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Predicting Brain Age in Autism Spectrum Disorders Using Graph Neural Networks

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Introduction/Background

Autism Spectrum Disorder (ASD) diagnosis is complicated by symptom variability and traditional labor-intensive methods. This study explores using "brain age," derived from neuroimaging data, to quantify developmental delays in ASD. Leveraging advanced GNN models, we aim to enhance early, accurate diagnoses and intervention strategies.

Methods/Intervention

The study used the ABIDE dataset, an open-source resource containing preprocessed neuroimaging data from 1112 individuals across 20 international sites, including 539 with ASD and 573 controls. The data were preprocessed using the Data Processing Assistant for Resting-State fMRI (DPARSF) and analyzed with the "Dosenbach160" ROI set. Graph construction involved defining node and edge connections, with nodes representing regions of interest (ROIs) and edges representing functional connections. Three Graph Neural Network (GNN) architectures were employed: Graph Attention Networks (GAT), Chebyshev Graph Convolutional Networks (ChebNets), and Graph Isomorphism Networks (GIN)

Results/Outcome

The GNNBrainAgePredictor models using GAT, ChebNet, and GIN architectures were evaluated for predicting brain age. The GAT model, with two GAT layers, global mean pooling, and a linear regression layer, achieved a MAE of 4.8915 for the autism group and 6.3125 for the control group. The ChebNet model, using Chebyshev polynomials for graph convolutions, achieved a MAE of 5.2876 for the autism group and 6.6340 for the control group. The GIN model, with two GINConv layers, achieved a MAE of 4.9252 for the autism group and 6.3012 for the control group. Unexpectedly, the MAE was lower for the autism group across models, suggesting developmental delays rather than pathological processes.

Conclusion

The GIN model emerged as the most effective, outperforming GAT and ChebNet models in predicting brain age with the lowest MAE observed. The lower MAE for the autism group challenges conventional understanding and indicates potential developmental delays. Further investigation is required to understand the neurobiological underpinnings of these findings.

Statement of Impact

Our study highlights the potential of advanced GNN architectures, particularly GIN, for accurately predicting brain age and enhancing our understanding of brain development in ASD. These findings suggest that leveraging machine learning techniques can significantly improve early diagnosis and intervention strategies, ultimately leading to more personalized and effective treatments for individuals with ASD.

