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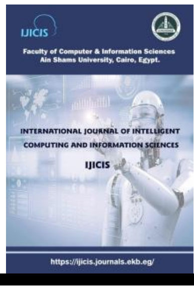

DEVELOPING A METHOD FOR CLASSIFYING ELECTRO-OCULOGRAPHY (EOG) SIGNALS USING DEEP LEARNING

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Abstract: *Recently, a significant increase appears in the number of patients with severe motor disabilities even though the cognitive parts of their brains are intact. These disabilities prevent them from being able to move all their limbs except for the movement of their eyes. This creates great difficulty in carrying out the simplest daily activities, as well as difficulty in communicating with their surrounding environment. With the advent of Human Computer Interfaces (HCI), a new method of communication has been found based on determining the direction of eye movement. The eye movement is recorded by Electro-oculogram (EOG) using a set of electrodes placed around the eye horizontally and vertically. In this work, The horizontal and vertical EOG signals are filtered and analyzed to determine six eye movement directions (Right, left, up, down, center, and double blinking). The deep learning models namely Residual network and ResNet-50 network have been examined. The experimental results show that the ResNet-50 network gives the best average accuracy 95.8%.*

Keywords: *Human computer interface (HCI), Electro-oculogram, Deep learning , Residual network.*

1. Introduction

It has been observed in the past few decades that many diseases cause paralysis of patients as they lead to the weakness of neuromuscular cells. This is even though the cognitive areas in the brains of patients are completely intact. However, it causes atrophy and gradually stops the voluntary muscles until their motor limbs become suspended and do not perform their vital functions [1,2]. It does not take long for

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the patient to become paralyzed in all his motor limbs. Unfortunately, the number of these patients increases with the emergence of new diseases that cause paralysis as well. According to a World Health Organization survey, 785 million people aged 15 years or older have some form of motor disability. This number represents 15.6% of the world's population, which means that one person out of 7 healthy people is infected. This number is due to many genetic factors, and environmental factors, wrong diet [3,4].

One of the most common diseases that causes permanent total paralysis is amyotrophic lateral sclerosis (ALS). It is a motor neuron disease that causes the loss of neurons responsible for controlling movement. And gradually stop sending nerve signals to the upper and lower extremities. The motor limbs are affected by muscular atrophy, and the muscles of the hands, fingers, and legs begin to weaken and relax. After a period of infection with the disease, the symptoms increase and the health status of patients becomes worse, as swallowing and breathing are very difficult. In addition, it may cause respiratory failure in the last stages of the disease. However, there are muscles that are not affected by atrophy, which are the muscles that control eye movement [5]. No clear causes of amyotrophic lateral sclerosis have been found. It is more likely to contract the disease if a family member has a history of illness with this disease. But it is recognized by its clear and distinct symptoms from others. The most important of these symptoms are frequent involuntary tremors in the hands and feet, drooling of saliva, and a noticeable change in the patient's voice. This disease affects five out of every 100,000 people worldwide. People with this disease become unable to carry out the simplest daily tasks. Their lives become almost halted because they are unable even to communicate with the people who accompany them [6].

Diseases leading to atrophy and loss of motor neurons are numerous, including Guillain-Barre syndrome (GBS) and myasthenia gravis. They cause comprehensive damage to all motor muscles. Thus, the limbs stop receiving nerve signals and completely stop moving [7]. The reason for the incidence of such diseases lies in the environmental conditions surrounding patients, such as being in areas that are constantly exposed to electromagnetic waves or heavy metals. In some cases, the cause is genetic factors or patients' practice of some incorrect habits such as smoking. In the end, these patients have no way of communicating except through the movement of their eyes [8].

Recently, and especially after the emergence of human-computer/machine interfaces (HCI/HMI), it has become the main support for these patients, as they depend on eye movement to take a certain action among a set of procedures that are displayed on the computer screen, and the effect of this procedure can be monitored on-screen too. Thus, the human-computer interfaces become a link between patients and the computer. By determining the direction of the movement of the patient's eye, a specific act that the patient desires are chosen and implemented, and its result appears on the computer screen, for example, writing a specific text [9]. Most of these interfaces depend on the four main directions (right, left, up, down) in addition to blinking, which usually means confirming the selection of the action. The reason for the dependency on only the four directions is the difficulty of determining the sub-directions correctly [10]. Human-computer interfaces are being developed to be effective and impactful in many applications such as controlling portable robots and controlling wheelchairs [11].

