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EEG-Based Emotion Recognition Using Genetic Algorithm Optimized Multi-Layer Perceptron

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***Abstract*—Emotion Recognition is an important problem within Affective Computing and Human Computer Interaction. In recent years, various machine learning models have provided significant progress in the field of emotion recognition. This paper proposes a framework for EEG-based emotion recognition using Multi Layer Perceptron (MLP). Power Spectral Density features were used for quantifying the emotions in terms of valence-arousal scale and MLP is used for classification. Genetic algorithm is used to optimize the architecture of MLP. The proposed model identifies a. two classes of emotions viz. Low/High Valence with an average accuracy of 91.10% and Low/High Arousal with an average accuracy of 91.02%, b. four classes of emotions viz. High Valence-Low Arousal (HVLA), High Valence-High Arousal (HVHA), Low Valence-Low Arousal (LVLA) and Low Valence-High Arousal (HVHA) with 83.52% accuracy.The reported results are better compared to existing results in the literature.**

***Index Terms*—EEG, Emotions, Power Spectral Density, Multi-Layer Perceptron, Genetic Algorithm.**

I. Introduction

Emotion recognition using Electroencephalography (EEG) has gained significant attention in Affective Computing and Human-Computer Interaction. Emotions are substantial in day-to-day life activities such as personal development, communication and decision making. Research within human-machine interfaces has focused on interpreting emotional states with an aim to cater more natural interactions in the fields of personalized recommender systems, rehabilitation robotics, etc. [1]. Various methods to emotion recognition such as speech, skin conductance, facial expressions have been proposed. It is seen that physiological signals can be more advantageous for machine intelligence as compared to visual or vocal data [2].

There are two taxonomy to recognise and interpret emotions a. discrete model and b. dimensional model [3]. The discrete taxonomy depicts six elementary emotions that includes surprise, fear, sadness, joy, disgust, and anger. The dimensional model characterises emotions in terms of two principal dimensions:valence and arousal. The valence depicts the pleasant or unpleasant feeling about something and ranges from unhappiness to happiness. Arousal is the intensity of emotion provoked by a stimulus and depicts the level of affective activation, that ranges from sleep to excitement. The valence and arousal of the dimensional model maps to discrete emotions, and thus identifies different emotional states [4].

Recent works have explored the correlation between the emotional states and the physiological signals such as EEG [3]. EEG have been widely used for interpreting emotions because of its ease to use, non-invasiveness, portability, low cost and high temporal resolution. Soleymani et al. [5] classified emotions using EEG and peripheral physiological signals with Support Vector Machine (SVM) into three levels of valence and arousal. They have obtained 57.0% and 52.4% of accuracy for valence and arousal respectively using Power Spectral Density (PSD) features [5]. Literature also reports works on various machine learning algorithms that includes Multiple-Kernel Learning (MKL) [6], Bayes Classifier [7], SVM [8], Artificial Neural Network [1] as well as Deep Learning Models such as Convolutional Neural Network (CNN) [9], Temporal Convolutional Network (TCN) [9] and Long Short Term Memory (LSTM) [9], [10]. Deep Learning Models are computationally extensive to train.

This paper aims to design an emotion recognition system exploiting genetic algorithm (GA) optimized multi-layer perceptron neural network (MLP). GA [11] has been used to find optimized neural network architectures. The idea of using GA to design optimized MLP is derived from Bacanin et al. [12]. Bacanin et al. [12] has employed GA to attain optimized bias and weights in the network. Jenkins et al. [13] have described four variants of GA: Generational GA (GGA), Steady State GA (SSGA), Steady-Generational GA(SGGA) and Random GA where they have tested with combination of different values for the crossover and mutation. While considering the Mid-Point Crossover and low mutation probability, the GGA has considerably better performance than the SSGA, SGGA and Random GA. In our work, we have used the GGA with single point crossover and low probability rate for the mutation to generate the off springs. Exploring the GA optimized MLP reported in this paper using other variants of GA would provide interesting insights. However, this is outside the scope of the experiment reported here. GA has been employed in our paper to achieve optimized number of neurons of the hidden layers. PSD features were used to quantify emotions based on dimensional model in terms of Valence-Arousal scale [14], [15]. Classification of emotional states into Low/High Valence (sad/unhappy to joyful/happy) and Low/High Arousal (bored/calm to stimulated/excited) have been investigated [14]. In addition to this, classification of emotions into four classes i.e. High Valence-Low Arousal (HVLA), High Valence-High Arousal (HVHA), Low Valence-Low Arousal (LVLA) and Low Valence-High Arousal (HVHA) have also been considered [14].

