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Development of electrooculogram based human computer interface system using deep learning

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ABSTRACT

The patients with diseases that cause severe movement disabilities was noticeably increasing. These disabilities made patients unable to carry out their daily activities or interact with their external environment. However, the existence of human-computer interfaces (HCI) gave those patients a new hope to be able to interact once again. HCI enabled these patients to communicate with their environment by recognizing the movement of their eyes. Eye movements are recorded by an electro-oculogram (EOG) through some electrodes that are put vertically and horizontally on the eyes. In this paper, EOG vertical and horizontal signals were analyzed to detect six eye movements (up, down, right, left, double blinking, and center). Three deep learning models namely convolution neural network (CNN), visual geometry group (VGG), and inception had been examined on filtered EOG signals. The experimental results reveal the superiority of the inception model in providing the best average accuracy 96.4%. Accordingly, a writing system is presented based on the detected movements.

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1. INTRODUCTION

Many diseases have emerged around the world that cause temporary or permanent paralysis for patients despite the integrity of the cognitive parts of their brains. However, they cause the muscle neurons to weaken, which leads to the suspension of voluntary muscles. Thus, their limbs are unable to carry out their vital functions [1], [2]. Unfortunately, the number of patients is increasing. As stated by the World Health Organization, there are more than 1,000 million people with disabilities all over the world, and they constitute approximately 15% of the world's population (i.e. one person out of 7). This is due to many factors including genetic factors, diet and environmental factors [3].

One of the famous diseases is amyotrophic lateral sclerosis (ALS). ALS is a motor nerve disease that causes atrophy in the muscles of the body and ultimately leads to paralysis, due to the weakness of the motor nerves of the upper and lower extremities, and gradually they stop sending nerve signals to the extremities. Consequently, the limbs stop performing their task and the patient loses control over them. However, some muscles survive this atrophy, including the muscles that support eye movement [4].

This disease usually begins at the age of 50. ALS affects five out of every 100,000 people worldwide. There are no known causes for this disease so far unless a family member had it before. There are clear signs and symptoms that distinguish it; first, the weakness of the motor nerves leads to a slight involuntary tremor in the fingers, hand and feet, and it develops with a change in sound and drooling, and in the final stage it reaches difficulty in breathing and death. Thus, the lives of these people remain difficult and painful for them. They cannot carry out the tasks of their normal life, and they cannot communicate with their external environment except through the movement of their eyes [5].

There are many diseases that also lead to atrophy and death of the motor nerves, such as myasthenia gravis disease where the muscles are damaged and unable to receive nerve signals to the extremities, as well as Guillain-Barré syndrome (GBS) and other diseases. The causes of these diseases are due to environmental conditions, such as constant exposure to some heavy metals or electromagnetic waves, diets that lack basic elements or wrong habits such as smoking or genetic factors. However, the result remains the same, which is the inability of patients to practice their lives normally due to disability [6], [7]. Nevertheless, these patients still have the last tool for communication, which is the movement of their eyes, to be the only supporter of interfaces that help them to act and express what is inside them.

In the past few decades, human-computer interfaces/human machine interfaces (HCI/HMI) have emerged and are known as human-machine interaction. They are designed and implemented to be the link between the human being and the computer, where the individual can take actions based on selecting from actions displayed on the computer screen. The effect of these actions can also be seen on the screen/machine. Many efficient human computer interfaces have been developed, such as electrical wheelchair control mobile robot control [8], [9]. From here, these interfaces can help these patients to overcome their disabilities by providing a mean to facilitate communication with their external environment by identifying directions of eye movements and using them in determining a specific procedure or writing a text. These interfaces depend on four main directions (top, bottom, right and left) with a blinking to indicate the choice of procedure as in most studies or other sub-directions (top left, top right, bottom left, and right) as in few studies [10], [11].

Eye movement directions can be determined using an electro-oculogram (EOG) that measures the signals produced by the electrical potential difference between the cornea and the retina. When the eye moves in different directions, positive pulses form on the cornea in the front, negative pulses on the retina in the back, and the eyeball become a bipolar with the positive cornea and the negative retina [12]. The amplitude of pulse will increase with the increment of rolling angle, and the width of the positive (negative) pulse is proportional to the duration of the eyeball rolling process [13], as shown in Figure 1. EOG is usually recorded using five electrodes placed around the eyes, a pair is placed above and below the left eye to measure vertical movement, a pair is placed to the right and left of the eye to measure horizontal movement, and the last one is placed on the center of the forehead to represent the ground.

