Efficient Classification of Horizontal And Vertical EOG Signals For Human Computer Interaction

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Efficient Classification of Horizontal and Vertical EOG Signals for Human Computer Interaction

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Abstract

Human-computer interaction (HCI) using Electrooculography (EOG) 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 most important biomedical signals for measuring and analyzing the direction of eye movements. The EOG is used to produce both activities in vertical and horizontal directions of human eye movements. In this paper, different human eye movement tasks from vertical and horizontal directions are studied. The dataset of EOG signals were obtained from Electroencephalography (EEG) electrodes from 27 healthy people, 14 males and 13 females. This process resulted from two dipole signals, the vertical-EOG signals and the horizontal-EOG signals. These signals were filtered by band-pass at 0.5–5Hz. A total of 54 datasets from these 27 healthy individuals, each lasting 30 seconds, were given. The Bo-Hjorth parameter was implemented for feature extraction on the preprocessed EOG signals. For classification, Decision Tree (DT), K-Nearest Neighbor (KNN), Ensemble Classifier (EC), Kernel Naive Bayes (KNB) and Support Vector Machine (SVM)) were utilized. The obtained results reveal that the best classifiers on horizontal and vertical signals are the Support Vector Machine (SVM), the Cosine KNN and the Ensemble Subspace Discriminant with having 100% percentage accuracies. Through designing the proposed algorithm for feature extraction, the highest performance of classification can be obtained for rehabilitation purposes and other applications that help the handicapped to take decisions for better life quality, by providing possible human interaction with a computer.

Keywords— Electrooculography (EOG), feature extraction, classifications, Horizontal eye movements, Vertical eye movements, Human Computer Interface (HCI).

1. INTRODUCTION

Research in the field of HCI can greatly improve life quality, in particular for the people with severe disabilities suffering from spinal injuries, joint deformities, muscle spasms, amyotrophic lateral sclerosis (ALS), etc. These patients have difficulty with this pursue their goals, because they have no control over their muscles voluntarily. They are still conscious, however, and can control eye movements. Many devices are used to record human eye activities, but most have their limitations [1].

Electroculography (EOG), Infrared Oculography (IROG), Infrared Video System (IRVS), Search Coil (SC), Purkinje Dual Purkinje Image (DPI) and Optical Eye Tracking System are a variety of techniques that can be done using in eye movement detection [2, 3]. Compared to other bioelectrical signals, the electrooculographic signal (EOG) offers the advantages of high amplitude, low frequency and easy reception and transmission of information with high activity [4]. The EOG is turned out to be the simplest of technique to measure the eye movement directions. It is easy to create EOG systems with surface electrodes around the orifice and modify them in real time. The EOG system allows us predict the presence of the disease in a simple and economic way, the symptoms of which are strongly characterized a simple way and cost-effective by eye movements [5].

EOG can be used to diagnose eye movements and skin rashes by measuring the potential difference between the front and back of the eyeball. There is a direct relationship between eye movements and EOG amplitude in the EOG signal [6]. On either hand, EOG could be a good engineering alternative by detecting electrical activity produced by the human eye, that further acts as an electrical dipole and has positively and negatively electrodes in the retina and cornea. In reality, it is known for causing a voltage change known as the Corneal Retinal Potential (CRP), which creates an electrical field. In particular, by a series of gel-based electrodes located around the eye, the EOG detects non-invasive electrical activity induced by CRP [7, 8].

The EOG potential is generated by electrical signals produced during Different horizontally and vertically movements of the eye, such as blinking, staring, and anger [9]. EOG amplitude ranges from 15 to 3500 microvolts and frequency fractions from 0 to 100 Hz. Its voltage range, characterized by unique and easy to detect signals, makes EOG ideal to be used as an input signal for applications requiring. [10, 11].

The EOG is essential to scientists and physicians because it offers a wealth of information on neuropathology. Without hand movements or speech for HCI, the EOG is an efficient alternative. In HMI applications such as computer control and wheelchairs the EOG signals are widely used, as both programs allow people with disabilities to navigate and manage their computer applications [12].

Thus the, EOG is a suitable candidate to be chosen as an input to the eye movement. Indeed, a number of HCI indicators using EOG have been proposed as inputs, like control of electric wheelchair [11], control of mobile robot, recognition activity [7], and recognition of eye writing [13,14], etc.

In [15], the authors introduced a new electrode placement method based on eye glasses, a base line drift and noise removal method called DOSbFC. The results showed that the average accuracy utilization of BPF and wavelet transformation was 61 per cent and 64 per cent, respectively, while the DOSbFC long-term eye movement detection was 94 per cent. In [16], the authors focused on calculating the thematic position of the eye, identifying different eye movements based on EOG signals and developing new coding techniques that can be used by users to communicate with EOG-based virtual keyboards. This trend allows direct and asynchronous access to any image from anywhere on the screen. The accuracy of the saccade and blink labelling in this system was 99.92 per cent and 100.00 per cent respectively.

In [17], the authors described the main features of EOG, related metrics, signaling and design knowledge algorithms, and lists of the various programs mentioned in the literature. EOG signals to be an important source of communication and a useful tool for people with amyotrophic lateral sclerosis. In [18], this article presents a multi-disciplinary strategy used to differentiate demand and non-demand decisions by measuring the EOG period with channels obtained using a drought sensor. The average accuracy of 93.89 per cent at an information transfer rate (ITR) of 62.64 per cent (bps) was achieved for command recognition and execution.

In [19], the authors suggested the use of a HCI to control electrocardiograms. Dynamic stupid algorithm are used to classify the EOG signals. The average success rate was 77.5% of the overall success rate, which is further enhanced by the training of volunteers on the device. In [20], the authors used the "ESR" model to classify the signals from the basic eye movement unit into different functions, export the Hjorth parameter, and create contextual relationships using the "AR" model. The mean accuracy of the description was 88.15%.

In [21], the EOG system was designed to detect eye movements that can restore communication skills of patients with dysfunctional facial muscles and limbs. For the feature extraction and classification scheme of horizontal and vertical channel data, for classifications models: the DT, KNN, EC, KNB and SVM were used. This system has achieved an accuracy of 78%.

In this Article, the EOG signals were recorded using a horizontal and vertical channel data acquisition system. MATLAB R2019b (MathWorks) has been employed in this article. An HP laptop with processor configuration Intel (R) Core (TM) i7-8565U CPU @ 1.80GHz 1.99 GHz, 8GB RAM, 64-bit version of windows was also used in this study.

The main thrust of this study was to evaluate and compare the results of the different classifications: DT, KNN, EC, KNB and SVM according to the accuracy of the classification. The trained classifiers are used to classify the different directions of eye movements. The study also explores a way of feature extraction using the Bo-Hjorth parameter used on the pre-processed EOG signals. We hope that this study will help to develop an efficient and easy algorithm for the classification of EOG signals.

The rest of this article is structured as follows. Section 2 presents the basics of EOG signals and data collection. In Section 3, the proposed system methodology has been discussed. Section 4 presents the experimental results. Finally, Section 5 presents the conclusion of this work.

2. *Basics of EOG signals and data collection*

2.1 Foundation of EOG signals

EOG is a technique for measuring the standing potential of human cornea-retina between the leading and trailing edges of the human eye movements. When there is an active nerve in the retina, a potential difference of 10 to 30 mV compared to the front of the eye exists, as shown in Figure 1.a [22].

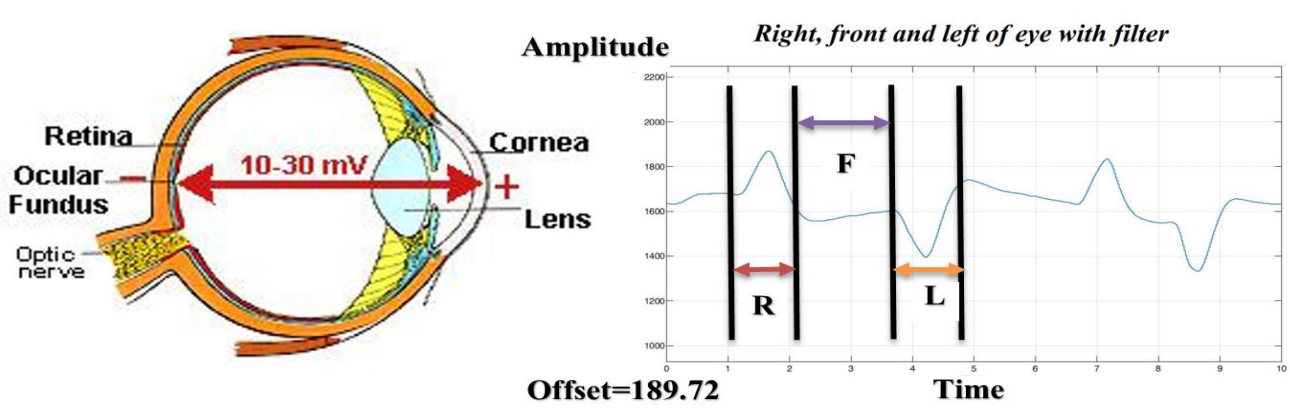


Fig.1 Basic principles of EOG signals: (a) Eyeball Anatomy, (b) Pulse of EOG filtered with marked segments showing three main characteristics of eye movement: Pulse of Right (R), Pulse of Front (F) and Pulse of Left (L).

This difference in voltage between the cornea and the retina is due to the wonderful active presence of the nervous system in the retina of the anterior part of the eyeball, this can be seen as a steady electrical dipole with a negative pole and a positive pole in the retina and the cornea. (See Figure 1.a) [23], the resulting signal is called an electrocologram (EOG).

The EOG signal normally consists of 2 pulses. The first pulse represents the beginning of the EOG signal and the second pulse reveals the stop of the EOG signal. Properties of different human eye movements are mentioned in Table 1.

Table 1 – Properties of different human eye movements.

