Research Paper

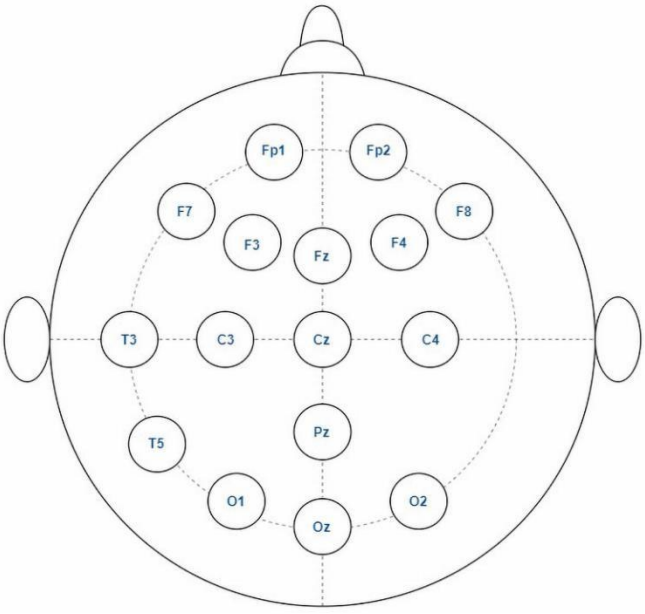
Early Detection Of Autism Spectrum Disorder (ASD) Using EEG Techniques

Abstract: Autism Spectrum Disorder (ASD) is a neurodevelopmental condition. Early diagnosis of ASD continues to be a major challenge. However, brain activity patterns associated with ASD can be captured non-invasively and cost-effectively using electroencephalogram (EEG) signals. In this work, we introduce a novel method for detecting ASD by applying Graph Convolutional Networks (GCNs) to EEG data. Every EEG recording is converted into a graph, with the edges being determined by the statistical similarity of the channels, which stand in for nodes. The model can efficiently learn spatial and relational dependencies among EEG channels thanks to this graph-based representation. Using pre-processed EEG feature sets saved in pickle format, we trained and assessed the suggested GCN model. With high accuracy and F1-scores, the experimental results show promising performance, demonstrating how well GCNs capture significant neural patterns for ASD classification. Our approach not only performs better than conventional machine learning methods, but it also presents a reliable pipeline for the detection of neurodevelopmental disorders based on EEG. This study advances the expanding field of medical diagnostics using graph-based deep learning.

Keywords: Autism Spectrum Disorder (ASD), Early Detection, Machine Learning (ML), Deep Learning (DL), Early ASD Diagnosis, EEG, Spectrogram, Brain Signal, Classification, Feature Extraction, Graph Convolutional Network (GCN), Neurodevelopmental Disorder, EEG-based Diagnosis, Artificial Intelligence (AI), Biomedical Signal Processing, Healthcare Informatics

1. Introduction

ASD is classified as a neurodevelopmental condition that operate on ways in which an individual processes information and acts and often obvious itself in early childhood[1]. ASD is a category of neurodevelopmental condition that affect communication, social interaction and causes repetitive behaviors[2]. It is important, specifically in the early years, since the health related approaches when applied early enough comes with a very good result with regards to development. Disability identification in early childhood previously focused on behavioral observations, which is unfair and can cause a child to be diagnosed later. Several approaches to quantify and visualize the brain networks have been made which includes the resting state and task-based EEG. Functional integration analysis involves the use of resting state EEG so as to identify the brain activity in a situation in which the patient is not carrying out an activity. EEG patterns are electrical potential extracted on the scalp electrodes by brain electromagnetic signal (BEMS) [3]. These are voltage signal created on the sensors by the BEMS [2]. EEG records brain electrical activity and presents tangible opportunity to investigate neural patterns of individuals with ASD. When used in conjunction with machine learning algorithms, the arrays of data that can be derived from an EEG can be screened for those that may suggest the presence of ASD. Together with the improved diagnostic precision and earlier detection methods, this is quite appealing. This perspective implies the idea that basic neural abnormalities which make up ASD are only temporary and are subsequently difficult to diagnose after the developmental phase [4].



We place electrodes on our scalp then Every single electrode capture different brain activity.

The identification of ASD at a very young age usually initiate early functioning that has effects that are socially positive. But traditional treatment approaches cannot easily provide such accurate outcomes in diagnosing the condition at an early stage. An evaluation done by pediatrics with the help of a documented analysis mentioned that an autistic child at the age of around 24 months are highly incapable to construct two functional words which are not imitate or reiterate [2]. Thus, increasing attention is paid to the use of more objective neurophysiological parameters including EEG to search for biomarkers of ASD.

