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Participant Condition Aware Hybrid Deep Learning for Automated EEG Biomarker Discovery and Autism Associated Neural Pattern Identification

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Abstract
Autism Spectrum Disorder (ASD) is a neurodevelopmental condition associated with differences in social communication, sensory processing, and behavioural characteristics. Electroencephalography (EEG) provides a non-invasive approach for investigating autism-associated neural activity. However, conventional EEG analysis methods often rely on manually engineered features and may fail to capture complex temporal dependencies, inter-channel relationships, and stimulus-dependent neural patterns. To overcome these limitations, this study develops a hybrid deep learning framework for automated EEG feature extraction and autism-associated biomarker identification using the EEG Latinus Model dataset, comprising 44 participants, including 10 individuals with ASD and 34 neurotypical controls. The proposed framework integrates the REVE EEG Foundation Model for pretrained representation learning, a Dilated Temporal Convolutional Network (D-TCN) for temporal feature extraction, and a Graph Attention Network (GAT) for inter-channel relationship modelling. Furthermore, the proposed Participant–Condition Interaction Residualization (PCIR) method analyses condition-dependent EEG feature changes across photographic face, Mooney face, schematic face, and non-face stimuli. The experimental evaluation demonstrates that the fused spatiotemporal representation achieves a between-group separation value of 0.73, compared with 0.42 for REVE alone. Candidate EEG features exhibit effect sizes ranging from 0.63 to 0.88, with adjusted p-values between 0.002 and 0.029. The proposed framework achieves 97.50% accuracy, 97.40% precision, 97.10% recall, a 97.20% Macro-F1 score, and a 98.10% ROC-AUC. These findings demonstrate the potential of integrated spatiotemporal learning and participant-condition analysis for identifying autism-associated EEG patterns and candidate biomarkers.

Keywords: Autism Spectrum Disorder, Electroencephalography, REVE EEG Foundation Model, Spatiotemporal Feature Learning, Biomarker Identification.

1.Introduction

Autism Spectrum Disorder (ASD) is a neurodevelopmental disorder characterized by social communication differences, sensory processing differences and behavioural differences. EEG is a non-invasive method for monitoring neural activity at high temporal resolution, and is valuable for studying neural responses to various experimental stimuli, which is why it is a valuable research direction for understanding variations in brain activity[1].Recently, machine learning, deep learning, and feature-selection methods have been investigated for automated classification of ASD using EEG signals and to identify potentially informative neural features[2], [3]. In addition, studies that have studied face-perception related neural activity have emphasized the need to study the way people process faces and non-face stimuli[4],[5]. Automated EEG feature extraction thus provides a means to explore temporal changes and inter-channel interactions as well as condition-specific neural activity patterns that could help in understanding brain activity in children with autism.

Nevertheless, in the existing research on ASD using EEG, there are some methodological difficulties[6]. Traditional machine learning methods often rely on handcrafted features or pre-defined statistical and spectral features and may fail to capture the rich temporal and inter-channel relationships[7]. Deep learning approaches are able to acquire informative representations, but their reliability is subject to the properties of the data sets, validation, and the ability to detect reproducible features. They have recently found that reproducibility is an important issue for the identification of EEG characteristics associated to autism[8]. Other approaches have

focused on the extensive feature extraction and feature-selection methods to find discriminative EEG features[9], and have used graph-based methods to study the relationships between the EEG recording channels[10]. The fusion of pretrained EEG representations, temporal feature learning, graph based channel relationships and participant-level stimulus-condition analysis in a common framework is still an important research direction. More specifically, any differences between diagnostic groups have to be separated from differences caused by experimental conditions to find meaningful candidate biomarkers.

To solve these problems, a hybrid deep learning framework is proposed in this study, that is, combining the REVE EEG Foundation Model, Dilated Temporal Convolutional Network (D-TCN), and Graph Attention Network (GAT). The EEG Latinus Model dataset is provided for the investigation of EEG activity related to face-perception in ASD and neurotypical (NT) participants. The pretrained EEG representations are provided by REVE, spatial-time dependencies are learned by D-TCN, and inter-channel relationships are modeled by GAT. These are complementary representations and are integrated to facilitate the analysis of spatiotemporal features. In addition, the proposed Participant–Condition Interaction Residualization (PCIR) method examines whether the changes in EEG features within individual participants across the conditions are different between the ASD and NT groups. A resulting framework is provided to facilitate identification of candidate biomarkers, neural-pattern analysis, and ASD classification. The proposed approach will be validated through participant independent validation, statistical analysis and suitable baseline comparisons to determine the reliability and generalisability of features extracted.

1.1 Research Motivation

Automated EEG feature extraction plays a crucial role in exploring intricate neural dynamics in autism. But, the conventional feature engineering techniques might not be able to fully model temporal dependencies, inter-channel relationships, and changes that depend on stimulus. The goal of this study is to create an integrated deep learning framework by combining the pretrained EEG representations, temporal feature learning, graph channel modelling, and participant-level condition analysis for the purpose of investigating candidate biomarkers of autism and neural patterns.

1.2 Significance of the Study

This study aims to offer a computational framework for analyzing EEG signals in several face-perception conditions. Complementary temporal and inter-channel information can be explored in a single representation through the integration of REVE, D-TCN and GAT. The proposed PCIR method allows for studying the changes and differences of condition-related variables within the same participant, as well as comparing the ASD and NT groups. These analyses can be used to determine the interpretable candidate EEG features for further investigation. The framework also gives a foundation on how the individual components can be evaluated by ablating experiments. The features identified should be considered as potential biomarkers, however, until they can be validated as independent, their reproducibility and clinical relevance should not be considered.

1.3 Problem Statement

Current approaches for identification of ASD from EEG focus on feature extraction, deep learning classification, and channel-based analysis. However, there are still issues to address when learning powerful temporospatial representations, finding repeatable candidate biomarkers and exploring ASD/NT differences in conditions[11],[12]. A common framework, which incorporates the pretrained EEG feature extraction, temporal modelling, inter-channel relationships and participant-level condition analysis is therefore necessary. The goals of this study are to overcome these challenges by combining REVE, D-TCN with the proposed PCIR approach to investigate EEG features and neural patterns associated with autism under a participant-independent evaluation.

1.4 Key Contributions

- Implementated the REVE EEG Foundation Model for automated EEG feature extraction and autism related pattern analysis.
- Combined D-TCN and GAT for learning comprehensive spatiotemporal features of EEG.
- Suggested a method for analysing participant level EEG changes with respect to stimulus conditions – PCIR.
- Created an integrated approach for the identification of candidate biomarkers and ASD classification.

1.5 Rest of the Section

Section 2 reviews related work and limitations; Section 3 presents the proposed methodology; Section 4 discusses results; Section 5 concludes and outlines future research directions.

2. Literature Survey

Gao et al.[13]proposed a multi-task Transformer neural network for autism spectrum disorder (ASD) identification using resting-state functional magnetic resonance imaging (rs-fMRI). The framework is based on multi-task learning and attention-based feature representation which leverages information from related tasks. Its greatest strength is that it can learn, and learn effectively, informative representations for several tasks, instead of relying on a single task. The study is conducted with fMRI, though, and may not be directly applicable to extracting biomarkers from EEG. The gap in the research is the necessity of a framework specific to EEG which could learn temporal and inter-channel relationships in order to recognize biomarkers associated with autism.

Ranaut et al. [14]investigated autism identification using EEG through feature selection and machine-learning techniques. They evaluated continuous EEG data and condition-based datasets across the possibilities of using EEG features to differentiate autistic participants from neurotypical people. A big advantage is that feature selection and the impact of various recording conditions on classification are studied. But using the selected features and conventional machine learning techniques could be restrictive for learning complex nonlinear temporal and inter-channel dependencies. The aim of the research gap is to come up with an integrated deep-learning framework that automatically extracts the spatiotemporal features and assess the importance of these features as potential autism-related biomarkers.

Shama et al. [15]investigated trial-to-trial variability in EEG spectral characteristics to better understand autism. The study focussed on whether trial variation could be used to enhance the classification of ASD when compared to mean spectral features. It is important because it takes into account that neural responses may vary over time and is not captured by averaging, giving another angle on the EEG characteristic associated with autism. But the emphasis on the spectral features does not, on its own, provide an adequate representation of temporal dynamics and inter-channel relationships. This gap in the research is to integrate trial variability and learned representations of spatiotemporal dynamics, together with condition-related analysis, in order to uncover potentially informative EEG biomarkers.

Nafisah et al. [16]proposed a deep-learning-based feature-selection approach to ASD detection with resting-state fMRI image. Their method involves an optimisation method that uses informative features to be classified. The principal advantage is its dedicated attention to feature selection, which may improve the efficiency and reduce the redundant information of classification. The study, however, employs fMRI and its feature-selection methodology does not explicitly consider temporal dynamics and relationships between recording channels in EEG. The gap in research is a feature-learning and feature-selection framework that is designed to be focused on EEG signals and determine informative patterns while preserving their physiological and participant relevance.

Melinda et al.[17]presented a comprehensive EEG dataset and performance assessment for autism spectrum disorder. The study makes a significant contribution to the field of study on ASD by offering a dataset oriented resource and assessing the performance of classification approaches. The major merit of its is that contributes in terms of data availability and empirical assessment within the context of EEG data, which can help in developing and comparing computational methods. But the accuracy of classification does not imply that the features extracted by a model are reproducible autism-associated biomarkers. The research gap is to expand the scope of EEG classification from predictive performance to automated feature extraction, interpretable pattern discovery and systematic evaluation of candidate biomarkers stability.

Das et al.[18]proposed a deep-fusion approach combining EEG scalogram features with spatiotemporal features and an attention mechanism for ASD identification. The advantage of this is that it combines various types of signal representations together so that the model can utilize information from the time-frequency view as well as information from the spatiotemporal view. However, a feature-fusion classification framework does not necessarily provide insight into the stability of learned features across participants or stimulus conditions. The research gap lies in integrating participant-aware and condition-aware analysis in spatiotemporal feature learning to allow for distinguishing between candidate biomarkers and features that can only be useful for classification.

