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Comparison of LSTM And SVM For Classification of Eye Movements in EOG Signals

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ABSTRACT

People with disabilities suffer from inability to communicate with their surroundings, so Human-Computer Interaction (HCI) technologies are used to have a means of communication for people with disabilities with their surroundings. HCI is an emerging technology in the disciplines of Artificial Intelligence and Biomedical Engineering. To power an external device, HCI technology uses several basic signals such as ECG, EMG, and EEG. Electrooculography (EOG) is a technique for measuring the potential difference between the cornea and the retina located between the front and back of the human eye, and the main application of EOG is to determine the directions of different eye movements. This study aims to assess eye movement for communication by persons with disabilities using electrocardiogram (EOG) data. In this study, the Supporting Vector Machine (SVM) and Long- Short term memory (LSTM) classification techniques was used and two types of features (statistical and time domain features) were used. Classification accuracy was 90.7% and 93.9% when using SVM with statistical domain and time domain features, respectively ,whereas Classification accuracy was 90.1% when using LSTM .

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1. Introduction

In recent years ,various bio-signals have worked with technology based on the Human Computer Interface (HCI) [1,2] . Motor neuron deficiencies can result from diseases including amyotrophic lateral sclerosis, spinal cord damage, and others, making it harder to control limb motions. Through the use and implementation of computer-based human rehabilitation aids through various bio-signal modalities, where an EOG is an effective method, HCI technology can help in restoring the activities of a lost or damaged body part by providing a motor, sensory, or cognitive modality [1]. It's non-invasive, affordable, simple to obtain, and may be treated in real time. Eye movement has been shown to have a linear relationship with EOG amplitude to a certain extent. Neuroprosthetic devices [2], computer cursor movement control [3], and rehabilitation wheelchair system control can all benefit from EOG-based device control[4]. Various ways for assessing and implementing EOG for controlling were used [5,6,7,8,9] The EOG has proven to be the most straightforward method for determining eye movement directions. EOG systems with surface electrodes around the orifice are simple to build and alter in real time. The EOG method enables us to forecast the existence of disease in a simple and cost-effective manner, with the symptoms of which being uniquely described by eye movements [10] . The EOG is a good alternative to hand gestures and speech for HCI. EOG signals are commonly employed in Human-Machine Interface (HMI) applications such as computer control and wheelchairs, as these programs allow individuals with impairments to navigate and manage their computer applications [11]. As a result, the EOG is a good candidate for being used as an eye movement input. The main objective of this research is to evaluate and contrast the accuracy of classification and training duration of Supporting Vector Machine (SVM) classifiers for horizontal eye motions (right and left). The approaches for extracting EOG signals are also examined in this study (statistical features and time domain features).

2. Related Work

Lim Jia Qi (2018) proposed a study that compares and evaluates the effectiveness of different classes (ANN and SVM) in terms of classification accuracy and training duration to find the best method for classifying EOG signals. Moreover, compare three different features (statistical features, AR coefficients derived from Borg method, PSD estimation using Yule-Walker method). According to the study, using SVM along with statistical feature extraction outperforms ANN as a classifier by 69.75 percent and requires less training time [12].

Geer Teng, Yue He, Hengjun Zhao, Dunhu Liu, Jin Xiao, and S.Ramkumar (2019) have developed a system that provides nine-state human-computer interface control using EOG signals to help people with disabilities. Using band strength features and HHT and a PRNN classifier, the system accuracy was 92.17% and 91.85% using the two types of features, respectively [13].

Ihsan Al-Kabeer, Faisal bin Shaheen and Muhammad Kafiol Al-Islam (2020) developed a system to extract the EOG signal through the different movements of the eyes and use it to control the computer cursor, through the use of machine learning algorithms such as (SVM, MLP) to classify the different patterns resulting from eye movement. The classification accuracy of the system was 80% when using MLP, 93% when using SVM [14].

