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Active-reflective learning style detection using EEG and abrupt change detection

Rifkie Primartha[a,b], Teguh Bharata Adji[a], Noor Akhmad Setiawan[a,*]

[a]*Department of Electrical and Information Engineering, Universitas Gadjah Mada, Yogyakarta 55281, Indonesia*
[b]*Department of Informatics, Universitas Sriwijaya, Palembang 30662, Indonesia*

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Abstract

Recognizing the varying learning styles of students is vital to creating customized educational approaches and maximizing academic success. While commonly used, conventional evaluation methods such as self-report surveys are frequently characterized by subjective biases and inconsistent accuracy. To address this limitation, this present study proposes an EEG-driven approach for learning style classification, specifically targeting the Active and Reflective dimensions of the Felder-Silverman Learning Style Model (FSLSM). Data was acquired from 14 participants using an 8-channel OpenBCI headset, with cognitive engagement stimulated through Raven's Advanced Progressive Matrices (RAPM). Initially, the raw EEG data underwent bandpass filtering process purposely to remove noise. Subsequently, the data was divided into consecutive 1-second segments. For feature extraction, the CUSUM algorithm was employed, with an aim to effectively capture significant signal variations. These features were then fed into an LDA classifier for style discrimination. The performance evaluation revealed impressive results—98.26% accuracy in standard Train-Test validation, and an even higher 99.29% under LOOCV testing. Notably, our approach consistently outperformed existing techniques including 1-DCNN and TSMG across all metrics. Notably, computational efficiency and reliability were improved, with the "Odd-only" subset yielding peak accuracy (99.24%). These findings demonstrate that integrating EEG signals with conventional machine learning enables real-time, high-precision learning style detection. Additionally, this work addresses the computational constraints and dataset limitations observed in recent studies, providing a robust foundation for adaptive learning systems. It is recommended that future research explore larger, more diverse datasets and additional FSLSM dimensions to enhance generalizability and practical implementation of the research.

Keywords: Learning-style detection; EEG features; cusum; feature extraction; felder–silverman learning-style

1. Introduction

Learning styles refer to the preferred ways individuals absorb, process, and retain information, which significantly determine their academic performance and overall learning experience [1,2]. Identifying these styles is crucial for the personalization of education, enabling educators to tailor instructional methods and materials to meet the diverse needs of learners, thereby enhancing engagement and effectiveness [3,4]. Conventional assessment methods, such as questionnaires, frequently exhibit deficiencies in terms of accuracy and objectivity. This then has prompted researchers to explore automated detection techniques through machine learning and behavioral analysis [1,2]. Of these approaches, models such as the Felder-Silverman Learning Style Model (FSLSM) have demonstrated high efficacy in identifying learning styles through data-driven techniques, achieving notable accuracy rates [4,5]. This paradigm shift towards automated detection supports the development of adaptive learning environments that dynamically respond to individual learning preferences.

Electroencephalogram (EEG) signals provide a viable approach for identifying learning preferences, delivering direct, moment-to-moment data on neural patterns linked to different cognitive functions. Contrasting to conventional methods, EEG directly captures neural patterns correlated to learning preferences, thereby reducing subjectivity and enhancing reliability. Contemporary research has employed electroencephalogram (EEG) recordings to enhance computational models in this domain. To illustrate this, Yuvaraj and colleagues (2024) [6] constructed an analytical system incorporating probabilistic metrics and ensemble decision trees, subsequently attaining a classification precision of 78.45%. Parallel findings by Zhang's team (2021) [7] proposed the Temporal-Spatial Multiscale Graph (TSMG) architecture, a neural network-based solution that elevated detection performance by 5 percentage points relative to

* Corresponding author.
Email: noorwewe@ugm.ac.id
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conventional techniques. These findings emphasize the potential of EEG in advancing personalized educational interventions, despite limitations such as high computational demands and reliance on public datasets that may lack diversity.