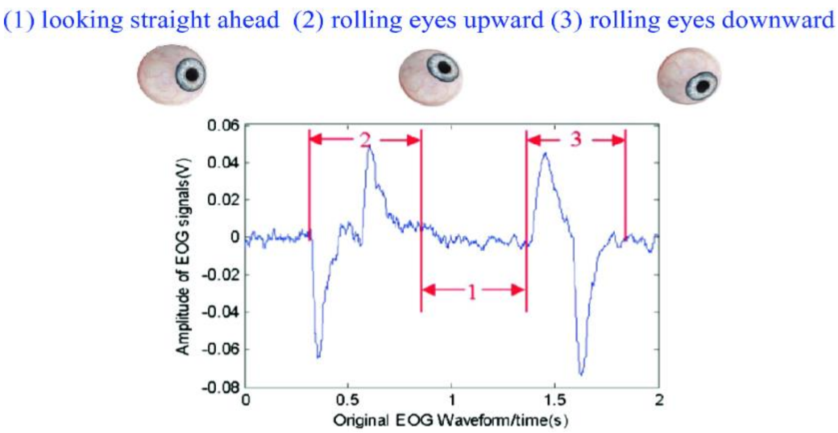


Figure 1. The waveform of eye upward and downward movements

In this paper, the EOG signals have been acquired using PSL-IEOG2 device. This device is dedicated to recording EOG signals by placing the device's electrodes around the eye vertically and horizontally. Hence, the EOG signals are analyzed and six different directions of eye movement are determined (up, down, right, left, double blink, and center). A dataset of 500 pairs of EOG signals for each movement has been collected. Each pair of EOG signals (horizontal and vertical) is preprocessed and concatenated to represent the input for the examined models. Three models are examined in this study namely, convolution neural network (CNN), visual geometry group (VGG), and inception. The VGG and Inceptions architectures are modified to fit the task at hand. Furthermore, a user interface is proposed to ease the paralyzed people's daily life. The remaining of this paper is organized as follows: section 2 discusses the existing studies; section 3 presents the proposed method; the achieved results are provided in section 4, and finally the conclusion is given in section 5.

2. LITERATURE REVIEW

In recent years, many studies have considered the development of HCI systems based on the EOG signals [14]–[20]. According to the utilized techniques, these studies can be categorized in two main categories: i) studies that consider simple techniques such as thresholding and simple rules and ii) studies that consider sophisticated classifiers, such as support vector machine (SVM), linear discriminant analysis (LDA), decision tree and artificial neural networks (ANN). Key studies are summarized as follows:

Research by Heo *et al.* [14] proposed a new practical electrode position on the forehead to measure EOG signals. Low pass filter with cutoff 10 Hz is used to avoid noise. the maximum peak and minimum valley values and their positions are captured as features. These features are classified using specific threshold. If the amplitude value crosses the high threshold, 300 samples are extracted centered on the peak and the max value, min value, max position and min position are defined, and if the difference between max position and min position is greater (less) than zero, it means right (left) movement. The vertical movements are classified in the same way. Six types of eye movements are classified (up, down, left, right, blink, and double blink) by this algorithm. The upper and lower thresholds of each channel are optimized according to individual EOG characteristics. The cursor is placed over the letter “E” which is at the center of the virtual keyboard. The cursor can move step by step according to the user eye movements. A character can be selected by double blink movement, then automatically the cursor is returned to ‘E’. This writing system has achieved an accuracy 91%.

Research by Ang *et al.* [15] designed a user-friendly HCI system. Only EOG produced by one eye movement (double blink) is used to encode user’s intentions, control, and guide an automatically moving cursor on screen. In preprocessing stage, wavelet filtering is used instead of traditional band pass filtering to remove noise from raw recordings. The extracted features from EOG signal are L1-norm, entropy and kurtosis. L1-norm measures the signal's magnitude by summing the absolute values of all samples in the vector, entropy measures the amount of information in the signal and kurtosis measures the climaxing of the signal. Subsequently, the feature vectors are fed into SVM classifier. The experiments were carried out on eight subjects in both indoor and outdoor conditions. The average accuracy achieved is 84.42% for indoor and 71.50% for outdoor conditions.

Research by Qi and Alias [16] collected EOG signals from five subjects. The EOG signals are preprocessed to remove noise and other interferences by Chebyshev 4th order band pass filter of frequency range between 0.1-50 Hz. Thereafter, three types of feature extraction have been utilized and they are as follows: autoregressive coefficients using burg method, statistical parameters such as kurtosis coefficients, Interquartile range, and power spectral density using Yule-Walker method. For classification, ANN and SVM have been examined, the latter has achieved the best accuracy 69.75%.