Eyeball movements	First Pulse	Second Pulse	Channel	Pulse duration
Right	Positive	Negative	Horizontal	400-600 ms
Left	Negative	Positive	Horizontal	400-600 ms
UP	Positive	Negative	Vertical	400-600 ms
Down	Negative	Positive	Vertical	400-600 ms

When the eyeball moves 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 produced, respectively, in the vertical or horizontal channel (see figure1.b).

2.2 Data collection (Dataset)

This section presents the dataset of EOG signals used in the proposed system. The major difference between this dataset and others is that it focuses only on EOG artifacts. The EOG signals are obtained from EEG electrodes from 27 healthy people, 13 females (mean age: 27.1 ± 5.2) and 14 males (mean age: 28.2 ± 7.5), in the closed-eye session. 19 electrodes (T3, T4, T5, T6, Fz, CZ, Pz, C3, C4, P3, P4, O1, O2, F7, F8, FP1, FP2, F3, F4) under the international system 10-20 were placed [24].

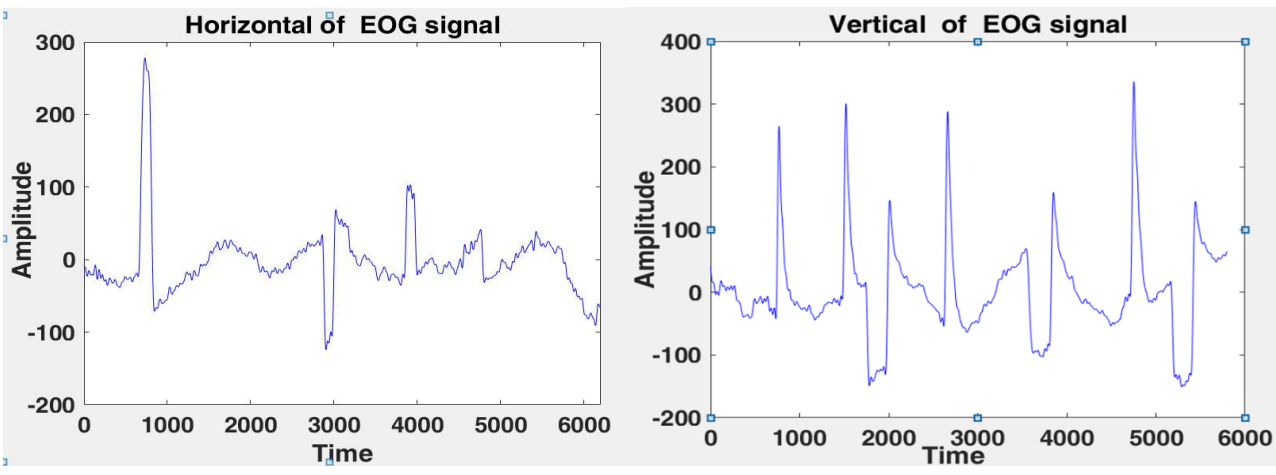


Fig.2. Samples of EOG vertical and horizontal signals are used in the experiments.

By used the band-pass filtered (BPF) at 0.5 – 40 Hz and notch filtered at 50 Hz, the signal was filtered. A total of 54 signals from these 27 healthy individuals, each lasting 30 seconds were obtained. The resulting dataset was carefully examined to ensure it was free from considerable pollution of biological or external particles. Using four electrodes placed two more on the outer bronchus of each eye and up and down the left eye, EOG signals were obtained through the opening state of the eye.

In this method, two dipole signals are recorded, namely vertical EOG (VEOG) and horizontal EOG (HEOG) recordings. Which is equivalent to the up-down electrode and the left-right EOG electrode. With a BPF of 0.5–5Hz, the EOG signals were filtered [25]. Samples of EOG signals in both vertical and horizontal are shown in Figure 2.

Dataset are available for download without restriction using this URL:

https://techedubsuedu-my.sharepoint.com/:f:/g/personal/dr_abdelgawad_techedu_bsu_edu_eg/Egnx6bUqKd1MnTwaZ9uiEn8BJOUklL20puqRm7ZNubkjJA?e=dWQdRr

3. Proposed Methodology

3.1 Proposed System Architecture

Block diagram architecture of the proposed system as shown in Figure 3 has four functional modules: data preparation of vertical and horizontal EOG signals (.mat files), data pre-processing, feature extraction and classification models using MATLAB R2019.b.

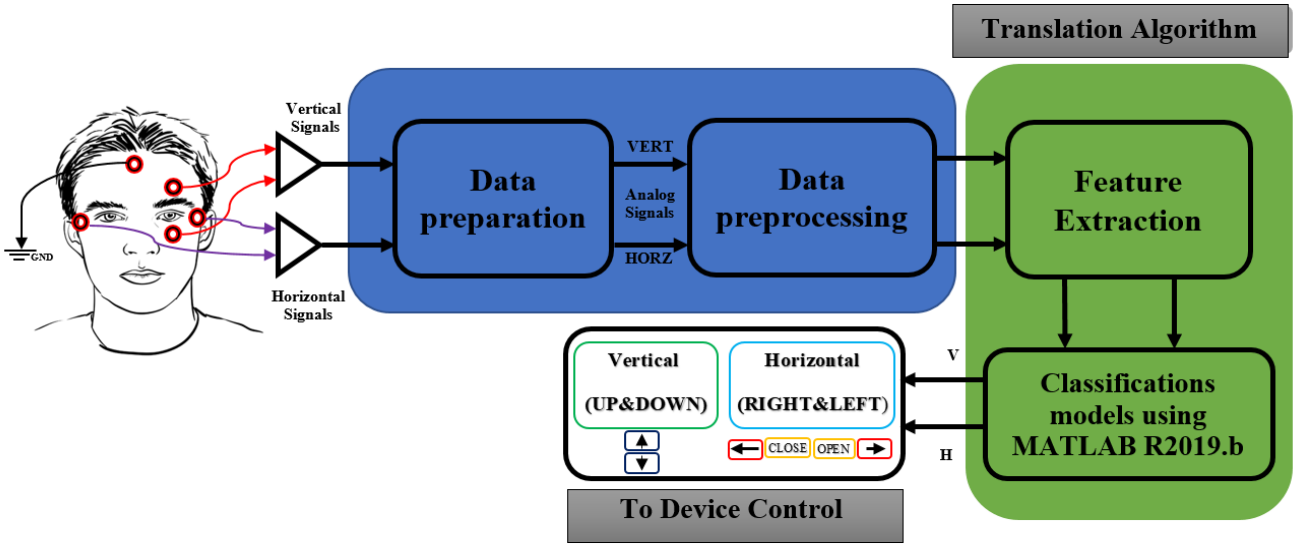


Fig. 3. Proposed system architecture.

3.1.1 Horizontal and Vertical data preparation of EOG signals

The horizontal and vertical data were obtained and prepared by EOG for 27 healthy individuals by using two channels. These channels were used to obtain the horizontal signals, which include the right, middle and left, to obtain the vertical signals that include the up, middle and down. A total of 54 signals from 27 healthy individuals, each lasting 30 seconds were obtained. With a BPF of 0.5–5Hz, the EOG signals were filtered, and this data is illustrated in Section 2.2.

3.1.2 Data Pre-processing

In general, the component with the highest pure eye movement signal frequency (EOG signal) is less than 10 Hz [26]. Take the following factors into consideration:

(1) Keeping the active ingredients of the EOG ingredients such as saccadic EOG signal extreme edge, primary signal amplitude, etc.

(2) Delete the baseline drift that occurs by interference with the polarization of the electrode or the background signals. Suppressing noise that goes beyond 10 Hz such as noise of power lines, high-frequency components from different sources, movement of the electrodes. With a BPF of 0.5–5Hz was designed to preprocess, the EOG signals were filtered.

In addition, all preprocessed signals are divided into testing and training datasets [20].

3.1.3 Horizontal and Vertical Feature extraction of EOG signals

This section presents the attributes of the algorithms used in our experiments for the features extraction. Figure 4 shown the flowchart of the features extraction was developed and implemented in MATLAB (R2019.b).

Primary signals, which appear in their divergent form, it is not easy to distinguish certain features of the signal. Therefore, the clear signals are highlighted in order to extract the different features. Equation (1) was used to representation the first order of the signal.

$$\overline{x} = Ef(x) - Ef(x-1) \qquad (1)$$

where $\overline{x}$ is the first-order differentiation of the filtered EOG signal with respect to time and $Ef(x)$ is the filtered EOG signal.

