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A web-based system to support autism spectrum disorder screening using EEG analysis and machine learning

Um sistema web para suporte ao rastreamento do transtorno do espectro autista usando análise de EEG e aprendizado de máquina

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ABSTRACT

Introduction: Diagnosing Autism Spectrum Disorder (ASD) remains challenging, particularly in resource-limited settings. Clinical Decision Support Systems (CDSS) offer a promising strategy to enhance healthcare delivery. **Objective:** To present MONAN, a web-based CDSS for ASD screening using electroencephalographic (EEG) signals. **Method:** The methodological architecture prioritizes computational modularity, signal processing traceability, and experimental reproducibility. A J48 algorithm-based classifier was developed using a dataset of 62 individuals. **Results:** The classifier achieved 99.40% accuracy and a kappa statistic of 0.9882, with consistent performance in the validation subset. **Conclusion:** These findings demonstrate the model's strong discriminative capacity in distinguishing ASD from control groups based on neurophysiological features extracted from EEG signals.

Keywords: Signal Processing; Computer-Assisted; Autism Spectrum Disorder; Machine Learning.

RESUMO

Introdução: O diagnóstico do Transtorno do Espectro Autista (TEA) permanece desafiador, especialmente em cenários com recursos limitados. Sistemas de Suporte à Decisão Clínica (SSDC) oferecem uma estratégia promissora para aprimorar a prestação de cuidados à saúde. **Objetivo:** Este estudo apresenta o MONAN, um SSDC baseado na web para rastreamento de TEA a partir de sinais eletroencefalográficos (EEG). **Método:** A arquitetura metodológica prioriza a modularidade computacional, a rastreabilidade do processamento de sinais e a reprodutibilidade experimental. **Resultados:** Utilizando um conjunto de dados de 62 indivíduos, o classificador baseado no algoritmo J48 alcançou 99,40% de acurácia e estatística kappa de 0,9882, com desempenho consistente no conjunto de validação. **Conclusão:** Esses achados demonstram a forte capacidade discriminativa do modelo em diferenciar o TEA de grupos controle com base em características neurofisiológicas extraídas de sinais de EEG.

Descritores: Processamento de Sinais Assistido por Computador; Transtorno do Espectro Autista; Aprendizado de Máquina.

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1 INTRODUCTION

Autism Spectrum Disorder (ASD) is a neurodevelopmental condition characterized by persistent alterations in social communication, restricted patterns of behavior, and heterogeneous sensory manifestations, presenting with varying levels of support needs and functional impairment [1]. In recent decades, the rising prevalence of the disorder has substantially increased the demand for more accessible, rapid diagnostic strategies capable of facilitating the early identification of neurofunctional alterations associated with ASD [2].

Despite advances in clinical and neuropsychological instruments employed in the diagnostic process, ASD diagnosis continues to rely predominantly on behavioral assessments conducted by specialized multidisciplinary teams [3,4]. This scenario renders the diagnostic process frequently time-consuming, susceptible to inter-rater variability, and dependent on the availability of qualified professionals, challenges that are particularly pronounced in resource-limited settings and public health systems [5,6].

In this context, artificial intelligence techniques applied to biomedical signal analysis have been investigated as complementary tools to support clinical decision-making [7,8]. Among the neurophysiological signals utilized in these approaches, electroencephalography (EEG) stands out due to its non-invasive nature, relatively low cost, and high temporal resolution, enabling dynamic analysis of cerebral electrical activity.

Recent studies have demonstrated that features extracted from EEG signals may capture neurophysiological patterns potentially associated with ASD [9-11]. When integrated with machine learning algorithms, these characteristics enable the development of computational systems capable of distinguishing between individuals with ASD and neurotypical controls.

Against this backdrop, this study aims to develop a prototype of the MONAN system, a computational framework designed to support Autism Spectrum Disorder screening through automated electroencephalographic signal analysis and machine learning techniques. The proposed approach integrates neurophysiological preprocessing, automated feature extraction, supervised classification, and the generation of interpretive reports within a structured web-based environment.

1.1 Related Work

Diverse approaches have been investigated to support Autism Spectrum Disorder (ASD) diagnosis, including eye-tracking, genetic biomarkers, electroencephalographic (EEG) signals, and wearable devices integrated with artificial intelligence [12,13]. Wei *et al.* (2024) employed eye-tracking combined with machine learning algorithms in a sample of 449 children, achieving optimal performance with random forest (76.9% accuracy) [14]. Ahmed *et al.* (2022) also utilized eye-tracking, applying spatial image analysis and artificial neural networks to reach 99.8% accuracy, albeit with limitations related to small sample size [15].