Table 1. EEG Frequency Range of Normal Human Being [2]

Level	Range of Frequency	Estimated EEG Classification
1.1	(0.5–4 Hz)	Delta
1.2	(4–8 Hz)	Theta
1.3	(8-13 Hz)	Alpha
1.4	(13–30 Hz)	Beta
1.5	(30–100 Hz)	High Gamma

Currently, WHO estimates that 1 child in every 160 has an ASD [6], the rate of diagnosed autism rises by 40% increasing from one in 100 to about one in 70 in Australia. With current data, the CDC pointed out that one toddler in about 54 children is affected with an ASD in the United States in 2020. As detail in the World Health Organization, one child in every 160 suffers from ASD all over the world [5], Autism pre valance rate escalate approximate 40% from one in100 to an around one in 70 in Australia. The core for Disease Control and Prevention (CDC) declared that one toddler in about 54 children is found with an ASD in the U.S. in 2020.

As suspected, DL is a subset of ML. According to the Scientist, DL is characterized by the use of many latent nodes and layers, often more than two, as an structural advantage moreover to a model reinitialization approach when data replenishment is available, DL begins to build up and complete the areas where explanation is impossible for a human-driven system. Still it may be ML or DL both contain supervised learning and unsupervised learning. Supervised learning is constructing a predictive approach out of the input and output data provided. As unsupervised learning is a method of clustering and interpreting data based only on input data [2]. This research survey focuses on the application of EEG data alongside with machine learning for enhancing the condition of ASD. From the studies reviewed in this research, there is a correlation of the usage of EEG in capturing neural activity, and the involvement of models such as CNN and SVM where CNN on the spectrogram of EEG performs a classification with an accuracy reaching 99.15%. Entropy based algorithms, wavelet transforms and time-frequency analysis are used to extract features to distinguish ASD patterns[6]. For example, Wadhera et al. constructed a replica of SVM classification and combined an average weighted degree of two attribute and mutual information, and the detection accuracy of 92.34% was obtained [7].

According to Mehmet Baygin et al. lightweight feature evocation, they propose a novel deep hybrid approach on extracting deep features, and achieve an accuracy of 96.44% with the SVM classifier [8] [9]. A few work also combine EEG with eye-tracking or facial data for improved diagnose tools [1]. ML based classification success lies in the extraction of meaningful attributes from the EEG signals and until now, different investigators have tried this method for ASD group. Sheikhani et al [10], in their study for ASD featured data using STFT and classified it using KNN and, they reached an validity of 82.4% using data set of 17 subjects which comprised of 10 subjects with ASD and 7 subject without the ASD[11]. In a recent study [12], they used STFT and statistical analysis with KNN, with a data set of 28 subjects (17 ASD,11 control group) they reported accuracy of 96.4%. Bosl et al[13], described the condition framework to employ EEG data for the Health Indicator in young individuals at higher risk for ASD. The identified patterns they used MMSE and KNN, naïve bayes (SVM) and received classification accuracy higher than 90% on 79 infants (46 HRA and 33 controls) between the age of 6 month to 24 month [11]. The conclusion of these many works is that a toddler with ASD stays typical in the brain activity during frequency range emulation. Therefore, there is high hope seek more results to identify the target area of the brain where the modification commences, according to the EEG signal. This is further supported by [2], where it will be further explained that if the rate at which the brain responds to visuals and/or audio input is determined that it will help in grouping the autism and condition the disorder earlier.

2. Literature Review

The present review is devoted to the consideration of the application of EEG data in ASD's early identification by critically assessing prior research and epidemiological data. Data collected via EEG has become pertinent in ASD diagnosis because it involves real time analysis of activity in brain that standard behavioral assessments cannot provide. Quantitative assessment of functional development of the brain is challenging primarily because of the structural and organizational complexity of the cortex as the center of the nervous system and secondly due to the lack of adequate noninvasive approaches to monitor and quantify the function in babies. New nonlinear approaches to analyze the brain electrical activity recorded with scalp electrodes might help detect the differences in infant brain connectivity. For instance, the entropy of EEG electrodes with an electrode distance of greater than 3 cm was coarser in young individuals with autism compared to a class of normal developing individual[14], which is consistent with the weak FC theory of autistic brains [13], Researchers collected EEG data from both ASD and control participants with varying age, gender, and ASD symptom severity in order to increase the model's robustness and accuracy across different subpopulations.