An Electrooculogram (EOG) is a method for determining the direction of eye movement, as it measures biological signals resulting from the presence of an electrical potential difference between the retina and cornea of the eye. When the eye moves upward, negatively charged impulses are formed on the retina in the back, while the cornea is formed by positively charged impulses, and vice versa when the eye moves downward, and this is evident in the vertical channel. Likewise, when looking to the right and left, the effect appears in the horizontal channel. The eyeball becomes bipolar with the retina and cornea, and this is what Figure 1 shows. Increasing the angle of eye-rolling increases the amplitude of the pulse, and the duration of eye-rolling is directly proportional to the width of the pulse, whether positive or negative. In most cases, electrocardiogram signals of the eye are recorded using five electrodes. To measure the horizontal movement, a pair of electrodes are placed on the right and left of the eye, and to measure the vertical movement, a pair of electrodes are placed above and below the left eye. Finally, the last electrode, which represents the reference, remains in the middle of the forehead [12].

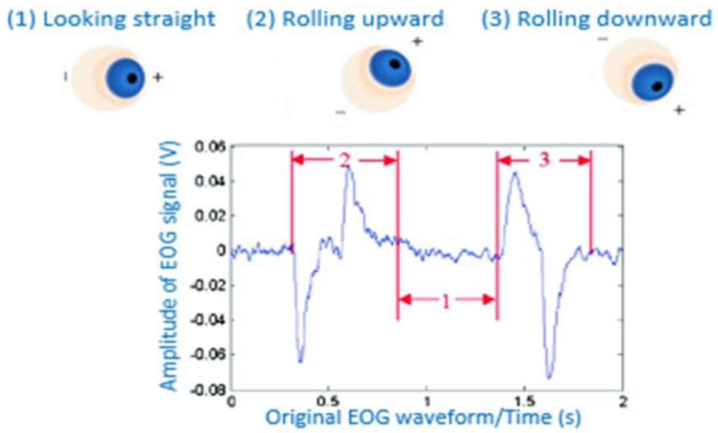

Figure. 1: The EOG waveform corresponding to the eye roll

In this research paper, the EOG signals were recorded using a dedicated device where the electrodes were placed vertically and horizontally around the eye. Vertical and horizontal cues were analyzed to identify six different eye movement directions (right, left, up, down, double blinking, and no movement). The aggregate dataset contains 500 EOG signals per channel. The horizontal and vertical signals were filtered before being approved as inputs to the deep learning models that were examined.

The rest of the paper is organized as follows: the second section explains the relevant Literature, the third section explains the proposed approach, the fourth section presents the experimental results and finally, the conclusion is presented in the fifth section.

2. Literature Reviews

Currently, a lot of literature has emerged that works on developing human-computer interfaces based on the use of EOG signals. Existing studies can be categorized into two groups. The first group depends on traditional machine learning such as logical rules, threshold, and artificial neural networks (ANN) [13-19]. The second one uses deep learning models such as convolutional neural networks (CNN) [20-23]. The key studies are discussed in terms of the utilized techniques, and the achieved accuracy as follows:

Usakli and Gurkan [13,14] developed a text writing system based on detecting horizontal and vertical EOG signals by using five electrodes that are put around the eye for acquisition, and then the signal is digitized and transferred to PC. The signals are filtered by a band pass filter with a cut of frequency range 0.1 -30Hz to remove the noise. Four eye movement directions along with blinking are classified using Nearest Neighborhood. Experiments were conducted on a data set of twenty subjects. The experimental results show that the achieved accuracy is 95% and the writing speed is five characters per 25 seconds.

Aungsakul et al. [15,16] proposed a Human-computer interface system based on fourteen features extracted from vertical and horizontal EOG signals such as the peak and valley amplitude positions (PAP/ VAP), the peak, and valley amplitude values (PAV/ VAV), and other features. This study classifies eight movements along with blinking using the discrimination rules. The experiments show that the classification accuracies are close to 100% for some subjects but the performance degrades in real-time.

