Source Level Brain Connectome Based Visual Field Prediction with 3D Convolutional Neural Networks

Master Thesis Defence

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Agenda

Introduction

Research Questions

Related Work

Methodology

Results

Discussion

Introduction

- Stroke came as the second most frequent cause of death
- Less than half of people who have had a stroke would survive more than one year

Figure: An example of the stroke patient's brain[1]

[1] *React "FAST" to the signs of stroke*. URL: www.hamiltonhealthsciences.ca/share/stroke-signs/

Introduction

- Nearly half of people with a stroke have a visual field loss situation
- Homonymous hemianopia (HH) is a highly seen type

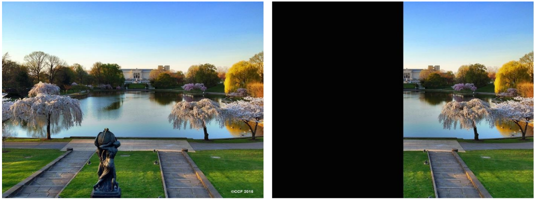


Figure: The normal vision VS Left HH vision[2]

[2] *What is homonymous hemianopsia?* URL: https://my.clevelandclinic.org/health

Background Knowledge

Brain Connectome

- is a map of neural connections in the brain
- could be represented as the anatomical (structural), the functional, and the effective network
- consists of nodes and links

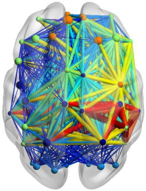


Figure: An example of brain connectome

Dataset

Input Data (Brain Connectome)

- was provided by the Institute of Medical Psychology, Otto-v.-Guericke University of Magdeburg
- was recorded from 24 stroke patients with hemianopia and 24 age-matched healthy controls
- was recorded as EEG and then was preprocessed to **brain connectome matrix** on source level

Dataset

Output Data (Visual Field)

- was recorded by a special high-resolution computerbased campimetric test battery: High Resolution Perimetry (HRP)[3]
- was simulated and presented in a grid of 21 * 21

For patients, two months after treatment: imporved or not

[3] Bernhard A. Sabel, Hans Strasburger, and Erich Kasten. "Programs for diagnosis and therapy of visual field deficits in vision rehabilitation". In: *Spatial Vision* 10.4 (1Jan. 1997), pp. 499–503

Motivation

- Explore the correlation between stroke patients' brain connectome and visual field distribution
- Contribute clinically from a computer scientist perspective

Research Questions

1. Predict the possibility that patients benefit from the treatment, given their brain connectome data.
2. Classify the subject, given their brain connectome data.
3. Reconstruct the visual field for the stroke patients, given their brain connectome data.
4. Predict the percentages of different visual field conditions, given their brain connectome data.

Related Work

Wada et al.[4] proposed a six-layer CNN for recognition and classi cation of Alzheimer's disease (AD) and dementia with Lewy bodies (DLB) at the individual subject level with the accuracy of 0.73.

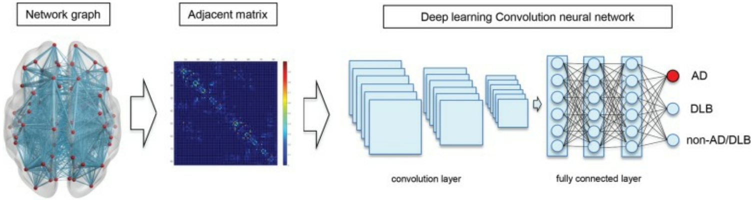


Figure: Architecture of the Model

[4] Akihiko Wada et al. "Differentiating Alzheimer's Disease from Dementia with Lewy Bodies Using a Deep Learning Technique Based on Structural Brain Connectivity". In: *Magnetic Resonance in Medical Sciences* 18 (July 2019), pp. 219–224

Related Work

Zhang et al.[5] proposed a method to extract the graph embeddings based on GCN and used an MLP for the final regression output.