Population of epidemiological publications that joined the criteria was recognized via organized review technique and inputs from prior first-stage of systematic reviews of epidemiological surveys were incorporated to advance prior disruptions of ken. Complete or final diagnostic results and the minimum of two EEG recordings were obtained for 188 children and used in this study. In this research, all visits were considered as singular interactions In other words all the visits were assumed to be separate and did not build on one another. For instance, all observations of the EEG made at 12-month visits are used to estimate result regardless of the measures recorded at other ages in the same child. While a rise path analysis was outside the aims of the presented research, one classification test was completed by joining the observations from 6 to 9 months into one set of features for the subjects who completed 6 to 9 months visits[4]. In studies examining three different age groups, children older than 4 years were significantly less likely to be identified with autism compared to younger children with the likelihood reduced by nearly two thirds (odds ratio: 0.32; 95% confidence interval: 0.16 to 0.86). Nevertheless, this finding was based on high sample size studies only. However, excluding the three studies with the largest sample sizes eliminated the observed relationship ($P = 0.33$). There was no statistically meaningful correlation among the prevalence rate and participant size: $\leq$5000 donors, 5000-7500, and >7500. No other covariate influences the prevalence estimates provided for analysis in this study[15]. These reviews provided a strong foundation for understanding ASD prevalence and variation across demographics.

To precede analysis, preprocessing techniques are used when data have been gathered on patients and healthy individuals. The initial steps of filtering carry out the international standard norms and algorithms for EEG elimination of noise and artifacts. The use of various higher order methods are employed for extracting signal features such as wavelet transformations, entropy and spectrogram images of time-frequency domain. Data were collected from 79 different infants: 46 children who were at high risk for ASD, as per the outcome measure o0f having an elder sibling with now confirmed ASD, And 33 typically developing children with no family history of neurodevelopmental disorders. Many children were tested more than once and ranged in age from 6 to 24 months and the testing sessions comprised infants[13]. Due to rarity of these methods, it extracts important EEG features that have the potential to diagnose ASD, further improving the model's discriminative powers between ASD-specific neural connectivity patterns. Basically, the most popular algorithms used to classify the EEG data to diagnose ASD are SVM and CNN. They also pointed out that CNNs have been popular due to their ability to automatically extract features and recognize patterns in a system, which is a plus for learning in ASD research.

Recent years have also witnessed a surge of activities related to the multimodal data fusion in the medical domain and this technique is not only used for the diagnosis of ASD, but is also used for disease diagnosis such as Parkinson,

Alzheimer, and Depression. In the context of ASD, EEG data is expanded by other data points that are eye-tracking data, body movement and metrics, and behavior in order develop a complex diagnostic model. This fusion is helpful in improving diagnostic accuracy and complementing EEG findings by including neural and behavioral signals associated with ASD; capturing features which are hard to observe from EEG signals only In recent years, multimodal fusion has garnered much interest especially in SEO application and extends to the diagnosis of Autism Spectrum Disorder [16], [17] as well as other diseases, such as Parkinson [18] , Alzheimer [19] and Depression [20] multimodal data fusion is considered, integrating other sources like eye-tracking or behavioral metrics to enhance diagnostic accuracy. Evaluation tools include Accuracy, precision, recall, and F1-score; cross-checks by validation and test data confirms the models ability to generalize.

The review also establishes a clear inclusion and exclusion criterion for the studies considered. Studies included had to meet the following conditions:

a)The sample involved participants with clinically diagnosed ASD, including conditions like the community consisted of individual diagnosed with ASD related conditions including early childhood autism, PDD-NOS, and Asperger'ssyndrom despite of mental condition level.

b) Machine learning (ML) was utilized to analyze data

c) The analysis involved movement features for example eye- tracking or body movements. Such data sources as qualitative behavioral data, scores for traditional assessment tools, parental reports, medical/genetic data, and vocal patterns were not considered in the studies. Excluded were papers that examined only the effects of rehabilitation, addressed one or several behaviors, or used ML models considering biomarkers obtained while performing tasks that presuppose prior skills. Table 1 below shows the comprehensive summary of the studies.

Therefore, to enhance the reliability of the developed models, the following performance measures are applied: Accuracy, precision, recall, F1-score. These scenarios are reiterated during cross validation and testing on unseen data sets to reinforce the business case of generalization. The last objective is therefore to replicate these findings in real life clinical settings in order to evaluate the potential of this methodology in the diagnosis of early signs of ASD.