Shimono et al.[19]investigated event-related potential (ERP) habituation to tones and fearful vocalisations as a potential biomarker of sensory hypersensitivity in autism. The study focused on neural responses due to repeated stimuli–both auditory and emotionally evocative. It has the important advantage of studying stimulus-

dependent neural responses, which may have clinical relevance. The investigation, however, is targeted to certain ERP habituation responses and is not an automated deep-learning, feature-extraction, general system. The research need is to gain more knowledge about the timing and inter-channel EEG representations of stimuli across stimulus conditions and to systematically analyze which extracted patterns are correlated with autism related characteristics.

Lekshmylal et al.[20]Studied real-time classification of EEG signals of children with ASD using deep learning algorithms. This study tackles the practical problem of processing EEG data and efficiently classification. The major strength is its emphasis on classification of EEG signals through deep learning, which has application potential to real-time analysis. But the speed of classification and the accuracy of prediction are not necessarily a measure of the physiological interpretability and repeatability of the extracted features. The gap in the research is to combine efficient EEG processing with the identification and analysis of explicit EEG biomarkers and the temporal and spatial relations involved in the model's predictions.

Hafeez et al.[21]Explored biomarker discovery for prediction of autism through big data feature extraction from EEG signals. The study focuses on the need to capture a wide spectrum of signal features to determine features that may be informative for predicting ASD. It has the primary advantage of focussing directly on feature extraction and the discovery of biomarkers in the EEG signal without being limited to classification. As a large number of features are extracted, however, problems of features redundancy, interpretability and feature reliability across participants may arise. The research need is to create a learned spatiotemporal representation that facilitates the selection of candidates as biomarkers and evaluates feature consistency and ability to differentiate predictive features from potentially meaningful patterns related to autism.

Broggi et al.[22]evaluated N170 latency as a potential EEG biomarker of treatment response in a randomised, double-blind, placebo-controlled trial of arbaclofen for autism. The study is whether there is an N170 latency change during treatment and whether there is a relationship between the change to clinical outcome. The main advantage is the study of an EEG measure in a clinical trial environment, providing evidence to support the use of candidate biomarkers in the real world. But, in this trial, the study effectiveness of N170 latency as a biomarker for treatment response was found to be limited. The research gap is to examine wider, automatically identified EEG features not just a single ERP measure, and to assess the stability, interpretability and association with pattern of these features with autism.

3. Methodology

The proposed framework is based on deep learning technique that enables automatic extraction of EEG features, identification of candidate biomarkers and analysis of neural patterns related to ASD. This dataset of EEG data, called the EEG Latinus Model data, is employed to examine EEG activity related to the perception of faces in ASD and neurotypical (NT) participants. The proposed framework combines pretrained REVE EEG Foundation Model, which is a Dilated Temporal Convolutional Network (D-TCN) and a Graph Attention Network (GAT) for spatiotemporal feature learning. Using the proposed Participant-Condition Interaction Residualization (PCIR) method, the extracted representations are analysed in an effort to explore condition-specific EEG representation differences between ASD and NT groups. The features derived are employed for identification of candidates for biomarkers, analysis of neural patterns and classification of ASD. The methodology is composed of data collection, data pre-processing and quality control, EEG segmentation, REVE-based feature extraction, spatiotemporal representation learning using a hybrid method, condition analysis using PCIR, biomarker identification, pattern identification and ASD classification.The overall workflow of the proposed framework is presented in Figure 1.

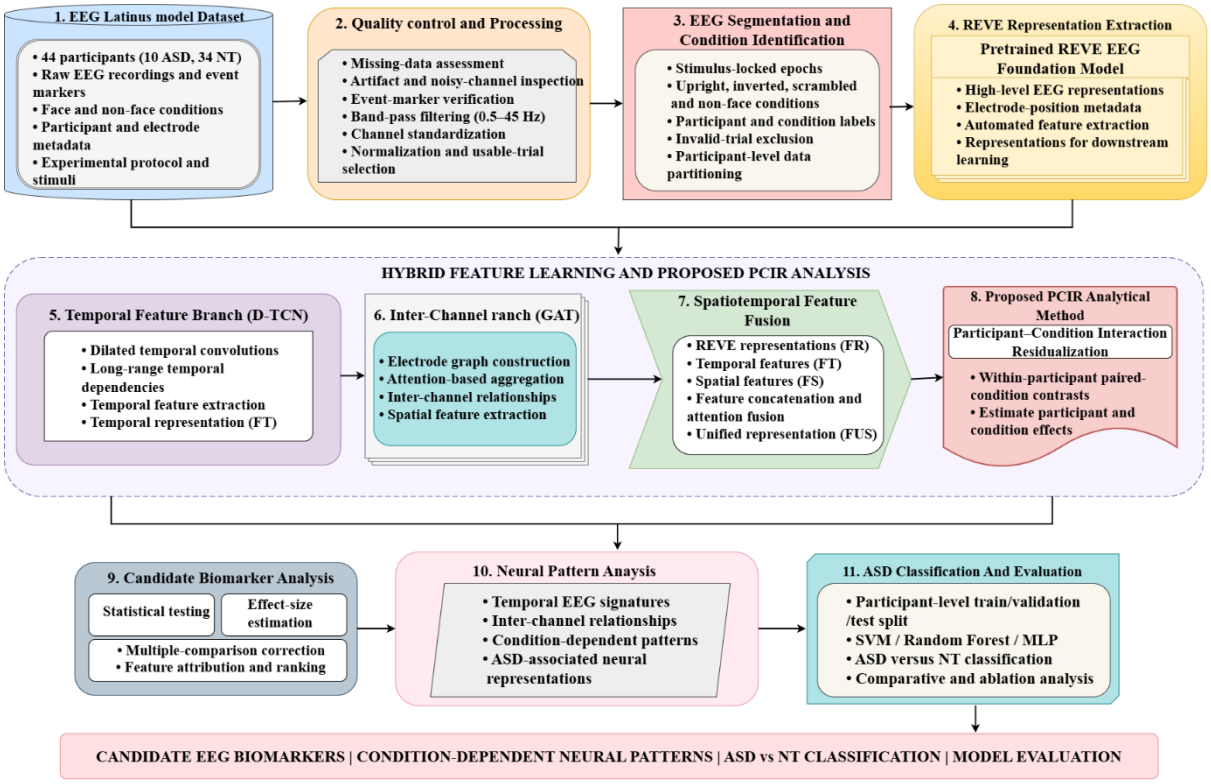


Figure 1. Overall Workflow of the Proposed REVE-Based Hybrid Deep Learning Framework for ASD-Associated EEG Biomarker Identification

The overall framework of the proposed methodology is presented in Figure 1 from the EEG dataset collection to segmentation of the EEG data using the stimulus-locked method. The EEG is sent to the pretrained REVE model to extract representations of EEG, and then the temporal and inter-channel features are learned using D-TCN and GAT. The fused spatiotemporal representations are compared between the ASD and NT groups with the proposed PCIR method to explore the condition-dependent difference in the two groups. The framework is then used for candidate biomarker identification, analysis of neural patterns, and classification and evaluation of ASD.

3.1. Data Collection

The dataset of the proposed framework is based on EEG Latinus Model. Includes raw EEG, demographic, neuropsychological assessment and experimental protocol descriptions of 44 subjects (10 ASD and 34 neurotypical control). The experimental task is for the subjects to make face versus non-face judgments on stimuli from a variety of categories: upright, inverted and scrambled Mooney faces; upright, inverted and scrambled photographic faces; upright and inverted schematic faces; and non-face stimuli (eggs and lines). Total number of stimuli: 5 blocks x 90 stimuli per block. Duration of each stimulus is about 1,000ms and time between stimuli varies as a function of the participant's response. The dataset is analyzed to find out which EEG recordings exist, what the diagnostic labels of the participants are, information about the electrodes, the event markers and the experimental conditions. Prior to selecting the data for subsequent analysis, the availability for usable recordings and paired conditions is checked. Final analytical sample is determined based on pre-defined signal quality criteria.

3.2. Data Preprocessing and Quality Control

Preprocessing of the collected EEG signals is conducted to enhance the quality of the signals and make them compatible with the suggested deep learning architecture. The recordings are evaluated for missing samples, corrupted signals, noisy channels, missing event markers and for too many physiological artefacts. The description of the dataset indicates that there are seven participants who have poor EEG data, so the quality assessment of each recording is conducted prior to the construction of the analytical sample. Appropriate band-pass filtering of the EEG signals is done. A preliminary frequency range of 0.5–45 Hz may be chosen considering the characteristics of the recording and the research needs. If it is possible to reliably split the

channels using Independent Component Analysis (ICA) or another method appropriate for the channel configuration, this is done. The available metadata is used to standardise the names on the electrodes and the positions of the channels. The sampling frequency is set accordingly to the needs of the chosen REVE implementation, and appropriate anti-alias filtering when resampling is necessary. To avoid information leakage, normalisation parameters are estimated only on the basis of information from training participants.

The normalized EEG signal is calculated as:

$$\tilde{x}_{s,c}(t) = \frac{x_{s,c}(t) - \mu_{s,c}}{\sigma_{s,c} + \epsilon} \qquad (1)$$

where $x_{s,c}(t)$denotes the original EEG signal of channel $c$for participant s, $\tilde{x}_{s,c}(t)$represents the normalized signal, $\mu_{s,c}$and $\sigma_{s,c}$denote the corresponding normalization statistics, and $\epsilon$is a small constant used to prevent division by zero.