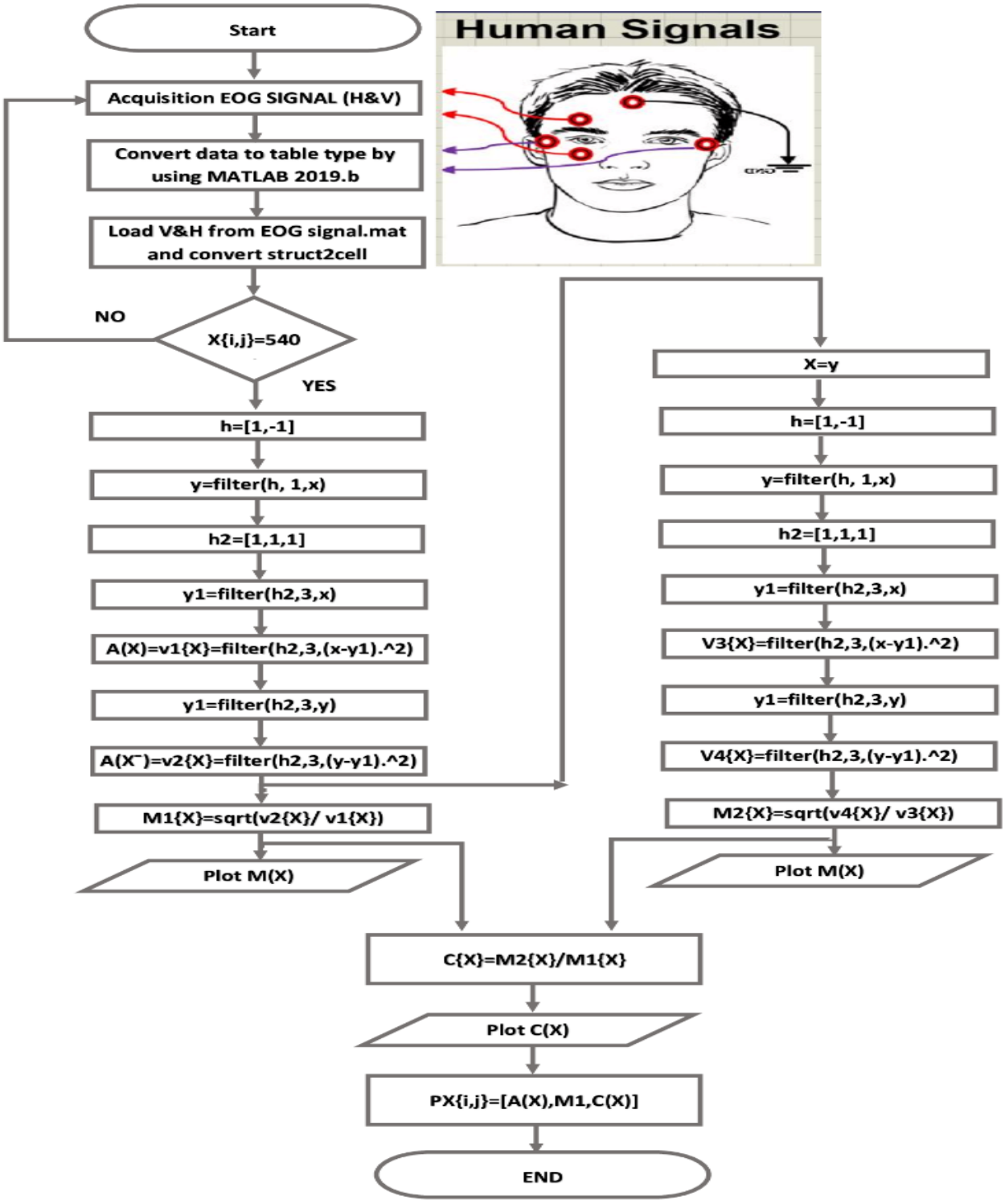


Fig.4 Flowchart of the feature extraction algorithms in the proposed system.

From pre-processed EOG signals, the BO-Hjorth features are extracted, these signals as illustrated in Section 2.2 to maintain a balance between the performance of the proposed algorithm and complexity. The characteristics of the observation signals are presents by: Activity $A(X)$, mobility $M(X)$, and complexity $C(X)$. These are time-domain features extracted from the EOG signal [27].

Specially, activity $A(x)$ specifies the variance of the input signal, mobility $M(x)$ indicates the average signal frequency and complexity $C(x)$ detection of signal variations from the sine shape. The definitions are given below for an input signal $x(n)$ of length N.

$$A(x) = var(x) \tag{2}$$

$$var(x) = \frac{\sum_{n=1}^{N}(x(n) - \overline{x})^2}{N} \tag{3}$$

$$M(x) = \sqrt{\frac{A(\overline{x})}{M(x)}} \tag{4}$$

$$C(x) = \frac{M(\overline{x})}{M(x)} \tag{5}$$

where $\overline{x}$ denotes the first derivative of the input EOG signal $x(n)$ and $var(x)$ denotes the biased variance of signal $x(n)$ with mean value $\overline{x}$.

Because the BO-Hjorth Parameters they help in capturing the stationarities and reducing the non stationarities, these are used in case of bio-signals by using higher-order derivatives of the input signal [28]. Bo-Hjorth parameters are computed, to represent stability on small staggered windows of equal length, then for a given case, those parameters are averaged over all windows.

We have obtained three values corresponding to activity, mobility, and complexity for each case of each the two horizontal and vertical channels of the EOG signal, the Bo-Hjorth parameters were represented, see equation 6. This is illustrated in the flowchart as shown in figure 4. Six features per-instance concatenating the features per-channel have been obtained.

$$PX(x) = [A(x), M(x), C(x)] \tag{6}$$

3.1.4 Classifiers for vertical and horizontal EOG signals

This section presents the different classifiers of vertical and horizontal EOG signals used in our experiments. Five classifiers from the most popular classifiers models, DT, KNN, EC, KNB and SVM, were used in this study. All of these classifiers were used for horizontal and vertical channel data after feature extraction of EOG signals.

Figure 5 shown the block diagram of a common workflow for training classifier models.

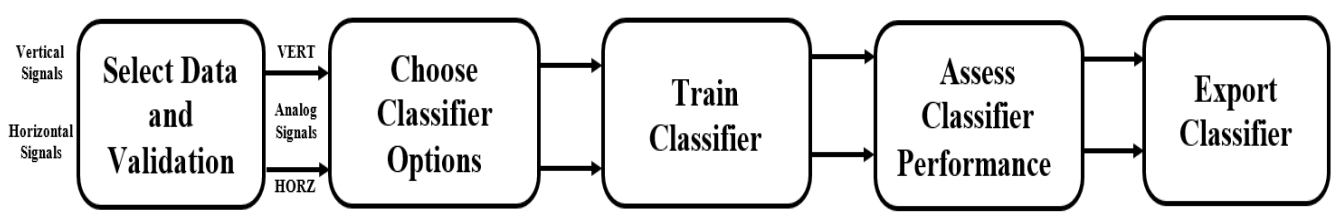


Fig.5 Block diagram for training classifier models.

A) Support Vector Machine (SVM)

The basic idea of SVM is to create a group that separate the two vertical and horizontal EOG signals, which are only used in some cases when navigation patterns are separated. To solve this problem, the data was placed in larger spaces using the main feature [29, 30].

For different fields of research, SVM is an effective classification algorithm. It includes application of: classification of text [31], detection face [32] and breast cancer diagnosis [33]. SVM is a binary classifier that attempts to find the optimum hyperplane. The distance between the decision boundary and the data of both classes should be as distant as possible, at the

same time the linear decision-making surface that divides the n-dimensional space into two parts means the optimum hyperplane.

B) Ensemble Classifier (EC)

The Ensemble Classifier is one of the types of classifiers used to define the category of test samples by combining their individual predictions (weighted voting). It is more accurate to rely on a group of workbooks than to rely on a single decision-making workbook [34, 35].

There are two important criteria for the selection of classifiers, the first criteria must be diverse (different error in the new dataset) and the second criteria must be accurate (error rate better than random guessing). To predict the class of the sample classifier, each of the features in the dataset is used. Two such popular methods to implement algorithms in the ensemble classifiers are baggage and boosting [36, 37].

There are n samples from the original dataset on the boot in cases where a dataset is generated by random extraction (by substitution). The dataset obtained by booting the original dataset in the bagging process are trained the classifiers. The diversity between the weak classifiers is achieved by the re-sampling procedure used. T times is decided to take place by the re-sampling. At the end, to infer the class of the unknown sample the majority vote is used.

C) K-Nearest Neighbour (KNN)

K-Nearest Neighbor is one of the easiest and oldest case-based learning methods. Use the method of prediction whenever a new note is classified and a classifier is built. So it's different from other classifiers. The nearest-neighbor classification is based on the nearest distance metric and the nearest distance number (k variable). One parameter is fixed by a different parameter, at a time [38].

By compares the new data to the data used during the training session. The KNN is known as an instance based learning algorithm. In this workbook, to be defined in order to apply a specific type of classification, the multiple parameters are required. To compare the testing data with the training set in terms of distance metric, hamming distance and euclidean distance were used.

D) Decision Tree (DT)

The decision tree algorithm is managed by training a set of cases, including classroom labels. The decision tree algorithm is relatively easy to use. It begins with all states that fall into a single cluster or node, called a root node [39].

Entire expectations variables are examined for the purpose of finding a decision or segmentation that best separates the categories. In the binary tree case, the results split in a left and right node. These nodes are further examined to see if they need to be split again. In the event that further stratification is required, the forecasters, including those adopted in previous decisions, will be fully reviewed to rediscover the most appropriate division [40].

All cases within the node will be marked as linked to the same class if the node is not split and the node becomes a paper node or a terminal point. Two possibilities which arise for each node the decision node or the terminal node. It starts from the root symmetric of the tree and ends at the last point in the form of a leaf node, resulting in a data classification that gives the class the output. When it ends at a net node where the pure node belongs to only one class for classification, the decision tree stops the separation of the data [41].

E) Kernel Naive Bayes (KNB)

Kernel Naive Bayes is classification probabilistic relies on Bayes' theory. It is relies on the Maximum Suffix Principle (MAP) and can be trained using supervised learning. This method may extend to more than two classes represented as the labels of the class are drawn from the finite set and the vectors for the attribute values, see equation 7 and equation 8 [42].

$$P(Ck|x1, \dots \dots, x(n) \qquad (7)$$

$$(posteriori)P(Ck|x) = \frac{P(Ck)P(x|Ck)}{P(x)} \qquad (8)$$

Where {x1, … xn} are the features vectors, (Ck) is the probability for each class and (n) large number of features.

3.2 Training and testing process

In this section, we present the training and testing processes in the presented system. The flowchart shows the steps of this processing as shown in figure 6. In our experiments, 70% of the dataset was used for the training process and 30% of the dataset was used for the testing process.

