

INVESTIGATION AND CLASSIFICATION OF EOG SIGNAL DEVIATION OF NORMAL AND SYMPTOMATIC EYES WHILE USING DIGITAL SCREEN

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ABSTRACT. *This study delves into analyzing and classifying electrooculogram (EOG) deviations in the eyes that have ocular symptoms (lower visual acuity), in contrast to normal eyes while using a digital screen (DS). Continuous wavelet transformation (CWT) is done to decompose the signal, and the spectral power of the EOG signal is computed. The obtained p values and effect sizes (d) indicate the significant changes in the EOG signal at different time segments. For symptomatic eyes, the lower p values compared to the presumed significance level of 0.05 and medium to large level effect sizes are observed, indicating irregular and uncontrolled eye movement. Classification of the EOG deviation is done using several supervised machine learning algorithms, and a consistent classification accuracy of 91.67% is achieved by utilizing spectral powers with SVM (linear), and LDA. This study will be helpful for physicians in making critical decisions regarding the purpose of their diagnosis based on the EOG signal.*

Keywords: Digital screen, Ocular symptom, EOG, Screen time, Eye health

1. Introduction. Computer vision syndrome is the aggregate term for several eye-related conditions brought on by the extended use of digital screens [1]. Prolonged use of digital screens can lead to several eye issues, such as dry eyes, blurred vision, and eye strain. A study in the literature showed that prolonged use of screens resulted in ocular symptoms. The study showed that most people exposed to digital screens faced the ocular symptoms of dry eyes and blurred vision, and some had light sensitivity problems [2]. Another study investigated the prolonged use of DS and found computer vision syndrome is closely related to exposure to DS for a long time [3]. An article in the literature sought that prolonged exposure to DS is responsible for eye fatigue and hampers the quality of life [4]. A study in China found that 57% of college students who used DS experienced eye fatigue [5]. Another US study using DS estimated that around 65% of university employees experience eye fatigue and are deprived of quality of life [6]. According to studies, teenagers (ages 13 to 18) now use screens for non-educational purposes for an average of 7 hours and 22 minutes per day. This takes up almost 43% of their waking hours, and most of their screen time is spent on social networking, gaming, and watching videos.

In order to ensure quality lifestyle, the application of technology is booming in the medical sector. Smart health care monitoring framework is becoming popular to the researchers [7,8]. EOG is beneficial to investigate the disorders of the retina's outermost layer and the retinal pigment epithelium. Eye movements that are either active or passive are identified and categorized using EOG signals. Pathologies of the oculomotor system, such as neurodegenerative diseases and sleep disorders, can be diagnosed from the EOG recording [9,10]. In the literature, research related to EOG signal classification that dealt with ocular symptoms interwinds with the prolonged use of DS is least found. In [11], researchers considered the EOG signals of five volunteers, used ANN and SVM algorithms for eye movement detection purposes, and achieved 69.8% classification accuracy. Another study in the literature analyzed the importance of feature selection procedures and applied the SVM algorithm to detecting eye movements, achieving 83.3% classification accuracy [12]. Researchers in [13] used several supervised machine learning algorithms (KNN, SVM, and DT) for classifying five different types of eye movements (left, right, up, down, and blink). They achieved a classification accuracy of 69.4%, 76.9%, and 60.5%, respectively, for KNN, SVM, and DT. EOG signal was utilized for sleep stage classification using random under-sampling boosting (RUSBoost), RF, and SVM models and achieved 90%, 91%, and 91.7% accuracies, respectively [14]. The use of the EOG signal for sleep stage scoring and classification is found in another study in the literature, with a classification accuracy of 73% [15]. The researchers utilize the empirical mode decomposition technique [16] for EOG signal decomposition for sleep stage scoring. A random forest classifier was further used for classification, and accuracy was achieved at 82%. Another similar study of sleep stage scoring utilized EOG signals by extracting time, frequency, and time-frequency features. It also used a Random Forest classifier and got 87.9% accuracy [17]. As per the observation of the authors of this study, the least of the previous works in the literature investigated the EOG signal deviation during the use of DS.

This study aims to analyze and classify the fluctuation of EOG signals of normal people and those suffering from lower visual acuity which is sometimes referred as blurred vision. This research is limited to investigate the EOG deviation while using DS of normal eyes and those having lower visual acuity (according to Snellen chart score) and compared the effects by utilizing the spectral powers at different time segments. The spectral power of EOG signal is computed to observe the deviation of EOG at different time segments of both normal and symptomatic eyes. Finally, three supervised machine learning algorithms namely support vector machine (SVM) with linear and RBF kernel, linear discriminate analysis (LDA), and Naïve Bayes, are applied to classifying the deviation of EOG of normal people compared to those having lower vision.

