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An RNN-based Hybrid Model for Classification of Electrooculogram Signal for HCI

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ABSTRACT In recent years, there has been a rise in the amount of research conducted in the field of human-computer interaction (HCI) employing electrooculography (EOG), which is a technology that is effectively and widely used to detect human eye activity. The use of EOG signals as a control signal for HCI is essential for understanding, characterizing, and classifying eye movements, which can be applied to a wide range of applications including virtual mouse and keyboard control, electric power wheelchairs, industrial assistive robots, and patient rehabilitation or communication purposes. In the field of HCI, EOG signals classification has continuously been performed to make the system more effective and reliable than ever. In this paper, a Recurrent neural network model is proposed for classifying eye movement directions utilizing several informative feature extraction methods and noise filtering. Our classification model is comprised of Gated Recurrent Unit (GRU) with a Bidirectional GRU followed by dense layers. The classifier is investigated to find a better classification performance of four directional eye movements: Up and Down for the vertical channel, along with Left and Right for the horizontal channel of EOG signals. The classifier achieved 99.77% and 99.74% accuracy for vertical and horizontal channels, respectively, which outperforms the compared state-of-the-art studies. The proposed classifier allows disabled people to make life-improving decisions using computers, achieving the highest classification performance for rehabilitation and other applications.

KEYWORDS EOG, RNN, GRU, Bi-GRU, HCI, Vertical channel, Horizontal channel.

I. INTRODUCTION

IN recent years, exponential growth in the development of the Human-Computer Interface (HCI) has been noticed significantly. These systems have been applied for a wide range of purposes, like controlling a computer cursor, a virtual keyboard, or a wheelchair. Moreover, it is also used for patient rehabilitation and communication. HCI systems can make use of different input signals such as voice, near-infrared spectroscopy (NIRS), electromyography (EMG), electrocardiography (ECG), electroencephalography (EEG), and electrooculography (EOG). HCI using EOG signals has been a growing area of research in recent years. The HCI provides communication channels between the human and the external device. Today, EOG is one of the essential biomedical signals for measuring and analyzing the direction of eye movements.

Electrooculography, often known as EOG, is a method that is used to measure the corneo-retinal standing potential that exists between the anterior and posterior segments of the human eye. The signal that is produced is referred as the electrooculogram. A potential difference of 10 to 30 mV exists between the back of the eye and the front of the eye whenever there is an active neuron in the retina, as seen in Fig. 1.

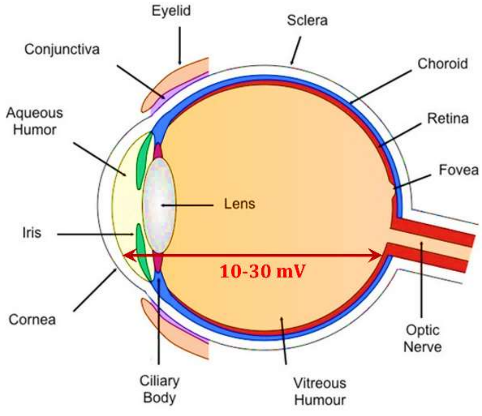


Figure 1. Eyeball Anatomy

Since the neurological system is so actively located in the retina of the anterior section of the eyeball, there is a voltage differential between the cornea and the retina. This can be seen as a stable electrical dipole with a negative pole in the retina and a positive pole in the cornea. The EOG signal typically consists of two pulses, the first of which indicates the start of the signal and the second of which indicates its ending. When the eyeball rotates to the right, the front, and the left or to the top, the front, the bottom and to the center, the positive and the negative pulses are created, respectively, in the vertical or horizontal channel. There are two channels, vertical (V) and horizontal (H), that record the EOG signals. Typically, V and H measurements can be taken separately. However, in the V channel, the EOG signal from the left or right side is identical. Therefore, just one right eye is employed to record signals. Five surface electrodes are placed around the eyes, which shown in Fig. 2. Vertical leads are obtained on the right eye's upper and lower halves, Ch.V+ and Ch.V-. Ch.H+ and Ch.H- electrodes are placed to the right and left of the outer canthi obtain horizontal leads. A reference electrode G is placed on his forehead.

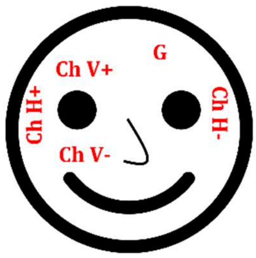


Figure 2. EOG electrodes placement

In order to integrate any classification model into an HCI, it is necessary for the detection model to provide effective and reliable performance results. Again, an appropriate preprocessing unit is required to build a superior detection model that can be achieved by several data cleansing schemes for the biomedical signals. For instance, the acquisition of biomedical signals from the subject body generates several noises that degrade the overall effectiveness of such signal that can be eliminated by adopting a proper filtering method. In addition to that, a reliable feature selection scheme has the ability to transform raw data into workable numerical features while still preserving the relative information of the original data.

