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The Effect of Myopia on Brain Signals: Insights from EEG Studies

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Abstract

Refractive vision disorders, such as myopia, can significantly influence an individual's cognitive performance, particularly their ability to perceive and interpret visual stimuli. Myopia, a common refractive error affecting children and adults, can be assessed using various methods, including electroencephalography (EEG). The primary objective of this investigation was to identify distinctive brain signals associated with myopia. This study delves into analyzing brain signals in myopic individuals by employing EEG data and spectral entropy analysis through MNE-Python. EEG data were collected from five myopic participants during a 10-minute session, both with and without their corrective glasses. The collected data underwent preprocessing and power spectral density calculations. Subsequently, spectral entropy analysis was employed to assess the complexity and distribution skewness of EEG frequency patterns. The results of this study revealed notable differences in brain activity, particularly in the occipital region, between individuals wearing glasses and those without them. This variance could be attributed to the enhanced visual clarity experienced by individuals wearing glasses, enabling them to perceive better and process the visual stimuli presented in the study videos. Specifically, spectral entropy values were lower in children without glasses (averaging 1.0) than those with glasses (averaging 3.5), indicating a higher degree of irregularity in the brain activity of myopic children who do not wear corrective eyewear. In conclusion, this study indicates an increase in brain activity irregularities among children without glasses. The findings suggest that specific factors, such as blinking and hand movements, play a role in exacerbating this irregularity. These findings reveal how myopia affects brainwave patterns and indicate that EEG and spectral entropy analysis can enhance our understanding of refractive vision disorders.

Keywords: *Myopia; EEG; MNE-Python*

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INTRODUCTION

The human brain's response to various stimuli, including visual and auditory stimuli, is often captured in the form of signals. These signals are instrumental in medical research, with techniques such as Magnetic Resonance Imaging (MRI), functional Near-Infrared Spectroscopy (fNIRS) [1], and electroencephalography (EEG) being widely employed [2]. Given the pivotal role of the brain in orchestrating bodily movements, EEG is a prominent tool for investigating how the brain reacts to different stimuli, including visual inputs [2].

EEG has been utilized as a diagnostic modality for depressed feelings [3], various forms of human emotions [4-8] and epilepsy [9] y monitoring an individual's brain electrical activity and documenting its wave patterns. It has also been employed to investigate potential biomarkers of schizophrenia to identify SZ using EEG signals. This is attributed to EEG being regarded as the current benchmark due to its affordability, non-invasiveness, and portability. EEG captures irregular and constantly changing time-series data, which represents the recording of the brain's self-generated electrical patterns [10,11]. EEG is also utilized to investigate the patterns, characteristics, and specific anomalies occurring in the brains of individuals infected with SARS-CoV-2 to understand the involvement of the SARS-CoV-2 pathogen in brain activity [12].

Another study used EEG recordings to investigate the brainwave capacity in a resting state, with eyes in an open position. The researchers found that participants with an average age of 20.4 years had higher delta and theta waves than older people (average 68.2 years) [13]. A neuroimaging study has shown that individuals with high myopia are associated with abnormalities in brain anatomy [14]. Research also shows that brain activity in individuals with high myopia may differ from those who do not have myopia. A study showed that individuals with myopia have higher brain activity in visual areas and areas related to visual information processing. Myopia can affect brain anatomy through genetic and environmental factors, including gadget use habits, environmental factors, diet, and nutrition [15]. Furthermore, several studies on myopia using MRI have yielded information regarding the influence of myopia on brain conditions, including changes in Gray Matter Volume (GMV) [16], a decrease in cortical thickness in visual areas [17], and even emotional conditions that can also be discerned through brain signals in the posterior region [18].

In addition to investigating refractive errors, EEG has been employed to examine brain signals associated with autism spectrum disorder (ASD) in children [19,20], particularly focusing on alpha, beta, and gamma brainwaves [21]. The collected signals undergo comprehensive processing, encompassing statistical methods [2], artifact removal via Matlab, and data analysis using Python [22]. Python has gained widespread recognition for processing EEG data, facilitating tasks such as graphical modeling and psychological signal classification [23,24]. One study demonstrated the utility of combining eye-tracking and EEG techniques to investigate the mental processing demands during the learning of text-picture combinations. The findings provide insights into the cognitive processes involved in integrating and processing textual and pictorial information [25]. However, this study presents insights into the distinctiveness compared to existing research, particularly concerning the brain signal conditions influenced by low myopia. Notably, the data processing employed MNE Python, providing a robust and efficient means to analyze brain signals in the context of myopia.

