



ENHANCED EEG SIGNAL CLASSIFICATION FOR AUTISM SPECTRUM DISORDER USING RIEMANNIAN GEOMETRY AND ENSEMBLE LEARNING TECHNIQUES

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ABSTRACT

Autism spectrum disorder (ASD) poses a severe challenge to effective communication and social interaction abilities for a large number of individuals worldwide. The P300 signal is difficult to detect in individuals with ASD due to noise, low amplitude, and increased latency compared to others. We enhance in this work the P300 classification in electroencephalogram (EEG) signals for autism disease using Riemannian geometry along with various conventional classifiers and ensemble learning approaches like bagging and boosting techniques (AdaBoostM1, GentleBoost, and LogitBoost), and developing sophisticated pre-processing methods for feature extraction. Using the BCIAUT-P300 dataset, our work achieved 96.37% accuracy, 97.51% sensitivity, and 91.11% specificity compared to existing processes, ranging from 67.2% to 92.3% accuracy. This work highlights the potential of our technique in assisting in diagnosis and supportive ASD technologies.

KEYWORDS

Autism; ASD; BCI; Electroencephalography; EEG; Ensemble Learning; Feature Extraction; Machine Learning; P300; Riemannian Geometry; Signal Processing.



1. INTRODUCTION

Over the past decades, technological progress has led to remarkable advancements in medicine and engineering, which have improved the quality of medical signals like the electroencephalography (EEG) and the cardiac signals (ECG). For example, advanced methods of signal processing have been utilized to recover twin fetuses ECG signals (Talib et al., 2021) and to design chaotic binary sequences to boost communication systems (Falih, 2017). In addition, human-computer interactions have been essential to boost smart user interfaces and interactive systems in all domains, ranging from medical to fields of engineering (Kheder, 2023). These applications are useful in bettering user interfaces and assist in the design of brain-computer interface (BCI) systems to serve individuals with autism spectrum disorder.

Autism Spectrum Disorder (ASD) is a serious communication and social interaction problem. P300 wave is positive and tends to come up following 300 ms of stimulation. It is also one of the key elements of cognitive processing and attention. Identification of the wave is difficult due to its high variability in the EEG signal and other characteristics inherent in ASD (Oberman et al., 2005; Krzemi et al., 2020; Simões et al., 2020).

The BCIAUT-P300 of the IFMBE 2019 challenge, as reported by (Simões et al., 2020), is a benchmark to study P300-based BCIs in ASD, and other research has utilized convolutional neural networks (CNN) and other algorithms to more accurately classify EEG signals.

The BCIAUT-P300 dataset, as utilized by (Krzemi et al., 2020), was treated using Riemannian ensemble methodology to classify the P300 component, with significant improvements in terms of accuracy. The model employs Riemannian geometry and also ensemble learning. Pre-processing of EEG data using a filter bank is done to extract covariance matrices and Event-Related Potential (ERP) prototypes to utilize training of an ensemble of Linear Discriminant Analysis (LDA) classifiers on subsets of channels, trials, and frequencies. The output class is picked as the max probability of evidence from all ensembles with an average classification ability of 81.2%.

Miladinović et al. (2020) further developed it for optimization of BCI protocol with the help of robust logistic regression with Automatic Relevance Determination based on full Variational Bayesian inference (VB-ARD) to improve joint-attention capabilities in subjects with ASD. They obtained an accuracy of 81.5.

On the contrary, the CNN-FEBAC is utilized for measurement and analysis of ASD patients' EEG signals using the BCIAUT-P300. Adopt the following format for the dataset, as proposed by (Patel et al., 2023). Their model consists of a feature extractor using CNN followed by a shallow classifier, with an accuracy of 91%.

Another research by (Borra, Fantozzi and Magosso, 2020) proposed a light and interpretable shallow CNN, the Sinc-ShallowNet, for EEG decoding on the BCIAUT-P300 dataset. The light methodology was found to perform efficiently and to demonstrate the ability of CNN to independently look for relevant features to perform the classification and thereby boost the performance of EEG decoding without requiring handcrafted features. Their rate of correctness was 92.3%, providing a comforting level of performance.

In the recent research work of (Peketi and Dhok, 2023), a new application of the variational mode decomposition (VMD) technique was proposed to a BCI system to extract autism ASD subjects' signals. As was discovered through the work, combining the fifth mode of VMD with the support vector machine using a fine Gaussian kernel classifier led to better results with a percentage accuracy of 91.12%, a score of 91.18%, and area under the curve of 96.6%. This was better than all the existing methods out now and left everyone amazed with the prowess of the VMD technique.

The present work proposes a technique giving novel insight into EEG signal processing with the P300 wave. This is achieved by integrating ideas from the methods of BCI and Riemann geometry and ensemble learning. This is done to enhance the efficiency and effectiveness of the system of BCI in individuals with ASD. Pre-processing methods, Riemannian geometry, and ensemble learning strategies are employed to design a better BCI system in the current study. This methodology is tested using the BCIAUT-P300 dataset. Comparisons with the existing research are provided in detail in the discussion section, which presents the advancements and improvements in the current study. **Error! Reference source not found..** Presents the summary of the methods and outcomes of existing studies and the improvements made in the current study.

The following sections describe the methodology in section 2 and clarify the results in section 3. We also show the discussion in section 4, and finally, we illustrate in section 5, we show the conclusion and suggest future research directions.

2. METHODOLOGY

The study uses a two-trial method that combines Riemannian geometry with ensemble learning to improve EEG signal classification, specifically targeting identifying the P300 component. The first trial focuses on extracting features within specific time windows, while the second trial adopts a comprehensive approach by analyzing the entire signal length. This combined strategy is designed to optimize classification accuracy, particularly in distinguishing cognitive responses in individuals with autism.

Section 3.1, Pre-processing, details our methodology, as does Section 3.2, which discusses the methods used to extract features. Finally, Section 3.3 explains ensemble learning and provides an overview of the methods used for the BCIAUT-P300 dataset, as illustrated in Fig. 1.