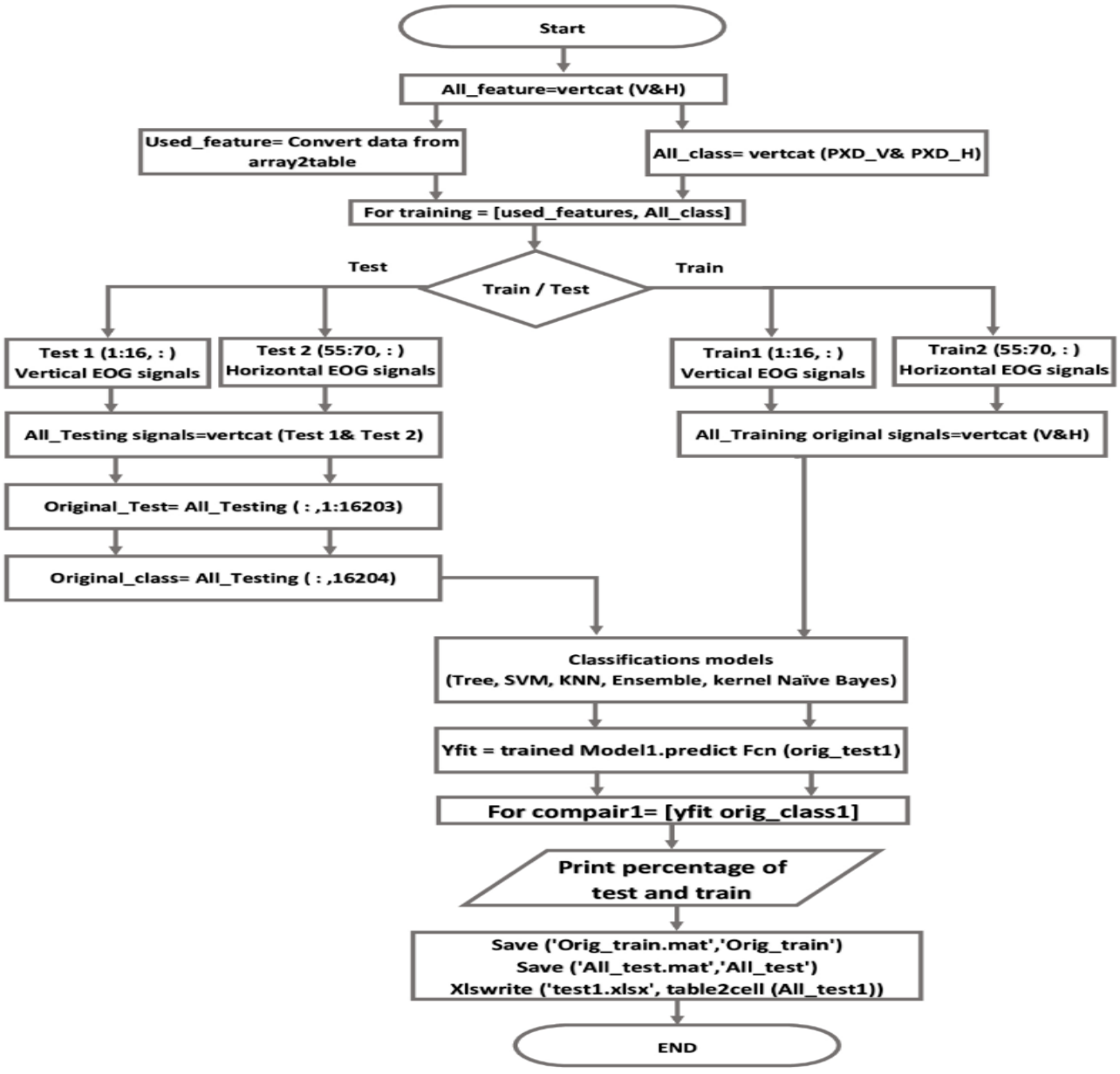


Fig.6 Flowchart of training and testing in the proposed system.

4. Experimental results

This section presents the training and testing processes, as well as the performance evaluation of each classifiers. In addition, the performances of the classifiers are analyzed and compared with the confusion matrix, receiver operating characteristics (ROC) curve and performance indicators including accuracy for training and testing.

$$Accuracy\ of\ train = \frac{TH + TV}{TH + FH + TV + FV} * 100 \qquad (9)$$

$$Accuracy\ of\ test(vertical) = \frac{TH - FH}{TH + FH} * 100 \qquad (10)$$

$$Accuracy\ of\ test(horizontal\ ) = \frac{TV - FV}{TV + FV} * 100 \qquad (11)$$

where TH represents the truly-classified horizontal signals, FH represents the falsely-classified of horizontally-classified signals, TV represents the truly-classified of vertically-classified signals and FV represents the falsely-classified of vertically-classified signals. Using cross validation, the data has been divided into parts. After that, by using MATLAB (R2019.b) the feature matrix has been loaded into the classifiers.

By using the dataset that are described in section 2.2, the experiments are conducted. The dataset includes: vertical and horizontal EOG signals. For each class, 54 signals (horizontal & vertical) are provided with a total of 108 samples of EOG signals were illustrated in the link located in section 2.2.

4.1 Confusion Matrix (CM)

Classifier performance in each class can be subject to confusion matrix. The confusion matrix is a table format that shows the performance of the classifiers. In this table, the true category and expected class are shown as rows and columns of the table, respectively. The diagonal cells denote where the true class and the predicted class are equal. If the green cells in this table display a high percentage, this indicates that the classifier rates the true category correctly.

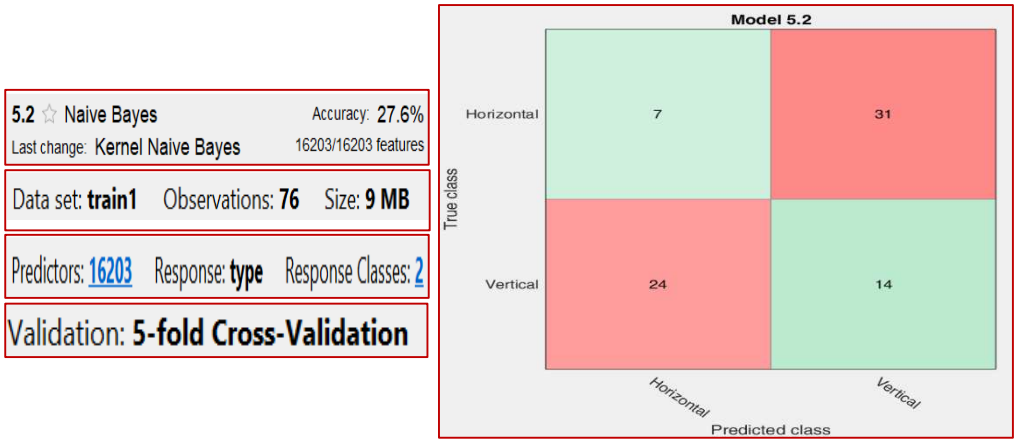
4.2 Simulation Result for Training

Simulation experiments have been carried to classify EOG signals using the above-mentioned classifiers. The used dataset 108 samples of EOG signals were mentioned in section 2.2 [24-25]. The used features are those illustrated in Eq. (1) to Eq. (6). Two classed are discriminated: horizontal and vertical signals. In our experiments, 70% of the dataset was used for the training process and 30% of the dataset was used for the testing process.

A. Confusion matrix for Kernel Naive Bayes (KNB)

In this classifier, through experiments that we conducted on these type, the following results was given: 27.6% for KNB. Table 2 shown the results Confusion matrix of the KNB classifier training.

Table 2 – Confusion matrix of KNB classifier training in the presented system.

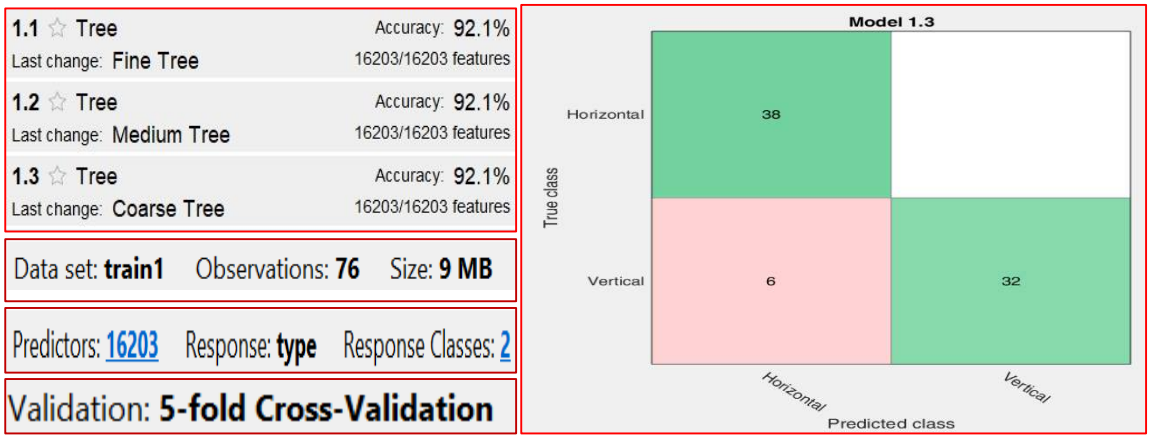


It is clear from Table 2 that 7 out of 38 horizontal eye movement observations were classified correctly with an 18.42% percentage. In addition, 14 out of 38 vertical eye movement observations were correctly classified with a percentage of 36.84%. These results reveal that there is a need to enhance the vertical and horizontal signals classification results.

B. confusion matrix for DT

This classifier has three types: fine tree, medium tree and coarse tree. Through experiments that we conducted on these types, the following results were given: 92.1% for each type of DT. Confusion matrix results of the DT classifier training are shown in Table 3.

Table 3 – DT Confusion matrix for classifier training in the presented system.

