Course Project Report

Age Classification Using Multinet Graph Neural Networks Based on Brain Connectivity Patterns

Submitted By

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as part of the requirements of the course

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in partial fulfillment of the requirements for the award of the degree of

Bachelor of Technology in Artificial Intelligence

under the guidance of

Dr. Sowmya Kamath S, Dept of IT, NITK Surathkal

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DEPARTMENT OF INFORMATION TECHNOLOGY

National Institute of Technology Karnataka, Surathkal

<u>C E R T I F I C A T E</u>

This is to certify that the Course project Work Report entitled **"Age Classification Using Multinet Graph Neural Networks Based on Brain Connectivity Patterns"** is submitted by the group mentioned below -

Details of Project Group

Name of the Student	Register No.	Signature with Date
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this report is a record of the work carried out by them as part of the course **Social Computing (IT480)** during the semester **Dec-Apr 2024**. It is accepted as the Course Project Report submission in the partial fulfillment of the requirements for the award of the degree of **Bachelor of Technology in Artificial Intelligence.**

(Name and Signature of Course Instructor)
Dr. Sowmya Kamath S

DECLARATION

We hereby declare that the project report entitled **"Age Classification Using Multinet Graph Neural Networks Based on Brain Connectivity Patterns"** submitted by us for the course **Social Computing(IT480)** during the semester **Dec-Apr 2024**, as part of the partial course requirements for the award of the degree of Bachelor of Technology in Artificial Intelligence at NITK Surathkal is our original work. We declare that the project has not formed the basis for the award of any degree, associateship, fellowship or any other similar titles elsewhere.

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Age Classification Using Multinet Graph Neural Networks Based on Brain Connectivity Patterns

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***Abstract*—This research delves into the intricate dynamics of brain states across different developmental stages, focusing on children aged 3 to 11 years. Leveraging a dataset from OpenNeuro comprising samples from 155 subjects, functional magnetic resonance imaging (fMRI) analysis is employed to investigate neural activity patterns during a common task, such as movie-watching. The preprocessing stage involves utilizing the Nilearn library to extract brain signal time series and construct connectivity matrices representing functional interactions between regions of interest (ROIs). Model architecture incorporates a connectivity-based graph convolution network (cGCN), which processes correlation coefficients of ROIs to capture unique features from each connectivity matrix instance. Furthermore, a Multinet graph is utilized for data augmentation, exposing the model to diverse connectivity patterns. Structural analysis reveals characteristics of small-world and scale-free networks within the brain graph, indicative of efficient communication and hub nodes with higher degrees. Training the model involves independent processing of each connectivity matrix instance, enabling the capture of unique developmental features. Overall, this study contributes to understanding the nuanced dynamics of brain development in young individuals, shedding light on cognitive and emotional processing during common activities.**

***Index Terms*—cGCN,McGCN,Deep Learning**

I. Introduction

The human brain stands as an intricate marvel of biological evolution, orchestrating a symphony of neural networks that underpin every aspect of human experience. From the rudimentary motor functions to the most intricate cognitive tasks, the brain's complexity knows no bounds. Central to this complexity are the interconnected neural networks that facilitate cognition, perception, emotion, and behavior. Unraveling the mysteries of these networks has been a focal point in neuroscience, prompting researchers to explore brain activity across various states and developmental stages.

In this context, understanding the dynamic interplay of neural networks becomes paramount. Through the lens of neuroscience research, the exploration of brain activity across different states and stages of development offers profound insights into how the human mind processes stimuli and matures over time. By utilizing advanced neuroimaging techniques such as functional magnetic resonance imaging (fMRI), researchers can delve deep into the neural substrates underlying cognitive and emotional responses.

This study embarks on a journey to unravel the intricate dynamics of brain states across different developmental stages, with a particular focus on children aged 3 to 11 years. By leveraging a rich dataset from OpenNeuro, which contains samples from 155 subjects, this research employs fMRI analysis to investigate neural activity patterns during common activities, such as watching a movie.