In the genomics domain, Tang *et al.* (2023) investigated genetic biomarkers using deep neural networks applied to gene expression analysis, achieving accuracy up to 85%, though constrained by operational costs and the clinical heterogeneity of the autism spectrum [16]. Within the neurophysiological domain, Hafeez *et al.* (2026) applied advanced feature extraction and selection techniques to resting-state EEG signals, employing classifiers such as SVM-RBF, random forest, and multilayer perceptron to achieve 100% accuracy; however, the authors noted potential overfitting and the absence of external validation [17].

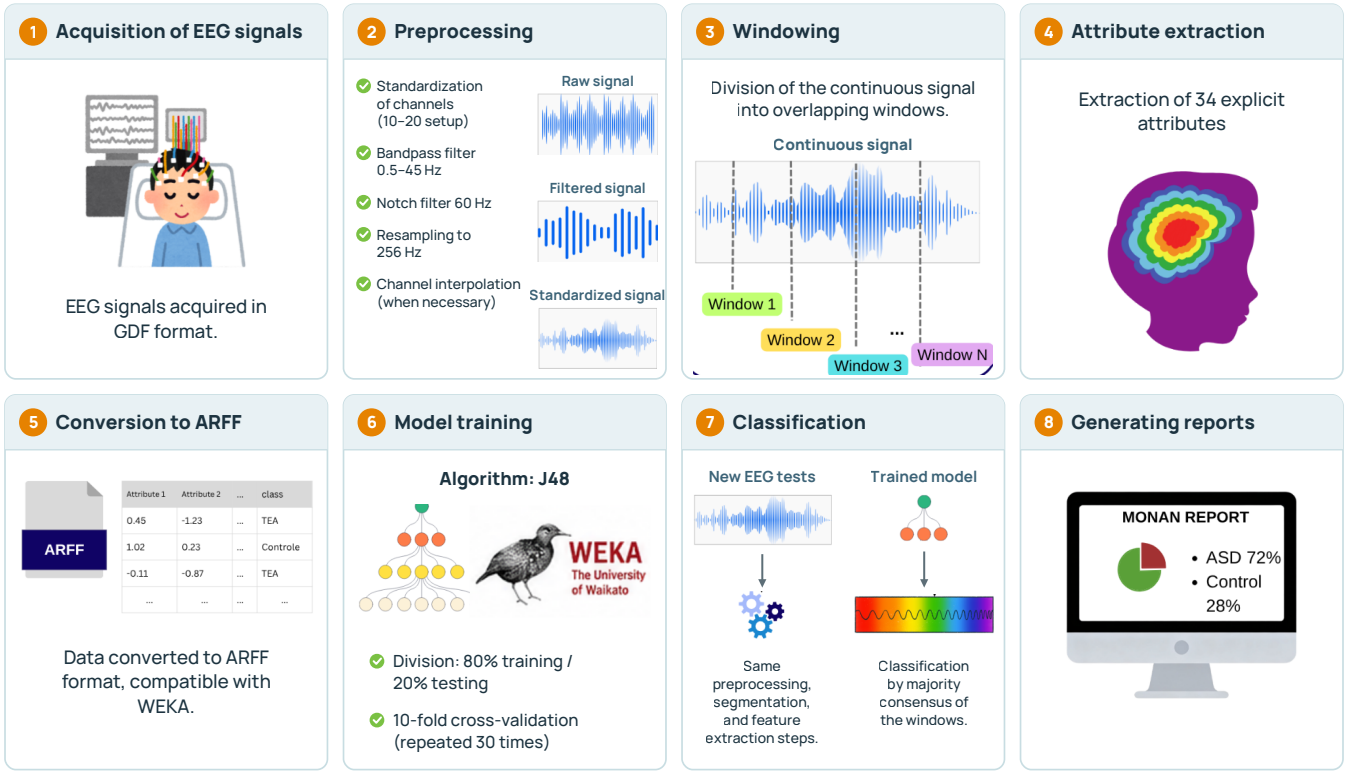
Seeking greater accessibility and portability, Sheeraz *et al.* (2024) developed an ear-worn wearable device for continuous EEG acquisition integrated with shallow neural networks for real-time identification of ASD-compatible patterns [18]. Complementarily, Alhassan *et al.* (2023) proposed a low-power embedded model for EEG analysis using machine learning, achieving accuracy exceeding 95% [19]. Despite these promising results, existing studies still present limitations related to sample size, model generalization, and clinical validation, underscoring the need for more robust and accessible research endeavors.

2 METHODS

This study proposes the development of MONAN, a computational system designed to support Autism Spectrum Disorder screening through the automated processing of electroencephalographic (EEG) signals and the application of supervised machine learning techniques. The methodological architecture was designed to ensure computational modularity, traceability of signal processing, and experimental reproducibility, essential attributes for applications in health informatics and clinical decision support systems. In this context, MONAN is presented as a proof-of-concept computational prototype, aiming to demonstrate the feasibility of integrating EEG processing, machine learning-based classification, and web-based visualization of results. Further studies will be required to evaluate usability, security, performance, and applicability in real clinical scenarios.