It is noticeable that there is a compromise between accuracy and processing time. Moreover, to the best knowledge of authors, most of the existing studies have utilized traditional classifiers and this can be justified by the limited public data resources. Hence, in this study, we have collected our own dataset of 500 pair of EOG signals for each eye movement and we are trying to improve the recognition accuracy without effecting the processing time.

3. THE PROPOSED METHOD

The proposed system architecture for HCI includes four stages, which are data acquisition (DAQ), preprocessing, classification, and user interface as shown in Figure 2. The first one is data acquisition (DAQ) which has been applied to collect digital data. The following stage is filtering data from noise and raising data quality, whichis called the pre-processing stage. The classification stage is in which the eye direction of the test data is determined. Finally, the user interface stage has been designed to integrate all system functionality and display to users. In the following subsections, each stage will be described in detail.

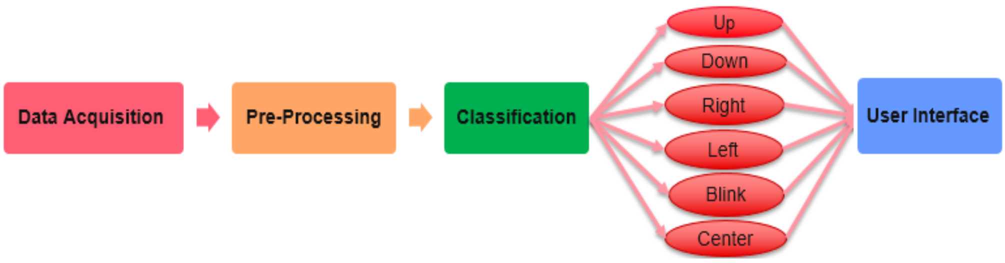


Figure 2. The proposed architecture for the EOG based HCI

3.1. Data acquisition

Modern DAQ systems consist of three essential components: sensors, DAQ measurement hardware, and a computer with software application. A sensor is a device that captures the change in a physical phenomenon and converts it into a measurable analog signal like voltage. A DAQ device converts the noisy signals into accurate forms by using signal conditioning circuit and also digitize analog signals into a stream of digital data by analog to digital converters (ADCs). The software programs can visualize, analyze and store the digitalized data on the computer with different formats. Due to the lack of public reliable EOG datasets, in this study, data have been acquired and collected using a special hardware that can measure EOG.

3.1.1. Hardware device

The sensors are silver chloride Ag/AgCl electrodes that are placed around the eye, horizontally and vertically. They are standard pre-gelled and self-adhesive disposable electrodes, that are the most used reference electrodes in electrochemical measurements for control systems. These electrodes outperform the others in retaining an essentially constant composition.

The device includes two units: PSL-iEOG2 and PSL-DAQ (Figure 3). PSL-iEOG2 is a two channels EOG module, that produces EOG analog signal and EOG direction event that represent the actions in the signals. It uses DC 5 V input power with 750 V/V amplification. PSL-DAQ is designed to receive analog two-channel signals and digitalize these signals for reading, analysis, and processing. It is running at a sampling rate of 1,000 samples per second. The signal range is from 0 to 3.3 V with a center of 1.65 V. The hardware is connected to a powerful software to monitor and store the signals as LabVIEW and visual C++ libraries with 16-bit resolution [21].

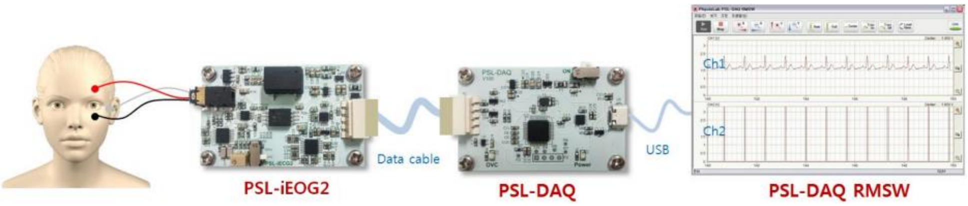


Figure 3. PSL-iEOG2 and PSL-DAQ configuration

3.1.2. Software (PSL-DAQ RMSW)

The software has two main screens DAQ view and load view. DAQ view screen monitors the two channels signal generated by the PSL-DAQ unit in real-time. This requires communication between the PSL-DAQ unit and the computer through the USB port. Finally, the two channels' signal data are saved simultaneously in PDQ format.

