Classification of EEG signals for facial expression and motor execution with deep learning

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ABSTRACT

Recently, algorithms of machine learning are widely used with the field of electroencephalography (EEG) brain-computer interfaces (BCI). The preprocessing stage for the EEG signals is performed by applying the principle component analysis (PCA) algorithm to extract the important features and reducing the data redundancy. A model for classifying EEG, time series, signals for facial expression and some motor execution processes had been designed. A neural network of three hidden layers with deep learning classifier had been used in this work. Data of four different subjects were collected by using a 14 channels Emotiv EPOC+ device. EEG dataset samples including ten action classes for the facial expression and some motor execution movements are recorded. A classification results with accuracy range (91.25-95.75%) for the collected samples were obtained with respect to: number of samples for each class, total number of EEG dataset samples and type of activation function within the hidden and the output layer neurons. A time series EEG signal was taken as signal values not as image or histogram, analysed and classified with deep learning to obtain the satisfied results of accuracy.

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1. INTRODUCTION

It is well known that, the system which connects human brain signals with appliances or devices without requiring of any physical contact is called brain-computer interfaces (BCI). It has been seen as a new way for communication, where the brain activity has been used as a reflected form by electric brain signals to manage external system such as computers, wheelchairs, switches, or neuro prosthetic extensions [1]-[6].

Electroencephalography (EEG) is the process of fetching the electrical brain's signals and recording them, so the activity of human can be analyzed making the real processing of the brain clear to the user. Electrodes are put on the human scalp, in an easy way, to collect brain's electrical signals. An EEG signal is band limited in frequency (0.1-60 Hz), EEG signals are modeled and classified into five types: (theta, delta, beta, alpha, and gamma waves), which are responsible to capture different associated brain activities inside the brain [7], [8]. EEG signals contain a high redundancy in the collected data, so the important stage before being classifying those signals, is feature extraction stage. In fact, a feature illustrates a distinctive attribute, identifiable measure, and functional element getting from a segment of samples. Feature extraction used to maintain the significant information in the signal and minimizing their lost as much as possible, as well as to simplify the needed resources for describing the huge amount of data in an accurate manner. So, this will lead to a simple implementation that reduces the processing cost for the information, and eliminates the need for data compression [9]-[14]. In this work, principle component analysis (PCA) method is used for unsupervised feature extraction process. This method is a descriptive statistical technique which describes the differences between the samples of the dataset and the most correlated samples. PCA detects the principle component of dataset of the signal, so it will perform the dimension reduction of the data [15].

Algorithms for classifying EEG-based BCIs were classified into four main classes: matrix and tensor, adaptive, deep learning, and transfer learning classifiers as well as a few other diverse classifiers [2], [12], [16]-[20]. In EEG researches, machine learning had been used to discover the related information for neuroimagingý and neural classification. The advances in machine learning and the availability of huge EEG data sets led to deep learning deployment in analyzing EEG signals and in the field of understanding brain functionality by defining collected information inside it [6], [21]-[24]. The use of deep learning with EEG applications in genera,l fell into five groups: motor imagery,emotion recognition, mental task workload, seizure observation, event related potential (ERP) tasks detection, and sleep states recording [25].

2. RESEARCH METHOD

The work in this paper focuses on EEG signal features to identify the EEG signals for facial expressions (FEs) and some motor execution actions. FEs include: surprise, smile, left wink, right wink, and mouth opened. While, motor execution actions include: right hand lifting, left hand lifting, right rotating of head, left rotating of head , and clapping. All these signals first collected by Emotiv EPOC+ 14 channel mobile brainwear headset, and fetched by the licensed software of Emotiv Pro with python environment. A model for classifying those signals had been designed. Figure 1 shows the research methodology block diagram. The detail of each step will be explained in the next subsections.