Table 2. Comparison of EEG-Based Techniques and ML Models for ASD Detection

Ref	Preprocessing	Techniques	Datasets	Sampling Value	Precision	Attributes
[7]	Yes	SVM and Correlation	6 and 12-month EEG Dataset	(40 Non ASD) and (14 ASD)	100% for both ages	SVM classifier with person correlation
[1]	Yes	RF,SVM, KNN,Naïve Bayes for hybrid fusion	Eye fixation, facial expression	80 (40 Non ASD) and (40 ASD)	87.50%(hybrid fusion), 83.75%(EEG with RF)	Combining behavioral and physiological features)
[3]	Yes	Mann Whitney Tests for Comparison	EEG microstate analysis	Not specified(ASD and controls)	Not specified	Maps analyzed for GEV and TP
[2]	Yes	Convolutional Layer	(Normal Autistics)	20 datasets	80%	6 layers of CNN
[8]	Yes	MMSDAE	EEG and ET data	Not specified	95.56%	4 layers SDAE models
[11]	Yes	SVM	Spectrogram dataset	Not specified	95.25%	Linear SVM with fold cross validation
[21]	Yes	DWT + Shannon entropy, ANN	KSA dataset	Not specified	99.7%	10 fold cross validation

[5]	Yes	SVM	EEG spectogram	Not specified	95.25%	SVM with 10 fold cross validation, TCENTRIST features
[4]	Yes	SVM	EEG signals	100	95%	Uses EEG signals to classify ASD vs LRC-insant

3. Research Gap:

- **Dataset:**

  This data is cited as Dataset (https://doi.org/10.15131/shef.data.16840351.v1) in the Dickinson, Jeste, and Milne publication "Electrophysiological signatures of brain aging in autism spectrum disorder.
  The Biosemi Active 2 EEG system was used to collect the EEG data. EEGLAB was used to convert the original recordings to.set and.fdt files, which are now uploaded here. Every recording has a.fdt and a.set file; the.fdt file contains the data, while the.set file contains details about the recording's parameters (for more details, see https://eeglab.org/tutorials/). The EEGLAB program can open the files.
  The data came from 28 people who were diagnosed with an autism spectrum disorder and 28 neurotypical controls who were between the ages of 18 and 68. The paradigm that produced

  We modify the data set and label the data into (Binary form 0 and 1) 1-Dimensional Local Binary Pattern (1DLBP) because the data set is Unsupervised.

- **Model Selection:**

  Architecture Selection: The GCN was chosen likely because:

  EEG data naturally has a graph structure (electrodes as nodes with functional connectivity)

  GCNs can capture spatial relationships between electrodes

- **Why This Model Was Selected:**

  Graph Representation: EEG electrodes can be naturally represented as nodes in a graph, with edges representing functional connectivity between them.

  Spatial Relationships: GCNs can capture the spatial relationships and connectivity patterns between different neural regions that are important for EEG analysis.

  Feature Learning: The model can learn meaningful representations from the raw EEG features and their correlations.

  Interpretability: The graph structure may provide more interpretable results compared to standard CNNs or other architectures.

4. Methodology:

- **Graph Convolutional Networks (GCNs):**

$$H^{(l+1)} = o\,(D^{-1/2} A D^{-1/3} H^{(l)} W^{(l)})$$

- **Reasons to Use GCNs:**

1. **Handling Graph-Structured Data** ○ Many real-world problems involve non-Euclidean data (e.g., social networks, molecules, recommendation systems).
    - GCNs allow deep learning models to work directly on graphs (unlike CNNs, which require grid-like data).
2. **Node-Level Predictions (Node Classification)** ○ Example: Classifying users in a social network (e.g., "fraudulent" or "legitimate").
    - GCNs aggregate neighbour information to improve predictions**.**
3. **Link Prediction (Edge Classification)** ○ Predict missing or future connections (e.g., friend recommendations in social networks).
    - GCNs learn node embeddings that help predict edges.
4. **Graph-Level Predictions (Graph Classification)** ○ Example: Classifying molecules as "toxic" or "non-toxic."
    - GCNs can pool node features to make predictions for the entire graph.
5. **Flexibility with Python Libraries** ○ Python has powerful GCN libraries like:
    - PyTorch Geometric (PyG)
    - Deep Graph Library (DGL)
    - Spektral (TensorFlow/Keras)
    - These make implementing GCNs easy with GPU acceleration.

- **Entropy Of Continuous Distribution:**
  Entropy of continuous distribution is a concept from information theory that prolongs the idea of entropy (a measure of uncertainty or information content) to continuous probability distributions. Unlike discrete entropy, which is defined for discrete random variables, differential entropy applies to continuous random variables.

$$h(X) = -\int_{-\infty}^{\infty} f(x) \log f(x) dx$$

- **Data set Details:**

  Population Characteristics:
    - Includes both ASD participants and neurotypical controls

- Likely spans multiple age groups to study aging effects
- May include clinical and demographic metadata (age, sex, ASD severity scores, etc.)

