

Independent Vector Analysis for Resting-State EEG Classification in Autism Spectrum Disorder

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Abstract—This study investigates Independent Vector Analysis (IVA) for the joint analysis of resting-state electroencephalography (EEG) recordings from individuals with autism spectrum disorder (ASD) and neurotypical controls. The proposed pipeline organizes EEG data into group-wise datasets, estimates IVA-derived latent representations, extracts temporal, spectral, and nonlinear features, selects features using mRMR, and classifies subjects using a Support Vector Machine. In experiments involving 28 subjects, the best IVA-based configuration achieved an accuracy of 75,4%. The most recurrent selected features were predominantly spectral, suggesting that IVA-derived representations may emphasize information relevant to ASD versus control discrimination.

Keywords—Autism Spectrum Disorder, Electroencephalography, Independent Vector Analysis, Biomarkers.

I. INTRODUCTION

Autism Spectrum Disorder (ASD) is a neurodevelopmental condition characterized by impairments in social interaction and communication, as well as restricted and repetitive patterns of behavior. Its clinical presentation is heterogeneous, which makes diagnosis a complex process that remains strongly dependent on specialized behavioral assessments. In this context, there is growing interest in objective biomarkers that may complement clinical evaluation and provide neurophysiological evidence associated with the disorder [1].

Among the investigated approaches, electroencephalography has emerged as a non-invasive method for recording the electrical activity of the brain. The resulting signal, known as the electroencephalogram (EEG), provides high temporal resolution and enables the investigation of rapid changes in neural dynamics. In ASD studies, EEG has been used to analyze spectral differences, temporal patterns, complexity measures, functional connectivity, and machine learning-based approaches, with encouraging results for diagnostic support and neurophysiological characterization of the disorder [1].

Kuriyakose and Gowsalya [2] analyzed the same dataset using microstates combined with explainable artificial intelligence techniques. In general, these approaches focus on building classifiers from features extracted directly from the signals or from specific derived representations, such as microstates.

In this context, Independent Vector Analysis (IVA) constitutes a relevant methodological alternative. Inserted within the framework of Joint Blind Source Separation (JBSS), IVA generalizes Independent Component Analysis (ICA) to multiple

datasets analyzed simultaneously, exploiting the statistical dependence between corresponding components across datasets while preserving independence between distinct sources. This property makes IVA particularly attractive in multisubject and multimodal problems, where the estimation of comparable latent representations across groups or modalities is desirable. In the literature, IVA has been employed in several biomedical applications, including Functional Magnetic Resonance Imaging (fMRI), multisubject analysis, EEG signal processing, and studies involving neurological and psychiatric conditions such as schizophrenia and Parkinson's disease [3], [4].

Despite this potential, the use of IVA for EEG-based ASD classification remains underexplored, particularly in strategies based on group-wise data organization. In particular, its use in strategies that organize subjects into group-wise datasets remains unexplored in this context. This work proposes an IVA-based approach to jointly decompose resting-state EEG signals from individuals with ASD and neurotypical controls, estimating latent representations across groups. From these IVA-derived representations, temporal, spectral, and nonlinear features are extracted, dimensionally reduced using the Minimum Redundancy Maximum Relevance (mRMR) [5] criterion, and classified using a Support Vector Machine (SVM). Thus, the main contribution of this study is to assess the potential of IVA-derived latent representations for distinguishing individuals with ASD from neurotypical controls. To the best of our knowledge, IVA has not yet been investigated for resting-state EEG classification in ASD.

The remainder of this paper is organized as follows. Section II discusses EEG signal characteristics in ASD. Section III presents the theoretical formulation of IVA. Section IV describes the experimental protocol, including the dataset, preprocessing, and proposed IVA-based pipeline. Section V details the feature extraction stage. Section VI presents the dimensionality reduction and classification procedures. Section VII discusses the experimental results. Finally, Section VIII concludes the paper.