Figure 1 provides an overview of the methodology proposed in this study.

Figure 1. Flowchart of the proposed method.



Source: Prepared by the authors (2026).

2.1 System Architecture and Development

The system was developed using the Python programming language and the Django framework, enabling the implementation of a web-based architecture designed for the management of electroencephalographic (EEG) examinations, persistent storage of analytical outputs, and structured delivery of results via a dedicated web interface.

The computational architecture was organized modularly, with clear separation between the stages of neurophysiological preprocessing, feature extraction, supervised training, automated classification, and interpretive report generation.

EEG signal processing routines were implemented using specialized scientific libraries tailored for neurophysiological analysis and numerical computation. For the supervised machine learning pipeline, the Weka environment was employed, integrated into the system via a command-line interface (CLI) to automate the training, validation, and classification routines for EEG examinations.

Additionally, the system incorporates mechanisms for full traceability of analytical procedures, centralized management of submitted examinations, and persistent storage of processed results.

2.2 Data Acquisition and Organization

The electroencephalographic signals used in this study were organized into a dataset comprising recordings from individuals with Autism Spectrum Disorder and neurotypical controls. The experimental dataset was constructed by integrating two distinct data subsets derived from the study by Duville *et al.* (2023) [20]. In total, the dataset included 62 participants, equally distributed between the two study groups. The dataset consisted exclusively of anonymized EEG recordings and did not include any personally identifiable information, such as names, addresses, identification numbers, or other sensitive personal data. Likewise, no demographic or clinical metadata beyond the information required for the classification task were made available to the authors. Consequently, this study was conducted using anonymized secondary data from a publicly available dataset, without any direct interaction with human participants. The ethical procedures, including approval by the appropriate ethics committee and informed consent from participants, were conducted by the authors of the original study, as described in the source publication [20].

Examinations were stored in formats compatible with the General Data Format (GDF) standard, ensuring interoperability with specialized neuroscientific libraries for biomedical signal processing. However, due to structural differences between the original datasets, including varying sampling rates and differing numbers of electrodes, a standardization procedure was required to harmonize the EEG channels used across experiments.

To ensure compatibility between the datasets, only 14 EEG channels distributed across frontal, central,

temporal, and parietal regions were selected: P3, C3, P4, F7, T7, P8, Pz, F4, T8, F3, Fz, Cz, C4, and FP1. The selection of these channels considered both anatomical compatibility across datasets and the neurophysiological relevance of these regions in ASD-related research, particularly in investigations involving brain connectivity, social processing, attention, and sensory integration [9-11].

Signals were organized in a structured manner, enabling persistent storage of examinations, traceability of performed analyses, and direct integration with the automated classification mechanisms implemented in the MONAN system.

2.3 EEG Signal Preprocessing

EEG preprocessing was performed using the MNE-Python library. Initially, signals underwent channel nomenclature standardization and automatic application of an electroencephalographic montage based on the international 10–20 system. Subsequently, a band-pass filter ranging from 0.5 Hz to 45 Hz was applied to attenuate low-frequency components associated with signal drift and slow oscillations, as well as to suppress high-frequency artifacts related to muscle activity and electromagnetic interference.

A 60 Hz notch filter was also employed to mitigate power-line interference. Following filtering, signals were resampled to a fixed sampling rate of 256 Hz, ensuring temporal uniformity across examinations regardless of their original acquisition frequency.

To minimize inconsistencies arising from missing channels in certain recordings, the system incorporated automated spatial interpolation mechanisms leveraging topographic information from EEG electrode positioning. This strategy enhanced system robustness in handling the heterogeneity of processed examinations [9-11].

After preprocessing, EEG signals were segmented into 1-second windows with 0.5-second overlap. This approach aimed to increase sample density and improve sensitivity to subtle electrophysiological microvariations present in cerebral signals, thereby enabling the transformation of continuous recordings into multiple independent instances for model training.

Each window was processed individually, allowing for localized extraction of neurophysiological patterns over time. This methodology ensured an expanded number of training instances, thereby facilitating supervised learning from distributed local patterns across EEG examinations. Although each window corresponds to a distinct temporal segment of the EEG signal, windows originating from the same participant may still share subject-specific electrophysiological characteristics. Consequently, the adopted window-level partitioning strategy may provide a more optimistic estimate of the classifier's performance when compared with subject-level validation protocols. Nevertheless, window-based analysis was adopted in this study because the proposed framework was designed to learn local temporal patterns from EEG recordings. Future studies will investigate subject-level partitioning, in which participants are assigned to the training and testing sets prior to signal segmentation, ensuring that all windows from the same individual remain exclusively within a single subset and enabling a more rigorous assessment of the model's generalization capability.