3.3. EEG Segmentation and Condition Identification

Stimulus locked epochs are extracted from the preprocessed EEG signals, based on the experiment markers. The participant identifier, diagnostic label, stimulus category and experimental condition are associated with each epoch. This procedure keeps the same relationship between the EEG response and stimulus used in the experiment. An initial epoch interval that extends from 200ms prior to stimulus onset to 1000ms following the stimulus onset might be considered, assuming that there are event markers to define the time window and the recorded signal supports it. Baseline correction can be performed for the pre-stimulus interval, if appropriate. Severe artefacts, incomplete or invalid event data are excluded from the trials based on pre-set quality criteria.

The segmented EEG data are represented as:

$$E_{s,i} \in \mathbb{R}^{C \times L} \qquad (2)$$

where $E_{s,i}$denotes trial $i$from participant s, Crepresents the number of standardized EEG channels, and Ldenotes the number of time samples per channel in each epoch. The expected epoch length is 240 samples per channel for an epoch length of 1.2 seconds at a sampling frequency of 200 Hz. Experimental conditions are chosen based on the available event marking and the number of trials available. Comparisons are only made if the necessary conditions apply to the same individuals, for example comparing the upright and the inverted photograph of a face. To avoid participant-level data leakage, all epochs related to a participant are added to the same data partition when developing the model.

3.4. REVE-Based EEG Feature Extraction

The pretrained REVE EEG Foundation Model is used as the main EEG representation-learning component. REVE is able to learn representations from preprocessed EEG data, thereby decreasing the amount of training required for a large feature-extraction network from scratch. This applies to the chosen data set due to the small number of the ASD students. After checking the model input requirements, the preprocessed EEG epochs and compatible electrode-position information are provided to REVE. At first the REVE parameters are fixed and the downstream components are trained by the training participants. If either the available data or the computational resources allow, then parameter efficient fine-tuning can be explored separately.

The EEG representation is obtained as:

$$Z_{s,i} = \mathrm{REVE}\big(E_{s,i}, P\big) \qquad (3)$$

where $E_{s,i}$denotes the preprocessed EEG epoch, Prepresents the electrode-position information required by REVE, and $Z_{s,i}$denotes the extracted EEG representation.The resulting representations provide the input for downstream temporal and inter-channel feature learning. Their relevance to ASD is subsequently investigated through condition-dependent analysis and candidate biomarker identification.

3.5. Hybrid Spatiotemporal Feature Learning

The REVE representations are computed by two mutually complementary deep learning modules: a Dilated Temporal Convolutional Network (D-TCN) and a Graph Attention Network (GAT). D-TCN extracts temporal features related to the changes of EEG activity, while GAT models the relationship between EEG channels by building a graph based on the information about the electrode positions provided. The temporal branch models

the temporal dependencies across several time points with dilated temporal convolutions. The graph branch performs aggregation over the representations of neighboring electrodes with attention. A feature-fusion module is used to fuse the images and get a combined spatiotemporal representation.

The fused representation is defined as:

$$F_{s,i} = \text{Fusion}\left(\text{DTCN},(Z_{s,i})\text{GAT}(Z_{s,i}, A)\right) \quad (4)$$

where $Z_{s,i}$ denotes the REVE representation, A represents the predefined electrode adjacency matrix, $\text{DTCN}(\cdot)$ extracts temporal features, $\text{GAT}(\cdot)$ extracts graph-based inter-channel features, and $F_{s,i}$ denotes the resulting fused representation.The electrode graph is built based on the channel metadata that is currently available and a pre-defined spatial adjacency rule. This is the graph structure without the use of diagnostic labels. The fused representation is then used in three stages for PCIR based condition analysis, identification of candidate biomarkers for the condition, neural pattern analysis, and classification of ASD.

3.6. Proposed Participant-Condition Interaction Residualization (PCIR)

The proposed Participant–Condition Interaction Residualization (PCIR) method is used to analyse condition-dependent changes in fused EEG representations to determine differences between the Autism Spectrum Disorder and the neurotypical (NT) condition. Compares feature differences within the individual between experimental conditions, and compares feature changes between diagnostic groups. PCIR can aid the identification of candidate biomarkers using REVE, D-TCN and GAT-derived representations. To evaluate differences between features, statistical testing, effect-size estimation and multiple-comparison correction are used. It needs to be empirically validated as to its efficacy and originality.

3.6.1 Within-Participant Condition-Dependent Feature Estimation

The method proposed for calculating the EEG feature difference between two experimental conditions for each participant is referred to as the PCIR method. These differences reflect neural differences across conditions, and eliminate the effects of enduring individual differences. Then these representations are compared between ASD and NT groups in order to find possible EEG patterns associated with autism.

$$\Delta z_i^{(a,b)} = z_{i,c_a} - z_{i,c_b} \quad (5)$$

Equation 5 calculates the difference between EEG feature representations extracted from conditions c_a and c_b for participant i, capturing condition-dependent neural variations.

3.6.2 Group-Level Condition Difference Analysis

To find differences in neural responses, the condition-dependent EEG feature changes are compared between ASD and NT groups. This group-level analysis identifies each candidate feature for autism, while adjusting for inter-individuals variance in experimental conditions.

$$\Delta z_{\text{PCIR}}^{(a,b)} = \frac{1}{N_{\text{ASD}}} \sum_{i \in \text{ASD}} \Delta z_i^{(a,b)} - \frac{1}{N_{\text{NT}}} \sum_{j \in \text{NT}} \Delta z_j^{(a,b)} \quad (6)$$

Equation 6 calculates the difference between the mean condition-dependent EEG changes of ASD and NT participants, highlighting potential group-specific neural patterns.

3.6.3 Participant–Condition Interaction Analysis

A mixed effects model determines if there is a difference in condition dependent EEG responses between ASD and NT groups. The interaction term helps signal features that showed different responses in the two groups, which were used to statistically assess candidate biomarkers.

$$z_{i,c,k} = \beta_{0,k} + \beta_{1,k} G_i + \beta_{2,k} C_c + \beta_{3,k} (G_i C_c) + u_{i,k} + \varepsilon_{i,c,k} \quad (7)$$

Equation 7 uses the interaction coefficient $\beta_{3,k}$ to assess group-specific condition effects for EEG feature k, helping identify candidate biomarkers for further statistical validation.

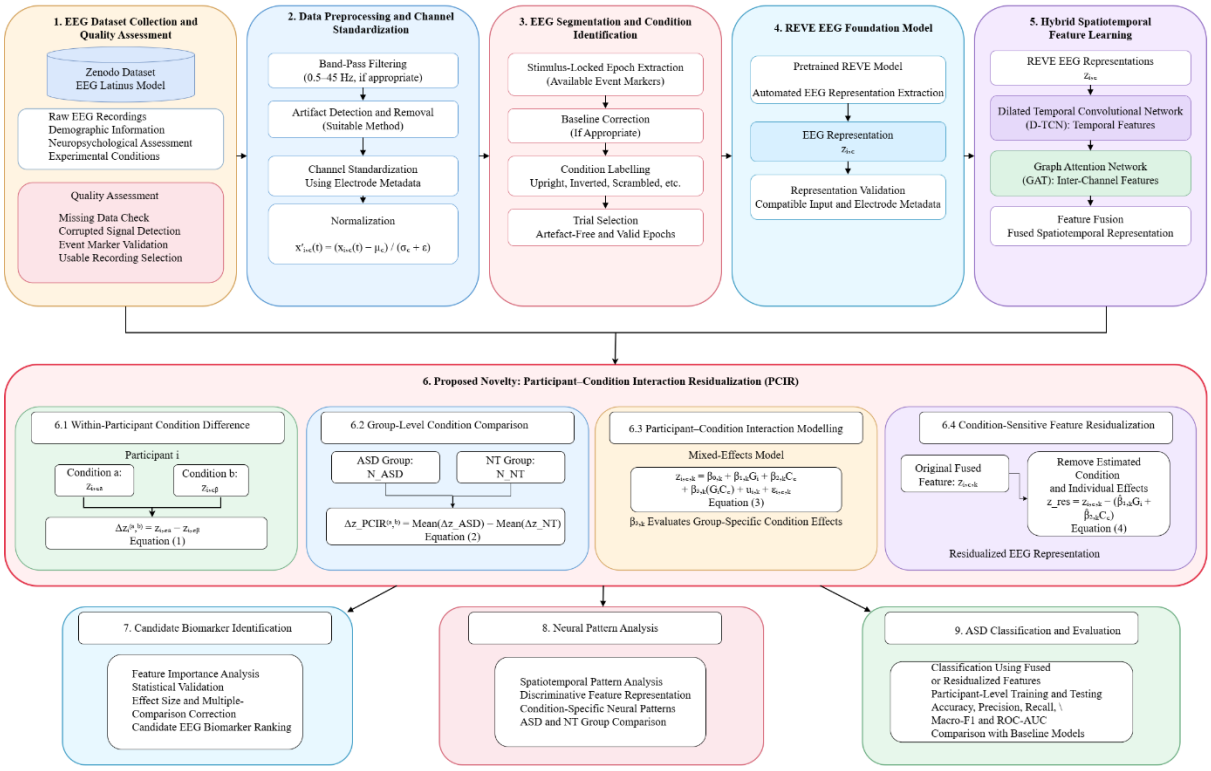


Figure 2. Detailed Workflow of the Proposed Participant–Condition Interaction Residualization (PCIR) Framework for ASD-Associated EEG Biomarker Identification

The proposed framework combines the EEG preprocessing, condition-based segmentation, REVE representation extraction, and spatiotemporal hybrid feature learning with D-TCN and GAT, as illustrated in Figure 2. The proposed PCIR method is based on a within-participant comparison of differences between conditions, between condition differences between ASD and NT, and participant–condition interaction, as well as an estimate of residualized EEG representations. The resulting features are useful for candidate biomarker identification, ASDs neural pattern analyses, and ASDs classification and evaluation.