2. Method.

2.1. Whole procedure. This work has been conducted by following the steps depicted in Figure 1. First, the effects of prolonged use of DS were studied from the literature, and university-going students were selected as the targeted subjects for this study. The EOG data of the selected subjects were collected at different time stages while the subjects were guided to use DS. The subjects were broadly categorized into two groups, namely normal and symptomatic (lower visual acuity) according to the Snellen chart score. Next, filtering removes unexpected frequency bands from the recorded signal after collecting the data. Then, the CWT has been done to extract features from the recorded EOG signal. The average spectral power of the EOG signal after performing CWT is computed to do statistical analysis. The Shapiro-Wilk test is done to check whether the data (spectral powers at different time segments) are normally distributed or not for dictating which

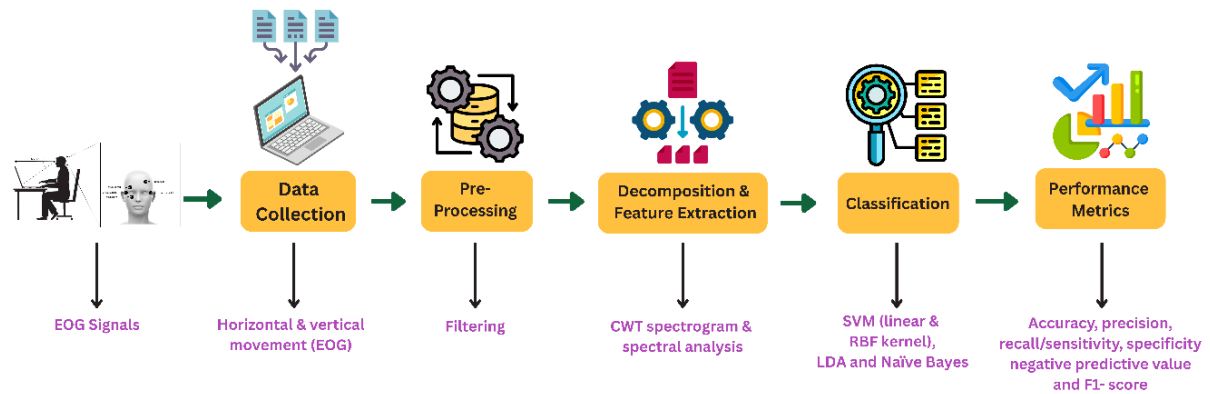


FIGURE 1. Brief pictorial description of methodological steps

statistical test (parametric or non-parametric) is suitable for the investigation of spectral power deviation of EOG signal. The Wilcoxon signed-rank test including Bonferroni correction to avoid type-I error risk and Cohen's d are performed using the spectral power of the EOG signal to investigate how significantly the EOG signal varied at different time stages for both normal and symptomatic eyes. Finally, three machine learning algorithms, namely support vector machine (SVM) with linear and RBF kernel, linear discriminate analysis (LDA), and Naïve Bayes, are used to classify the effect of prolonged use of DS on normal subjects compared to the subjects with ocular symptoms by utilizing spectral powers of EOG signal at different time segments.

2.2. Subjects and data acquisition.

2.2.1. Participants. University-going students are targeted as the participants for the convenience of the study and practical analysis. For data acquisition, a sample size of 100 voluntary university-going students (58 male and 42 female) aged 18 to 22 years was primarily selected. Before starting the data acquisition step, the written consent from the participants regarding their voluntary participation and no objection to data utilization for research purposes were taken. Moreover, the departmental authority of the Department of Biomedical Engineering of Jashore University of Science and Technology, Bangladesh, gave the ethical approval of data collection and future use of the recorded data only for research purposes. An expert physician thoroughly checked the participants' eye status to ensure which participants had normal eye conditions and who had ocular symptoms. By utilizing Snellen chart score the visual acuity of the participants was measured and sorted the participants into two categories as normal and symptomatic.

2.2.2. Experimental protocol. Before collecting the EOG signal, each subject was prepared to record the signal, i.e., the recording electrodes were placed around the eyes, asked to sit on a chair to rest in an ambient room condition, and instructed on the data collection procedure. The experimental layout and electrode placement for signal acquisition are depicted in Figure 2. After finishing the subject pre-processing steps, the subjects were left to relax for three minutes. Four data segments (Base case, D.C.S-01 to D.C.S-03) were collected. In each segment, a 60-second EOG signal was recorded. The participants were not exposed to any DS during the 60-second recording period that followed three minutes of relaxation. After finishing the first recording stage (Base case), the participants were allowed to use a 14-inch computer display from 45 cm away. During the experimental time, the participants were given to read journal articles with full concentration. The following three data collection segments were arranged in 20-minute intervals. The second data was