The research aims to create a system that can be easily attached to a communication or mobility aid device, such as a wheelchair, any kind of dictation app, or even just a mouse, computer, and virtual keyboard. The most important aspect of using the EOG signal on the HCI to indicate the right direction is classification. To attain the goal, the main purpose of this study is to classify EOG signal eye movement. The overall contribution of this paper, which will be outlined in the following paragraphs, has been broken down into four distinct parts.

- To study and analyze the EOG signal dataset, reduce its noise and correct its baseline drift.
- In order to enhance the efficiency of the classifier, the most compacted and significant set of features of EOG signal has been extracted for both horizontal and vertical channels before employing specific machine learning algorithms.
- A classification model has been proposed for the sake of detecting eye-movement direction using deep learning algorithms.
- For each directional movement detection, a set of performance parameters have been reviewed and analyzed. To test the robustness and superiority of the proposed model, the observational results have been compared with the state-of-the-art studies.

The overall works of this paper have been structured in following fashion. Section 2 represents all the associated literature review for EOG signal analysis. In Section 3, the proposed approach for this work is given along with an in-depth discussion of overall methodologies. All the relative observational results are included in Section 4 and finally Section 5 presents the Conclusions.

II. RELATED WORKS

For establishing an effective HCI, integrating through a better classification model for various biomedical signals, several detection schemes have been used in the field of EOG signals over the years, which include thresholding, edge detection, Machine learning and many others.

Three feature extraction approaches were used in [1], namely, statistical parameters, autoregressive (AR) coefficients using the Burg method, and power spectral density (PSD) using the Yule-Walker method. The study utilized Artificial Neural Networks (ANN) and Support Vector Machines (SVM) as classifiers, where statistical parameters and SVM provided the highest classification accuracy of 69.75%. In study [2], the EOG signal was in digital form used as the control signal for HCI. Several applications with EOG-based HCI were designed to make the system robust. Two ensemble methods were used as classifiers, namely, bagging and adaptive boosting algorithms for the classification of eye movement in paper [3], where maximum accuracy of 92.27% was obtained. In paper [4], a pulse detection method was developed to classify four eye movements (up, down, left, and right) from EOG signals, mainly designed for disabled people. AC-coupled channels were used to overcome the signals' baseline drifting. A pulse timer was utilized to reduce false identification because of head movements. The system was integrated into the Human to Television Interface (HTI) and tested by six subjects, where a 93.41% average performance was found. The article [5] used a frequency-based approach using an AR model and template matching as a time-based method to improve EOG signal analysis. This paper also utilizes wavelet decomposition for feature extraction and Linear Discriminant Analysis (LDA) for classification. In paper [6], VHDL was used to construct a Deterministic Finite Automata (DFA) classifier to distinguish 128 EOG states from processed horizontal and vertical eye signals depending on threshold values specific to individuals. In the pre-processing stage, AC coupling was utilized to mitigate baseline drift. Authors of [7] designed an Arduino-based EOG signal acquisition system to control the computer cursor with eyeball movement. They used SVM and LDA to classify live data for the horizontal and vertical channels. In [8], the authors focused on the feature extraction method for the classification of EOG signals from both class separability and robustness perspectives. The authors of [9] portrayed the classification of the flag with online information. The framework is based on open-source environments, the Raspberry Pi single-board computer, the OpenBCI bio signal securing gadget, and an open-source python library. SVM is utilized for classifying the four headings of eye developments which cruel precision is 90%. In [10], the authors used several classifiers such as Decision Tree (DT), K-Nearest Neighbor (KNN), Ensemble Classifier (EC), Kernel Naive Bayes (KNB), and Support Vector Machine (SVM) where SVM, Cosine KNN, and Ensemble Subspace Discriminant were the best horizontal and vertical channel signal classifiers. In study [11], the authors analyzed and statistically contrasted the results of numerous methods for reducing baseline drift, including regular DC reference resets, signal differencing, high-pass filtering, wavelet decomposition, and polynomial fitting. The researchers of [12] examined an eye-writing system for patients with severe amyotrophic lateral sclerosis (ALS) who have lost their oral-speaking and hand-writing abilities, with a symbol set consisting of 10 Arabic number symbols and 4 mathematical operators. The recognition rate for eleven subjects with different symbols ranged from 50 to 100 percent. A wheelchair was made by authors of [13] to help people with severe disabilities where saccadic eye movements were detected by using implementing an inverse eye model as a control technique. In study [14], a microcontroller-based wheelchair was developed, which was commanded with eye movements. The proposed system reduced the cost and gave high classification accuracy. The authors of [15] proposed a threshold-based method for eye movements from EOG signals in real-time and interfaced the techniques with the proposed asynchronous EOG-based virtual keyboard. In study [16], a wearable forehead EOG measurement system was developed for use in a virtual keyboard with 91.25% mean accuracy. In [17], a signal processing algorithm was developed to detect eye movements, where the algorithm worked with two types of inputs. One was derivative, used to detect signal edges, and another was amplitude level which was used to filter noise. The authors of [18] developed an artificial neural network (ANN) based eye movements detection model, which also involves the detection of tic and blinking of the eye. A saccadic signal recognition algorithm was proposed in [19], which used independent component analysis (ICA). The authors adopted SVM as the classifier for four saccadic detections, which provided the classification accuracy of 99%, and after sample optimization, the improved accuracy was upgraded to 99.57%.