Figure 2 illustrates the windowing and feature extraction process.

2.4 Feature Extraction

For each segmented EEG window, an automated process was implemented to extract statistical, temporal, and spectral attributes, aiming to achieve a quantitative representation of the neurophysiological characteristics present in the electroencephalographic signals.

In total, 34 explicit features were extracted for each EEG channel analyzed. The extracted attributes encompass descriptive statistical measures, spectral parameters, and neurophysiological descriptors widely employed in EEG analyses, including mean, standard deviation, variance, minimum and maximum amplitude, signal energy, spectral entropy, skewness, kurtosis, and Hjorth parameters.

Additionally, measures related to the spectral distribution of the signal across the delta, theta, alpha, beta, and gamma frequency bands were computed, enabling quantitative characterization of cerebral oscillations across distinct frequency ranges.

Each EEG channel generated a specific set of numerical attributes, forming multivariate feature vectors subsequently used as input for the supervised classification algorithm. The extracted features were organized in the Attribute-Relation File Format (ARFF), ensuring structural standardization of the data employed during the supervised training and classification stages.

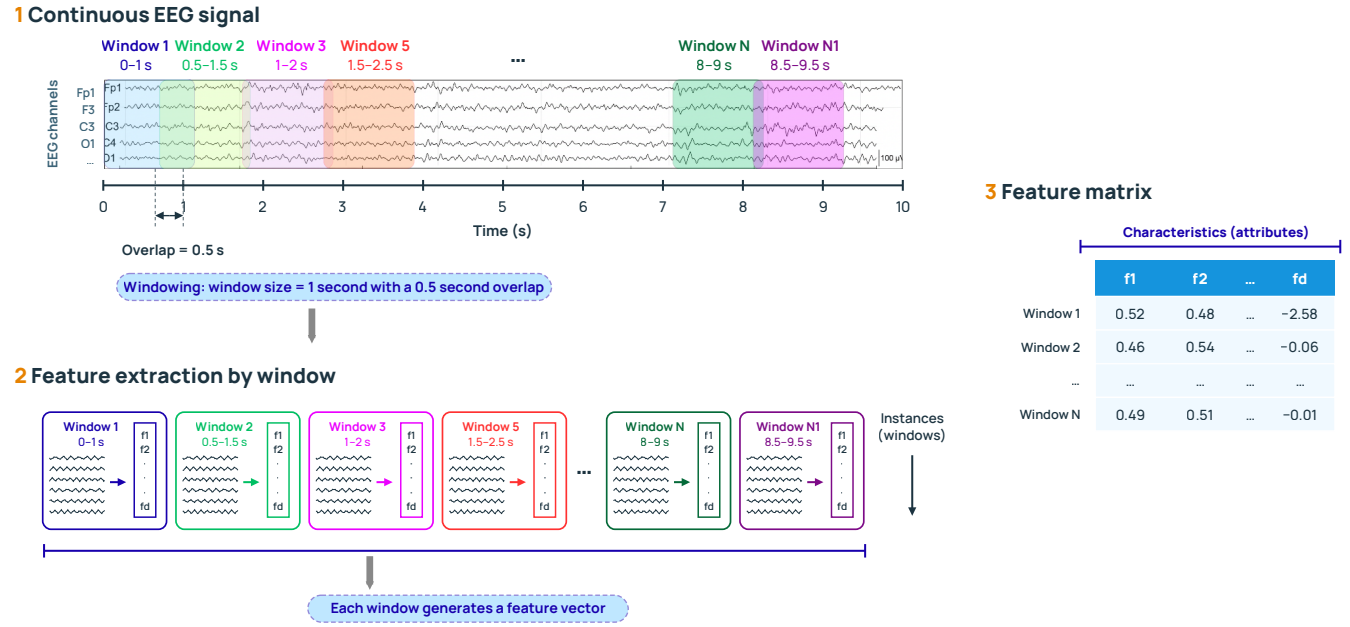
2.5 Model Training and Testing

Model training was conducted using the J48 algorithm, Weka's implementation of the C4.5 decision tree. This algorithm was selected due to the structural interpretability inherent to decision trees, a feature of particular relevance in clinical decision support applications.

Initially, the dataset was randomized and partitioned into independent training/validation (80%) and testing (20%) subsets. During model selection, stratified 10-fold cross-validation repeated across 30 independent

runs was applied to the training subset to evaluate statistical stability and classifier performance across

Figure 2. Representation of the temporal segmentation process (windowing) of EEG signals with 0.5-s overlap, feature extraction per window, and construction of the attribute matrix for supervised training of machine learning models.



Source: Prepared by the authors (2026).

varying data distributions.