Ramkumar et al. [17] implemented a human-computer interface that detects eleven different eye movements. Each one of them is a different task to help the disabled elderly. EOG signals have been evoked from ten subjects. Each recording trial lasts for two seconds. Ten trials have been recorded for each task. In preprocessing step, a notch filter is applied to remove the 50Hz power line artifacts. Then 16 features are extracted from the frequency domain to train neural network classifiers. Finally, classification is done using Feed Forward Neural Network and Time Delay Neural Network. The results show that the mean performance of FFNN varies from80.72% to 91.48%. On the other hand, TDNN is comparatively better with mean classification rates varying from 85.11% to 94.18 %.

Alberto López et al. [18] developed a keyboard interface, in preprocessing stage, the Wavelet decomposition tree is used to filter the input signal, then the amplitude value is extracted as a feature from the EOG signal, EOG signal is classified into five patterns using a voltage threshold: left, right, up, down, and straight. When the threshold values are exceeded in any of the four directions, the cursor moves in the corresponding direction. Thus, before using the proposed system, it is necessary to record the user's physiological parameters to set the threshold values. The voluntary blinking pulses are also detected using a threshold. Writing the word "Hello" is achieved with an average accuracy of 95.2% and an average typing speed of only 2.37 characters/min.

Ji Qi and Alias [19] collected EOG signals from five subjects. The EOG signals are filtered by Chebyshev 4th order band pass filter with a frequency range [0.1 -50Hz] to remove noise and other interferences. Three feature types are extracted: statistical features, the derived AR coefficients from the Burg method, and estimated PSD using the Yule-Walker method. For classification, Artificial neural network (ANN), and support vector machine (SVM) are used. The best-achieved accuracy is 69.75% using SVM.

Fernando Andreotti et al. [20] provided new insight into classifying individual robotic sleep periods using convolutional neural networks (CNN). The classification has been performed for the polysomnography group. It includes electromyogram (EMG), electrooculogram (EOG), electroencephalogram (EEG) signals. The Features from the time-frequency domain are determined for each signal using a continuous wavelet transform (CWT). Experiments were conducted on 20 healthy subjects. The convolutional neural network has achieved an average accuracy of 90% with 10-fold cross-validation.

Huy Phan et al. [21] improved the sleep phase recognition system. This system is used in diagnosing and treating sleep disorders. A general data set containing 20 subjects is relied upon. In preprocessing step, Fast Fourier Transform (FFT) is used with applying the frequency-domain filter bank. Multitasking Convolutional Neural Network is used for its effectiveness in defining the framework for classification. In addition, it uses adjacent epochs to predict the output also aggregation model to decrease computational expenditures. The results demonstrate a significant increase in the classification accuracy, where the overall accuracy reached 83.6%.

Fan Jiahao et al. [22] designed a new approach to determine the automatic gradient of sleep. The electrooculogram (EOG) signals are used instead of relying on electroencephalographic (EEG) signals. This is because obtaining confirmed information from EEG signals is cumbersome and inconvenient. In addition, the extracted information from the EOG signals is more suitable for determining the spontaneous gradient of sleep. The Convolutional Neural Network (CNN) is used to extract features from the EOG signals. A recurrent neural network (RNN) also is used to capture long-range sequential information. The results have been computed from the Sleep-EDF database that contains the EOG signal for twenty subjects. The system has achieved a total accuracy of 81.2%.

Thibhika Ravichandran et al. [23] presented a sophisticated method for classifying the electrooculography (EOG) signals. The EOG signals have been recorded by four electrodes put on the eye horizontally and vertically along with the reference electrode. The horizontal and the vertical signals are classified into four movement classes: upward, downward, left movement, and right movement. Two deep learning classification models are evaluated namely convolutional neural network (CNN) and long-term memory (LSTM). As a result, LSTM has recorded an accuracy of 88.33%, while CNN has recorded an accuracy of 90.3%.