On the other hand, load view is a screen to review and print the saved signal data. It also allows many options to utilize it like trace, center, auto, and full. Finally, it supports the conversion of multiple files from PDQ extension to txt extension to be compatible with different programs as MATLAB and others. To maintain synchronization between the horizontal and vertical eye signals, the combination of two units of PSL-IEOG2 is necessary. The first records the signal horizontally and the second records the signal vertically. Subsequently, the two units are connected to PSL-DAQ gender. It works as an electrical switch to control the transmission of the signal horizontally and vertically, and then the outputs can be digitized by PSL-DAQ, as shown in Figure 4.

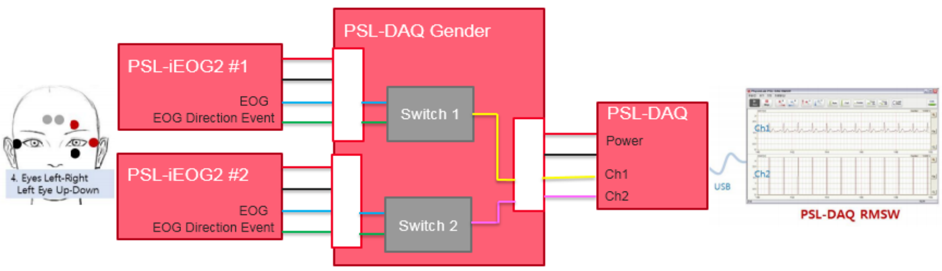


Figure 4. Modular connection for synchronization

3.1.3. Dataset

Data were collected from 50 healthy subjects with normal vision (26 males and 24 females) ranging in age from 20 to 55 years. The electrodes were placed around their eyes as follows, a pair of electrodes to the right and left of the eye for the horizontal channel, another pair above and below the left eye for the vertical channel, and a pair in the center of the forehead for reference. The signal was recorded by giving a set of commands in the following order: up, down, right, left, double blinking, and center, each command representing a class of the data set. The duration of recording the full signal ranges from 12 to 20 seconds so that the difference between each command and the other is 1 second. The recording was done ten times for each one of the subjects to obtain ten different signals. Hence, the total number is 500 signals. Each signal has been segmented into six different signals; each one represents specific movement from the six classes. Thus, 500 pairs of EOG signals have been obtained for each movement. Each pair of EOG signals (horizontal and vertical) represents the system inputs.

3.2. Pre-processing

After the signal acquisition phase, the preprocessing phase is carried out in two steps. In the first step, the EOG signal is filtered using a second-order Butterworth band pass filter. The filter order has been empirically chosen. The filter is applied with a cut-off range from 0.5 to 20 Hz which is the bandwidth of EOG signals. Figure 5(a) shows the EOG signal before filtering. In contrast, Figure 5(b) shows the waveform of EOG signal after filtering. The second step is applying down sampling for EOG filtered signals to get the best accuracy with minimum computation. Hence, each signal is down sampled to 100 samples without losing any significant information from the signal.

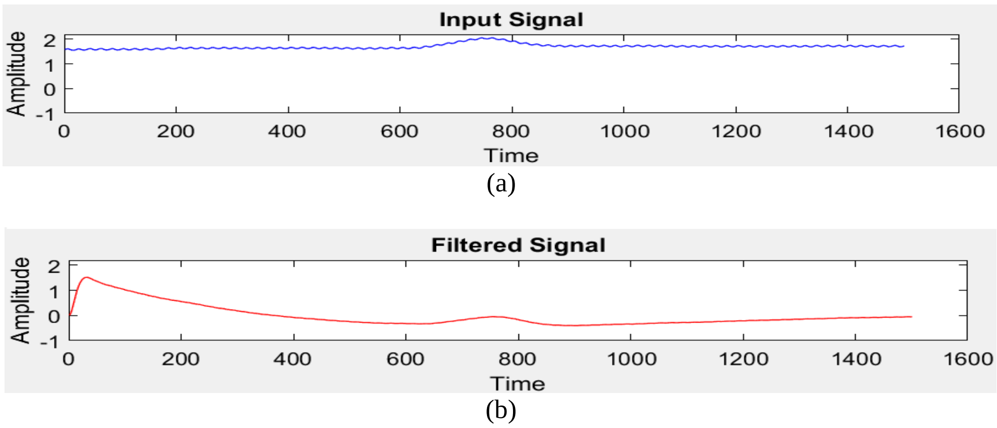


Figure 5. EOG signal (a) before filtering and (b) after filtering

3.3. Classification

Regarding the classification phase, the filtered signals are fed into a deep learning model to be classified to one of the six eye movements: up, down, left, right, center, and double blinking. For comparison, three deep learning models have been evaluated namely CNN, VGG and inception models. Each model can be discussed briefly as follows:

3.3.1. Convolutional neural network

CNN is considered a version of a multilayer perceptron network for supervised learning. It consists of an input layer, multiple hidden layers, and output layers. The input passes to the network through the input layer and the hidden layers consist of convolutional layers and pooling layers followed by fully connected layers that are used as output layers [22].