Following cross-validation, the selected model was retrained on the complete training subset and subsequently evaluated on the independent test set, which was reserved exclusively for final performance validation. Classifier performance was assessed using standard classification metrics, including accuracy, Cohen's Kappa statistic, area under the receiver operating characteristic curve (AUC-ROC), sensitivity, and specificity. Results from each experimental run were automatically logged by the system, ensuring full traceability of analyses and enabling comparative assessment of classifier performance across validation iterations.

Upon completion of validation, the finalized model was serialized and integrated into the system architecture to enable automated classification of incoming electroencephalographic examinations.

2.6 Classification

During the classification phase, newly submitted EEG examinations undergo the same neurophysiological preprocessing, temporal segmentation, and feature extraction procedures employed during supervised model training.

Each EEG window is classified independently by the trained model, generating individual votes for either the ASD or control class. The final examination outcome is determined by a majority voting rule across all processed windows.

In addition to the final classification, the system automatically generates interpretive reports detailing quantitative information regarding the distribution of votes between classes, the consensus percentage achieved during classification, and performance metrics associated with the supervised model.

The experiments conducted in this study were structured at the instance level, with each instance derived from segmented EEG windows. This approach enabled the expansion of the sample pool utilized for training and validating the supervised classifier.

3 RESULTS

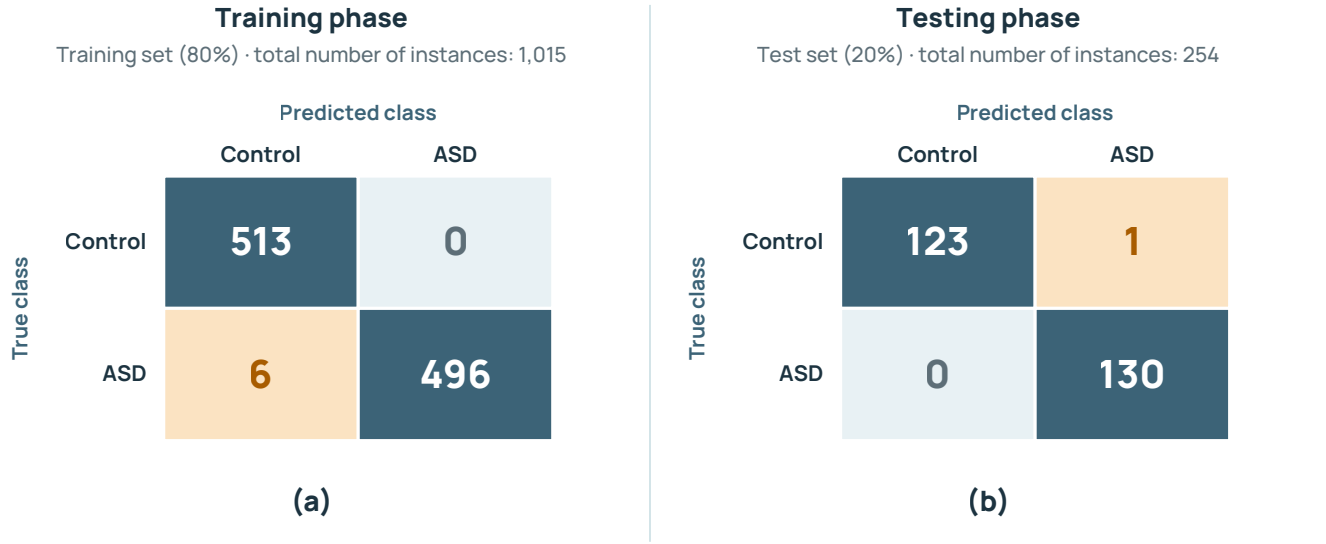
The experiments conducted in this study demonstrated the computational feasibility of using electroencephalographic (EEG) signals combined with supervised machine learning techniques to support Autism Spectrum Disorder (ASD) screening.

Model training was performed using the J48 algorithm, without applying artificial data oversampling techniques, as the dataset already exhibited a balanced distribution between ASD and control classes. The dataset was initially randomized and subsequently partitioned into independent training (80%) and testing (20%) subsets, totaling 1,015 instances allocated for model training and 254 instances reserved for independent validation.

Considering the global mean across the 30 experimental runs, the model achieved an accuracy of 99.40%, Cohen's Kappa statistic of 0.9882, mean area

under the ROC curve (AUC-ROC) of 0.997, sensitivity of 98.80%, and specificity of 100.00%.

Figure 3. Confusion matrices of the J48 model during the training and testing phases.



Source: Prepared by the authors (2026).

The obtained results evidence the model's strong discriminative capacity in differentiating between ASD and control groups based on neurophysiological features extracted from EEG signals. Statistical stability was observed across cross-validation iterations, with minimal variation in performance metrics throughout the experimental runs, indicating consistent classifier behavior.

