ISSN: 2251-9246
EISSN: 2345-6221
pp. 279:288

Optimizing Feature Selection for Eye Movement Classification Using EOG Signals

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Abstract

This study presents a novel classification system using Electrooculography (EOG) signals for Human-Computer Interaction (HCI), focusing on eye movement detection. Three feature-selection techniques, Decision Tree, Principal Component Analysis (PCA), and Particle Swarm Optimization (PSO), were applied to statistical time-domain features (mean, variance, power, integral, skewness, kurtosis, Shannon entropy, minimum, maximum, median) extracted from horizontal and vertical EOG signals recorded from 30 participants. Selected features were evaluated with k-Nearest Neighbors (KNN) and a Multi-Layer Perceptron (MLP). The PSO-selected features paired with MLP yielded the best performance (TPR = 75.44%, accuracy = 74.2%, precision = 77.6%, F1-score = 76.5%). Results support EOG as a non-invasive, cost-effective modality for assistive control interfaces and highlight PSO-guided selection as an effective route to robust eye-movement classification.

Keywords: Electrooculography (EOG); human-computer interaction (HCI); eye-movement classification; feature selection; particle swarm optimization (PSO); multi-layer perceptron (MLP).
Article history: Received 2025/10/14; Revised 2024/10/19; Accepted 2025/11/20, Article Type: Research paper

https://doi.org/10.82234/IJSEE.2025.1221170

1. Introduction

HCI is a diverse research area that focuses on crafting computer technology, particularly emphasizing how people (users) interact with computers. Utilizing tracking technology, devices like Virtual Reality (VR), Augmented Reality (AR), and Mixed Reality (MR) offer users a nearly natural and satisfying experience [1].

While HCI encompasses a broad range of disciplines such as computer science, cognitive science, and ergonomics, the application of EOG signals in HCI remains an underexplored area with great potential for assistive technologies [2].

The applications of HCI are increasingly significant in various fields such as space, aerospace, medical, deep-sea exploration, banking, hospitality, and home services [3]. further enhances user interactions with HCI, allowing more intuitive control and communication through natural user interfaces, such as voice and gesture recognition, improving accessibility for diverse users, including those with disabilities. The integration of HCI with IoT boosts system responsiveness and automation, making environments like smart homes, healthcare, and industrial automation more adaptable to user needs, ensuring technology serves human purposes more effectively [4].

Eye tracking in HCI utilizes technologies like Histogram of Oriented Gradients (HOG), Support Vector Machines (SVM), and Long Short-Term Memory (LSTM) neural networks to recognize eye movements for computer commands. This non-invasive, cost-effective method improves accessibility by enabling hands-free actions like scrolling and clicking [5]. Similarly, Virtual Reality (VR) offers engaging educational environments that enhance learning and cognitive training, improving both understanding and retention [6].

HCI provides significant benefits, including improved accessibility and cost-effectiveness. It enables intuitive, seamless interactions, making digital platforms more user-friendly, especially for people with disabilities, promoting inclusivity and wider access to technology. Additionally, HCI supports the development of cost-effective virtual learning environments, reducing the need for physical resources. Virtual labs and simulations lower traditional training costs, offering scalable and economical education solutions to a global audience [7].

In recent years, the development of human interfacing techniques has attracted significant attention from researchers. These techniques have found widespread applications, successfully transitioning into commercial products in diverse fields such as medical care, aeronautics, and bioinformatics. Among these, using EOG for HCI is particularly promising for more research and real-world use Click or tap here to enter text..Click or tap here to enter text..Click or tap here to enter text..Click or tap here to enter text..Top of Form

[8].

In recent years, EOG technology has gained significant attention due to its non-invasive nature and potential for controlling assistive devices. It allows communication and device control using signals generated from eye movements, an especially valuable tool for individuals with severe motor disabilities. The ability to monitor horizontal and vertical eye movements through electrodes is critical in developing effective assistive technologies [9][10]. The human eye's movement is intricately controlled by motor neurons that handle both the position and the velocity of the eye through direct and indirect neural pathways. EOG is crucial in understanding and categorizing various types of eye movements, such as saccades, smooth pursuit, and the vestibular ocular reflex, each with distinct functions and characteristics. These movements are essential for tasks like reading and observing moving objects, demonstrating the capability of EOG to monitor and analyse eye behaviour comprehensively [10]. In this study, we captured horizontal and vertical eye movements.