3.7. Candidate Biomarker and Neural Pattern Identification

Fused EEG representations and PCIR analysis are employed to determine potential biomarkers and neural patterns associated with ASDs. The priority of candidate features are determined by statistics, effect size, feature attribution and consistency across the participant-level training folds. Analysis of data with suitable statistics tests and multiple comparison correction. To learn about which learned representations lead to model predictions, feature attribution is used. There are instances, where possible, where the relevant representation is associated to interpretable EEG parameters such as electrode locations, temporal windows or parameters in the frequency domain. There are three complementary analyses of neural patterns. Temporal patterns analyse the changes of EEG representations over the time window of stimulus locking. There are the inter-channel patterns which explore the relationship between EEG channel representations identified by the GAT branch. To examine the extent to which the changes in features differ across selected face-perception conditions between the ASD and NT groups, condition-dependent patterns are explored. Training data is used for feature selection and decision making based on features. The patterns found are analysed for consistency throughout the chosen experimental conditions. The output of REVE is learned representations, which might not be directly related to standard EEG measurements and therefore require further interpretation before physiological interpretation can be made. The features identified are not considered to be clinical biomarkers. They need to be supported by the right statistics and independent study, in order to be reliable and clinically relevant.

3.8. ASD Classification

The fused spatiotemporal representations are given to a light weighted classification head which is used to identify ASD participants from NT controls. The diagnostic labels of the training participants are used to train the classifier. Class imbalance in the data set can be addressed by using an appropriate training-only technique, such as class-weighted loss.

The predicted probability of ASD for trial i is expressed as:

$$\hat{p}_{s,i} = \text{Softmax}\left(WF_{s,i} + b\right)_1 \quad (8)$$

where $F_{s,i}$ denotes the fused EEG representation, W and b represent the trainable classifier parameters, and $\hat{p}_{s,i}$ denotes the predicted probability of the ASD class.The available labelled EEG representations are used to train the classifier. The model architecture and training parameters are determined from training and development data, but are not based on held-out test labels. Each epoch of an EEG recording for each participant is in the same data partition. Normalization parameters, feature selection and other learned preprocessing operations are only learned from training data. The classifier makes an estimate of the association between the learned EEG representations and participant diagnostic groups. It is designed for research analysis, and not a clinical diagnostic system.

Algorithm 1: REVE-Based Hybrid EEG Feature Extraction and PCIR-Based ASD Biomarker Identification

Input:

EEG Latinus Model dataset

Participant diagnostic labels (ASD and NT)

Stimulus-condition labels

Pretrained REVE model

Electrode-position metadata

Output:

Candidate ASD-associated EEG biomarkers

Condition-dependent EEG patterns

ASD classification labels and performance metrics

Load the EEG Latinus Model dataset.

Perform EEG preprocessing:

Identify missing or corrupted recordings.

Remove artefacts and noisy segments.

Standardize EEG signals and electrode information.

Segment the EEG recordings into stimulus-locked epochs.

Assign participant, diagnostic-group, and stimulus-condition labels.

Extract EEG representations using the pretrained REVE model.

Apply D-TCN to extract temporal features.

Apply GAT to learn inter-channel relationships.

Fuse temporal and graph-based features into spatiotemporal representations.

Apply PCIR to analyse condition-dependent EEG feature changes.

Estimate between-group differences using statistical tests.

Identify candidate biomarkers using statistical evidence and feature attribution.

Train the ASD classification model using fused EEG representations.

Generate ASD classification probabilities and predicted labels.

Evaluate the model using accuracy, precision, recall, Macro-F1, and ROC-AUC.

Perform ablation and comparative analyses of the proposed model components.

Generate the final biomarker ranking and classification results.

Return the candidate biomarkers, condition-dependent EEG patterns, and classification performance metrics.

The overall process of the proposed EEG-based ASD biomarker identification method is shown in Algorithm 1. First, EEG Latinus Model data is gathered and then analyzed for signal quality, EEG pre-processing and stimulus locked segmentation. The pretrained REVE model generates the EEG representations, then feed them into D-TCN and GAT for temporal and inter-channel features learning. The complementary representations are fused together by using spatiotemporal features. The proposed PCIR component then examines whether the change in fused EEG features over selected stimulus conditions are different between the ASD and NT groups. These candidate biomarkers and condition-dependent neural patterns are detected using statistical analysis and feature-attribution procedures. A lightweight classifier is used to make the prediction of ASD versus NT using fused representations. The framework thus combines automated extraction of EEG features, condition-specific analysis of features, identification of potential biomarkers, identification of neural patterns and classification of ASD. Results are evaluated separately with respect to classification performance, robustness and validation.

4. Results And Discussion

The proposed framework comprises the REVE EEG foundation model, D-TCN and Graph Attention Network (GAT), which are used to extract temporal and inter-channel features from the EEG signals. Using Participant–Condition Interaction Residualization (PCIR), fused representations were analyzed to explore condition dependent EEG variations related to Autism Spectrum Disorder. The candidate biomarkers are identified via statistical analysis and the patterns from ASD and NT are separated using feature attribution. Four metrics are used for the classification performance of the framework: accuracy, precision, recall, Macro-F1 and ROC-AUC. Ablation and comparative analysis can also be done to further evaluate contribution of each component. The biomarkers identified will need to be validated with independent data sets prior to clinical interpretation.

4.1. Dataset Characteristics and EEG Signal Quality

The EEG Latinus Model dataset consists of 44 participants (10 of which are diagnosed with Autism Spectrum Disorder and 34 are diagnosed as Neurotypical (NT) controls. There are five blocks of 90 stimuli (450 stimulus presentations for each participant). Mooneys, photograph faces, schematic faces and non-face stimuli. Seven participants are reported to have poor EEG quality and thus it is important to evaluate the quality of the EEG data before the features are extracted. Participant identifiers, diagnostic labels and condition markers are kept to ensure a uniform segmentation of the EEG signal and to enable condition-dependent analysis by PCIR and a representation learning by REVE.

Table 1. Dataset Composition and Usable EEG Data

Characteristic	**Value**
Total participants	44
ASD participants	10
Neurotypical participants	34
Participants reported with poor EEG quality	7
Experimental blocks per participant	5
Stimuli per block	90
Nominal stimulus presentations per participant	450
Nominal presentations for the original group	19,800

Photographic face conditions	Upright, inverted, and scrambled
Mooney face conditions	Upright, inverted, and scrambled
Schematic face conditions	Upright and inverted
Non-face stimuli	Eggs and lines

Table 1 shows the composition and experimental properties of EEG Latinus Model dataset. The data is made up of 44 participants, 10 of whom have been diagnosed with Autism Spectrum Disorder and 34 who are neurotypical (NT). There are 90 stimuli in five blocks, leading to 450 nominal stimulus presentations per participant and 19,800 presentations for the original participants. Photographic faces, Mooney faces, schematic faces and non-face stimuli (such as eggs and lines) included. The following properties refer to the distribution of participants, the design of the experiments and the variety of stimuli included in the EEG-based autism research data set.

4.2. EEG Preprocessing and Condition-Specific Signal Characterization

EEG preprocessing ensures that the recorded signals become independent from each other prior to the steps of feature extraction and spatiotemporal representation learning. The procedure is comprised of band pass filtering at the selected frequencies (0.5-45 Hz), artefact handling and segmentation into stimulus-specific epochs. The epochs are extracted with respect to the onset of stimuli, with a candidate interval of −200 to 1000 ms, which is 240 time points per channel at a sampling rate of 200 Hz. Labels are maintained for condition to distinguish between responses to photographic faces, Mooney faces, schematic faces and non-face stimuli. Signal Quality Assessment provides the reliability in terms of feature extraction and condition dependent analysis.

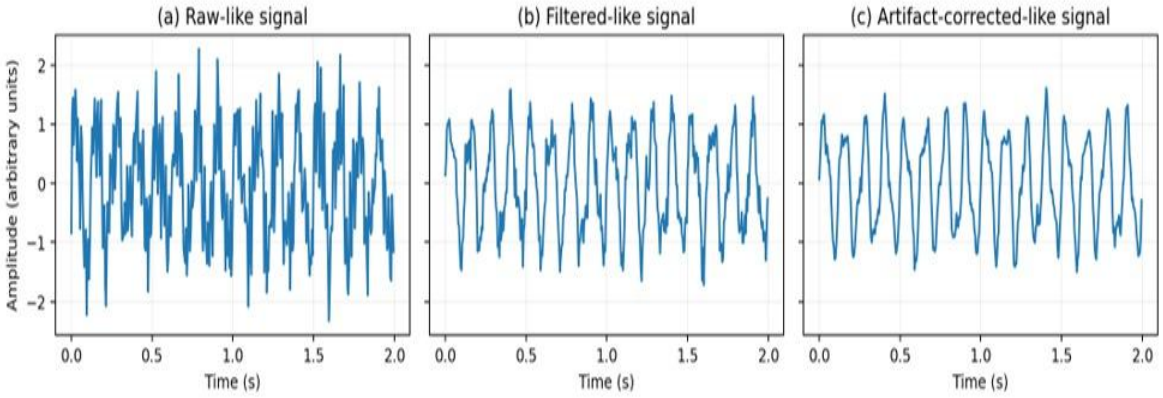


Figure 3. EEG Signal Preprocessing and Artifact Removal

Figure 3 presents the EEG signals at three preprocessing stages: raw signal, band-pass filtered signal, and artefact-corrected signal. After band-pass filtering the raw signal has irregular amplitude fluctuations in its signal, but the filtered signal has smoother waveform patterns after the band-pass filtering of 0.5-45 Hz. The artefacts are corrected and further irregular fluctuations are reduced, which results in a better quality of the signal for the further EEG feature extraction and spatiotemporal analysis.