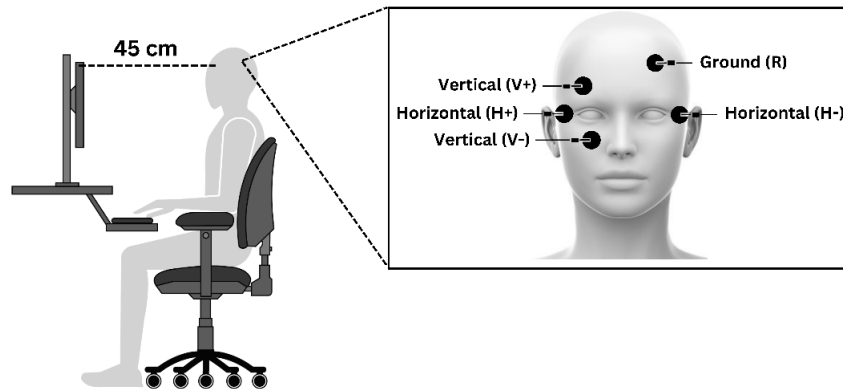


FIGURE 2. Experimental layout and electrode placement

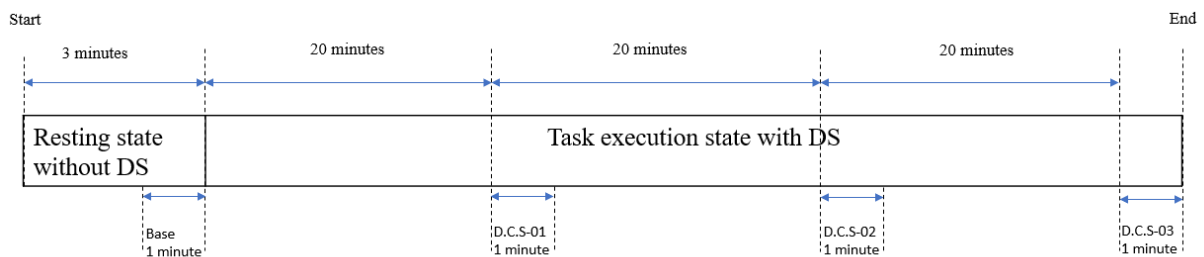


FIGURE 3. A pictorial description of the experimental protocol

collected just 20 minutes after using DS and, respectively, the other stages. In this whole process, each participant was exposed to the DS for 61 minutes without intervention. Figure 3 depicts a brief pictorial description of the experimental protocol. The EOG signal was recorded using the BIOPAC MP45 (United States) data acquisition system and BSL 4 software. The Ag/AgCl electrodes were used to acquire the signal at the indicated points in Figure 2. Horizontal and vertical eye movements were recorded with the designated channels during signal acquisition.

2.2.3. Data screening. Once after completing the experiment, the EOG data was primarily screened by an eye specialist, and the final selected participants were taken in an interview session to check the participant's eye status by using Snellen chart. After the interview session, the participants were broadly categorized into normal and symptomatic eyes (lower visual acuity). This study's primary sample size was 100, but data from 28 participants were excluded after completing the data collection stage. The reason for such exclusion was that the participants did not follow the instructions correctly, and some could not hold their attention at DS during the 61 minutes of the data collection period. After the exclusion, the final sample size was 72, aged 18 to 22. In the final sample size, 40 participants (22 male and 18 female) had ocular symptoms, and the rest, 32 (19 male and 13 female), were normal. Figure 4 shows the Snellen scores of different participants (left and right eye).

2.3. Pre-processing. The recorded EOG signal of selected signals comprised noises and artifacts. To use this raw signal for further steps, the signal was filtered to remove unwanted bands of frequencies. A 0.1-30 Hz bandpass filter was employed to remove noises and artifacts. In addition to eliminating power line noise, 50 Hz notch filtering was done.

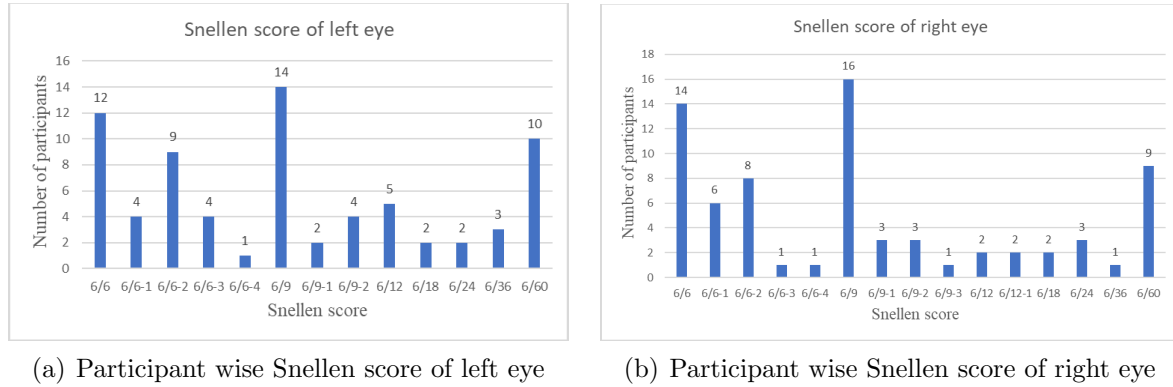


FIGURE 4. Participant wise Snellen chart score of left (a) and right (b) eye

The EOG signal was recorded in four stages, as mentioned in the previous section and depicted in Figure 3. Horizontal and vertical channel signals were recorded in each stage for 60 seconds. That is why the data structure becomes $72 \times 4 \times 2$, where 72 is the number of subjects, 4 is the data collection segments for each subject, and 2 is the number of channels.