The confusion matrices corresponding to the training and testing phases are presented in Figure 3.

As shown in Figure 3a, which corresponds to the training phase, the model correctly classified 513 instances belonging to the control class and 496 instances belonging to the ASD group. Only six misclassifications were observed, wherein ASD instances were incorrectly labeled as control; no false positives associated with the control class were recorded.

In the evaluation performed on the independent validation subset comprising 20% of the samples, which was executed as a single run, the model achieved an accuracy of 99.60%, Cohen's Kappa statistic of 0.9921, ROC area of 0.996, sensitivity of 100.00%, and specificity of 99.19%.

The confusion matrix presented in Figure 3b demonstrates that the model correctly classified 123 instances belonging to the control class and all 130 instances belonging to the ASD group. Only one misclassification was observed, involving a control instance incorrectly labeled as ASD.

The quantitative results obtained suggest that the model exhibits high capacity for identifying statistical and spectral patterns potentially associated with the neurophysiological alterations present in the analyzed electroencephalographic signals.

Beyond the experimental validation of the J48 classifier, the MONAN web system demonstrated adequate functionality during computational integration testing, enabling automation of EEG examination upload, signal conversion to ARFF format, execution of supervised classifications, and automatic generation of interpretive reports.

The system's main interface allows submission of electroencephalographic examinations in formats compatible with the General Data Format (GDF) standard, automatically organizing and preparing the data for processing. Following upload, the system executes the signal preprocessing stages, neurophysiological feature extraction, and supervised classification using the previously trained model.

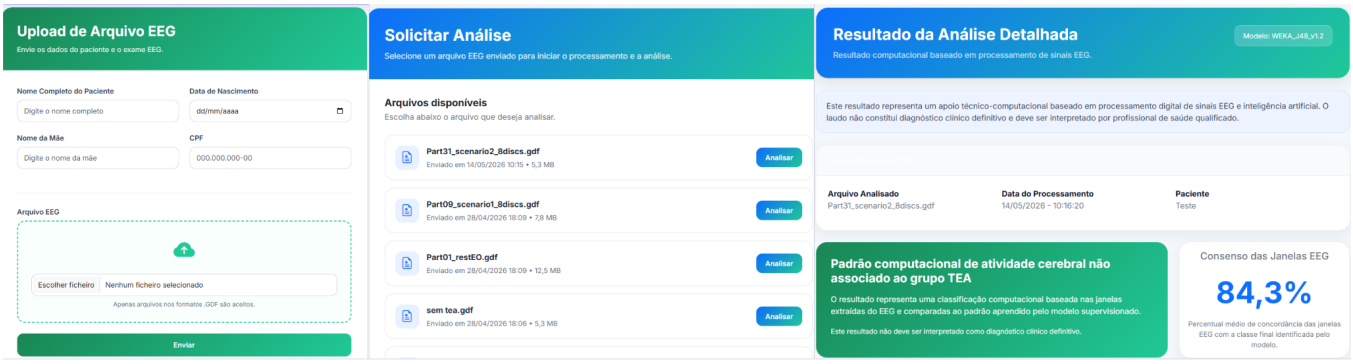
During processing, the system displays real-time information regarding analysis progress, enabling users to monitor the computational steps being executed. Upon completion of classification, results are presented in a structured format, including the final predicted class, vote distribution between ASD and control, and performance metrics associated with the supervised model.

Additionally, the system automatically generates interpretive reports containing textual descriptions of the obtained results, contributing to the organized documentation of information produced during electroencephalographic analysis.

The developed interfaces demonstrated seamless integration among the neurophysiological processing,

machine learning, and results visualization modules within a structured web-based environment.

Figure 4. MONAN system interfaces.



(A) Upload of EEG exams. **(B) Automated processing and classification** **(C) Visualization of results**

Source: Prepared by the authors (2026).

4 DISCUSSION

The obtained results demonstrate the potential of combining electroencephalographic signal processing techniques with machine learning to provide computational support for Autism Spectrum Disorder (ASD) screening. The high values observed for accuracy, ROC area, sensitivity, specificity, and Cohen's Kappa statistic during validation stages indicate strong discriminative capacity of the model in differentiating between ASD and control groups.

The confusion matrices further reinforce these findings by revealing a low number of misclassifications between the analyzed classes, suggesting that the statistical and spectral attributes extracted from EEG signals were capable of representing neurophysiological features relevant to the supervised classification process. Moreover, the stability observed across the 30 independent cross-validation runs indicates statistical consistency of the implemented approach within the studied dataset.

