	73.30±0.85	72.12±1.26	70.85±0.85
EEG ShallowConvNet	92.01±0.70	90.94±0.68	91.53±0.77	90.76±0.83
EEG DeepConvNet	90.21±0.43	88.62±0.44	87.60±0.61	86.37±0.64

EEG - Electroencephalography

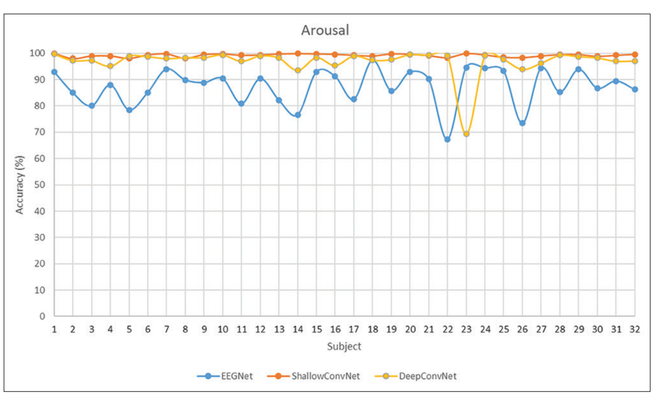

Figure 2: Accuracy of three networks in the subject-depended method for the arousal dimension. ACC – Accuracy

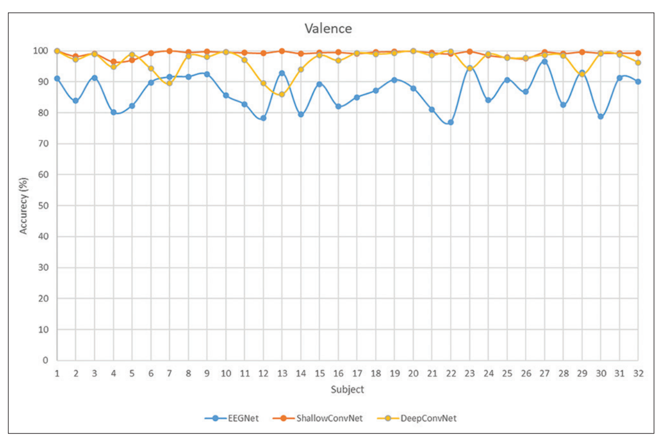

Figure 3: Accuracy of three networks in the subject-dependent method for the valence dimension. ACC – Accuracy

As shown in Table 5 and Figures 2, 3, EEG ShallowConvNet is more accurate in the subject-dependent method for both the arousal and valence dimensions. Furthermore, Table 4 shows that EEG ShallowConvNet works more accurately in the subject-independent method, too. Therefore, we used this network in the embedded system.

To compare the results with other studies, we presented Table 6. To be comparable, the studies on the DEAP dataset are selected. As the table shows, our method is more accurate in both the arousal and valence dimensions than the methods presented in other articles.

Hardware implementation

In this study, a Raspberry Pi processor (version 4) was used to design an embedded system. This hardware has Quad-core, 64-bit ARM-Cortex-A72 running at 1.5GHz, 2 Gigabyte LPDDR4 RAM, ARMv8 based, and has different communication interfaces.

Table 5: Classification results of the subject-dependent method using electroencephalographyNet, electroencephalography ShallowConvNet, and electroencephalography DeepConvNet

Model	Valence (on average)		Arousal (on average)	
	Accuracy	F score	Accuracy	F score
EEGNet	75.91±1.41	73.30±0.85	72.12±1.26	70.85±0.85
EEG ShallowConvNet	92.01±0.70	90.94±0.68	91.53±0.77	90.76±0.83
EEG DeepConvNet	90.21±0.43	88.62±0.44	87.60±0.61	86.37±0.64

EEG - Electroencephalography

In the implementation step of this study, the operating system (Armbian) was installed on the SD card. Commands were fed to the board using the Secure Shell protocol, and socket programming was used to provide the data to the processor.

