Classification of steady-state visual evoked potential signals using a dense convolutional neural network for brain-computer interface

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Abstract

Brain-computer interface (BCI) is a communication system in which user commands are transmitted to the outside world without involving the natural exit routes of surrounding nerves and muscles. BCI is especially important for users with reduced mobility such as the disabled. However, programs are being developed for a wide range of users to continue activities in the fields of safety, security and entertainment. In non-invasive BCIs, electroencephalography (EEG) is usually used due to its high resolution, ease of acquisition and cost-effectiveness in comparison with other brain activity monitoring methods. BCI based on SSVEP can automatically identify user commands through a series of signal processing steps including pre-processing, interference detection or correction, feature extraction and feature classification. BCI performance is usually evaluated in terms of classification accuracy, classification speed and number of available choices. One of the upcoming challenges is the need for a large amount of data for feature extraction, so the use of convolutional neural network as a solution to select the best features and automatically extract it works well even in small data. In this research, experiments were conducted on two SSVEP data sets using EEGNET and the classification results were compared with common methods such as CCA, LDA, and SVM, and the accuracy was 86.6% for the SSVEP-EXOSKELETON data set and 69.2% for the data set MASAKI NAKANISHI was obtained.

BCI is an artificial intelligence system that can reveal a specific set of patterns in brain signals during five consecutive steps, which are: signal acquisition, pre-processing or signal amplification, feature extraction, classification and control interface.

Keywords: Brain Computer Interface, SSVEP, convolutional Neural Networks

1.Introduction

Considering the applications of brain-computer interface (BCI) and SSVEP in particular, currently including robotic control, exoskeleton control, smart homes, driver fatigue detection, automatic typing of texts, Selection of numbers and progress towards human-machine interaction in the future and the fact that the most recent category of machine learning is deep learning and new approaches such as voice commands and control through brain waves have been proposed, so research in this field is very important and necessary. Therefore, the use of convolutional networks for better classification of steady state visual evoked potential signals will be evaluated in this research.

According to the research on the classification of visual evoked potential signals, the steady state research variables are divided into independent and dependent variables.

A- independent variables:

Steady-state visual evoked potential signal characteristics in the time and frequency domains, such as excitation frequency, signal strength, signal statistical characteristics, such as mean and variance, skewness, frequency coefficients, and frequency-time coefficients.

B- Dependent variables:

Stimulation signal output classes, classification accuracy, information transfer rate.

Theoretical literature and research history

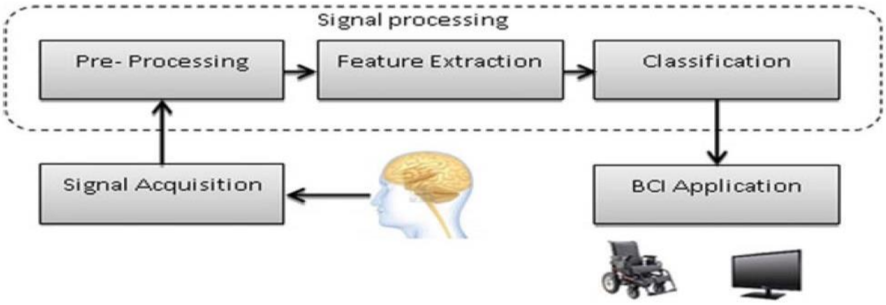

Figure 1- Brain and computer interface

Brain activities and its measurement methods

Brain activity is revealed as a response to external stimuli in specific ways and brain regions. In addition, a similar brain signal can behave completely differently based on how it is measured, and some measurement techniques are more complicated, expensive, or invasive than others. Therefore, the types of brain activity acquisition methods are divided based on:

invasion, time resolution, spatial resolution and electrical or hemodynamic origin. Figure (2) shows the methods of measuring brain activities [2].

Measurement Method	Type of activity	Temporal Resolution	Spatial Resolution	Risk
EEG	Electrical	$0.05s$	$10mm$	Non-Invasive
MEG	Magnetic	$0.05s$	$5mm$	Non-Invasive
ECoG	Electrical	$0.003s$	$1mm$	Invasive
Intracortical	Electrical	$0.003s$	$0.5mm$ to $0.05mm$	Invasive
fMRI	Metabolic	$1s$	$1mm$	Non-Invasive
NIRS	Metabolic	$1s$	$5mm$	Non-Invasive

Figure 2 - Methods of measuring brain activities

Visual evoked potential signal

When the human eye is stimulated by an alternating stimulus, the signal is transmitted by the optic nerve to the primary visual areas. Figure (3). The resulting brain response can be identified as a peak band power in the brain activity of the primary visual areas (in the posterior lobe) with the frequency of stimulation. In addition, a lower amplitude peak can also be observed in the excitation frequency harmonic [5].

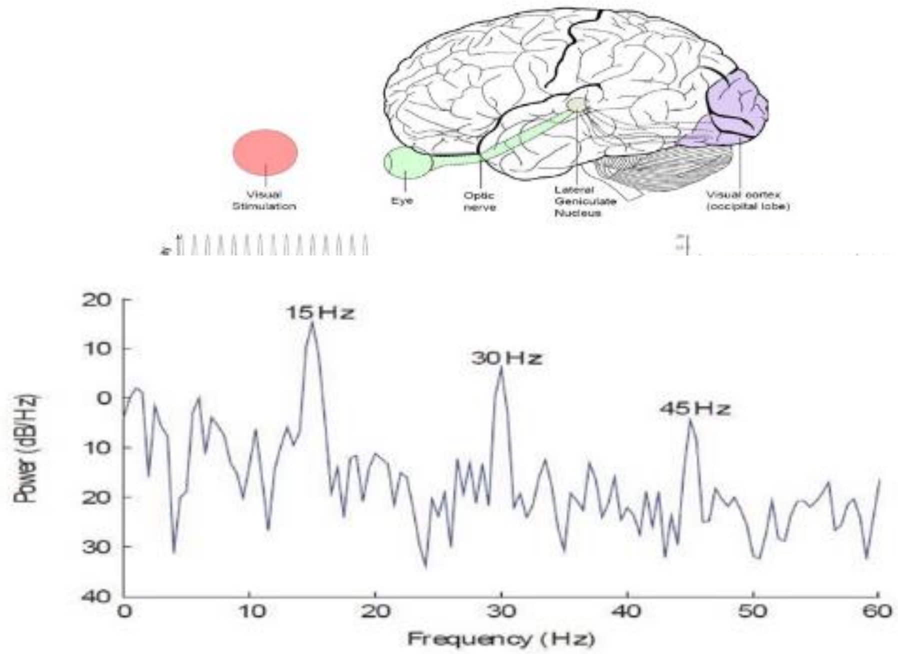

Figure 4-Generation of SSVEP stimulation frequency harmonics

Conventional correlation analysis

Conventional Correlation Analysis (CCA) is a statistical analysis method that finds basic correlation between two multidimensional data sets. According to the two multidimensional variables X and CCA, Y follows the weight vectors Wx and Wy in such a way that their corresponding linear predictions x = XTWx and y = Y TWy have maximum mutual correlation. According to relation (1), these predictions are made by solving the following objective function