III. PROPOSED WORK

The conceptual framework of this research is divided into two stages: data pre-processing and eye movement classification as shown in Fig. 3. The pre-processing stage is mainly concerned with the transformation of the EOG signal data which consists of two key steps. First, the undesired signal has been eliminated from the EOG signal, followed by the correction of its baseline drift in order to achieve optimal signal classification. Secondly, the features from the raw EOG signal have been extracted for the sake of characterizing the behaviors of the bio-events. Following the completion of the data pre-processing stage, a neural network has been formed for classification purposes. For the sake of classifying the direction that an eye movement is moving in, we have presented a recurrent neural network that includes GRU. Upon completion of the pre-processing phase, all extracted features are subsequently provided to the detection model for classification.

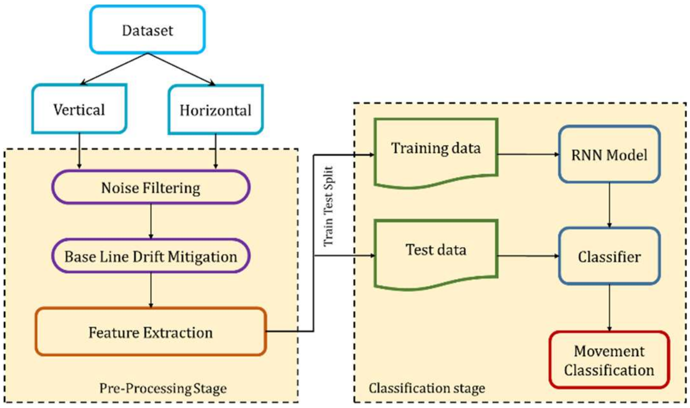


Figure 3. Flow diagram of step by step for classification of EOG

A. DATA PRE-PROCESSING

Preprocessing, in general, is the act of converting raw data into a format that is more suited for future analysis and user interpretation. Preprocessing EOG data usually entails reducing noise from the data to come closer to the genuine ocular signals.

The component with the strongest pure eye movement signal (EOG signal) usually has a frequency of less than 10 Hz. For signal pre-processing, the following factors must be taken into consideration:

- Keeping active EOG samples such as saccadic EOG signal extreme edge, primary signal amplitude, and so on.
- Removing any baseline drift caused by interference with the electrode's polarization or background signals. Suppressing noise, such as noise from power lines, high-frequency components from many sources, and electrode movement.
- Selecting key features of each sample of EOG data.

Noise Cancellation and Baseline Drift Correction:

Bio signal includes noise caused by heat created in the electronics, static electrical impulses in the environment, and motion between the subject and sensors. Since noise corrupts the signal of interest, noise must be eliminated in order to extract useful information from the signal. Therefore, filtering of signals is the first step of pre-processing stage. For the sake of noise filtering and baseline correction, fourth order Butterworth low pass filter has been used with 2hz cutoff frequency.

B. FEATURE EXTRACTION OF EOG SIGNAL

In order to improve performance in the categorization of biological data, feature extraction is necessary. The purpose of the feature extraction process is to locate the most condensed and informative collection of features for the sake of improving the performance of the classifier. In addition, feature extraction is used to extract features from the primary signal to achieve reliable classification. The extraction of features is the most important step in the process of classifying biomedical signals. This is due to the fact that the classification performance may suffer if the features are not picked appropriately.

Different types of feature extraction techniques for EOG signal are stated below where N length of the EOG signal $x[k]$ as a function of the discreate time variable k and μ is the mean.

Maximum Peak Amplitude Value (PAV): The maximum value of each sample is constructed, and the peak value for both the horizontal and vertical channels are found.

Maximum Valley Amplitude Value (VAV): The maximum value of the valley sample is constructed, and the negative peak value for both channels.

Average: It is the average of each horizontal and vertical channel's samples.

RMS Value: The root mean square (RMS) is a statistical measure of varying signals that can indicate signal intensity. The square of a signal's RMS value represents its average power.

$$RMS\ value = \sqrt{\frac{\sum_{k=1}^{N} x[k]^2}{N}}. \quad (1)$$

Scale variance (SV): Scale variance is the measure of log-variance that can be expressed as:

$$SV = \frac{\log(var(x[k]))}{\log 2}. \quad (2)$$

Mean absolute deviation (MAD): This is the result of determining the average distance from each data point to the mean.