Recent advancements have leveraged EOG in Human-Machine Interfaces (HMI), offering a less invasive alternative to EEG. Furthermore, the integration of artificial intelligence algorithms enhances the classification of EOG signals, enabling the refined control of devices such as wheelchairs, orthotics, and assistance robots [11]. Unlike electroencephalography (EEG), electromyography (EMG), and Electrocardiography (ECG), which measure vital bodily functions crucial for diagnosing diseases, EOG primarily facilitates extensive human-machine interactions [12].

Despite the advancements in HCI, the specific application of EOG signals for eye movement detection in controlling devices remains relatively underexplored. While previous studies have demonstrated the feasibility of using eye-tracking methods in HCI, such as those utilizing laptop cameras and neural networks, the full potential of EOG-based systems, especially in terms of accuracy, usability, and cost-effectiveness, has not been fully realized.

The challenge lies in identifying and optimizing the features that can enhance the classification of eye movements based on EOG signals. EOG offers a non-invasive and affordable method of detecting eye movements, making it an ideal candidate for assistive technologies. However, the current methods for feature selection and classification in EOG-based systems often fail to achieve the desired accuracy for practical, real-world applications. Many classification models and feature extraction methods, such as traditional machine learning techniques, struggle to reliably distinguish between complex eye movements due to noise, artifacts, and variations across individuals.

This study aims to address this gap by exploring and optimizing feature selection techniques using Decision Tree, PCA, and PSO. By improving the accuracy of EOG signal classification, we seek to develop a more reliable system that can distinguish between different eye movements for controlling assistive devices, such as wheelchairs or communication aids. The main research question guiding this study is: How can different feature selection methods, particularly PSO, enhance the accuracy and robustness of EOG-based eye movement classification for assistive technology applications? Decision Tree and PCA were selected as benchmark feature selection methods due to their simplicity and interpretability, while PSO was chosen to explore the benefits of a metaheuristic approach for identifying optimal feature subsets and improving classification accuracy. The research focuses on identifying the most relevant features from EOG signals to enhance the performance of classifiers, including KNN and MLP, providing a scalable solution for individuals with motor disabilities. The roadmap of this study is shown in Figure 1. Electrode montage and processing pipeline for EOG-based eye-movement classification. Horizontal (left–right) and vertical (up–down) bipolar EOG are amplified and digitized, then passed to feature extraction and classification. Five classes are modeled: up, down, left, right, forward gaze.

Unlike previous studies that focused mainly on conventional classifiers or single-stage feature selection techniques, this study integrates metaheuristic optimization (PSO) for feature selection with machine learning classifiers, namely MLP and KNN, to improve the accuracy of EOG-based eye movement detection. It provides a comparative evaluation of three feature selection methods, including Decision Tree, PCA, and PSO, applied to both real and benchmark datasets. The proposed PSO-based feature selection combined with MLP demonstrates superior robustness to signal variability and noise, offering a reproducible and scalable approach for assistive technology applications. This combination has not been systematically analyzed in prior EOG-based HCI studies.

The process of collecting eye movement signals is notably straightforward, as these signals are non-invasively collected and feature simple characteristic patterns. These patterns are more distinguishable due to the higher amplitude range of the signal compared to the EEG and EMG [13]. The simplicity of the signal acquisition process is also reflected in the affordability of designing a data acquisition system. Eye movements prove to be a reliable control mechanism even for individuals suffering from severe paralysis due to various neurological diseases. This reliability is maintained even in the most challenging conditions, highlighting its effectiveness and enduring utility in adverse situations [14].

The EOG signal is widely utilized as a tool for HCI, primarily for controlling signals and playing a vital role in analyzing and categorizing eye movements [9]. EOG is particularly promising for individuals with severe motor disabilities. It provides a method to enable communication and device control without relying on speech or hand movements by utilizing signals generated from eye movements, often the only controllable function in severely disabled individuals. This system operates by capturing changes in the electrical signal strength around the eyes to generate device interaction commands [15].

EOG technology finds application in various areas, including eye writing [16], electric wheelchair operation [17], cursor mouse selection [18], eye movement recognition [19], and directing mobile robots [20]. To enhance the accuracy in detecting and classifying EOG signals, multiple techniques have been developed. These include the derivative technique, threshold evaluation, slope analysis, and peak detection methods. Table 1 provides a detailed overview of recent studies, highlighting the methods used for preprocessing, classification, and their respective results. Additionally, the extraction of features and the analysis of EOG artifacts represent significant challenges in this domain [9].