The journey begins with preprocessing, where the Nilearn library is utilized to extract brain signal time series and construct connectivity matrices representing functional interactions between regions of interest (ROIs). Moving forward, the model architecture is crafted with precision, incorporating a connectivity-based graph convolution network (cGCN). This network is designed to process correlation coefficients of ROIs, thereby capturing unique features from each connectivity matrix instance.

Furthermore, the introduction of a Multinet graph for data augmentation amplifies the model's exposure to diverse connectivity patterns, enriching its capacity to capture diverse relationships and model better than single branch model like cGCN. Structural analysis uncovers fascinating insights, revealing characteristics of small-world and scale-free networks within the brain graph. These characteristics hint at efficient communication pathways and hub nodes with higher degrees, essential components of neural information processing.

Training the model is a meticulous process, involving the independent processing of each connectivity matrix instance. This approach enables the model to capture the nuanced developmental features inherent in the dataset, thereby enhancing its predictive capacity.

In essence, this study represents a significant step toward understanding the nuanced dynamics of brain development in young individuals. By shedding light on the cognitive and emotional processing during common activities, it contributes valuable insights to the broader field of neuroscience, paving

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the way for future advancements in understanding the human brain.

A. *Major contributions of our work:*

- **Introduction of the Multinet graph methodology**:We have Created 155 separate graphs with 100 views each. This enriches dataset with diverse connectivity patterns, hence enhancing model's ability to generalize and capture complex brain dynamics.
- **Detailed structural analysis uncovers insights into brain network organization:**We have examined key metrics like average degree and clustering coefficient and reveals hub-like nodes and efficient communication pathways.This provides deeper understanding of brain network dynamics.
- **Node importance analysis identifies regions crucial for information flow:**
  Assesses centrality metrics to pinpoint influential nodes and also Unveils hubs or bridges within the network which illuminates neural mechanisms underlying cognitive processes.

In the following sections, we start by reviewing the existing literature available in SECTION II . Then, a brief description about our dataset. Following the Problem Statement that we intend to resolve by this paper and the objectives to achieve in SECTION III. In SECTION IV we have detailed about our Proposed Methodology which includes in-depth descriptions about the model used. After the proposed methodology, the results of all the experimentations done are included in detail in SECTION V. Finally, conclusion in SECTION VI and detailed references and citiations.

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II. Literature Survey

In the paper[1] Vinod and Menon focus on paper reviewing of different authors to study brain development and synthesize their findings to understand how the brain really works . Liau, J. Liu, T.T [2] Foccused mostly on reducing the noise from the BOLD signals by identifying the ROIs in the Brain,one drawback in this approach is that it is a data driven approach and depends Anatomical dataset.

Li et al. (2020) [3] proposed an approach to symbolise brain as graph structure and the ROIs in the brain as the nodes of the brain but it wasnt a good approach when it comes to finding the bio markers in the brain.

[4] J. Rongyao Hu, Yonghua Zhu proposed a multigraph method to generate heterogeneous brain graphs for representaion learning for understanding brain functionality.This approach was a landmark in deepening our understanding in how actually the brain is connected functionally and was also an inspiration to our multiGraph model

One drawback of this approach was that it was analysed based on pearson coefficient which dosent generalise good results which have complex relationships and less linearity. By reviewing above litreatures , we understood the need for a sophisticated architecture which can align with the complexity of the brain and address issues like finding biolevel markers in the brain by leveraging the power of graphical convolution neural networks and providing a more nuanced insights on the overall brain functional connectivity.

III. Problem Statement

Develop a Multinet Connectivity-based Graph Convolution Network (McGCN) for the analysis of functional magnetic resonance imaging (fMRI) data to predict the age group of participants(Predicting whether its a child or adult), addressing the challenges of handling complex graph structures

A. *Objectives:*

- The objective of our study is to delve into the nuanced dynamics of brain states across various developmental stages, specifically focusing on individuals aged 3 to 11 years.
- Develop a Novel branched architecture based on the concept of Multinet to capture diverse relationsips within the brain .
- Compare our proposed architecture with the existing cGCN architecture on accuracy .