The convolutional layer is the power of a CNN. In this layer, a mathematical operation called convolution is utilized. The convolution operation is carried out by applying a filter, usually called a convolutional kernel that slides over the input and applies appropriate mathematical operations between them to extract certain features or patterns for the original input. CNN may include more than one convolution layer, where the first hidden layers extract simple and clear features, and as it goes deeper into the hidden layers, the complexity of the features increases. Therefore, all values resulting from the convolution process are stored in the feature map. Thereafter, the outputs are normally passed through an activation function like the rectified linear unit (RLU). In the pooling layer, the size of the activation map is reduced. This minimizes the number of parameters and computations, which prevents overfitting. The process is carried out by applying one of the max or average functions. The most popular function is max pooling with a small window to keep the largest values and reduce the map size. The fully connected layer is the layer through which the classification process takes place. A fully connected multi-layer perception with softmax activation function is utilized. The output is an array of values; each value represents the probability that the current input belongs to one of the considered classes. The winner class is the one with the largest probability [23], [24].

In this study, a one dimensional (1D CNN) is considered for the task at hand. For the proposed 1D CNN, the convolutional layer creates a filter that passes over a single temporal dimension for the EOG signal to produce a tensor of outputs. Figure 6 shows the architecture of the proposed 1D CNN. The proposed 1D CNN model is built from four basic blocks. Each of them consists of two convolutional layers to extract the main features using the RLU activation function and one max pooling layer to reduce the size of the feature map and recording the most distinctive features. The four blocks differ in terms of the size of the filters in the convolutional layer (32, 64, 215, and 1,024). Thereafter, a dropout layer is added with a percentage of 50% to prevent the model from overfitting at each update of the training phase. Finally, a flatten layer is added to put the feature vector as input to the output layer, which is a fully connected layer consisting of six output classes (up, down, right, left, double blink, and center). the softmax activation function is utilized to compute their probabilities to classify the signal according to the maximum probability. The best results are achieved by training the model for 200 epochs using Adam optimizer with a learning rate equals to 0.0001.

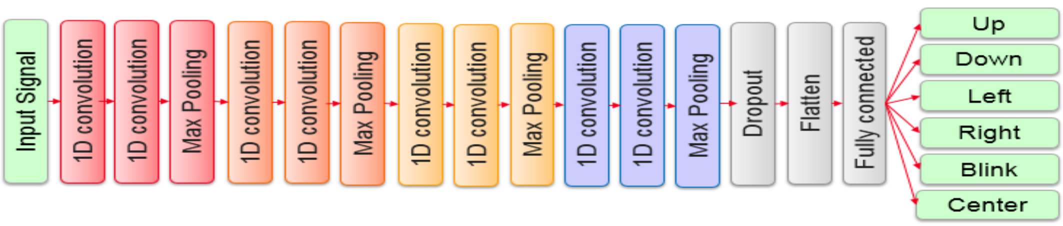


Figure 6. The proposed 1D CNN design

3.3.2. Visual geometry group network

VGG network represents a pre-trained model of CNN that was proposed by the visual geometry group of Oxford University [25]. It was one of the best and famous models that have been submitted to imagenet large scale visual recognition challenge (ILSVRC2014). Where it has performed very well and achieved an accuracy of 92.7% with the imagenet dataset (14 million images with 1,000 classes) [25].

In this study, the input signal is passed to a stack of 1D convolutional layers by using the kernels with a small size to capture the patterns from all signals. Figure 7 shows the utilized VGG architecture in this study. The convolutional layers are included in five blocks. The number of filters utilized is 64, 128, 256, 512, and 512 for the five blocks, respectively. The spatial pooling is performed by five max-pooling layers, each one of them follows a block of the convolutional layers. Finally, there are three fully connected layers that have different depths with dropouts to reduce any overfitting. In the last connected layer, the softmax activation function is used to produce the probabilistic value for each of the six classes (up, down, right, left, double blink, and center). The input signal is classified to the class with the largest probabilistic value. The best results have been achieved, when the model is trained by 250 epochs using Adam optimizer with the valid padding. Considering that the batch size is 64 to obtain the best distinct features and to reach the proper classification of EOG signals.