$$\max_{W_x,W_y}\rho(x,y) = \max_{W_x,W_y}\frac{E[W_x^T X Y^T W_y]}{\sqrt{E[W_x^T X X^T W_x]E[W_y^T Y Y^T W_y]}} \qquad (1)$$

Classifiers based on CCA usually calculate the correlation between a few-second signal segment and a series of reference signals. To use BCI, accurate reference signal is expected. A correlation value is calculated for each class, which indicates the similarity of the EEG signal to the stereotypical reference signal.

Signal feature classification by deep learning method

In classical programming, according to figure (2-8), rules and input data are applied to the system on the input side, and system responses are generated on the output side. With machine learning, humans enter the data and also the answers that are expected from the data and the rules are generated in the output. These rules can then be applied to new data to generate original answers. Instead of being explicitly programmed, a machine learning system is trained with many examples related to a task, and based on the statistical structure of the system's data, it provides rules for automating the task.

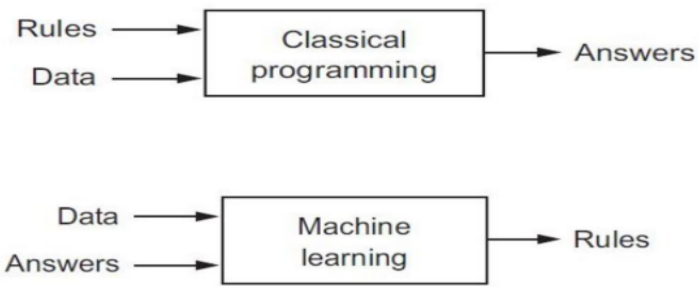

Figure 5- Comparison of traditional programming and machine learning

Machine learning is closely related to mathematical statistics, but it differs from statistics in several important ways. Unlike statistics, machine learning tends to deal with large and complex datasets such as datasets of millions of images each consisting of tens of thousands of pixels, where classical statistical analysis such as Bayesian analysis would be impractical. As a result, machine learning and especially deep learning needs relatively little mathematical theory and is more engineering oriented [6].

In general, to perform machine learning, there are two approaches of supervised and unsupervised training. In supervised training, input data and expected output data are available and ready so that the input data has an expected output data point. In unsupervised learning, we have the input data and we are interested in predicting the expected output.

As a first step, the given data is divided into three datasets: training, validation and testing. There is no hard rule about what percentage of data should be training, validation and testing datasets. It can be 20-10-70, 10-30-60, 25-25-50 or any other case.

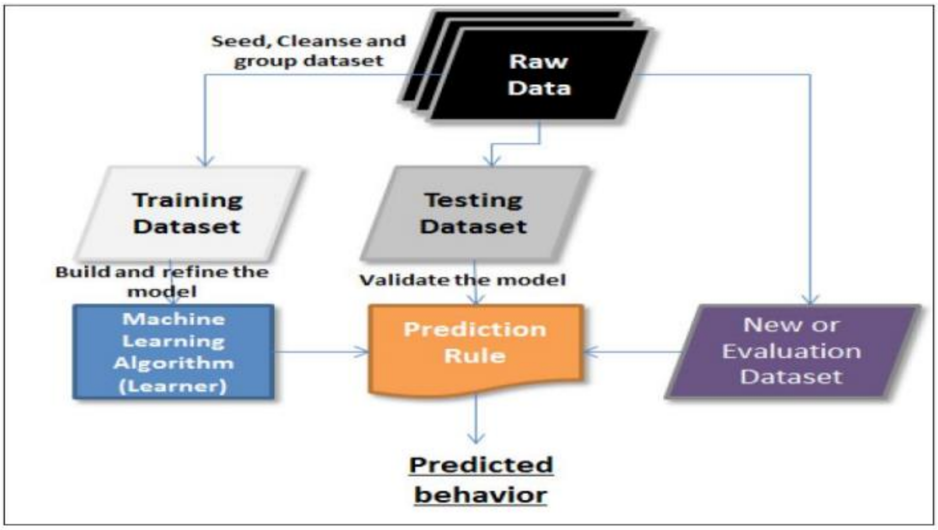

Figure 6- Steps of training, validation and testing of the learning model

Deep learning has two advantages. First, it works directly on raw brain signals, thus avoiding time-consuming processing and feature engineering. Second, deep neural networks can capture both high-level discriminative features and latent dependencies through deep structures.

The new approach to learning representations from data is an emphasis on learning through successive layers with increasingly meaningful representations. "Deep" in deep learning does not refer to any kind of deeper knowledge resulting from the approach, but is related to the idea of successive layers of representations. In deep learning, these representations are learned layer by layer through models known as neural networks, which are structured from layers stacked on top of each other. The term neural network is a reference to neuron biology, but some of the basic concepts in deep learning have been developed to some extent inspired by brain cognition. According to Figure (2-10), the deep network is a multi-stage information extraction process in which the information passes through successive filters and is increasingly filtered out.