The rest of the paper is organized as follows: The dataset used in the study is presented in Section II and the methodology is presented in Section III. Section IV and Section V presents and discusses the experimental results. Section VI concludes the findings and presents the future works.

II. Materials

EEG signals from the DEAP dataset [16] was used for our experiments. EEG data were recorded using 32 active electrodes (See Fig. 2) following 10-20 international system at a sampling frequency of 512 Hz from 32 subjects while watching one-minute long music videos. EEG signals were downsampled to 128 Hz. At the end of each video, the emotional state was rated by using a subjective scale, Self Assessment Manikin (SAM) [17] in terms of valence, arousal, dominance and liking. (For detailed discussion, refer to [16]).

Here we use the valence and arousal ratings and ignore the ratings of dominance and likelihood. For valence and arousal, the subjective scale is with a value from 1 to 9. In this work, the ratings (1-9) are divided into two levels of valence and arousal states. The rating in the range of 1-5 was categorized as Low valence/arousal state and rating in the range of 5-9 was categoriaed as High valence/arousal states. The two level mapping (with a threshold of 5) on the DEAP dataset is in accordance with Koelstra et. al [16].

III. Method

For our proposed framework, emotion recognition encompass three main tasks: signal preprocessing, extraction of features, and classification of the emotions (see Fig. 1).

A. EEG Signal Pre-Processing

The EEG data was processed excluding the 3-second pre-trial baseline. The EEG data were then low-pass filtered (45 Hz) and the artefacts were removed using Independent Component Analysis. EEG data were then subtracted by common average reference.

B. Feature Extraction

A lot of research is reported in the literature to pick the most effective EEG channels to recognise human emotions. It is reported that the right and left frontal areas of the brain have the most significant contributions during the experience of emotions [14], [18], [19]. In our experiments, we have employed four EEG electrodes: Fp1, Fp2, F3 and F4 to infer emotions. Fig. 2 shows the 10-20 electrode placement. The electrodes marked in yellow in the figure were used for analysis.

Welch's average periodogram method [20] has been implemented on those four channels for estimating PSD. In Welch's average periodogram method we divide the time domain signal data into successive blocks/sections to form the periodogram for each block/sections and then we take the averages of the spectra for each block/section, which leads to reduce the effects of temporarily unstable signals or noises from the signal.

Brain wave comprises of five principal frequency bands: delta (0.5-4 Hz), theta (4-7.5 Hz), alpha (8-13 Hz), beta (13-30 Hz) and gamma (30-45 Hz). Delta waves are mainly associated with deep sleep [21], we are excluding it for our classification problem.

We have taken mean power of each frequency band associated with each channel as a statistical features as follows:

$$Mean(\mu_x) = \frac{1}{N}\sum_{i=1}^{N} X_i$$

where, X_i is the spectral data obtained after the PSD for a particular band and a particular channel, N is the total no of spectral data points of that particular frequency band and particular channel, and μ_x represents the mean power of the frequency band.

Here for each EEG electrode, we have 4 frequency bands. The mean power for each band for each channel were extracted. Hence, the feature vector for each trial can be represented as follows:

feature_vector = < Fp1_theta_mean, Fp2_theta_mean, F3_theta_mean, F4_theta_mean, Fp1_alpha_mean, Fp2_alpha_mean, F3_alpha_mean, F4_alpha_mean, Fp1_beta_mean, Fp2_beta_mean, F3_beta_mean, F4_beta_mean, Fp1_gamma_mean, Fp2_gamma_mean, F3_gamma_mean, F4_gamma_mean, >

The feature extraction process for each subject yields 40(trials)*16(features).

