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A novel approach for migraine detection using localized component filtering and electroencephalographic spectral asymmetry index

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Keywords
Electroencephalography; Migraine Disorders; Clustering; Artifact Rejection; Detection Method

Abstract

Background: This study aims to improve the accuracy and reliability of migraine detection by combining the localized component filtering (LCF) method with the electroencephalographic (EEG) spectral asymmetry index (SASI) method. The integration of LCF and SASI in the frequency domain under 3 Hz photic stimulation offers a novel approach for robust classification.

Methods: EEG recordings from 13 control subjects and 15 migraineurs were used in this study. The SASI values, obtained from LCF pre-processed signals, served as features for classification. The K-means clustering algorithm was applied, and the accuracy was evaluated using the silhouette values method.

Results: The combination of the LCF method with the SASI technique resulted in a 17% improvement in clustering accuracy, achieving an overall accuracy of around 87%. This new approach outperformed the histogram K-means clustering method and the SASI technique used alone. The accuracy attained by this combined approach was as high as multi-layer perceptron (MLP) and superior to K-means clustering, which are two well-known approaches of artificial and machine learning (ML) clustering methods, respectively.

Conclusion: This study presents a novel and effective approach by combining LCF and SASI for migraine detection, which enhances classification accuracy and provides valuable insights into migraine-related brain activity. Accurate and reliable detection of migraine can lead to more effective treatment and management of the condition, ultimately improving the quality of life for migraine sufferers.

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Introduction

Migraine is a neurological disorder characterized by recurrent and intense headache attacks that can result in significant disability and reduced quality of life for those affected.[1] Electroencephalography (EEG) is a widely used technique to study brain activity and has been employed to investigate the abnormalities associated with migraine.[2-4] One intriguing finding is the presence of EEG asymmetry in individuals experiencing migraine attacks.[4,5] Research has indicated that many individuals with migraines exhibit elevated alpha activity in one hemisphere and reduced activity in the other, highlighting asymmetry in brain functioning during migraine episodes.[6,7]

The observed imbalance in alpha activity in individuals with migraines may offer valuable insights into the fundamental mechanisms of the condition. Analysis hints that this unconventional brain activity could be correlated with changes in cerebral blood flow, metabolism, and levels of neurotransmitters in the impacted hemisphere. The asymmetry in alpha activity is thought to be correlated with the one-sided manifestation of migraine headaches, where individuals commonly encounter pain on a single side of the head.[8,9]

Altered alpha activity, particularly the increased variability in peak alpha frequency, has been observed during migraine attacks. This increased variability in alpha-band oscillations could result from an instability in the thalamic generators of alpha rhythms, contributing to the cortical hyperexcitability seen in migraineurs.[10]

Understanding this phenomenon is crucial as it provides insights into the underlying mechanisms of migraines and assists in the development of targeted treatments. To this aim, examining asymmetry in EEG patterns, particularly changes in alpha activity, demonstrates the potential for enhancing diagnostic and therapeutic approaches for individuals suffering from migraines. This analysis possesses the capacity to distinguish between different kinds of migraines, like hemiplegic migraine and migraine with or without aura, by recognizing specific EEG patterns such as asymmetrical slow-wave activity and variations in alpha-band phase synchronization, which aid in precise diagnoses and customized treatment plans.[11] Moreover, the inspection of EEG patterns, involving the asymmetry in alpha activity, gives valuable perspectives into the underlying neural mechanisms of migraine pathophysiology, for example, thalamic generator instability associated with cortical hyperexcitability in patients with migraine.[4] Monitoring alterations in distinct EEG patterns, such as the normalization of alpha asymmetry, can serve as a significant biomarker for assessing the effectiveness of treatments and facilitating well-informed decisions regarding personalized treatment strategies. Drawing upon findings from EEG analysis of migraine asymmetry not only improves diagnostic precision but also enables the customization of treatment plans, thus optimizing the management of migraines.[10] Ongoing research in this field could potentially lead to the establishment of reliable EEG-based biomarkers, further propelling the progress of personalized medicine in migraine healthcare.

