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# A PROPOSED SIGN LANGUAGE MODEL FOR SPEECHLESS PERSONS USING EEG SIGNALS

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***Abstract*- Recently, algorithms of machine learning are widely used in the field of electroencephalography (EEG) -Brain-Computer interfaces (BCI). In this paper, a sign language software model based on the EEG brain signal was implemented, to help the speechless persons to communicate their thoughts to others. The preprocessing stage for the EEG signals was performed by applying the Principle Component Analysis (PCA) algorithm to extract the important features and reducing the data redundancy. A model for classifying ten classes of EEG signals, including Facial Expression (FE) and some Motor Execution(ME) processes, had been designed. A neural network of three hidden layers with a deep learning classifier had been used in this work. Data set from four different subjects were collected using a 14 channels Emotiv epoc + device. A classification results with an accuracy of 95.75% were obtained for the collected samples. An optimization process was performed on the predicted class with the aid of the user, and then the signing class will be connected to the specified sentence under a predesigned lock-up table.**

## I. 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 BCI. It has been seen as a new way for communication, where the Brain activity has been used as a refected form by electric brain signals to control external systems such as computers, wheelchairs, switches, or neuroprosthetic extensions [1]- [6]. Electroencephalographic (EEG) signals mean that the continuous potential or voltage fluctuation collected in a non- invasive manner from a human's scalp. A special EEG headset having many EEG sensors (electrodes) put on special points on the head depending on the international 10/20 system electrode pattern. The obtained signal is interpreted as a randomly determined time-series signal with multiple lengths and tiny amplitudes (tens of microvolts)[2], [3]. EEG signals are modelled 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 the 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 its loss as much as possible, as well as to simplify the needed resources for describing the huge amount of data accurately. So, this will lead to a simple implementation that reduces the processing cost for the information, and eliminates the need for data compression [3], [9]-[13]. In this work, Principle Component Analysis (PCA) method was used for the unsupervised feature extraction process. This method is a descriptive statistical technique that describes the differences between the samples of the dataset and the most correlated samples. PCA detects the principal component of the dataset of the signal, so it will perform the dimension reduction of the data [14]-[16]. 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 [16]-[20]. In EEG researches, machine learning had been used to discover the related information for neuroimaging and

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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 [17], [18], [22]-[25].

## II. Research Methodology

The work in this paper focuses on EEG signal features to identify the EEG signals classes 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, head rotating to right, head rotating to left and clapping. All these signals first collected by EMOTIV EPOC + 14 Channel Mobile Brain wear headset, and fetched by the licensed software of EMOTIV Pro with python environment. A model for classifying those signals had been designed. Fig. 1 shows the research methodology block diagram. The details of each step will be explained in the next subsections.

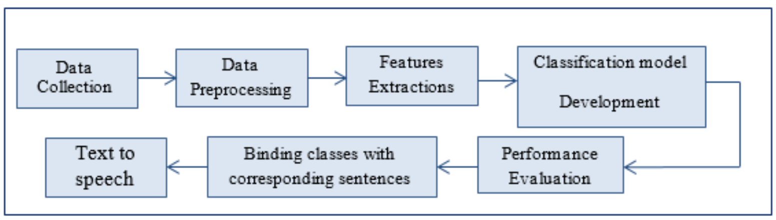


Figure 1: Research methodology block diagram

### A. *Data Collection*

The EEG signal data set samples were collected using 14 channels EMOTIV Epoc + headset device with a sampling frequency of 128 Hz and a built-in digital notch filter at 50 Hz and 60 Hz and a digital band-pass filter of 0.16-45 Hz. The 14 channels extended around the head according to international 10/20 system electrode pattern placement as shown in Fig. 2. The data was collected from four subjects of different ages (10-50 years), males and females while they are doing of 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 the python environment. During the recording process, about 6487 EEG samples were collected. Table I shows some samples of the collected EEG data for lifting the left hand for one subject.

### B. *Data Pre-Processing*

This stage is the removal of the artefacts 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 sampled down to 128 Hz or 256 Hz.