TensorFlow Lite tools were used to reduce the size of the model and to increase the speed. TensorFlow lite model version is executed efficiently on devices with limited resources. In this work, different quantization techniques were applied to optimize the size of the model more. Quantization reduces the precision of the numbers used to represent a model's parameters. Optimization and conversion reduce the model's size and the latency, with minimal (or no) loss in ACC.

In this work, down-sampling, filtering, and ICA were performed on the computer, and the rest of the preprocessing steps were performed onboard. Of course, all preprocessing steps can be done on the board, but it was not considered in this study. The emotional states were recognized for every 3-s epoch of received signals. These steps were performed for the ShallowConvNet model that provided the best results, both for subject-dependent and subject-independent, and for a variety of mentioned optimization techniques. In fact, in this study, this board can be used to receive data in real time, to perform preprocessing and processing based on trained TensorFlow models. This solution can also be integrated with an EEG recording device using an appropriate communication protocol.

The results of applying two quantization techniques are shown in Tables 7 and 8 for subject-dependent and subject-independent settings of the ShallowConvNet model, respectively. Optimization and conversion result

Table 6: Comparison of the accuracy in different studies on emotion recognition

Study	Year	Methods	Accuracy
[30]	2021	ECLGCNN	90.45% in valence and 90.60% in arousal
[31]	2020	RACNN	96.65±2.65 in valence and 97.11±2.01 in arousal
[32]	2020	Lagged Poincare Indices, RSSF, SVM	98.97% in valence and 98.94% in arousal
[33]	2021	SVM, CNN	52.50±11.29% in valence and 56.00±12.46% in arousal
[34]	2020	LSTM	94.69% in valence and 93.13% in arousal
[35]	2021	BiDCNN	94.38% in valence and 94.72% in arousal
Methods used in this paper		EEGNet, EEG ShallowConvNet, EEG DeepConvNet	99.10% for valence and 99.20% for arousal (on average, using the subject-dependent method and EEG ShallowConvNet)

CNN - Convolutional neural network; EEG - Electroencephalography; ECLGCNN - Emotion Classification Graph Learning CNN ; RACNN - Regional-Asymmetric CNN; RSSF - Random Subset Feature Selection; SVM - Support vector machines; LSTM - Long short-term memory; BiDCNN - Bi-hemisphere discrepancy CNN

Table 7: Subject-dependent results on board

Technique	Dimension	Accuracy	F-score	Latency (ms)	Model size (K bytes)
Without Quantization	Arousal	99.20	99.20	12.5629	221
	Valence	99.10	99.13		
Posttraining dynamic range Quantization	Arousal	99.20	99.21	12.5554	61
	Valence	99.09	99.12		
Posttraining float16 quantization	Arousal	99.19	99.20	12.8859	114
	Valence	99.09	99.13		

Table 8: Subject-independent results on board

Technique	Dimension	Accuracy	F-score	Latency (ms)	Model size (K bytes)
Without quantization	Arousal	90.94	92.01	12.7359	221
	Valence	90.76	91.53		
Posttraining dynamic range quantization	Arousal	90.95	92.02	12.5564	61
	Valence	90.77	91.54		
Posttraining float16 quantization	Arousal	90.94	92.01	12.5254	113
	Valence	90.77	91.54		

in a significant reduction in the model's size and faster computation (in most of the cases) without loss of ACC. According to the results, the best model for implementation is the EEG ShallowConvNet subject-dependent resized with the posttraining dynamic range quantization.

Conclusion

In this study, we recognized the emotional states from EEG signals, by implementing three convolutional networks, EEGNet, EEG ShallowConvNet, and EEG DeepConvNet. For every network, we used two methods: subject-dependent and subject-independent. The best average classification accuracies of 99.10% in the valence and 99.20% in the arousal were achieved using EEG ShallowConvNet and the subject-dependent method. Furthermore, since the models did not need feature extraction and selection steps, the processing steps were reduced. This makes it possible to implement the algorithm on embedded systems. We used the Raspberry Pi processor in our embedded system. After optimization and quantization, we achieved a lightweight model that could recognize emotional states for every 3-s epoch of received signals. It is possible to use such hardware in applicable devices like emotion detection wearable headbands.