However, detecting migraine EEG asymmetry poses significant challenges, and this is where machine learning (ML) algorithms come into play. ML algorithms have the potential to extract patterns and features from vast amounts of EEG data, enabling the identification of subtle differences between migraineurs and healthy individuals. These algorithms can then be trained to recognize specific EEG patterns characteristic of migraine asymmetry, thereby aiding in diagnosis and treatment decisions.[5,6,8]

One of the primary challenges in detecting migraine EEG asymmetry is the presence of artifacts in the EEG recordings. Artifacts, such as eye movements and muscle contractions, can distort the EEG signals and lead to misinterpretation of the data. This can result in false positives or false negatives, leading to inaccurate diagnosis and treatment decisions.[4,9,10] Therefore, it is essential to develop techniques to identify and remove artifacts from the EEG recordings. One technique that has been proposed to reject artifacts and improve the accuracy of detecting migraine EEG asymmetry is localized component filtering (LCF).[11] LCF effectively eliminates artifacts from EEG recordings, ensuring high-quality data for analysis. LCF is a data-driven method that identifies and separates EEG signals into localized components using independent component analysis (ICA) and spatial filtering. The localized components represent the underlying neural activity, while the non-localized components represent noise and artifacts. By removing the non-localized components, the accuracy of detecting migraine EEG asymmetry can be improved.[11]

To detect asymmetry, this study proposes the use of the spectral asymmetry index (SASI) in detecting accuracy. The SASI index is a measure of asymmetry in the spectral power of EEG signals between the left and right hemispheres. Previous studies have shown that the SASI index is effective in detecting depression and other abnormalities.[4,12,13] The SASI method assesses the spectral asymmetry of 15 EEG channels, distinguishing migraineurs from healthy subjects using a linear asymmetry detection method. This approach reduces complexity and time costs compared to other frequency domain methods. The contribution of our study is to investigate the role of artifacts in the accuracy of detecting migraine EEG asymmetry and evaluate how much artifact rejection can enhance the efficacy of using the SASI index. We propose a novel approach that benefits from the synergy of LCF artifact rejection and the SASI index to detect migraine EEG asymmetry. By using both techniques, we aim to improve the accuracy of detecting migraine EEG asymmetry and reduce the impact of artifacts on the classification results.

To evaluate the efficacy of our proposed approach, we conducted experiments on a dataset of EEG recordings obtained from patients with migraine and healthy controls. We compared the performance of our approach to another classification algorithm, namely, K-means clustering, and evaluated the impact of artifact rejection on the accuracy of detection.

The paper describes two methods, LCF and SASI respectively. The results of simulations using these methods are discussed in Results. In Discussion, the efficiencies of the proposed detection method and the histogram K-means clustering method presented in[14] are analyzed and compared.

Materials and Methods

Migraines are classified into various subtypes, including episodic and chronic migraines, with or without aura. Episodic migraines manifest on fewer than 15 days monthly, whereas chronic migraines occur on 15 or more days every month, persisting for over three months, and entail a minimum of eight days with migraine symptoms. Migraines with aura are characterized by visual or other sensory disruptions that come before or coincide with the headache, while migraines without aura lack such manifestations. This research examines individuals experiencing episodic migraines without aura. The study examines how photic stimulation at 3 Hz and open eyes with no photic stimulation affect the EEG spectrum of individuals with migraines during the interictal phase. The research explored changes in the brain and the waves in the T5 and T6 channels of the EEG.[3] T5 and T6 channels were opted for to scrutinize the occipital regions of the brain where the migraine symptoms manifest themselves. These channels are crucial for analyzing the electrical activity in the occipital region, where migraine symptoms often manifest. Research has shown that the occipital region plays a key role in migraine pathophysiology, with changes in brain activity observed in this area among patients with migraine.[15] Additionally, studies have highlighted the importance of T5 and T6 channels, along with other channels like T3, F7, O1, and O2, in diagnosing and analyzing migraine through EEG signals.[16]