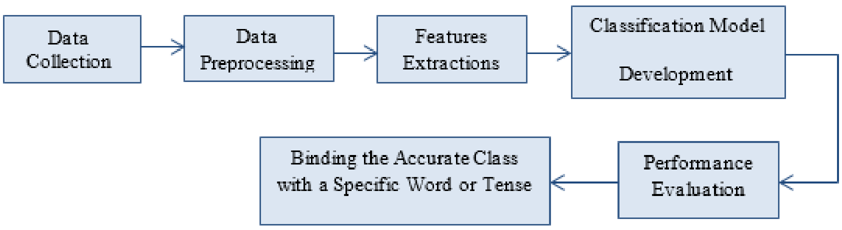

Figure 1. Research methodology block diagram

2.1. Data collection

The first stage of research methodology begins with collecting dataset samples by using Emotiv Epoc+ head set device with 14 channels extended around the head. The data was collected from four subjects with different ages (10-50 years), males and females while they doing the required facial expressions and the motor execution actions. The EEG signals were recorded by the monthly licensed Emotiv software (Emotiv Pro) and saved as excel files (.csv files) to be used later in training the neural network within python environment. during the recording process about 6487 EEG samples were collected. Table 1 shows some samples of the collected EEG data for lifting left hand for one subject.

2.2. Data pre-processing

This stage is the artifacts removal of EEG signals, which is doing by the Emotiv headset itself, where the data is recorded directly as it is received from the headset. There is a good amount of signal processing and filtering in the headset to remove artifacts and harmonic frequencies. So, the signals appear clean when we gained a good contact quality. The signals had been sampled at 2048 Hz sampling frequency, and then applied to a dual notch filter at 50 Hz and 60 Hz as well as a low pass filter at 64 Hz cutoff frequency. Finally, the data was filtered down to 128 or 256 Hz.

2.3. Feature extraction

In this stage, the obtained preprocessed data from Emotiv headset is processed with PCA algorithm to improve the classifier's accuracy. PCA is a technique used for reduction of dimensionality of the large data sets. This can be achieved by converting the huge set of variables into a smaller one which contains most of the information in the large set [15], [26]. We have 6487 samples from each one of the 14 channels of the headset. To implement PCA, the mean values must be computed firstly, so that we can compute the standardization (Z) of the initial values of the dataset, as in (1), to transform all the variables to the same range [26].

$$Z = \frac{\text{Value}-mean}{\text{Standard deviation}} \tag{1}$$

Table 1. EEG datasets samples example for left hand lifting from Emotiv headset

EEG.AF3	EEG.F7	EEG.F3	EEG.FC5	EEG.T7	EEG.P7	EEG.O1	EEG.O2	EEG.P8	EEG.T8	EEG.FC6	EEG.F4	EEG.F8	EEG.AF4
4627.308	6175.769	7376.923	7018.461	7112.82	3223.461	3223.846	1274.103	3862.051	629.7436	8023.974	7521.795	8334.743	3344.359
7502.436	5615.513	6324.231	6095.513	1287.821	7299.872	7261.41	6439.615	1462.692	7645.513	3923.974	3256.539	107.6923	6799.615
5662.18	5518.461	4492.308	3957.436	5409.359	4291.667	715.6411	4300.897	3987.821	6205.385	7224.103	7947.18	3203.974	4669.103
5591.566	5528.655	4493.29	4027.343	5410.139	4219.964	723.8898	4265.287	3929.946	6159.411	7237.689	7829.861	3138.312	4696.339
5520.952	5538.849	4494.271	4097.25	5410.919	4148.262	732.1386	4229.675	3872.07	6113.437	7251.276	7712.542	3072.649	4723.576
5450.338	5549.042	4495.254	4167.158	5411.699	4076.56	740.3873	4194.064	3814.195	6067.463	7264.864	7595.224	3006.986	4750.813
5379.725	5559.236	4496.236	4237.065	5412.479	4004.858	748.6361	4158.453	3756.32	6021.489	7278.451	7477.905	2941.323	4778.05
5309.111	5569.43	4497.218	4306.972	5413.26	3933.156	756.8849	4122.842	3698.445	5975.516	7292.038	7360.586	2875.66	4805.287
5238.497	5579.624	4498.2	4376.879	5414.04	3861.454	765.1337	4087.231	3640.57	5929.542	7305.625	7243.268	2809.997	4832.523
5167.883	5589.817	4499.182	4446.787	5414.82	3789.752	773.3824	4051.62	3582.695	5883.568	7319.212	7125.949	2744.334	4859.76
5097.27	5600.011	4500.164	4516.694	5415.6	3718.05	781.6312	4016.009	3524.82	5837.594	7332.799	7008.631	2678.672	4886.997
5026.656	5610.205	4501.146	4586.601	5416.38	3646.347	789.88	3980.398	3466.945	5791.62	7346.386	6891.312	2613.009	4914.233
4956.042	5620.398	4502.127	4656.508	5417.16	3574.646	798.1287	3944.787	3409.07	5745.646	7359.973	6773.994	2547.346	4941.47
4885.428	5630.592	4503.11	4726.416	5417.94	3502.943	806.3775	3909.176	3351.195	5699.673	7373.56	6656.675	2481.683	4968.707
4814.814	5640.786	4504.092	4796.323	5418.721	3431.241	814.6263	3873.565	3293.32	5653.699	7387.147	6539.356	2416.02	4995.944