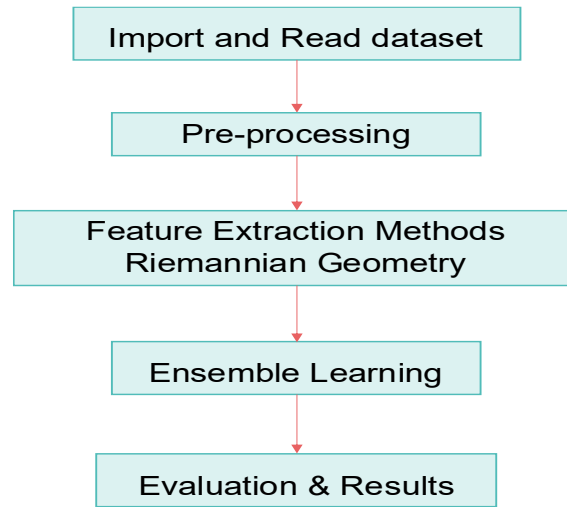


Fig. 1: Overview of Methodological Approach for EEG Signal Analysis

2.1. Dataset Acquisition

Our study uses the BCIAUT-P300 dataset from the 15th Mediterranean Conference on Medical, Biological Engineering and Computing (Medicon, 2019)(Henriques & Neves, 2019). The dataset is critical for our research because it consisted of the electroencephalography recordings from a clinical trial that trained individuals diagnosed with autism spectrum disorder to recognize and respond to social cues. Electroencephalography (EEG) data were recorded using a G.Nautilus system with eight active electrodes placed at specific locations on the scalp (C3, Cz, C4, CPz, P3, Pz, P4, and Poz) Fig.2.

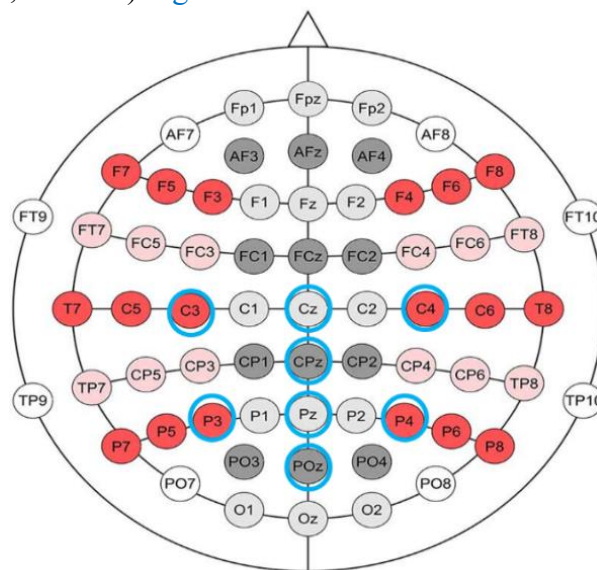


Fig.2 : The eight electrodes are used to record EEG signals (Smolka, et al., 2015)

The data, sampled at 250 Hz, was divided into seven sessions, each representing a distinct period during which EEG signals were recorded for each participant. These sessions ensured a comprehensive analysis of P300 variations over time, with training and test subsets. Fifteen individuals participated in a task that simulated real-world social interactions within a virtual environment. They were asked to identify and highlight one of eight objects, a process essential to our study goal of enhancing social signal recognition in ASD.

Our in-depth analysis, conducted in MATLAB, highlights the potential of combining Riemannian geometry, principal component analysis (PCA) and ensemble learning techniques. The publicly available BCIAUT-P300 dataset on Kaggle is vital for future research into BCI technologies to aid autism spectrum disorder, promoting innovation and replication of our findings.

2.2. Pre-Processing

According to (Jang et al., 2024), studies demonstrate that autistic persons differ in P300 signaling from non-autistic persons. Again, the neural structuring and functional connectivity in the brains differ for each group, and P300 signals in autistic persons differ in processing sensory input and attention from those of typically developed persons. The differences identify that the P300 signaling is instrumental in diagnosing and furthering the study of autism, since fresh intervention approaches and treatment will surface. Thus, pre-processing of electroencephalography (EEG) signals is important to processing the P300 wave information for cognitive processing in BCI applications. Improved quality and data purity are important to enable the P300 wave to be separated. It is instrumental in researching cognitive processing for autistic persons. In our pre-processing chain, we used a bandpass filter of frequency range 0.5–30 Hz. A choice of the frequency range was because it had been demonstrated in previous research to perform well in separating significant components of the EEG, specifically the P300 signal (Chatterjee et al., 2020a; Zhao et al., 2020a). It is important in separating the frequency range within which the P300 component is likely to occur and where noise and irrelevant frequency components are removed. Fig. 3 demonstrates for that the EEG signals are first passed through this broad frequency bandpass (0.5–30 Hz) to separate critical frequency components. Following the baseline (-0.3 to 0.0 seconds) is removed to take away any drift and to ensure the P300 component gets recorded correctly. Elimination of the baseline protects against any drift or slow changes in the signal from interfacing with the analysis of the P300 component. Pre-processing of the EEG signal is two-fold, as demonstrated in Fig. 3. Each is designed to highlight the most significant facets of the P300 component of the event-related

potentials (ERPs).

2.2.1. First Trial: Targeted Time Window and Diverse Feature Sets

The first trial is derived according to (Krzemi et al., 2020); we implemented a detailed pre-processing pipeline to enhance the EEG signal for detecting P300. Involved applying two specific filters: a broadbandpass filter with a range of 0.5 to 30 Hz and a lowpass filter with a 0.5 to 8 Hz range. Additionally, we carefully removed the baseline at -0.3 to 0.0 seconds pre-stimulus. This method effectively captured the P300 wave within the specified time window, significantly improving the signal-to-noise ratio. Demonstrates the efficacy of our approach.

We created eight feature sets in this trial, each capturing different spectral properties. These sets included data from the total, central, and posterior electrodes, covering broad, low-frequency bands over a time window ranging from -100 to 800 ms. In addition, we used the entire raw signal to create a comprehensive set of features. The first trial focuses on enhancing the EEG signal quality through pre-processing techniques to ensure accurate feature extraction, as detailed in Algorithm 1. The algorithm follows multiple steps to filter the data, remove the baseline, and select appropriate electrode configurations for feature extraction.