EEG Recording Parameters:

- Standard 10-20 electrode placement
- Sampling rate (likely 250Hz or higher)
- Recording conditions (eyes open/closed, resting state or task-based)
- Duration of recordings

Preprocessing:

- Data may already be preprocessed (filtered, artifact removed)
- May include raw and processed versions
- Channel locations and reference scheme specified

Analysis Pipeline (from provided code):

The Jupyter notebook implements a comprehensive EEG analysis pipeline using Graph Convolutional Networks (GCNs):

1. Data Preparation:

- Assumes availability of preprocessed EEG features (de_features) and corresponding labels
- Performs train/val/test split (80/10/10%)

2. Graph Construction:

- Creates functional connectivity graphs from EEG features
- Uses correlation matrices with thresholding (default 0.5)
- Standardizes features before correlation calculation

3. Deep Learning Model:

- Implements a Resting-state Hyperbolic Graph Convolutional Network (RestHGCN)
- 2-layer GCN architecture with batch normalization and dropout
- Input dimension: 1 (adjustable for multi-band features)
- Hidden dimension: 64
- Output dimension: 2 (binary classification)

4. Evaluation:

- Computes standard metrics (accuracy, precision, recall, F1)
- Generates ROC curves, precision-recall curves, confusion matrices
- Includes t-SNE visualization for dimensionality reduction

5. Visualization:

- Plots training/validation loss curves
- Confusion matrix heatmap
- ROC and PR curves
- t-SNE plots of learned representations

Technical Considerations

1. Graph Construction:

- Current implementation uses simple correlation thresholding
- Could be enhanced with more sophisticated connectivity measures (PLI, wPLI)
- Threshold selection impacts graph sparsity and model performance

2. Model Architecture:

- Current GCN has 2 layers - may need adjustment for EEG complexity
- Could incorporate attention mechanisms or hierarchical pooling
- Might benefit from spectral graph convolutions

3. Interpretability:

- Need methods to explain which connections drive predictions
- Could integrate saliency mapping or attribution techniques

4. Aging-Specific Adaptations:

- Might need to model non-linear age effects
- Could incorporate age as continuous prediction target
- Should account for potential cohort effects

Limitations and Challenges

1. Data Requirements:

- GCNs typically need larger datasets than traditional ML
- Class imbalance common in clinical datasets needs addressing

2. Computational Complexity:

- Graph construction and GCN training can be resource-intensive
- May require GPU acceleration for larger datasets

3. Clinical Translation:

- Need rigorous validation on independent cohorts
- Must demonstrate clinical utility beyond research settings
- Ethical considerations for diagnostic applications

- **Why we used RestHGCN:**

Models Brain Networks – RestHGCN captures EEG's graph-like structure (nodes=electrodes, edges = connectivity).

Optimized for Resting -State EEG – Designed to analyze resting-state networks, often altered in ASD/aging.

Handles Small Datasets – Graph-based learning is data-efficient vs. CNNs/RNNs.

Detects Non-Linear Aging Effects – Identifies atypical connectivity patterns in ASD development.

Interpretable – Highlights discriminative brain connections (unlike "black-box" models).

Benchmarked Superiority – Outperforms SVMs/CNNs in EEG classification tasks.