Thibhika Ravichandran, Nidal Kamel ,Abdulhakim A. Al-Ezzi ,Khaled Alsaih ,Norashikin Yahya(2021) They classified four separate eye motions using EOG data obtained from four sensors positioned on the eye movement control muscles in both horizontal and vertical directions. To control a wheelchair or any other gadget created to assist ALS patients with their daily demands, the classifier's output is employed. wherein they used two deep learning algorithms to categorize the four movements (CNN and LSTM). With accuracy of 88.33 percent for the LSTM network and 90.3 percent for the CNN network, the results indicated that the CNN model performed relatively better than the LSTM model[15].

3. Methodology

Work is presented to create a system capable of distinguishing horizontal eye movements through EOG signals. The methodology is organized as follows: After the signals are obtained, EOG signal preprocessing, feature extraction, and classification are performed. Finally, the results are compared to see the best performance of the classifier depending on the type of features used with it.

3.1 data set

The usefulness of EOG signals in categorizing horizontal eye movements is being investigated using a publicly available data collection. The EOG Database was employed in this study as the data source. Electrooculography (EOG) data from six healthy people (2 males and 4 females; mean age 24.73.1 years) is included in this data collection. On a separate cue on the screen, subjects were asked to identify their point of view (POG). A total of four trials were recorded, as shown in Figure 1, in which the subject was requested to complete a goal originating from the center of the screen to a random target location in the first one second. After that, there was a return movement.in the following seconds, matching to the middle of the screen, flashing in the last two seconds of each trial Each subject had 300 trials recorded in three consecutive sessions, with 100 trials recorded in each session. Between sessions, there were intermittent pauses. The EOG signals were acquired with a sampling frequency of Fs = 256 Hz using the g.tec g.USBamp bio-signal amplifier device (g.tec medical engineering GmbH, Austria) [16].

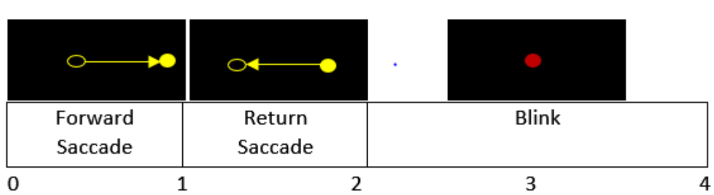

Fig1: EOG capture session [16] .

3.2 signal Preprocessing

Electrooculography signals are regularly corrupted by noisy Eye blinks, powerline intervention, and other sources of interference , head movements, and so on. A Chebyshev 4th order bandpass filter in that frequency range was utilized because the effective frequency range of EOG signals is between “0.1Hz (DC) and 50Hz”.This is done to reduce power supply interference while also suppressing it [17]. Noise was also removed using median filtering. The EOG signal was particularly valuable because it kept Scud's extremely steep character [18].

3.3 Feature extraction

Feature extraction is a method of extracting important features from the original data without losing important information. This step is used to reduce the size of the data [19]. We employed two feature extraction algorithms in this paper.

3.3.1 Statistical Features

In this study ten statistical features were extracted to present the characteristic of EOG signal. Those statistical feature are [18] :

1. Min, Max: The sample maximum and sample Minimum, often known as the largest and smallest observation, are the values of a sample's greatest and least elements.
2. The First Quartile (Q1): is the number that falls in the midpoint of the data set's smallest and median values.
3. Third Quartiles (Q3): is the data set's intermediate value between the median and highest value .
4. The Interquartile Range (IQR): is the difference between a collection of data's first and third quartiles .
5. Mean: the average of a group of numbers. The mean is calculated by multiplying all of the numbers in the data set by the number of elements in the data set
6. The Mode :is the value that appears the most frequently in a set of data. It's not unusual for a data set to contain multiple modes. This occurs when two or more elements in the data collection occur with equal frequency.
7. Median: the value in an ordered series that is in the middle .
8. Standard deviation (): is a measure of the dispersion of the data. Show how the data is scattered. A low standard deviation indicates that the data observations are close to the mean, while a high standard deviation shows that the data are scattered across a wide range of values

$$Standard\ Deviation\ (\sigma) = \sqrt{\frac{\sum_{i=1}^{N}(x_i - mean)^2}{N-1}} \qquad (1)$$

Where:

- x_i=Value of the ith point in the data set.