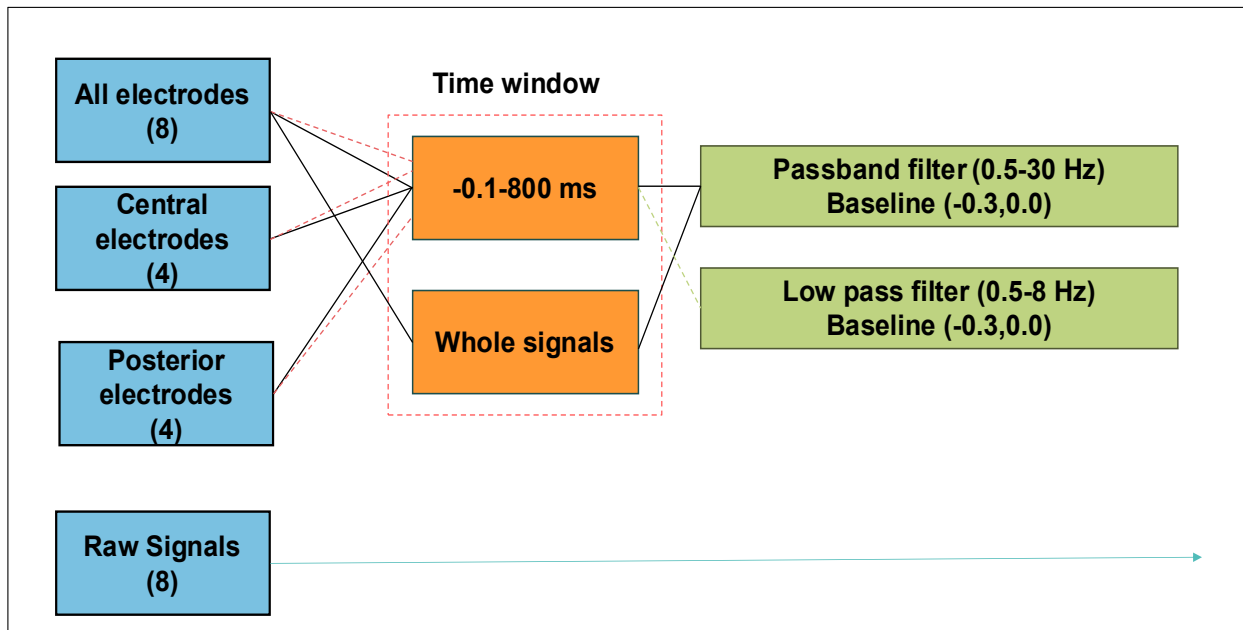


Fig. 2: Pre-processing pipeline

Algorithm 1: Trial One Pre-processing and Feature Set Formation

Inputs: EEG Data (D), Bandpass Filter Range (BFR), Lowpass Filter Range (LFR), Baseline Time Range (BTR), Time Window (TW)

Output: Feature Sets (FS)

1: **procedure** TrialOnePreprocessing(D, BFR, LFR, BTR, TW)

```

2:   Initialize FS as an empty set
3:   For each electrode configuration EC in {All, Central, Posterior}, do
4:     FilteredData = BandpassFilter(D, BFR)
5:     FilteredData = LowpassFilter(FilteredData, LFR)
6:     FilteredData = RemoveBaseline(FilteredData, BTR)
7:     If EC != All then
8:       FilteredData = SelectElectrodes(FilteredData, EC)
9:     end if
10:    WindowedData = ApplyTimeWindow(FilteredData, TW)
11:    FS = FS  $\cup$  ExtractFeatures(WindowedData)
12:  end for
13:  Return FS
14: end procedure

```

D: The raw EEG data.

BFR: The bandwidth range used for data filtering.

LFR: The low-frequency range applied for secondary data processing.

BTR: The time range for baseline removal from the signal.

TW: The time window applied to data post-filtering.

EC: The different electrode configurations used on the scalp.

FS: The final feature set extracted for classification.

2.2.2. Trial Two: Whole Signal Analysis for a Holistic Approach

Unlike Trial One, Trial Two embraced a holistic approach, disregarding the time-window constraint and considering the full signal length. Our pre-processing, which included a broad bandpass filter and baseline removal, was consistent with the first trial. However, we refrained from segmenting the signal temporally. This comprehensive perspective allowed us to fully understand the brain's response, ensuring every potentially informative component was considered. The features extracted from the EEG data in the first trial are then utilized in the second trial to improve classification accuracy using a variety of classifiers. Building on the pre-processed data from the first trial, the second trial employs a holistic approach to classification, as outlined in Algorithm 2. The algorithm undertakes the tasks of filtering data, removing baselines, extracting features, training classifiers, and assessing classifier accuracy.

Algorithm 2: Trial Two Whole Signal Analysis

Inputs: EEG Data (D), Bandpass Filter Range (BFR), Baseline Time Range (BTR), Classifiers (C)

Output: Model Accuracy (Acc)

```

1: procedure TrialTwoAnalysis(D, BFR, BTR, C)
2:   FilteredData = BandpassFilter(D, BFR)
3:   FilteredData = RemoveBaseline(FilteredData, BTR)
4:   FS = ExtractFeatures(FilteredData)
5:   For each classifier CL in (C) do
6:     TrainClassifier(CL, FS)
7:   end for
8:   Acc = EvaluateClassifiers(C)
9:   return Acc
10: end procedure

```

D: The raw EEG data.

BFR: The bandwidth range used for data filtering.

BTR: The time range for baseline removal from the signal.

C: The list of classifiers used in the analysis.

CL: The chosen or intended classifier who performs the classification.

FS: The feature set extracted from the data post-preprocessing.

Acc: The final classification accuracy achieved by the classifiers.

The entire process concludes with the generation of the final result and the attainment of classification accuracy. Our two-pronged strategy went beyond merely diversifying signal processing; it was a deliberate attempt to highlight the most significant features of the P300 component classification. Comparing the results of both experiments, each with its distinct focus on pre-processing, we aimed to develop an approach that maximizes classification accuracy. The comprehensive feature set, a key pillar of our research, derived from the selective window of Trial One and the overview from the complete signal analysis of Experiment Two, was crucial in informing our group's learning models, which achieved noteworthy accuracy in detecting the P300. The dual methodology emphasizes our commitment to accuracy, flexibility, and adaptability in EEG signal pre-processing, laying the groundwork for subsequent classification processes and playing a crucial role in advancing and propelling forward Brain-Computer Interface technology.

2.3. Hybridization of Riemannian Geometry and Ensemble Learning

Riemannian geometry and ensemble learning techniques are mixed in this study to improve the accuracy of classifying P300 signals in EEG data. The process involves two key stages:

Feature Extraction using Riemannian Geometry: We calculate covariance matrices based on Riemannian geometry to capture the spatial relationships between different EEG channels. This process provides a robust feature space that confidently retains important information for classification.

Ensemble Learning: We apply ensemble learning techniques, including bagging and boosting (AdaBoostM1, GentleBoost, LogitBoost), to improve classification accuracy. Combining these techniques allows for better generalization and reduces overfitting, especially in cases of imbalanced data.