C. Classification of Emotional States

To evaluate the correlation between the EEG and emotional states, the classification into different emotional states have been performed using MLP. GA has been used to attain an optimized neural network architecture (See Fig. 1). The output is an optimized MLP which classifies a. two classes emotions viz. Low/High Valence and Low/High Arousal and b. four classes emotions viz. HVLA/HVHA/LVLA/LVLA.

In GA, multiple solutions are computed for a given problem and are evolved through a number of generations. Each solution possess the parameters that help to improve the performance. In case of Neural Networks, weights in all the layers plays a vital role in attaining high accuracy. Hence, in our experiment, a single solution of GA comprised of all weights in the Neural Network.

Individuals in the population are composed of numbers of neurons in the hidden layers. Number of neurons in the

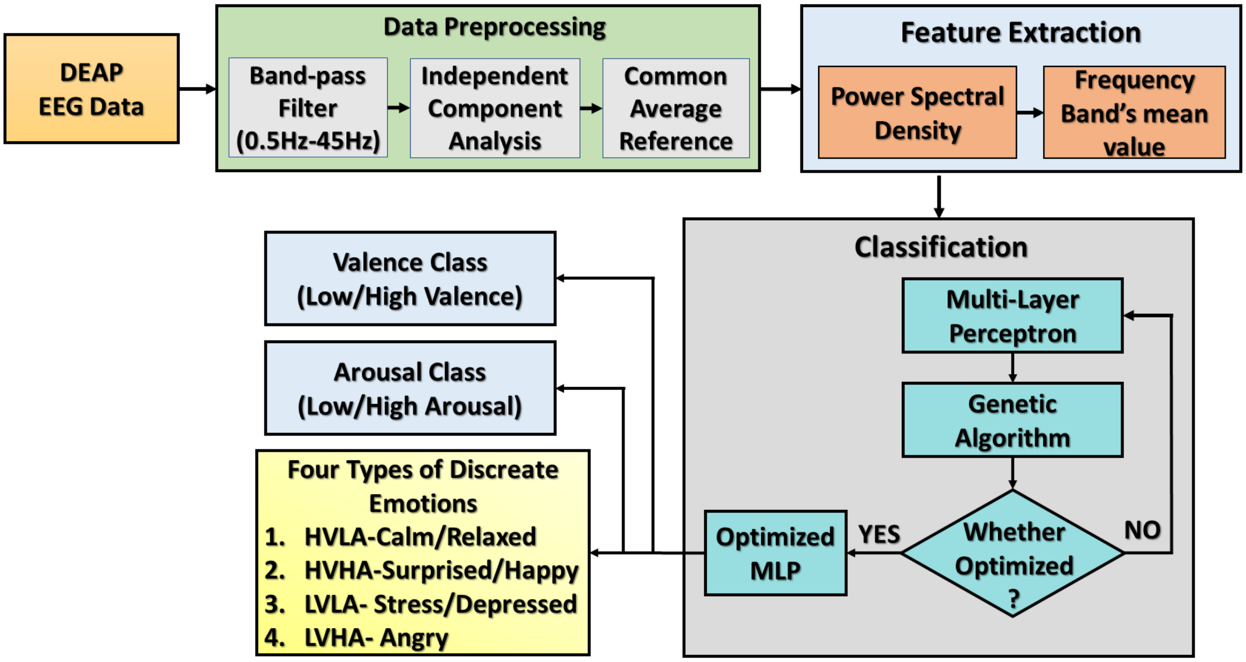

Fig. 1. The proposed model of Emotion Recognition

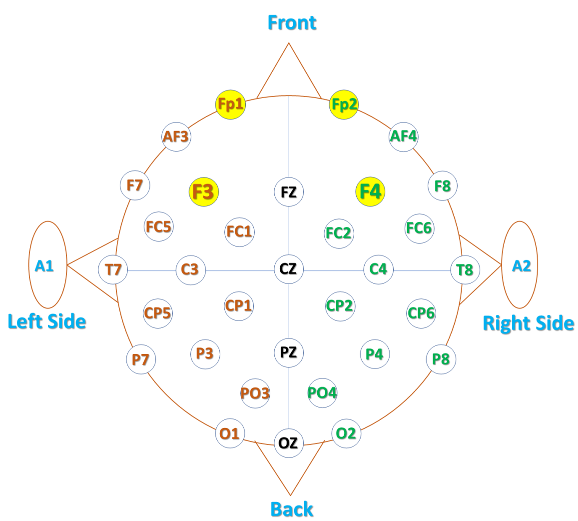

Fig. 2. EEG electrode locations according to the 10-20 International system used for recording EEG data in Deap Dataset. The yellow marked electrodes were used for our experiments.

hidden layers are the genes of the chromosome structure and those genes are basically a discrete integer value. To represent those discrete integer valued genes, integer representation or integer encoding is desirable. An individual data structure will look like

<no. of neurons in 1st layer,
no. of neurons in 2nd hidden layer>

The Neural Network used in our experiment has one input layer, two hidden layers and one output layer. GA algorithm evolve the generation through three different phases: Selection, Crossover, and Mutation.

1) Phase 1: Selection: The algorithm selects the best individuals by their fitness value. For calculating the fitness value, the MLP classifier[1] is trained with the following parameters:

1) In our algorithm, we have chosen the Activation function for the hidden layer randomly from the list of different activation functions: Tanh (hyperbolic tangent), Sigmoid (Logistic), Linear (Identity) and ReLU (Rectified Linear Unit).
2) Weight optimization is also randomly chosen from the aforesaid list of weight optimizer: L-BFGS [22], Stochastic Gradient Descent (SGD) [23], and ADAM [24].
3) We have two hidden layers but the size of the layer has been randomly chosen in between 2 to 50.