- $mean$ =The mean value of the data set.
- N = The number of data point in the data set.

9. kurtosis

Kurtosis is a measurement of whether the data is heavy-tailed or light-tailed relative to a normal distribution. Usually high kurtosis datasets contain heavy tails or outliers. Data sets with low kurtosis tend to have mild tails or lack outliers .

For univariate data $X1, X2, ..., XN$, the formula for kurtosis is:

$$\text{kurtosis} = \frac{\sum_{i=1}^{N}(x_i - \bar{x})^4}{s^4} \tag{2}$$

3.3.2 Time Domain Features

In this paper , five Time Domain feature were extracted for EOG signal . these feature with define in were presented as [20]:

1. Maximum peak amplitude value : This is a measurement of the EOG signal's amplitude at its highest point, as well as the greatest positive and negative values.

2. Maximum valley amplitude value : This is the highest negative value of the EOG signal's amplitude at its lowest point.

3. Maximum peak amplitude position value : This is a measurement of the amplitude position value of the EOG signal at its highest point, as well as the maximum positive and negative values.

4. Maximum valley amplitude position value : This is the amplitude position value of the EOG signal at its lowest point, with the highest negative value.

5. Area Under Curve : AUC of EOG signal is a summation of absolute value of the amplitude under both positive and negative curves in horizontal channel. as shown in Figure 2.

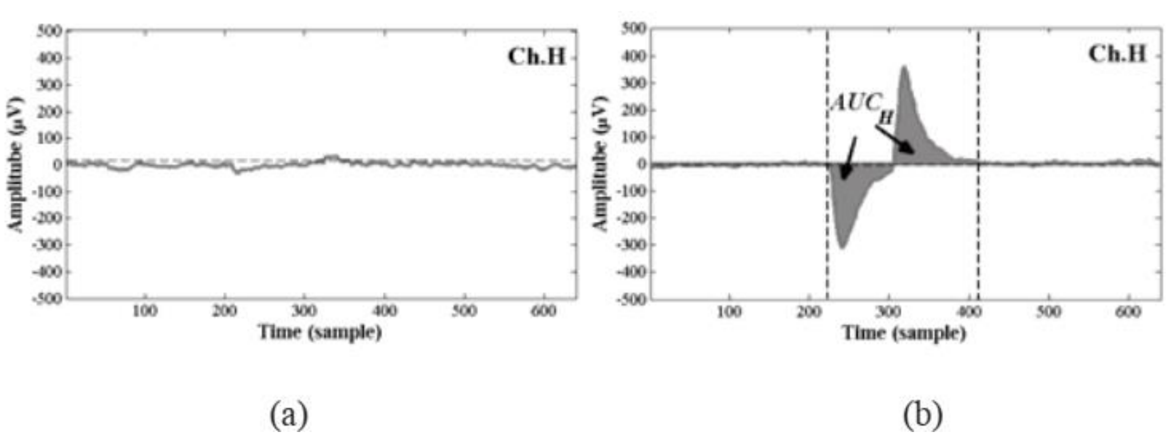

Fig 2 : Areas under curve values [19].

4. Classification

In the classification stage, two classification algorithms were used to compare the performance of the two classifiers and to obtain a higher classification accuracy, as follows.