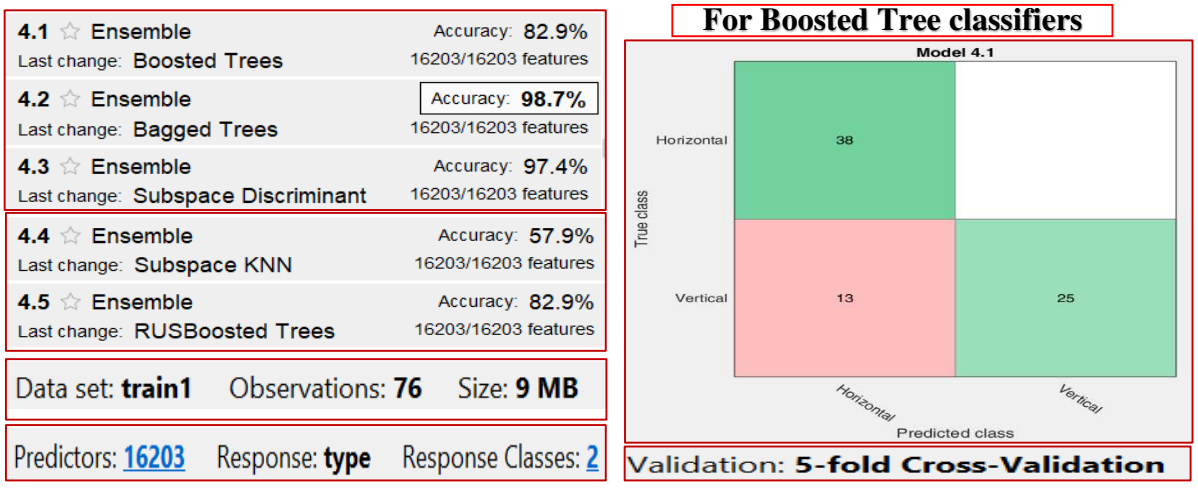


It is clear from Table 3 that 38 out of 38 horizontal eye movement observations were classified correctly with a 100% percentage. In addition, 32 out of 38 vertical eye movement observations were correctly classified with a percentage of 84.21%. These results reveal that there is a need to enhance the vertical signal classification results.

C. Ensemble Classifier (EC)

This classifier has five types: Boosted Trees, Bagged Tree, Subspace Discriminant, Subspace KNN and RUSBoosted Trees. Through experiments that we conducted on these types, the following results were given: 82.9%, 98.7%, 97.4%, 57.9% and 82.9% respectively. Confusion matrix results of the EC classifier training are shown in Tables 4, 5, 6, 7 and 8 respectively.

Table 4 – Confusion matrix of Boosted Trees classifiers in the presented system.



For the Boosted Trees classifier, it is clear from Table 4 that 38 out of 38 horizontal eye movement observations were classified correctly with a 100% percentage. In addition, 25 out of 38 vertical eye movement observations were correctly classified with a percentage of 65.78%. These results reveal that there is a need to enhance the vertical signal classification results.

For the Bagged Trees classifier, it is clear from Table 5 that 38 out of 38 horizontal eye movement observations were classified correctly with a 100% percentage. In addition, 37 out of 38 vertical eye movement observations were correctly

classified with a percentage of 97.36%. These results reveal that the vertical and horizontal signals classification results are the best with a 98.7% percentage.

For the Subspace Discriminant classifier, it is clear from Table 6 that 38 out of 38 horizontal eye movement observations were classified correctly with a 100% percentage. In addition, 36 out of 38 vertical eye movement observations were correctly classified with a percentage of 94.73%. These results reveal that there is a need to enhance the vertical signal classification results.

Table 5 and 6 – Confusion matrix of Bagged Tree and Subspace Discriminant classifiers in the presented system.

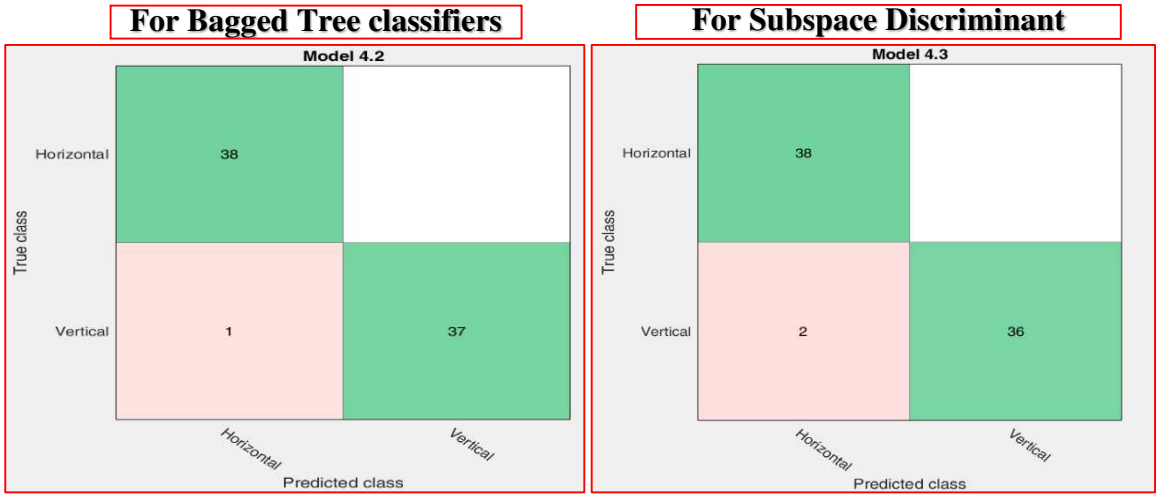
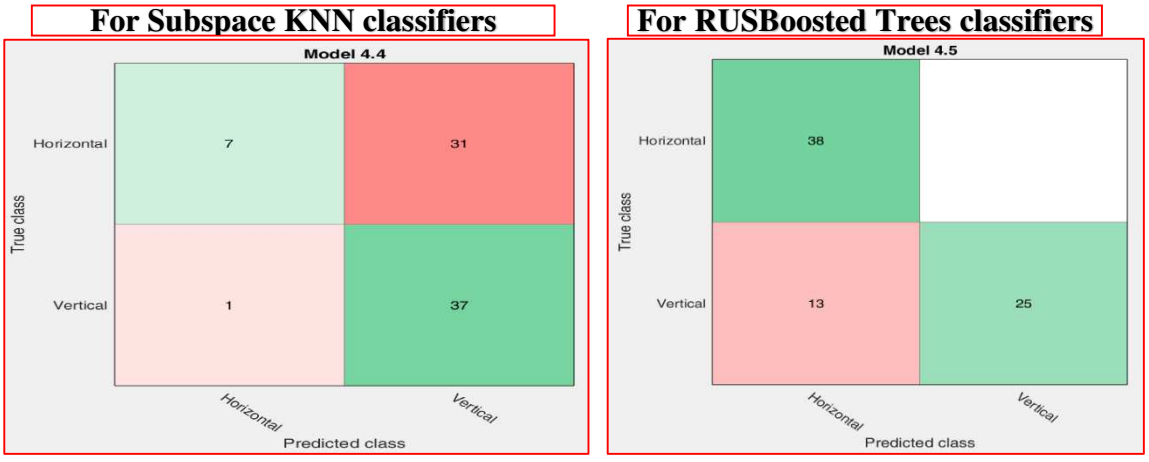


Table 7 and 8 – Confusion matrix of Subspace KNN and RUSBoosted Trees classifiers in the presented system.



For the Subspace KNN classifier, it is clear from Table 7 that 7 out of 38 horizontal eye movement observations were classified correctly with an 18.42% percentage. In addition, 37 out of 38 vertical eye movement observations were correctly classified with a percentage of 97.36%. These results reveal that there is a need to enhance the horizontal signal classification results.

For the RUSBoosted Trees classifier, it is clear from Table 8 that 38 out of 38 horizontal eye movement observations were classified correctly with a 100% percentage. In addition, 25 out of 38 vertical eye movement observations were correctly classified with a percentage of 65.78%. These results reveal that there is a need to enhance the vertical signal classification results.

D. K-Nearest Neighbor (KNN) Classifier

This classifier has six types: Fine KNN, Medium KNN, Coarse KNN, Cosine KNN, Cubic KNN and Weighted KNN. Through experiments that we conducted on these types, the following results were given: 56.6%, 55.3%, 47.4%, 98.7%

96.1% and 59.2% respectively. The type results for training of KNN classifiers are shown in Table 9. Confusion matrix results of the KNN classifier training are shown in Tables 10, 11, 12, 13 and 14 respectively.

Table 9 –Results for KNN of training classifiers in the presented system.

3.1 ☆ KNN	Accuracy: 56.6%	3.4 ☆ KNN	Accuracy: 98.7%
Last change: Fine KNN	16203/16203 features	Last change: Cosine KNN	16203/16203 features
3.2 ☆ KNN	Accuracy: 55.3%	3.5 ☆ KNN	Accuracy: 96.1%
Last change: Medium KNN	16203/16203 features	Last change: Cubic KNN	16203/16203 features
3.3 ☆ KNN	Accuracy: 47.4%	3.6 ☆ KNN	Accuracy: 59.2%
Last change: Coarse KNN	16203/16203 features	Last change: Weighted KNN	16203/16203 features

Table 10 and 11 – Confusion matrix of Fine KNN and Medium KNN classifiers in the presented system.

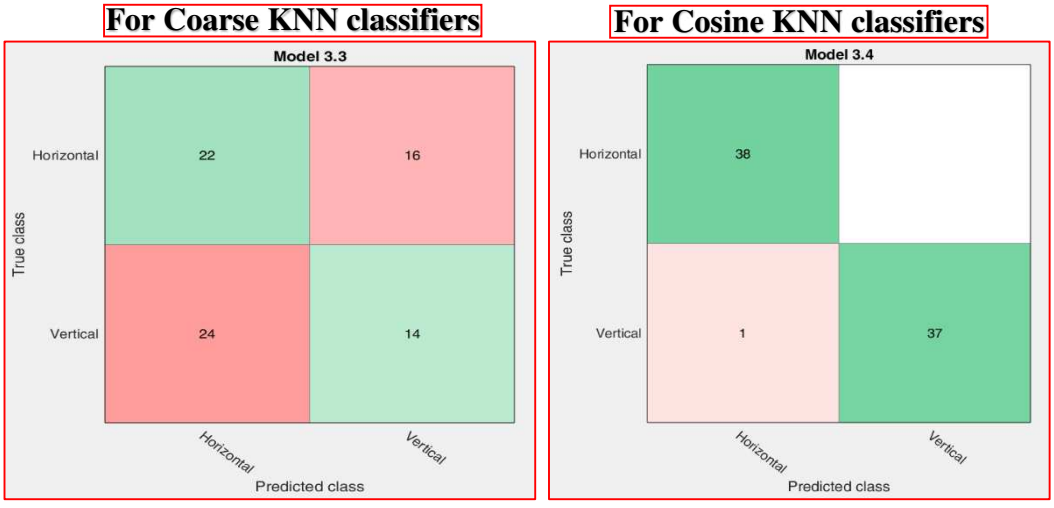
For Fine KNN classifiers **For Medium KNN classifiers**

For the Fine KNN classifier, it is clear from Table 10 that 7 out of 38 horizontal eye movement observations were classified correctly with an 18.42% percentage. In addition, 31 out of 38 vertical eye movement observations were correctly classified with a percentage of 81.57%. These results reveal that there is a need to enhance the horizontal and vertical signals classification results.