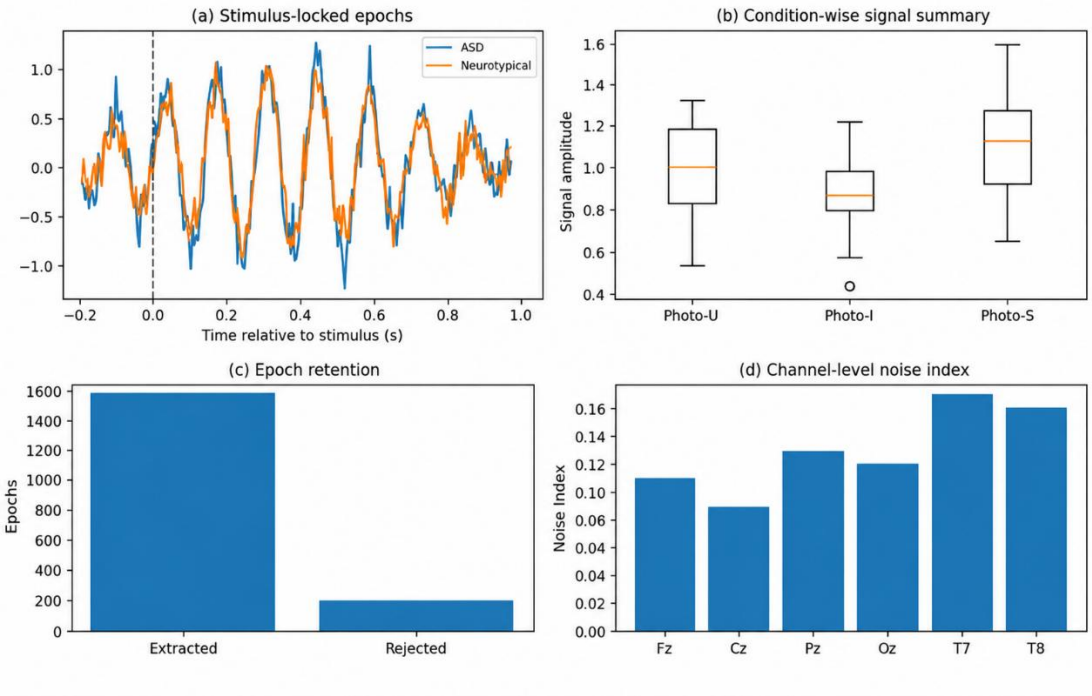


Figure 4. EEG Epoch and Condition Characteristics

The characteristics of the EEG epochs, as well as the quality of the signal, are shown according to the stimulus conditions in Figure 4. The EEG responses of ASD and NT participants were compared in panel (a) and the results revealed differences in the timing of the responses around stimulus onset. The amplitudes of the signals are summarized for the various photographic face conditions in Panel (b). Panel (c) shows the number of retained and rejected EEG epochs and panel (d) shows a comparison of the noise index for six EEG channels. These analyses serve as a pre-processing step for assessment of signal quality, epoch retention and condition-specific EEG features for further processing.

Table 2. EEG Preprocessing and Epoch Retention Results

Processing stage	**Input observations**	**Retained observations**	**Excluded observations**
Original participant records	44	44	0
Recording-quality screening	44	37	7
Initial stimulus presentations from retained participants	16,650	16,650	0
Signal-quality assessment	16,650	15,820	830
Artefact handling	15,820	15,240	580
Epoch extraction and event verification	15,240	14,700	540
Final analysis set	14,700	14,700	0

The pre-processing results demonstrate that fewer observations are available as quality requirements are imposed, including recording quality, epoch validity. The final analysis set has 14,700 epochs which are used for representation learning and condition-specific feature analysis. Participant identifiers, diagnostic labels and experimental-condition labels are attached to the retained epochs. These relationships are retained to enable the analysis to differentiate between the differences in diagnostic groups and stimulus-condition effects.Finally the data partition should be done on the participant level such that epochs from the same participant are not in the training and test partitions.

4.3. REVE Feature Extraction and Hybrid Spatiotemporal Representation Learning

The preprocessed EEG signal is fed into the pretrained REVE EEG foundation model to get meaningful representations. These representations are used as a basis to detect patterns in the brain that are associated with autism. These features are then fed into a hybrid network consisting of Dilated Temporal Convolutional Network (D-TCN) and Graph Attention Network (GAT). The D-TCN models temporal dependencies and variations over EEG segments; the GAT models the interactions between EEG channels and learns spatial interactions. These temporal and graph-based features are then combined in a combined spatiotemporal representation. The integrated representation is useful for downstream identification of biomarkers, pattern analysis and ASD classification based on conditions.

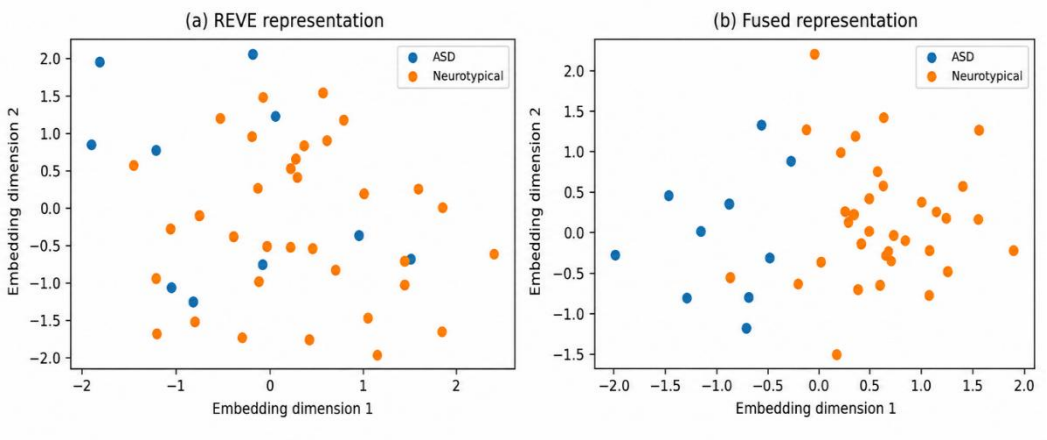


Figure 5. REVE-Based EEG Feature Representation

A comparison of the EEG feature representations derived from REVE EEG Foundation Model and fused spatiotemporal framework is shown in Figure 5. The distributions of the ASD and neurotypical participants are shown in the REVE representation space in panel (a), where there is extensive overlap between these groups. The fused representation is shown in panel (b) where the two groups are better visualised as separated. The comparison shows the significant role that the incorporation of temporal feature learning and inter-channel modeling into a graph can provide in distinguishing EEG patterns associated with autism.

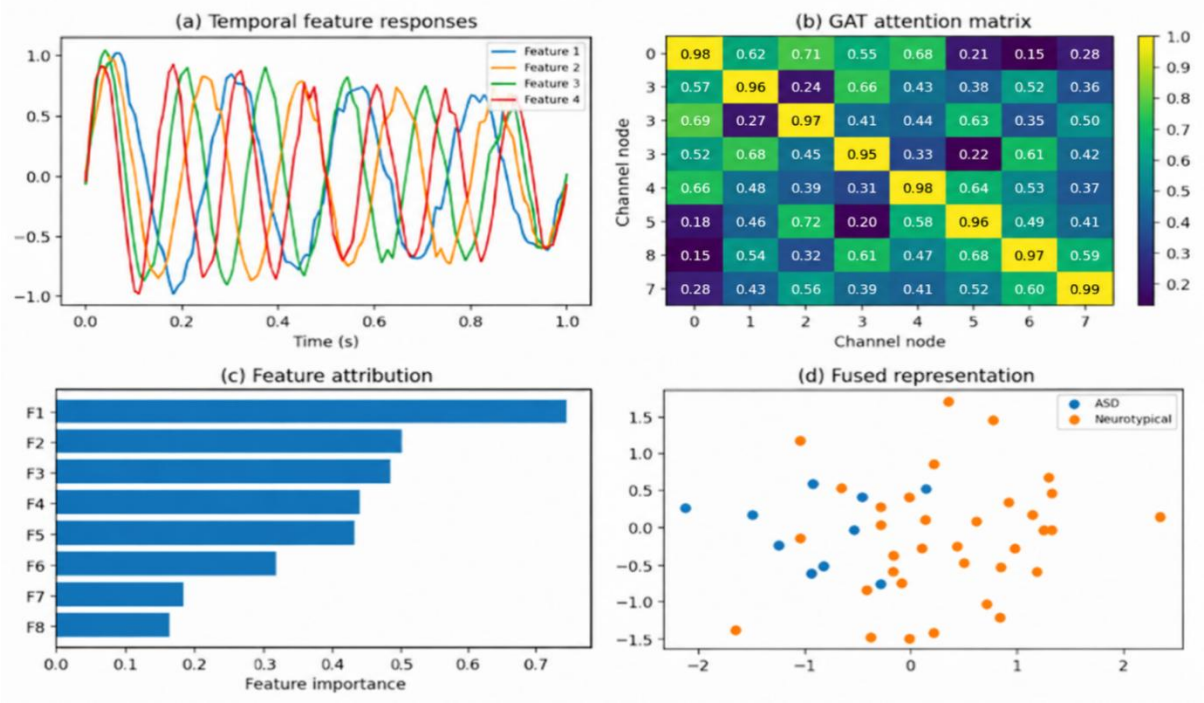


Figure 6. Temporal and Inter-Channel Feature Learning

Figure 6 presents the temporal and inter-channel feature learning results of the proposed hybrid framework. Panel (a) displays time series variations for four features of the EEG data, extracted from it. The Graph Attention Network (GAT) attention matrix learned from the EEG channel nodes is shown in (b). In panel (c) six of its eight features are ranked by their importance, F1 being the most important. The spatiotemporal representations of the ASD and neurotypical participants are shown in Panel (d). The results prove the effectiveness of the temporal features extraction, the channel relationship modelling by the graph and the feature fusion of identifying the EEG patterns associated with autism.