II. ELECTROENCEPHALOGRAPHY IN ASD

Electroencephalography has been widely employed in the investigation of biomarkers associated with ASD, mainly because it enables the analysis of neural activity with high temporal resolution across different frequency bands. In resting-state EEG studies, spectral descriptors are among the most recurrent findings, with emphasis on alterations in the delta (1–4 Hz), alpha (8–13 Hz), and gamma (>30 Hz) bands, which have been associated with neurophysiological differences between individuals with ASD and neurotypical controls [6].

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Previous comparative analyses have reported differences in these frequency ranges, suggesting that low-frequency components, alpha rhythms, and gamma activity may carry relevant information for characterizing the disorder [7], [8].

Among the most explored spectral descriptors are absolute and relative band power, as well as measures derived from alpha activity, such as peak alpha frequency (PAF). PAF has been considered a relevant marker for investigating maturational and neurophysiological differences, since alterations in alpha dynamics may reflect changes in functional brain organization and development [7], [9]. In addition to spectral measures, EEG studies on ASD frequently combine temporal, statistical, and nonlinear descriptors, reflecting the multifaceted nature of the signal and the need to represent different aspects of neural activity, including amplitude variability, spectral organization, and signal complexity [1], [6].

Despite its potential, EEG analysis in ASD remains challenging due to physiological variability across subjects and acquisition-related noise, such as ocular movements, muscle activity, baseline drift, and external interference. These artifacts may affect temporal and spectral descriptors, making pre-processing, data representation, and feature extraction critical for reliable machine learning-based classification [10], [1].

III. INDEPENDENT VECTOR ANALYSIS

Independent Vector Analysis (IVA) is an extension of Independent Component Analysis (ICA) designed for the joint blind source separation problem of multiple datasets. While ICA estimates statistically independent sources from a single set of observations, IVA jointly analyzes multiple datasets by preserving the independence between distinct sources and exploiting the statistical dependence between corresponding components across datasets [3].

Consider K datasets, each composed of N samples obtained from linear mixtures of M latent sources. For the k -th dataset, the mixing model can be written as:

$$\mathbf{x}^{(k)}(n) = \mathbf{A}^{(k)} \mathbf{s}^{(k)}(n), \quad 1 \leq n \leq N, \quad 1 \leq k \leq K, \quad (1)$$

where $\mathbf{x}^{(k)}(n) \in \mathbb{R}^M$ is the observed data vector with M mixtures from the k -th dataset, $\mathbf{s}^{(k)}(n) \in \mathbb{R}^M$ is the source vector, and $\mathbf{A}^{(k)} \in \mathbb{R}^{M \times M}$ is the unknown mixing matrix associated with the k -th dataset.

The objective of IVA is to estimate, for each dataset, a separation matrix $\mathbf{W}^{(k)} \in \mathbb{R}^{M \times M}$ in order to retrieve an estimation of the original sources. The first step towards separation is data whitening:

$$\mathbf{z}^{(k)}(n) = \mathbf{V}^{(k)} \mathbf{x}^{(k)}(n), \quad (2)$$

where $\mathbf{V}^{(k)}$ denotes the whitening matrix, obtained from the eigendecomposition of the covariance matrix of $\mathbf{x}^{(k)}$.

The latent components are estimated from the whitened data:

$$\mathbf{y}^{(k)}(n) = \mathbf{W}^{(k)} \mathbf{z}^{(k)}(n). \quad (3)$$

IVA relies on source component vectors (SCVs), which groups corresponding components across datasets. Components within each SCV may be statistically dependent, whereas

different SCVs are independent, making IVA suitable for multisubject and multimodal analyses.

In this study, EEG signals from individuals with ASD and neurotypical controls (CTRL) were analyzed to investigate whether IVA-derived representations could emphasize information relevant for discriminating between ASD and control groups. Therefore, the separation matrices $\mathbf{W}^{(\text{ASD})}$ and $\mathbf{W}^{(\text{CTRL})}$ are used to project each subject into both learned spaces, generating IVA-derived representations for feature extraction and classification.