For the Medium KNN classifier, it is clear from Table 11 that 38 out of 38 horizontal eye movement observations were classified correctly with a 100% percentage. In addition, 4 out of 38 vertical eye movement observations were correctly classified with a percentage of 10.52%. These results reveal that there is a need to enhance the vertical signal classification results.

Table 12 and 13 – Confusion matrix of Coarse KNN, Cosine KNN classifiers in the presented system.

For Coarse KNN classifiers **For Cosine KNN classifiers**

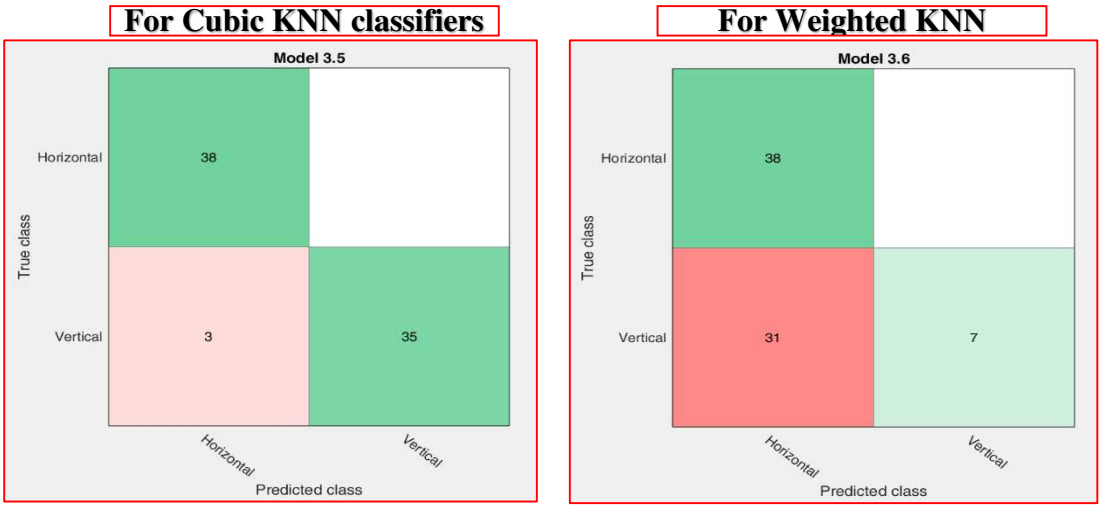


For the Coarse KNN classifier, it is clear from Table 12 that 22 out of 38 horizontal eye movement observations were classified correctly with a 57.89% percentage. In addition, 14 out of 38 vertical eye movement observations were correctly

classified with a percentage of 36.84%. These results reveal that there is a need to enhance the horizontal and vertical signals classification results.

For the Cosine KNN classifier, it is clear from Table 13 that 38 out of 38 horizontal eye movement observations were classified correctly with a 100% percentage. In addition, 37 out of 38 vertical eye movement observations were correctly classified with a percentage of 97.36%. These results reveal that the vertical and horizontal signals classification results are the best with a 98.7% percentage.

Table 14 and 15 – Confusion matrix of Cubic KNN and Weighted KNN classifiers in the presented system.



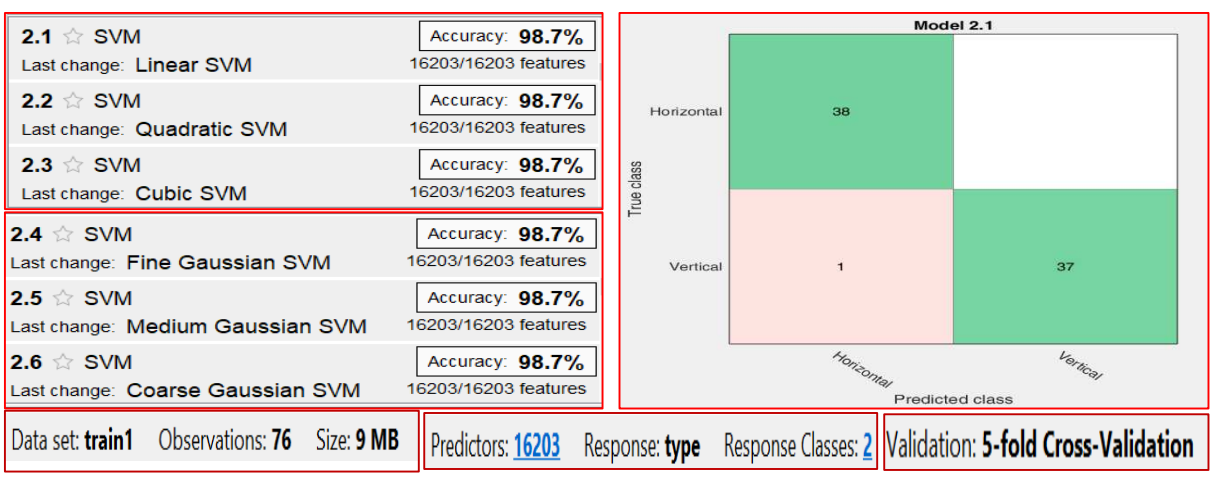
For the Cubic KNN classifier, it is clear from Table 14 that 38 out of 38 horizontal eye movement observations were classified correctly with a 100% percentage. In addition, 35 out of 38 vertical eye movement observations were correctly classified with a percentage of 92.10%. These results reveal that there is a need to enhance the vertical signal classification results.

For the Weighted KNN classifier, it is clear from Table 15 that 38 out of 38 horizontal eye movement observations were classified correctly with a 100% percentage. In addition, 7 out of 38 vertical eye movement observations were correctly classified with a percentage of 18.42%. These results reveal that there is a need to enhance the vertical signal classification results.

E. Support Vector Machine (SVM) Classifier.

This classifier has six types: Linear SVM, Quadratic SVM, Cubic SVM, Fine Gaussian SVM, Medium Gaussian SVM and coarse Gaussian SVM. Through experiments that we conducted on these types, the following results were given: 98.7% % for each type of SVM. Confusion matrix results of the SVM classifier training are shown in Table 16.

Table 16 – SVM classifiers Confusion matrix in the presented system.



It is clear from Table 16 that 38 out of 38 horizontal eye movement observations were classified correctly with a 100% percentage. In addition, In addition, 37 out of 38 vertical eye movement observations were correctly classified with a percentage of 97.36%. These results reveal that the vertical and horizontal signals classification results are the best with a 98.7% percentage.

Table 17 presented the accuracy for all classifier of the training in the presented system was indicated by using equations 9.

Table 17 - The accuracy for all classifier training in the presented system.

Classifier Used	Accuracy
Decision Tree (DT)	**92.1%**
Kernel Naive Bayes (KNB)	**27.6%**
Support Vector Machine (SVM)	**98.7%**
Fine KNN	**56.6%**
Medium KNN	**55.3%**
Coarse KNN	**47.4%**
Cosine KNN	**98.7%**
Cubic KNN	**96.1%**
Weighted KNN	**59.2%**
Ensemble Boosted Trees	**82.9%**
Ensemble Bagged Tree	**98.7%**
Ensemble Subspace Discriminant	**97.4%**
Ensemble Subspace KNN	**57.9%**
Ensemble RUSBoosted Trees	**82.9%**

It is clear from Table 17, these results reveal that the SVM, Cosine KNN and Ensemble Bagged Tree are the best performance of classifier training with a 98.7% percentage.

4.3 Receiver Operating Curve (ROC)

The ROC curve is a histogram describing the discriminatory power of the binary classifier system with respect to the variable threshold value. The classifier output is a threshold value for each class. The values of the false-positive rate and the true-positive rate are estimated from each category threshold.

Table 18 shows a summary of the area under the ROC curve (AUC) for different classifiers in the horizontal and vertical signals. Examples of these ROC curves are shown in Figure 7.

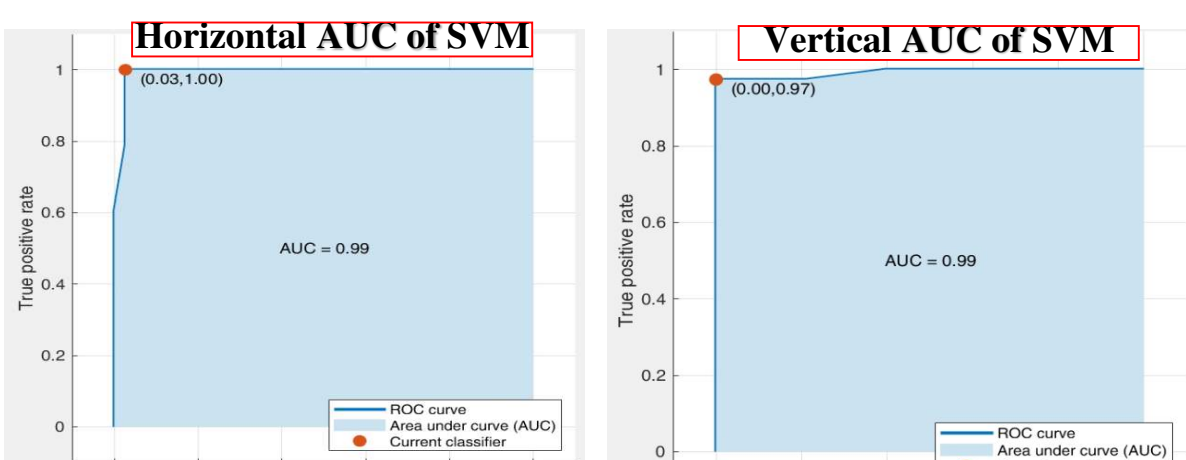


Fig. 7. Example of AUC for horizontal and vertical SVM with AUC=0.99.