Despite the extensive application of EEG and Python in signal processing, there remains a need to differentiate the effects of visual impairment when individuals wear corrective glasses versus when they do not. This study addresses this by leveraging MNE-Python to discern distinct brain signals associated with visual impairment. Thus, this study aimed to investigate the impact of myopia on brain signals.

METHOD

In this study, dataset was derived from a sample of five student participants who wore corrective glasses. These glasses are designed to enhance the visual clarity of individuals with myopia, aiding them in perceiving shapes accurately at specific distances. The video provided during data recording was a silent 5-minute Wonderful Indonesia video when the child was not wearing glasses. Furthermore, the video will be replayed to record when the child wears glasses. The data collection occurred during recording sessions held at the Biophysics Laboratory ITB in June 2023. The number of children in this study was five children, with ages ranging from 22 to 25 years old, and they have myopia as their condition. The Emotiv EEG system equipped with 14 electrodes was utilized for data acquisition. Subsequent data processing was conducted within the advanced Physics Laboratory at Sam Ratulangi University. The procedural flow of the current research is visually depicted in Figure 1.

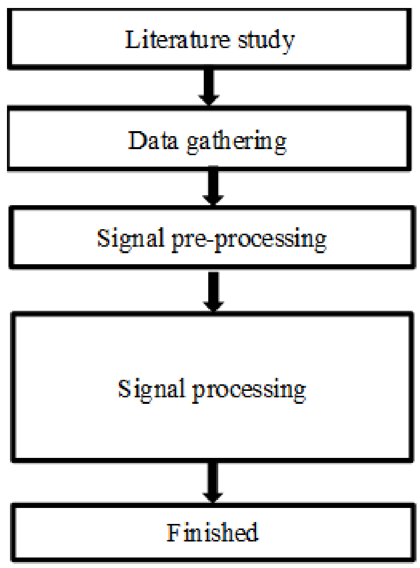

Figure 1. Flowchart of the research process

The process that takes place is based on Figure 1, where the literature Study involves evaluating and synthesizing previous research on the relevant topic. The next step was data gathering. In this step, the process of collecting necessary data for the study, such as measurement data or observational data. Signal pre-processing entails cleaning and preparing raw data for further analysis, including error detection and correction procedures. Signal processing uses MNE Python to understand or extract information from the data, such as filtering, feature extraction, or model fitting. The last step was to finish concluding the data analysis, drawing conclusions based on the findings, and completing the report or scholarly publication that explains the findings and research methodology.

Signal Pre-Processing

The collected data underwent processing using the Python programming language [26], with the primary library employed being MNE-Python [27]. Additionally, the NumPy package [28] was utilized to handle numerical operations, and NumPy can be combined with various other Python libraries, such as Matplotlib [29] which aided in the graphical visualization of the results.

MNE-Python played a crucial role in converting the data from the EDF format into a digital representation, which was then visualized as a graph depicting voltage (μV) against time (s). Data processing encompasses several stages, including centering, filtering, and rejection. After numerical data processing using NumPy, the data is visualized as graphs, making it easier for researchers to read the results of EEG data.