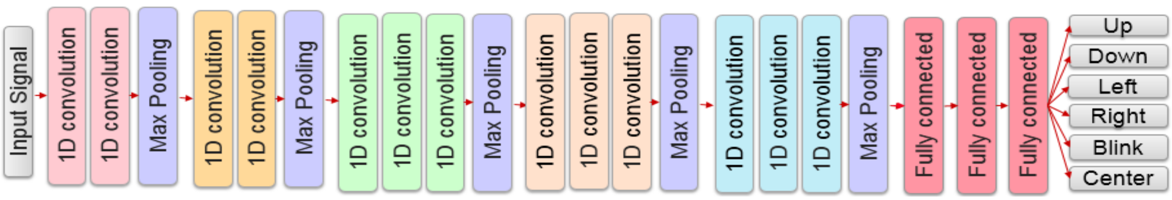


Figure 7. VGG network architecture

3.3.3. Inception network

Inception network [26] has been launched to create new significant innovations for deep learning models. There are two models of the Inception network: The naïve inception model and the dimension reductions module. The naïve inception model (Figure 8(a)) [26] encompasses multiple blocks. Each block includes multiple convolutional layers that work on the same level. Each layer consists of a number of filters with a specific kernel size (1×1, 3×3, and 5×5). Finally, the concatenation of outputs is reduced by applying max-pooling operation and sent to the next inception block.

In this study, the inception model with dimension reduction is applied for the task in hand as shown in Figure 8(b). 1×1 convolutional layers are applied before the 3×3 and 5×5 convolutional layers, and also after the pooling layer. Thus, each inception module is reduced to decrease computational cost and avoid any overfitting. In the last layer, the softmax activation function is used to produce the probabilistic value for each class of the six classes (up, down, right, left, double blink, and center). The input signal is classified to the class with the largest probabilistic value. The proposed architecture is based on five sequential inception modules. For each module, the outputs are concatenated and sent to the next inception module as inputs. The best results are obtained by training the model over 100 epochs using Adam optimizer with a learning rate equals to 0.0001. Considering that the batch size is 32 to obtain the best distinct features and to reach the proper classification of EOG signals.