However, existing literature on EEG-based learning style detection exhibits certain limitations. Numerous research efforts, such as those conducted by Yuvaraj and colleagues (2024) [6] and Zhang's research group (2021) [7], employed sophisticated algorithms such as neural networks and ensemble decision trees. Despite the efficiency of these techniques, their computational demands could pose challenges for implementation in resource-limited settings. Furthermore, reliance on standardized datasets may not adequately represent the variability in neurocognitive responses observed among different populations. To address these issues, this present study utilizes a self-collected dataset recorded from 14 participants using an OpenBCI device. By leveraging the Cumulative Sum (CUSUM) method for feature extraction, the objective of this research is to capture rapid changes in EEG signals associated with learning styles, enabling efficient analysis without the necessity for computationally intensive processes.

This research aims to enhance the precision and computational efficiency of learning style classification through EEG signal analysis. Utilizing EEG data obtained from 14 participants, this research aims to differentiate Active and Reflective learning styles through the quantification of abrupt change employing the CUSUM method [8] and classification employing Linear Discriminant Analysis (LDA) [9]. This approach facilitates the more rapid analysis of the changes in EEG pattern without compromising accuracy. By addressing the computational and dataset limitations in prior studies, this research contributes to the development of a more practical and efficient framework for supporting learning style-based educational interventions. Recent research in Communications in Science and Technology has also explored machine learning-based classification of EEG signals, demonstrating the relevance of efficient feature extraction and classification techniques in similar contexts [10].

2. Materials and Methods

To ensure a comprehensive and systematic investigation of EEG-based learning style classification, this study was conducted through a series of structured phases. These include participant selection and experimental design, EEG data acquisition, and the presentation of stimuli during the recording sessions. The research workflow was subsequently established to guide the processing pipeline, followed by the implementation of appropriate data analysis techniques. The ensuing sections provide a comprehensive overview of each phase of the methodology, purposely to ensure transparent documentation of both experimental protocols and computational approaches implemented in this investigation.

2.1. Participants and experimental design

The EEG acquisition protocol was performed under standardized laboratory conditions to maintain signal integrity and experimental consistency. Fourteen university students (seven male, seven female) aged between 18 and 21 years were recruited for the study and classified in accordance to their dominant learning modalities using the Felder-Silverman Learning Style Model (FSLSM), with verification through the established Index of Learning Styles (ILS) instrument [11]. The cohort was balanced between Active and Reflective learner classifications. During experimental sessions, participants engaged with Raven's Advanced Progressive Matrices (RAPM) assessment, completing 10 standardized problems selected to trigger distinct cognitive states [12,13]. Each problem trial comprised two-timed phases, with a 15-second period allocated for problem comprehension followed by a subsequent 15-second period for response generation. Continuous EEG monitoring was employed to document dynamic neural responses throughout the experiment.

2.2. EEG data acquisition

Brainwave data was collected by means of an OpenBCI Cyton headset equipped with eight electrodes positioned at standard scalp locations (Fp1, Fp2, O1, O2, F3, F4, C3, and C4) in accordance with the 10-20 international system. The signal preprocessing stage involved the implementation of a bandpass filter with a frequency range of 13-30 Hz to extract Beta frequency components, proven to correlate with cognitive processing and mental exertion [14,15]. The continuous recordings were partitioned into non-overlapping 1-second epochs, generating a dataset that was uniformly distributed for computational analysis. Each temporal segment was systematically labeled according to the participant's predetermined learning style classification (Active/Reflective), thereby maintaining data integrity for subsequent pattern recognition tasks.

A B

Fig. 1. Participants (A: male, B: female) performing RAPM tests with EEG recording setup to capture brain activity during cognitive tasks

The utilization of the OpenBCI EEG setup offered a balance between cost-efficiency and accuracy, capturing neural signals critical for studying cognitive processes. The setup adhered to the established protocols, as illustrated in Fig. 1, where participants were shown performing the RAPM test while EEG signals were recorded.

As portrayed in Fig. 1, two participants, a male and a female, underwent cognitive stimulation using the RAPM test, in which brain activity was recorded via an 8-channel EEG system using

OpenBCI. The participants were wearing EEG caps connected to electrodes strategically positioned to capture neural signals. The acquired neural signals were wirelessly transmitted to a processing unit for immediate analysis, enabling continuous observation of cortical dynamics throughout task performance. The RAPM test, a device utilized to evaluate abstract reasoning and problem-solving skills, challenged the cognitive abilities of participants, rendering it an ideal tool for studying brain function during complex tasks [16].