4) For converging the algorithm, we have used hybrid convergence criteria. We have used 1000 iterations to terminate and while training when the accuracy score is not improving in all of the previous 80 numbers of iterations then we are terminating the MLP classifier training process.

Rest of the parameters have been kept as the default values as mentioned in the Sklearn Python package[1].

[1]https://scikit-learn.org/stable/modules/generated/sklearn.neural_network.MLPClassifier.html

The accuracy of the MLP classifier is considered as the fitness value of the individual. Based on the fitness value, the best individuals for the next generation has been chosen. In this classification task, objective of the genetic algorithm is to maximize the accuracy of the neural network.

2) Phase 2: Crossover and Mutation:

a) Crossover Operator: Crossover is an operator used to combine the information of two parents to generate new individuals. The recombination used here is Single Point Crossover.

b) Mutation Operator: To further increase genetic variability and avoid local minima, another operator used is mutation.

Literature reported a lot of prior research to tune the value of different parameter to get the optimum solution using GA. The parameters that we need to take care for the classification problem are Crossover probability, Mutation probability and the population size in each generation.

Generally, there are three different ways to find those parameter values [25]. DeJong [26] suggested the optimal range values for the population size is in between 50 to 100 individuals. He also stated that the mutation probability must be very less for the proposed population size as high mutation probability leads the search to be random. For the crossover parameter rate, it must be intermediate in the range of 0 to 1.

We have taken a high cross over rate of 0.95 and low mutation rate of 0.001 respectively. The number of populations for each generation is taken as 50 as refered by DeJong [26].

Further, in our experiments, we have taken 10 generations, as we observed that we got the optimal values in 10 generations. Thereafter, the values are approximately same.

Illustrative Example

A simple and brief example of GA based optimized MLP for one generation is illustrated here. Let us consider an initial population with 6 individuals as follows:

[['81', '33'], ['40', '45'], ['20', '50'], ['8', '14'], ['25', '37'], ['35', '28']]

where each individual is enclosed by square brackets; first integer is the no. of neurons in the first hidden layer and second is the no. of neurons in the 2nd hidden layer. Let us consider the fitness value attained for each of the individual is: [0.875, 0.75, 0.71, 0.375, 0.75, 0.75].