IV. PROPOSED METHOD

A. Dataset

The EEG signals were obtained from the dataset associated with Electrophysiological Signatures of Brain Aging in Autism Spectrum Disorder [9]. The original dataset is composed of recordings from adults with ASD and control subjects, acquired during an eyes-closed resting-state condition, with an approximate duration of 2.67 minutes per recording and a sampling rate of 512 Hz.

During the file review process, differences were observed in the number and arrangement of channels across the available recordings. To ensure data standardization and comparability among participants, the sample was restricted to 28 individuals, including 14 with ASD and 14 controls. The selection was based on two criteria: (i) the availability of a common set of 15 EEG channels across all retained recordings, and (ii) age compatibility between groups. Accordingly, only subjects aged between 36 and 74 years were included. The channels used were AF3, C3, C4, CP4, F3, F4, F7, FZ, O1, O2, P1, P10, P5, P8, and POZ.

B. Pre-processing

Prior to the execution of the proposed pipeline, the EEG signals underwent a preprocessing stage. First, band-pass filtering between 1 and 100 Hz was applied to attenuate very low-frequency components, such as baseline drift, and to restrict the analysis to the spectral range of interest in this study. This choice preserved information up to 100 Hz, including gamma-band components, which are often associated with relevant findings in resting-state EEG studies on ASD [7].

Next, notch filtering at 50 Hz was performed to suppress power-line interference. Common Average Re-referencing (CAR) was then applied to reduce shared activity across electrodes and enhance spatial contrast [11]. Finally, the SOBI (*Second-Order Blind Identification*) algorithm was used to attenuate artifactual components before IVA [12].

C. Feature Extraction

After obtaining the subject-specific representations from IVA, temporal, spectral, and nonlinear features were extracted from each IVA-derived signal. Temporal features included variance, RMS, peak-to-peak amplitude, skewness, kurtosis, Hjorth mobility, and Hjorth complexity. Spectral features were estimated using Welch's method with 4-second windows and 50% overlap, including total power, absolute and relative

power in the delta, theta, alpha, beta, and gamma bands, peak alpha frequency, SEF95, gamma/alpha ratio, and spectral entropy [13], [14]. Nonlinear features included permutation entropy, Hurst exponent, and DFA [14].

For each subject, features computed from the IVA-derived signals were summarized using mean, standard deviation, maximum, and median, resulting in a single feature vector used for dimensionality reduction and classification.

D. Dimensionality Reduction and Classification

mRMR was applied to select relevant, non-redundant features based on mutual information, reducing dimensionality and overfitting [5].

Let C denote the set of candidate features, that is, the features that have not yet been selected, S the subset of features already selected, and c the class label. At each selection step, the mRMR criterion evaluates each candidate feature $x^i \in C$ according to the difference between its relevance to the class and its average redundancy with respect to the features already included in S :

$$\max_{x^i \in C} \left[I(x^i, c) - \frac{1}{|S|} \sum_{x^j \in S} I(x^i, x^j) \right], \quad (4)$$

where $I(x^i, c)$ represents the mutual information between the candidate feature x^i and the class label c . This term measures the relevance of x^i , indicating how informative this candidate feature is for distinguishing between the classes. In contrast, $I(x^i, x^j)$ represents the mutual information between the candidate feature x^i and a feature x^j that has already been selected, with $x^j \in S$. This term measures redundancy, indicating how much information the candidate feature shares with the features already included in the selected subset. The factor $1/|S|$ computes the average redundancy between x^i and the selected features.

Therefore, the mRMR criterion prioritizes features that are highly relevant to the class label while minimizing redundancy with those already selected. At each step, the method seeks to add complementary information that improves the discrimination between classes.