Table 18 - ROC for dimensions curves (AUC) for all classifier.

Classifier Used	AUC in the horizontal and vertical signals
Decision Tree (DT)	0.92
Kernel Naive Bayes (KNB)	0.18
Support Vector Machine (SVM)	0.99
Fine KNN	0.57
Medium KNN	0.80
Coarse KNN	0.47
Cosine KNN	0.98
Cubic KNN	0.98
Weighted KNN	0.80
Ensemble Boosted Trees	0.99
Ensemble Bagged Tree	0.98
Ensemble Subspace Discriminant	1.00
Ensemble Subspace KNN	0.58
Ensemble RUSBoosted Trees	0.97

4.4 Simulation Result for Testing

The performance of testing from where accuracy indices by used 30% of dataset for horizontal and vertical data for all testing classifiers are calculated by the Eq. (10) and Eq. (11). Table 19 shown the summarized of the comparative analysis of the performance indices for all five classifiers.

Table 19 – summarized of the comparative analysis of the performance indices for all five classifiers.

Classifier Used	Accuracy of Horizontal	Accuracy of Vertical	Average of accuracy
Decision Tree (DT)	100%	93.75%	96.875%
Kernel Naive Bayes (KNB)	Inverse (0%)	Inverse (0%)	0%
Support Vector Machine (SVM)	100%	100%	100%
Fine KNN	0%	100%	50%
Medium KNN	100%	6.25%	53.125%
Coarse KNN	16%	0%	8%
Cosine KNN	100%	100%	100%

Cubic KNN	**100%**	**75%**	**87.5%**
Weighted KNN	**100%**	**12.5%**	**56.25%**
Ensemble Boosted Trees	**100%**	**93.75%**	**96.875%**
Ensemble Bagged Tree	**100%**	**93.75%**	**96.875%**
Ensemble Subspace Discriminant	**100%**	**100%**	**100%**
Ensemble Subspace KNN	**0%**	**100%**	**50%**
Ensemble RUSBoosted Trees	**100%**	**93.75%**	**96.875%**

From above-mentioned accuracy in Table 19 it is clear that the KNB, Fine KNN, Medium KNN, Coarse KNN, Weighted KNN and Ensemble Subspace KNN testing classifiers as compared to other classifiers, these achieved low performance classification of EOG signals in the horizontal and the vertical eye movements.

On the other hand, the comparison of the classifier results between these five classifiers shows that the Decision Tree, Ensemble Boosted Trees, Ensemble Bagged Tree and Ensemble RUSBoosted Trees testing classifier achieved performance with a 96.875% percentage accuracy.

However, the comparison of the classifier results between these five classifiers shows that the SVM, the Cosine KNN and the Ensemble Subspace Discriminant testing classifier achieved the highest and the best performance with 100% percentage accuracy.

5. Link of the program

https://techedubsuedu-my.sharepoint.com/:f:/g/personal/dr_abdelgawad_techedu_bsu_edu_eg/Eqg6wHSutkVBuE11pCqCYCMB9j30dIV-KHQQeOeL3kFvOg?e=IehdUH

6. CONCLUSIONS

This paper presented an efficient algorithm for EOG signals classification to help the handicapped. This algorithm depended classifying EOG signals into horizontal and vertical signals for possible utilization these signals for further specific actions. Statistical features and a broad category of classifiers have tested for this purpose. The obtained results reveal that the best classifiers on horizontal and vertical signals are the SVM, the Cosine KNN and the Ensemble Subspace Discriminant with having 100% percentage accuracies. Hence it is possible to implement the proposed algorithm in communication support system, such as eye controlled arm robot and eye controlled wheelchair softwares to help the handicapped to take decisions for better life quality, by providing possible human interaction with a computer.

7. Conflict of Interest

All authors have seen and approved the final version of the submitted manuscript. This article is the original work of the authors, has not been previously published.

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Figures

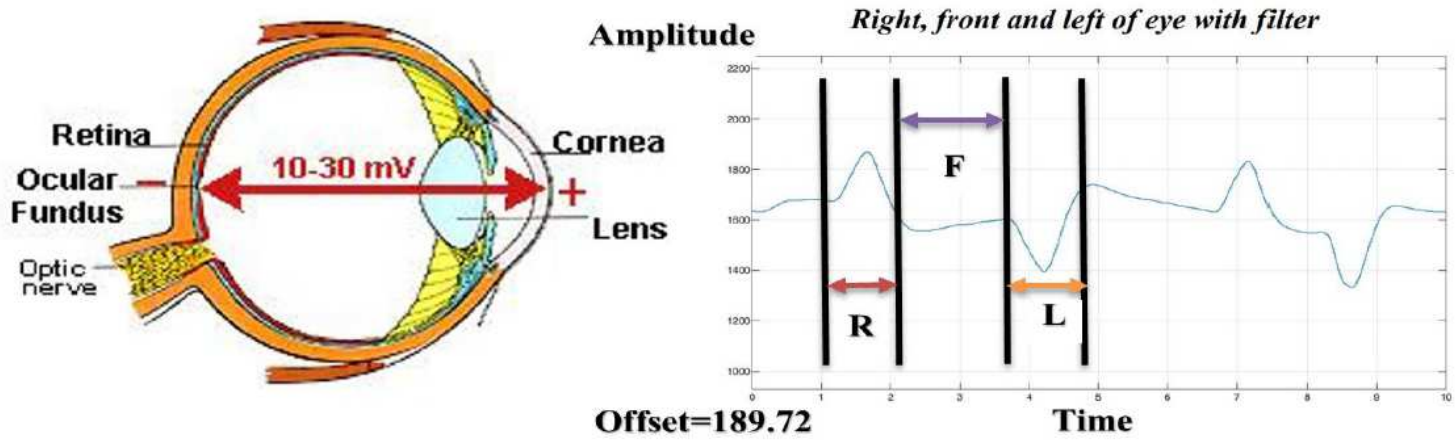

Figure 1

Basic principles of EOG signals: (a) Eyeball Anatomy, (b) Pulse of EOG filtered with marked segments showing three main characteristics of eye movement: Pulse of Right (R), Pulse of Front (F) and Pulse of Left (L).

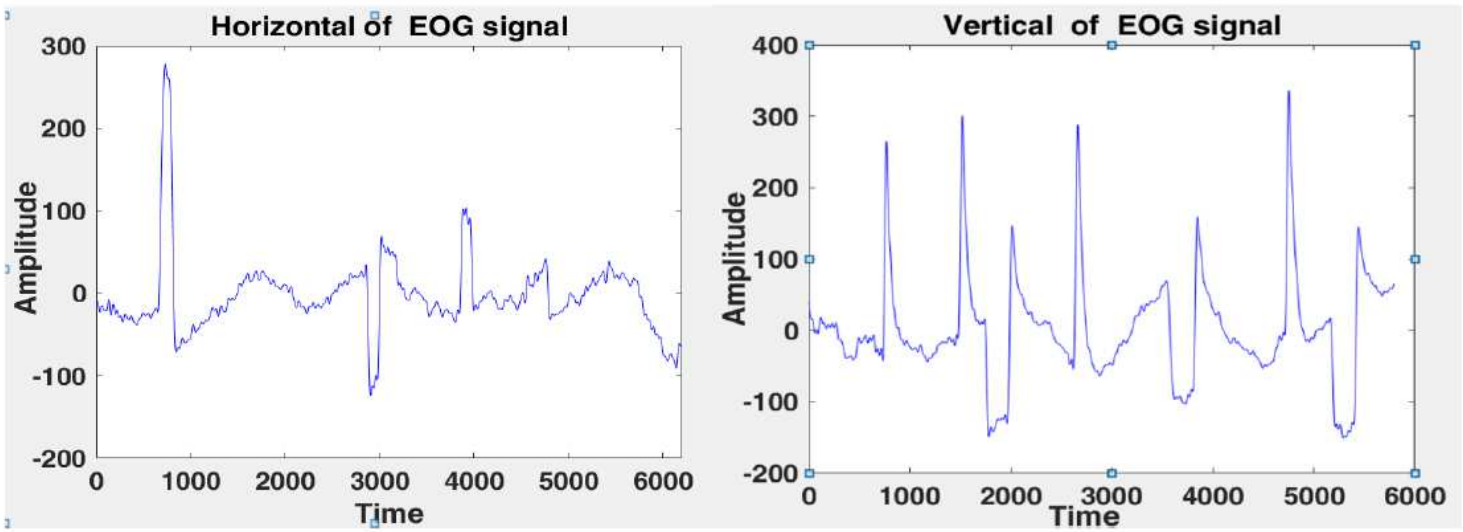

Figure 2

Samples of EOG vertical and horizontal signals are used in the experiments.