4.1 SVM Classifier

The classification is done using SVM algorithm on the feature set extracted from the raw EOG signal as mentioned before. SVM is a useful classification technique in a variety of disciplines of research. Its applications include text categorization, facial identification, breast cancer diagnosis, and more. SVM is a linear classification method that seeks for the best hyperplane . The term "optimal hyperplane" refers to a linear decision boundary that split N dimensional space (R^n) into two halves with resolution limits as far away from both subclasses' data as possible. Because Recession variables and kernel functions have been added, SVM can now be employed in Non-linear detachable situations with high dimensional data entry. In this investigation, The SVM is trained with a paired (feature and class) . Let a training set comprising of N classes with ƒ attributes, the set can be represented by $\{(x_i,y_i) \mid x_i \in R , y_i \in \{-1, 1\}\}$ where i=(1,…,N) If the input data is linearly distinguishable, the optimization phase can be defined as follows [21]:

$$\text{Min } w, b \ \ ||w||2 \qquad (3)$$

Where:

$Y_i (w . x_i + b) \geq 1$

w: is a weight vector.

b: is the bias term.

the hyperplane is defined by w. x+b=0 .

Suppose entity in the testing set is classified using the decision function

$$f(x) = w . x + b \qquad (4)$$

Where:

w: is a weight vector.

b: is the bias term.

If ƒ(x) < 0. As a result, the instance falls on one side of the hyperplane. However, the entity x is identified and put in the first class (y = −1), otherwise is classified into the second class (y = 1).the Radial Basis Function (RBF) was chosen for classification because it is often used and considered the first choice in literature .

4.2 LSTM Classifier

Long- Short term memory (LSTM) is a deep learning architecture that uses an artificial Recurrent Neural Network (RNN). LSTM contains feedback links, unlike regular feed-forward neural networks. It can process the entire data series as well as individual data points (eg image, speech or video). Right and left eye movement are categorized in this work using a five-layer LSTM architecture. The temporal and highly nonlinear structure of the EOG signal inspired the use of RNNs for its classification [22]. We used RNN with LSTM modules in this research. The network used the obtained EOG signals to produce a two-class (right, left) classification. The proposed RNN architecture in this study was as follows: a sequential layer with 30-time steps was used as the input layer, while LSTM layers were used to learn features from EOG signals. The fully connected layer (FC) was used to translate the output volume of the previous layers into the number of sleep phases needed to define them. The classification output layer produced the cost function after the softmax layer estimated the probability of each target group in all possible target groups. The potential range of the output is the main advantage of using the softmax activation function. The output values of this function range from 0 to 1, and the total number of possibilities is one. Here is its mathematical expression:

$$y_j^{(i)} = \frac{e^{z_j^{(i)}}}{\sum_j^c e^{z_j^{(i)}}} \tag{5}$$

The superscript i indicates the general training example, j for the general neuron of the FC layer, z for the output value of the FC layer, and C for the number of target groups. The cost function is a function of all weights and bias conditions, and is minimized during the network training process.

5. Results and discussions

In this section, we discussed the most important result of this work . For remove noise from the signals as shown in Figure 3, the raw data is filtered with a 0-30 Hz band-pass filter and a 50 Hz average filter to remove noise and other interferences that spoil the regularity of the EOG signals, such as eye blinks, power line interference, head movements, etc.

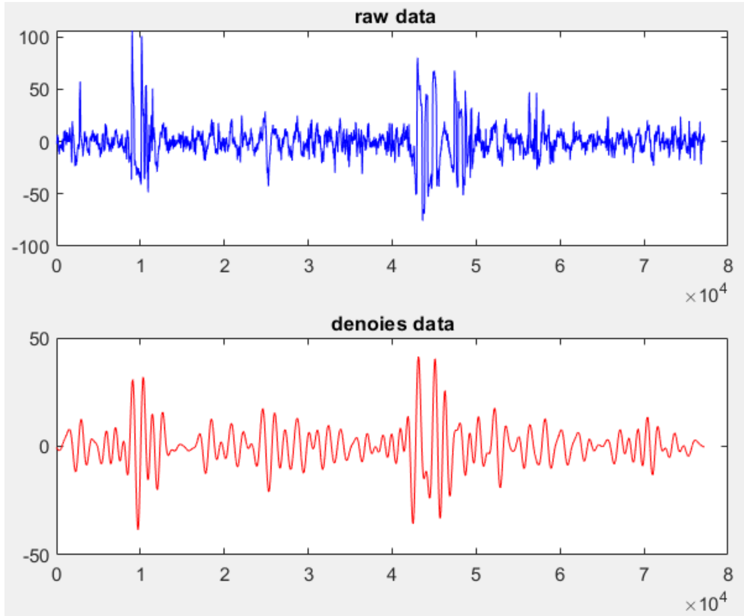

Fig 3: EOG signals before and after preprocessing .