EOG holds significant importance in the field of biomedical research and clinical applications, largely due to its high performance and the simplicity of its methods. Despite numerous previous studies, many aspects of EOG remain poorly understood, which underscores the ongoing need for further investigation into its capabilities and potential uses. The paper is organized into four main sections. Section 1 introduces the HCI, EOG, and eye movement, outlining the significance and objectives of the research. Section 2 details the materials and methods used, including the study design and data collection procedures. Section 3 presents the results and features analysis. Finally, Section 4 concludes the paper by summarizing the key findings, discussing their implications, and suggesting directions for future research.

2. Materials and Methods

The proposed method consists of three primary stages: preprocessing, feature extraction, and classification (Figure 2). The subsequent subsections offer a detailed explanation of each stage. Schematic diagram of the EOG-based HMI system for eye movement classification. Electrodes are positioned around the eyes to record horizontal (Left–Right) and vertical (Up–Down) EOG signals, with a reference electrode placed on the forehead.

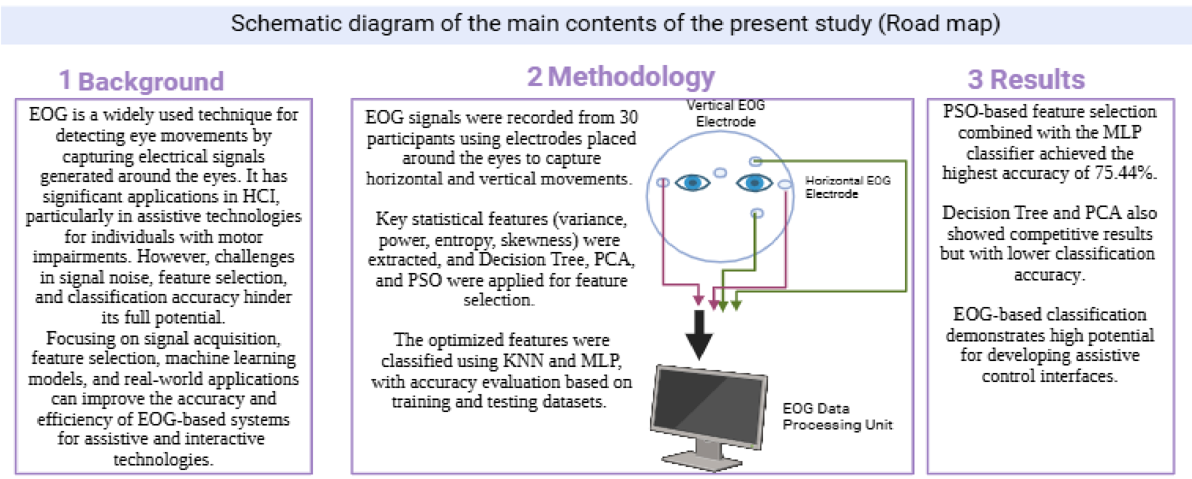


Fig. 1. Graphical abstract

Table.1.
Summary of EOG signal classification studies, detailing methods and results within specific experimental setups.