Furthermore, the use of T5 and T6 channels is supported by findings that suggest peculiar excitability of the visual cortex in patients with migraine, particularly in the parietal-occipital regions, which are crucial for understanding the characteristics of migraine without aura groups.[17] These channels provide valuable insights into the electrical activity changes associated with migraine, especially under flash stimulation, which is a common triggering method for migraine symptoms.[15,16]

EEG signals were recorded using a 32-channel digital EEG Nihon Kohden device, with a sample rate of 512 Hz and Cz as the reference electrode. Each recording session lasted for 30 minutes, during which 3 minutes were set aside for hyperventilation, and no migraine attacks occurred. The paper studies 500 EEG samples with photic stimulation at a frequency of 3 Hz. According to the 10-20 international system, electrodes were placed at Fp1, Fp2, C3, C4, O1, O2, A1, A2, F7, F8, T3, T4, T5, T6, T1, T2, X1, X2, X3, X4, X5, and X6. The data were obtained from the Neurology Department of Imam Khomeini Hospital, Tehran University of Medical Sciences, Tehran, Iran. The age range of the patients and control subjects was 14 to 60 years old. The migraineurs under examination were patients without aura who were diagnosed according to the International Classification of Headache Disorders, Third Edition (ICHD-3) beta criteria[17] by expert neurologists.

To obtain uncontaminated EEG signals, the LCF method was applied in the initial stage to enhance the equilibrium between artifact rejection and retention of neural activity.

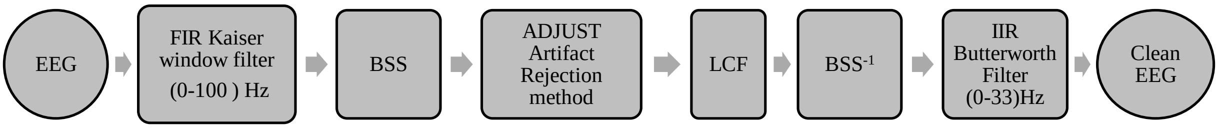

Figure 1. Electroencephalography (EEG) processing steps in order to obtain clean EEG signals

In the subsequent stage, an infinite impulse response (IIR) Butterworth filter was implemented to retain the 0 to 33 Hz frequency band and to excise other frequencies.

LCF: The LCF methodology is designed to localize time segments within components that are contaminated by artifacts. This algorithm works in conjunction with the blind source separation (BSS) preprocessing algorithm, directing the processing to localized segments in order to preserve the remaining parts of the component in their original form. The steps of the integrated BSS and LCF algorithm used in this study are illustrated in figures 1 and 2. These figures provide a visual representation of the process and highlight the key stages involved in the algorithm.

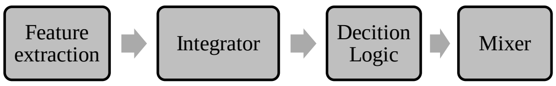

Figure 2. Localized component filtering (LCF) algorithm steps

SASI: When conducting an asymmetry analysis of EEG signals, various approaches can be employed, including both linear and nonlinear methods. While nonlinear methods may offer greater accuracy, the linear SASI method[18] was chosen for its simplicity and low computational cost. According to this method, the power spectra of both upper and lower frequency bands are examined with respect to the alpha frequency as the central frequency band (fc).

The boundary frequencies of the lower frequency band (f1, f2) are defined as:

$$f_1 = (f_c - 6)\ Hz,\ \ f_2 = (f_c - 2) \qquad 1$$

while the upper boundary frequencies (f3, f4) are defined as:

$$f_3 = (f_c + 2)\ Hz,\ \ f_4 = (f_c + 26) \qquad 2$$

as shown in equations 1 and 2. It is worth noting that the selected frequency bands in equations 1 and 2 may not necessarily match with the traditional EEG frequency bands. For this study, the lower and upper frequency bands considered were 3-8 Hz and 13-33 Hz, respectively.