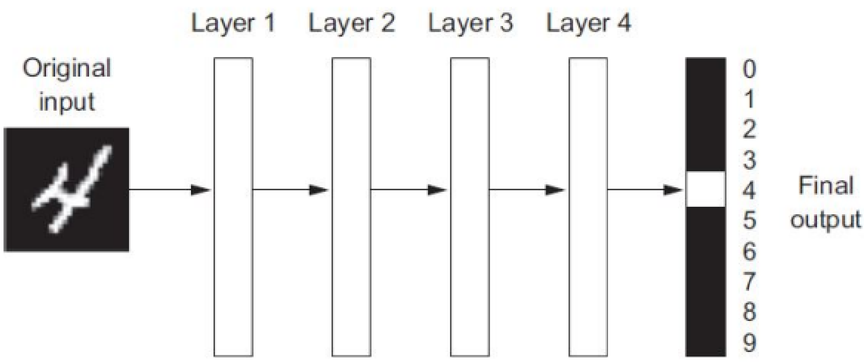

Figure 7- Feature extraction in deep neural network for number classification

The border between unsupervised learning and supervised learning is not formally defined and many machine learning technologies can be used in both types. Based on the chain rule of probability according to equation (2) of analysis of joint distribution, it is possible to solve the unsupervised modeling problem of P(x) by dividing it into n learning problem with superintendent.

$$P(x) = \prod_{i=1}^{n} p(x_i \mid x_1, \ldots, x_{i-1}) \qquad (2)$$

Or solved the problem of supervised learning P(y|x) by using unsupervised learning technology to learn the distribution of p(y|x) and referring to relation (3).

$$P(y \mid x) = \frac{\rho(x, y)}{\sum_{y'} \rho(x, y')} \qquad (3)$$

Understanding how deep learning works

Machine learning is related to the mapping of input to goals by observing many examples of input and goals. The deep neural network performs this "input to target" mapping through a deep sequence of simple data transformations in layers, and this data transformation is done using feature extraction in the data sample. The specification of what a layer does on the input data is stored in the layers' weights, which is essentially a numerical value, which in technical terms is said to parametrize the transformation implemented through a layer with its own weights. Sometimes the weights of the parameters of a layer are called. In this space, learning means finding a set of values for the weights of all layers in a network in such a way that the network correctly maps sample inputs to relevant targets. A neural network contains millions of parameters. To control the output of a neural network, it is necessary to calculate the amount of error in the network, which is done through the loss function 1 by calculating the predictions of the network with real goals, and this error is used as feedback to adjust the weights in order to reduce the network error through the optimizer and the use of the so-called algorithm. It will be implemented as "post-release". At the beginning, the weights of the network layers are randomly applied and then the weights are modified to the correct values through the loss function repeatedly in the training and validation process so that the network error is reduced and reflected in the network output in an optimal model prediction.

Anatomy of a neural network

The neural network consists of the following components and their interaction is shown in figure (8).

1- Layers, which are combined into a network (or model).

2- Input data and corresponding goals.

3- Loss function, which defines the feedback signal used for learning.

4- Optimizer 1, which determines the learning progress.

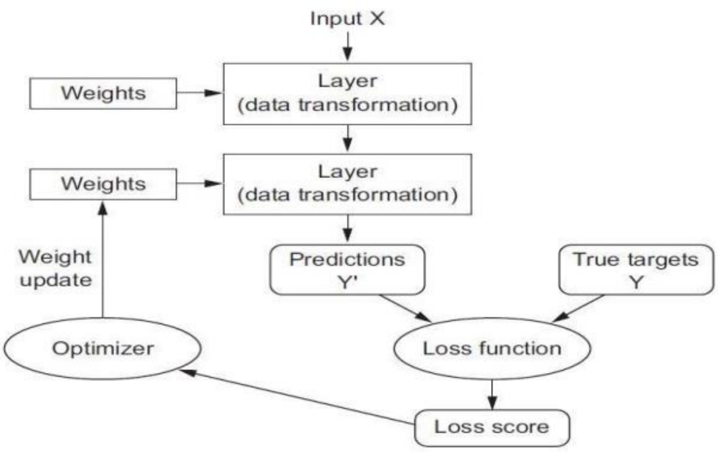

Figure8- The structure and components of the neural network and the process of adjusting the weights of the layers

One of the common methods of solving the optimization problem in neural networks is back propagation.

$$Q(W) = \sum l(h_w(xi), yi) \quad \text{(4) Loss function}$$

Convolution neural network

The convolutional neural network known as convnet introduces a type of deep learning model that is widely used in computer vision applications. The main difference between the dense connection layer and convolution is that the dense layer learns comprehensive patterns in the feature space of its inputs, while the convolution layer learns local patterns. the features of convnets are:

1- Learned patterns are immutable to displacement. That is, after learning a specific pattern, it can recognize it anywhere in the feature space, so they need less training samples for learning. See figure (9).

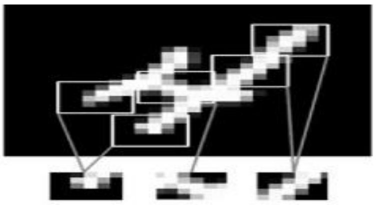

Figure 9-Images can be broken into local patterns such as sides, textures, etc

2- They can learn the spatial hierarchy of patterns. For example, the first layer of convolution learns a local pattern such as the sides of a shape, the second layer learns a larger pattern composed of the features of the first layer, etc. This feature of convnets allows to efficiently learn complex and abstract visual concepts. See figure (10).

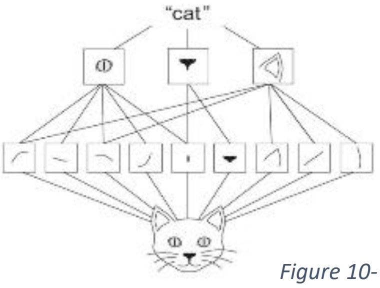

Figure 10- Hierarchical learning of the components of an image and abstract formation of the image

Cannulation operation

The convolution operation is defined as the equation (5) where s(t) is the output of the feature map, x is the input vector, and w is called the kernel. Convolutions work on three-dimensional vectors called feature maps, which include two spatial axes (height and width) and depth (called the channel axis). According to figure (11), the convolution operation extracts pieces from the input feature map and applies a similar transformation on these pieces. This map is three-dimensional. The three-dimensional vector depth component of the filter is applied on the spatial data axis.