The second step of PCA is to compute the covariance matrix, to check if there is any relationship or correlation between the variables of the dataset to reduce the information redundancy as much as possible. First of all, the covariance between all potential pairs of the initial dataset variables was computed using (2), in order to instruct the entries of the covariance matrix, which is a p×p symmetric matrix.

$$cov[X,Y] = \frac{\sum_{i=1}^{p} X_i Y_i - p\bar{X}\bar{Y}}{p} \tag{2}$$

where;
$\bar{X}$ means the mean value of variable X
p is the dimension's number

The third step of PCA is to compute the eigenvectors and eigenvalues for the dataset values, in order to locate their principal components. The principal components are the new uncorrelated variables and have the most of information about the dataset is compressed in the first components and it gradually descends. The fourth step is to find the feature vector, which is represented by matrix with columns of eigenvectors for the required component from the previous step. This will lead to keep only k components (eigenvectors) instead of the total number of them (p). The final step of PCA is the reformation of the original dataset axis to the axis of the selected principal components, by multiplying the transpose of feature vector as in (3):

$$\text{Final dataset} = \text{FeatureVector}^{T} * Z^{T} \tag{3}$$

2.4. Classification model development

In this work, a neural network with deep learning was built to classify the EEG signals for the ten actions including facial expression and motor execution. The main facility of applying deep learning mechanism is that, it often continues to improve as the size of the dataset increases. This task was implemented with spider3.3.1\Python environment by importing Keras libraries, which is a deep learning API written in Python. A Sequential model, which is a linear stack of layers, with 3 hidden layers which contain (1024, 512 and 256) neurons respectively was built, with activation function of type tanh(X). The output layer consists of 10 output neurons with activation function of type softmax(X). Figure 2 shows the sequential model of the work.