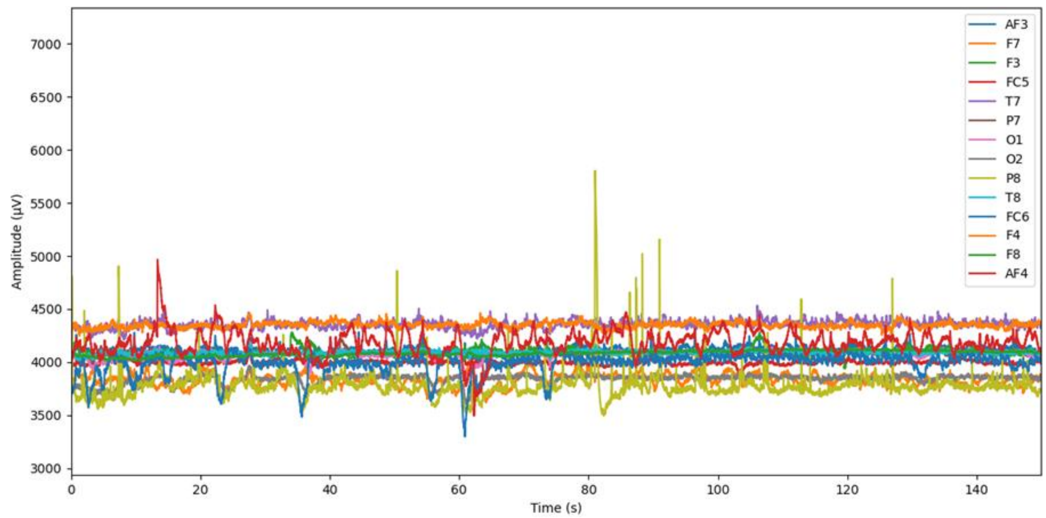

Figure 2. Signal before centering process

As part of the data processing pipeline, centering mitigates amplitude variations within the integrated Emotiv signal. In this study, the amplitude values exhibited fluctuations exceeding 4000 μV, as illustrated in Figure 2. Following the centering process, the signal stabilized around 0 μV, facilitating a more precise visualization of signal fluctuations, as depicted in Figure 3.

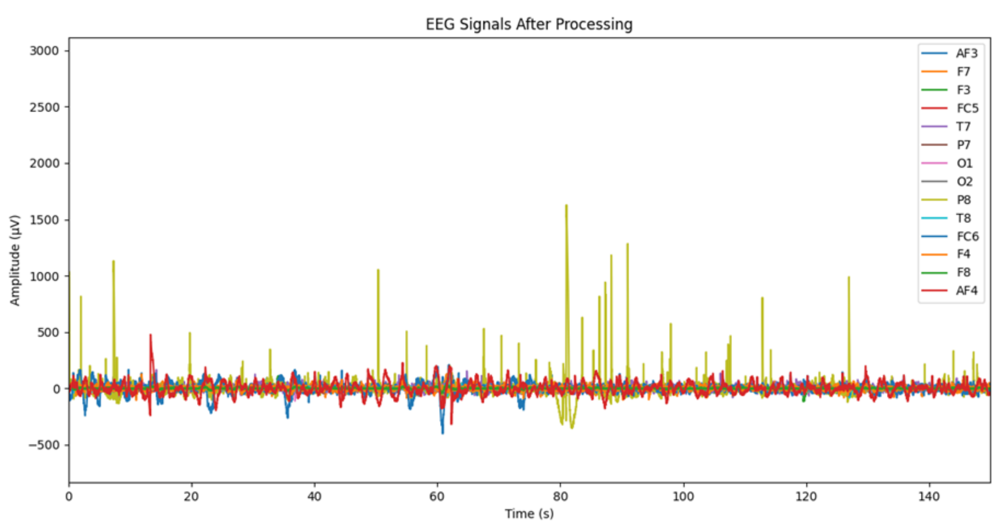

Figure 3. After signal pre-processing

Following the centering process, the data underwent filtering. This filtering step employed the Band Pass Filter (BPF) [30] technique utilizing the MNE module in Python. The BPF was used to extract the target signal within the frequency range of 0.5 to 35 Hz, effectively attenuating signals below 0.5 Hz (signal cutoff) and those above 35 Hz.

Subsequently, a rejection process was applied to eliminate any biased or irrelevant information. The outcomes of these sequential processes are depicted in Figure 3.

Signal Processing

The Periodogram Welch method relies on the utilization of the periodogram spectrum concept [31,32,33]. This approach involves converting the signal from the time domain to the frequency domain, thereby extracting spectral information from the signal. The Python code for this process is presented in Figure 4.

```
psd_data = spectrum.get_data() * 1e12  # Convert data to
microvolts^2/Hz

frequencies = spectrum.freqs
channel_names = spectrum.ch_names  # Get the names of all channels

# plotting all channels
plt.figure(figsize=(10, 6))

for i, channel_name in enumerate(channel_names):
    psd_value = 10*np.log10(psd_data[i])
    plt.plot(frequencies, psd_value, label=channel_name)

plt.xlabel('Frequency (Hz)')
plt.ylabel('Power Spectral Density (µV$^2$/Hz)')
plt.title('Power Spectral Density')
plt.xlim([0.5,35])
plt.legend(loc='upper right')
plt.show()
```