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Figure 2: International 10/20 system electrode pattern placement

TABLE I
EEG Datasets Samples for Left-Hand Lifting

| | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | title:samples _exportAreej | start timestam p:159829 4889.908 185 | stop timestam p:159829 4959.508 452 | headset type:EPO CPLUS | headset serial:3B 9AD9B0 | headset firmware :3011 | subject name:dr. eija-2019 | channels: 165 | sampling rate:eeg_128;mot_ 64;pm_0.1;pow_8 | samples: 283 | version:2 .0 | | | | | | | | |
| 2 | Timestamp | EEG.Coun | EEG.Interp | 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 | EEG.RawC | E |
| 3 | 1598294890 | 34 | 0 | 4627.308 | 6175.769 | 7376.923 | 7018.461 | 7112.82 | 3223.461426 | 3223.846 | 1274.103 | 3862.051 | 629.7436 | 8023.974 | 7521.795 | 8334.743 | 3344.359 | 47606 | |
| 4 | 1598294893 | 243 | 0 | 7502.436 | 5615.513 | 6324.231 | 6095.513 | 1287.821 | 7299.871582 | 7261.41 | 6439.615 | 1462.692 | 7645.513 | 3923.974 | 3256.539 | 107.6923 | 6799.615 | 57867 | |
| 5 | 1598294894 | 141 | 0 | 5662.18 | 5518.461 | 4492.308 | 3957.436 | 5409.359 | 4291.666504 | 715.6411 | 4300.897 | 3987.821 | 6205.385 | 7224.103 | 7947.18 | 3203.974 | 4669.103 | 36448 | |
| 6 | 1598294894 | 14 | 1 | 5591.566 | 5528.655 | 4493.29 | 4027.343 | 5410.139 | 4219.964355 | 723.8898 | 4265.287 | 3929.946 | 6159.411 | 7237.689 | 7829.861 | 3138.312 | 4696.339 | 60652 | |
| 7 | 1598294894 | 15 | 1 | 5520.952 | 5538.849 | 4494.271 | 4097.25 | 5410.919 | 4148.262207 | 732.1386 | 4229.675 | 3872.07 | 6113.437 | 7251.276 | 7712.542 | 3072.649 | 4723.576 | 18343 | |
| 8 | 1598294894 | 16 | 1 | 5450.338 | 5549.042 | 4495.254 | 4167.158 | 5411.699 | 4076.560303 | 740.3873 | 4194.064 | 3814.195 | 6067.463 | 7264.864 | 7595.224 | 3006.986 | 4750.813 | 35825.53 | |
| 9 | 1598294894 | 17 | 1 | 5379.725 | 5559.236 | 4496.236 | 4237.065 | 5412.479 | 4004.858154 | 748.6361 | 4158.453 | 3756.32 | 6021.489 | 7278.451 | 7477.905 | 2941.323 | 4778.05 | 35618.04 | |
| 10 | 1598294894 | 18 | 1 | 5309.111 | 5569.43 | 4497.218 | 4306.972 | 5413.26 | 3933.156006 | 756.8849 | 4122.842 | 3698.445 | 5975.516 | 7292.038 | 7360.586 | 2875.66 | 4805.287 | 35410.55 | |
| 11 | 1598294894 | 19 | 1 | 5238.497 | 5579.624 | 4498.2 | 4376.879 | 5414.04 | 3861.453857 | 765.1337 | 4087.231 | 3640.57 | 5929.542 | 7305.625 | 7243.268 | 2809.997 | 4832.523 | 35203.06 | |