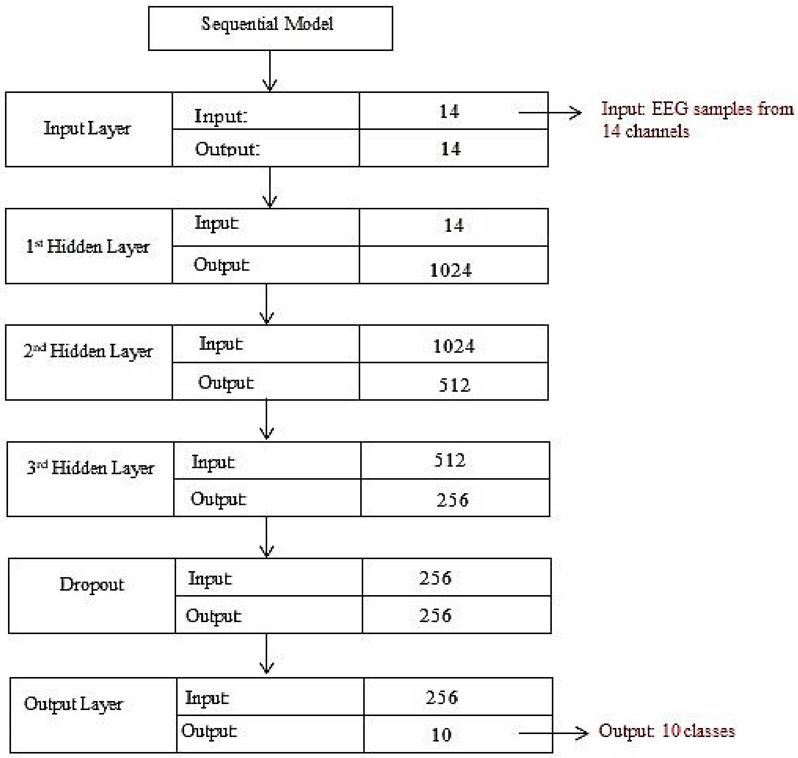

Figure 2. Sequential model representation

2.5. Preformance evaluation

The collected dataset samples are divided into two groups: 80% training dataset and 20% testing dataset to construct the sequential model of the classification to be tested. The performance is evaluated in each epoch with respect to two parameters: loss-values and accuracy of the classification. Accuracy calculates the percentage of predicted values (yPred) that match with actual values (yTrue). When running the model, important parameters effect must be observed since they significantly affect the accuracy and the processing time of the classification process. The parameters include: number of samples for each class, total number of samples, and the type of the activation function applied within the hidden and output layers neurons. When using an equal number of samples for each class, this will give better classification accuracy than those with a random number of samples per class as well as to the obvious reduction in the number of epochs required to train the neural network, and hence the overall processing time will be reduced, as shown in Figure 3.

The total number of samples is the size of the collected samples, as this size increases the deep learning will give a better classification results but this increase cannot be continued since the processing time will be increased as well as to the stability of the accuracy results to a specific value. Finally, there are many types of activation functions such as: sigmoid, relu, softmax, tanh and exponential activation function, so after implementing those types within the hidden layer's neurons. The most acceptable accuracy level was obtained when using tanh(x) activation function, while the softmax(x) was used within the output layers neurons. Root mean square (RMS) optimizer was used to minimize the error while learning the neural network.

Total no. of samples	Accuracy % (epoch 150)	Accuracy % (epoch 100)	No.of samples \class
6487	93.04%	91.75%	random no. of samples/class
5943	91.94%	92.43%	random no. of samples/class
4168	93.01%	94.24%	random no. of samples/class
3173	88.73%	93.14%	random no. of samples/class
2270	93.77%	93.72%	random no. of samples/class
2001	93.56%	93.00%	200 samples / class
973	94.47%	95.75%	100 samples / class
751	93.33%	93.00%	75 samples / class
501	95.25%	95.00%	50 samples / class
276	92.73%	93.64%	25 samples / class
101	92.50%	91.25%	10 samples / class

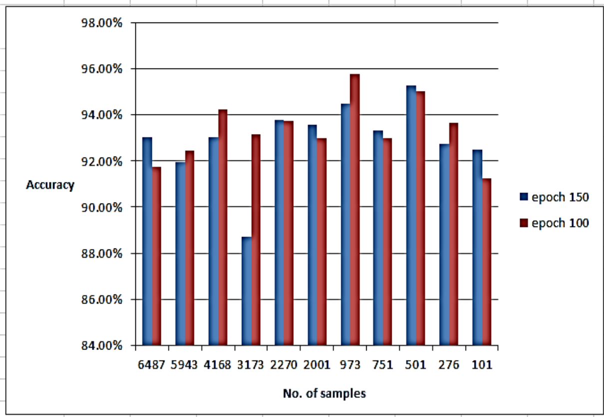

Figure 3. Classification accuracy levels

3. RESULTS AND DISCUSION

Firstly, EEG signals classification of 10 classes of facial expressions and motor executions actions was implemented for four subjects. The performance of the classification model was evaluated, as mentioned in the previous section. The training accuracy is ranging from (91.25% to 95.75%), and the best results were obtained when training the model with 100 samples/class with 973 total number of samples. These results will be used in the future work with many applications such as binding those classes with specific tenses or words in order to help the speechless persons to represent their thoughts, so the main goal of this paper is to design a simple EEG classifier, to be utilized for helping the speechless persons, so that giving them the ability to represent their intended thoughts.

4. CONCLUSIONS

In this paper, ten classes of EEG time series signal values were classified by building deep neural network and implementing deep learning techniques. A specialized dataset samples was recorded. In the offline training, the classification accuracy results reached to 95.75% with minimizing cost of computation and storage requirements by applying only the PCA algorithm on EEG data set signals values without any other filtering as well as to feed the deep nueral network with EEG signal values not as image or histogram.

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