Table 1. Dataset summary

Number of participants	14 (7 Active, 7 Reflective)
Age range	18–21 years
EEG recording device	OpenBCI (8 channels)
Electrode placement system	Fp1, Fp2, F3, F4, C3, C4, O1, O2
Frequency range (bandpass filter)	13–30 Hz
Task	Raven's Advanced Progressive Matrices (RAPM)
Data segmentation	1-second intervals

This dataset is highly valuable for studying the relationship between EEG signals and learning styles. The high-quality EEG signals with well-annotated labels has made it ideal for developing machine learning models. Table 1 provides a summary of the dataset structure, including the number of participants, recording duration, learning tasks, and EEG channel configuration. The experimental protocol was conducted in accordance with the guidelines stipulated from previous studies on the detection of EEG-based learning style [17].

The utilization of an 8-channel OpenBCI setup highlights a balance between cost-efficiency and the capacity to acquire critical neural data [18,19] . This configuration is particularly effective for focused studies requiring manageable data volumes while maintaining high reliability. The findings from these investigations provide insights into of mental processing mechanisms, electrophysiological signatures, and their correlation with task-solving efficiency. Furthermore, this methodology has shown promising utility for creating neuroadaptive systems, learning enhancement technologies, and individualized mental skill development frameworks.

This objective of this study was to categorize learning styles into Active and Reflective based on the FSLSM through the analysis of by EEG signals. The experimental procedure comprised participant selection, EEG signal acquisition, feature extraction, and model training.

2.3. Participants and experimental design

The final study sample consisted of fourteen meticulously selected participants (aged 18-21 years, M=19.4, SD=0.8) undergoing rigorous screening with the Index of Learning Styles (ILS) questionnaire, yielding equal distribution between Active and Reflective learners (n=7 per group). The experimental sessions were conducted under standardized laboratory conditions to control environmental variables, employing established protocols that have previously validated the ILS as an effective tool for learning style classification.

2.4. Stimuli and EEG data acquisition

For cognitive assessment, RAPM, which is a gold-standard neuropsychological test with established reliability ($\alpha > 0.85$) and validity for measuring fluid intelligence, was administered. The RAPM's pattern-completion design specifically assesses two key dimensions: (1) non-verbal abstract reasoning and (2) complex problem-solving under time constraints, rendering it particularly sensitive to individual differences in higher-order cognitive processing among young adults. The protocol administered 10 test items using a standardized two-phase trial structure: a 15-second stimulus presentation period followed by a 15-second response interval per item. This temporal configuration, derived from evidence-based experimental designs, was implemented to maintain cognitive load within optimal parameters while mitigating mental exhaustion effects.

Neural signals were acquired via an 8-channel OpenBCI Cyton system with electrodes placed at standard 10-20 locations covering four primary cortical regions: frontal (Fp1, Fp2), prefrontal (F3, F4), sensorimotor (C3, C4), and visual processing areas (O1, O2). This optimized configuration enabled reliable capture of task-related brain activity while balancing spatial resolution with practical experimental constraints. This configuration provides comprehensive coverage of cortical areas involved in diverse cognitive processes while maintaining the practical benefits of mobile EEG technology. This optimized montage provides balanced hemispheric coverage of key cortical areas involved in higher cognitive functions while maintaining the practical advantages of portable EEG systems. This consumer-grade EEG technology has been empirically validated in multiple studies [7,17], demonstrating comparable signal quality to research-grade systems for cognitive monitoring applications, particularly in experimental paradigms requiring naturalistic participant movement and engagement.

The structure of this research focuses on detecting learning styles based on EEG data using a systematic and data-driven approach. The workflow, as illustrated in Fig. 2, starts with the collection of raw EEG signals from participants engaged in cognitive tasks designed to differentiate Active and Reflective learners. The EEG data undergo pre-processing steps, including bandpass filtering (13–30 Hz) to isolate Beta wave activity relevant to cognitive processes and slicing the signals into 1-second intervals for detailed analysis.