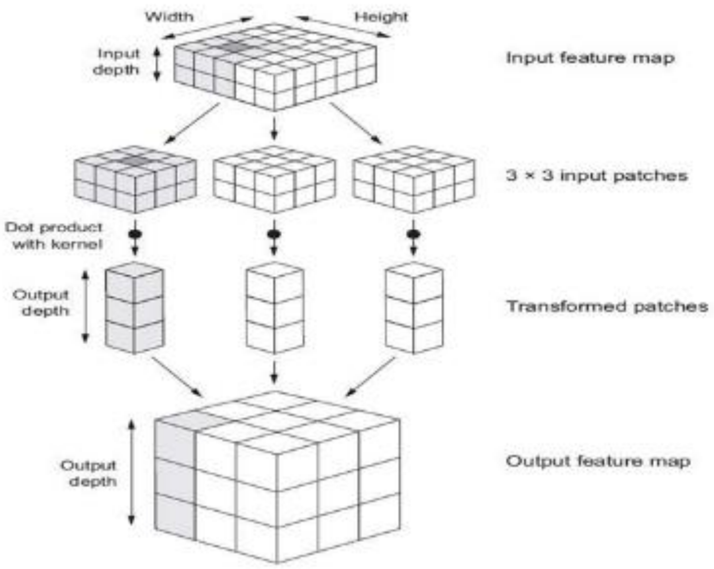

Figure 11- How to work cannulation

$$s(t) = (x * w)(t) = \sum_{a=-\infty}^{\infty} x(a)w(t-a) \quad (5)$$

Convolution is defined by two key parameters:

1- The size of the pieces extracted from the inputs, which is usually 3x3 or 5x5 in this window.

2- The depth of the output feature mapping, which is the number of filters calculated by convolution.

Implementation of deep networks

Various formats have been used by developers and researchers to implement deep networks. Keras, Tensorflow are mostly used according to figure (12). Keras has the following main features:

1- It allows the same code to be executed on CPU or GPU.

2- It has a user-friendly API that facilitates rapid prototyping of deep learning models.

3- It has internal support of convolution networks (for computer vision), return networks (for sequence processing) and any combination of the two.

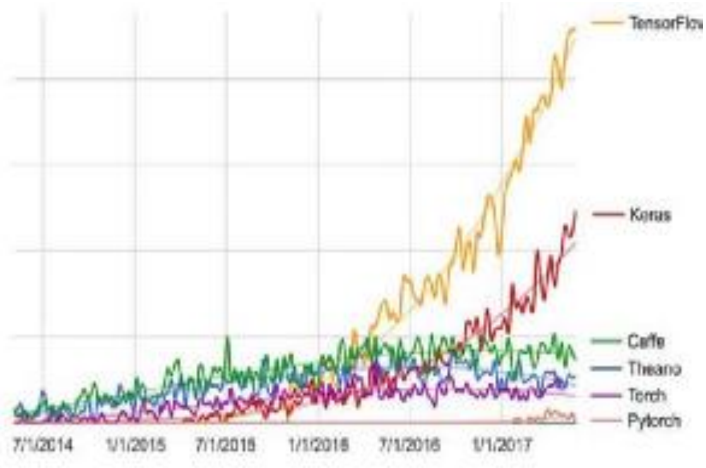

Figure 15- Tendency to search the Google web for different deep learning frameworks over time [6].

4- It supports arbitrary network architectures: multi-input or multi-output models, layer sharing, model sharing, etc. This means that Keras is suitable for building basically any deep learning model, from a generative adversarial network to a neural Turing machine.

Keras is distributed under the MIT License, which means it can be freely used in commercial projects. It is compatible with any version of Python from 7.2 to 6.3 (as of mid-2017).[6]

Deep learning models

Deep learning is an offshoot of machine learning techniques that learns representations and thus performs advanced tasks based on multiple neural layers, while the standard neural network architecture consists of an input layer, a hidden layer, and an output layer, a deep neural network. generally, has more than one hidden layer. Deep learning is divided into several categories based on the goal:

1-Discriminative deep learning models. 2- Representative deep learning models. 3- Generative deep learning models. 4- Hybrid deep learning models.

Deep Learning	Input	Output	Function	Training method
Discriminative	Input data	Label	Feature extraction, Classification	Supervised
Representative	Input data	Representation	Feature extraction	Unsupervised
Generative	Input data	New Sample	Generation, Reconstruction	Unsupervised
Hybrid	Input data	–	–	–

Figure16- Summary of different models of deep networks

Advantages of deep neural network:

Deep neural networks have the ability to simultaneously learn effective features and different classes from raw EEG data. Considering their effectiveness compared to other previous methods, deep neural networks will certainly lead to the creation of better features and classes, and as a result, a much stronger EEG classification.

The Compact-CNN method uses a deep learning approach that enables the discovery of the main feature in the SSVEP signals that associates the blink with its meaning in the signal in a relatively small training dataset. In particular, this approach uses a deep learning model which is a dense convolutional neural network and operates on EEG signals with a wide filter. Its compact nature allows it to work on smaller data sets, while its convolutional structure enables the automatic extraction of task-relevant EEG features. Without using any user-specified calibration, Compact-CNN achieves relatively better classification accuracy than CCA and Combined-CCA. Furthermore, the basic feature of the representations built by our Compact-CNN showed that the deep learner is able to extract additional phase and amplitude features associated with SSVEP signals [9].

2.Method and Material

SSVEP-EXOSKELETON dataset [22]

This dataset includes SSVEP-based BCI recordings from 12 subjects while performing a joint control task, upper limb exoskeleton. The exoskeleton is controlled either with a touch interface that recognizes hand gestures or with a SSVE-based BCI.

Signal acquisition - hardware and software

1. Arm exoskeleton: The exoskeleton used here is a robotic arm that was created to compensate for muscular dystrophy in the shoulder and elbow muscles that occurs in several degenerative diseases, which affects the large muscles, but it prevents from the wrist and the movement of the hands.

2. Touchless interface: Our touch user interface includes 5 IR sensors that can be adjusted according to the user's needs in different locations. The control system relies on an iterative KNN scheme to learn the manual modes of each user.

3. Visually evoked potentials: g. Mobilab + device is used to record EEG at 256 Hz in 8 channels. To stimulate the SSVEP, the flash stimulation method is chosen. To avoid the limitation imposed by the refresh rate of the computer screens, the microcontroller is set for the flash drives with light emitting diodes (LED) at frequencies F = {13, 17, 21} Hz. The device is controlled and the LED blinking is accurate to milliseconds. According to the 10/20 system, eight electrodes are placed on O1, Oz, 2PO7, PO4, PO3, POz, O and 8PO. The ground was placed on Fz and the reference was placed on the right (or left) side of the mastoid hearing.