In each fold, feature selection was performed exclusively on the training data, and the selected features were then applied to the corresponding test subjects to avoid information leakage. The number of selected features was progressively refined: the search initially varied the feature subset size in steps of 10, followed by refinements in steps of 5 (40, 45 and 50) and then 1 (45 up to 50) within the most promising range. Based on this procedure, 49 features were selected from an initial set of 108 features, corresponding to the configuration that achieved the best classification performance among the evaluated settings.

As the final stage of the pipeline, a SVM was adopted as the classifier. Before SVM training, the selected features were standardized using parameters estimated exclusively from the training set in each fold and then applied to the corresponding test set, avoiding information leakage. SVM is a supervised learning method that seeks to define an optimal decision boundary between classes by maximizing the margin between

the closest samples from each class, known as support vectors [5]. This property makes SVM suitable for classification problems involving high-dimensional feature spaces, such as EEG-based representations. In this study, the classifier was trained to discriminate between ASD and control subjects using only the features selected by mRMR in each fold.

E. Proposed IVA-based Pipeline

The proposed IVA-based pipeline is shown in Fig. 1. It was designed with the objective of preprocessing the data, estimating the IVA components, and subsequently, extracting features for the classification of EEG signals searching to differentiate between the ASD and control groups.

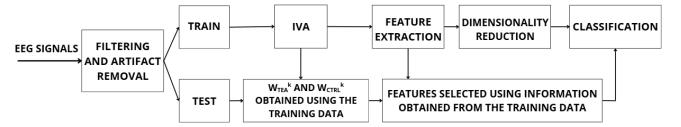


Fig. 1. Overview of the proposed system for classifying individuals with ASD and neurotypical controls based on resting-state EEG signals.

Algorithm 1 summarizes the main steps of the procedure. The separation matrices $\mathbf{W}^{(\text{ASD})}$ and $\mathbf{W}^{(\text{CTRL})}$ are stacked before projecting the data of each subject. This procedure is necessary because, during testing, labels are unknown. Features are then extracted from the estimated latent components, as detailed in Section V.

Algorithm 1: IVA-based EEG classification pipeline

Split subjects into training and test sets.

for each fold **do**

Concatenate training subjects by class:

$$\mathbf{X}_{\text{ASD}} \text{ and } \mathbf{X}_{\text{CTRL}}$$

Construct group-wise IVA tensor:

$$\mathbf{X}_{\text{IVA}} \in \mathbb{R}^{15 \times N \times 2}$$

Estimate IVA separation matrices:

$$\mathbf{W}^{(\text{ASD})}, \mathbf{W}^{(\text{CTRL})} \leftarrow \text{IVA}(\mathbf{X}_{\text{IVA}})$$

for each subject k in training and test sets **do**

$$\mathbf{Y}_k = \begin{bmatrix} \mathbf{W}^{(\text{ASD})} \mathbf{X}_k \\ \mathbf{W}^{(\text{CTRL})} \mathbf{X}_k \end{bmatrix} \in \mathbb{R}^{30 \times N}$$

$$\mathbf{f}_k \leftarrow \text{FeatureExtraction}(\mathbf{Y}_k)$$

end

Form training and test feature matrices:

$$\mathbf{F}_{\text{train}}, \mathbf{F}_{\text{test}}$$

Select features using only training data:

$$S \leftarrow \text{mRMR}(\mathbf{F}_{\text{train}}, \mathbf{I}_{\text{train}})$$

Apply selected features to training and test data:

$$\mathbf{F}_{\text{train}}^* = \mathbf{F}_{\text{train}}[:, S], \quad \mathbf{F}_{\text{test}}^* = \mathbf{F}_{\text{test}}[:, S]$$

Train classifier using training data:

$$\mathcal{M} \leftarrow \text{SVM}(\mathbf{F}_{\text{train}}^*, \mathbf{I}_{\text{train}})$$

Predict test labels:

$$\hat{\mathbf{I}}_{\text{test}} \leftarrow \mathcal{M}(\mathbf{F}_{\text{test}}^*)$$

end

V. RESULTS AND DISCUSSION

The experimental results were obtained using a paired leave-out train-test strategy with randomized pair assignment. Since the dataset included 14 ASD subjects and 14 control subjects, the procedure was repeated for 14 folds. In each fold, one ASD subject and one control subject were reserved for testing, while the remaining subjects were used for training. The test pairs were selected without replacement, ensuring that each subject appeared in the test set only once.