According to the current studies in the literature, Comparative analysis has been performed which can be summarized in the following observations set: Firstly, the scarcity of public data sources. In addition, the largest published data set is only 20 subjects. Secondly, the use of EOG signals that represent only the four major eye movements in most of the literature implies. Thirdly, many factors that affect the accuracy of the HCI system must be considered, such as electrodes positions and their materials, the capabilities of the EOG signal device, the distance between the subject and the interface, and if the subject is pre-trained or not. Fourthly, extracting many distinctive features for classification increases the accuracy rate to a limit it reaches in some literature almost 100%. However, it negatively affects the processing time in the system. Finally, a major drawback is observed in all previous studies, that the only evaluation measurement is overall accuracy. However, in the case of imbalanced datasets, overall accuracy will be biased to the dominant class.

3. The Proposed Method

The architecture of the proposed method consists of three phases: data acquisition to extract EOG signals, preprocessing to filter signals from any noise, and classification to determine the direction of the EOG signal into one of six directions, as shown in Figure 2. The details of each phase will be discussed in the following subsections.

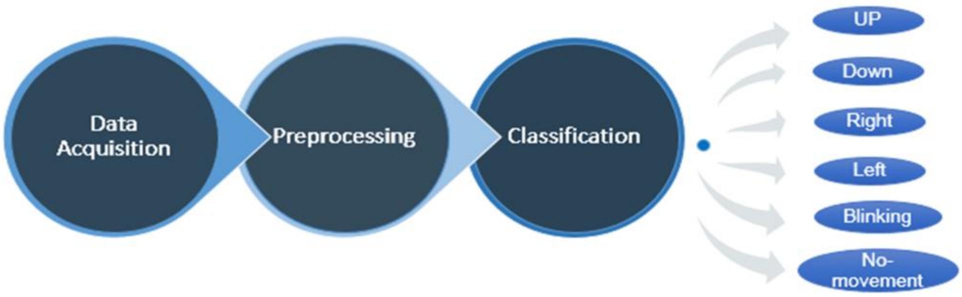

Figure. 2:The architecture of the proposed method.

3.1 Data Acquisition

The purpose of the data acquisition process is to acquire analog signals that measures physical or electrical phenomena and converts them into digital signals so that they can be analyzed and stored using a computer. Data acquisition systems include three main components: sensors, a DAQ device, and a computer with a software program. Sensors detect changes in physical phenomena and represent them in analog signals that can be processed. DAQ measurement devices convert those analog signals to digital signals and use a signal conditioning circuit to get rid of noisy signals by converting them into tiny patterns. The software application can display and store the digital signals in more than one extension. There is a marked lack of public EOG data sets according to the literature analysis as in the previous section. Hence, in this study, the data set was collected using a dedicated device that measures the electrooculography signals.

The sensors of the solid device are six silver chloride electrodes placed vertically and horizontally around the eye. These electrodes are the most widely used in control systems for electro-physical measurements, as they are distinguished from other electrodes in maintaining a stable base form [24]. The device consists of two chips: PSL-iEOG2 and PSL-DAQ. The PSL-iEOG2 measures the EOG signals and produces two channels, the first contains the analog EOG signals and the second contains the EOG direction event to represent the events within the signals with amplification of 750 V and input power of 5 V.