$$MAD = \frac{1}{N}\sum_{k=0}^{N-1} |x[k] - \mu.| \quad (3)$$

Variance: A signal's variance can be found by squaring its mean deviation. The formula is the standard deviation squared. The power of a signal can be represented by its variance, which is defined as:

$$VAR = \frac{1}{N-1}\sum_{k=0}^{N-1}(x[k] - \mu)^2. \quad (4)$$

Zero Crossing (ZC): Zero crossing indicates the number of times the EOG signal crosses the zero line. It can be calculated as:

$$ZC = \sum_{k-1}^{N-1} sgn(X_k * X_{k-1}) \cap |X_k - X_{k-1}| \geq Threshold,$$

$$\text{where: } sgn(x) = \begin{cases} 1, & x \geq Threshold \\ 0, & Otherwise \end{cases}. \quad (5)$$

C. OUR PROPOSED CLASSIFICATION MODEL

The neural network that we propose for the classification of eye movement consists of four sequential deep learning layers as shown in Fig. 4. The main idea of the hybrid model is based on combining or integrating different individual learning models to achieve improvement over the discrete model performance. GRU is less complex than other variants of improved RNN, it requires less time to process data and completes its operation. However, the limitation of it is that it has the capability of evaluating data only in one direction. Unlike GRU, Bi-GRU has the ability to utilize information from both sides. Due to the presence of an additional layer, it can reverse the direction of information flow. This leads to better processing of features and superior performance of the overall model.

A GRU layer has been utilized in the beginning of the process in order to learn the sequential characteristics of the input bytes. After that, the bidirectional GRU layer is used to conduct an analysis of the substantial degree of traffic bytes for the purpose of acquiring finer grained and more prominent features for EOG signal classification. Next, two successive dense layers are used to combine outputs of the previous layer before analyzing the classification result. Hyperparameters values of the proposed model are presented in Table 1.

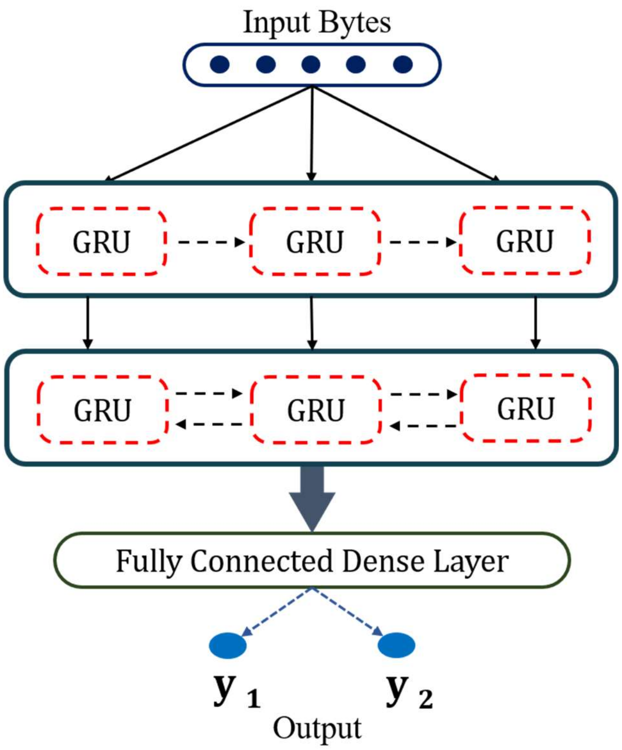


Figure 4. Architecture of the EOG signal classifier.

Table 1. Fundamental hyperparameter values of the learning model

Hyper-Parameters	Functions / Values
GRU	Activation = tanh, Neurons=32
Bidirectional GRU	Activation= ReLu, Neurons=32
Dense (1) Dense (2)	Activation = ReLu, Neurons = 16 Activation= Sigmoid, Neurons = 1
Optimizer	Adam
Cost function	Binary Cross Entropy
Learning rate	0.0001
Batch size	20
Iterations	100

GRU and Bi-GRU Layers

The GRU is one of the most recent variants of conventional RNN that was created to combat its disappearing gradients issue. The GRU cell architecture is shown in Fig. 5.

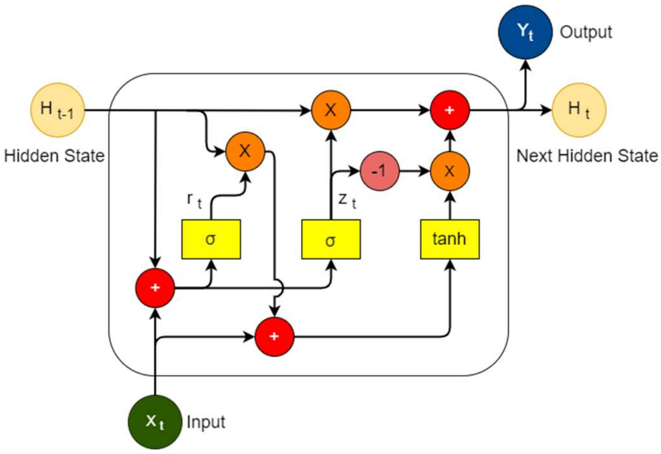


Figure 5. Architecture of GRU Cell

Compared to a regular RNN block, a typical GRU cell has some additional benefits, which include its increased functionality of handling long-term data sequences and improved operation execution of temporal attributes [20]. Therefore, a GRU block has been added to our neural network in order to more easily and effectively extract the signal features from the dataset. For the same batch size and sequential length, it provides more reliable execution of dataset features which ensure better functionality of the overall learning model. GRU requires only two gates to achieve its proper functionality. These are,