This strategy kept the test set balanced across classes in all folds. Moreover, IVA estimation, mRMR-based feature selection, and SVM training were performed exclusively on the training data, while the reserved subjects were used only for testing. This procedure avoided information leakage and ensured that the reported results reflected the generalization of the proposed pipeline to unseen subjects.

To identify the most suitable configuration for the proposed pipeline, different IVA-based experimental settings were evaluated. The optimization approaches tested included gradient, quasi-Newton, and Newton methods [15]. For each approach, the number of IVA iterations was varied from 100 to 500 in steps of 100, and the step size was evaluated using the values 0.05, 0.1, 0.5, and 1.0. In the classification stage, SVM models were assessed using linear and radial basis function (RBF) kernels, with the regularization parameter C set to 0.1, 1.0, and 10.0. The number of features selected by mRMR, denoted by f , was also varied. Initially, f was evaluated in broader intervals, considering 30, 40, 50, 60, and 70 selected features. After identifying the most promising range, additional refinements were performed using smaller intervals, first in steps of 5 and then in steps of 1.

Table I presents results obtained using the complete proposed pipeline, including IVA, feature extraction, mRMR feature selection, and SVM classification. Since the best performance was obtained using the Newton optimization approach with 500 iterations, a step size of 1.0, an RBF kernel, and $C = 10.0$, these settings were fixed for the results reported in Table I. The best IVA-based configuration was obtained with $f = 49$, achieving an accuracy of 75.4%, precision of 76.9%, recall for ASD of 71.4%, and F1-score of 74.1%.

For comparison purposes, an additional experiment without IVA was also considered. In this baseline configuration, feature extraction, selection, and classification were performed directly on the preprocessed EEG signals, without the use of IVA. The same paired leave-out train-test strategy was used. The best non-IVA result was obtained with 30 selected features, an RBF kernel, and $C = 1.0$, achieving an accuracy of 67.8%, precision of 64.7%, recall for ASD of 78.5%, and F1-score of 70.9%.

Although the non-IVA baseline achieved higher recall for ASD, the best IVA-based configuration improved accuracy, precision, and F1-score, suggesting a more balanced overall discrimination between ASD and control subjects. This result suggests that IVA-derived latent representations may provide complementary discriminative information compared with features extracted directly from the preprocessed EEG signals.

When compared with EEG-based ASD classification studies that also used the public Sheffield dataset, the proposed IVA-

based pipeline achieved competitive performance. Kuriyakose and Gowsalya reported an SVM accuracy of 74.51% using microstate-informed multidomain EEG features, while Logistic Regression reached 72.82% within the same experimental framework [2]. In the present study, the best IVA-based configuration achieved 75.4% accuracy, suggesting that IVA-derived latent representations may capture discriminative information comparable to other EEG-based approaches. However, this comparison should be interpreted with caution, since studies may differ in the subset of subjects used, preprocessing procedures, feature representations, and evaluation protocols.