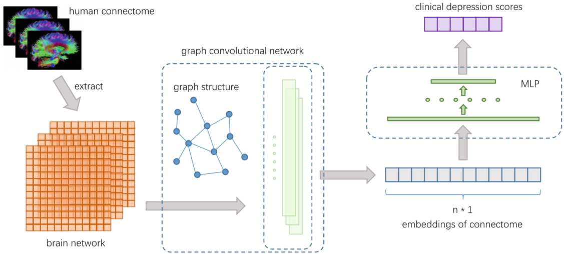


Figure: Architecture of the Model

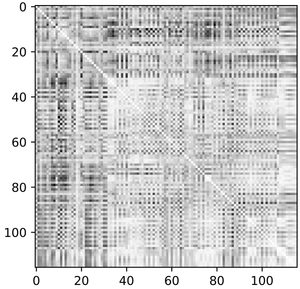
[5] Yanfu Zhang and Heng Huang. "New Graph-Blind Convolutional Network for Brain Connectome Data Analysis". In: *Information Processing in Medical Imaging*. Ed. by Albert C. S. Chung et al. Cham: Springer International Publishing, 2019, pp. 669–681

Methodology

Details of Data

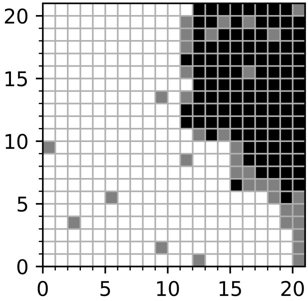
- EEG for 5 minutes - 2 seconds/piece - 100 instances
- 100 EEG to 50 coherence matrix
- Patients had 3 stages: Pre (50), Post (50), Follow-up (50)
- 24 Patients: 1200, 1200, 1200
- 24 Healthy controls: 1200

Details of Input Data



- Shape: 30 * 116 * 116
- Coherence of brain regions
- Symmetric along the diagonal (Adjacent Matrix)

Details of Output Data



- Black: Impaired
- Grey: Partial impaired
- White: Normal

Research Question 1: improved or not

ID	Label	ID	Label	ID	Label
1	0	**2**	1	**3**	0
4	1	**5**	1	**6**	1
7	0	**8**	0	**9**	0
10	1	**11**	1	**12**	1
13	1	**14**	1	**15**	1
16	1	**17**	1	**18**	1
19	1	**20**	0	**21**	1
22	0	**23**	0	**24**	0

Table: Results after treatment: 0 means non-improved, 1 means improved

- 15 patients had improved, 9 patients had not improved
- 1200 pieces of Pre data as input
- 1200 matching labels as output

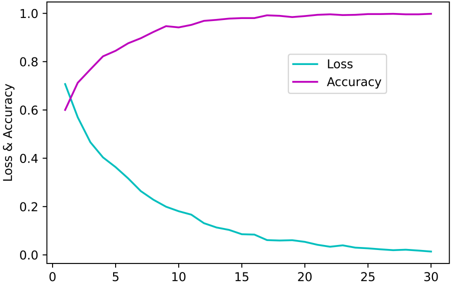
Research Question 1: improved or not

3D CNN Models

Input Layer	Input_shpae = [30,116,116,1]				
Layer	**Filter**	**Dropout**	**AF**	**Pooling**	**Norm?**
Conv3D 1	[2,3,3] * 32	0.3	ReLU	Max	Yes
Conv3D 2	[2,3,3] * 64	0.5	ReLU	Max	Yes
Conv3D 3	[2,3,3] * 32	0.5	ReLU	Max	Yes
Flatten Layer					
Dense 1	Unit = 1024		ReLU		
Dense 2	Unit = 512		ReLU		
Output Layer	Unit = 1		Sigmoid	**10,038,209 Paras**	

Table: Parameters and details of the best 3D CNN model for question 1

Research Question 1: improved or not



- Cross validation (k = 4)
- Epoch = 30
- Training accuracy = 99%
- Testing accuracy = 95%

Research Question 2: patients or not

- 24 healthy controls: 1200 instances - label 1
- 24 patients: 3600 instances - label 0