For feature extraction, the CUSUM algorithm was employed purposely to detect statistically significant transitions in EEG patterns corresponding to cognitive state changes. The resulting feature vectors were then partitioned into distinct training (70%) and testing (30%) subsets using stratified sampling to maintain balanced class distributions across both datasets. The training set is employed to construct a classification model using LDA, which is selected for its simplicity and efficiency in managing any small datasets [20,21]. The classification model is validated on the testing set, where the predicted outputs are aggregated using a majority voting mechanism to determine the participant's learning style as either Active or Reflective.

2.5. Research workflow

This structured approach ensures a balance between computational efficiency and classification accuracy. By leveraging well-established signal processing and machine learning techniques, this study addresses several primary challenges in detecting EEG-based learning style, as highlighted in prior studies [6,17].

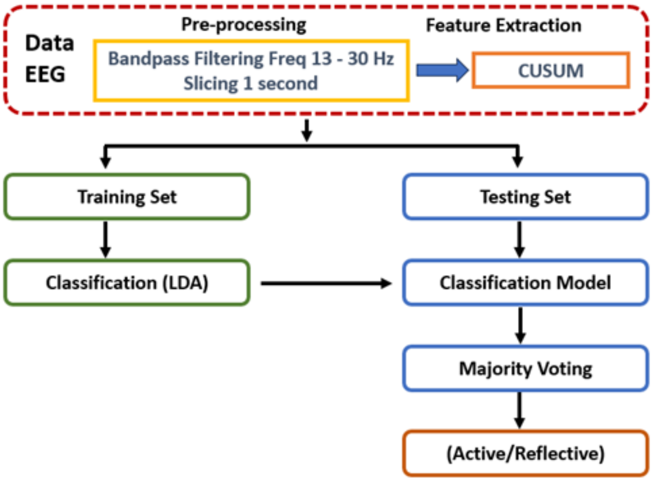

Fig. 2. Research workflow for EEG-based learning style classification, including pre-processing, feature extraction, classification, and majority voting

Fig. 2 illustrates the comprehensive analytical pipeline for the classification of EEG-based learning style (Active vs. Reflective). The workflow initiates with raw neural signals that undergo systematic pre-processing: (1) spectral filtering (13-30 Hz bandpass) to extract task-relevant beta-band oscillations, followed by (2) temporal segmentation into 1-second epochs to capture transient cognitive signatures. Subsequent to this, the refined data enters the feature extraction phase where the CUSUM algorithm identifies transition points, which are statistically significant in cognitive engagement levels. These discriminative features successively feed into the classification module, which employs a machine learning model trained to distinguish between the two learning modalities based on characteristic neural patterns.

Subsequent to the feature extraction, the dataset was divided into training (70%) and testing (30%) subsets by means of stratified sampling purposely to preserve class distribution. The training subset was utilized to develop the classification model, with LDA being employed for its efficacy demonstrated in neural pattern discrimination. Model performance was thoroughly evaluated on the held-out testing subset, with classification accuracy that served as the primary metric. The final output categorized each subject's learning style as either Active or Reflective based on their distinctive neurophysiological signatures. This end-to-end analytical pipeline transformed raw electrophysiological data into interpretable cognitive profiles, establishing a reliable methodology for personalized learning assessment.

As presented in Table 2, the subjects have been distributed according to two categories: gender (male and female) and learning styles (active and reflective). The number of female subjects exhibiting an Active learning style was found to be the highest, with a total of 5 subject, indicating dominance in this category. In contrast, the number of male subjects with an Active learning style was significantly limited (only 2). For the Reflective learning style, males dominated with 4 subjects, while females accounted for 3. Overall, the total number of subjects was 14, demonstrating a varied distribution of learning styles by genders.