Part	*Pre-processing*	*Method*	*Classification Methods*	*Eye movement*	*Recorded Bio signal*	*Results*	*Ref*
20	Butterworth filters 8–13 Hz	Delta Band Signals for Gaze Detection EOG artifacts	Minimum Distance Classifier	Left/ Right Middle	EEG EOG	97.88%	[21]
3	BPF(Bandpass filter) 1-500Hz	PAV(maximum peak amplitude value), VAV(maximum valley amplitude value) , VAP(Valley amplitude positions) AUC(area under upper and lower curves), VAR(variance of EOG signal)	Evaluation of features with robust classifiers or threshold techniques in future studies.	Up/ Down Right/ Left up-left, up/ right Down-left	2-channel EOG	p-value of <0.0001	[22]
14	BPF 0.05 Hz to 30 Hz	PAV	Fuzzy logic Deterministic finite automata	Forward, Backward Left, Hard Left Right, High Right Stop	2-channel EOG	95.63%	[23]
1	LPF(Lowpass filter)with a cut-off frequency of 30 Hz	Minimum Maximum Mean Variance Sharpness Singular Values	MLP(Multi-Layer Perceptron), ART, including the FUZZY ART(Adaptive Resonance Theory), ART1 ART2A, ART2 networks	12 movements	2-channel EOG	MLP 90% ART2AE over 70%.	[24]
28	Band-reject FIR filter with 50 Hz cut-off frequency	Minimum Maximum	KNN(k-nearest neighbors)	Right Left Double blinking	2-channel EOG	98% when k is set to 3	[25]
20	Notch filter with a range of 50 Hz	Convolution theorem	ERNN(Elman Recurrent Network model) DTDNN(Distributed Time Delay Neural Network)	Right/Left, Up Right Down Right, Up Left Down Left, Open/Close, Stare	2-channel EOG	ERNN 90.82% DTDNN 90.56%	[15].
N/I	Digital notch filter	Amplitude Signal derivatives Signal area	MLP decision tree NB, K-NN Logistic Classifier SVM	Left, Down Right, Up Stop	2-channel EOG	Random Forest: 98.4% Random Tree: 98.4% J48: 97.5% KNN-1: 97.7% Logistic Regression: 74.4% MLP: 79.5% SVM: 76.1% Naïve Bayes: 78.2%	[8].
N/I	Notch filter with a range of 50 Hz	EOG Pv(Peak Amplitude) EOG Gv(Signal Gradient Amplitude)	Multiple regression. Non-linear logistic regression	Horizontal Vertical	channel EOG Head pose and position data	Eye movement detection and labelling F-score: Close to 90%	[26]
10	Frequency range of 0.1 to 15 Hz 4th Butterworth band pass filter	J48, Random Forest, Random Tree k-NN	-Jumping a bottom line -Back movements as reading	Read a 12-point Times New Roman font text written with Turkish language consisting of five lines	2 channel EOG	J48:92%, Random Forest: 98%, Random Tree 90%, k-NN 98%	[27]

6	BPF(Bandpass filter)between 0 and 30 Hz 50 Hz notch filter	Optimal Bayes' classifier	EOG peak amplitude EOG signal gradient	Saccades Blinks	2 channel EOG	Saccade labelling accuracy: 99.92% Blink labelling accuracy: 100.00%	[28]

The system distinguishes five eye movement classes: up, down, left, right, and forward gaze. Signals are amplified and transmitted to a processing unit for feature extraction and classification, enabling accurate detection of eye movement directions for non-invasive control applications.

A) Datasets

Two datasets were used in this study: the publicly available University of Malta dataset [26], and a newly recorded dataset collected specifically for this research. Both datasets included five classes of EOG signals corresponding to eye movements in four directions (up, down, left, right) and one forward gaze. Each class contained 400 signal pairs composed of horizontal and vertical components sampled at 176 Hz for a duration of 5 seconds (880 samples per trial).

Malta Dataset: The Malta dataset consisted of recordings from eight healthy participants (six males and two females, mean age = 25.8 ± 5.8 years). The study was conducted under non-stationary head conditions, allowing participants to move their heads naturally while maintaining gaze fixation on a target. EOG signals were collected using electrodes placed near the outer canthi and above and below one ocular socket, providing both horizontal and vertical bipolar channels. The dataset captured various eye movement types, including fixations, saccades, blinks, and vestibulo-ocular reflex (VOR) events, making it valuable for evaluating EOG-based HCI systems under dynamic head movement scenarios [26].

Recorded dataset: A second dataset was recorded at Azad University of Science and Research, Tehran Branch, using the Biopac MP150 system (Figure 3). The setup includes eight amplifier channels for simultaneous multi-signal acquisition, a data acquisition unit, and an oscilloscope for signal visualization and calibration. This configuration enables accurate measurement of horizontal and vertical eye movements by ensuring low noise and high signal fidelity. (Units: EOG signal amplitude measured in µV; sampling frequency = 256 Hz.) Thirty healthy participants (18 males, 12 females) with normal or corrected-to-normal vision and no neurological or visual impairments were included. Participants performed five distinct eye movements (up, down, left, right, forward gaze), each repeated 10 times, yielding 1,500 trials (30 participants × 5 movements × 10 repetitions). Electrodes were positioned above and below the right eye for vertical channels, at the outer canthi for horizontal channels, and at the forehead as reference. The sampling rate was 176 Hz. Each movement was sustained for approximately 5 seconds, with participants minimizing blinking and head motion.