| 12 | 1598294894 | 20 | 1 | 5167.883 | 5589.817 | 4499.182 | 4446.787 | 5414.82 | 3789.751709 | 773.3824 | 4051.62 | 3582.695 | 5883.568 | 7319.212 | 7125.949 | 2744.334 | 4859.76 | 34995.57 | |
| 13 | 1598294894 | 21 | 1 | 5097.27 | 5600.011 | 4500.164 | 4516.694 | 5415.6 | 3718.049561 | 781.6312 | 4016.009 | 3524.82 | 5837.594 | 7332.799 | 7008.631 | 2678.672 | 4886.997 | 34788.09 | |
| 14 | 1598294894 | 22 | 1 | 5026.656 | 5610.205 | 4501.146 | 4586.601 | 5416.38 | 3646.347412 | 789.88 | 3980.398 | 3466.945 | 5791.62 | 7346.386 | 6891.312 | 2613.009 | 4914.233 | 34580.6 | |
| 15 | 1598294894 | 23 | 1 | 4956.042 | 5620.398 | 4502.127 | 4656.508 | 5417.16 | 3574.645508 | 798.1287 | 3944.787 | 3409.07 | 5745.646 | 7359.973 | 6773.994 | 2547.346 | 4941.47 | 34373.11 | |
| 16 | 1598294894 | 24 | 1 | 4885.428 | 5630.592 | 4503.11 | 4726.416 | 5417.94 | 3502.943359 | 806.3775 | 3909.176 | 3351.195 | 5699.673 | 7373.56 | 6656.675 | 2481.683 | 4968.707 | 34165.62 | |
| 17 | 1598294894 | 25 | 1 | 4814.814 | 5640.786 | 4504.092 | 4796.323 | 5418.721 | 3431.241211 | 814.6263 | 3873.565 | 3293.32 | 5653.699 | 7387.147 | 6539.356 | 2416.02 | 4995.944 | 33958.13 | |
| 18 | 1598294894 | 26 | 1 | 4744.201 | 5650.979 | 4505.074 | 4866.23 | 5419.501 | 3359.539063 | 822.8751 | 3837.954 | 3235.445 | 5607.725 | 7400.734 | 6422.038 | 2350.357 | 5023.181 | 33750.64 | |
| 19 | 1598294894 | 27 | 1 | 4673.587 | 5661.173 | 4506.056 | 4936.138 | 5420.281 | 3287.836914 | 831.1238 | 3802.343 | 3177.57 | 5561.751 | 7414.321 | 6304.719 | 2284.695 | 5050.417 | 33543.15 | |
| 20 | 1598294894 | 28 | 1 | 4602.973 | 5671.367 | 4507.038 | 5006.045 | 5421.061 | 3216.134766 | 839.3726 | 3766.732 | 3119.695 | 5515.777 | 7427.908 | 6187.4 | 2219.032 | 5077.654 | 33335.66 | |
| 21 | 1598294894 | 29 | 1 | 4532.359 | 5681.56 | 4508.02 | 5075.952 | 5421.841 | 3144.432617 | 847.6214 | 3731.121 | 3061.819 | 5469.804 | 7441.495 | 6070.082 | 2153.369 | 5104.891 | 33128.17 | |
| 22 | 1598294894 | 30 | 1 | 4461.746 | 5691.754 | 4509.001 | 5145.859 | 5422.622 | 3072.730469 | 855.8702 | 3695.51 | 3003.944 | 5423.83 | 7455.082 | 5952.763 | 2087.706 | 5132.127 | 32920.68 | |
| 23 | 1598294894 | 31 | 1 | 4391.132 | 5701.948 | 4509.983 | 5215.767 | 5423.401 | 3001.02832 | 864.119 | 3659.899 | 2946.069 | 5377.856 | 7468.669 | 5835.445 | 2022.043 | 5159.364 | 32713.19 | |