Future studies aim to use mobile and wearable sensors to collect physiological signals such as ECG and EEG, and combine them in an appropriate framework to improve ACC in real-time emotion detection. In this study, emotions have been identified in two dimensions, valence and arousal, like most papers in the literature. Expanding the model to include additional dimensions may also be considered in future approaches. For example, by analyzing situational information, the subject can be predicted in a three-dimensional model of emotions, namely, arousal, valence, and position.

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Conflicts of interest

There are no conflicts of interest.

References

1. Zhang J, Yin Z, Chen P, Nichele S. Emotion recognition using multi-modal data and machine learning techniques: A tutorial and review. Inf Fusion 2020;59:103-26.
2. Egger M, Ley M, Hanke S. Emotion recognition from physiological signal analysis: A review. Electron Notes Theor Comput Sci 2019;343:35-55.
3. Al-Nafjan A, Hosny M, Al-Ohali Y, Al-Wabil A. Review and classification of emotion recognition based on EEG brain-computer interface system research: A systematic review. Appl Sci 2017;7:1239.
4. Russell JA. A circumplex model of affect. J Pers Soc Psychol 1980;39:1161-78.
5. Javidan M, Yazdchi M, Baharlouei Z, Mahnam A. Feature and channel selection for designing a regression-based continuous-variable emotion recognition system with two EEG channels. Biomed Signal Process Control 2021;70:102979.
6. Ko BC. A brief review of facial emotion recognition based on visual information. Sensors (Basel) 2018;18:401.
7. Lieskovská E, Jakubec M, Jarina R, Chmulík M. A review on speech emotion recognition using deep learning and attention mechanism. Electronics 2021;10:1163.
8. Villarejo MV, Zapirain BG, Zorrilla AM. A stress sensor based on Galvanic Skin Response (GSR) controlled by ZigBee. Sensors (Basel) 2012;12:6075-101.
9. Goshvarpour A, Goshvarpour A. The potential of photoplethysmogram and galvanic skin response in emotion recognition using nonlinear features. Phys Eng Sci Med 2020;43:119-34.
10. Nikolova D, Mihaylova P, Manolova A, Georgieva P. ECG-based human emotion recognition across multiple subjects. In: Poulkov V, editor. Future Access Enablers for Ubiquitous and Intelligent Infrastructures. Cham: Springer International Publishing; 2019. p. 25-36.
11. Zhang Q, Chen X, Zhan Q, Yang T, Xia S. Respiration-based emotion recognition with deep learning. Comput Ind 2017;92-93:84-90.
12. Koelstra S, Muhl C, Soleymani M, Lee JS, Yazdani A, Ebrahimi T, *et al*. DEAP: A database for emotion analysis ; using physiological signals. IEEE Trans Affect Comput 2012;3:18-31.
13. Ayata D, Yaslan Y, Kamaşak M. Emotion Recognition Via Random Forest and Galvanic Skin Response: Comparison of Time Based Feature Sets, Window Sizes and Wavelet Approaches. In: 2016 Medical Technologies National Congress (TIPTEKNO); 2016. p. 1-4.
14. Domínguez-Jiménez JA, Campo-Landines KC, Martínez-Santos JC, Delahoz EJ, Contreras-Ortiz SH. A machine learning model for emotion recognition from physiological signals. Biomed Signal Process Control 2020;55:101646.
15. Keren G, Kirschstein T, Marchi E, Ringeval F, Schuller B. End-to-End Learning for Dimensional Emotion Recognition from Physiological Signals. Presented at the July, 2017.
16. Sepúlveda A, Castillo F, Palma C, Rodriguez-Fernandez M. Emotion recognition from ECG signals using wavelet scattering and machine learning. Appl Sci 2021;11:4945.
17. Tarnowski P, Kołodziej M, Majkowski A, Rak RJ. Combined Analysis of GSR and EEG Signals for Emotion Recognition. In:

2018 International Interdisciplinary PhD Workshop (IIPhDW); 2018. p. 137-41.
18. Goshvarpour A, Abbasi A, Goshvarpour A. An accurate emotion recognition system using ECG and GSR signals and matching pursuit method. Biomed J 2017;40:355-68.
19. Tan C, Ceballos G, Kasabov N, Puthanmadam Subramaniyam N. FusionSense: Emotion classification using feature fusion of multimodal data and deep learning in a brain-inspired spiking neural network. Sensors (Basel) 2020;20:5328.
20. Wang XW, Nie D, Lu BL. Emotional state classification from EEG data using machine learning approach. Neurocomputing 2014;129:94-106.
21. Suhaimi NS, Mountstephens J, Teo J. EEG-based emotion recognition: A state-of-the-art review of current trends and opportunities. Comput Intell Neurosci 2020;2020:8875426.
22. Zhang Y, Ji X, Zhang S. An approach to EEG-based emotion recognition using combined feature extraction method. Neurosci Lett 2016;633:152-7.
23. Tripathi S, Acharya S, Sharma R, Mittal S, Bhattacharya S. Using deep and convolutional neural networks for accurate emotion classification on DEAP data. Proc AAAI Conf Artif Intell 2017;31:4746-52.
24. Khateeb M, Anwar SM, Alnowami M. Multi-domain feature fusion for emotion classification using DEAP dataset. IEEE Access 2021;9:12134-42.
25. Moon SE, Jang S, Lee JS. Convolutional Neural Network Approach for Eeg-Based Emotion Recognition Using Brain Connectivity and its Spatial Information. In: 2018 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, Calgary, AB; 2018. p. 2556-60.
26. Gannouni S, Aledaily A, Belwafi K, Aboalsamh H. Emotion detection using electroencephalography signals and a zero-time windowing-based epoch estimation and relevant electrode identification. Sci Rep 2021;11:7071.
27. Li X, Song D, Zhang P, Zhang Y, Hou Y, Hu B. Exploring EEG features in cross-subject emotion recognition. Front Neurosci 2018;12:162.
28. Lawhern VJ, Solon AJ, Waytowich NR, Gordon SM, Hung CP, Lance BJ. EEGNet: A compact convolutional neural network for EEG-based brain–computer interfaces. Journal of neural engineering 2018;15:056013.
29. Schirrmeister RT, Springenberg JT, Fiederer LD, Glasstetter M, Eggensperger K, Tangermann M, *et al.* Deep learning with convolutional neural networks for EEG decoding and visualization. Hum Brain Mapp 2017;38:5391-420.
30. Yin Y, Zheng X, Hu B, Zhang Y, Cui X. EEG emotion recognition using fusion model of graph convolutional neural networks and LSTM. Appl Soft Comput 2021;100:106954.
31. Cui H, Liu A, Zhang X, Chen X, Wang K, Chen X. EEG-based emotion recognition using an end-to-end regional-asymmetric convolutional neural network. Knowl Based Syst 2020;205:106243.
32. Goshvarpour A, Goshvarpour A. A novel approach for EEG electrode selection in automated emotion recognition based on lagged Poincare's indices and sLORETA. Cogn Comput 2020;12:602-18.
33. Li R, Liang Y, Liu X, Wang B, Huang W, Cai Z, *et al.* MindLink-Eumpy: An open-source python toolbox for multimodal emotion recognition. Front Hum Neurosci 2021;15:621493.
34. Nath D, Singh M, Sethia D, Kalra D, Indu S. A Comparative Study of Subject-Dependent and Subject-Independent Strategies for EEG-Based Emotion Recognition Using LSTM Network. In: Proceedings of the 2020 the 4th International Conference on Compute and Data Analysis. New York, NY, USA: Association for Computing Machinery; 2020. p. 142-7.
35. Huang D, Chen S, Liu C, Zheng L, Tian Z, Jiang D. Differences first in asymmetric brain: A bi-hemisphere discrepancy convolutional neural network for EEG emotion recognition. Neurocomputing 2021;448:140-51.