Table 2. Distribution of subjects by gender (male and female) and learning style (active and reflective)

Gender	Class	Number
Male	Active	2
Female	Active	5
Male	Reflective	4
Female	Reflective	3
		14

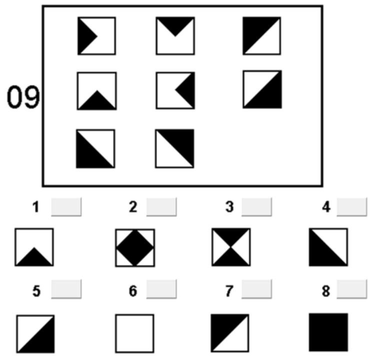

Fig. 3. Example questions from the Raven's advanced progressive matrices (RAPM) test

Fig. 3 displays a representative item from the RAPM assessment. The RAPM assessment is a psychometrically validated instrument frequently employed to evaluate higher-order cognitive functions including non-verbal abstract reasoning and complex problem-solving capacities. The primary grid contains a 3x3 matrix of patterns that adhere to a logical progression or rule. The task is purposely to determine the missing piece in the bottom-right corner by identifying the pattern or relationship among the given elements in rows or columns. The options numbered 1 to 8 represent possible answers, with only one fitting the logical sequence. The successful completion of these tasks demands the identification of spatial configurations, the inference of systematic connections among components, and the implementation of analytical cognition to arrive at accurate solutions. Such evaluative instruments specifically assess fluid cognitive capacity, expressing one's aptitude for adaptive logical thought and innovative problem-resolution when confronted with unfamiliar scenarios.

2.6. Data analysis technique

The data analysis in this research encompassed a multi-step process including pre-processing, feature extraction, and classification to accurately identify learning styles based on EEG signals. The pre-processing step incorporated the implementation of a bandpass filter (13–30 Hz) to isolate Beta waves, which are associated with cognitive engagement and problem-solving [22,23]. The filtered signals subsequently were segmented into 1-second intervals to ascertain uniformity and facilitate the detailed feature extraction.

This step is crucial to eliminate noise and artifacts, thereby enhancing the quality of the EEG signals for analysis. Feature extraction was performed utilizing the CUSUM method, which quantifies abrupt changes in the EEG signals [24,25]. CUSUM is mathematically defined as:

1. Change point density

$$D = N\_cp/W \quad (1)$$

N_{cp}: Number of change points in the time window
W: Length of the time window

2. Time between change points

$$T_{avg} = \frac{1}{N_{cp}-1} \sum_{i=1}^{N_{cp}-1} (t_{i+1} - t_i) \quad (2)$$

t_i: Time or index of the i-th change point
t_{i+1}: Time or index of the next change point
N_{cp}: Total number of change points in the window

3. Magnitude of change

M = 1/N_cp ∑_(i=1)^(N_cp)▒〖|μ_post (i)- μ_pre (i)|〗 (3)

μpost(i): Average value of segments after change point i
μpre(i): Average value of segments before change point i
Ncp: Total number of change points

4. CUSUM value

$$CUSUM_i = \sum_{j=1}^{i} (x_j - \mu) \quad (4)$$

xj: The value of the j-th observation
μ: The average (mean) or target value of the dataset
$CUSUM_{cp_i}$: The CUSUM value at the i-th change point

5. Duration of stable period

$$S = \frac{1}{N_{cp}-1} \sum_{i=1}^{N_{cp}-1} (t_{i+1} - t_i) \quad (5)$$

Ti: Time or index of the i-th change point
Ti+1: Time or index of the next change point
Ncp: Total number of change points

For pattern classification, the implementation of LDA emerges as a prominent approach. LDA refers to a parametric statistical method that projects feature vectors onto a hyperplane, with the purpose of maximizing between-class variance while minimizing within-class dispersion. This transformation yields an optimal decision boundary in a reduced-dimensional space, effectively separating the Active and Reflective learner categories based on their distinct neural signatures. The operation of this algorithm entails the calculation of hyperplanes that simultaneously maximize inter-class Euclidean distances and minimize intra-class scatters. This is accomplished through eigendecomposition of the feature covariance matrices, thereby achieving maximum class separability in the projected space. Mathematically, LDA aims to maximize the Fisher criterion.