After the noise removal phase, the data set was divided into 70% of the EOG signals as training data while the remaining 30% is used for testing purposes, as these percentages gave the highest classification accuracy. These data produce ten statistical features and five time domain features. Training vectors are used to train SVM and LSTM classifiers, while test vectors are used to evaluate the accuracy and usefulness of the learned models.

In the signal classification stage, the SVM classification algorithm was applied with the two types of features that were previously referred to as input data for the classifier ,on the other hand , LSTM classification algorithm was applied with EOG signal as input data to algorithm . After the classification process was completed, the performance of the classifiers was tested according to the test accuracy and training time to evaluate and compare performance. The fraction of actual positives that are expected to be positive is used to assess classification accuracy [23].

$$\text{Classification accuracy } (\%) = (TP + TN) / (TP + TN + FP + FN) \qquad (6)$$

where NT denotes the number of correct predictions and NF denotes Number of times incorrect predictions. Through the results presented in Table 4 , And by use two classification methods ,A higher classification accuracy rate was 93.9% and with a low training time it was 5.9 s when using SVM classifier with time domain feature . All detail results are shown in Tables 1 ,2 and 3 . as can be seen in tables SVM classifier gave better results when using it with time domain features in terms of classification accuracy rate and training time compared to the results obtained from using it with statistical features and when using the deep learning algorithm LSTM , it can be seen from Table 1. On the other hand, the results of the SVM classifier with the statistical parameters as inputs also achieve a high accuracy of 90.7 % and training time of 6.6 s . As shown in Table 2. By noting Table 3, the LSTM classification algorithm achieved a classification accuracy of 90.1%. But with a very long training time compared to the SVM classifier, the average training time was approximately 41 minutes.

Table 1. Classification results for time domain features with SVM classifier.

Subjects	S1	S2	S3	S4	S5	S6
Classification accuracy (%)	96.3	96.3	94	91.3	91.7	94.3
Training time (s)	5.9	5.9	5.9	5.9	5.9	5.9

Table 2. Classification results for statistical features with SVM classifier.

Subjects	S1	S2	S3	S4	S5	S6
Classification accuracy (%)	95.3	93	89.7	87.7	87.7	91
Training time (s)	6.6	6.6	6.6	6.6	6.6	6.6

Table 3. Classification results LSTM classifier.

Subjects	S1	S2	S3	S4	S5	S6
Classification accuracy (%)	91	97	92	91	98	72
Training time (M)	35	36	35	41	50	50

Table 4 . Compare the results when using a two-classifier algorithm .

Subjects	SVM classifier with time domain feature	SVM classifier with time domain feature	LSTM classifier
Classification accuracy (%)	93.9	90.7	90.1
Training time (s)	5.9	6.6	2460