IV. Proposed Methodology

A. *Data Pre-Processing*

1) Dataset Selection and Preprocessing: :

The dataset selected is MRI data of 3–12-year-old children and adults collected while they watched Pixar's "Partly Cloudy." The dataset has been preprocessed using **fMRIPrep**, which includes denoising, normalization, and smoothing to ensure reliable results.

B. *Feature Extraction:*

- Brain signal time series data is extracted from regions of interest (ROIs) defined by an atlas using the **Nilearn** library.
- BOLD (Blood Oxygenation Level Dependent) signals, representing the activity of each ROI over time, are obtained. These signals indicate changes in blood-oxygen levels in response to neural activity.

C. *Connectivity Matrix Calculation*

- Connectivity matrices are calculated based on the correlations between BOLD signals of different ROIs.
- Two types of connectivity measures are considered: correlation and partial correlation.
- Correlation coefficients represent the strength of connectivity between ROIs, while partial correlation accounts for the influence of other ROIs, creating sparse graphs.

D. *Graph Representation:*

Connectivity matrices are converted into graph representations, where ROIs represent nodes and edges represent connections between ROIs. Each node's features are initially defined by its correlations with other ROIs. Partial correlation matrices are used to define the edges in the graph.

TABLE I: Summary of Literature Survey

Authors	Methodology	Merits	Limitations
Menon, Vinod	It reviews the existing literature on Brain. Uses techniques like meta-analysis data synthesis techniques.	It provides insightful review of Brain Network and its related disorders.	Doesn't provide generalized findings. Gives scattered outputs since sources are so variable.
Behzadi, Y., Restom, K., Liau, J. & Liu, T. T.	Aims to reduce noise in BOLD data by identifying ROIs.	It is a data-driven approach to noise reduction. Application of CompCor helped in increased sensitivity.	It is highly dependent on Anatomical dataset. Difficult to identify when noise and ROIs overlap in the brain regions.
Li et al. (2020)	Proposes an approach to identify each brain as a graph and each ROIs as its nodes. Uses ROI-based graph embeddings to do fMRI prediction.	A unique approach to mapping functional activation patterns and performing cognitive task decoding. GNN design facilitates model interpretability by regulating intermediate outputs with a novel loss term for enforcing similarity of pooling score.	Not an optimal approach to find bio-level markers.
J. Rongyao Hu, Yonghua Zhu, Junbo Ma, Ziwen Peng, and Guorong Wu	It proposes a multi-graph fusion method to generate homogeneous and heterogeneous brain graphs.	Multi-graph fusion method allows for representation learning for understanding brain functionality.	The Pearson correlation analysis assumes a linear relationship between variables, which may not always hold true in complex biological systems like the brain.