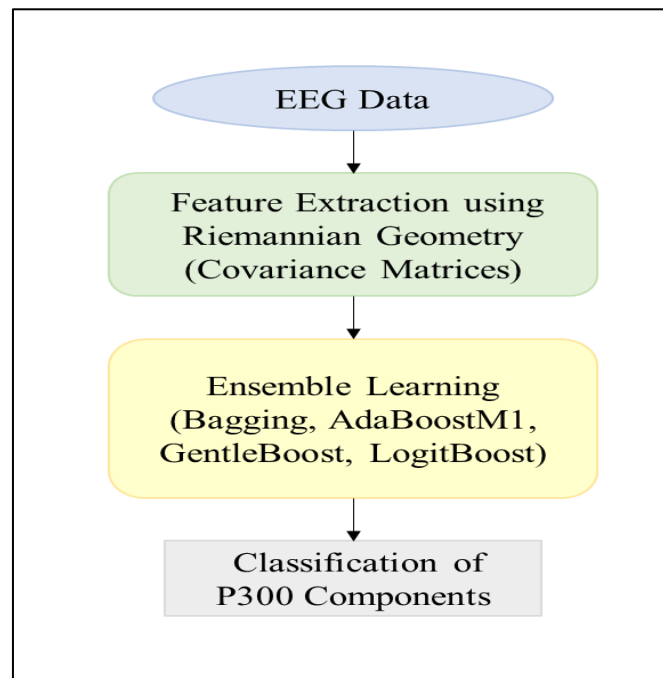


Fig. 3: Hybridization of Riemannian Geometry and Ensemble Learning Techniques for P300 Component Classification

2.4. Feature Extraction Methods

The most fundamental step in the development of our study is the feature extraction from the EEG data. Our study relies much on extracting features of the P300 data. The features extracted based on pre-processing that were discussed are two-fold in these two trials, which involved:

Riemannian Covariance Matrices (Trial 1 and Trial 2): We compute covariance matrices, which were inspired by Riemannian geometry (Krzemi *et al.*, 2020), and capture the spatial relationships of components of the EEG signal. We use geodesic filtering, focusing on the characteristics of the EEG signal that should differentiate this study of cognitive processes. Matrices, in this manner, construct the backbone of our feature space since they represent EEG dynamics in great detail.

Dimensionality Reduction (Trial 2): We apply principal component analysis (PCA) for dimensionality reduction, as in practice, toward features coming from Riemannian covariance matrices. PCA works as data projection in a space of lower dimension while retaining the most variant components. Thus, it ensures that the feature set is lower complexity yet highly informative when finally adapted to the classifier.

Prototype Merging (Trial 1, Trial 2): We use the prototype-based method, which combines extracted features with prototype signals. This increases the power of identifying the model with the patterns of EEG data.

Flattening of SPD Matrices (Trial 1, Trial 2): The covariance calculations result in Symmetric Positive Definite (SPD) matrices, which are then transformed into vectors. This transformation allows the data to be utilized with machine learning algorithms, including ensemble learning techniques such as voting, boosting, and bagging. These methods involve combining the predictions of multiple classifiers in Euclidean space to enhance accuracy.

The feature extraction process, as detailed in Fig. 5, is integral to improving the classification of EEG signals. Each step, from creating ERP prototypes to flattening SPD matrices, ensures that critical data is preserved and utilized effectively in subsequent classification stages.

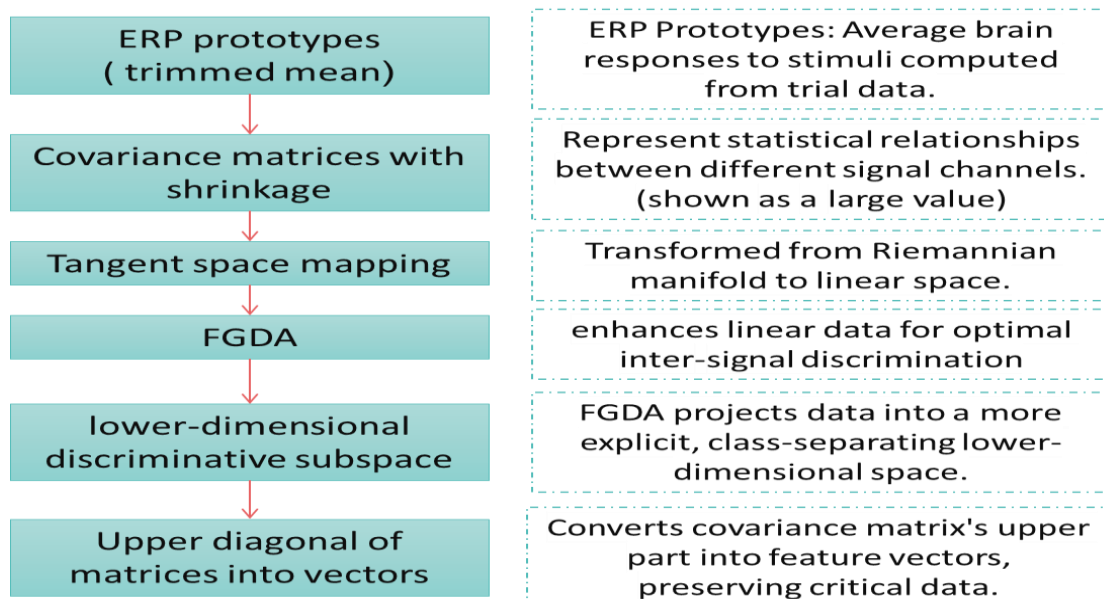


Fig. 4: The pipeline steps, from pre-processing and feature extraction to classifier training.

2.5. Ensemble Learning

In this work, we employ sophisticated ensemble learning methods to better examine brain signals. Probabilistic voting and various ensemble methods, such as Bagging and Boosting techniques like AdaBoostM1, GentleBoost, and LogitBoost, are the dominant ensemble approaches utilized. Probabilistic voting pools the votes of many classifiers to maximize overall

accuracy. All of these methods are elaborated in greater detail in Section 3, where we illustrate how all of these methods substantially better the classification accuracy, demonstrating significantly better outcomes than the previous methods we employed for the task at hand..

3. RESULTS AND DISCUSSION

In this important contribution, we propose a new methodology to utilize the strength of ensemble learning methods in classifying EEG signals. This methodology validates the cognitive response to the stimulus with particular emphasis placed on the P300 component. We have exhaustively examined our method in all the participants and all the sessions, marking the height of innovation above earlier works, which only experimented with one to three sessions (Simões et al., 2020). Our work sets a new standard in neuroscience and machine learning by working with all the sessions.

In our research work, we isolated and picked features from EEG signals as per the neural relevance associated with autism spectrum disorder (ASD). P300 has been a prominent feature amongst the features as the feature has been associated with the sensory information process and attention response. From studies, it has been established that ASD patients exhibit different P300, i.e., response time delay or decrease in amplitude, and thus the signal is useful to test cognitive ability (Daskalov et al., 2020).

We used some simple classifiers such as MDM, SVM, neural network, Random Forest, and LDA to classify EEG signals. We implemented our approaches to feature extraction using Riemannian geometry and principal component analysis (PCA). Covariance matrices computed with the aid of the 'Shcov' method describe the spatial interdependencies between the signal's components and were geodesically filtered prior to preprocessing to achieve improved precision. The extracted features are responsible to increase signal classification precision.