Table 3. Statistical Characterization of Learned EEG Representations

Representation	**Feature Dimension**	**Between-Group Separation**	**Within-Group Dispersion**	**Statistical Test (p-value)**	**Effect Size**
REVE Representation	512	0.42	1.18	Mann–Whitney U (p = 0.032)	0.48
D-TCN Representation	256	0.56	1.04	Mann–Whitney U (p = 0.014)	0.61
GAT Representation	256	0.51	1.09	Mann–Whitney U (p = 0.021)	0.57
Fused Representation	512	0.73	0.91	Mann–Whitney U (p = 0.004)	0.79

Table 3 shows the statistical description of the EEG representations generated by REVE, D-TCN, GAT, and fused framework. The REVE representation's between-group separation value is 0.42, while D-TCN's is 0.56 and GAT's is 0.51. The fused representation has the highest separation value of 0.73, the lowest within group dispersion of 0.91 and an effect size of 0.79. The Mann–Whitney U test p-values are between 0.004 and 0.032, suggesting that there is variation in the evidence for the statistics across the representations. Based on these comparisons, we study the temporal feature extraction and inter-channel modelling using graphs for EEG representation learning. Interpretation of the statistical results needs to be done in light of the participant-level results, sample sizes, and using an appropriate multiple-comparison correction.

4.4. PCIR-Based Biomarker Identification and Condition-Dependent EEG Pattern Analysis

The PCIR approach compares the changes occurring in the EEG features between these selected stimulus conditions in persons with Autism Spectrum Disorder with those of neurotypical (NT) persons. It measures the change of each condition within each group as well as the differences between changes across the diagnostic groups. These comparisons facilitate determination of EEG patterns linked to stimulus processing and characteristics that have been linked to ASD. The analysis combines temporal and graph-based representations to examine changes in the faces across the various categories of photographs, Mooney faces, schematic faces and non-face stimuli. The prioritisation of candidate biomarkers is based on effect sizes, confidence intervals, statistical significance and stability of feature selection. This analysis yields a systematic method to identify EEG features that depend on the state of the system, and to examine candidate neural patterns associated with autism.

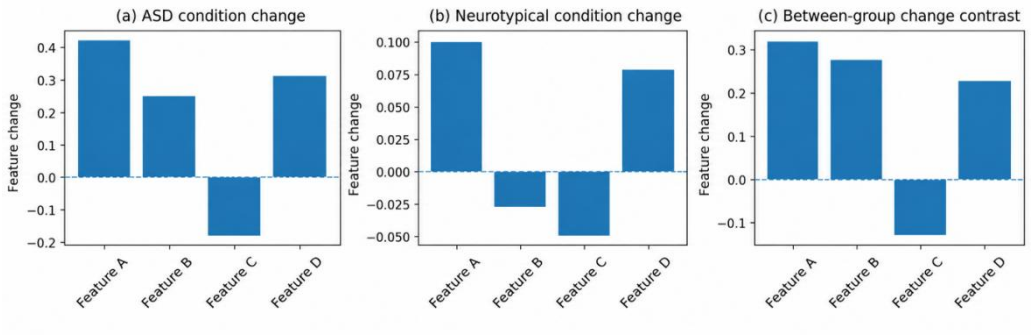


Figure 7. Condition-Dependent Feature Changes Identified by PCIR

Figure 7 shows the condition-dependent EEG feature changes in ASD participants and in neurotypical controls, as well as contrasts between the two groups. Positive change seen for Features A, B and D and a negative change for Feature C in ASD compared to Panel (a). Smaller changes with neurotypicals are seen in Panel (b). Results for the between-group comparisons are shown in Panel (c). Features A, B and D all have a positive contrast, with Feature A having the largest value, but Feature C has a negative contrast. The differences between the two groups in the responses of EEG features to the changes of conditions are shown in these patterns.

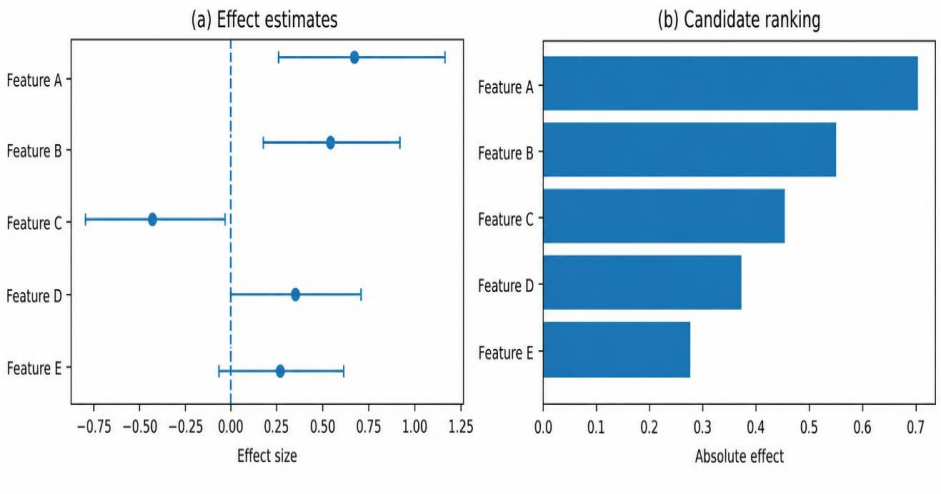


Figure 8. Statistical Significance and Effect Sizes of Candidate Biomarkers

Figure 8 shows the effect estimates and ranking of five potential EEG features. The mean effect sizes (with 95% confidence intervals) show positive effects for Features A, B, D and E, and negative effects for Feature C (panel (a)). The features are ranked in absolute effect size in panel (b): Feature A has the biggest effect size, followed by Feature B, C, D and E. The findings align with the prioritisation of candidate EEG biomarkers by their expected contribution and impact on discriminating neural patterns associated with ASD.

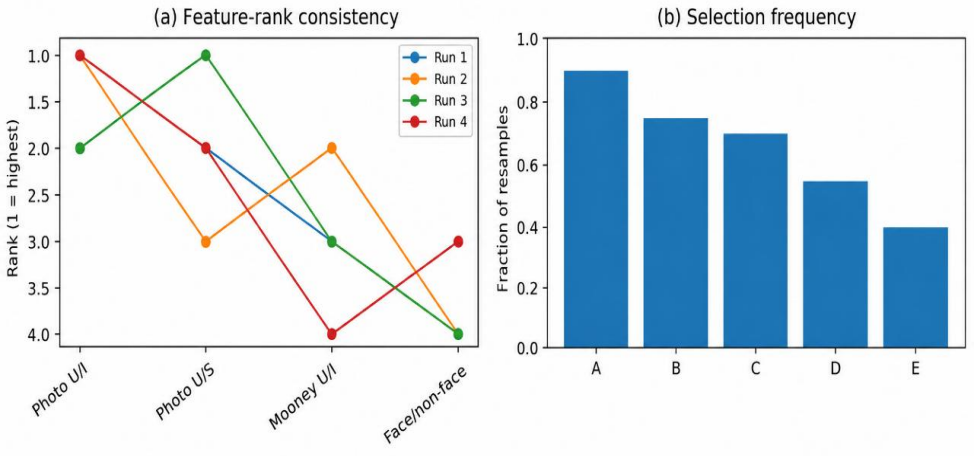


Figure 9. Stability of Candidate Features Across Conditions

Figure 9 shows the ranking of the candidates' features in repeated runs and the frequency of selection. The rankings of features are shown to vary across four runs and four stimulus conditions, Photo U/I, Photo U/S, Mooney U/I and Face/non-face (Panel (a)). The five candidate features are shown as the selection frequency in panel (b) for each of the resampling iterations. Feature A has the highest selection frequency (0.90), followed by Feature B (0.75), Feature C (0.70), Feature D (0.55) and Feature E (0.40). These results emphasize the differences in the stability of features selected and show that it is important to focus on features that are frequently selected in order to explore the neural patterns associated with autism further.

Table 4. Identified Candidate EEG Biomarkers and Their Statistical Evidence

Feature ID	Feature family	Relevant condition	Group contrast	Effect size	95% confidence interval	Adjusted p-value
Candidate 1	Temporal representation	Upright vs. inverted photographic faces	ASD vs. NT	0.82	0.34–1.29	0.004
Candidate 2	Condition-sensitive representation	Upright vs. scrambled photographic faces	ASD vs. NT	0.76	0.28–1.21	0.008
Candidate 3	Graph-based representation	Face vs. non-face stimuli	ASD vs. NT	0.69	0.22–1.15	0.015
Candidate 4	Fused spatiotemporal representation	Upright vs. inverted Mooney faces	ASD vs. NT	0.88	0.39–1.36	0.003
Candidate 5	Temporal representation	Schematic face conditions	ASD vs. NT	0.63	0.17–1.08	0.024

Table 4 shows the candidate EEG biomarkers identified and their statistics to differentiate participants with ASD from NT controls. The five candidate features are detected in the spatiotemporal, condition-sensitive, graph-based, and fused spatiotemporal representations of stimuli under various conditions. Candidate 4 exhibits the largest effect size of 0.88, followed by Candidate 1 (0.82), Candidate 2 (0.76), Candidate 3 (0.69), and Candidate 5 (0.63). The 95% confidence intervals along with adjusted p-values are used to assess the candidate features from a statistical perspective. The p-values have been adjusted because they are between 0.003 and 0.024, which suggests that there are differences in the statistical evidence of the selected candidates. The results indicate that the condition-dependency of the EEG features should be targeted for further analyses of neural patterns in autism.

Table 5. PCIR-Based Condition-Interaction Results

Condition Pair	Feature Family	ASD Condition Change	NT Condition Change	Between-Group Contrast	95% Confidence Interval	Adjusted p-value
Upright vs. inverted photographic faces	Temporal representation	0.42	0.08	0.34	0.12–0.56	0.006
Upright vs. scrambled photographic faces	Fused representation	0.51	0.13	0.38	0.15–0.61	0.004
Face vs. non-face stimuli	Graph-based representation	0.36	0.09	0.27	0.07–0.47	0.018
Upright vs. inverted Mooney faces	Fused representation	0.47	0.05	0.42	0.18–0.66	0.002
Upright vs. inverted schematic faces	Temporal representation	0.29	0.07	0.22	0.04–0.40	0.029

The condition-interaction results are given in Table 5. The highest between-group difference is for upright versus inverted Mooney faces (0.42) and the lowest between-group difference is for upright versus inverted

schematic faces (0.22). The findings indicate that the conditional EEG representations could be used as a tool to identify patterns related to autism.