yosif left hand

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### *C. Feature Extraction*

The goal of this step is to characterize the EEG signals depending on few related values called "features" , which should capture the related information within the EEG signals which is relevant to characterize the distinctive nature of the brain mental states to be identified, while refusing the noise and other non-relevant information [26]. In this stage, the obtained preprocessed data from the EMOTIV headset is processed with a PCA algorithm to improve the classifier's accuracy. PCA is a technique used for the 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. 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 to transform all the variables to the same range [16], [27], [28] .

$$Z = \frac{value - mean}{Standard\, deviation} \tag{1}$$

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 Eq. 2, to instruct the entries of the covariance matrix, which is a p $\times$ 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, 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 a matrix with columns of eigenvectors for the required component from the previous step. This will lead to keeping 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 the feature vector as in Eq. 3

$$Final\, dataset = FeatureVectorT * ZT \tag{3}$$

### *D. 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 a 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 an activation function of type tanh(X). The output layer consists of 10 output neurons with an activation function of type SoftMax(X). Fig. 3 shows the sequential model of the work.

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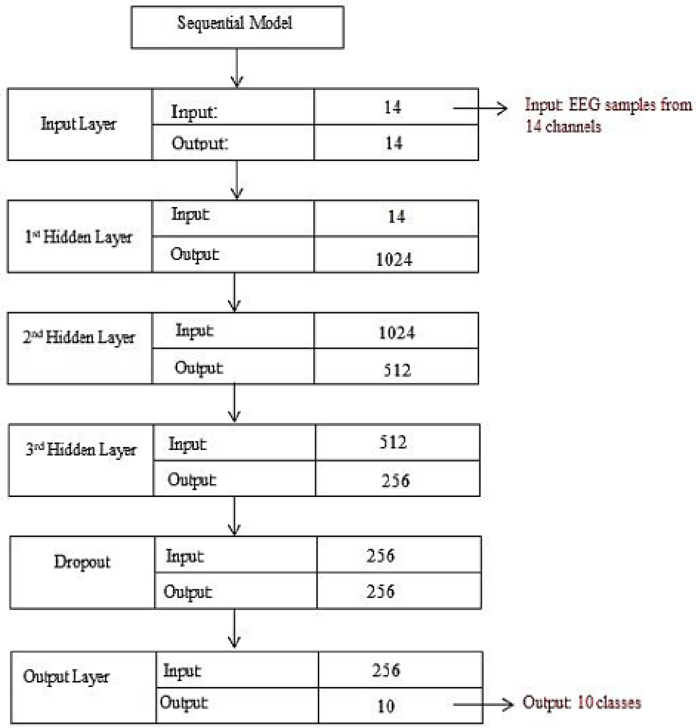


Figure 3: Sequential model representation

*E. Performance 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 concerning 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,the 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 different 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 Fig. 4. The total number of samples is the size of the collected samples, as this size increases the deep learning will give a better classification result but this increment 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 neurons of the hidden layer, the most acceptable accuracy level was obtained when using tanh(X) activation function, while the SoftMax(X) was used within

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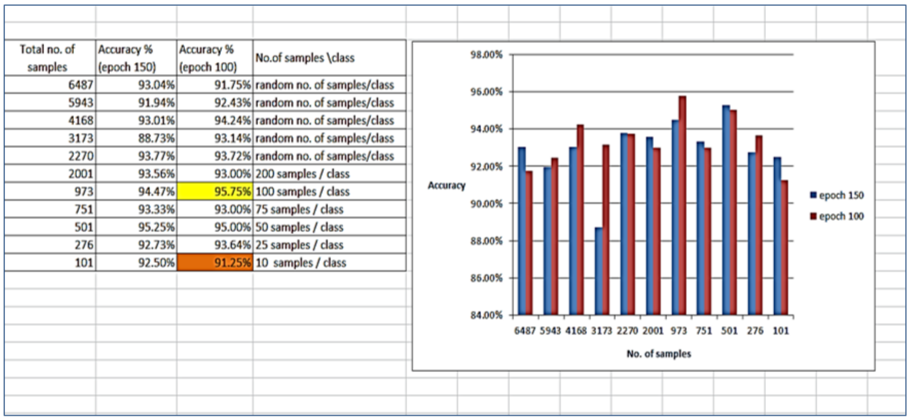
the output layers neurons. Root Mean Square (RMS) was used as an optimizer to minimize the error while learning the neural network.



| 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 4: Classification accuracy levels

### *F. Binding Classes with Corresponding Sentences*

After acquiring the predicted class of the specific sign an optimization process will be followed, by asking the user about the validity of the detected sign, if it is true then a lockup table will be searched to bind the sign with the corresponding sentence, else the prediction process will be repeated until reaching the required sign. Table II shows the binding of sings with sentences. Then the selected sentence will be transferred to a speech by intended text to speech instruction in python.

TABLE II
Binding of Sings with Sentences

| EEG Signal Type | Class Number | Class Label | Sentence |
|---|---|---|---|
| FE | 1 | Surprise | I have headache |
| | 2 | Smile | Thank you |
| | 3 | Right wink | I have eye pain |
| | 4 | Left wink | I need help |
| | 5 | Mouth opened | I'm hungry |
| ME | 6 | Left-hand lifting | I need my son |
| | 7 | Right-hand lifting | I need my daughter |
| | 8 | Head to right | I need my parents |
| | 9 | Head to left | I have stomach |
| | 10 | Clipping | I want to go outside |

## III. Conclusion

In this paper, the classification of EEG time series signal was done by building a deep neural network and implementing deep learning techniques. Ten classes of EEG signal were classified from specialized dataset samples recording. In the offline training, the classification accuracy results reached to 95.75% with minimum processing requirements. So, the sign language model for binding those classes with the corresponding sentences, became more accurate and faster than those models which toke the images for EEG signal segments to feed the deep learning neural network.

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