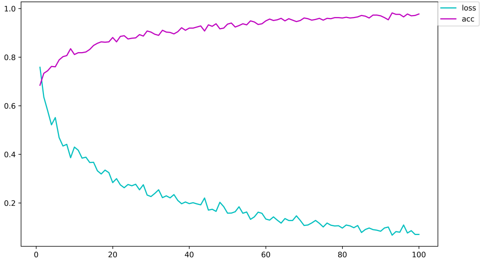
Research Question 2: patients or not

3D CNN Models

Input Layer	Input_shpae = [30,116,116,1]				
Layer	**Filter**	**Dropout**	**AF**	**Pooling**	**Norm?**
Conv3D	[3,3,3] * 16	0.5	ReLU	Max	Yes
Conv3D	[3,3,3] * 32	0.5	ReLU	Max	Yes
Conv3D	[3,3,3] * 32	0.5	ReLU	Max	Yes
Flatten Layer					
Dense 1	Unit = 1024		ReLU		
Output Layer	Unit = 1		Sigmoid	**9,481,537 Paras**	

Table: Parameters and details of the best 3D CNN model for question 2

Research Question 2: patients or not



- Cross validation ($k = 5$)
- Epoch $= 100$
- Training accuracy $=$ 85%
- Testing accuracy $=$ 72%

Research Question 3: distribution prediction

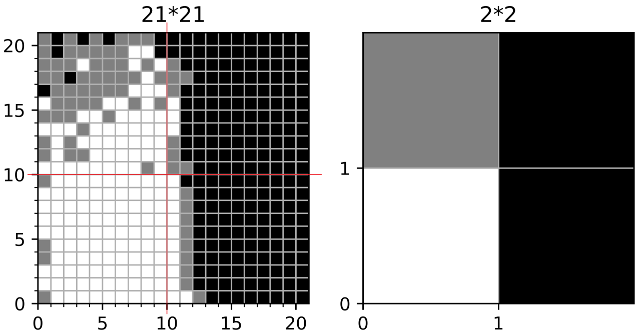


Figure: A visual comparison of the original and new matrices

Research Question 3: distribution prediction

3D CNN Models

- 3600 instances
- Cross validation (k = 5)
- Training accuracy = 60%
- Testing accuracy = 40%

Research Question 3: distribution prediction

2D CNN Models

- Band 1: 0 to 4 Hz; Band 2: 4 to 12 Hz; Band 3: 12 to 30 Hz
- MobileNet[6] as the backbone, input shape: [3,116,116]
- Training Accuracy = 80%
- Testing Accuracy = 71%

[6] Andrew G. Howard et al. "MobileNets: Efficient Convolutional Neural Networks for Mobile Vision Applications". In: *CoRR* abs/1704.04861 (2017)

Research Question 3: distribution prediction

GCN Models

Measure	Format
Coherence	[116, 116]
Degree	[1, 116]
Strength	[1, 116]
Clustering Coefficient	[1, 116]
Betweenness Centrality	[1, 116]

Table: Format of each measure for an instance

Research Question 3: distribution prediction

GCN Models

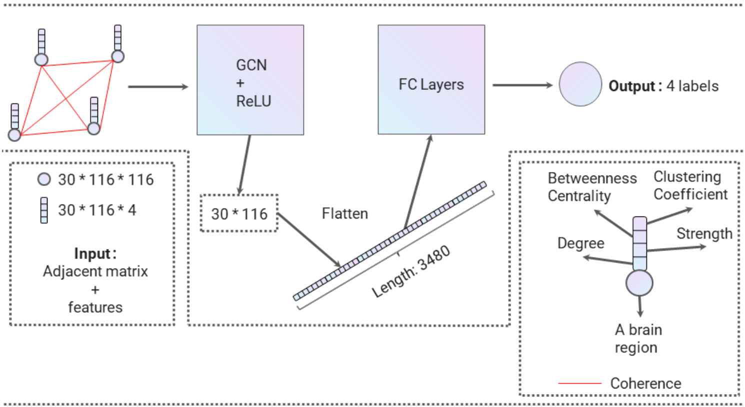


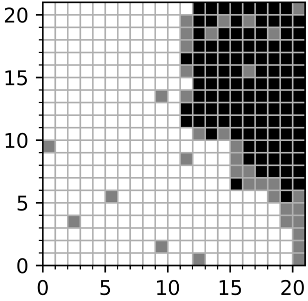
Figure: Architecture of the proposed GCN model