Figure 4. Python code to generate and plot the Power Spectral Density (PSD) value

Spectral Entropy

Spectral entropy measures the degree of irregularity within a dynamic system. One notable advantage of the spectral entropy algorithm is its ability to distinctly assess entropy contributions across various frequency ranges. This involves analyzing the power spectral amplitude evolution for each frequency component. Additionally, spectral power is normalized using equation 1:

$$P_n(f) = \frac{P_w(f_i)}{\sum_0^1 P_w(f_i)} \tag{1}$$

The outcomes of the normalization process are employed to compute the spectral entropy value [34] using equation 2:

$$SE = -\sum_0^1 P_n(f)\, log_2\ |P_n(f)| \tag{2}$$

Where P_w is Power spectral density (PSD) [35] with Welch periodogram, P_n is normalized PSD and SE is spectral entropy.

RESULTS AND DISCUSSION

EEG data analysis revealed notable distinctions in brainwave patterns between students without and with glasses. Cheng et al. from Nanchang University found that individuals with low myopia exhibit differences in low-frequency amplitude values in certain brain lobes, specifically between the right anterior cerebellum and the right frontal lobe [36].

Furthermore, Table 1 provides an overview of the channels where signal surges were detected. Significant signal differences were observed in the left frontal lobe for students with myopia who do not wear glasses, indicating distinctive brain activity during the recording process. Concurrently, both the left and right occipital lobes (O2) displayed signal spikes. This suggests that visual impairment could influence brainwave patterns in response to visual stimuli lacking auditory cues. This condition is mentioned in the body anatomy guide, which states that the occipital part of the brain can affect visual processing [37]. However, specific information regarding the condition of myopia in the occipital part may require scientific research or more particular sources due to the lack of references and related research. Table 1 shows several channels identified signal surges in students without and with glasses.

Table 1. Channels identified with signal surges in students without and with glasses

Condition	Subject				
	1	**2**	**3**	**4**	**5**
Without Glasses	FC5, F7, T7, O1, AF4 and F4	F7, FC6 and F3	O2, P8, and F7	P8, FC5, and FC6	P8, O2, and FC6
With Glasses	F7, FC5, AF4, O2 and F4	AF3, O2, FC5, and F4	F3, FC8, F5, and O2	P8, and FC6	F7, T7, P8 and O2

In EEG measurements, letters and numbers refer to the location of electrodes on a head. Letters indicate specific lobes of the head, while numbers indicate particular sides of the head. Based on the Table 1, FC5: Frontocentral 5, this electrode is located at the front and center of the head on the left side. FC6 and FC8: Frontocentral 6 and 8 are located at the front and slightly of the head on the right side. F7, F5, and F3: Frontal 7, 5, and 3 are located at the front of the head on the left side. T7: Temporal 7, this electrode is located at the side of the head on the left side. O1 and O2: Occipital 1 and 2 are located at the back of the head on the left and the right side. P8: Parietal 8, this electrode is located at the top of the head on the right side.AF4: Anterofrontal 4, this electrode is located at the front and slightly to the right of the head. F4: Frontal 4, this electrode is located at the front of the head on the right side. AF3: Anterofrontal 3, this electrode is located at the front and slightly to the left of the head.

In contrast, students wearing glasses exhibited artifacts primarily in the frontal lobes (F7, FC5, F4, and FC6), especially on the left and right sides. The occipital lobe displayed fewer spikes, particularly on the left side. This could be attributed to the corrective effect of glasses, enhancing visual clarity and reducing irregular neural responses. The identified signal surges are quite random for the same condition. This randomness could be due to the degree of refractive disorder, which may vary among individuals.

Additionally, auditory input, body movements, and feeling comfortable contributed to signal spikes, particularly in the frontal regions [38,39,40]. In summary, the randomness of signal surges in students wearing glasses could be due to the degree of refractive disorder, auditory input, body movements, and the involvement of the frontal eye field and occipital lobe in visual processing and eye movements.