Riemannian geometry helps to increase the model's interpretation because it is derived from the geometrical relations of the signal and facilitates better insights towards the patterns of the neurons associated with ASD. The obtained set of features was also complemented with Principal Component Analysis (PCA), a robust technique of dimension reduction that facilitates efficient data processing by selecting the most important components. We have utilized various techniques for clustering, namely AdaBoostM1, GentleBoost, Bagging, and LogitBoost, to further enhance the performance, and the outcomes revealed that each of the methods played different roles in the enhancement of the classification accuracy, demonstrating the significance of such feature sets to process EEG signals and identify the neural processes related to ASD.

Our classification approach and implementation of clustering learning methods surpassed earlier works where Riemannian geometry alone was utilized, validating the novelty of the approach in this work.

3.1. First Approach: Probabilistic Voting (Trail 1)

A probabilistic voting algorithm was proposed in the initial experiment, utilizing Linear Discriminant Analysis with 500 learners. Each learner learned from subsets of data, each of which consisted of 50% of the samples and 70% of the features. This trial was conducted across various pre-processing configurations, including:

Passband filtering (0.5-30 Hz) and baseline removal (-0.2 to 0.0 ms) with sub-selections for central, posterior, and all electrodes.

Low pass filtering (0.5-8 Hz) baseline removal (-0.2 to 0.0 ms) with sub-selections for central, posterior, and all electrodes.

Given the above settings, the probability voting configurations have undergone an iteration of meticulous testing across several of the sets of electrode data. It was done for all possible combinations of central and posterior electrodes without/with time window restrictions. Such pervasive testing has been designed strategically to ensure that the classifier is tested in the most robust form possible so that the derived results are very confidence-empowering and would best prove the validity of the approach at hand.

Trial 1 results were significant and showed a great evolution in detecting P300 components. Our ensemble learning method achieved an excellent accuracy rate of 95.20%. The detailed breakdown of the ensemble's performance metrics is as follows:

Area Under the Curve (AUC): 0.92 ± 0.049

Average Ensemble Accuracy: $95.20\% \pm 3.89\%$

Average Precision: $97.26\% \pm 2.22\%$

Average Sensitivity (Recall): $97.26\% \pm 2.22\%$

Average F1 Score: $97.26\% \pm 2.22\%$

Average Specificity: $80.79\% \pm 4.82\%$

These metrics were calculated using the following equations:

Accuracy (Acc):

$$Acc = \frac{TP + TN}{TP + TN + FP + FN} * 100 \quad (1)$$

F1 Score:

$$F - Score = 2 \times \left(\frac{Pre \times Recall}{Pre + Recall} \right) \quad (2)$$

Precision (P):

$$Pre = \frac{TP}{TP + FP} \quad (3)$$

Recall (R), also known as Sensitivity (Sen):

$$Sen(TAR, recall) = \frac{TP}{TP + FN} \quad (4)$$

Specificity (Spec):

$$Spe(TFR) = \frac{TN}{TN + FP} \quad (5)$$

Where TP is True Positive, FP is False positive, TN is True Negative, and FN is False Negative.

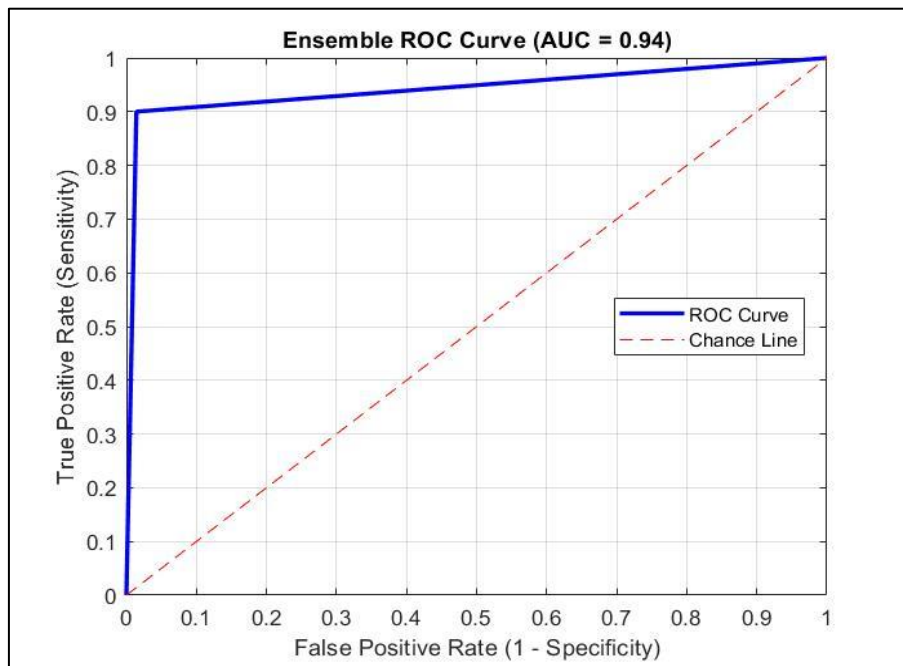


Fig. 5: ROC Curve illustrates the trade-off between sensitivity and specificity (Trail 1)

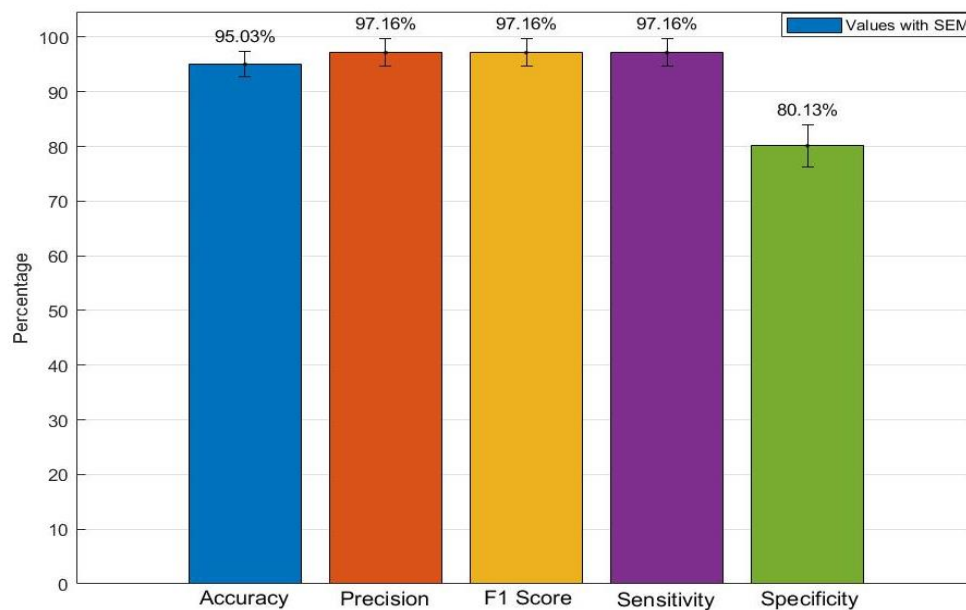


Fig. 6: Performance Metrics with SEM (Trail1)

The ROC Curve and distribution of predicted probabilities chart visually represent the metrics, demonstrating the classification model's performance. Fig. Fig. 6 and Fig. 7 Show that our ensemble approach can effectively differentiate between classes and is particularly efficient in handling imbalanced data.