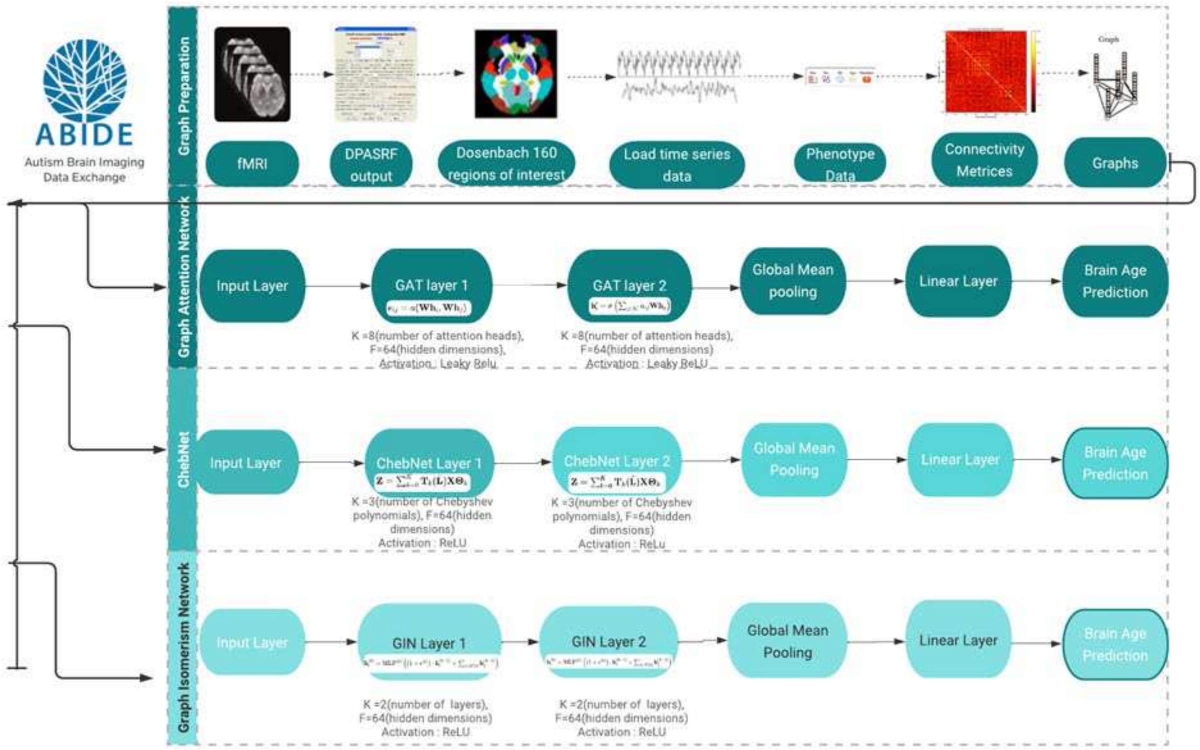
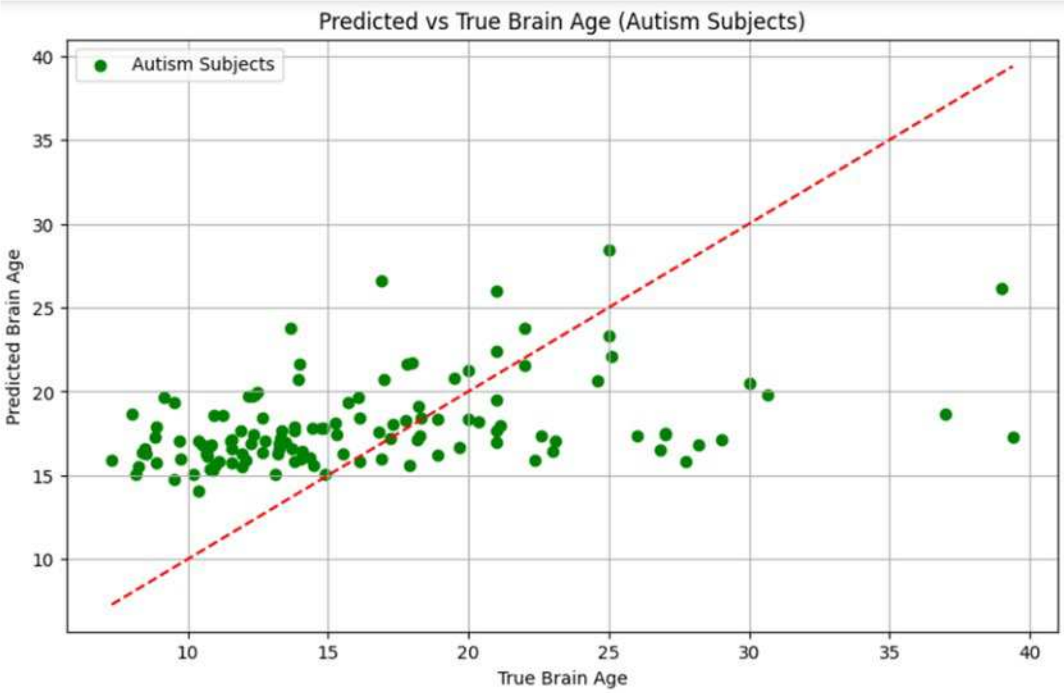