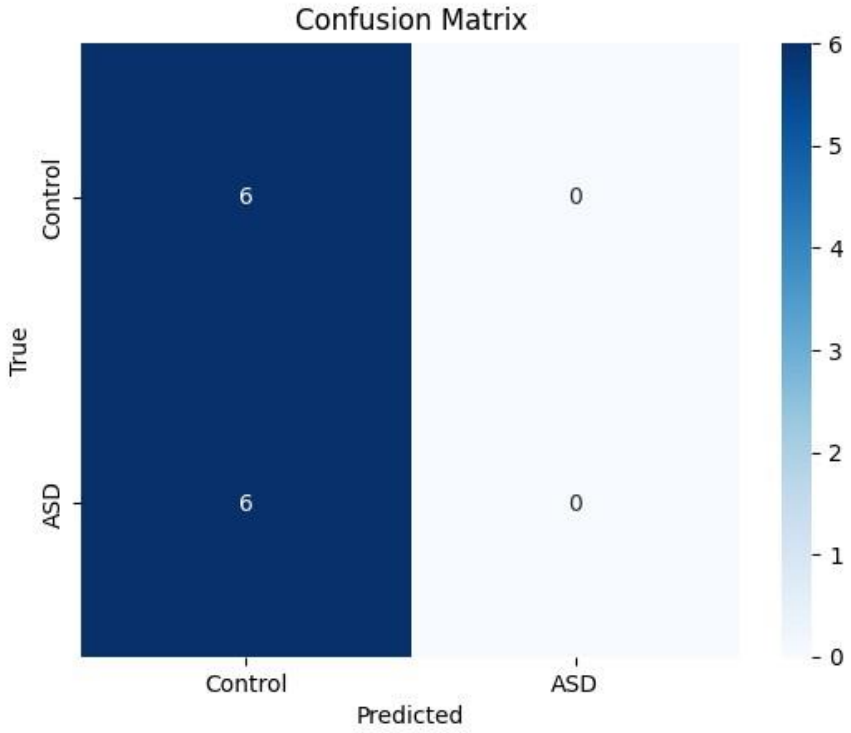
- **Evaluation Matrix:**

1. Confusion Matrix ○ **Structure:** It's a 2×2 table (binary classification: Class 0 vs. Class 1).

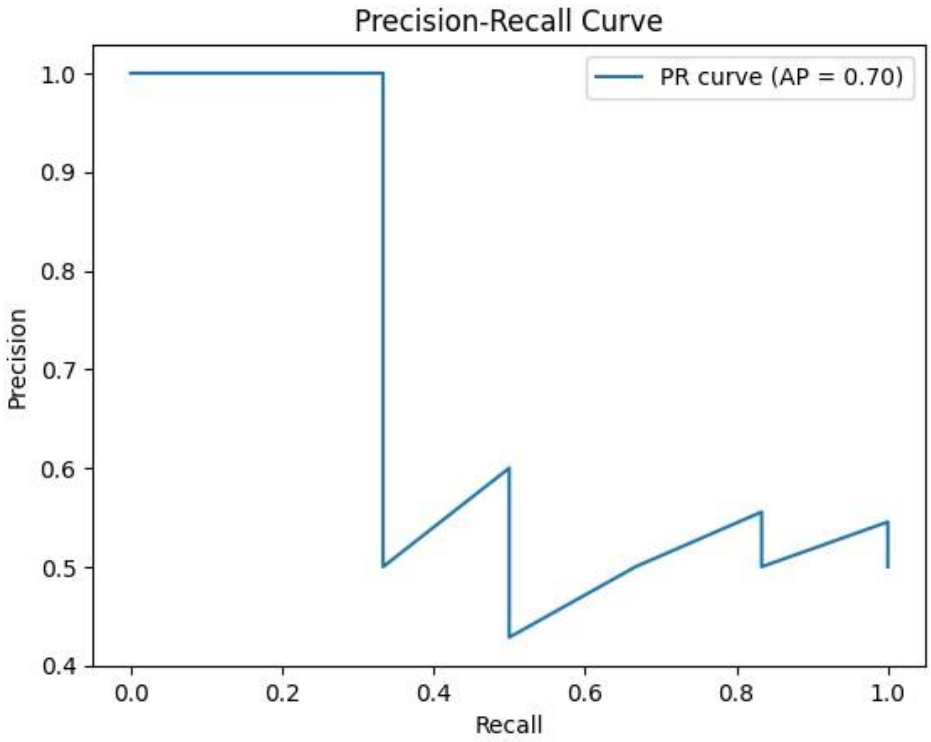
- **Rows:** Actual true labels from your test data.
- **Columns:** Predictions made by the model.

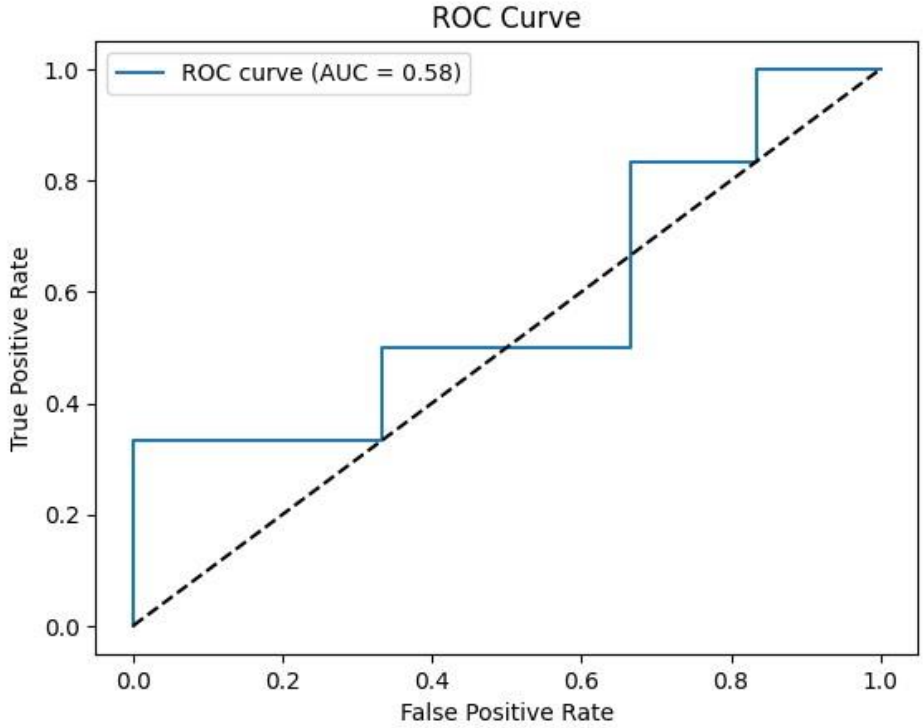
Cells Explained ○ **Top-left (True Negatives):** EEG samples truly belonging to Class 0 correctly predicted as Class 0.