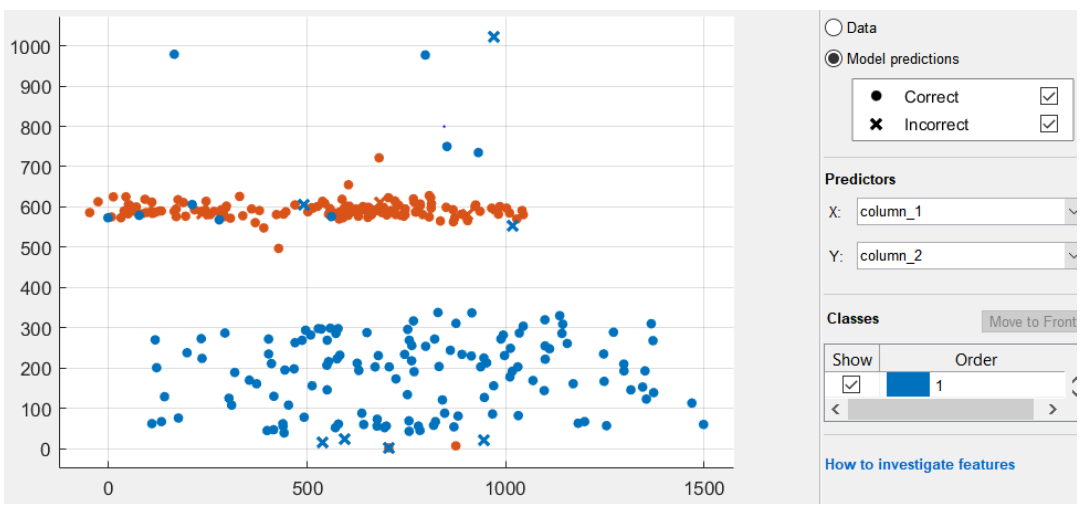

Fig 4: The process of training data using the SVM classifier with time domain feature .

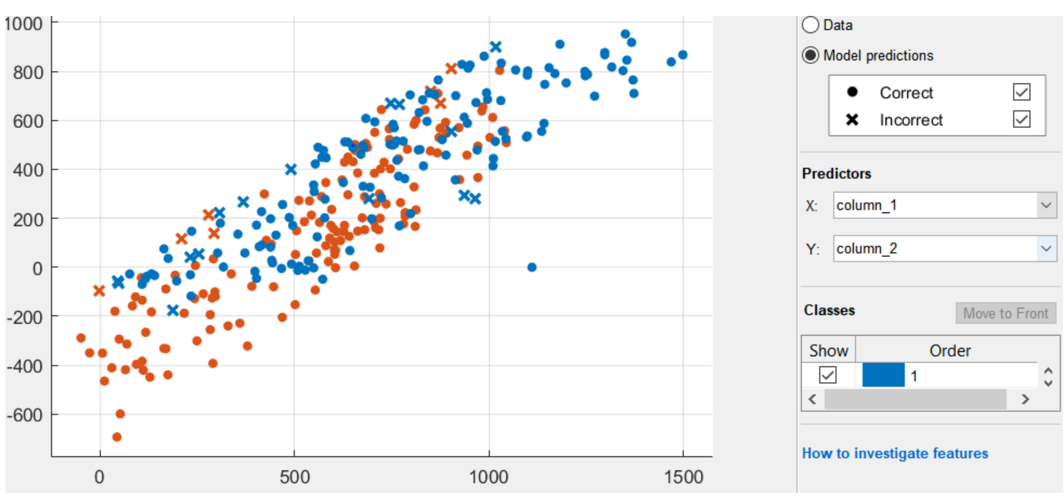

Fig 5: The process of training data using the SVM classifier with statistical feature .