Figure 1: Overview of the Graph Neural Network (GNN) Architectures for Brain Age Prediction using Functional Connectivity Data from the ABIDE Dataset This figure illustrates the comprehensive workflow for predicting brain age using three different GNN architectures: Graph Attention Network (GAT), Chebyshev Graph Convolutional Network (ChebNet), and Graph Isomorphism Network (GIN). The process begins with data preparation, including acquiring functional magnetic resonance imaging (fMRI) data from the ABIDE dataset and preprocessing it using the Data Preprocessing Assistant for Resting-State fMRI (DPARSF). The preprocessed data is then parcellated into 160 regions of interest (ROIs) based on the Dosenbach atlas, and the time series data for each ROI is loaded. Phenotypic information, such as age at scan, is also loaded from the ABIDE dataset. Functional connectivity (FC) matrices are calculated using correlation measures between ROI time series data, and these matrices are used to construct graphs representing the functional brain network. The constructed graphs serve as input to the GNN architecturesThe Graph Neural Network (GNN) architecture for brain age prediction using functional connectivity data from the ABIDE dataset comprises three distinct models: Graph Attention Network (GAT), Chebyshev Graph Convolutional Network (ChebNet), and Graph Isomorphism Network (GIN). Each model starts by processing fMRI data through the DPARSF pipeline, parcellating it into 160 regions of interest (ROIs), and constructing functional connectivity (FC) matrices. The GAT model employs attention mechanisms to focus on relevant nodes, ChebNet leverages Chebyshev polynomial filters for localized spectral information, and GIN ensures invariance to graph isomorphism through robust node feature aggregation. All models include global mean pooling layers to aggregate node features into graph-level representations and utilize final linear layers for brain age regression. This architecture captures intricate brain region relationships, facilitating accurate brain age predictions and insights into neurodevelopmental differences in autism.



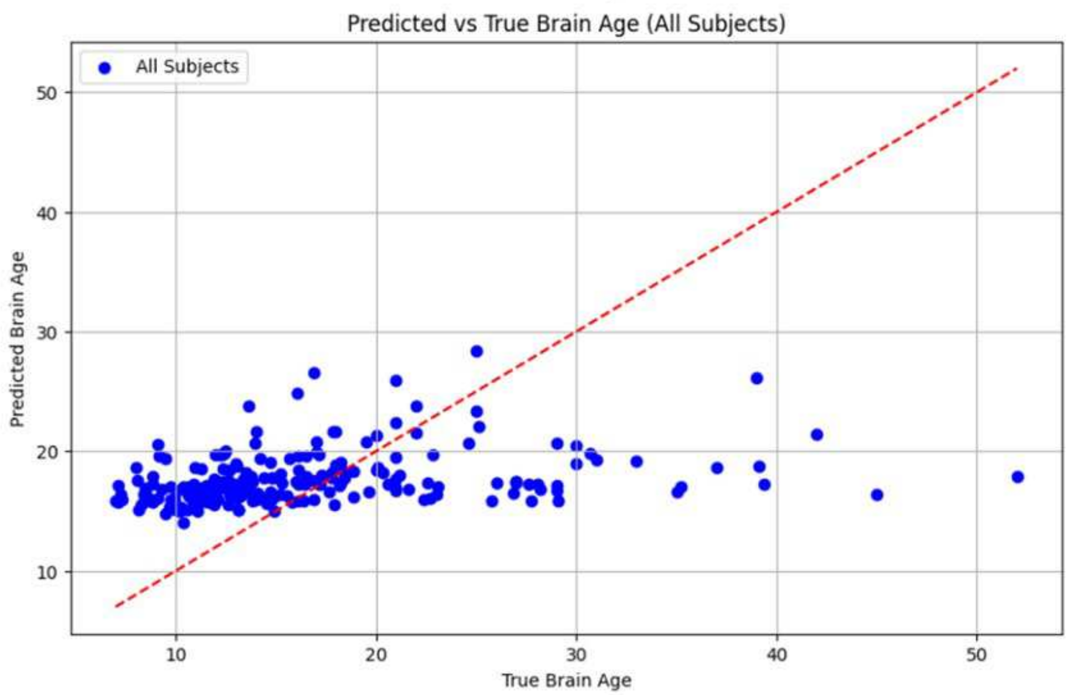


Figure 2: Predicted vs. True Brain Age Scatter Plots These scatter plots compare the predicted brain ages against the true brain ages for all subjects and autism subjects separately. The red dashed line represents the ideal prediction where predicted brain age equals true brain age. Plot A (All Subjects): This plot shows the brain age prediction performance for all subjects in the dataset. Each blue dot represents an individual subject. The distribution and deviation from the ideal prediction line indicate the accuracy and bias of the prediction model across the entire dataset. Plot B (Autism Subjects): This plot focuses on the subset of subjects diagnosed with autism. Each green dot represents an individual autism subject. The plot highlights the model's performance specifically within the autism group, providing insights into any differences in prediction accuracy and bias compared to the overall dataset.