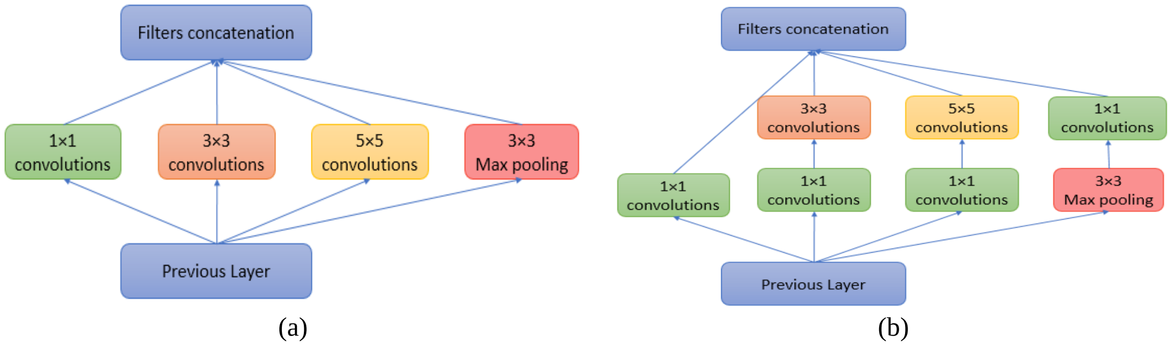


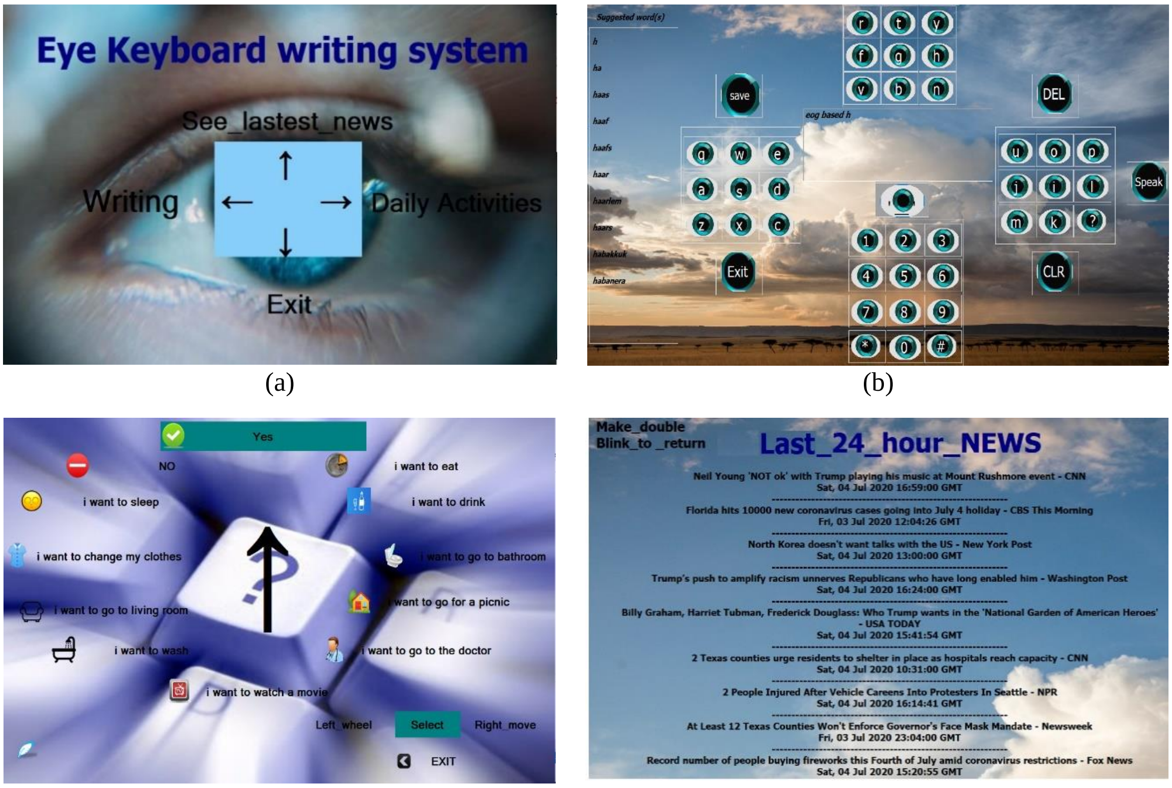
Figure 8. Inception model version (a) inception model naive version and (b) inception module with dimension reduction

3.4. User interface

The graphical user interface has been designed in such a way that paralyzed users can write messages and texts on the computer using their eye movements in an easy and completely non-stressful way. The provision of all facilities that enable the disabled to communicate effectively with their community in all life situations has been taken into consideration. That they can live better and freely communicating their words and ideas.

The main window has four actions (Figure 9(a)): i) the user can write data and messages by looking to the left and selecting "writing" and thus go to the virtual keyboard window (Figure 9(b)); ii) user can select from daily activities, by looking at the right and chooses “daily activities”, which takes the user to another window (Figure 9(c)) where the common daily activities are listed in such a way the user can choose from them also by eye movements; iii) user can see the latest news loaded from different websites by looking up in the main window and chooses “ see latest news” (Figure 9(d)); iv) user can terminate the application by looking down in the main window and chooses “exit”. Choosing any option or character is done by double blinking.

In the writing window (Figure 9(b)), the characters and numbers are divided into four groups: up, down, right, and left in a way consistent with the basic eye movements. First, the cursor is on the button in the middle of the window. When the user wants to write a particular letter, the user should look in the direction of the group where the letter is located and select it through a double blinking movement. After selecting the group, the user moves the curser through eye movements in the direction where the character exists in that group and selects it. Each chosen character will be written in the text box. To speed up the process and do not strain the user's eyes, an auto-completion feature is added to the application through a dictionary. The user only selects the initial letters of the word and then a list of words matching these letters appears on the left of the window so that the user can choose the desired word from it. Moreover, if the user chooses the button “speak”, all that is written in the text box will be pronounced.



(a) (b)

(c) (d)

Figure 9. The user interface system (a) system main window, (b) writing window, (c) daily activities window, and (d) last 24-hour news window

4. EXPERIMENTAL RESULTS

The experiments have been conducted using the data set described in section 3.1. Five-fold cross validation is considered for evaluation. The dataset includes six categories: left, right, up, down, center, and blinking. The horizontal and vertical EOG signals are preprocessed as discussed in section 3.2. The three considered models CNN, VGG, and inception have been examined and evaluated by four measurements: sensitivity, specificity, precision and overall accuracy. These criteria are extracted from the confusion matrix for each of the deep learning models as (1)-(4):

$$Sensitivity(Recall) = TP/(TP + FN) \tag{1}$$

$$Specificity = TN/(TN + FP) \tag{2}$$

$$Precision = TP/(TP + FP) \tag{3}$$

$$Overall\ Accuracy = (TP + TN)/(TP + TN + FP + FN) \tag{4}$$

Where TP is true positive, TN is true negative, FP is false positive, FN is false negative. Tables 1-3 show the achieved results. Figure 10 summarizes the results which reveal the superiority of the proposed inception model. Moreover, Table 4 provides a comparison with previous studies which reveals the superiority of the proposed models. Moreover, the proposed system needs 1 sec for performing one complete selection.