The SASI method estimates the spectral asymmetry of the EEG spectrum using a parabolic function, with the alpha band as its maximum point. It is important to ensure that the selected upper and lower bands compensate for the EEG spectral density, which is calculated using Welch's averaged periodogram method.[19]

The SASI factor, which is used as a criterion for detecting migraine disorder, is calculated using equation 3:

$$SASI_{mn} = \frac{P_{Hmn} - P_{Lmn}}{P_{Hmn} + P_{Lmn}} \qquad 3$$

where P_{Lmn} and P_{Hmn} are the power of the lower and upper frequency bands for each EEG channel m = T1, T4, T5, T6, and subjects n = 1, 2... 20, respectively. P_{Lmn} and P_{Hmn} are described as follows:

$$P_{Lmn} = \sum_{f=f_1}^{f_2} S(f)_{mn},\ P_{Hmn} = \sum_{f_3}^{f_4} S(f)_{mn} \qquad 4$$

where S(f) is the power spectral density of the recorded EEG signal. The signal is divided into a series of overlapped segments (50% overlapping) with a length of 1024 samples. Every segment is multiplied by the Hanning window function as follows:

$$\omega_n = 0.5\left(1 - cos\frac{2\pi i}{N-1}\right) \qquad 5$$

where "i" is a sample index and "N" is the number of samples in a segment.

Results

MATLAB software was used to process the EEG signals. Figure 3 illustrates stimulated and non-stimulated EEG signals of patients with migraine and healthy subjects.

Figure 3 demonstrates that the EEG response to optic stimulation is elevated in individuals with migraines compared to those without migraines. This implies that migraine sufferers exhibit an increased sensitivity to optic stimulation when contrasted with individuals without migraines.

In figure 4, we present a comparison of amplitude distribution at 3 Hz between EEG recordings with and without photic stimulation in nine out of fifteen patients with migraine and nine out of thirteen control subjects from our study sample, serving as the training set.

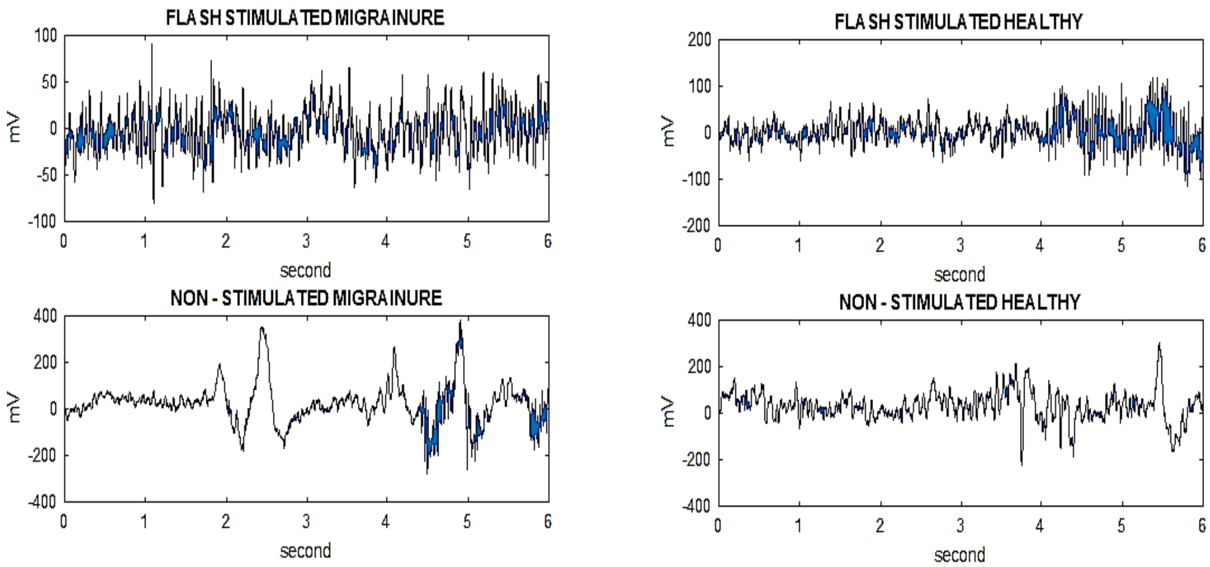

Figure 3. Flash stimulated and non-stimulated open eyes migraineur and healthy subject electroencephalography (EEG) signal