MASAKI NAKANISHI dataset [23]

Data acquisition

The visual stimuli of 12 targets (6 x 6 cm each) were presented in a 27-inch LCD monitor (ASUS 278VG) with a refresh rate of 60 Hz and an image resolution of 1280 x 800 pixels. As shown in Figure (17), The stimuli are arranged in a 4x3 matrix as a virtual keyboard of a telephone and labeled with different frequencies (Δf=0.5Hz, $f0$=9.25Hz) and phases.The horizontal and vertical distance between two neighboring stimuli was 5 cm and 1.5 cm, respectively. The stimulation sequence was generated using equation (6).

$$s_n(t) = s(f_0 + (n-1)\Delta f, \phi_0 + (n-1)\Delta\phi, t), n = 1,2, \ldots, N_f \quad (6)$$

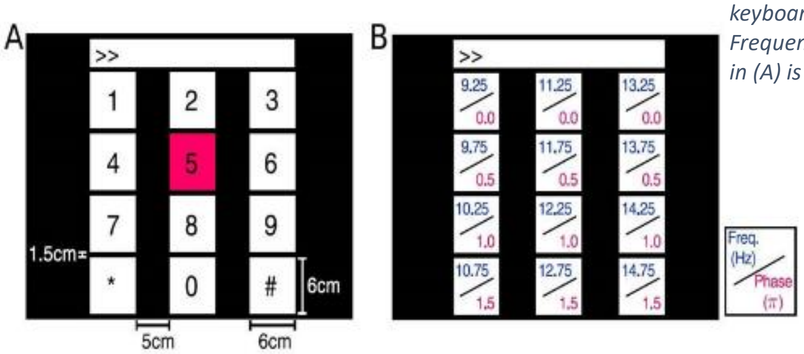

Figure 17- Designing the drive system of 12 BCI targets. (A) Virtual keyboard user interface for a telephone dialing program. (B) Frequency and phase values specified for each target. The red square in (A) is the pictorial cue that represents the target symbol "5"

Ten healthy subjects (9 men and 1 woman, average age: 28 years) with normal or corrected-to-normal vision participated in this study. EEG data was recorded with eight Ag/AgCl electrodes using the BioSemi ActiveTwo EEG system (Biocemi region).

The EEG signals were amplified and digitized with a sampling rate of 2048 Hz, and all electrodes were close to Cz by referring to the CMS electrode. The event stimuli that represent the attacks of visual stimuli are sent to the EEG system from the parallel port of the computer and are recorded in an event channel synchronized with the EEG data. People were sitting in a comfortable chair 60 cm in front of the monitor in a dimly lit room.

The reference signals of figure (18) are made for each of the K frequency stimuli, where each set includes the harmonic Nh of the fundamental frequency fk.

$$Y_k = \begin{pmatrix} \sin(2\pi f_k t) \\ \cos(2\pi f_k t) \\ \vdots \\ \sin(2\pi N_h f_k t) \\ \cos(2\pi N_h f_k t) \end{pmatrix}$$

Figure 18 reference signal YK

Scikit-learn (Sklearn) machine learning algorithm is the most useful and powerful library for machine learning in Python. This set of efficient tools for machine learning and statistical modeling including classification, regression, clustering and dimensionality reduction provides a compatible interface in Python.

EEGNET network

EEGNet is a compact convolutional neural network for EEG-based BCIs. Figure (19) shows the overall architecture of the EEGNet network. This network starts by using a temporal convolution (Conv2D layer) to learn frequency filters, then uses a depth convolution (DepthwiseConv2D layer) which is separately connected to each feature map, to learn frequency-specific spatial filters. The separable convolution (SeparableConv2D layer) is a combination of a depth convolution that learns the temporal information for each feature map separately, followed by a point convolution that learns how to optimally blend the feature maps together.[24]

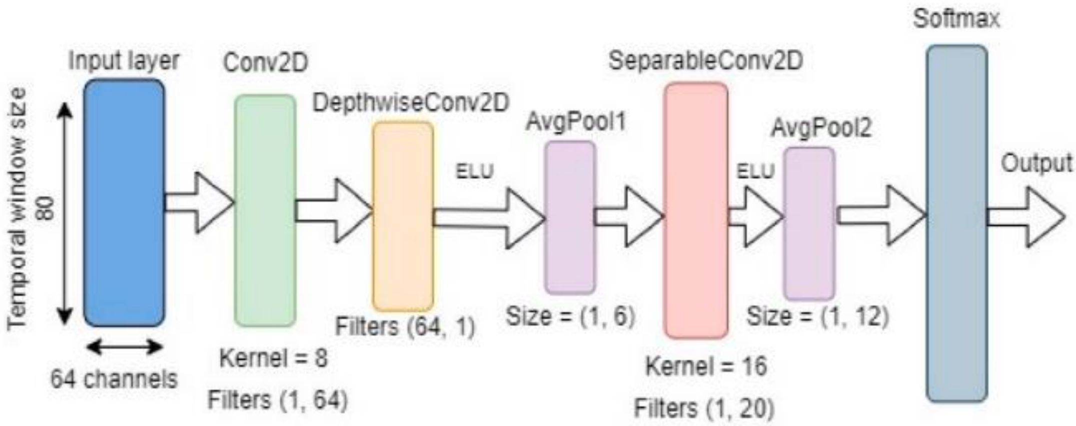

Figure 19- The architecture of EEG-NET is a type of compact convolutional neural network

According to Figure (20), in the Compact-CNN method, the data related to the excitation frequencies are loaded and a feature vector is created from the linear order of the excitation frequencies. Then a vector for the frequency labels is also made linearly for data preprocessing, if the city electricity noise removal filter is not taken from the data set, the desired filter is applied. To extract the feature in the frequency range of stimuli, the feature vector of the pass filter is then transformed into Fourier transform. Then we divide the data into three groups: training, validation and testing. We define the desired convolutional neural network according to the EEGNET architecture. Then we prepare the dimensions of the data and labels to enter the convolutional neural network EEG-NET. We adjust and train the desired parameters and network for training and validation. For evaluation, we examine the network with test data and obtain its accuracy [9].