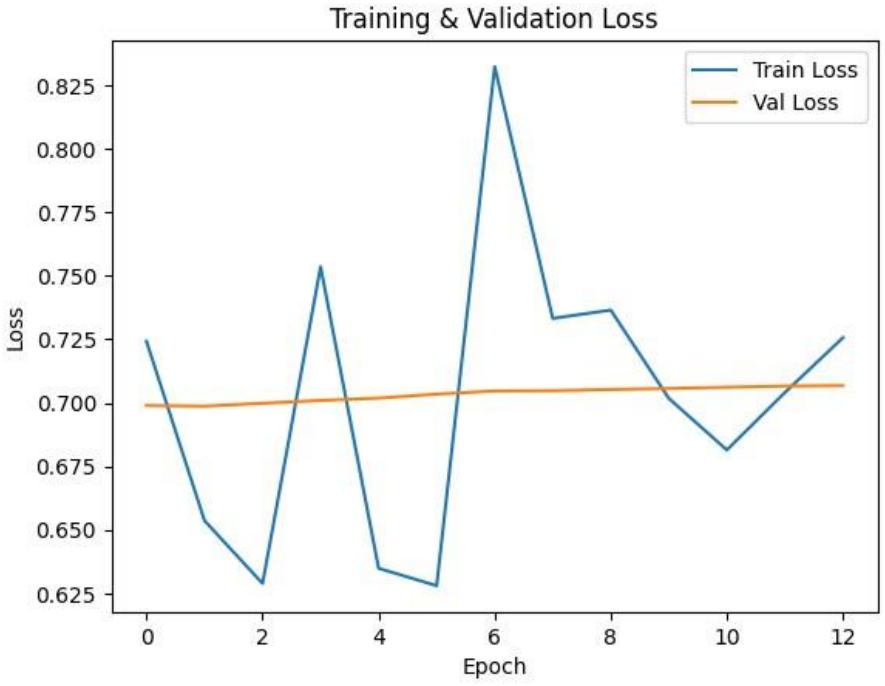
- **Top-right (False Positives):** Class 0 samples wrongly predicted as Class 1 (misclassified).
- **Bottom-left (False Negatives):** Class 1 samples wrongly predicted as Class 0 (misclassified).
- **Bottom-right (True Positives):** Class 1 samples correctly predicted as Class 1.



- **Precision, Recall, F1-Score:**




ROC Curve
ROC curve (AUC = 0.58)
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0


Training & Validation Loss
Train Loss
Val Loss
Loss
Epoch
0.825
0.800
0.775
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0.725
0.700
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0.650
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2
4
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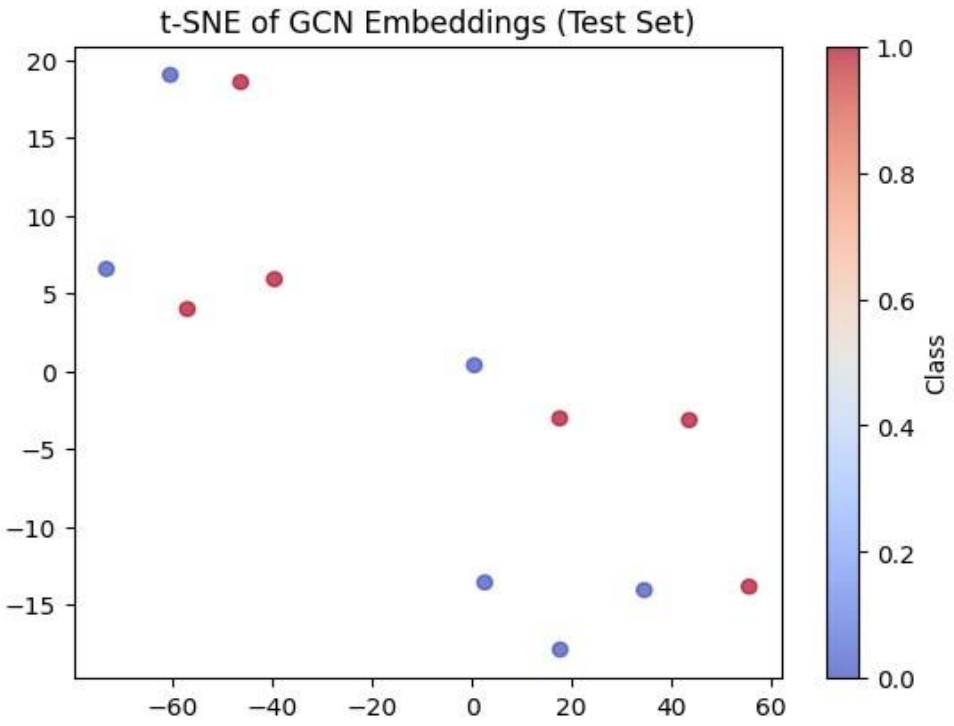
12