The histogram depicted in figure 4 illustrates that a majority of patients with migraine show increased asymmetry in the mean EEG signals between the left and right hemispheres during stimulation compared to non-stimulation conditions, with asymmetry levels returning closer to normal in the absence of stimulation. Specifically, the analysis focuses on EEG channels from the right hemisphere, including Fp2, F4, C4, P4, O2, A2, F8, T4, and T6, while the left hemisphere is assessed using EEG signals from Fp1, F3, C3, P3, O1, A1, F7, T3, and T5.

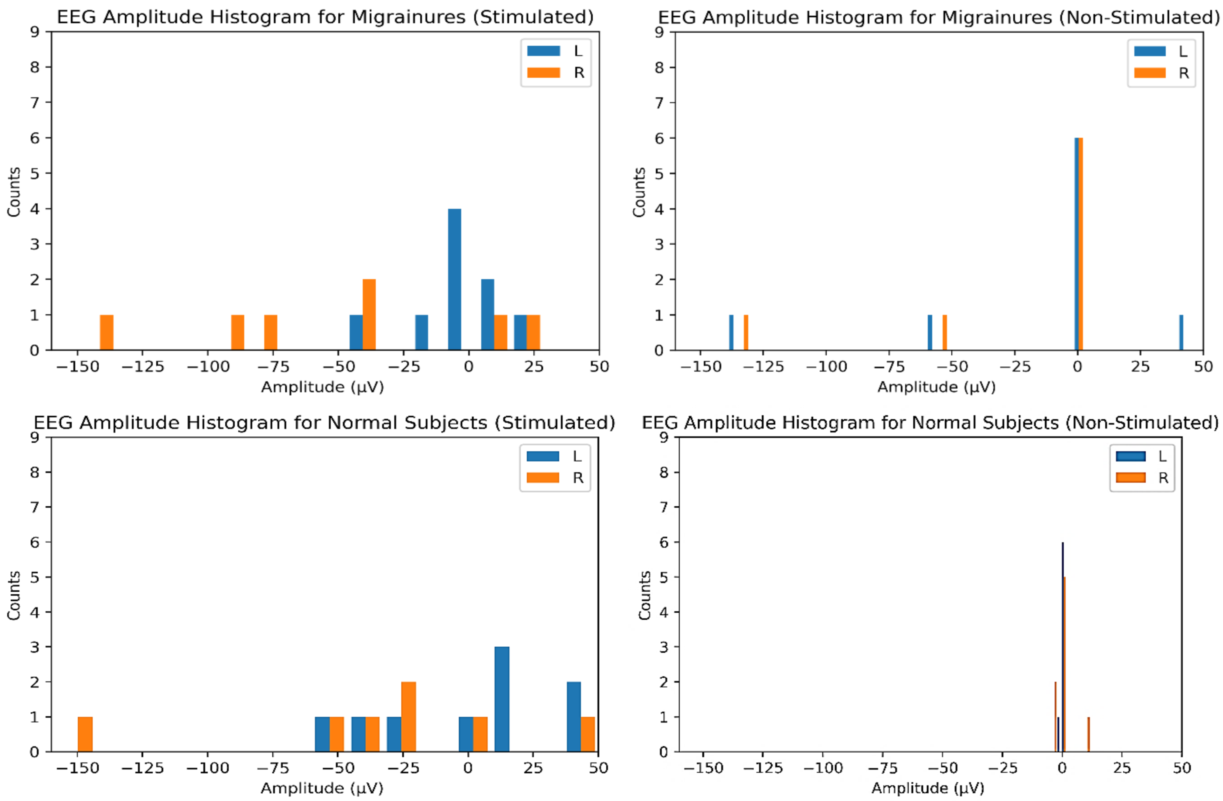

Figure 4. Histogram of mean non-stimulated and stimulated electroencephalography (EEG) signals of left and right hemispheres for healthy and patient groups