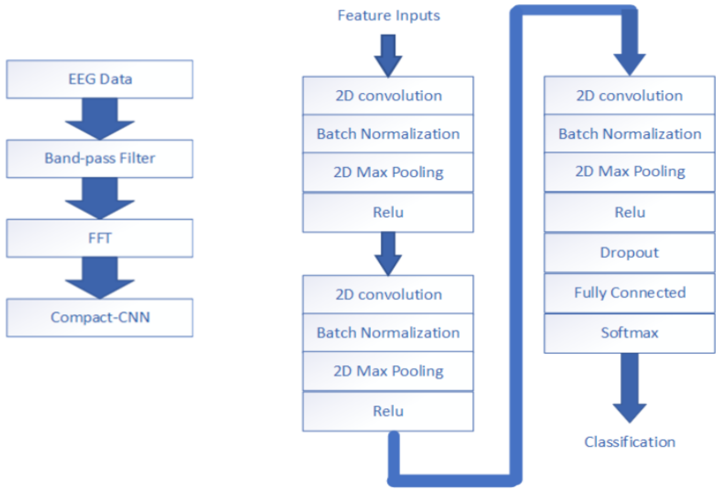

Figure 20- EEGNET network performance and network input data preparation

Advantages and disadvantages of the proposed method

Advantages	**Disadvantages**
Feature engineering is done automatically	The computational complexity for training and testing is high
It works better in small data sets	High performance computing tools are required
No need for special expertise in this field	The duration of training and calibration is long

3.Results

To evaluate the efficiency of the algorithms, the accuracy criterion 1 is used, which is obtained according to the formula (7):

$$Accuracy = \frac{Tp + TN}{TP + TN + FP + FN}$$

where TP, TN, FP, and FN represent the number of confusion matrix diagnoses, which are true positive, negative positive, true negative, and false negative items, respectively. And the formula (8) has been used to evaluate the speed of information transfer:

$$ITR = \frac{60}{T} * \left[log_2^N + P * log_2^P + (1-P) * log_2^{\left(\frac{1-P}{N-1}\right)}\right]$$

Comparison of SSVEP-EXOSKELETON dataset results

The improvement of the classification results by the proposed method is due to full feature extraction through frequency convolution filters and deep convolution, a combination of spatial and point filters, optimal feature selection and automatic data dimension reduction through Max Pooling or Average Pooling layer.

Algorithm	**EEG NET**	**CCA**	**LDA**	**SVM**
Subject1	85	41	46	49
Subject2	83	40	61	54
Subject3	90	41	38	41
Subject4	93	49	44	42
Subject5	88	38	53	53
Subject6	83	38	57	48
Subject7	88	40	38	38
Subject8	88	37	41	51
Subject9	83	33	50	37
Subject 10	85	39	39	41
Subject 11	85	31	50	61
Subject 12	88	30	48	43
Average	86/6	38/1	47/1	47/5
Data transfer rate	1/0839	1/6017	1/9772	1/9522

Table 1- Results of classification with 1 second tests

Algorithm	**EEG NET**	**CCA**	**LDA**	**SVM**
Subject1	94	59	47	58
Subject2	90	57	62	38
Subject3	88	44	41	84
Subject4	92	37	26	78
Subject5	90	46	58	56
Subject6	85	45	52	44
Subject7	89	45	27	76
Subject8	82	37	38	77
Subject9	85	30	31	75
Subject10	92	46	41	45
Subject11	87	58	38	43
Subject12	89	47	42	59
Average	88/58	45/92	41/92	61/8
Data transfer rate	7/4093	3/8559	2/5222	5/1796

Table 2- Results of classification with 5 second tests

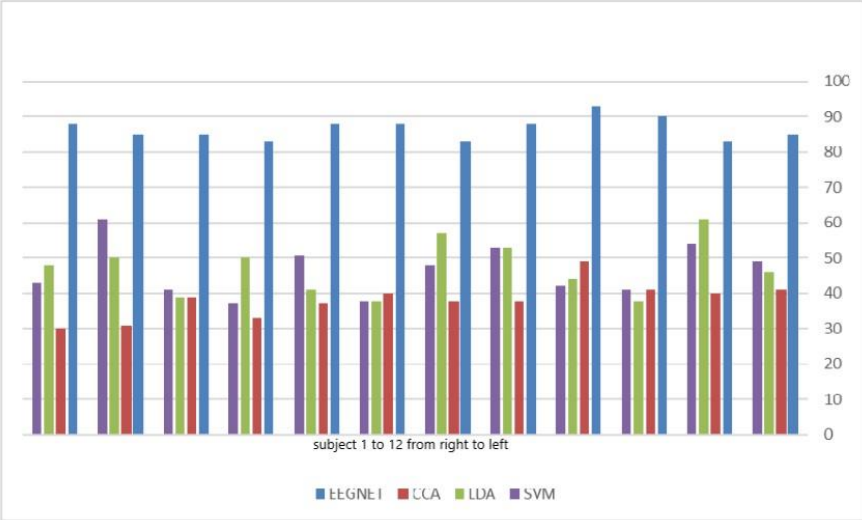

Diagram 1- Algorithm comparison diagram with one-second tests

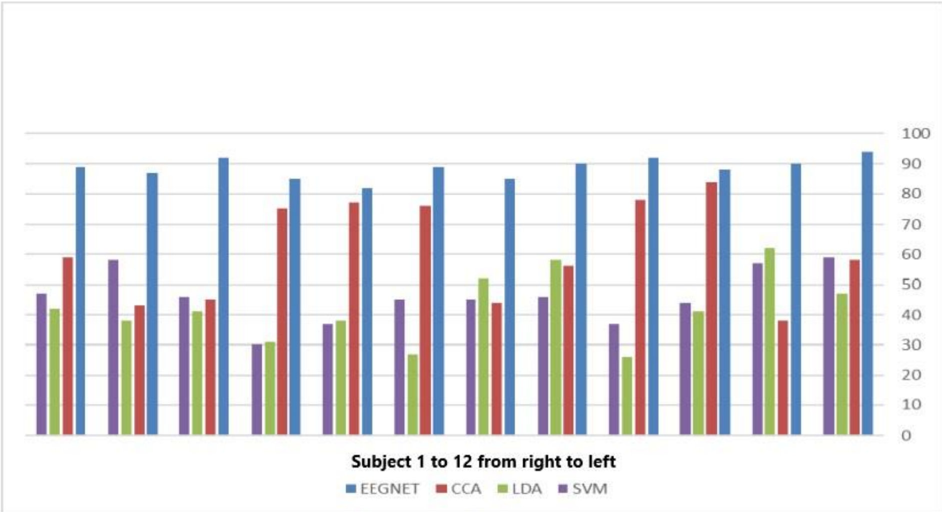

Diagram 2- Algorithm comparison diagram with five-second tests

- We conducted another test to investigate the Kernel Length parameter in the EEGNET network with the values of 128, 64, 32 and 16. According to table (3), the classification accuracy for 64 kernel length = 92.86% is the highest.