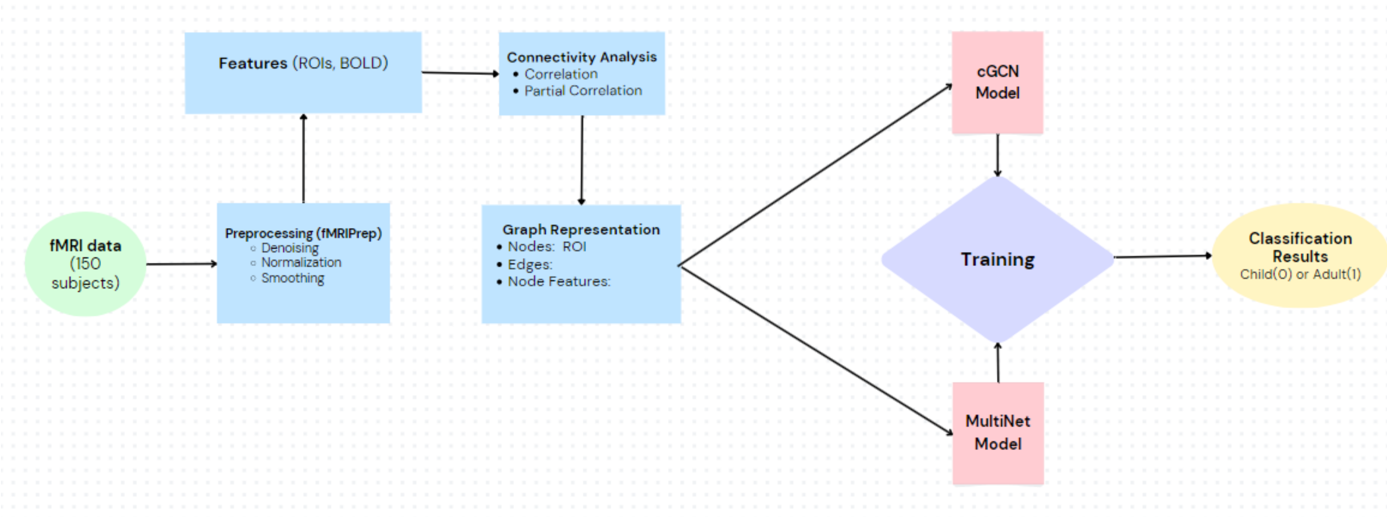

Fig. 1: Work Flow

E. Models

1) Graph Neural Network (GNN) Model: The GNN used is a variant of **cGCN (connectivity-based graph convolutional network)**. Each subject's time series data is split into multiple graphs, each corresponding to a different time step. Initial node features in each graph are the BOLD signals of the corresponding ROIs. The GNN performs message passing on each graph separately using a graph convolutional layer known as EdgeConv. The update rule for each node involves passing messages from neighboring nodes, followed by max pooling to aggregate information from neighbors. Several layers of message passing are applied, with batch normalization and ReLU non-linearities between layers. Global mean pooling is performed over node features to obtain a final graph-level representation. A weight matrix is learned to make predictions based on the graph-level representation.

2) ***MutliNet:*** The MultinetGraphNetwork uses multiple parallel GCN branches, each processing a copy of the node features. Each branch has its own MLP, EdgeConv, and BatchNorm layers. The outputs from all branches are concatenated before global pooling.

Here's the MultinetGraphNetwork class represented in table form: fig(2). The Multinet Graph Neural Network architecture comprises multiple branches, each containing an EdgeConv layer followed by batch normalization and ReLU activation. Within the constructor method, the network's architecture is initialized, specifying the number of branches and creating a ModuleList to hold them. During the forward pass, the input data is processed through each branch iteratively. Within each iteration, the input undergoes EdgeConv operation, followed by batch normalization and ReLU activation. This process ensures that each branch extracts relevant features from the input data. After processing through all branches, the outputs

Layer	Description
self.mlp1	Multi-layer perceptron (MLP) for the first EdgeConv layer.
self.mlp2	MLP for the second EdgeConv layer.
self.mlp3	MLP for the third EdgeConv layer.
self.conv1	EdgeConv layer using self.mlp1.
self.conv2	EdgeConv layer using self.mlp2.
self.conv3	EdgeConv layer using self.mlp3.
self.bn1	Batch normalization layer for the first EdgeConv layer.
self.bn2	Batch normalization layer for the second EdgeConv layer.
self.bn3	Batch normalization layer for the third EdgeConv layer.
global_mean_pool	Global mean pooling layer to obtain a graph-level representation.
self.linear	Linear layer for final classification.

Fig. 2: Model Architecture of cGCN

Functions	Description
self.num_networks	Number of network branches.
self.gcn_branches	ModuleList containing branches of the network.
Loop (for each branch)	Iterate over the specified number of branches.
mlp	MLP for each branch.
conv	EdgeConv layer for each branch.
bn	Batch normalization layer for each branch.
self.linear	Linear layer for final classification.

Fig. 3: Model Architecture of McGCN

are concatenated and fed into a global mean pooling layer to aggregate information across all branches. Finally, the aggregated features are passed through a linear layer for the final classification. This design allows the network to effectively capture and utilize information from multiple perspectives, enhancing its ability to classify subjects into appropriate age groups based on brain connectivity patterns.