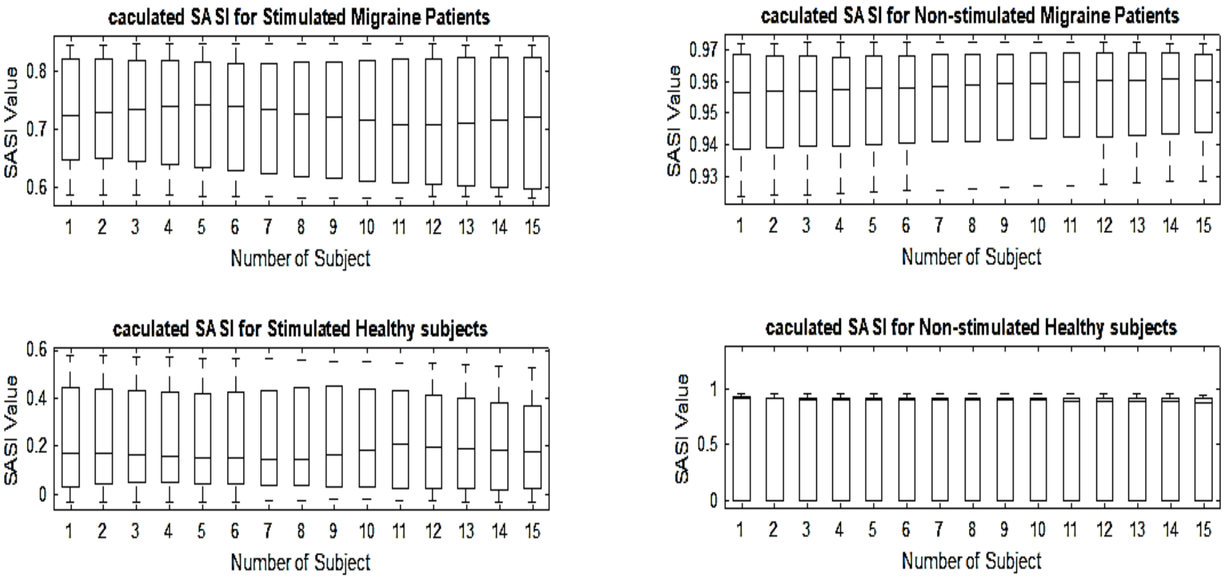

Figure 5. Spectral asymmetry index (SASI) values of 9 migraineurs and 9 controls

Figure 5 illustrates the average of the calculated SASI values for stimulated and non-stimulated migraineurs and healthy subjects sequentially in T5 and T6 channels for 70% of EEG samples, as a training dataset.

Figure 5 illustrates the median SASI values for both patients with migraine and healthy subjects under both stimulation and non-stimulation conditions. The SASI values for patients with migraine are consistently higher than those for healthy subjects, with the calculated SASI values for patients with migraine under stimulation exceeding 0.6, while the SASI values for healthy subjects remain below 0.6.

Furthermore, the plot reveals that the range of SASI values for healthy subjects is wider than that for patients with migraine, suggesting greater variability in the SASI values of healthy subjects.

The t-value for the SSI values is 1.97804052, which indicates a moderate effect size for the difference between the two groups. This difference is statistically significant at the 0.05 level (P = 0.0507), suggesting that the observed difference between the two groups is unlikely to have occurred by chance.

These findings highlight the potential of SASI values as a biomarker for migraine detection, as they demonstrate a consistent and significant difference between patients with migraine and healthy subjects. This difference could provide a valuable tool for identifying and diagnosing migraine, enabling more effective treatment and management of the condition. To evaluate the proposed method, table 1 presents the accuracy of classification results using proposed SASI with LCF, SASI without LCF, multi-layer perceptron (MLP),[15] and K-means clustering[14] on a 30% test sample of the EEG dataset. The clustering results are assessed using silhouette values.[20] This comparison allows for assessing the accuracy of the proposed method relative to established methods.