2.4. Statistical analysis by power spectrum features. A widely used transformation method for the time-frequency analysis of a signal is CWT. CWT offers an in-depth investigation of the time-frequency domain using temporal and frequency resolutions. In the literature, many works found the effectiveness of CWT for signal processing [19,20]. The complex Morlet wavelet is used as a mother wavelet to compute the spectral power of the EOG signal, which is 60 seconds long, a scale of s (1,128) is used for attaining high frequency resolution, and a color range (0 to 4) is used to visualize the spectrogram images. In search for appropriate statistical test (parametric or non-parametric), the Shapiro-Wilk test is done to check whether the power spectral feature set at each time segment is normally distributed or not. The lower p (< 0.05) values at each time segment moved this study to select the Wilcoxon signed-rank (non-parametric) test to investigate the level of significant deviation of EOG spectral powers at three different time segments (D.C.S-01, D.C.S-02, and D.C.S-03) compared to base stage. The deviation of spectral power from base stage to other three-time segments for both horizontal and vertical channels for each type of group (normal and symptomatic) is investigated and this may lead to type-I error risk. In order to avoid such type of error risk, the Bonferroni correction is done to set new corrected significant level ($0.05/3 = 0.0167$). Cohen's d is also calculated in this study. Cohen's d measures the effect size, which indicates the difference between the means of the two groups in standard deviation [21]. The effect size value also helps to investigate the significance level of results. It evaluates the degree of a relationship between two variables or the effect's practical importance. A higher effect size means greater practical and clinical significance, suggesting a stronger correlation between the variables or a more tremendous difference between the groups. The value of Cohen's d is generally chosen as $d = 0.2$, $d = 0.5$, and $d = 0.8$ for small, medium, and large effects, respectively [22].

2.5. Classification by machine learning algorithms. The power spectral features are utilized to classify the effect of prolonged use of DS on normal and symptomatic eyes. Three popular supervised machine learning algorithms such as support vector machine (SVM) with linear and RBF kernel, linear discriminate analysis (LDA), and Naïve Bayes are used as classifiers. The performance metrics employed in this classification purpose

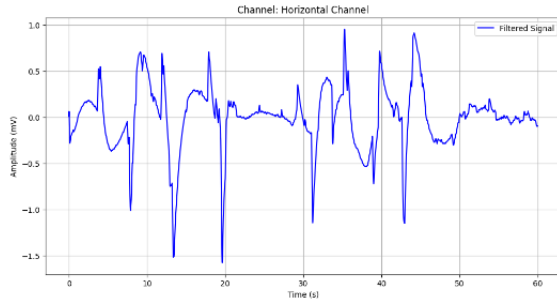
are accuracy, precision, recall/sensitivity, specificity, negative predictive value, and F1-score. In order to train the classifier, 80% of the total feature set are used and the rest 20% are used to test the performance of the classifiers. For achieving balanced feature set and avoiding the risk of biased results, in training and testing of the algorithms, random feature set of 32 symptomatic samples out of 40 is chosen.

- $Accuracy = \frac{TP + TN}{TP + FN + FP + TN}$
- $Precision = \frac{TP}{TP + FP}$
- $Recall/Sensitivity = \frac{TP}{TP + FN}$
- $Specificity = \frac{TN}{TN + FP}$
- $Negative\ predictive\ value = \frac{TN}{TN + FP}$
- $F1\text{-score} = \frac{2 * Precision * Recall}{Precision + Recall}$

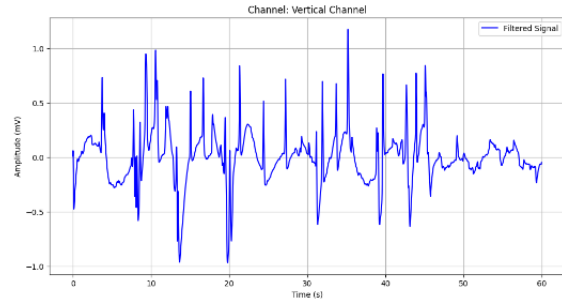
3. Results.

3.1. Feature of EOG signals. The deviation of the time series of the EOG signal leads to the variation in the corresponding spectrogram images. Different deviations are observed at different time stages for both normal and symptomatic eyes while using DS. Figure 5 depicts the EOG time series and corresponding spectrogram images of a randomly selected symptomatic and a normal eye at the D.C.S-02 stage while using DS. The horizontal and vertical axes of the time series represent time in seconds and amplitude in millivolts, respectively. On the other hand, the horizontal and vertical axes of spectrogram images represent the time in seconds and frequency in hertz and the power in the color bar in mV^2 . Based on the figure, it may be inferred that subjects with ocular symptoms are more likely to have irregular, uncontrolled, and frequent eye movement while using a digital screen. The other stages (D.C.S-01 and D.C.S-03) also had similar tendencies. The discomfort associated with prolonged exposure to DS could be the factor of such unusual deviation. On the other hand, normal eyes are less likely to move excessively. The normal eye can focus on a task and control movement based on visual demands.