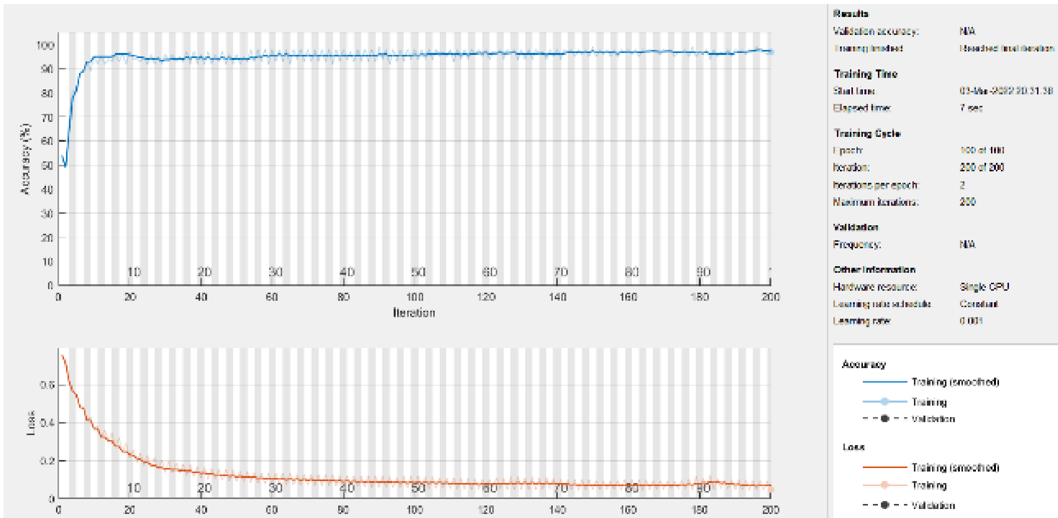

Fig 6: The process of training data using the LSTM classifier.

6. Conclusion

EOG signals have great potential for use in communications such as eye-controlled wheelchairs and virtual keyboards. In the classification stage of EOG signals, the features collected from the data set play an important role. This paper looked at different ways to improve the analysis and classification of the EOG signal in order to reach higher classification results than the results presented in the previous studies section. The presented approach for extracting time domain features from the EOG badge showed superiority over other options in terms of classification accuracy and training duration, although the statistical advantage mapped using the SVM algorithm gave high results in terms of accuracy up to 90.7% and with little training time, it gave the LSTM algorithm also results in high accuracy up to 90.1% but it takes a long time to train. However, it was found that combining the time domain feature extraction method with SVM produces better results, with 93.9 percent classification accuracy and lower training time. Our future plan is to try other methods of signal classification and feature extraction, in order to obtain higher classification accuracy. We also hope to classify additional eye movements in the future.

References

[1] F. Cincotti *et al.*, "Non-invasive brain–computer interface system: towards its application as assistive technology," *Brain Res. Bull.*, vol. 75, no. 6, pp. 796–803, 2008.

[2] R. Barea, L. Boquete, M. Mazo, and E. López, "System for assisted mobility using eye movements based on electrooculography," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 10, no. 4, pp. 209–218, Dec. 2002, doi: 10.1109/TNSRE.2002.806829.

[3] J. Keegan, E. Burke, J. Condron, and E. Coyle, "Improving electrooculogram-based computer mouse systems: The accelerometer trigger," *Bioeng. Irel.*, vol. 201, no. 1, 2011.

[4] R. Barea, L. Boquete, M. Mazo, and E. López, "Wheelchair guidance strategies using EOG," *J. Intell. Robot. Syst.*, vol. 34, no. 3, pp. 279–299, 2002.

[5] T. Wissel and R. Palaniappan, "Considerations on strategies to improve EOG signal analysis," *Int. J. Artif. Life Res.*, vol. 2, no. 3, pp. 6–21, 2011.

[6] G. Teng, Y. He, H. Zhao, D. Liu, J. Xiao, and S. Ramkumar, "Design and Development of Human Computer Interface Using Electrooculogram With Deep Learning," *Artif. Intell. Med.*, vol. 102, p. 101765, 2020, doi: 10.1016/j.artmed.2019.101765.

[7] R. Barea, L. Boquete, J. M. Rodriguez-Ascariz, S. Ortega, and E. López, "Sensory system for implementing a human—computer interface based on electrooculography," *Sensors*, vol. 11, no. 1, pp. 310–328, 2010.

[8] N. Itakura and K. Sakamoto, "A new method for calculating eye movement displacement from AC coupled electro-oculographic signals in head mounted eye–gaze input interfaces," *Biomed. Signal Process. Control*, vol. 5, no. 2, pp. 142–146, 2010.