Table 1. Classification accuracy comparison

Classification method	Accuracy (%)
SASI with LCF	87
SASI without LCF	70
MLP[20]	87
K-means clustering[15]	85

SASI: Spectral asymmetry index; LCF: Localized component filtering; MLP: Multi-layer perceptron

From table 1, it is evident that the accuracy of SASI in migraine detection is reduced when LCF is not used, as the classification results are adversely affected by artifacts. However, utilizing the LCF approach in the pre-processing stage enhances the classification results by rejecting artifact effects, leading to an increase in accuracy by up to 17%. Our method statistically improved the accuracy of migraine detection by up to 17% compared to not using artifact rejection. This enhancement demonstrates the effectiveness of incorporating LCF in the pre-processing stage to mitigate artifact effects, resulting in more reliable classification outcomes.

The comparison results indicate that the combination of SASI as a linear approach with LCF pre-processing can detect migraine as accurately as MLP, a nonlinear classification method, and outperforms the K-means clustering approach. This superiority may stem from the simplicity and linearity of the SASI with LCF approach, making it more suitable for this specific classification task where the relationships between features are not highly complex, unlike the case with K-means clustering, which may struggle with non-linear separability in the data.

Furthermore, SASI, when combined with LCF, provides a robust feature representation that captures essential information for migraine detection, enhancing the model's ability to differentiate between migraine and non-migraine patterns. Although SASI values have been studied for different brain disorder diagnoses, such as depression detection,[21] or utilized as a biomarker combined with ML algorithms,[21-27] studies indicate that this feature alone presents lower than 80% accuracy as an index for detecting disorders.[21,22] Our results confirm this issue when artifact rejection is not employed. However, when LCF artifact rejection is integrated with the SASI approach as a simple and linear method, a significant improvement in diagnosis accuracy is achieved, matching the accuracy of nonlinear methods like MLP.

Discussion

The present investigation sought to examine two primary concerns pertaining to the utilization of SASI in the detection of migraines. Firstly, we evaluated to determine whether SASI can be deemed a fitting characteristic for effectively identifying migraines. Our outcomes evinced that when used in conjunction with LCF pre-processing, SASI improves the precision of migraine detection. However, it is imperative to note that in the absence of LCF pre-processing, SASI may not yield dependable accuracy for the classification of migraines. Secondly, we delved into the function of artifacts in the classification outcomes produced via the utilization of SASI. Our discoveries brought to light the crucial significance of rejecting artifacts as an essential measure to augment the accuracy of classifications. The amalgamation of SASI with LCF pre-processing can produce outcomes of satisfactory quality in migraine detection. Nevertheless, further scrutiny of more extensive datasets is suggested to enhance the accuracy of the outcomes in forthcoming research.

Our findings reveal that integrating LCF pre-processing enhances migraine detection accuracy by up to 17% by mitigating artifact effects. Additionally, the combination of SASI with LCF pre-processing matches the accuracy of nonlinear methods like MLP and outperforms K-means clustering due to its simplicity and linearity, which are well-suited for this classification task.

By and large, the outcomes of this research possess the potential to significantly contribute to the advancement of more precise and trustworthy methods for the identification of headaches utilizing EEG signals.

Conclusion

This research demonstrates that the integration of SASI with LCF pre-processing significantly enhances the accuracy of migraine detection using EEG signals. The findings underscore the importance of artifact rejection in improving classification outcomes, suggesting that SASI can be a valuable tool for identifying migraines when appropriately processed. The results indicate a promising direction for developing more precise and reliable methods for headache identification through EEG analysis. Future studies should focus on larger datasets to further validate these findings and explore additional enhancements in detection methodologies.

Conflict of Interests

The authors declare no conflict of interest in this study.

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