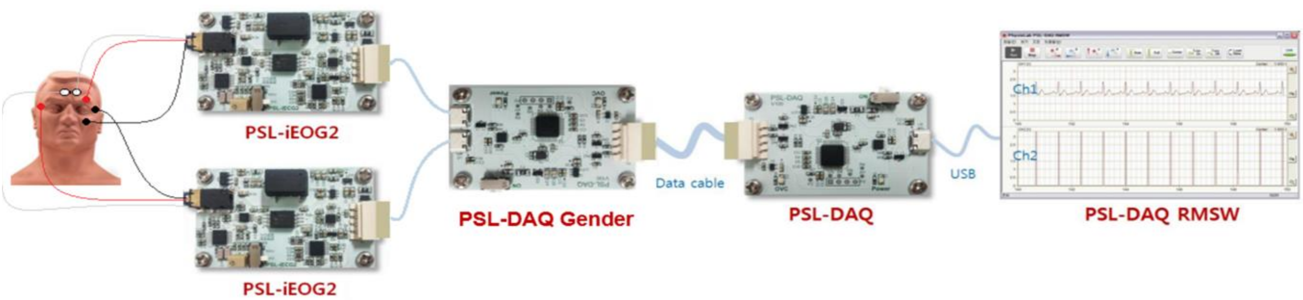

Figure. 3: PSL-iEOG2 and PSL-DAQ Connection Model

Two units of PSL-iEOG2 are combined. The first unit measures the horizontal EOG signals and the second measures the vertical EOG signals, to ensure that synchronization is maintained between the horizontal and vertical EOG signals. For these signals to reach the PSL-DAQ chip, two PSL-iEOG2 units had to be connected first to the PSL-DAQ Gender unit. It works as a switch to transmit the horizontal and vertical signals to the PSL-DAQ. Thus, it is the link between the two chips as shown in Figure 3. The PSL-DAQ takes analog EOG signals and digitizes them at a sampling rate of 1000 samples per second to be able to be analyzed and processed. The device is connected to a modern program to display the output signals with a range from 0 to 3.3V and store them with a resolution of up to 16 bits [25].

It is necessary to connect the PSL-DAQ chip to the computer via a USB port to activate the software program. The program includes two forms, the first one is called the DAQ view form, which is responsible for displaying the signals of the horizontal and vertical EOG channels and saving them in real-time in pdq extension. The second form is the load view form to track signals, print their data, and support their files to be saved in more than one extension when they are converted from a pdq format to a text format to suit multiple programs.
The data set was collected from 50 normal subjects. They are between 20 and 55 years old (26 are males and 24 are females). They have good normal vision. The measurement for each of them was as follows: Six electrodes were put on the subject's eye. Two electrodes were put above and below the left eye to measure the vertical EOG signals and the two others to the left and right of the eye to measure the horizontal EOG signal. Finally, two electrodes were put on the middle of the forehead as reference electrodes. Each signal was recorded according to a sequence of measures: right, left, up, down, double blinking, and no movement where each measure represented a specific eye movement classification category. Ten different EOG signals were recorded for each subject separately. The duration of each signal measurement was approximately 12 to 20 seconds. The total number of recorded EOG signals is 500 horizontal signals and the same number as vertical signals. Each signal was divided into six different measurements, each of them is a category of classification classes. Thus, 500 EOG signals were collected for each category of six eye movements horizontally and vertically.

3.2 Pre-Processing

The preprocessing phase of the acquired signals is applied in two successive steps. The first step is to filter those signals through a second order Butterworth band-pass filter with a cut-off range [0.5 - 20 Hz] where it is the ideal bandwidth for Electro-oculogram signals. Figure 4 shows the effect of filtering on the EOG signal. It displays the waveform of a signal before and after filtering. After filtering the EOG signals, the second step represents reduce the number of samples of these signals to 100 samples per signal, to reach the lowest calculations and raise the accuracy as much as possible.

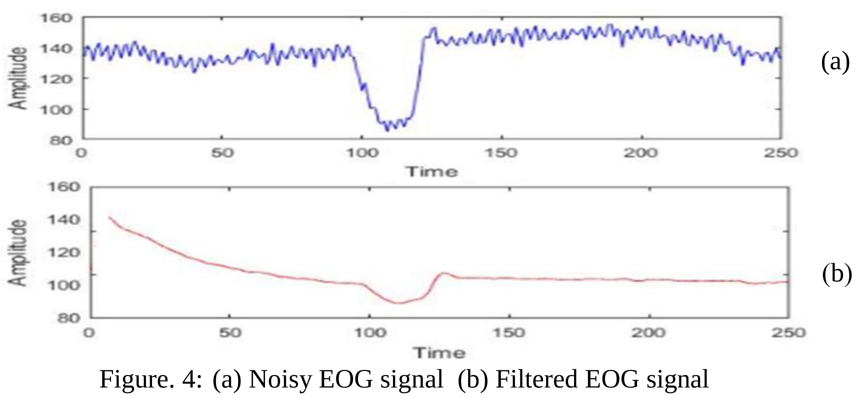

Figure. 4: (a) Noisy EOG signal (b) Filtered EOG signal

3.3Classification

In the classification phase, the revised filtered signals from the previous phase are entered as inputs to the deep learning models for training and testing. Signals are classified into one of six directions of eye movement: right, left, up, down, double blinking, and no movement. Two deep learning models have been examined and compared, namely, the Residual network and the ResNet-50 network. Each model can be described as follows:

Residual network

The residual network is an advanced architecture that stems from a convolutional neural network. It was introduced as one of the winning models in the ImageNet Large Scale Visual Recognition Challenge 2015. The residual network is the building block for many applications of computer vision. It is also consisted of the basic layers of deep learning models: the convolutional layer, the pooling layer, and the output layer. In the convolutional layer, the features of the input EOG signals are extracted by applying an algorithmic convolution between those signals and one or more filters, to ensure accurate features are obtained. These features are extracted by the Rectified Linear Unit RLU as the activation function.
The importance of the pooling layer lies in reducing the size of the feature map and consequently reducing the time-consuming calculations while preserving the basic characteristics of the features of the input EOG signals. The Max function is usually used instead of the Average function to maintain the largest feature values and reduce the feature map size as possible [26].

In the output layer, the input EOG signals are classified according to the features extracted from the previous layers by a SoftMax activation function, where the output for each category is a probability value, and the class with the greatest probability is the chosen one. The great advantage of the residual network lies in the ability to train deep neural networks with high accuracy, even if the networks consist of 150 layers or more. The training of the deep models is very difficult due to the disappearance of the gradient.

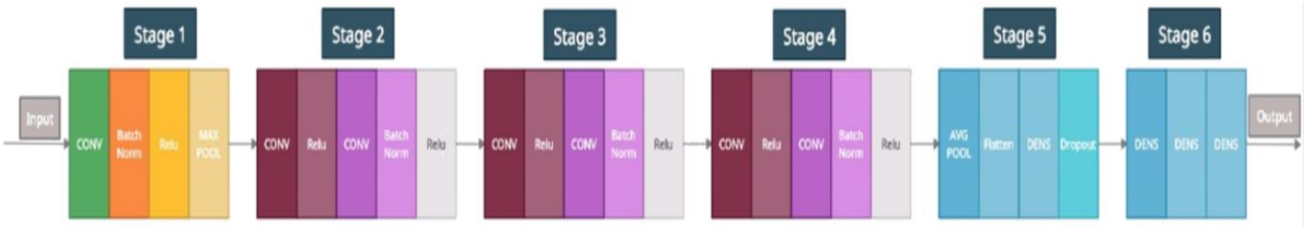

Figure. 5: The Residual Network Architecture

In this study, input layer and 1*7 convolution layer is applied. Thereafter, it is appended to five successive residual blocks of different filter sizes (64,128,256,512, 1024). Each of the five blocks consists of three convolutional layers with different filters. Their results are merged with the original input layer. Subsequently, a pooling layer to reduce the size of the feature array by the max function is utilized. To move to the output layer, a dropout layer is used to prevent overtraining, and a flatten layer is used to collect features in a vector that will be an input to the output layer as shown in Figure 5.
In the last output layer, SoftMax activation function is used to generate the probability values for the six classes: right, left, up, down, double blinking, and no movement, and choose the winning category with the greatest probability. Several factors affecting training have been tested. Best results are obtained with 550 training epochs, batch size 128, and using the Adam optimizer.

ResNet-50 Network

The ResNet-50 is a very deep convolutional neural network with a depth of 50 layers. It is a different type of Residual Network model. The main characteristic of its distinction is its formation of five successive stages, the main stages contain a convolution block and an identity block. The identity block includes three convolutional layers with the same number of filters, and the filter sizes are relatively small. The output from the third layer is an input to the first convolutional layer. The convolution block consists of three convolutional layers as well, but with different kernel sizes (128, 256, 512).

The architecture of the Resnet-50 network begins with the formation of a convolutional layer of kernel size 64, then the Max-pooling layer with a small stride size, the first stage ends. Thereafter, the following four stages consist of convolutional blocks and identity blocks [27]. Each of the four stages differs from the others in the number of iterations of the identity block as shown in Figure 6. Finally, it ends with an average pooling layer and an output layer to classify six of the classes. The best possible results are obtained by training the network for 100 epochs and using a batch size of 64, Adam's optimizer with a learning rate of 0.0001.