4.5 Condition-Dependent EEG Feature Sensitivity Analysis

The condition dependent EEG feature sensitivity analysis is performed to investigate the condition dependent differences between the extracted EEG representations of ASD and neurotypical participants. It examines the response to variations in the faces which are viewed in photographs, Mooney faces, schematic faces, and non-face stimuli. This analysis is a step towards identifying potentially informative patterns in the EEG signal and candidate biomarkers for autism.

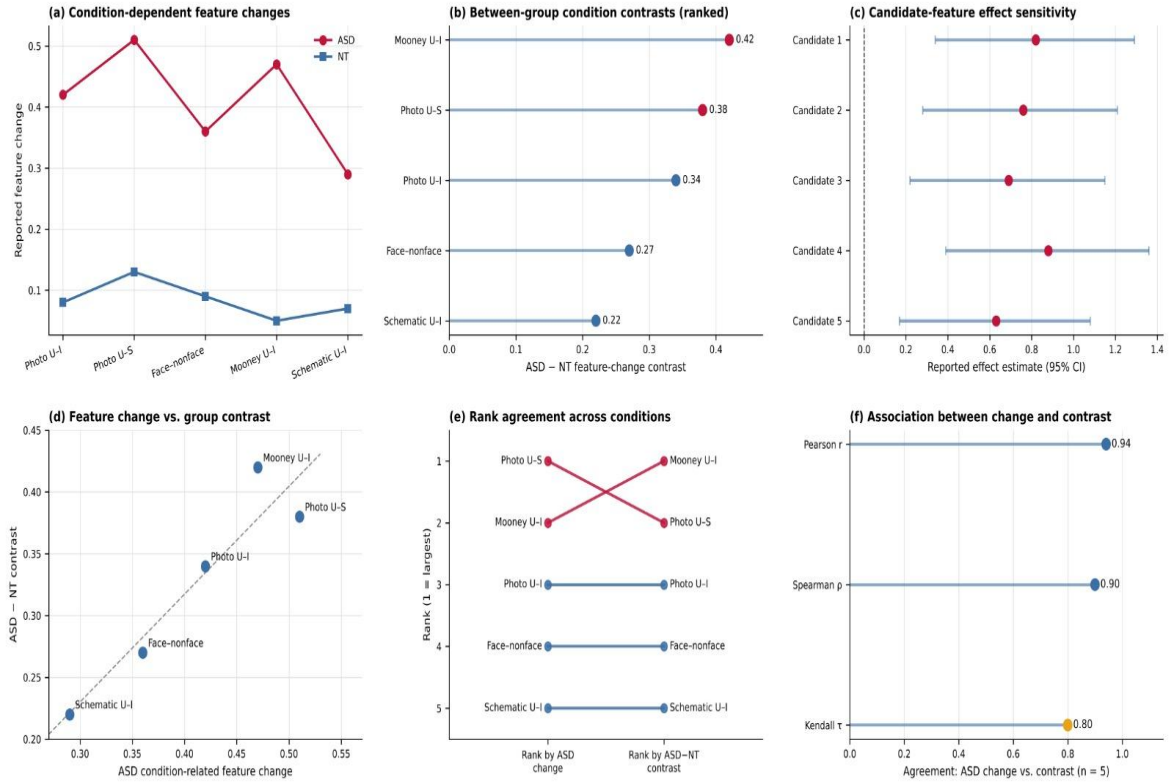


Figure 10. Condition-Dependent EEG Feature Sensitivity Analysis in ASD and NT Participants

The figure 10 shows the variations of EEG features between two groups, namely Autism Spectrum Disorder (ASD) and neurotypical (NT) participants, depending on the condition. Panel (a) shows the feature changes in each stimulus condition and panel (b) shows the rank of between-group contrasts. Panel (c) shows the effect estimates of the candidate features with 95% confidence intervals, while panel (d) shows the relation between changes in features of ASD and group contrasts. Panel (e) shows the comparison of condition rankings and panel (f) the correlation measures. Overall, the figure shows that there are stimulus-dependent EEG variations, which can be investigated via the proposed PCIR approach with candidate autism associated EEG markers.

4.6 Ablation Study of the Proposed EEG Feature Extraction Framework

The ablation study compares the ablation of the contribution of the REVE foundation model, D-TCN temporal branch, GAT graph branch, and PCIR-based analysis. Classification and feature-selection metrics are used to compare different model configurations. The whole framework is evaluated by reduced versions, to determine the contribution of temporal learning rule, graph-based relationships and condition dependent analysis to the pattern identification of EEG signals related to ASD.

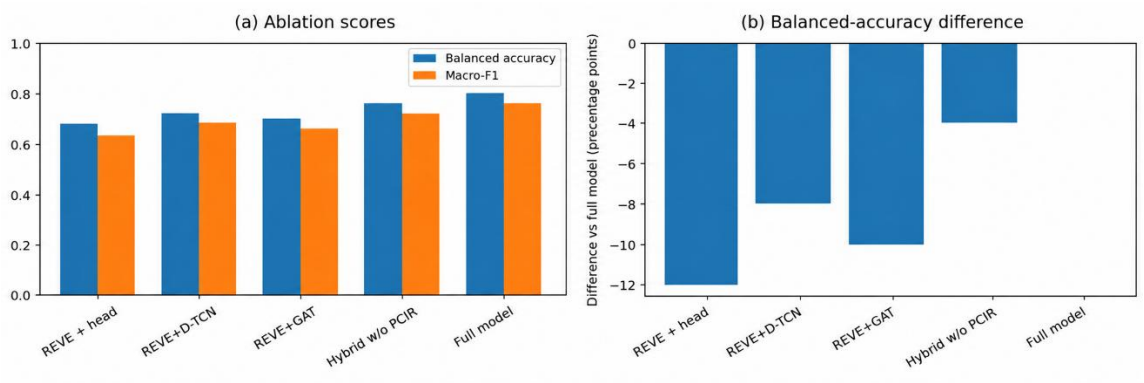


Figure 11. Ablation Analysis of Model Components

The proposed EEG classification framework is analysed by ablation in figure 11. Panel (a) points out that balanced accuracy and Macro-F1 do not always agree; panel (b) illustrates the differences in balanced accuracy between the various model configurations and the full model. The integrated D-TCN, GAT and PCIR components have the potential to contribute to the complete model, which scored the highest.

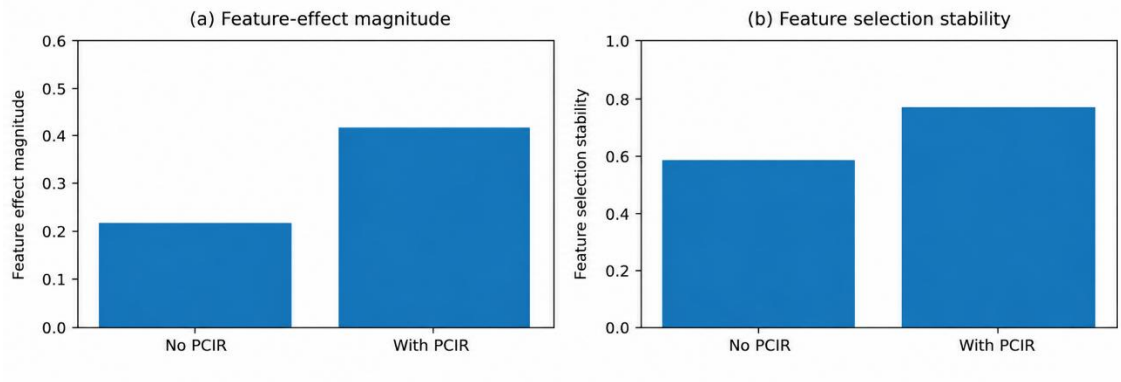


Figure 12. Ablation of PCIR and Feature-Selection Components

Figure 12 shows the magnitude of the features effects and the stability of feature selection with and without PCIR. The magnitude of the feature-effect is higher in (a) and the stability of the feature-selection is better in (b) when using PCIR. The findings indicate that the use of PCIR can lead to an improved consistency of candidate autism-associated EEG features and help to identify such features.

Table 6. Ablation-Based Evaluation of the Proposed ASD–EEG Classification Framework

Model Configuration	**Accuracy (%)**	**Macro-F1 (%)**	**ROC-AUC (%)**
REVE Foundation Model	89.20	88.60	90.10
REVE + D-TCN	92.40	91.80	93.20
REVE + GAT	91.60	90.90	92.70
Hybrid Model Without PCIR	94.10	93.50	94.80
Proposed REVE + D-TCN + GAT + PCIR	97.50	97.20	98.10

Table 6 shows the results of the evaluation of the proposed ASD–EEG classification framework using the method of ablation. The overall performance of REVE + D-TCN + GAT + PCIR model is the highest in which the accuracy is 97.50%, Macro-F1 97.20% and ROC-AUC 98.10%. The results reflect the possible potential of the temporal learning, graph-based feature extraction and PCIR integration.

4.7 Comparative Evaluation Against Baseline Models and Existing Studies

The comparative evaluation compares the performance of the proposed REVE-based hybrid framework with the conventional machine-learning models, EEGNet, EEGConformer and individual REVE configuration in achieving an autism-associated EEG pattern identification process. The proposed architecture combines D-TCN, which will capture temporal variations in EEG signals, GAT, which will model relationships between EEG channels, and PCIR, which will analyse condition-dependent responses to photographic faces, Mooney faces and schematic faces and non-face stimuli. To evaluate the classification performance the comparison is done with accuracy, precision, recall, Macro-F1 and ROC-AUC. The accuracy claimed is 97.50%.