Update Gate: In GRU cell, Update gate is responsible for determining the quantity of prior data that must be transmitted through to the next state. The mathematical formulation of an update gate can be represented as:

$$z_t = \sigma(W_z X_t + U_z H_{t-1} + b_z). \tag{6}$$

Reset Gate: The reset gate is employed in the model to determine how much past data is ignored. That is, determine if the state of the previous cell is important. The mathematical representation for the reset gate can be concluded as:

$$r_f = \sigma(W_r X_t + U_r H_{t-1} + b_r), \tag{7}$$

where X_t is the input data at time t and H_{t-1} is the previous hidden state value.

The final output has two effects based on how these two gates operate. The first one is the information currently stored in memory, which is represented as:

$$\widehat{h_t} = tanh\,(W_h X_t + U_h(r_t \otimes H_{t-1}) + b_h), \quad 8)$$

while the other one is the information at the current time step given by:

$$H_t = z_t \otimes \widehat{h_t} + (1 - z_t) \otimes H_{t-1}. \tag{9}$$

The non-linear activation function is used to produce the following sequence after merging the going before stages.

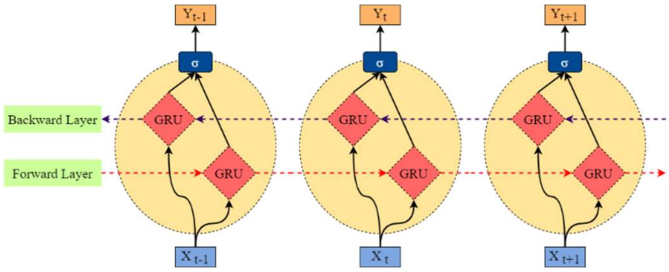


Figure 6. Architecture of BI-GRU Cell

For feature learning based on signal qualities, GRU can effectively take advantage of the context information of temporal data, where each data packet's attributes are sequentially input into a GRU cell, which creates a packet vector. In spite of having these advantages, a GRU can only evaluate data in one direction. Therefore, Bi-GRU, an enhanced version of GRU, has been utilized in the model in addition to the GRU cell to achieve bidirectional functionality for the classification model. A generalized structure of a Bi-GRU cell is shown in Fig. 6. A Bi-GRU is capable of generating the signal vector by means of a forward and a backward GRU block. The forward GRU can record features of the forward eye signal, whereas the backward GRU can record properties of the backward signals.

IV. EVALUATION

A. DATASET DESCRIPTION

The dataset is collected from the University of Malta's Center for Biomedical Cybernetics created on the basis of data from six healthy participants' electrooculography (EOG) [21]. Each individual had 600 saccades, 300 blink events, and 600 random ocular displacements recorded. A bio-signal amplifier with 256Hz sampling frequency was used to record EOG signals. The EOG potential differences between horizontally aligned and vertically aligned electrodes were measured to produce the horizontal and vertical EOG signal components. As illustrated in Fig. 2, these EOG electrodes were used for recording the eye movements which consist of two horizontally aligned electrodes positioned close to the lateral canthi and two additional electrodes vertically aligned with the right eye. In addition, a ground ('G') electrode was placed on the forehead.

B. EVALUATION METRICS

A confusion matrix is a table that depicts how well a classification model (or "classifier") performs on a set of test data for which the genuine values are known. The confusion matrix has been calculated for both horizontal and vertical datasets. It contains mainly True Positive, True Negative, False Positive, False Negative which can be further used to evaluate different performance parameters. The visualization of confusion matrix of four directional eye movement detections is shown in Fig. 7.

Actual Class	Predicted Class	
	UP/LEFT	DOWN/RIGHT
UP/LEFT	TP	FN
DOWN/RIGHT	FP	TN

Figure 7. Confusion matrix of EOG classification

- True Positive (TP): Up directive features that are truly predicted by the model.
- False Positive (FP): Down directive features that are falsely predicted by the model.
- True Negative (TN): Down directive features that are truly predicted by the model.
- False Negative (FN): Up directive features that are falsely predicted by the model.

All the experimental results of this work have incorporated around for well-known evaluation metrics. A brief explanation of each of these metrics is provided below.

Accuracy*:* Accuracy is calculated as the number of all correct predictions divided by the total number of the dataset.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN}\,. \tag{10}$$

Recall*:* The number of positive classes that have been accurately predicted is explained by the recall. It is also known as the true positive rate (TPR) and sensitivity.

$$Recall = \frac{TP}{TP+FN}\,. \tag{11}$$

Precision: Precision is described as how many of the positive classes predicted are positives.

$$Precision = \frac{TP}{TP+FP}\,. \tag{12}$$

F1 Score: The F1 score takes the harmonic average of the classifier and recalls accuracy to produce a single statistic. It is mainly used to compare the results of two different classifiers.

$$F1 = \frac{2*Recall*Precision}{Recall+Precis}\,. \tag{13}$$

Error rate (ERR): The ERR is determined by dividing the total number of inaccurate predictions by the total number of predictions in the dataset.

$$ERR = \frac{FP+F}{TP+TN+FP+FN}\,. \tag{14}$$

Specificity: The specificity is calculated by dividing the number of correct negative predictions by the total number of negatives (SP). A true negative rate (TNR) is another name for it.