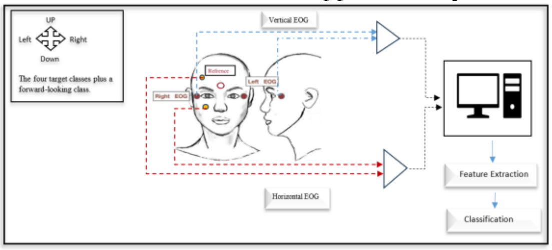


Fig. 2. Flowchart of the study

Fig. 3. The Biopack MP150 Device with its Modules and its connected amplifier modules is used for recording EOG signals.

B) Signal Processing

All recorded EOG signals underwent preprocessing to remove noise and artifacts, including blink artifacts and power-line interference, using a Butterworth band-pass filter with a passband of 0.5–20 Hz. After filtering, signals were downsampled to 50 samples per trial to improve computational efficiency and reduce redundancy. The resulting clean signals preserved the essential temporal and amplitude information required for reliable feature extraction.

C) Feature Extraction Methods

Ten time-domain statistical features were extracted from each horizontal and vertical EOG channel to represent key signal characteristics: mean, variance, power, integral, skewness, kurtosis, Shannon entropy, minimum, maximum, and median. These features effectively describe the signal’s amplitude, distribution, and energy, making them suitable for distinguishing different eye movement patterns. Feature extraction was implemented in MATLAB, and all features were normalized using z-score normalization to eliminate amplitude variability across participants and ensure consistency across datasets. These features are computed as described below.

Mean is defined as a feature in EOG signal analysis that calculates the average value of the signal over a given time interval. It provides insight into the overall behaviour of the signal during eye movements by averaging the amplitude of the signal. The formula for the mean is:

$$\bar{x}_i = \frac{1}{N}\sum_{n=1}^{N} x_i[n] \tag{1}$$

Where x_i [n]represents the n-th sample of the EOG signal, N is the total number of samples in the interval. This feature helps in capturing the central tendency of the EOG signal and is useful in classifying different eye movements.

Variance is a statistical measure that quantifies the degree to which individual data points in a dataset differ from the mean of the dataset. Specifically, variance is calculated as the average of the squared differences between each data point and the mean. It provides a way to understand the spread or dispersion of data points around the mean, with a higher variance indicating greater dispersion and a lower variance indicating that the data points are closer to the mean.

Power is a feature in EOG signal processing, calculated as the integral of the squared signal over a specified time interval. It quantifies the strength or intensity of the signal within that period. The formula for power is:

$$\sigma_{x_i}^2 = \frac{1}{N}\sum_{n=1}^{N} (x_i[n] - \bar{x}_i)^2 \tag{2}$$

Where x(t) is the EOG signal, t1 and t2 represent the start and end of the time interval. This calculation provides valuable insight into the overall energy of the signal during a specified period.

Integral is a feature extraction method that calculates the total area under the curve of an EOG signal over a specified time interval. It provides a cumulative measure of the signal's magnitude, which is useful for capturing overall trends in the signal. The formula for the integral is:

$$power = \frac{1}{t_2 - t_1}\int_{t_1}^{t_2} |x(t)|^2 \tag{3}$$

Where x(t) represents the signal at time t, t1 and t2 are the start and end times of the interval.

This feature is commonly used to quantify the energy or strength of the signal in EOG-based analysis.

$$Integral = \int_{t_1}^{t_2} x(t)dt \tag{4}$$

Skewness measures the asymmetry of a probability distribution around its mean. It is represented by the third standardized moment:

$$\gamma_3 = \frac{\mu_3}{\sigma^3} \tag{5}$$

where μ_3 is the third central moment and σ3 is the standard deviation raised to the third power. (γ_3>0) indicates a distribution with a longer or fatter tail on the right side, while negative skewness (γ_3<0) indicates a distribution with a longer or fatter tail on the left side. Skewness provides important information about the symmetry of the distribution, helping to understand how data points are spread relative to the mean.

Kurtosis is a statistical measure that quantifies the shape of a distribution, focusing on the extremities (tails) and peak. It is defined as the fourth standardized moment, represented by the formula:

$$\gamma_4 = \frac{\mu_4}{\sigma^4} \tag{6}$$

where μ_4 is the fourth central moment and σ4 is the standard deviation raised to the fourth power. Kurtosis describes whether data points are more or less concentrated in the tails and peak of a distribution compared to a normal distribution. Positive kurtosis indicates heavy tails and a sharp peak (leptokurtic), while negative kurtosis indicates lighter tails and a flatter peak (platykurtic).