The Brainwave Power Spectral Density (PSD) was determined using Welch's periodogram method, covering the 0.5-35 Hz frequency range. Figure 5 displays the PSD distribution for participants not wearing glasses. Certain electrodes, such as F8 and O1, exhibited reduced PSD values at higher frequencies, indicative of decreased energy in these frequency bands. Interestingly, the FC5 electrode demonstrated a distinctive pattern, initially decreasing at 15 Hz, followed by an increase. This phenomenon suggests that the left frontal brain region became increasingly engaged, optimizing its activity to comprehend the presented video stimulus. This video shows several colors, such as green, blue, and yellow [41,42,43] and the brightness level also affects the PSD values. Furthermore, Figure 5 shows the PSD value of students without glasses. Figure 5 shows the PSD value of students without glasses.

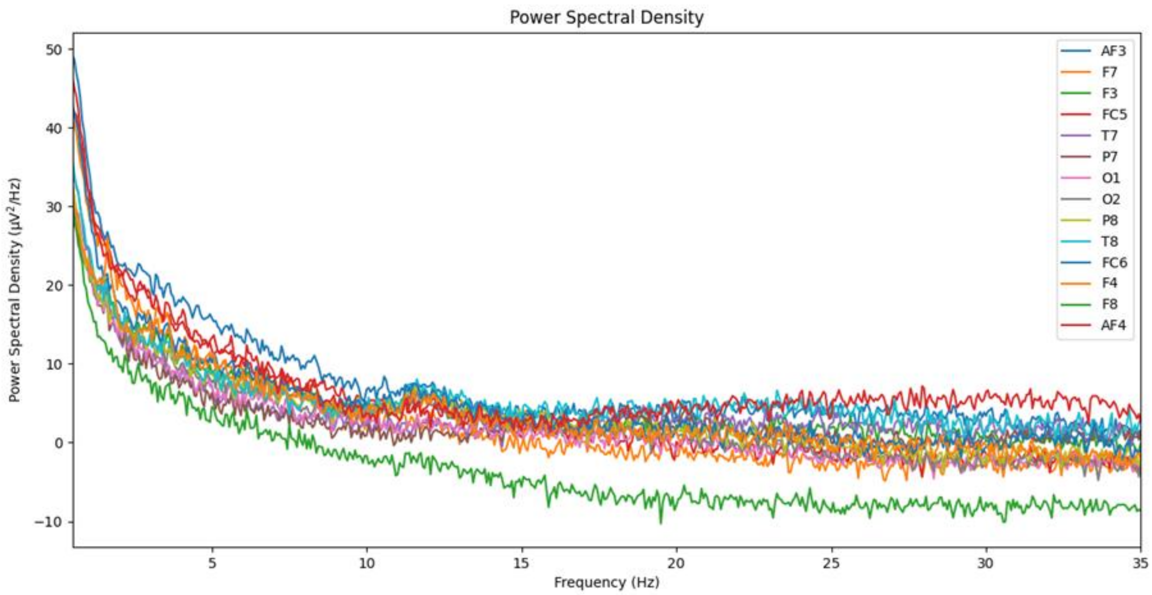

Figure 5. PSD graph of student without glasses

Notably, the PSD graph exhibits slight variations for students with glasses compared to the earlier graph. Electrode F8 displayed more frequent fluctuations than the PSD of students without glasses. This behavior can be attributed to the fact that the myopia level in the subjects was less than 0.75, resulting in comparable visual acuity both with and without glasses. Other studies have demonstrated that the frontal lobes, such as F8, F3, and F7, do not exhibit significant signal fluctuations [42]. This suggests a lack of concentration on the provided visual stimuli, which can be attributed to high myopia values.

For the right occipital area (O2) [42] in the frequency range between 15-20 Hz, there is an increase in the PSD value, which may be attributed to the presence of visual stimuli involving pupil size and high-level aberrations in the eye but unaffected by retinal defocus when individuals are wearing glasses [41]. The temporal lobes, namely T7 and T8, are brain regions that will significantly fluctuate at high frequencies due to the uncomfortable mental state [40]. This condition can be caused by boredom from the repeated measurement using the same video stimulus. Figure 6 shows the PSD graph corresponding to students who wore glasses.