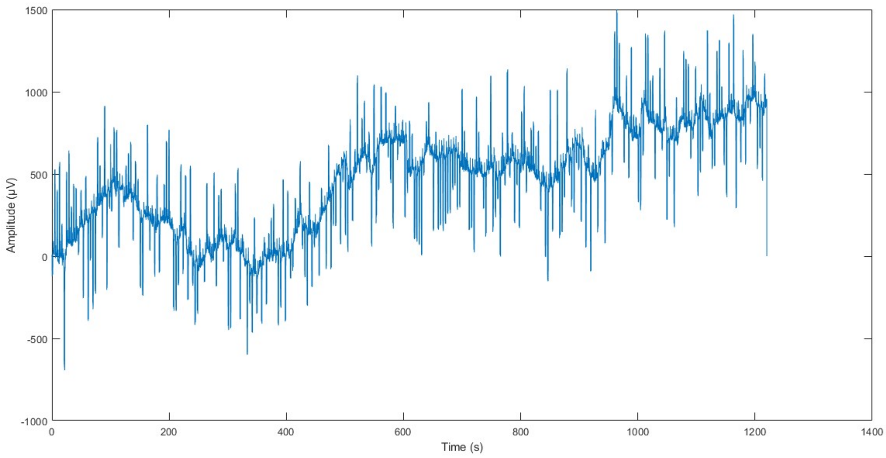
$$SP = \frac{TN}{TN+FP}\,. \tag{15}$$

C. EXPERIMENTAL RESULTS AND ANALYSIS

There are mainly two reasons associated with the prerequisite of an effective preprocessing stage for the EOG signal analysis. Firstly, since the raw signals contains a vast amount of noise within the data points, such unwanted noise need to be canceled out through a specific denoising process to obtain the optimum data points. Secondly, a filtering stage is called for achieving a symmetry along the signal points which ensures better employment of the eye signals.

As the EOG signal of the dataset for both horizontal and vertical contains noise, as shown in Fig. 8, noise reduction is our work's first concern. It can be also seen that, the baseline of the signal for both channels is not symmetric, so it must be corrected before feature extraction and classification.

A low pass filter has been applied such that the signal with a frequency that is lower than the 2 Hz cutoff frequency is allowed through while signals with a frequency that is greater than the 2 Hz cutoff frequency are attenuated. After the noise reduction, the signal can be represented in Fig. 9, where the x-axis has been limited because of the lucidity view.



(a)