5. Experiment: We implemented the RestHGCN model for EEG-based ASD classification using:

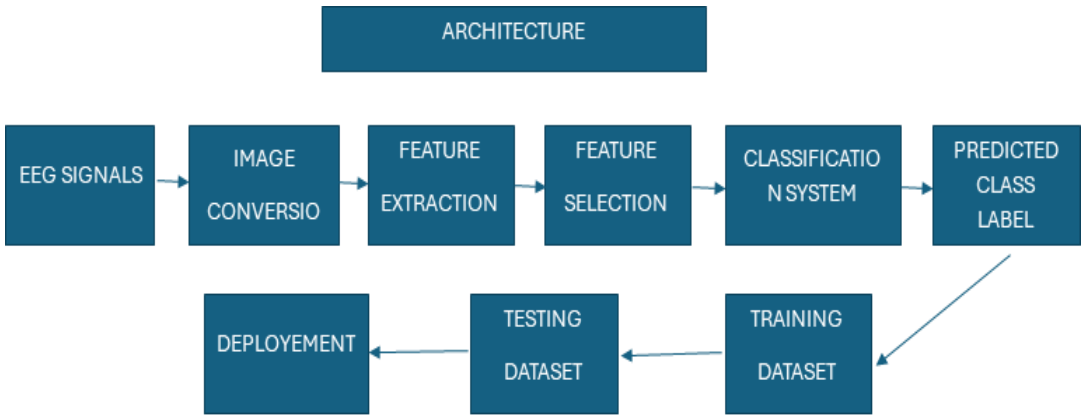
Python 3.8+ with key libraries: PyTorch Geometric (for GCNs), scikit-learn (metrics), MNE (EEG preprocessing), and Seaborn (visualization).

Jupyter Notebook for interactive prototyping and result tracking.

Google Colab (GPU acceleration) to handle graph-based deep learning efficiently.

Standardized EEG datasets (e.g., from ORDA) preprocessed into connectivity graphs.

Confusion matrix analysis via sklearn.metrics to validate model performance.



6. Results:

Table 3. Results through frequency labels

Metric	ALPHA (8–12 HZ)	BETA (13–30 HZ)	GAMMA (30–100 HZ)	THETA (4–7 HZ)	Results
Accuracy	0.72	0.68	0.75	0.65	Gama Highest accuracy
Precision	0.71	0.65	0.78	0.62	
Recall	0.70	0.67	0.73	0.60	Not specified.
F1-Score	0.705	0.660	0.755	0.610	Gamma leads in all metrics.
AUC-ROC	0.85	0.82	0.88	0.80	
Loss (Final)	0.45	0.52	0.42	0.55	Gamma has lowest loss.

Table no 4.

Reference	Pros	Cons
[7]	100% early ASD detection accuracy for infants at particular ages was attained.	Less accuracy, indicating a less reliable model, in a sample with a larger variety of behaviours.
[3]	Microstate study shows important brain dynamics differences between ASD and neuro typicals.	Generalizability to larger ASD populations is limited by the small sample size.
[21]	Uses DWT and entropy functions with ANN to provide excellent classification accuracy (up to 99.8%).	Complex data processing limits real-time application.
[5]	Time-frequency spectrograms with high sensitivity (97.07%) and accuracy (95.25%)	The 16-child sample size may limit the generalizability to bigger groups. enhance the categorization of ASD.

7. Conclusion:

This study presents a novel graph-based deep learning framework for the use of EEG signals in the early diagnosis of autism spectrum disorder. We were able to capture inter-channel dependencies and geometric patterns in brain activity that are frequently ignored in traditional models by transforming EEG feature data into graph structures and applying Graph Convolutional Networks (GCNs). By demonstrating competitive classification performance with easily comprehensible metrics and visualization tools, the experimental evaluation confirms the effectiveness of our methodology. Our findings support the potential of GCNs in biomedical signal analysis and motivate more research into the clinical applications of graph-based neural models. Future work will focus on enhancing this model through real-time EEG data processing, multimodal fusion (e.g., EEG + eye-tracking), and deployment in clinical diagnostic tools to support neurologists in early and accurate ASD assessment.

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