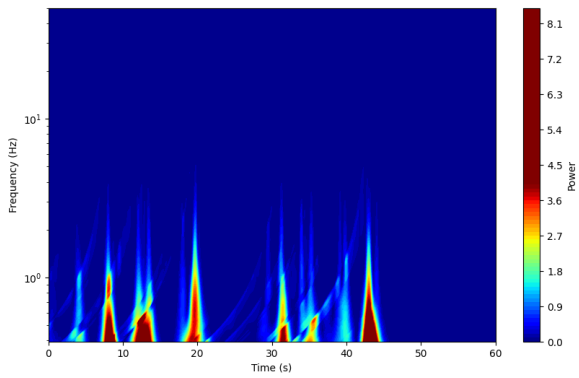
3.2. Statistical analysis. The spectral powers of both eye movements for symptomatic and normal eyes are depicted using box plots (Figures 6 and 7). Moreover, the results of the Shapiro-Wilk Normality test (p values), Wilcoxon Signed-Rank test (p values), and Cohen's d (effect size, d) are also included in Table 1, Table 2, and Table 3 for a better understanding of the data distribution, level of significance change, and effect size. The horizontal and vertical axes represent the data collection segment and spectral power. It is observed that spectral power deviates considerably from the Base case in the case of symptomatic eyes. In horizontal EOG, the 75th percentile values are 0.37, 0.34, and 0.35, respectively, in D.C.S-01, D.C.S-02, and D.C.D-03, significantly higher than the base EOG of 0.03. Higher spectral power values are noticeable for horizontal and vertical EOG. On the contrary, no significant deviation of spectral power is evident at the D.C.S-01 and D.C.S-02 stages compared to the Base stage for normal eyes, as depicted in Figure 7. For horizontal EOG, the 75th percentile values are found to be 0.05 and 0.04, respectively, in D.C.S-01 and D.C.S-02, which are very close to the Base case of 0.02. Similarly, for vertical EOG of normal eyes, the 75th percentiles, mean, and maximum spectral powers



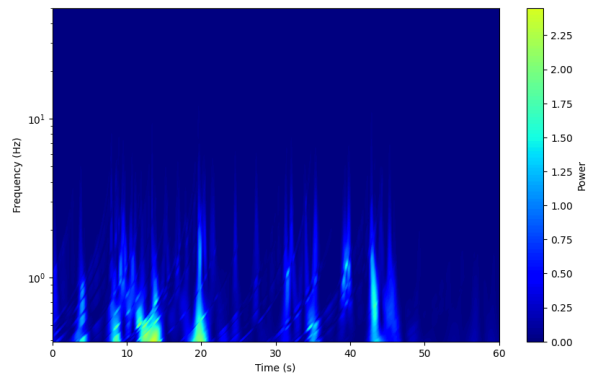
(a) Time series of horizontal EOG of symptomatic eye



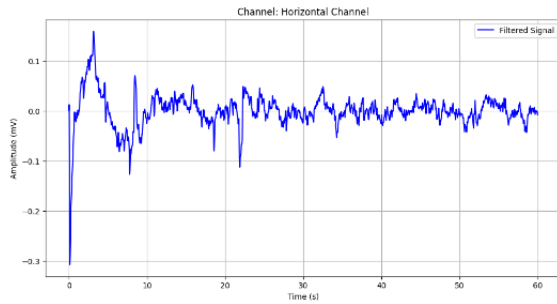
(b) Time series of vertical EOG of symptomatic eye



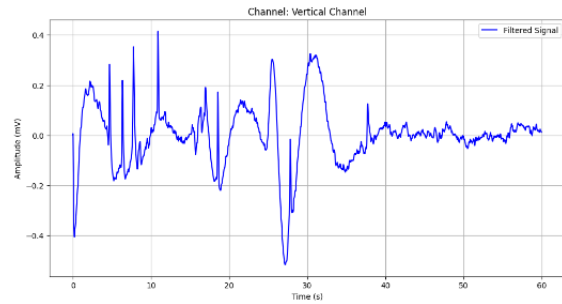
(c) Spectrogram of horizontal EOG of symptomatic eye



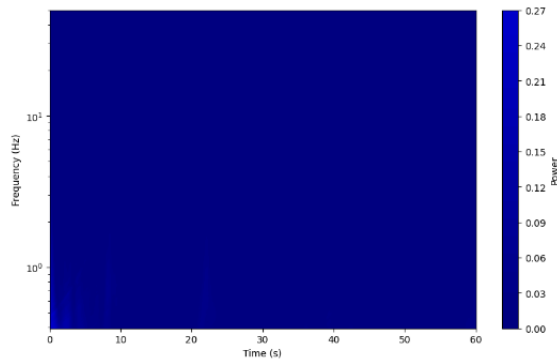
(d) Spectrogram of vertical EOG of symptomatic eye



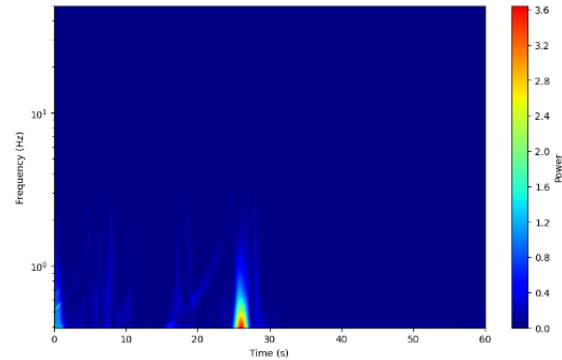
(e) Time series of horizontal EOG of normal eye