The model's performance was rigorously evaluated through dual validation approaches: (1) a conventional hold-out method utilizing a stratified 70-30 train-test partition [17,26], and (2) exhaustive leave-one-out cross-validation (LOOCV) [7,27,28]. Each observation sequentially served as an independent test set. This combined evaluation strategy ensured both computational efficiency and robust estimation of generalization capability across different validation paradigms. In the Train-Test scheme, the dataset was divided into 70% for training and 30% for testing to assess performance on previously unnoticed data. LOOCV, on the other hand, provides a more rigorous and exhaustive validation method iteratively utilizing a single sample for testing while the model is trained on all remaining samples. Given the high inter-subject variability of the EEG signal, leave-one-out cross-validation is implemented to better capture the model’s generalization across different individuals [7]. This method is particularly effective for small datasets, as it maximizes the utilization of available data and minimize variance in the evaluation process. By ensuring that every data point is used once as a test case, LOOCV offers a robust estimate of the model’s generalization ability. It is expected that this will yield enhanced accuracy and more reliable performance metrics for the assessment of the efficacy of the proposed framework.

This method is consistent with earlier research that employed EEG data to categorize learning preferences [17,29]. In this study, the combination of robust feature extraction and classification techniques led to high accuracy while addressing computational challenges. This demonstrates the viability of EEG-based learning style detection.

The effectiveness of the EEG-driven learning style identification model was assessed through two key indicators: classification accuracy and standard deviation. Accuracy quantified the percentage of correctly predicted learning styles relative to the total number of samples.

The standard deviation was computed to evaluate the consistency of the model's results across various data partitions and cross-validation runs. Furthermore, the assessment examined performance on distinct data segments, including "Odd only" and "6–10," to analyze how varying data patterns influence classification precision.

These evaluation metrics aim to confirm the effectiveness of combining the CUSUM method for feature extraction and LDA for classification in EEG-based learning style detection. The system's combination of strong predictive accuracy and minimal fluctuation highlights its suitability for dynamic adaptive learning systems. Subsequent research could enhance the analysis protocol through the integration of supplementary measures such as precision, recall, and F1-score, thereby enabling a more thorough evaluation of model effectiveness.

3. Results and Discussion

The proposed CUSUM–LDA framework achieved an accuracy of 98.26% under the Train-Test evaluation scheme and further enhanced to 99.29% when assessed using LOOCV.

This high classification performance indicates that the CUSUM-based feature extraction effectively captures abrupt EEG signal variations associated with cognitive transitions between Active and Reflective learning styles.

The superior LOOCV result suggests strong generalization capability despite the limited dataset size, as each sample is iteratively tested against all remaining data, thereby reducing bias in performance estimation.

The findings demonstrate that lightweight statistical classifiers, when combined with appropriate feature extraction, can achieve a level of accuracy comparable to or exceeding that of significantly more complex deep learning approaches while maintaining computational efficiency. This then renders the proposed method suitable for real-time and resource-constrained educational applications.

The detailed classification accuracy for each participant under the LOOCV scheme is presented in Table 3.

Table 3. EEG Classification Accuracy per Subject Using Leave-One-Out Cross-Validation (LOOCV)

Train	Test	All	Odd	Even	1-5	6-10
N-S1	S1	100	100	100	80	100
N-S2	S2	100	100	100	100	100
N-S3	S3	100	90	100	100	100
N-S4	S4	100	100	100	80	100
N-S5	S5	95	100	100	80	100
N-S6	S6	100	100	100	100	80
N-S7	S7	100	100	100	100	100
N-S8	S8	95	100	90	60	100
N-S9	S9	100	90	100	100	100
N-S10	S10	100	100	100	100	100
N-S11	S11	100	90	100	100	100
N-S12	S12	100	100	100	100	100
N-S13	S13	100	100	90	100	100
N-S14	S14	100	100	100	100	100
	Avg	99.29	97.86	98.58	92.86	98.57
	Stdev	1.75	4.10	3.5	12.21	5.15

An analysis of different data subsets revealed notable performance variations across configurations. Of all evaluated subsets, the Odd-only subset achieved the highest classification accuracy of 99.24%, outperforming other subsets such as the 6–10 configuration.

This performance difference may be associated with variations in cognitive load and problem structure within the RAPM tasks, where certain item sequences could elicit more consistent reasoning strategies and EEG patterns.