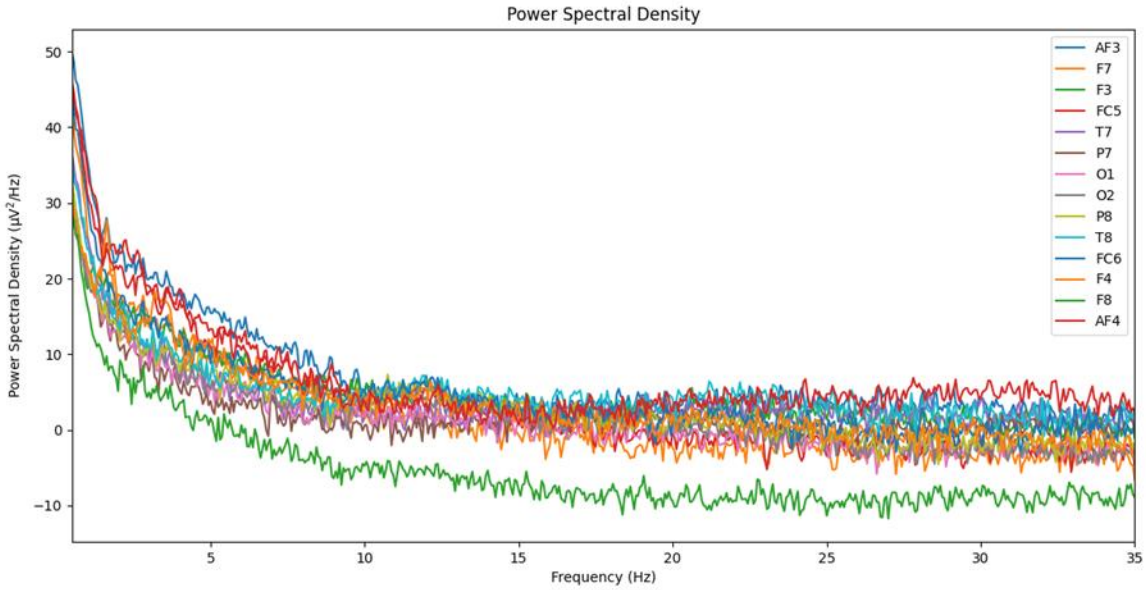

Figure 6. PSD graph of student wearing glasses

Figures 5 and 6 illustrate that the occipital graph without glasses exhibited a relatively larger pattern than that with glasses. This observation can be attributed to the behavior of students wearing glasses, who experienced enhanced clarity in perceiving the shapes and movements depicted in the video stimulus.

Spectral entropy draws on Shannon's entropy from physics, quantifying the degree of regularity or randomness within a power spectrum over a specific period. The obtained spectral entropy values are depicted in Figure 7. Notably, an increase in spectral entropy at electrode F4 in Figure 7.b signifies a more tranquil state during video viewing while wearing glasses. Electroencephalogram (EEG) signals can be analyzed using spectral and entropy biomarkers to identify emotional states during video viewing. Spectral entropy at electrode F4 in the frontal lobe can indicate a more tranquil state during video viewing while wearing glasses. Multiscale and Rényi entropy are examples of entropy-based methods used to analyze EEG signals. EEG recordings use active electrodes placed evenly over the scalp while participants watch video clips and report their emotional categories.

The curve in Figure 7 demonstrates that the spectral entropy value in students with glasses was generally higher compared to those without glasses. This discrepancy can be attributed to the improved ability of students wearing glasses to perceive video stimuli during the measurement. A higher spectral entropy value indicates a lower degree of irregularity. Conversely, a lower spectral entropy value suggests a higher level of irregularity.