From a clinical perspective, the observed results suggest that computational approaches based on EEG signals may eventually contribute as auxiliary tools in ASD screening processes, particularly in settings with limited specialist availability or high diagnostic demand. The ability to automatically obtain quantitative information derived from cerebral activity may serve as a complementary support to traditional clinical assessment, aiding in the initial identification of neurophysiological patterns potentially associated with ASD.

However, the presented results should be interpreted in light of the methodological characteristics of the experimental dataset used, which comprises a public repository with a limited number of participants. Furthermore, the experiments were conducted using instances derived from segmented EEG windows, an aspect that may partially influence the observed performance metrics. Therefore, future investigations involving patient-level validation and broader multicenter datasets may contribute to a more comprehensive assessment of the clinical generalizability of the proposed approach.

From a computational standpoint, the results also validate the developed architecture, demonstrating appropriate integration among neurophysiological processing, data mining, and web-based applications designed for clinical decision support. The use of the J48 algorithm proved suitable for the experimental context, particularly due to its structural interpretability and low computational cost, features of particular relevance in health informatics applications.

Thus, although the obtained results are promising as evidence of the computational feasibility of the proposed approach, additional studies involving patient-level validation, multicenter datasets, and larger samples remain necessary to more robustly investigate the clinical generalizability of the supervised model.

Nevertheless, the presented findings demonstrate the potential of the proposed solution as an experimental tool for computational support in neurophysiological analysis and health screening, contributing to research on the application of artificial intelligence in biomedical informatics.

5 CONCLUSIONS

This study presented the development of a computational system designed to support Autism Spectrum Disorder screening through the integration of electroencephalographic signal processing, supervised machine learning, and web-based applications tailored for health informatics.

The developed architecture enabled automation of neurophysiological preprocessing, feature extraction, classification, and interpretive report generation to support clinical decision-making by responsible professionals. Experimental results demonstrated the supervised model's high discriminative capacity in differentiating between ASD and control groups, evidencing the computational feasibility of the proposed approach.

Beyond the computational outcomes achieved, the developed proposal reinforces the potential of health informatics in constructing auxiliary tools capable of contributing to the organization, traceability, and support of neurophysiological analysis in clinical contexts. The application of automated methods to EEG may facilitate future strategies for screening support and monitoring of individuals with suspected neurodevelopmental alterations, particularly in settings characterized by high healthcare demand.

Although this study presents limitations related to validation at the level of segmented instances, the obtained results demonstrate the potential of the proposed solution as an experimental tool for computational support in neurophysiological analysis. For future work, we recommend expanding the dataset, conducting patient-level validation, and investigating more advanced machine learning approaches applied to EEG signal analysis.

Author contributions. The authors contributed equally to all stages of the article: conception and design of the study; data collection, analysis, and interpretation; drafting and critical revision of the manuscript; and approval of the final version.

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REFERENCES

1. Lord C, Brugha TS, Charman T, Cusack J, Dumas G, Frazier T, et al. Autism spectrum disorder. Nat Rev Dis Primers. 2020;6(1):5. doi: https://doi.org/10.1038/s41572-019-0138-4
2. Bosetti C, Ferrini L, Ferrari AR, Bartolini E, Calderoni S. Children with Autism Spectrum Disorder and Abnormalities of Clinical EEG: A Qualitative Review. J Clin Med. 2024;13(1):279. doi: https://doi.org/10.3390/jcm13010279
3. Bishop SL, Lord C. Commentary: Best practices and processes for assessment of autism spectrum disorder - the intended role of standardized diagnostic instruments. J Child Psychol Psychiatry. 2023;64(5):834-8. doi: https://doi.org/10.1111/jcpp.13802
4. Kim JI, Yoo HJ. Diagnosis and Assessment of Autism Spectrum Disorder in South Korea. J Korean Acad Child Adolesc Psychiatry. 2024;35(1):15-21. doi: https://doi.org/10.5765/jkacap.230009
5. Brian JA, Zwaigenbaum L, Ip A. Standards of diagnostic assessment for autism spectrum disorder. Paediatr Child Health. 2019;24(7):444-60. doi: https://doi.org/10.1093/pch/pxz117
6. Smith-Young J, Chafe R, Audas R. "Managing the Wait": Parents' Experiences in Accessing Diagnostic and Treatment Services for Children and Adolescents Diagnosed With Autism Spectrum Disorder. Health Serv Insights. 2020;13:1178632920902141. doi: https://doi.org/10.1177/1178632920902141
7. Silva de Oliveira AP, de Lima CT, de Souza GM, de Oliveira Silva AS, Queiroz Ribeiro AL, Martinez Accioly AR, et al. GeronGnosis: a database for diagnosing dementias using EEG and machine learning. Res. Biomed. Eng. 2026;42(2):29. doi: https://doi.org/10.1007/s42600-026-00477-z
8. de Lima CT, de Lima Simões CM, Dos Santos WO, Lins CS, Bezerra Cavalcanti JPC, de Oliveira Silva AS, et al. Emotion Recognition from Electroencephalogram Signals of Subjects with Dementia: the impact of feature selection by PSO on classification performance. In: 2025 IEEE Latin American Conference on Computational Intelligence (LA-CCI). [place unknown]: IEEE; 2025. p. 1-6. doi: https://doi.org/10.1109/la-cci66231.2025.11270434
9. de Oliveira Silva AS, Fonseca FS, Muniz MVS, de Melo AMN, Machado WG, de Santana MA, et al. Enhancing ASD Diagnosis with Low-Density EEG and Machine Learning. In: IFMBE Proceedings. Cham: Springer Nature Switzerland; 2025. p. 451-61. doi: https://doi.org/10.1007/978-3-031-94934-0_47
10. Fonseca F, Silva A, Muniz M, de Oliveira C, de Melo A, Passos M, et al. Supporting ASD Diagnosis with EEG, ML and Swarm Intelligence: Early Detection of Autism Spectrum Disorder Based on Electroencephalography Analysis by Machine Learning and Swarm Intelligence. AI Sensors. 2025;1(1):3. doi: https://doi.org/10.3390/aisens1010003