(f) Time series of vertical EOG of normal eye



(g) Spectrogram of horizontal EOG of normal eye



(h) Spectrogram of vertical EOG of normal eye

FIGURE 5. Time series of EOG and corresponding spectrogram images of the symptomatic eye (a)-(d) and normal eye (e)-(h) at D.C.S-02

in D.C.S-01 and D.C.S-02 are close to the Base case. However, normal eyes observe a noticeable spectral power change for horizontal and vertical movement at the D.C.S-03 stage. The 75th percentile values of 0.15 and 0.26 for horizontal and vertical EOG are considerably more significant than the base values of 0.02 and 0.10. Although normal eyes do not undergo substantial EOG spectral power deviation compared to symptomatic eyes, prolonged use of DS for a significant time will result in considerable EOG deviation from normal eyes. It is also observed that for both cases (horizontal and vertical EOG), the p -values are lower than the presumed significance level of 0.05 in the case of symptomatic eyes. The effect size (d) value indicates how much the EOG signal deviates from the Base stage. For horizontal eye movement of symptomatic eyes, a maximum of $d = 0.65$ is observed, which lies between medium to significant effect at the D.C.S-02 stage. On the other hand, the same effect size is observed at the D.C.S-03 stage for vertical eye movement. In overall observation, the symptomatic eyes experienced a medium level of DS effect during the experimental time.

In the case of normal eyes in Figure 7, it can be noticed that for both horizontal and vertical EOG, the p -value is considerably higher than the presumed significance level of 0.05, and it seems signal deviation is not significant at the D.C.S-01 and D.C.S-02 stages. On the contrary, a significant change occurred at the D.C.S-03 stage, as the $p < 0.05$ indicates considerable change. The d value for both the D.C.S-01 and D.C.S-02 stages for

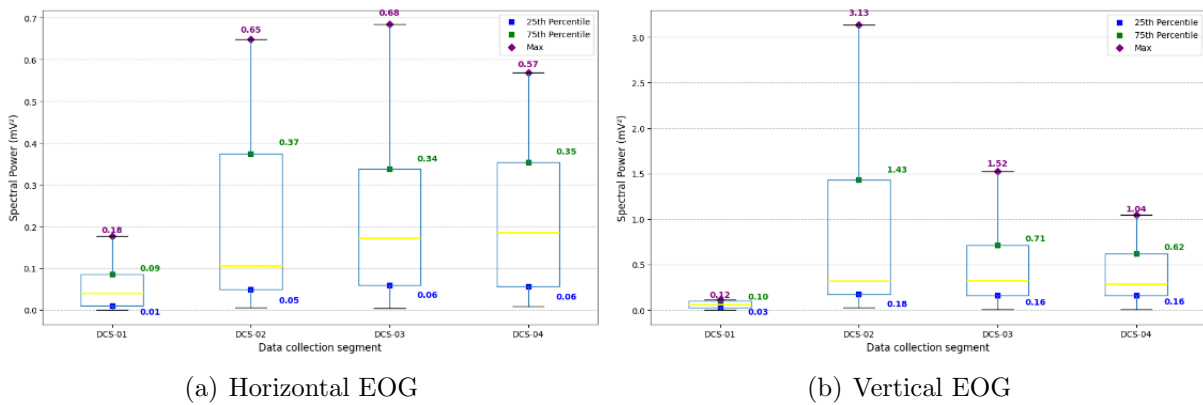


FIGURE 6. Spectral power deviation of (a) horizontal and (b) vertical EOG at different time segments of symptomatic eyes

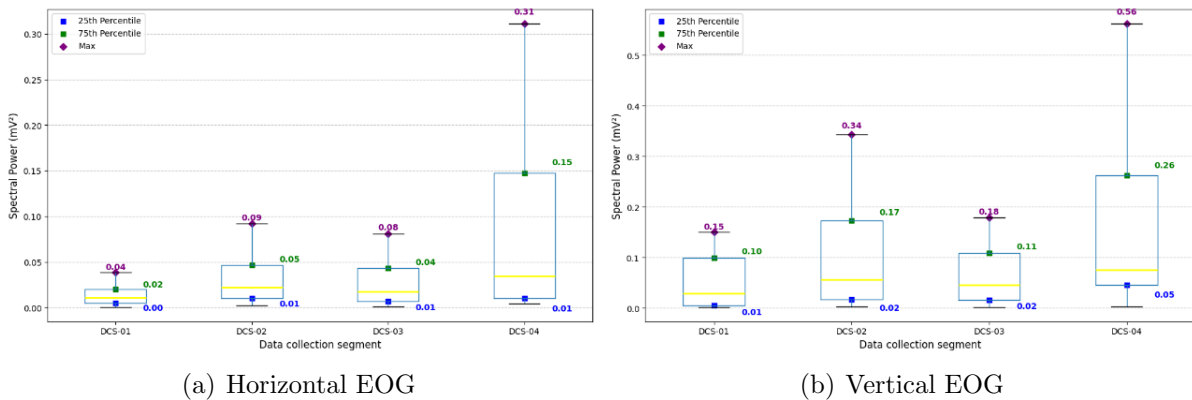


FIGURE 7. Spectral power deviation of (a) horizontal and (b) vertical EOG at different time segments of normal eyes