The results of our study were much better than previous works that used the same dataset and

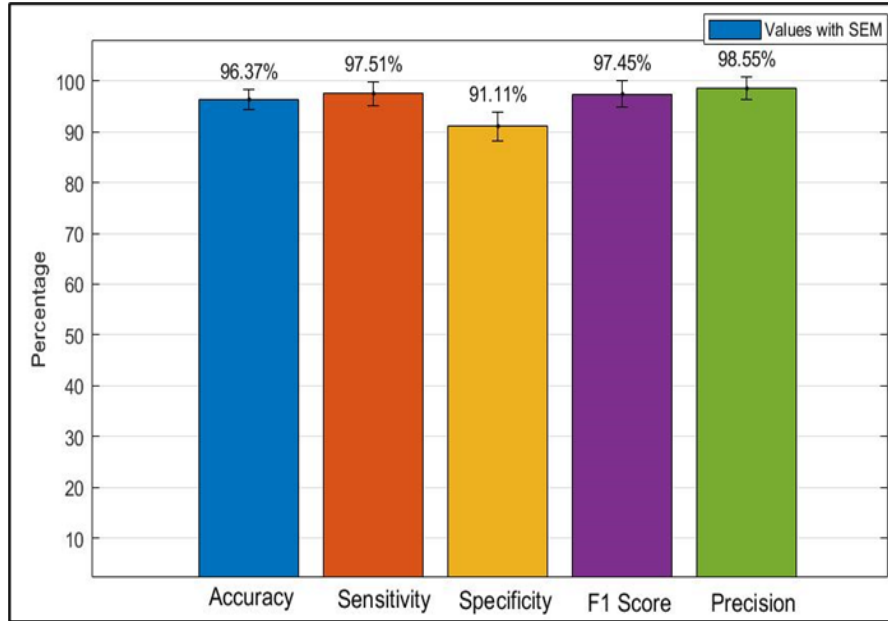


Fig.8: Performance Metrics with SEM (Trail 2)

even Riemannian geometry. Our approach has enabled us to go beyond those studies, as shown in Table 2. It confirms our approach's superiority, capability and accuracy, inspiring optimism about the future of EEG signal classification. Furthermore, it is in autistic patients from non-autistic individuals.

3.2. Second Approach: Various Ensemble Techniques

In the second experiment, we embarked on an advanced ensemble learning approach, skillfully combining multiple machine learning classifiers. The result was a significant improvement in the classification performance of EEG signals. This approach necessitated the coordination of various classifiers and clustering techniques, which significantly amplified the accuracy and robustness of the model. Fig. 7 presents the final results, that is, the accuracies of the various base classifiers employed in the experiment. Fig.8 presents the last ensemble model performance tested with the 15 subjects for complete accuracy across all the sessions. We accomplished that by examining various innovative ensemble learning techniques: boosting and bagging.

- **Boosting Techniques**

- Boosting is a strong ensemble method that strengthens weak classifiers' performances based on past errors (Tanha *et al.*, 2020). We implemented three different methods of

reinforcement within our research:

- **AdaBoostM1:** The weak classifiers are trained sequentially, with each classifier trying to improve on the errors of the previous classifier. The final ensemble mode derives a strong and comprehensive model from the weak classifiers (Tanha *et al.*, 2020).
- **GentleBoost:** A variation of AdaBoost, GentleBoost employs a less aggressive method of weight adjustment, which is very stable and lowers the risk of overfitting (Friedman *et al.*, 2000).
- **LogitBoost:** Logistic regression is applied in every iteration, optimizing the logistic loss to see how the classification performance is improved. (Li, 2010).

- **Bootstrap Aggregating**

Bootstrap Aggregating (Bagging) is another type of ensemble method, bagging with Bootstrap Aggregating. This technique improves model stability and accuracy by training on many versions of predictors pulled from different bootstrap data input samples and then averaging their predictions. The method reduces variability and helps to create a more reliable model (Breiman, 1996).

- **Stacking**

Besides the previously discussed ensemble methods, we also utilized the ensemble method called stacking. It is defined more generally as learning a set of base classifiers and then using another model, called a "meta-classifier," that learns how to combine the predictions of these base classifiers. However, the stacking approach achieved an accuracy of 94.10%, which was lower than the accuracy achieved using Trail 1 and Trail 2. Therefore, our second experiment used boosting and bagging to enhance the classification performance.

3.2.1. Base Classifiers

In Trial 2, we carefully selected a range of base classifiers to capitalize on their unique strengths in EEG signal classification, particularly for detecting the P300 component. Our approach employed varying numbers of base classifiers using Riemannian geometry and PCA, and different numbers of components were tested (10, 20, 30, 50, and 70). The number of best components for every base classifier was determined with care to promote signal analysis and accommodate the special characteristics of EEG signals. The base classifiers were:

Minimum Distance to Mean

It was chosen based on its high performance when covariance matrices derived from EEG are used for the target application (Daskalov *et al.*, 2020). Minimum Distance to Mean (MDM)

performs well when class means are separate and is strongly consistent with predictions, evidenced through a 94.04% average accuracy.

Support Vector Machine

SVM was selected due to its effectiveness when working with high-dimensional data (Christopher et al., 1998). Using Principal Component Analysis (PCA) for reducing dimensions, SVM successfully retained the most significant components and achieved a cross-validated average accuracy rate of 94.34%.

Neural Network

The neural network (NN) was used to model the complex, non-linear relationships between data (Avendaño-Valencia & Fassois, 2015). With PCA initially reducing features to the most significant components and then using a fully connected neural network, this classifier yielded a 90.27% mean accuracy. While less accurate than other classifiers, it is still a valuable ensemble contributor.

Random Forest

The PCA was applied to the principal components of the covariance matrices for the Riemannian geometry being explored (Jin et al., 2020). The number of best cross-validated components using KFold=10 was obtained. These characteristics were trained using a Random Forest classifier, and predictions were delivered through an ensemble approach. The overall model had an average accuracy rate of 91.94%.