- In another experiment, the number of spatial filters in the EEGNET network was evaluated. The values used for the number of filters were 96, 50, 30, and 120, which according to table (4), the number of filters 96 obtained higher accuracy.

Number of spatial filters	120	96	50	30
Subject1	90	94	85	96
Subject2	81	81	85	83
Subject3	90	81	85	88
Subject4	88	88	83	83
Subject5	81	79	81	85
Subject6	83	88	85	81
Subject7	90	89	90	93
Subject8	88	92	85	88
Subject9	86	86	88	85
Subject10	85	89	85	83
Subject11	81	88	83	84
Subject12	90	88	90	85
Average	86/08	86/92	85/42	86/17

Kernel Length	128	64	32	16
Subject1	85	94	90	94
Subject2	83	81	81	85
Subject3	90	81	83	88
Subject4	93	88	88	81
Subject5	88	79	81	79
Subject6	83	88	85	90
Subject7	88	89	89	86
Subject8	88	92	82	89
Subject9	83	86	89	89
Subject10	85	89	85	84
Subject11	85	88	82	85
Subject12	88	88	88	90
Average	86/58	86/92	85/25	86/67

Table 4- Comparison of the number of spatial filters with a one-second test

Table 3- Comparison of the results of different Kernel length with one second test

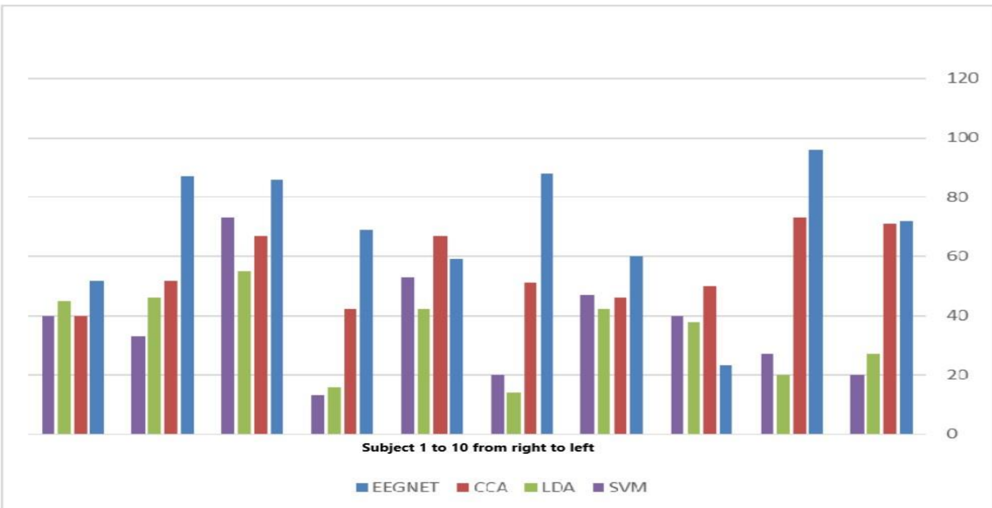

Diagram **2-** Comparison chart of algorithms with 1 second tests

Algorithm	EEGNET	CCA	LDA	SVM
Subject1	72	71	27	20
Subject2	96	73	20	27
Subject3	23	50	38	40
Subject4	60	46	42	47
Subject5	88	51	14	20
Subject6	59	67	42	53
Subject7	69	42	16	13
Subject8	86	67	55	73
Subject9	87	52	46	33
Subject10	52	40	45	40
Average	69/2	55/9	34/5	36/6
Data transfer rate	2/6595	2/1517	1/3334	1/4138

Table 5- Comparative results of algorithms with one second tests

Reliability, convergence and stability

Reliability

To measure the reliability of the proposed method, the standard deviation of the results based on the data in Table (1) for the classification of the 5-second tests on the exoskeleton data set is given. The error of deviation from the mean based on the equation (9) equals 86/. is. $SE = \frac{\sigma}{\sqrt{n}}$

Convergence

In this section, convergence charts are given to check the performance of the proposed algorithm. The convergence test of the proposed model for subjects 1 to 5 with the number of executions of 50 cycles 1 for the exoskeleton dataset is given. According to figures (20), (21), (22), (23) and (24), the convergence of the model is observed.