TABLE 1. The Shapiro-Wilk normality test result (p value)

Stage	Normal eye		Symptomatic eye	
	Horizontal movement	Vertical movement	Horizontal movement	Vertical movement
Base	1.7e-9	1.23e-8	3.681e-3	6.9e-9
DCS-01	8.958e-8	2.1461e-6	6.53e-8	8.254e-7
DCS-02	6.0e-10	1.10e-8	3.341e-6	3.19e-8
DCS-03	2.66e-8	1.823e-7	6.0e-10	2.659e-7

TABLE 2. The Wilcoxon Signed-Rank test result for normal eyes

Stage	Horizontal movement		Vertical movement		Bonferroni correction
	p	d	p	d	
DCS-01	8.37e-2	0.20	3.03e-1	0.29	0.0167
DCS-02	2.86e-1	0.18	1.49e-1	0.24	
DCS-03	3.15e-3	0.43	1.05e-2	0.39	

TABLE 3. The Wilcoxon Signed-Rank test result for symptomatic eyes

Stage	Horizontal movement		Vertical movement		Bonferroni correction
	p	d	p	d	
DCS-01	4.39e-5	0.55	1.11e-5	0.37	0.0167
DCS-02	1.26e-5	0.65	3.64e-4	0.46	
DCS-03	1.42e-5	0.43	6.03e-5	0.65	

horizontal and vertical movement also shows a lower effect of DS during the experimental time. However, the d value at D.C.S-03 for both movements indicate a medium DS effect during the experimental time.

3.3. Performance of the classifiers. Noticeable changes in EOG signal at different time segments are found while using DS for normal and symptomatic eyes compared to the base case, and this leads to the deviation of EOG spectral power of normal and symptomatic eyes. The performance metrics of three machine learning algorithms while classifying the impact of prolonged use of DS on normal and symptomatic eyes are listed in Table 4.

TABLE 4. The classification metrics of the classifiers

Performance metrics	SVM (linear)	SVM (RBF)	LDA	Naïve Bayes
Accuracy	91.67%	75.00%	91.67%	83.33%
Precision	85.71%	80.00%	100.00%	100.00%
Recall (Sensitivity)	100.00%	66.67%	83.33%	66.67%
Specificity	83.33%	83.33%	100.00%	100.00%
Negative predictive value	100.00%	71.43%	85.71%	75.00%
F1-score	92.31%	72.73%	90.91%	80.00%

4. Discussion.

4.1. Difference between normal and symptomatic eyes. The comprehensive analysis of this study depicts a nuanced understanding of EOG deviation because of using DS for both normal and symptomatic eyes. In the case of symptomatic eyes, considerable spectral power deviation for both horizontal and vertical EOG is observed in the D.C.S-01, D.C.S-02, and D.C.S-03 stages compared to the Base stage. It is noticed from the box plots that the spectral power has considerably increased during DS exposure periods, though the increasing patterns are inconsistent. It seems the participants with ocular symptoms did not experience normal eye movement; instead, their eye movements were irregular and more frequent. On the contrary, such an irregular rising pattern of spectral power is not observed for those having normal eye conditions. For the case of normal eyes, the power spectral rising scenarios in D.C.S-01 and D.C.S-02 are not so significant for horizontal eye movement as compared to vertical eye movement. However, in the D.C.S-03 stage, the spectral power rising scenario is significantly higher than in the D.C.S-01 and D.C.S-02 stages. It seems normal eyes did not experience abnormal horizontal eye movement, but there seemed to be a slight abnormality in vertical movement. On the other hand, at the D.C.S-03 stage for both movements, the normal eyes experience sufficient abnormality as the spectral power is considerably high compared to different stages.

The Wilcoxon Signed-Rank test and Cohen's d results enumerate the EOG deviation aspects at different time segments for both horizontal and vertical movement of both normal and symptomatic eyes. In the case of horizontal movement, the obtained p values at D.C.S-01, D.C.S-02, and D.C.S-03 time stages are $4.39e-5$, $1.26e-5$, and $1.42e-5$, respectively, for symptomatic eyes which is considerably lower than Bonferroni corrected value of 0.0167. This indicates that at these stages, the spectral power of EOG signals changes significantly from the Base stage. The effect size (d) corresponding to the p -value indicates how many changes happened at those stages. It is observed that d values at these three stages are 0.55, 0.65, and 0.43, which indicates a medium to large effect size. Although the effect size is inconsistent at the D.C.S-01, D.C.S-02, and D.C.S-03 stages, it indicates a significant impact of spectral power deviation from the Base stage. On the other hand, for vertical movement, the p values of $1.11e-5$, $3.64e-4$, and $6.03e-5$ are found respectively at the D.C.S-01, D.C.S-02, and D.C.S-03 stage, which is also the evidence of significant deviation of spectral power at these stages from the Base stage. The effect sizes (d) at this movement are 0.37, 0.46, and 0.65, which are also the proof of a consistent rise in effect level, and the effect level lies between medium to significant levels. On the contrary, the results obtained for the normal eyes are quite different for the D.C.S-01 and D.C.S-02 stages for both horizontal and vertical movement. The p -values obtained at these two stages are $8.37e-2$ and $2.86e-1$ for the horizontal case, and for the vertical case, the values are $3.03e-1$ and $1.49e-1$, which are much higher than the presumed significance level of 0.05 and Bonferroni corrected value of 0.0167. The d values of 0.20 and 0.18 for the horizontal case and 0.29 and 0.24 for the vertical case are the evidence of lower effect size in the D.C.S-01 and D.C.S-02 segments. However, the p values at the D.C.S-03 stage for horizontal and vertical movement are respectively $3.15e-3$ and $1.05e-2$, which is the evidence of a significant change of spectral power compared to the D.C.S-01 and D.C.S-02 stages from the Base stage. The d values at this D.C.S-03 stage for horizontal and vertical movement are 0.43 and 0.39, indicating the effect level nearest to the medium level. The effect of DS on normal eyes can be concluded as that at the D.C.S-01 and D.C.S-02 stages, no significant changes from the Base stage are observed. However, after a particular course of time, the effect of DS becomes substantial. Moreover, the spectral power