Shannon Entropy is a measure used to quantify the amount of uncertainty or information contained in a set of possible outcomes. It is calculated using formula 7 where pi represents the probability of the İth event. This measure is foundational in information theory and provides a way to evaluate the unpredictability or complexity of a system's state. Higher Shannon Entropy indicates greater uncertainty and more information content. Entropy is typically used to evaluate the complexity, disorder, or information content of a signal. Entropy is calculated using the following formula:

$$H(P) = -\sum_{k=0}^{n} p\, i \log pi \tag{7}$$

Indicates the middle value of the signal (in the time domain). To find the median, the signal values are sorted over time, and the middle value represents the median.

D) *Feature Selection*

In the classification phase, the feature vectors obtained from the previous step were used for both training and testing. The EOG signals were first imported into the MATLAB environment, and the predefined features were extracted from two channels for each participant. After preprocessing, three feature selection techniques were applied sequentially to identify ten optimal features.

First, a Decision Tree algorithm was used to rank the most discriminative features capable of distinguishing between the five eye movement classes. Then, the Particle Swarm Optimization (PSO) algorithm refined this selection by iteratively optimizing feature subsets based on a performance cost function, ensuring that only the most relevant features were retained. Finally, Principal Component Analysis (PCA) was employed to reduce data dimensionality by transforming the selected features into orthogonal components that captured the majority of variance in the dataset. A short explanation of each method is given below.

Decision Tree: The Decision Tree method was used to find which features were most helpful in separating different eye movement classes. It works by splitting the data into smaller parts based on feature values, forming a tree-like structure. Each branch represents a decision, and each leaf represents a class result. This method helps identify the most important features that have the strongest effect on classification performance [35].

Particle Swarm Optimization (PSO): PSO is an optimization method inspired by the movement of bird flocks and fish schools. In this method, many possible solutions, called "particles," move around in the search space to find the best answer. Each particle updates its position based on its own best result and the best result found by the group [36]. In this study, PSO was applied to select the most effective set of features for classifying eye movement signals. The algorithm was executed with a swarm of 20 particles for 20 iterations. The PSO parameters are detailed in Table 3.

Principal Component Analysis (PCA): PCA is a statistical technique used to reduce the dimensionality of a dataset while retaining as much variance as possible. It does this by transforming the original variables into a new set of uncorrelated variables called principal components, which are ordered so that the first few components capture most of the variability in the data [37].

E) Classification

The KNN and MLP classifiers were trained on 80% of the dataset and tested on the remaining 20%. Classification was based on a five-class model corresponding to the four main eye movement directions (up, down, left, right) and one for forward gaze. Each class contained 400 samples. For the KNN classifier, values of K=3,5,7, and 9were evaluated. The MLP classifier consisted of 10 input neurons (representing selected features), 6 hidden neurons, and 5 output neurons corresponding to the five movement classes. Both classifiers were executed 100 times, and average True Positive Rate (TPR) and False Positive Rate (FPR) values were recorded to ensure statistical reliability. A brief discussion of each classifier is provided below.

k-nearest neighbors (KNN): KNN is a nonparametric method used for classification and regression that assigns a data point to the most common class among its k closest neighbors or predicts a value based on the average of its nearest neighbors. It relies on the proximity of data points to make predictions [38].

Multi-Layer Perceptron (MLP): MLP is a type of neural network that consists of multiple layers of nodes, including an input layer, one or more hidden layers, and an output layer, where each node is a neuron that uses a nonlinear activation function except for the input nodes. It is a powerful model used to approximate functions and classify patterns in complex datasets [39]. The model's performance was measured using common statistical indicators, including accuracy, precision, recall, F1-score, and the area under the ROC curve (AUC). These metrics helped to evaluate how well the model identified each eye movement class. Since the dataset included five balanced classes, macro-averaged values were used for the final evaluation.

3. Results

A) Feature Selection Results

Three feature selection techniques, Decision Tree, PCA, and PSO, were used to identify the most relevant EOG signal features for eye movement classification. The Decision Tree algorithm identified 10 key features that provided the highest classification accuracy. These features included Shannon entropy (channel 1), variance (channel 1), minimum (channel 2), power (channel 2), and kurtosis (channel 1). The selected features are shown in Table 3. PSO was then applied to optimize the selection of features by iteratively updating particle positions based on previous experience. The algorithm converged after approximately 15 iterations, reaching a best cost of 0.0112862, demonstrating stable and effective optimization (Figure 4).