Linear Discriminant Analysis

Linear Discriminant Analysis was employed based on its performance for linear classification for well-separated datasets (Daskalov et al., 2020). The LDA model was also fine-tuned by experimenting with different PCA components and obtaining a mean accuracy of 93.37%.

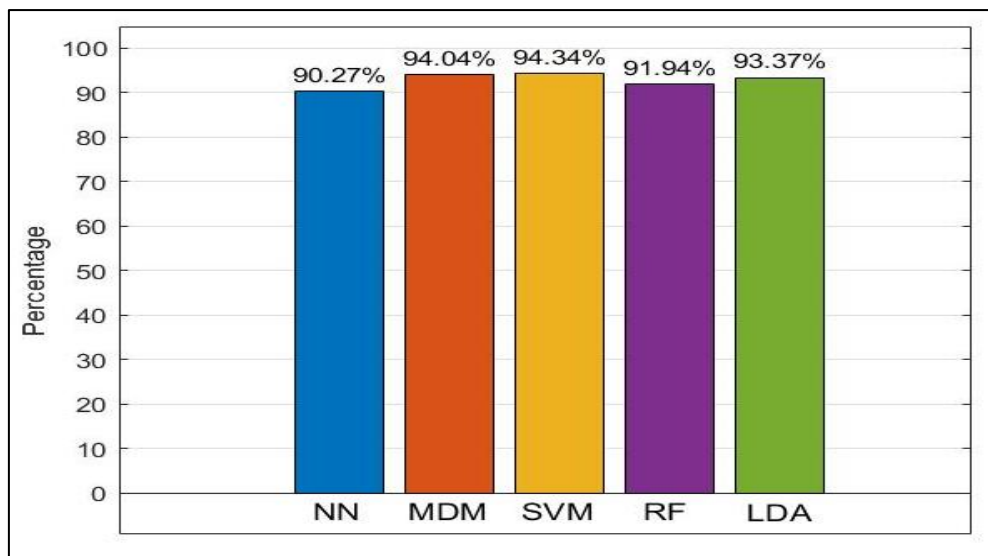


Fig.9: Average Base of the Classifiers Accuracy

These classifiers have been selected to be complementary, each bringing different advantages which, when ensembled, enhance the overall performance of the model. Collectively, the union of methodologies makes it so that the ensemble can robustly classify EEG signals, addressing the complexity within the data successfully.

3.2.2. Ensemble Techniques and Meta-Classifer Training

After their predictions, the base classifiers were combined into a matrix that was fed into the sophisticated classifier (meta-classifier). These classifiers were trained with various ensemble methods (AdaBoostM1, GentleBoost, LogitBoost, and Bagging) with NumLearningCycles = 200 to find out the optimum method for enhancing each participant and session's classification accuracy.

Table 1 summarizes the performance of the methods based on their ensemble accuracy,

Ensemble Method	No. of Session	Accuracy (%)	Sensitivity (%)	Specificity (%)	Precision (%)	Recall (%)	F1 Score (%)
Bag	25	96.73	96.62	91.14	98.64	96.62	97.54
AdaBoostM1	30	96.50	96.37	90.72	98.36	96.37	97.53
GentleBoost	37	96.01	96.70	91.20	98.63	96.70	97.26
LogitBoost	13	95.76	97.23	91.71	98.63	97.23	97.39
Bag	25	96.73	96.62	91.14	98.64	96.62	97.54

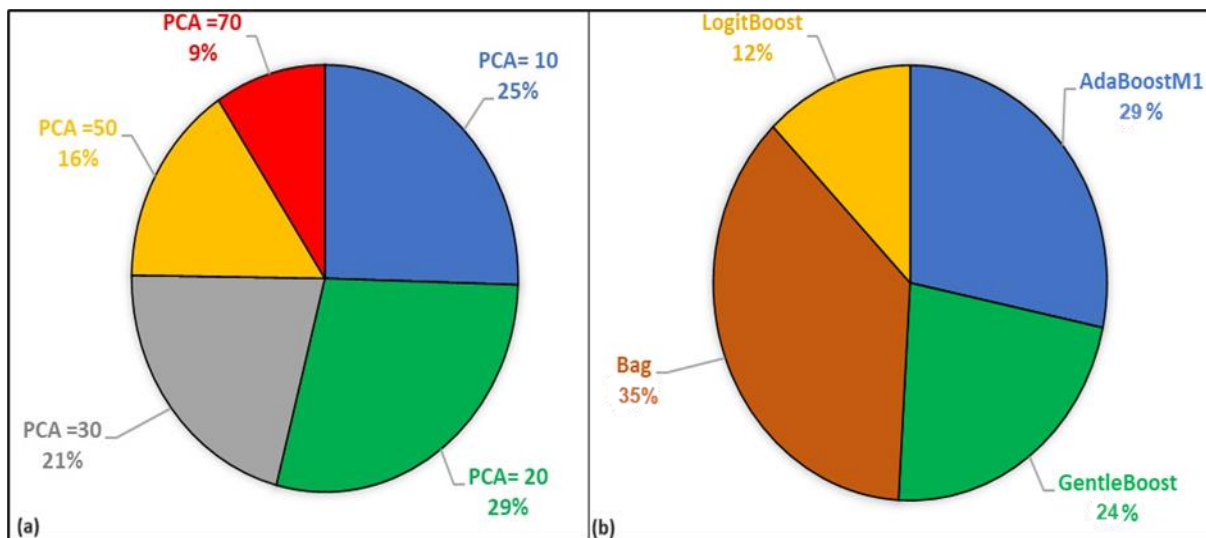
sensitivity, specificity, precision, recall, and F1 score. Performance results show that Bagging and AdaBoostM1 yielded the best performance of all the methods. The table illustrates that Bagging presented the best performance overall for 25 sessions with an accuracy of 96.73, while the best performance for 30 sessions was recorded by AdaBoostM1 with an accuracy of 96.50. Meanwhile, GentleBoost and LogitBoost presented good performance for 37 and 13 sessions, respectively.

Table 1: Performance Comparison of Ensemble Techniques

Ensemble Method	No. of Session	Accuracy (%)	Sensitivity (%)	Specificity (%)	Precision (%)	Recall (%)	F1 Score (%)
Bag	25	96.73	96.62	91.14	98.64	96.62	97.54
AdaBoostM1	30	96.50	96.37	90.72	98.36	96.37	97.53
GentleBoost	37	96.01	96.70	91.20	98.63	96.70	97.26
LogitBoost	13	95.76	97.23	91.71	98.63	97.23	97.39
Bag	25	96.73	96.62	91.14	98.64	96.62	97.54

The PCA components for the base classifiers and clustering methods are shown in Fig.10. The clustering ROC curve in Fig.11 has a high AUC of 0.97, which makes the proposed approach work better. In addition, the statistical results show that our approach achieved an average ensemble accuracy of 96.37 ± 2 , a recall sensitivity of 97.51 ± 2.3 , a specificity of 91.11 ± 2.83 , an F1 score of 97.45 ± 2.26 , and a precision of 98.55 ± 2.32 .