Research Question 3: distribution prediction

GCN Models

- Training Accuracy = 70%
- Testing Accuracy = 40%

Research Question 4: percentage prediction



Balck + Grey = 34.8%, White = 66.2%

- Calculate the percentage based on the distribution
- Regression task
- MSE, MAE, R-Squared

Research Question 4: percentage prediction

3D CNN & 2D CNN Models

- Similar process like in Question 3
- Easily overfitting for training data
- Negative R-squared score for testing data

Research Question 4: percentage prediction

1D CNN Models

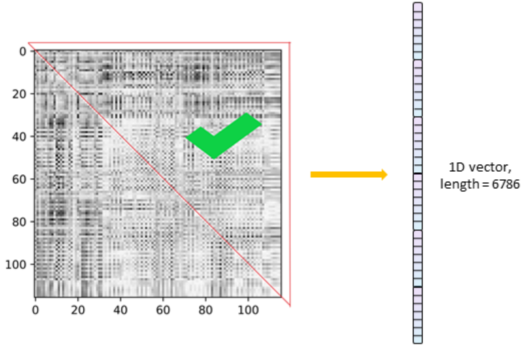


Figure: Converting coherence matrix to 1D vector

Research Question 4: percentage prediction

1D CNN Models

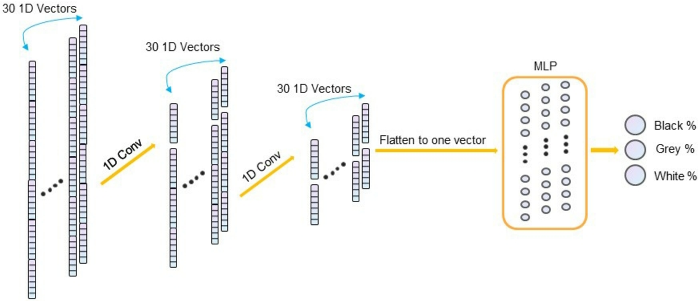
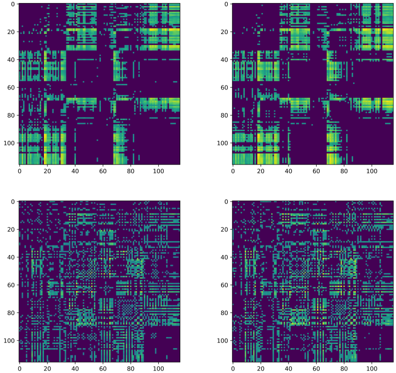


Figure: Architecture of 1D CNN model

Results

- Question 1: Accuracy $= 95\%$
- Question 2: Accuracy $= 72\%$
- Question 3: Accuracy $= 71\%$
- Question 4: Currently no

Discussion



- Size of available data
- Data quality
- Indirect data information
- Not best models

Discussion

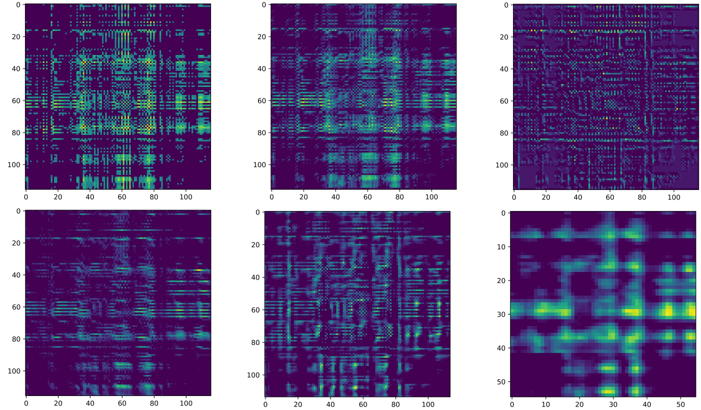


Figure: Visualization of feature maps of the proposed 3D CNN Model

Thank you!