Sorting the population based on fitness value will yield the following:

[[0.875, hidden_layer_sizes=(81, 33)], [0.75, hidden_layer_sizes=(40, 45)], [0.75, hidden_layer_sizes=(25, 37)], [0.75, hidden_layer_sizes=(35, 28)], [0.71, hidden_layer_sizes=(20, 50)], [0.375, hidden_layer_sizes=(8, 14)]]

Let us consider Parent 1 as [[81, 33], [40, 45],[25, 37]] and Parent 2 as [[35, 28],[20, 50],[8, 14]]. After crossover, Child 1 will be as [[81, 28], [40, 50],[25, 14]] and Child 2 as [35, 33],[20, 45],[8, 37]]. Once crossover is completed, mutation will be performed which will create randomness in the two child individuals. Let us consider after mutation the two child individuals are: [[81, 30], [42, 50],[25, 16]] and Child 2 as [35, 35],[22, 45],[8, 39]].

In this process, the algorithm iterates for 10 generations to select the best neural network architecture.

IV. Experimental Results

The samples were randomly split into training and testing partitions with 80% observations in the training portion and 20% observations in the testing portion.The efficacy of our proposed model is compared with different traditional machine learning methods(See Table I). The first column of the table shows the different classifiers employed on Deap Dataset, the second and third columns portrays the performance of the classifiers into classifying Low/High Valence and Low/High Arousal respectively in terms of Accuracy, Precision and Recall, while the fourth column presents the classification results of for classifying 4 types of discrete emotions viz. HVLA/HVHA/LVLA/LVLA in terms of Accuracy, Precision and Recall.

10-fold cross validation method is carried out with the proposed model to compare it with the state-of-the-art methods as mentioned in Table II. The first and second column of the table portrays the work carried out by researchers and the year of publication, while the third and fourth column shows the features and the classifiers used in the respective works. The fifth column shows the Accuracy obtained while classifying Low/High Valence and Low/High Arousal emotional states.

It is seen from Table I that our proposed model outperforms when compared to other machine learning methods in classifying Low/High valence, Low/High Arousal as well as the four emotional classes (HVLA/HVHA/LVHA/LVLA) with 88.28 %, 90.63% and 81.25% respectively.

While comparing the performance of our proposed model with different state-of-art methods (See Table II), it is seen that our proposed methodology outperforms the existing results with 91.10 % and 91.02% 10-fold cross-validation classification accuracy for Low/High Valence and Low/High Arousal emotional states respectively. It is also observed that only the Deep Learning models proposed by Liu et al. [30] attain better performance than our proposed model.

Table III presents the summary of the performance of GA optimized MLP Classifier.

V. Discussion

The results show the enhanced performance of the proposed EEG-based Emotion Recognitione System. The improved performance of the proposed methodology portrays the benefits of using GA optimized MLP. The comparisons were carried out with different machine learning algorithms (Table I) and the state-of-the-art methods (Table II) to present the benefits of the proposed framework. It is seen from Table I that the proposed framework achieved higher classification accuracy, precision and recall as compared to the traditional machine learning approaches.

TABLE I
COMPARISON OF THE PERFORMANCE OF *GA-MLP* WITH DIFFERENT MACHINE LEARNING ALGORITHMS BASED ON 80-20 SPLIT

Classsifier	Valence			Arousal			4−types of emotions		
	Precision	Recall	Accuracy	Precision	Recall	Accuracy	Precision	Recall	Accuracy
SVM (3rd order polynomial kernel)	64.40	80.38	60.16	60.27	70.45	66.80	25.31	28.18	41.66
SVM (RBF kernel)	47.86	76.43	56.64	52.73	70.31	66.4	24.87	27.95	40.63
Random Forest	63.22	67.47	63.28	58.77	69.97	63.67	38.24	38.02	43.40
XgBoost	67.71	72.64	64.84	67.1	73.75	68.98	38.85	38.47	44.23
k-Nearest Neighbors	63.35	70.8	64.45	54.88	73.23	62.89	41.68	35.55 44.28	
Linear Regression	65.06	73.10	67.20	60.62	70.12	61.72	38.26	34.72	42.19
ours	**90.23**	**93.54**	**88.28**	**93.13**	**94.32**	**90.63**	**84.87**	**73.00**	**81.25**