TABLE I
IVA-BASED PIPELINE PERFORMANCE FOR DIFFERENT NUMBERS OF
SELECTED FEATURES.

f	Accuracy	Precision	Recall ASD	F1-score
30	60.7%	60.0%	64.3%	62.1%
40	67.9%	64.7%	78.6%	71.0%
49	75.4%	76.9%	71.4%	74.1%
50	71.4%	68.8%	78.6%	73.3%
60	60.7%	60.0%	64.3%	62.1%
70	57.1%	58.3%	50.0%	53.8%

The confusion matrix obtained from the aggregated predictions across the 14 folds for the best IVA-based configuration is shown in Fig. 2. The model correctly classified 10 ASD subjects and 11 control subjects, while 4 ASD subjects were misclassified as controls and 3 control subjects were misclassified as ASD. This distribution suggests a relatively balanced classification behavior between the two groups, consistent with the reported accuracy, precision, recall, and F1-score. Nevertheless, given the limited sample size, these results should be interpreted as exploratory and require further validation in larger cohorts.

	Controle	TEA
	11	3
TEA	4	10
	Controle	TEA

Fig. 2. Confusion matrix for the best IVA-based configuration.

It is also worth noting that increasing the number of selected features does not necessarily improve classification performance. For instance, although the IVA-based configuration with $f = 50$ achieved a competitive accuracy of 71.4%, performance decreased when f was increased to 60 and 70. This behavior suggests that increasing the feature subset may introduce redundancy or less informative attributes, reinforcing the importance of dimensionality reduction in the proposed pipeline.

A. Recurrence of features selected by mRMR

Among the evaluated configurations, the best performance was obtained when mRMR selected 49 features, and this subset was used as input to the classifier in each training fold, with the same selected features subsequently applied to the corresponding test fold.

After applying mRMR, the recurrence of the features selected across the 14 folds was analyzed. This analysis aimed to identify the features that were most consistently relevant for discriminating between the ASD and control groups during the training process. Fig. 3 presents the 10 most frequently selected features.

Among the most recurrent features, spectral descriptors stood out, especially absolute and relative power measures in the delta band. Beta- and gamma-related descriptors also appeared among the selected features, particularly maximum and mean absolute beta power and the standard deviation of absolute gamma power. This predominance suggests that spectral information was the main source of discrimination in the adopted IVA-derived representations, consistent with resting-state EEG studies in ASD that associate spectral power measures with group differences [6], [7], [8]. However, these features were extracted from IVA-derived latent components rather than directly from the original EEG channels. Therefore, the features shown in Fig. 3 should be interpreted as spectral properties of latent components obtained after IVA projection, and not as channel-specific electrophysiological markers.

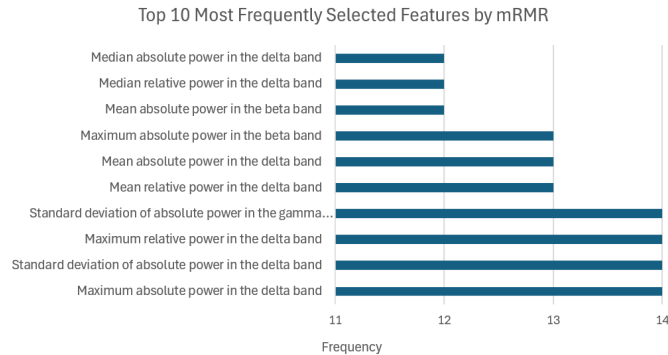


Fig. 3. Top 10 most frequently selected IVA-derived features by mRMR across the 14 folds.

VI. CONCLUSION

This study investigated IVA for resting-state EEG classification in ASD. The proposed pipeline estimated group-specific latent spaces, extracted IVA-derived features, applied mRMR-based feature selection, and performed SVM classification. The best configuration achieved an accuracy of 75.4%, precision of 76.9%, recall for ASD of 71.4%, and F1-score of 74%. The use of IVA improved accuracy by 7.6%, demonstrating the potential of the method to aid in discriminating between ASD and control subjects. The most recurrent selected features were mainly associated with spectral descriptors, especially delta-band power, suggesting that IVA-derived representations may emphasize spectral information relevant to ASD versus control

discrimination. Future work should evaluate larger datasets, additional IVA configurations, different classifiers, and nested validation strategies to further assess the robustness of the proposed approach.

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