Odd-indexed RAPM items may induce more stable cognitive engagement, thereby enhancing the discriminative capability of CUSUM-based features.

However, given that the difficulty level of individual RAPM items was not explicitly controlled in this study, these findings should be interpreted with caution and are acknowledged as a limitation, warranting further investigation in future work with controlled task difficulty.

A summary of classification accuracy across different data subset configurations is provided in Table 4.

Table 4. Accuracy results for different data subsets using the CUSUM method and LDA classifier

Number	Accuracy (%)
All	98.48
Odd-only	99.24
Even-only	98.46
1 – 5	98.39
6 – 10	96.77
Average	98.27
Stdev	0.81

When compared with existing approaches such as 1-DCNN and TSMG, the proposed CUSUM–LDA framework consistently demonstrated superior classification performance across all evaluation metrics.

Though direct numerical comparisons should be interpreted cautiously due to differences in datasets, EEG acquisition devices, and experimental protocols, the observed performance gains indicate that effective feature extraction plays a crucial role in learning style discrimination.

Contrasting to deep learning-based methods, which require large datasets and extensive computational resources, the proposed approach leverages interpretable statistical features and a lightweight classifier, enabling high accuracy with minimal computational overhead.

These findings suggest that simpler and more transparent models can rival, and in some cases outperform, complex deep learning architectures, particularly in scenarios involving limited data availability and real-time educational applications.

Table 5 provides a summary of a comparative performance overview between the proposed method and previously published EEG-based learning style detection approaches.

Table 5. Performance comparison of the proposed method with previous studies on EEG-based learning style detection

Method	Train-Test (%)	LOOCV (%)
[17] 1-DCNN	71.2	-
[7] TSMG	72.35	72.65 ± 2.9
Proposed	98.27	99.29 ± 1.75

Overall, the experimental results and comparative analyses demonstrated that the proposed CUSUM–LDA framework has the potential to offer an effective, accurate, and computationally efficient solution for EEG-based learning style detection. The method has been shown to consistently outperform both conventional and deep learning-based approaches under limited data conditions. This highlights the importance of appropriate feature extraction and model interpretability in educational signal processing. The findings in this study provide a robust basis for summarizing the key contributions of this study and outlining future research directions, as discussed in the subsequent conclusion.

4. Conclusion

This present study investigated the utilization of EEG signals for learning style detection based on FSLSM, with a specific focus on the Active and Reflective dimensions. EEG data were collected from 14 participants by means of an 8-channel OpenBCI device during cognitively demanding tasks based on RAPM and processed using bandpass filtering and 1-second segmentation. Feature extraction was performed utilizing the CUSUM algorithm, followed by classification with LDA. The proposed CUSUM–LDA framework demonstrated strong performance, achieving an accuracy of 98.26% under the Train-Test scheme and 99.29% using LOOCV, consistently outperforming previous approaches such as 1-DCNN and TSMG. These findings highlight the robustness, computational efficiency, and practical applicability of the proposed method, indicating that EEG-based learning style assessment provides a quantitative and empirically grounded alternative to conventional self-report instruments and supports the development of personalized adaptive learning systems. Nevertheless, this study is limited by the relatively small sample size and its focus on a single FSLSM dimension. It is recommended that future work involve larger and more diverse participant populations, explore additional learning style dimensions, and integrate real-time EEG processing and classification mechanisms to enhance generalizability and enable practical deployment in adaptive educational technologies.

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Data Availability

The EEG dataset collected and analyzed during this study is currently not publicly available, but it can be obtained from the corresponding author upon reasonable request.

Conflict of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

Author Contribution

The following section details the contribution of the authors. Conceptualization and formal analysis were undertaken by RP and NAS. Furthermore, RP oversaw conducting the data curation, visualization, writing original draft and software development. RP, TBA, and NAS were responsible for conducting investigation, and writing—review & editing. Funding acquisition was undertaken by NAS; and project administration was conducted by TBA. Finally, TBA and NAS were responsible for managing the validation of this research. All authors have read and approved the published version of the manuscript.

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