[9] T. Gandhi, M. Trikha, J. Santosh, and S. Anand, "VHDL based electro-oculogram signal classification," in *2007 15th International Conference on Advanced Computing and Communications*, 2007, pp. 153–158.

[10] A. Banerjee, M. Pal, S. Datta, D. N. Tibarewala, and A. Konar, "Eye movement sequence analysis using electrooculogram to assist autistic children," *Biomed. Signal Process. Control*, vol. 14, pp. 134–140, 2014.

[11] F. E. Samann and M. S. Hadi, "Human to Television Interface for Disabled People Based on EOG," *J. Duhok Univ.*, vol. 21, no. 1, pp. 54–64, 2018.

[12] P. Majaranta and A. Bulling, "Eye tracking and eye-based human–computer interaction," in *Advances in physiological computing*, Springer, 2014, pp. 39–65.

[13] R. Barea, L. Boquete, S. Ortega, E. López, and J. M. Rodríguez-Ascariz, "EOG-based eye movements codification for human computer interaction," *Expert Syst. Appl.*, vol. 39, no. 3, pp. 2677–2683, 2012.

[14] A. U. Kabir, F. Bin Shahin, and M. Kafiul Islam, "Design and Implementation of an EOG-based Mouse Cursor Control for Application in Human-Computer Interaction," *J. Phys. Conf. Ser.*, vol. 1487, no. 1, 2020, doi: 10.1088/1742-6596/1487/1/012043.

[15] T. Ravichandran, N. Kamel, A. A. Al-Ezzi, K. Alsaih, and N. Yahya, “Electrooculography-based Eye Movement Classification using Deep Learning Models,” *Proc. - 2020 IEEE EMBS Conf. Biomed. Eng. Sci. IECBES 2020*, pp. 57–61, 2021, doi: 10.1109/IECBES48179.2021.9398730.

[16] https://www.um.edu.mt/cbc/ourprojects/EOG/EOGdataset .

[17] L. J. Qi and N. Alias, “Comparison of ANN and SVM for classification of eye movements in EOG signals,” *J. Phys. Conf. Ser.*, vol. 971, no. 1, 2018, doi: 10.1088/1742-6596/971/1/012012.

[18] S. Roy, A. De, and N. Panigrahi, “Saccade and Fix detection from EOG signal,” *Proc. - 2019 IEEE Int. Symp. Smart Electron. Syst. iSES 2019*, pp. 406–408, 2019, doi: 10.1109/iSES47678.2019.00099.

[19] R. Zebari, A. Abdulazeez, D. Zeebaree, D. Zebari, and J. Saeed, “A Comprehensive Review of Dimensionality Reduction Techniques for Feature Selection and Feature Extraction,” *J. Appl. Sci. Technol. Trends*, vol. 1, no. 2, pp. 56–70, 2020, doi: 10.38094/jastt1224.

[20] S. Aungsakul, A. Phinyomark, P. Phukpattaranont, and C. Limsakul, “Evaluating feature extraction methods of electrooculography (EOG) signal for human-computer interface,” *Procedia Eng.*, vol. 32, no. January, pp. 246–252, 2012, doi: 10.1016/j.proeng.2012.01.1264.

[21] Y. LeCun, K. Kavukcuoglu, and C. Farabet, “Circuits and systems (ISCAS),” in *Proceedings of 2010 IEEE International Symposium on*, 2010, pp. 253–256.

[22] N. Michielli, U. R. Acharya, and F. Molinari, “Cascaded LSTM recurrent neural network for automated sleep stage classification using single-channel EEG signals,” *Comput. Biol. Med.*, vol. 106, no. January, pp. 71–81, 2019, doi: 10.1016/j.compbiomed.2019.01.013.

[23] M. M. Hasan, C. N. Watling, and G. S. Larue, “Physiological signal-based drowsiness detection using machine learning: Singular and hybrid signal approaches,” *J. Safety Res.*, vol. 80, pp. 215–225, 2022, doi: 10.1016/j.jsr.2021.12.001.