V. Experiments

We used general multinet graph duplications(10 different views for each graph) for data augmentation which resulted in overfitting while training, to address this problem we included this feature within the nuanced architecture (McGCN) which is specially designed for this purpose.

*1) **Structural Analysis** :* The structural analysis of the brain graph provides insightful metrics regarding its organization and connectivity patterns. The graph is identified as undirected,

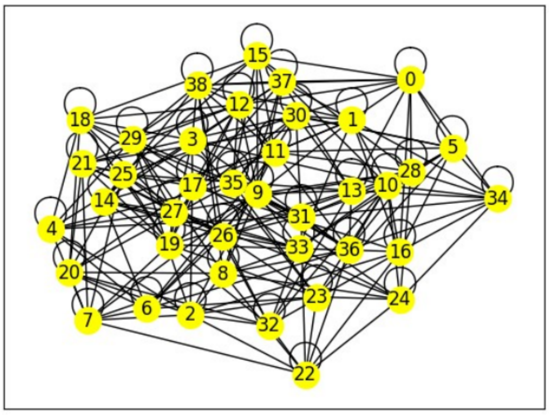

Fig. 4: Brain graph

indicating symmetrical connections between brain regions. With an average degree of approximately 12.36, the graph demonstrates a moderate level of connectivity among nodes. Further examination of the degree distribution reveals a right-skewed pattern, underscoring the presence of hub nodes with higher degrees. Specifically, 16 nodes have a degree of 11, 10 nodes have a degree of 12, and there are 3 nodes with a degree of 13. This distribution highlights the hierarchical nature of the brain's functional network, where certain regions exhibit heightened connectivity and influence over others.

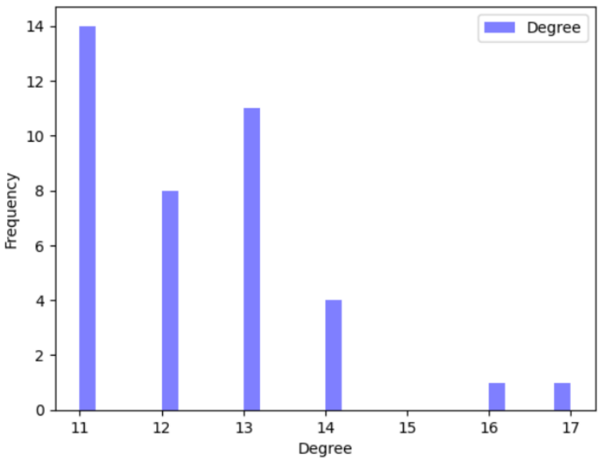

Fig. 5: Degree distribution

*2) **Centrality measures** :* Centrality measures offer quantitative assessments of individual node importance within the brain graph. Across various metrics, such as betweenness centrality, closeness centrality, and eigenvector centrality, specific nodes emerge as key players in information flow and integration. For instance, Node 9 holds the highest betweenness centrality value of 0.0437, indicating its crucial role in connecting disparate regions within the network. Additionally, Node 19 exhibits a high closeness centrality value of 0.623, signifying its proximity to other nodes in the graph. Furthermore, the eigenvector centrality values highlight nodes with significant influence, such as Node 9 with a centrality value of 0.2365. These numerical insights shed light on the intricate interplay of