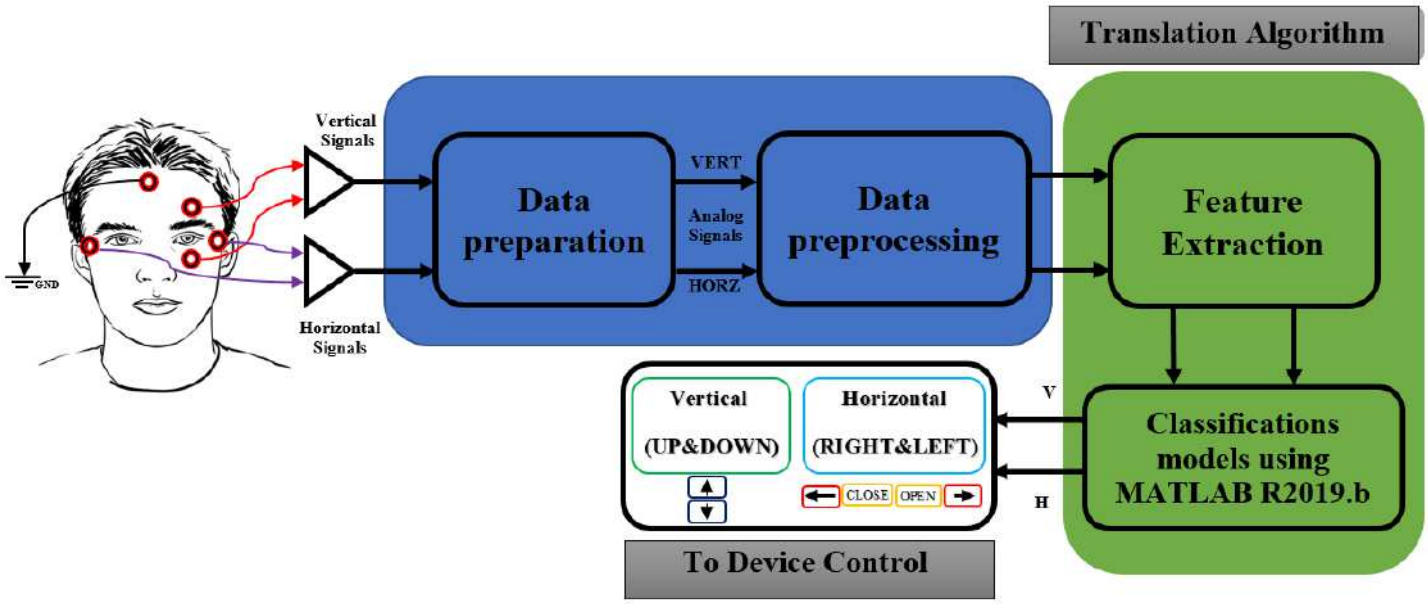

Figure 3

Proposed system architecture.

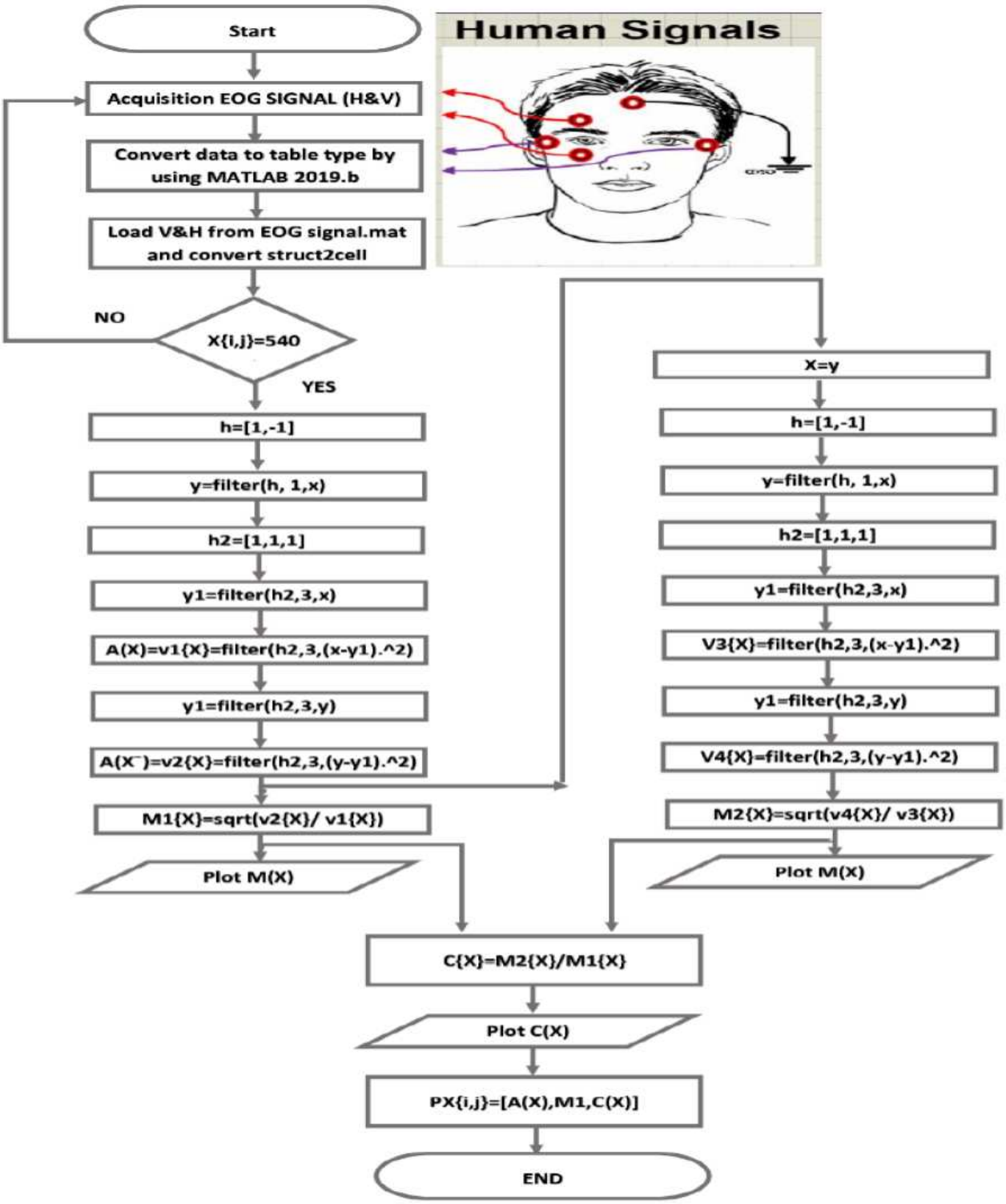

Figure 4

Flowchart of the feature extraction algorithms in the proposed system.

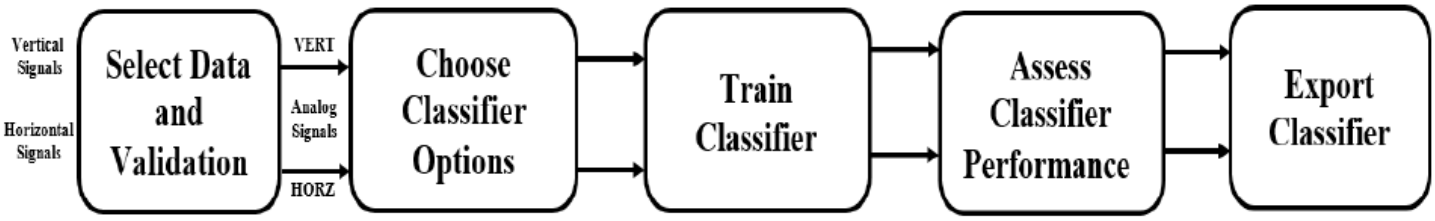

Figure 5

Block diagram for training classifier models.

Figure 6

Flowchart of training and testing in the proposed system.

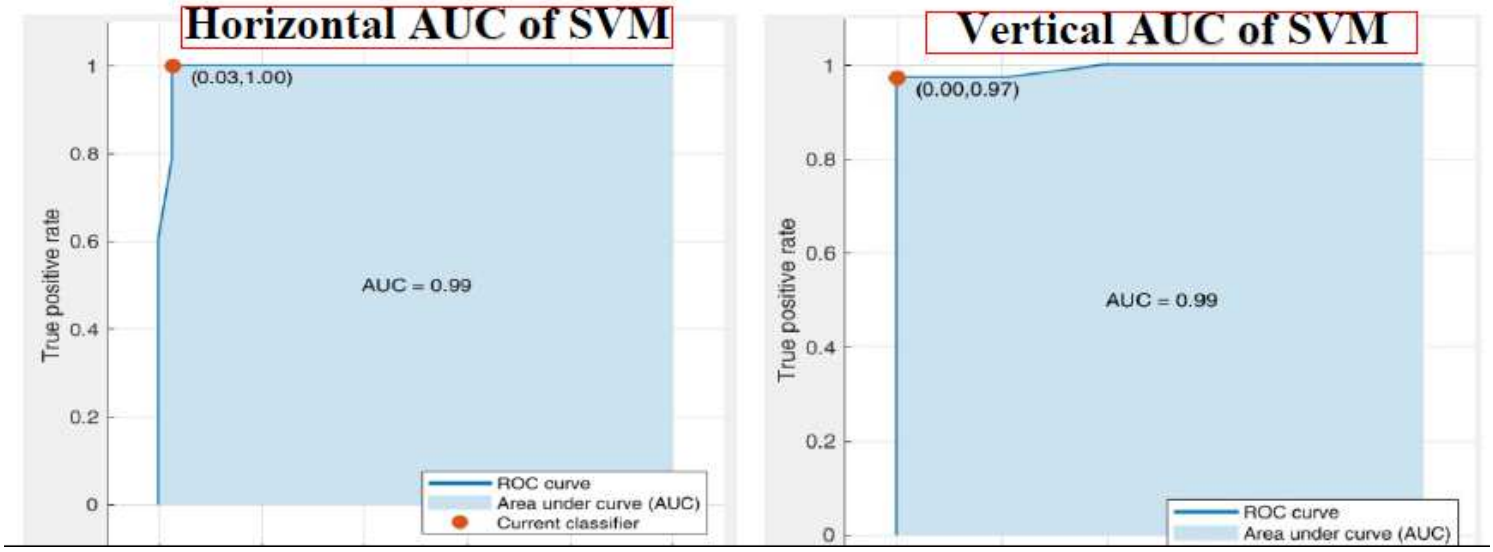

Figure 7

Example of AUC for horizontal and vertical SVM with AUC=0.99.