Table.2.
PSO Parameters

Parameter	***Value***
Maximum number of iterations	20
Population size (number of particles)	20 particles
Phi 1	2.05
Phi 2	2.05
Inertia weight (W)	0.729 constriction factor (χ)
Inertia weight adjustment factor	1
Personal learning coefficient (c1)	$\chi \times \phi 1$
Global learning coefficient (c2)	$\chi \times \phi 2$

Table.3.
Selected Features by Decision Tree

Feature	***Channel***
Shannon Entropy	1
Minimum	2
Power	2
Maximum	1
Kurtosis	1
Skewness	1
Median	1
Entropy	2

The best cost value decreased rapidly during the first five iterations and gradually stabilized after approximately 15 iterations, converging to a minimum cost of 0.0112862. This demonstrates that the PSO algorithm efficiently optimized the feature subset selection by balancing exploration and exploitation, ensuring robust convergence and preventing overfitting. PCA reduced data dimensionality while retaining the most informative components. Ten top features were extracted, capturing the majority of the dataset variance. The PCA-transformed dataset was then split into 80% for training and 20% for testing, preserving data integrity and generalization capability.

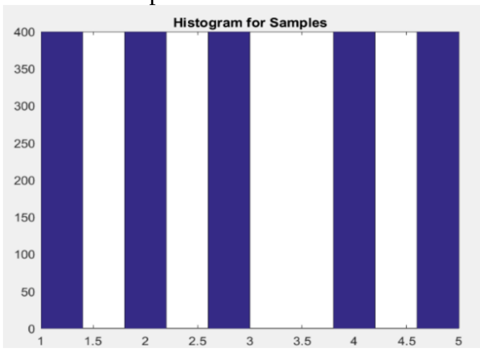
B) Classification Performance

The selected features were used to train and test KNN and MLP classifiers. The dataset included five movement classes —up, down, left, right, and forward —each containing 400 samples, ensuring balanced representation across the dataset (Figure 5a). The histogram in Figure 5a confirms this uniform distribution. Figure 5b illustrates the MLP training and validation performance, showing that the lowest mean squared error (0.094355) was achieved at epoch 25, where the training, validation, and test curves converge. This convergence indicates good model generalization and minimal overfitting.

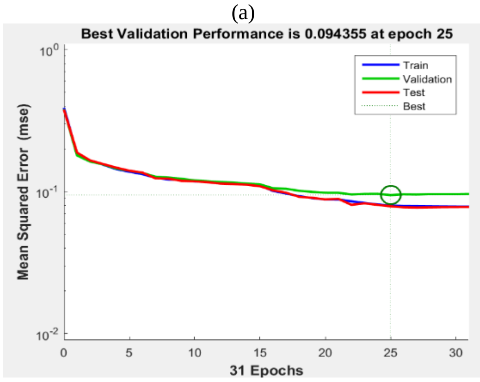
The overall classification performance, including TPR, FPR, accuracy, precision, and F1-score, is summarized in Table 4. Among the evaluated methods, the PSO–MLP combination achieved the best overall results (TPR = 75.44% ± 1.23; Accuracy = 74.2% ± 1.3; Precision = 77.6% ± 1.1; F1 = 76.5% ± 1.2). The Decision Tree–KNN model followed (Accuracy = 70.1% ± 2.5; F1 = 71.8% ± 2.6). PCA-based models were computationally efficient but showed lower separability (e.g., PCA-MLP Accuracy = 62.7% ± 3.9), indicating that dimensionality reduction removed some discriminative variance. These findings demonstrate that PSO–MLP provides the most reliable framework for EOG-based eye movement classification and will serve as the basis for further analysis in the Discussion section.

4. Discussion

This study aimed to classify eye movements using EOG signals through three feature selection techniques, PSO, Decision Tree, and PCA, combined with two classifiers, KNN and MLP. The PSO–MLP model achieved the highest accuracy, confirming that PSO efficiently identifies the most discriminative features when coupled with a nonlinear classifier capable of capturing complex signal relationships.