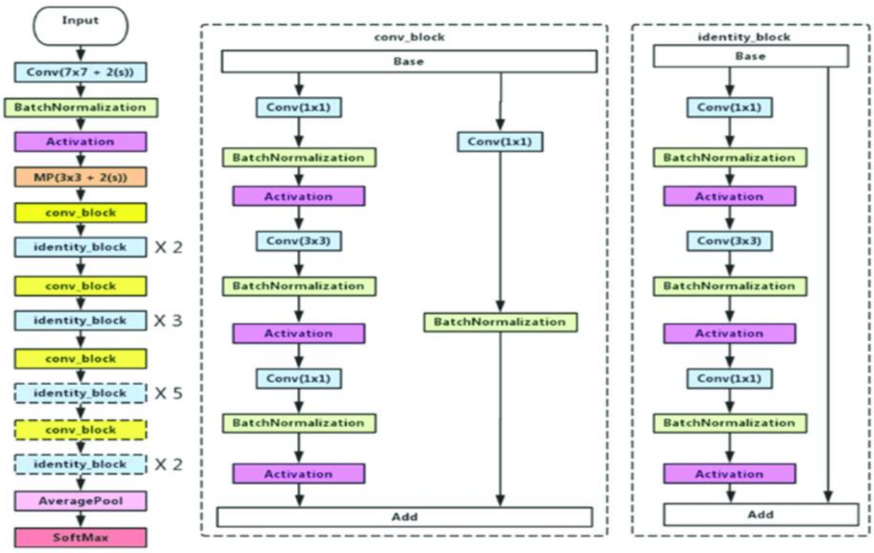

Figure. 6: The Resnet-50 Network Architecture

4. Experimental Results and Discussion

Experiments were conducted using the collected data set. The data for each class was divided into five groups of 100 signals each. Five different trials were considered for each experiment and the results were averaged. Each trial consists of four groups for training and one group for testing. Each group works as a one-time testing group. The signals were preprocessed to be classified into six categories: right, left, up, down, double blinking, No movement. Two models of deep learning models for classification, namely Residual Network and Resnet-50 Network have been evaluated through four standard criteria: Precision, sensitivity, specificity, and overall accuracy. They are calculated by the following equations:

$$\text{Precision} = \text{TP}/(\text{TP} + \text{FP}) \qquad \text{Eq. (1)}$$
$$\text{Sensitivity(Recall)} = \text{TP}/(\text{TP} + \text{FN}) \qquad \text{Eq. (2)}$$
$$\text{Specificity} = \text{TN}/(\text{TN} + \text{FP}) \qquad \text{Eq. (3)}$$
$$\text{Overall Accuracy} = (\text{TP} + \text{TN})/(\text{TP} + \text{TN} + \text{FP} + \text{FN}) \qquad \text{Eq. (4)}$$

Where, (FP) false positive, (FN) false negative, (TP) true positive, (TN) true negative.

Tables 1 and 2 show the results achieved by each of the classification models. The results reveal that the Resnet-50 model provides the best results, as shown also in Figure 7.

Table 1: The Achieved Results of Residual Network

Movement Classes	Accuracy	Sensitivity	Specificity	Precision	Overall Accuracy
Down	96.4%	96%	99.2%	96%	98.6%
Up	93.8%	94%	98.6%	93.06%	98%
Left	95.6%	96%	99.2%	96%	98.6%
Right	93.2%	93%	98.8%	93.9%	97.8%
Blinking	95.1%	95%	98.8%	94.05%	98.1%
No Movement	94.1%	94%	99%	94.9%	98.1%
Average± Stander deviation	94.7±1.2%	94.6±1.21%	98.9±0.24%	94.6±1.19%	98.2±0.32%

Table 2: The Achieved Results of Resnet-50 Network

Movement Classes	Accuracy	Sensitivity	Specificity	Precision	Overall Accuracy
Down	95.7%	96%	99.2%	96%	98.6%
Up	96.3%	96%	99%	95.04%	98.5%
Left	97.4%	97%	99.4%	97%	99%
Right	96.6%	97%	98.8%	94.17%	98.5%
Blinking	95.3%	95%	99.2%	95.9%	98.5%
No Movement	93.5%	94%	99.4%	96.9%	98.5%
Average± Stander deviation	95.8±1.34%	95.8±1.16%	99.1±0.23%	95.8±1.08%	95.8±0.2%