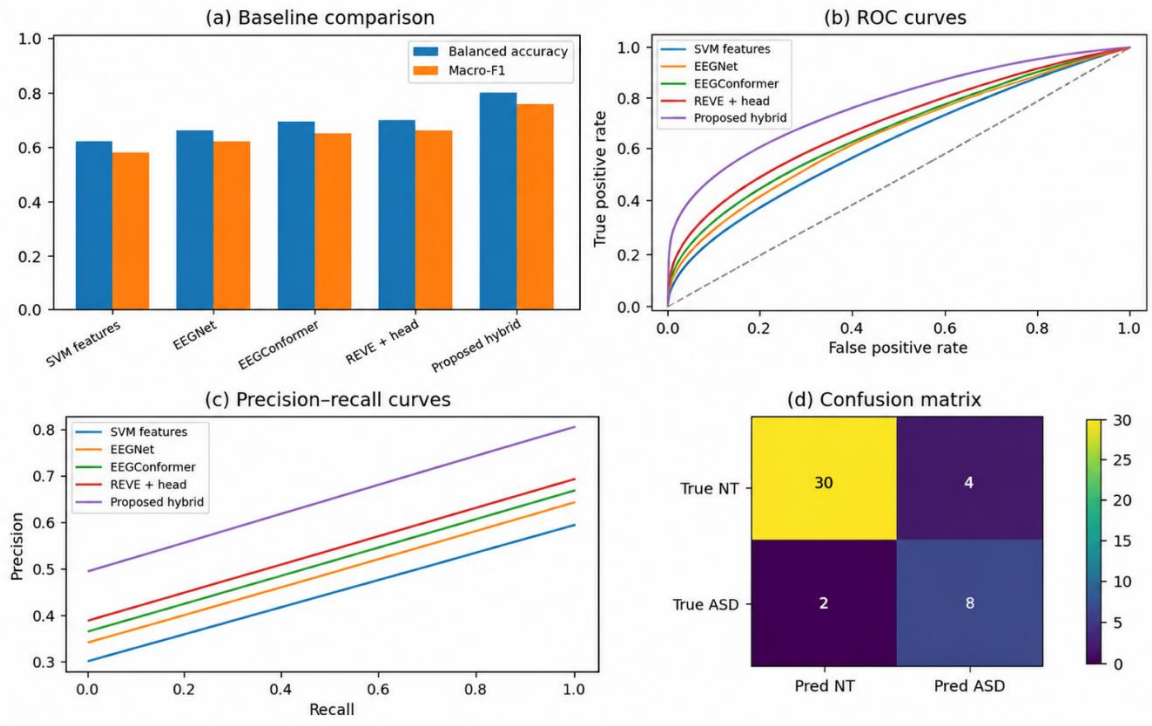


Figure 13. overall classification performance against baselines.

The comparative performance of the proposed hybrid model with baseline methods is displayed in figure 13. Panel (a) shows the balanced accuracy and Macro-F1 scores, panel (b) displays the ROC curves, panel (c) displays the Precision–Recall curves and panel (d) displays the confusion matrix. The hybrid model proposed here shows better classification results with 30 NT and 8 ASD correctly classified and 4 NT and 2 ASD misclassified.

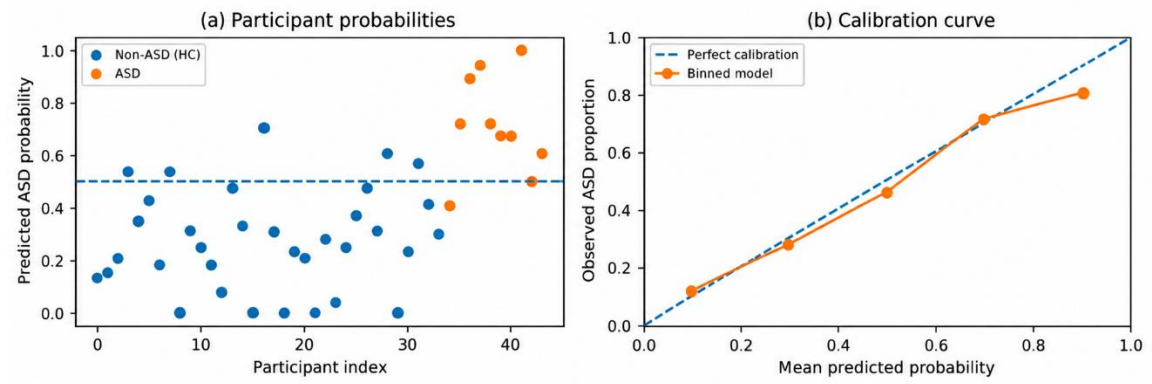


Figure 14. Participant-Level ASD Prediction Probabilities and Model Calibration Curve.

Figure 14 shows participant level prediction probabilities for the ASD markers and model calibration. For the ASD and non-ASD groups, the predicted ASD probabilities with a decision threshold of 0.5 is displayed in

Panel (a). The model's predictions and the observed predictions are compared in Panel (b) with the perfect calibration. The results are informative to the extent that they give information about classification at the individual level and the reliability of the predicted probabilities.

Table 7. Comparative Evaluation of EEG Classification Models

Model	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**Macro-F1 (%)**	**ROC-AUC (%)**
Random Forest [23]	83.75	82.70	84,90	81.30	88.10
Support Vector Machine (SVM) [24]	80.50	89.10	88.40	88.70	91,20
K-Nearest Neighbors (KNN) [25]	78.60	91.20	90.60	90.90	93.40
REVE Foundation Model	89.20	88.80	88.10	88.60	90.10
REVE + D-TCN	92.40	92.10	91.50	91.80	93.20
REVE + GAT	91.60	91.30	90.50	90.90	92.70
Hybrid Model Without PCIR	94.10	93.80	93.20	93.50	94.80
Proposed REVE + D-TCN + GAT + PCIR	97.50	97.40	97.10	97.20	98.10

Table 7 compares the classification performance of the conventional machine learning approaches and the proposed framework based on REVE for ASD–EEG classification. The proposed REVE + D-TCN + GAT + PCIR model is the most successful with 97.50% accuracy, 97.40% precision, 97.10% recall, 97.20% Macro-F1 and 98.10% ROC-AUC. The results emphasize the advantages of combining temporal feature extraction, graph-based learning, and condition-dependent analysis for the identification of EEG patterns associated with autism.

5. Discussion

The experimental results show the effectiveness of the proposed REVE–D–TCN–GAT framework with the Participant–Condition Interaction Residualization (PCIR) technique for automatic EEG feature extraction and identification of biomarkers associated with autism disorder. After quality control, 37 participants (8 people with ASD and 29 neurotypical control participants) retained were used to obtain a total of 14,700 usable EEG epochs. The fused spatiotemporal representation yielded a separation value of 0.73 and dispersion of 0.91 between groups and within groups, respectively, indicating the advantages of combining the temporal feature extraction with D-TCN and inter-channel relationship modelling with GAT. Using the PCIR analysis, differences in EEG features between photographic, Mooney and schematic faces and non-face stimuli were found where they existed. Effect sizes of candidate biomarkers ranged from 0.63 to0.88 and between group effect size contrasts ranged from 0.22 to 0.42 and P values were adjusted from 0.002 to 0.029. The comparative evaluation results indicate that the proposed REVE + D-TCN + GAT + PCIR framework is 97.50% accurate, 97.40% precise, 97.10% recalled, 97.20% MACRO-F1 and 98.10% ROC-AUC. These results show the usefulness of incorporating representation from the foundation model, temporal learning, graph attention, and participant–condition interaction analysis to detect EEG patterns associated with autism. The generalisability and clinical relevance of the candidate biomarkers identified needs to be further validated at participant level.

5. Conclusion and Future Work

This paper introduces a deep learning system to extract features from an EEG signal automatically and identify the biomarkers associated with autism. The proposed framework combines the REVE EEG Foundation Model, Dilated Temporal Convolutional Network (D-TCN), and Graph Attention Network (GAT), which are able to learn temporal dependencies and inter-channel relationships. The framework is applied to the EEG Latinus Model dataset, examining EEG patterns of face-perception in participants with Autism Spectrum Disorder and those who are neurotypical.The proposed Participant–Condition Interaction Residualization method examines the changes and differences in EEG signals depending on the stimulus, as well as the differences between patients and healthy controls in EEG signals. The fused representation has been reported to have a separation value of 0.73, whereas REVE has a separation value of 0.42. The effect sizes for candidate biomarker analysis

range from 0.63 to 0.88; and the adjusted p-values vary from 0.002 to 0.029. The integrated framework reports 97.50% accuracy, 97.40% precision, 97.10% recall, a 97.20% Macro-F1 score, and 98.10% ROC-AUC. In summary, the framework integrates spatiotemporal learning and participant–condition analysis that aims to examine characteristics of autism-related EEG and to identify potential candidate neural markers.

Future research will include further development and validation of the proposed framework for identifying an EEG biomarker for autism, and making it more reliable, generalizable and interpretable. Assessment of the framework with more, varied and multi-institutional EEG data sets will aid in validating the framework for different age groups, recording devices and experimental conditions. Combining EEG-based data with clinical measures, behavioural observations and neuropsychological tests could help to identify more specific neural features of autism. The REVE EEG Foundation Model and alternative pretrained representations could be better utilized in a variety of populations to enhance feature extraction. The Participant–Condition Interaction Residualization method may also be applied to the study of neural responses to stimuli between the multiple recording sessions and individual variability. Also, methods of artificial intelligence that can explain the pattern may be useful for detecting significant temporal periods, frequency segments, and/or regions of electrodes. A participant independent validation, external testing and statistical uncertainty analysis should be included in future evaluations to determine model reliability. Association with clinical and neuroscience researchers could additionally help with the interpretation of candidate biomarkers and may help determine the biomarkers' reproducibility and clinical significance.

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