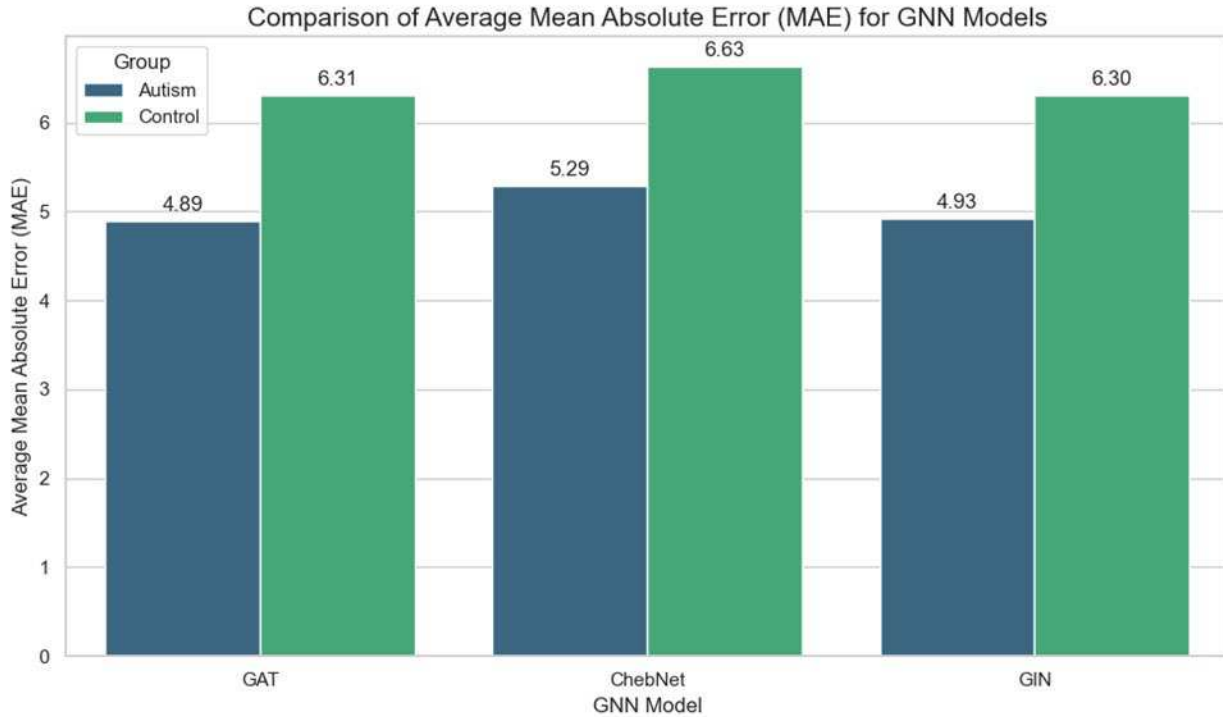


Figure 3: Comparison of Average Mean Absolute Error (MAE) for GNN Models This bar chart compares the average Mean Absolute Error (MAE) of three different GNN models (GAT, ChebNet, and GIN) in predicting brain age for autism and control groups. The blue bars represent the MAE for the autism group, while the green bars represent the MAE for the control group. The height of each bar indicates the average prediction error, with lower values representing better performance. GAT: Shows a lower MAE for the autism group (4.89) compared to the control group (6.31), indicating better performance in predicting brain age for autism subjects using the GAT model. ChebNet: Exhibits a higher MAE for both groups, with 5.29 for the autism group and 6.63 for the control group, suggesting relatively lower prediction accuracy compared to GAT. GIN: Displays a MAE of 4.93 for the autism group and 6.30 for the control group, indicating a performance similar to GAT for the autism group but with slightly higher error for the control group.

Keywords

Graph Neural Network; Autism; ABIDE; Brain age; fMRI; Brain Imaging