These results indicate that using different ensemble techniques, especially Bagging, significantly improves the performance of EEG signal classification, ensuring high accuracy and flexibility across different participants and sessions. These results indicate that using different ensemble techniques, especially Bagging, significantly improves the performance of EEG signal classification, ensuring high accuracy and flexibility across different participants and sessions.



**Fig.10: a) Distribution of PCA components selected for different classifiers.
b) Distribution of ensemble techniques used**

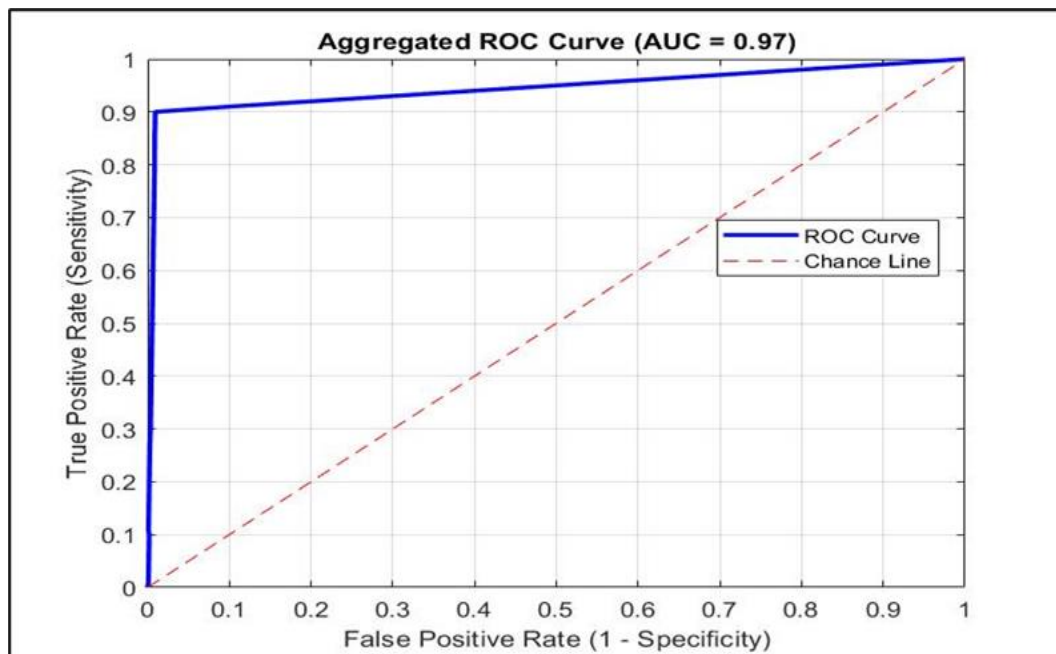


Fig.11: ROC Curve illustrates the trade-off between sensitivity and specificity (Trail 2)

Table 2. The provided compares our proposed approach with previous studies that used the same dataset BCIAUT-P300, highlighting the superiority of our methodology.

The comprehensive testing across all participants and sessions (seven sessions) marks a significant advancement over prior studies that typically limited evaluations to fewer sessions, setting a new benchmark in EEG signal analysis. This methodology enhances classification performance by using Riemannian geometry, PCA, and state-of-the-art ensemble approaches. It emphasizes the potential for high-level signal processing and machine learning approaches to propel next-generation advances in cognitive neurosciences.

While our study was spurred by (Krzemi *et al.*, 2020), ours built considerably on it by bringing on board a series of different methods of ensemble learning, e.g., AdaBoostM1, GentleBoost, and Bagging, and an implementation of PCA to further enhance component analysis. These enhanced the model's accuracy, which is our contribution to the study.

Table 2: Comparison with Previous Studies using the BCIAUT-P300 dataset

Author	Methodology	Sessions	Mean accuracy (%)	Other metrics
(Borra, Fantozzi and Magosso, 2020)	CNN based on EEGNet, epoch extraction, downsampling	7_4	92.3	Not Mentioned
(Santamaría-Vázquez <i>et al.</i> , 2020)	CNN-BLSTM, baseline normalization, epoch extraction	7_4	84.3	Not Mentioned
(de Arancibia <i>et al.</i> , 2020)	Combination of temporal features and CWT, PCA for feature reduction	7_4	82	F1 score
(Bittencourt-Villalpando and Maurits, 2020)	SVM, pseudorandom averaging of ERP segments, feature vector construction	7_4	81.50	Not Mentioned
(Krzemi <i>et al.</i> , 2020)	Riemannian framework, an ensemble of 400 LDA classifiers	7_4	81.20	Not Mentioned
(Miladinović <i>et al.</i> , 2020)	Bayesian logistic regression with automatic relevance determination (VB-ARD)	7_4	80.30	Computation time
(Chatterjee, Palaniappan and Gupta, 2020b)	BLDA, RUSBoost, and CNN classifiers, majority voting within each run	7_4	76.30	Not Mentioned
(Adama, Schindler and Schmid, 2020)	MLP, Pearson's correlation, feature extraction in specified time windows	7_4	70	Not Mentioned
(Zhao <i>et al.</i> , 2020b)	LDA, custom filter design, linear support vector regression as feature pre-selector	7_4	67.20	Not Mentioned
(Peketi and Dhok, 2023)	VMD-SVM method	all seven sessions	91.12	Accuracy, F1-score, and the area under the curve
Proposed		all seven sessions	95.03	Accuracy, Sensitivity (Recall), Specificity,

Riemannian Geometry and all seven Ensemble Learning: Trail 1, sessions Trail 2	96.37	F1-score, Precision and the area under the curve
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4. CONCLUSION

In summary, our work has shown a new and practical method for differentiating autistic patients' EEG signals from normal subjects. When used together with diverse ensemble methods, such an application based on Riemann geometry and PCA attained record-breaking accuracy and reliability. Our work shows an improvement in the classification process for the EEG signal, leading to higher reliability and robustness. The method was fruitful, and an average ensemble accuracy of 96.37 was achieved, having high sensitivity, specificity, and accuracy. These results are better than what is reported in the literature and create a new benchmark for the analysis of EEG signals. Success using such an approach shows massive promise for what machine learning methods and signal processing can help achieve for transforming cognitive neuroscientific research.

Future refinements of this cluster model might include extra classifiers and more sophisticated feature extraction methods, which could lead to further important improvements in EEG signal classification among autistic patients. The process continues to advance cognitive neuroscience.

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