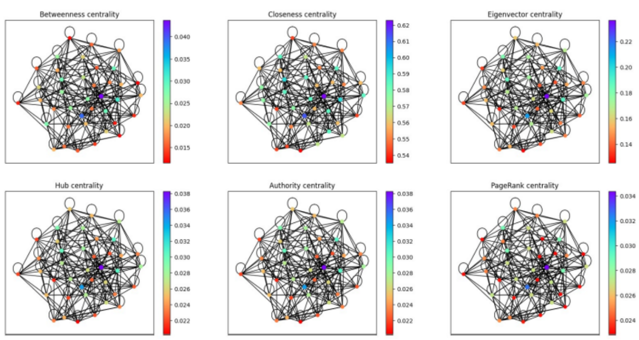

Fig. 6: Centrality measures of Brain graph

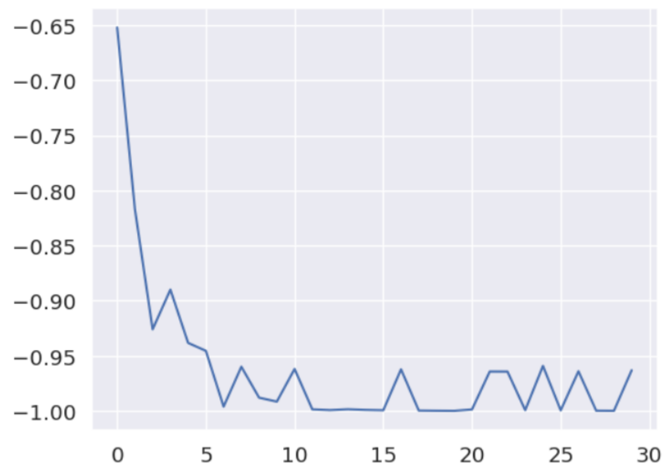

Fig. 7: Training Loss Curve for cGCN

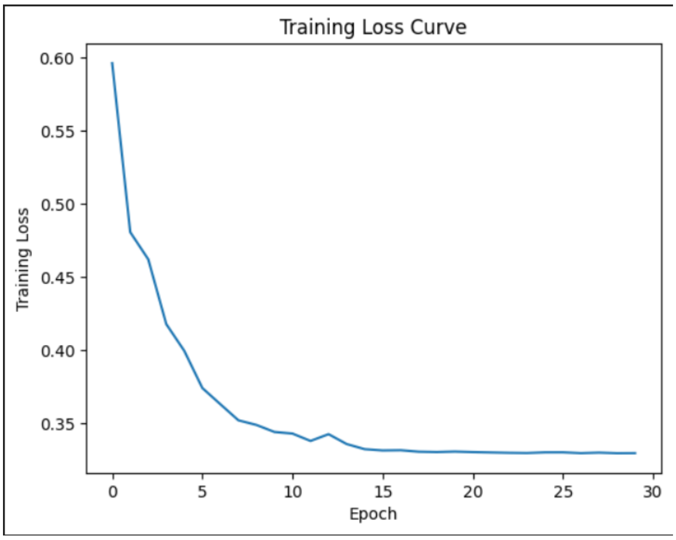

Fig. 8: Training Loss Curve for McGCN

nodes within the brain network, elucidating critical regions that drive information processing and communication dynamics.

VI. Results

The confusion matrix for cGCN architecture is shown in Fig.7 with its Classification report showing an accuracy of 94. Similarly, the confusion matrix for the MultiGraph Neural Network model is shown in Fig 9 with its classification report showing 22 true positive predictions (correctly identified class 0) and 8 true negative predictions (correctly identified class 1). There was only 1 false negative prediction, and no false positive prediction, hence predicting with an accuracy of 97

The precision for both classes is 0.96 and 1.00, indicating high precision for both class 0 (Child) and class 1 (Adult) predictions. As training progresses, the loss function decreases gradually. In McGCN model, the loss function curve is smooth. A smooth and decreasing loss curve indicates that the model is converging towards optimal parameters.