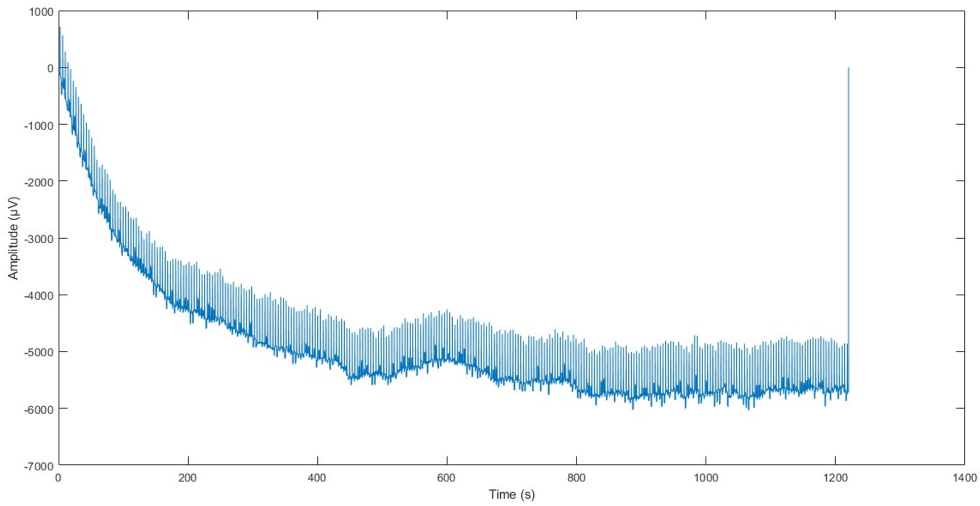
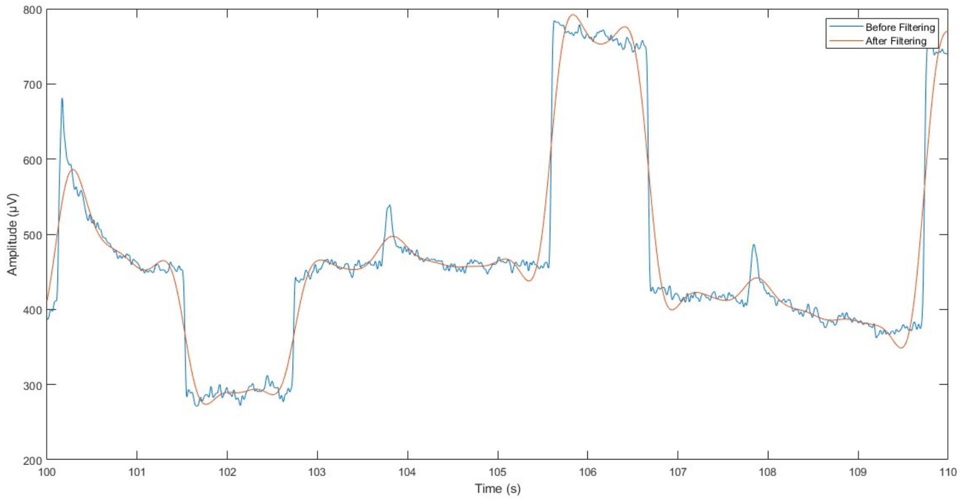
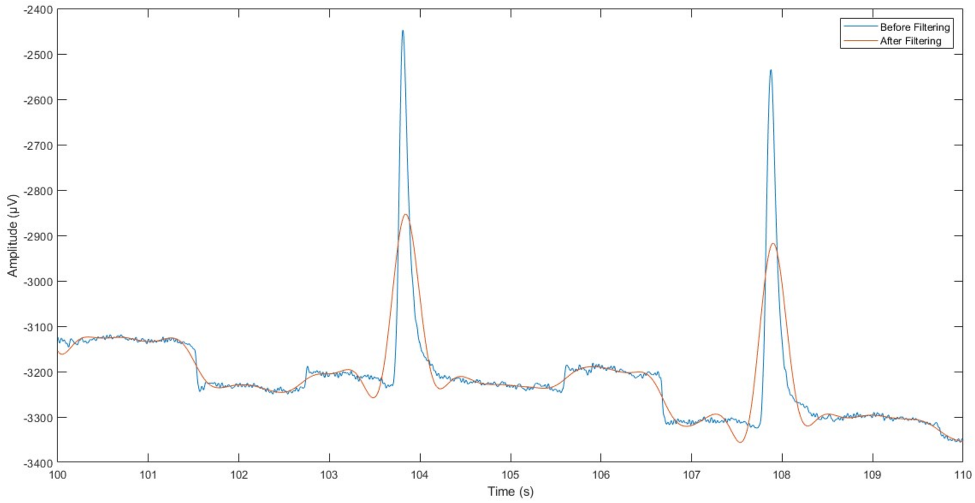


Figure 8. Raw signal of (a) Horizontal channel (b) Vertical channel

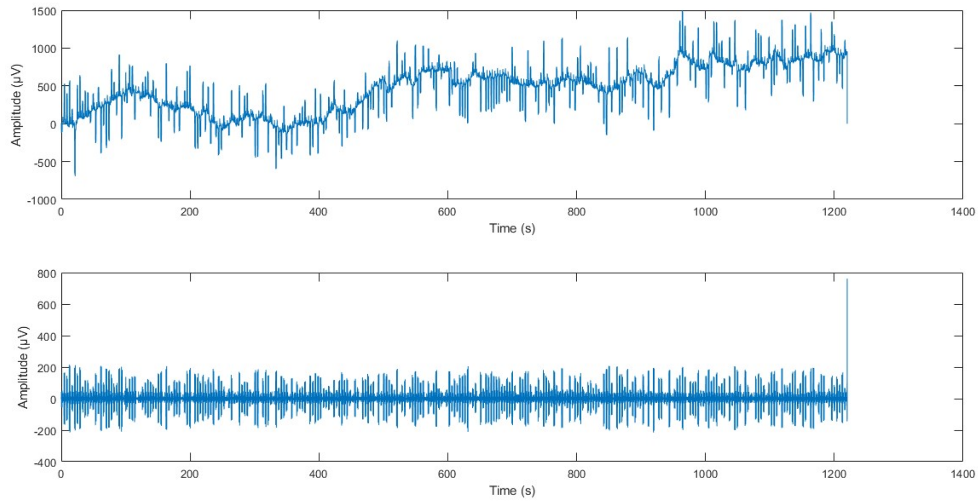


(a)