TABLE II
COMPARISON OF THE PERFORMANCE OF *GA-MLP* WITH THE EXISTING METHODS

Reference	Year	Features	Machine Learning		Accuracy	
			Classifier	Evaluation Method	Valence	Arousal
Koelstra et al. [16]	2011	Power spectral features	Naive Bayes	leave-one-trial-out validation	57.6	62
Kandemir at al. [6]	2014	Spectral power	MKL	Cross validation	66	65
Godin et al. [7]	2015	Spectral power and other physiological signals	Naive Bayes	Leave one out cross validation	62	57
Nitin et al. [1]	2016	Bispectrum	SVM	Holdout Partitioning	61.17	64.84
Zhuang et al. [27]	2017	The first difference of time series	SVM	leave one trial out validation	72	69.1
Alhagry et al. [28]	2017	LSTM	LSTM	4 fold cross validation	85.45	85.65
Arevalillo-Herraez et al. [15]	2019	Power spectral features	SVM	leave-one-subject-out validation	64	54
Hao Chao et al. [29]	2019	Multiband Feature Matrix	CapsNet	10-fold cross-validation	66.7	68.3
Liu et al. [30]	2020	Multi-level features	CapsNet	10-fold cross validation	97.97	98.31
Luo et al. [31]	2020	Discrete wavelet transform (DWT), variance and Fast Fourier transform (FFT)	Spiking Neural Networks	80-20 split	78	74
Li et al. [9]	2021	Spectrogram Representation	TCN	leave one out cross validation	69.1	71
Ours		Power Spectral Density	MLP (optimized by GA)	10-fold cross validation	**91.10**	**91.02**

TABLE III
OVERALL PERFORMANCE OF *GA-MLP* CLASSIFIER

Evaluation Method	Valence			Arousal			4−types of emotions		
	Precision	Recall	Accuracy	Precision	Recall	Accuracy	Precision	Recall	Accuracy
Randomly splitted training and testing with 80:20 partitions	90.23	93.54	88.28	93.13	94.32	90.63	84.87	73.00	81.25
10 fold cross validation	81.67	85.18	91.10	81.58	85.76	91.02	81.02	89.12	83.52

The proposed methodology attained an average 10-fold cross-validation accuracy of 91.10 % and 91.02% with PSD features, which is higher than the state-of-the-art methods for two class emotion classification on DEAP dataset to the best of our knowledge. It is also seen that only the Deep Learning models [30] achieved better performance than our proposed model. One acknowledged drawback of the Deep Learning Model is the high processing time and hence is computationally expensive to train. This may pose an extremely substantial limitation for the training phase of every BCI model.

The performance of the classifier also relies on the band-pass filters and the number of selected features. Thus picking up the appropriate frequency bands, and suitable and stable features plays a key role in enhancing the performance of the methodology.

VI. CONCLUSION

The paper presents an enhanced automated emotion recognition paradigm using GA optimized MLP. The proposed paradigm employs power spectral density features extracted from four electrodes of frontal lobe of the brain namely, Fp1,Fp2, F3 and F4. We have presented this as classification performance maximisation problem. DEAP dataset has been tested with different set of machine learning algorithms in terms of accuracy, precision and recall. The results with the proposed model on DEAP Dataset portrays that it performs better than that of traditional machine learning algorithms. The results also reveals that proposed method yields better performance as compared to the state-of-the art methods.

In future we plan to validate the proposed approach on other emotion recognition datasets and to test it with different combinations of features.

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