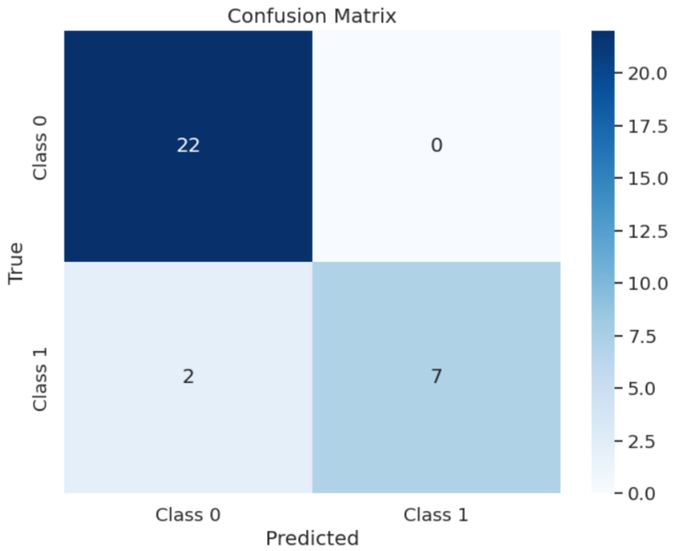

Fig. 9: cGCN confusion matrix

Classification Report:

	precision	recall	f1-score	support
0	0.92	1.00	0.96	22
1	1.00	0.78	0.88	9
accuracy			0.94	31
macro avg	0.96	0.89	0.92	31
weighted avg	0.94	0.94	0.93	31

Fig. 10: cGCN Model Result

Classification Report:

	precision	recall	f1-score	support
0	0.96	1.00	0.98	22
1	1.00	0.89	0.94	9
accuracy			0.97	31
macro avg	0.98	0.94	0.96	31
weighted avg	0.97	0.97	0.97	31

Fig. 11: McGCN Model Results

Convergence means that the model is improving its ability to make predictions on the training data.

VII. Conclusion

In conclusion, the project centered on advancing the field by introducing a novel architecture known as MultinetGraph. This innovative approach aimed to revolutionize our understanding of brain functionality across various age groups. By leveraging the concept of Multinet Graph, the study sought to capture diverse patterns inherent in the regions of interest (ROIs) within the brain. Through this comprehensive analysis, the research aimed to deepen our understanding of the intricate workings of the human brain. The architecture of our model

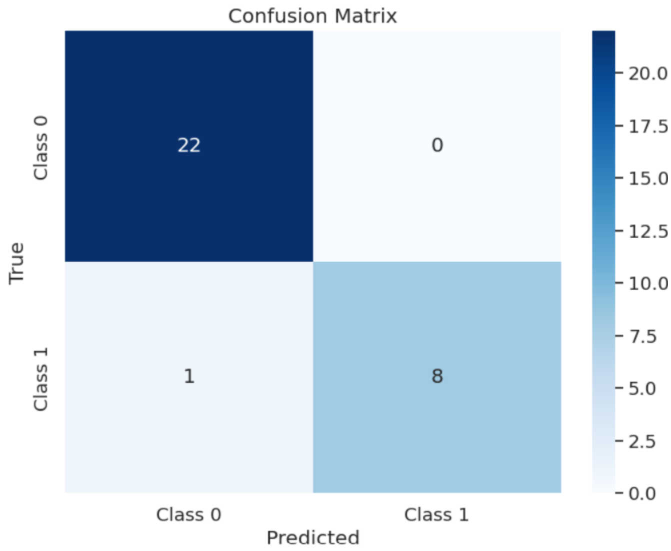

Fig. 12: McGCN confusion matrix

harnesses multiple branches with shared MLP, EdgeConv, and BatchNorm layers combines the advantages of independent processing in different branches with the efficiency and consistency gained from sharing key layers, ultimately enhancing the network's learning capabilities and performance of Brain to give an idea on different patterns analysis and analyze any cognitive disorders.

Comparing our results on accuracy with the Base paper model we achieved an overall accuracy of 97 which is a decent accuracy. We believe that there is a lot that can be done to improve our model in terms of Hyperparameter tuning, adding more number of layers to our MultiGraph Neural Network to help it capture better Brain connectivity.

This Research on understanding the Brain Functional Connectivity with the help of McGCN has opened new avenues for a novel research in the field of Cognitive Science and it general understanding of how our brain actually works.

Acknowledgment

We heartfully thank Dr. Soumya Kamath S for guiding us through the project.

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