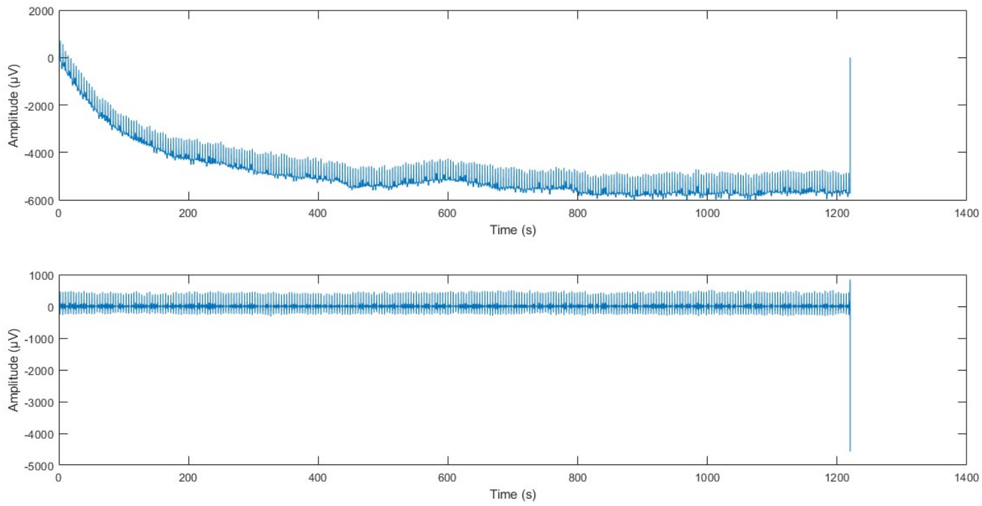


(b)

Figure 9. Before and after denoising EOG signal of (a) Horizontal channel (b) Vertical channel



(a)



(b)

Figure 10. Before and after baseline drift correction (a) Horizontal channel (b) Vertical channel signal

For avoiding misdetection of movement direction and mitigate DC offset, a high pass filter with a low cut off frequency has been applied for base line drift correction. Fig. 10 depicts the signal before and after baseline drift mitigation for both horizontal and vertical channels that does not reasonably introduce phase shift and handles the beginning and end.

After filtering and correction of the baseline drifts, the useful and informative features of EOG signal are extracted for the sake of improving classification performance. The model's efficiency in classifying eye movements depends on how good it performs on evaluation metrics. Notably, higher values for Accuracy, Precision, Recall, F1-Score, Specificity, and lower values for Error Rate indicate that the classifier is highly effective [22-24].

The corresponding confusion matrix resulting from classification for both horizontal and vertical channels is shown in Fig. 11.

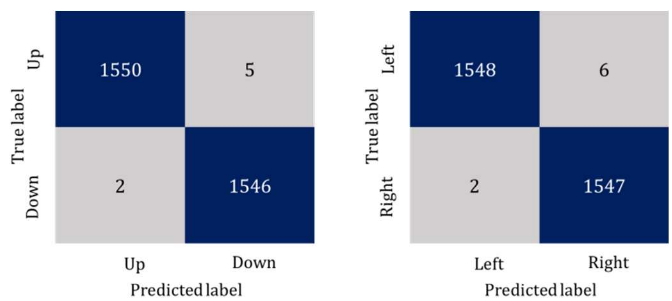


Figure 11. Confusion matrix of EOG signal classification (a) Vertical channel (b) Horizontal channel

The values of the evaluation metrics for the experiment are presented in Table 2, where all metrics are shown in percentages. According to our hypothesis, each and every metric that pertains to the dataset demonstrates that the deep learning model is superior.

Table 2. Performance analysis for vertical and horizontal channel

Performance Metrics	Vertical Channel (%)	Horizontal Channel (%)
Accuracy	99.77	99.74
Precision	99.68	99.61
Recall	99.87	99.87
F1 Score	99.77	99.74
Specificity	99.68	99.61
Error Rate	0.23	0.26

In Table 3, we present an apparent comparative analysis of the accuracy of the system compared to other state-of-the-art studies that have utilized various techniques for eye movement recognition, where accuracy is represented as percentage.

Table 3. Comparison of different research works

Study	Method	Accuracy (%)
[1]	SVM+ANN	69.75
[2]	Analog to Digital Conversion	90
[3]	Ensemble (Bagging, Boosting)	92.27
[4]	Pulse Detection	93.41
[5]	DWT+LDA	94.90
[6]	Deterministic Finite Automata	95.33
[9]	SVM	90
[14]	Analog Filtering	99
[16]	Thresholding	91.25
[17]	Signal Edge Detection	94
[18]	ANN	93.82
[19]	SVM	99
[19]	SVM + Sample Optimized	99.57
[25]	SVM	73.3
[26]	KNN	95
Proposed Work	**RNN**	**99.75**

V. CONCLUSION

In recent years, it has become possible for HCI systems to make use of electrooculography as an input signal which is applied for a wide range of purposes like computer cursor, virtual keyboard, or patient rehabilitation and communication. Therefore, it is become more vital to find a suitable classification model for EOG to improve HCI system efficiency. In this study, we propose a deep learning-based classification model with feature extraction methods in order to detect eye movement. Here, the primary architecture of the detection model is comprised of a sequence of GRU, Bi-GRU, and two back-to-back dense layers. EOG signal noise filtering and baseline drift correction can be used in order to extract valuable and important features from the dataset for ensuring both functionality and reliability of the proposed approach. The experimental findings demonstrate that our approach outperforms state-of-the-art in terms of EOG signal classification. Hence, the approach that is suggested is effective system integration with HCI.

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