Table 1. The achieved accuracies using CNN

Movement classes	Accuracy (%)	Sensitivity (%)	Specificity (%)	Precision (%)	Overall accuracy (%)
Down	94.4	94	99.2	95.9	98.3
Up	95.4	95	99	95	98.3
Left	97.2	97	99	95.09	98.6
Right	97.2	97	99	95.09	98.6
Blink	93.6	94	99.2	95.9	98.3
Center	96.6	97	99.4	97	99
Average±stander deviation	95.7±1.51	95.6±1.5	99.1±0.16	95.6±0.77	98.5±0.28

Table 2. The achieved accuracies using VGG network

Movement classes	Accuracy (%)	Sensitivity (%)	Specificity (%)	Precision (%)	Overall accuracy (%)
Down	90.8	91	98.4	91.9	97.1
Up	90.6	91	98	90.09	96.8
Left	96	96	98.4	92.3	98
Right	94.4	94	98.4	92.1	97.6
Blink	89.2	89	99	94.6	97.3
Center	93	93	98.6	93	97.6
Average±stander deviation	92.3±2.58	92.3±2.5	98.5±0.33	92.3±1.47	97.4±0.42

Table 3. The achieved accuracies using inception network

Movement classes	Accuracy (%)	Sensitivity (%)	Specificity (%)	Precision (%)	Overall accuracy (%)
Down	97	97	99.6	97.9	99.1
Up	96.6	97	99.2	96.03	98.8
Left	97.8	98	99.4	97.02	99.1
Right	97.4	97	99.2	96.03	98.8
Blink	93.8	94	99.2	95.9	98.3
Center	95.8	96	99.2	96	98.6
Average±stander deviation	96.4±1.45	96.5±1.38	99.3±0.17	96.5±0.81	98.8±0.31

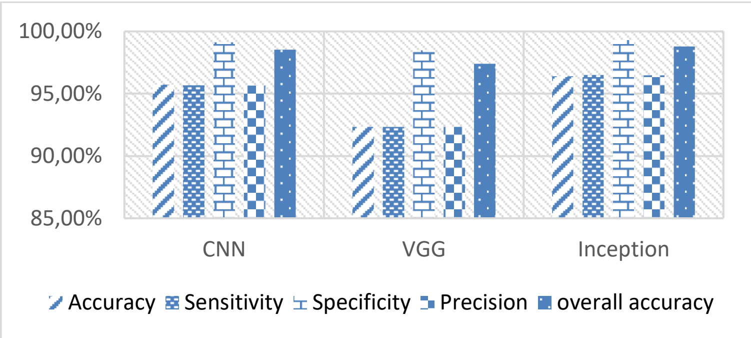


Figure 10. Summarized results for the three deep learning models

Table 4. Comparison between the proposed work and previous studies

Study	Dataset	Preprocessing	Feature extraction	Classification	Accuracy (%)
Zhang *et al.* [14]	8 subjects	Wavelet filtering	L1-norm, kurtosis and entropy	SVM	84.4
Ramkumar *et al.* [27]	10 subjects	Band pass filter	Parseval theorems	TDNN FFNN	89.6 94.1
Banerjee *et al.* [28]	4 subjects	Low pass filter High pass filter	Wavelet coefficients, auto-regressive and power spectral density	KNN	80
Usakli and Gurkan [29]	20 subjects	Band pass filter	_______	Nearest neighborhood	95
Proposed method	50 subjects	Band pass filter	_______	CNN VGG Inception	95.7 92.3 96.4

5. CONCLUSION

This research paper proposes a system for writing controlled by EOG signals. This system helps all patients who suffer from diseases, that cause them severe motion disabilities and paralyze their limbs. Thus, there is nothing left for them to communicate with their community except the movement of their eyes. Hence, the proposed system is based on detection and recognition of six categories of different eye movements; up, down, right, left, center, and blinking captured by EOG signals. These signals are filtered using second order butter worth band pass filter, then both vertical and horizontal EOG signals are concatenated in one vector to represent the input to three deep learning models. The three investigated models in this study are CNN, VGG and inception. The results reveal the superiority of Inception model that has achieved an average accuracy of 96.4% against the other two considered models and the existing studies. In addition, the processing time is one second for one selection to be accomplished which is comparable with the existing studies. Moreover, a user interface is proposed in this study and consists of four windows: the first one is the main window that displays all the provided features; the second window represents a virtual keyboard for writing texts; the third window includes the daily activities that patients may need; the last window displays the up-to-date news gathered from famous news sites. Finally, we are looking forward to improving the processing time and examine other state of art deep learning models.

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