11. Fonseca FS, de Oliveira Silva AS, Da Silva MEA, Muniz MVS, de Melo AMN, Machado WG, et al. Development of an Electrode Reduction Model to Support ASD Diagnosis Based on EEG and Machine Learning. In: 2024 IEEE Latin American Conference on Computational Intelligence (LA-CCI). [place unknown]: IEEE; 2024. p. 1-6. doi: https://doi.org/10.1109/la-cci62337.2024.10814856

12. Hus Y, Segal O. Challenges Surrounding the Diagnosis of Autism in Children. Neuropsychiatr Dis Treat. 2021;17:3509-29. doi: https://doi.org/10.2147/NDT.S282569

13. Han J, Jiang G, Ouyang G, Li X. A Multimodal Approach for Identifying Autism Spectrum Disorders in Children. IEEE Trans Neural Syst Rehabil Eng. 2022;30:2003-11. doi: https://doi.org/10.1109/TNSRE.2022.3192431

14. Wei Q, Dong W, Yu D, Wang K, Yang T, Xiao Y, et al. Early identification of autism spectrum disorder based on machine learning with eye-tracking data. J Affect Disord. 2024;358:326-34. doi: https://doi.org/10.1016/j.jad.2024.04.049

15. Ahmed IA, Senan EM, Rassem TH, Ali MAH, Shatnawi HSA, Alwazer SM, et al. Eye Tracking-Based Diagnosis and Early Detection of Autism Spectrum Disorder Using Machine Learning and Deep Learning Techniques. Electronics. 2022;11(4):530. doi: https://doi.org/10.3390/electronics11040530

16. Tang H, Liang J, Chai K, Gu H, Ye W, Cao P, et al. Artificial intelligence and bioinformatics analyze markers of children's transcriptional genome to predict autism spectrum disorder. Front Neurol. 2023;14:1203375. doi: https://doi.org/10.3389/fneur.2023.1203375

17. Hafeez N, Aslam AR, Altaf MAB. Biomarker Discovery for Autism Prediction Using Massive Feature Extraction Based on EEG Signals. Sensors (Basel). 2026;26(6):1862. doi: https://doi.org/10.3390/s26061862

18. Sheeraz M, Aslam AR, Drakakis EM, Heidari H, Altaf MAB, Saadeh W. A Closed-Loop Ear-Worn Wearable EEG System with Real-Time Passive Electrode Skin Impedance Measurement for Early Autism Detection. Sensors (Basel). 2024;24(23):7489. doi: https://doi.org/10.3390/s24237489

19. Alhassan S, Soudani A, Almusallam M. Energy-Efficient EEG-Based Scheme for Autism Spectrum Disorder Detection Using Wearable Sensors. Sensors (Basel). 2023;23(4):2228. doi: https://doi.org/10.3390/s23042228

20. Duville MM, Corona-González CE, Romo De León R, Rodríguez Vera A, Flores-Jimenez MS, Ibarra-Zarate DI, et al. Perception of task-irrelevant affective prosody by typically developed and diagnosed children with Autism Spectrum Disorder under attentional loads: electroencephalographic and behavioural data. Data Brief. 2023;48:109057. doi: https://doi.org/10.1016/j.dib.2023.109057

EDITORIAL NOTES

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This article was double-blind peer reviewed by specialists in the field. The editorial team used artificial intelligence tools, under human supervision, in the initial screening, in checking the text, references and numbers and, when needed, in redrawing figures, charts and tables, which the authors approved in the proof. The tools and safeguards are described in the journal's Policy on the use of artificial intelligence. Editorial decisions were made by people.

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