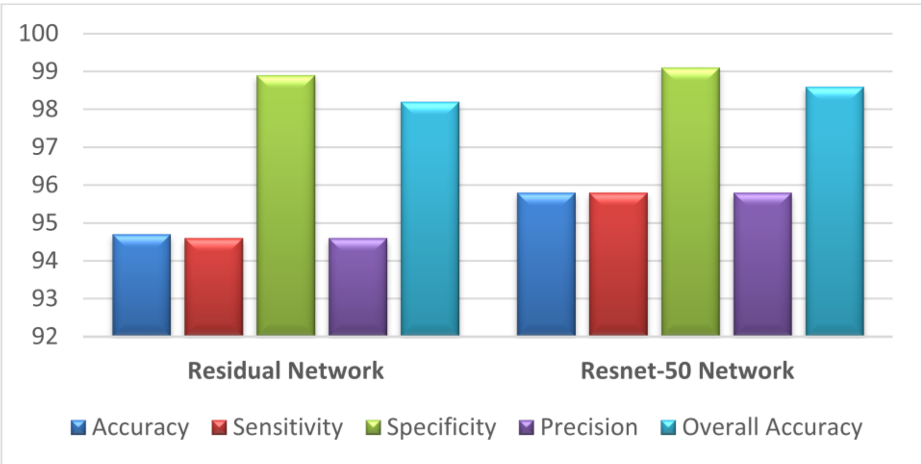

Figure. 7: Summarized results of deep learning models

According to the evaluation of deep learning models: Residual Network and Resnet50 Network. The best results achieved using Resnet50 Network are 95.8%, 95.8%, 99.1%, 95.8%, and 95.8%, which represent the accuracy, sensitivity, specificity, precision, and overall accuracy sequentially. The Resnet50 Network superiority can be justified by its ability to go deeper with identity blocks which avoid the network vanishing gradient problem and the complexity of training. Furthermore, the proposed approach is compared with some recent scholarly works, as shown in Table 3.

Table. 3:Comparison between the Proposed Method and Related Studies

Study	Dataset	Preprocessing	Feature Extraction	Classification	Accuracy
Ji Qi and Alias [19]	5 Subjects	Chebyshev Band-pass filter	Auto-regressive, Kurtosis coefficients, and power spectral density	TDNN	69.7%
Fan Jiahao et al. [22]	20 Subjects	_______	CNN	RNN	81.2%
Huy Phan et al. [21]	20 Subjects	FFT, Frequancy domain filte	_______	CNN	83.6%
Ramkumar et al.[17]	10 Subjects	Band pass filter	Parseval theorems	TDNN	89.6%
Fernando Andreotti et al. [20]	20 Subjects	High pass filter, Resampling	CWT	CNN	90%
Thibhika Ravichandran et al. [23]	10 Subjects	Low pass filter	_______	CNN LSTM	90.3% 88.33%
Proposed Method	50 Subjects	Band pass filter	_______	Residual Network Resnet-50 Network	94.7% 95.8%

A comprehensive comparison is made between the recent related studies and the proposed method, in terms of the number of subjects in the dataset, preprocessing, feature extraction, classification, and accuracy. The comparison shows better performance than the reported in the literature. In addition, the comparison proves the superiority of the proposed Resnet 50 Network. It is worth mentioning that the comparison is done using only average accuracy, the common performance measure between the existing studies.

5. Conclusion

This paper introduces a method for identifying EOG signals using deep learning models. Six different directions of eye movement are recognized. A data set was collected using a device dedicated to measuring and recording of EOG signals. The horizontal and vertical signals are filtered from any noise using second-order band-pass and grouped into a vector to be the input to the classification models. Two models of deep learning: Residual Network and Resnet-50 Network have been examined to classify the EOG signal into one of six categories representing six directions of eye movement: right, left, up, down, double blinking, and no movement. The experimental results show that the Resnet-50 Network model provides the best results. It has achieved an average accuracy of 95.8%. We are looking forward to examining other deep learning models.

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