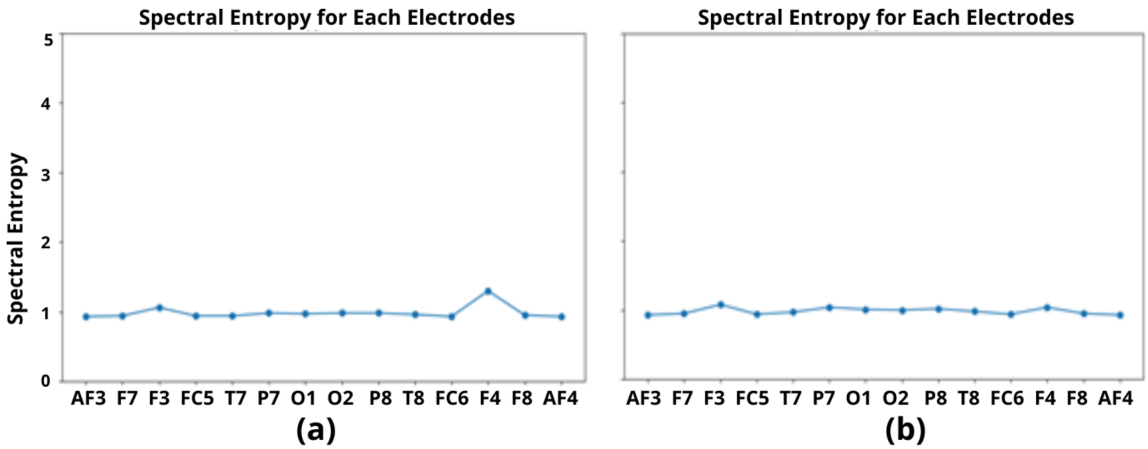

Figure 7. The spectral entropy values for each electrode: (a) without glasses, and (b) with glasses

Spectral entropy measures the distribution of signal energy in the frequency domain. In myopia, spectral entropy can be used to analyze the characteristics of optical signals, such as those obtained from the cornea or the retina. A higher spectral entropy value indicates a broader signal energy distribution across the frequency spectrum, which is associated with increased signal irregularity or complexity. Furthermore, an increase in the functional variability of the right anterior frontal lobe (F4), according to a study [44], tends to be higher than the left hemisphere, as indicated by odd numbers. This could be observed in corneal pulsation or retinal imaging in myopic eyes, where the spectral entropy of the optical signals may reflect the variability or irregularity of the underlying physiological processes [45]. The entropy values can be influenced by body posture [46] and This can also be caused by emotional changes during EEG recording [47]. On the other hand, a lower spectral entropy value indicates a more concentrated distribution of signal energy in the frequency domain.

High and low spectral entropy values in myopia provide valuable insights into signal energy distribution in the frequency domain and can help identify unique features of myopic eyes. These measures can be helpful for early detection, accurate diagnosis, prognostication, and evaluation of treatment for myopia, as well as for understanding the underlying physiological characteristics associated with this condition [48]. Apart from that, there was research to discover the causes of myopia by exploiting the influence of genes using microRNAs [49]. In conditions of high myopia, significant differences will be seen in the left and right parietal lobes, such as research that involves visuals to differentiate lobe activity in the human brain [50].

Based on the results and discussions as previously outlined, this study primarily focuses on overall frequency without delving into the influence of specific alpha, beta, theta, and delta wave conditions [49] in individuals with refractive abnormalities. There are several causes for these abnormalities, but this study specifically addresses myopia. Due to the limitations of this research, it is hoped that future studies will consider various forms of brainwave patterns based on their frequencies. Additionally, given the current relevance of refractive abnormalities, it is essential to include a wide range of conditions, such as hyperopia, astigmatism, eye strain, and amblyopia [50-53].

In conclusion, this research is a scientific foundation in medicine and neuroscience for developing technology and information. Furthermore, it can potentially enhance applications in neuroscience, thereby improving the quality of human life.

CONCLUSION

Upon data processing and thorough analysis, several conclusions can be drawn. Specifically, the spectral entropy value for students without glasses was consistently lower than that of students wearing glasses, with an average of 1.0 for the former and 3.5 for the latter. This discrepancy can be attributed to the heightened irregularity observed in the brain activity of children without glasses. For future research, expanding the sample size and considering variations in the severity of refractive error would be beneficial. Additionally, investigating the impact of different types of corrective eyewear on brainwave patterns could provide a more comprehensive understanding of the interaction between visual impairment and neural responses. Furthermore, exploring the effects of other visual stimuli parameters, such as intensity and complexity, on brainwave activity could yield valuable insights. Such endeavors could enhance our comprehension of how visual processing and brainwave patterns are intricately linked in individuals with refractive vision disorders.

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AUTHOR CONTRIBUTIONS

Ernawatil Gani: Conceptualization, supervising, methodology, analysis, and writing original draft; Afrioni Roma Rio: software and visualization; Mahendra Kusuma Nugraha: analysis, reviewing and editing; and Freddy Haryanto: reviewing and validation.

DECLARATION OF COMPETING INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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