(a)



(b)

Fig. 4. (a) Histogram of sample distribution across the five eye movement classes (up, down, left, right, and forward gaze). Each class includes 400 samples, ensuring balanced training and test data. (b) Validation performance of the MLP classifier showing the mean squared error (MSE) curve across 31 epochs. The best validation performance of 0.094355 was achieved at epoch 25, where the training, validation, and test curves converged, indicating effective generalization and minimal overfitting.

Table.4.
Classification Results

Feature Selection Method	***Class***	***TRP***	***FPR***	***Accuracy***	***Precision***	***F1-score***
PSO	MLP	75.44% ± 1.23	24.56%± 0.0	74.2±1.3	77.6±1.1	76.5±1.2
PSO	KNN	65.90% ± 2.58	34.10% ± 0.0	67.8±2.2	69.3±2.0	67.6±2.4
PCA	MLP	63.90% ± 4.52	36.07% ± 1.13	62.7±3.9	65.1±3.7	64.5±4.2
PCA	KNN	68.90% ± 5.01	31.10% ± 1.50	67.1±4.4	69.0±4	68.8±4.7
Decision Tree	MLP	63.12% ± 2.03	36.88% ± 1.18	62.4±1.9	64.2±1.7	63.6±1.8
Decision Tree	KNN	71.15% ± 2.71	28.85% ± 6.57	70.1±2.5	72.5±2.3	71.8±2.6

Compared with Decision Tree and PCA, PSO's global optimization capability enables it to balance exploration and exploitation, minimizing the risk of local minima and ensuring optimal feature selection. PCA, while effective in reducing dimensionality, can discard subtle but meaningful variations, thereby reducing classification accuracy. The Decision Tree method provided interpretable results and highlighted features such as Shannon entropy and skewness as significant for distinguishing movement directions, but the KNN classifier's sensitivity to overlapping classes limited its accuracy.

Based on the results, the highest average correct classification rate (75.44%) was achieved using the feature subset selected by PSO and classified with MLP. Moreover, the Decision Tree method identified Shannon entropy and skewness as the most important discriminative features, and the first channel generally produced more informative features than the second. Overall, PSO demonstrated superior performance, followed by PCA.

Although the achieved accuracy (75.44%) was slightly lower than those reported in some previous studies (up to 95%), this discrepancy likely stems from factors beyond algorithmic limitations. These include limited dataset size, laboratory-based recordings that lacked environmental variability, and deliberately simple feature extraction aimed at real-time, low-cost HCI systems. Additionally, the PSO parameters may not have been globally optimized.

Despite these constraints, the results demonstrate the robustness of EOG signals in representing eye-movement patterns and confirm the suitability of PSO-based optimization for biosignal analysis. The findings emphasize the potential of EOG for non-invasive, cost-effective HMI applications, particularly in assistive technologies. Future research should prioritize enhancing feature extraction and signal processing for more reliable EOG-based classification. Incorporating frequency-domain and time–frequency features (e.g., wavelet coefficients) and advanced signal decomposition methods like empirical mode decomposition could improve the representation of complex EOG patterns. Additionally, exploring metaheuristic optimization algorithms such as genetic or cuckoo search could refine feature selection. Expanding datasets with greater diversity will also be essential to strengthen model generalization and real-world applicability.

5. Conclusion

The findings from this study highlight the significant potential of using EOG signals to classify eye movements in the development of HMI systems. These systems can offer a non-invasive method for enabling communication and control for individuals with severe motor disabilities, using only their eye movements. This study highlights the strong potential of EOG signals for classifying eye movements in developing HMI. Such systems provide a non-invasive means of communication and control for individuals with severe motor impairments, relying solely on eye movement detection.

Among the three feature selection methods evaluated, PSO, Decision Tree, and PCA, the PSO algorithm proved to be the most effective. When combined with the MLP classifier, PSO achieved the best results (TPR = 75.44%, Accuracy = 74.2%, F1 = 76.5%), demonstrating its ability to optimize feature subsets for improved classification accuracy and generalization. Decision Tree and PCA also performed reasonably well, particularly the Decision Tree–KNN combination, though PCA's dimensionality reduction led to slight accuracy losses.

These results confirm that EOG, despite being a low-cost and non-invasive technique, can achieve robust performance in identifying eye movement directions. With further refinement, including the use of advanced signal features, optimized algorithms, and larger datasets, EOG-based systems can evolve into efficient and reliable tools for real-time assistive technologies. Future studies should continue integrating machine learning and intelligent hybrid models to enhance accuracy, adaptability, and user-friendliness in practical applications.

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