feature-based classification metrics of the algorithms indicate significant divergence of the EOG spectral power of normal and symptomatic eyes.

4.2. Comparison with other studies. Several studies were conducted on the assessment of the impact of DS. Ghannam et al. investigated the impact of digital device use on eye health during the COVID-19 pandemic [23]. They surveyed participants' digital device usage, awareness of digital eye strain, and experience of ocular symptoms. They found that participants experienced several eye issues such as blurry vision, burning eyes, light sensitivity, and dryness of eyes. Muntz et al. analyzed the extended screen uses and their impact [24]. They did an iPad-based survey on participants' screen use habits and ocular symptoms using dry eye questionnaires and found inconsistent blinking and dry eye issues. Malik et al. investigated the changes in ocular surface among university students and faculty members [25]. Researchers conducted an online questionnaire-based survey during the COVID-19 pandemic and found a positive relationship between ocular surface damage and prolonged digital screen exposure. Almuwwis et al. did a community-based survey to investigate the effect of prolonged screen use after setting ocular surface diseases index questionnaires related to dry eyes and their impact on vision [4]. The results depict that participant experienced dry eye syndrome, double vision, blurry vision, and headaches due to digital screen exposure during quarantine.

Although several past studies also investigated the impact of DS on human eyes, few articles discussed the impact of prolonged use of DS on EOG signal deviation. EOG signals are significantly related to eye movement, so analysis based on the EOG signals will give more subtle information about ocular movement than questionnaire-based survey analysis. We reported the impact of prolonged use of DS by using an EOG signal. The deviation of the EOG signal was considered for both normal and symptomatic eyes at different time segments while using DS to analyze the impact of digital screen use separately for normal and symptomatic eyes. CWT spectral power feature-based machine learning algorithms were deployed to classify the impact on normal and symptomatic eyes and achieved 91.67% classification accuracy for support vector machine (SVM) with linear kernel and linear discriminate analysis (LDA).

5. Conclusion. This present study is carried out to investigate the effect of prolonged use of DS and to classify the deviation of EOG signal of normal and symptomatic eyes (lower visual acuity). In the case of symptomatic eyes for horizontal eye movement, the p values after the Wilcoxon Signed-Rank test are observed as $4.39e-5$, $1.26e-5$, and $1.42e-5$, respectively, at D.C.S-01, D.C.S-02 and D.C.S-03 and the corresponding effect sizes (d) are 0.55, 0.65 and 0.43. On the other hand, for vertical eye movement, the p values are found to be $1.11e-5$, $3.64e-4$, and $6.03e-5$, respectively, at D.C.S-01, D.C.S-02, and D.C.S-03 and the corresponding effect sizes (d) are 0.37, 0.46 and 0.65. The lower p -values than the presumed significance level of 0.05 and Bonferroni corrected value of 0.0167 indicate a significant deviation of EOG signal during the use of DS. At the same time, the value of effect size (d) also shows the medium effect level for both horizontal and vertical movement aspects. On the contrary, for normal eyes, a significant effect has not been seen at the D.C.S-01 and D.C.S-02 time segments for both horizontal and vertical movement aspects. However, considerable deviation is observed at the D.C.S-03 stage, and medium effect size (d) is also found for both horizontal and vertical movement. The maximum classification accuracy of 91.67% is found for SVM linear kernel and LDA. It also indicates a significant deviation of the EOG signal of symptomatic eye movements compared to normal ones. The findings of this study suggest that compared to normal eyes, symptomatic eyes are more likely to make irregular, and uncontrolled eye movements while using digital screens.

Detailed investigation in linking spectral power changes to specific biophysical processes such as saccadic intrusions, microsaccades, or retinal potentials would provide valuable clinical context and will consider incorporating such analysis in future studies to enhance the physiological and clinical interpretability of our findings. This study is only limited to normal eye vision and lower visual acuity of university students and targeted to future inclusion of wide age range and more critical eye issues such as dry eye syndrome, and migraine.

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