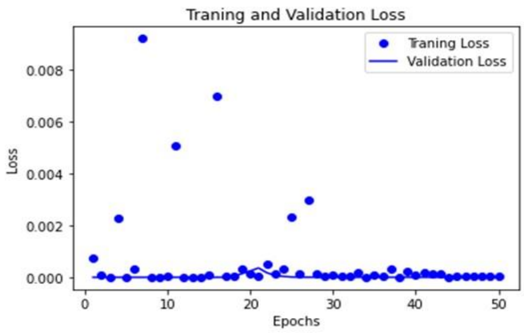

Figure 20- The convergence diagram of the first subject

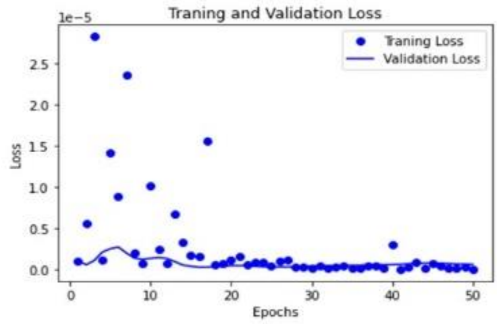

Figure 21- The convergence diagram of the second subject

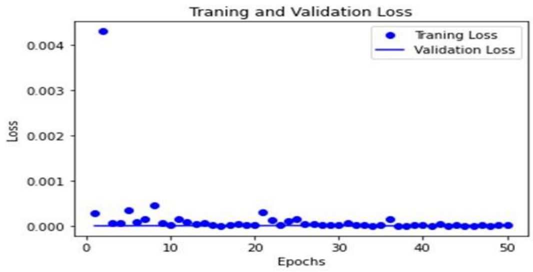

Figure 22- The convergence diagram of the third subject

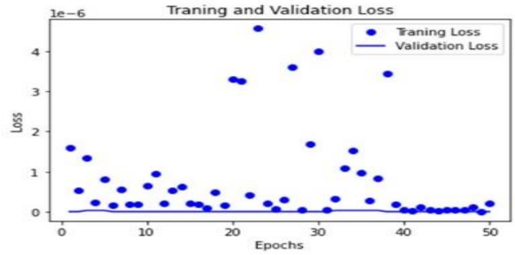

Figure 23- The convergence diagram of the foutrh subject

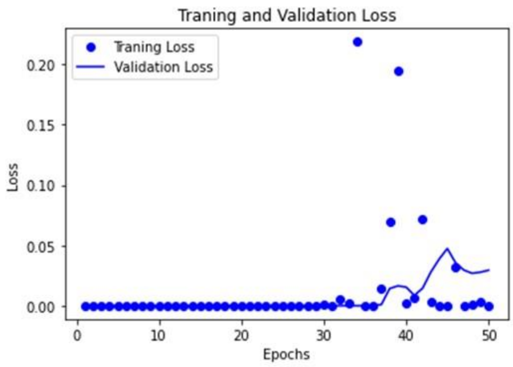

Figure 24- The convergence diagram of the fifth subject

Sustainability

In this part, to check the performance of the presented algorithm, the stability test of the model is investigated. The accuracy of the proposed model for subjects 1 to 5 with the number of executions of 10 times for the exoskeleton data set is given.

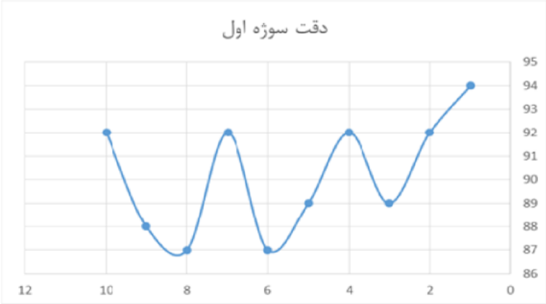

Diagram4-Stability diagram of the first subject in 10 times of running the algorithm

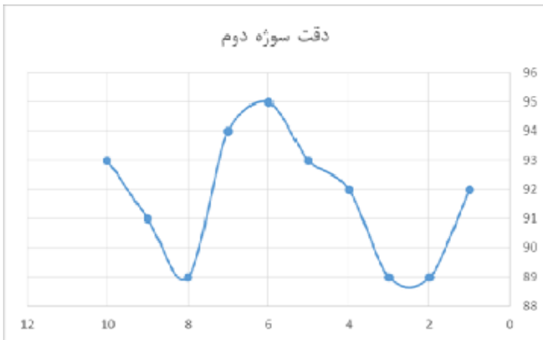

Diagram5-Stability diagram of the second subject in 10 times of running the algorithm

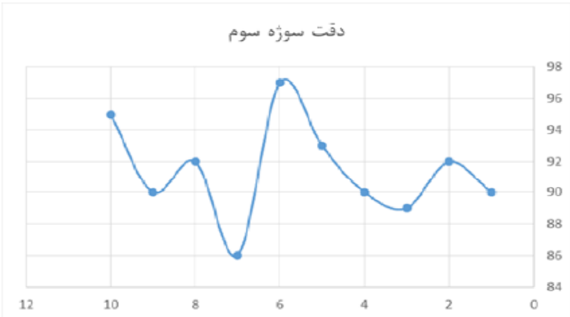

Diagram6-Stability diagram of the third subject in 10 times of running the algorithm

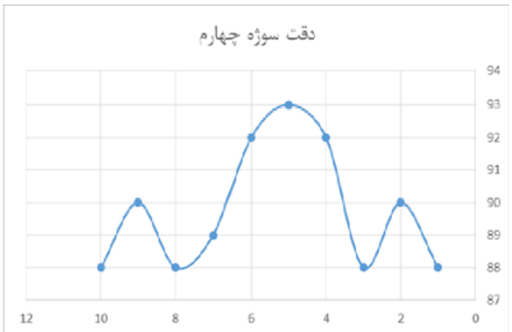

Diagram7-Stability diagram of the fourth subject in 10 times of running the algorithm

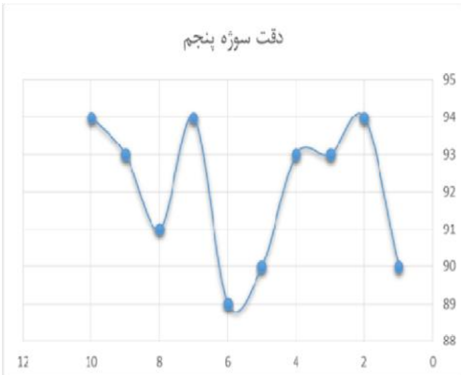

Diagram8-Stability diagram of the fifth subject in 10 times of running the algorithm

4.Conclusion

As a conclusion, it can be observed that according to the results, EEGNET has the best classification accuracy in terms of classification and has better ITR in some cases.

Therefore, due to the higher accuracy of classification and the extraction of internal features, this method is considered as the best option in terms of SSVEP signal classification in less amount of data. And based on the results of the experiments, it can be said that this method has performed better by 20 to 30 percent in our tested data.

5.Suggestions

In order to improve the results and increase the efficiency, it is suggested:

1- Evolutionary algorithms and collective intelligence such as genetics and PSO should be used to obtain the appropriate number of temporal and spatial filters as well as the optimal kernel length.

2-To extract the appropriate feature vector, it is better to use other methods such as Wavelet and Welch's PSD in addition to Fourier transform.

6.Reference

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