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Appendix

Model	No. of Parameters
VGG16	19,960,130
ResNet50	57,668,994
Xception	54,942,762
DenseNet121	17,001,538
MobileNet	13,192,898

Table: Parameters of the applied models

Appendix

Mathematical Definition of Degree: the degree of an individual node is equal to the number of links connected to that node

$$k_i = \sum_{j \in N} a_{ij} \tag{1}$$

Mathematical Definition of Clustering Coefficient: the fraction of triangles around a node and is equivalent to the fraction of node's neighbors that are neighbors of each other

$$C = \frac{1}{n} \sum_{i \in N} C_i = \frac{1}{n} \sum_{i \in N} \frac{2t_i}{k_i(k_i - 1)'} \tag{2}$$

Appendix

Mathematical Definition of Betweenness Centrality: the fraction of all shortest ways in the whole network, including the known node

$$b_i = \frac{1}{(n-1)(n-2)} \sum_{\substack{h,j \in N \\ h \neq j, h \neq i, j \neq i}} \frac{\rho_{hj}(i)}{\rho_{hj}} \quad (3)$$

Strength means the sum of weights of links connected to the node

Appendix

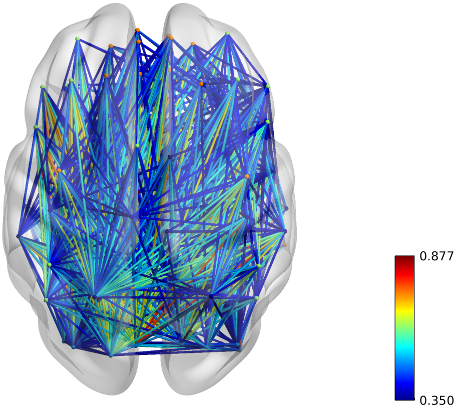

Figure: An example of healthy control's coherence connectivity network

Appendix

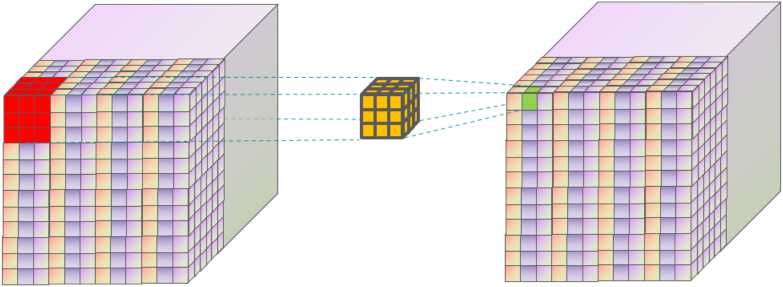

Figure: An example of 3D convolutional operation

Appendix

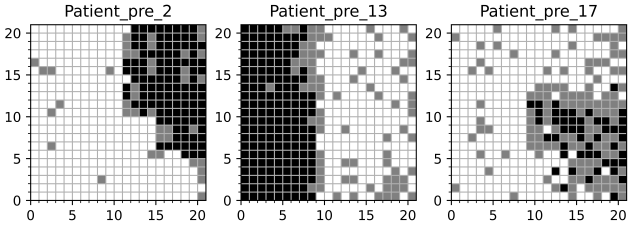

Figure: Patient ID = [2, 13, 17], pre-treatment stage

Appendix

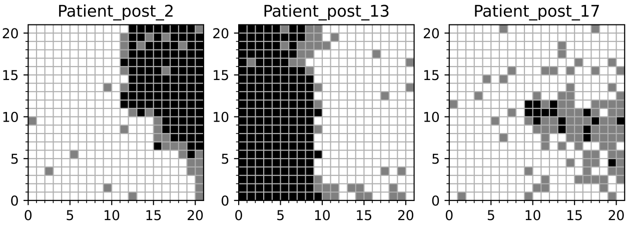

Figure: Patient ID = [2, 13, 17], post-treatment stage

Appendix

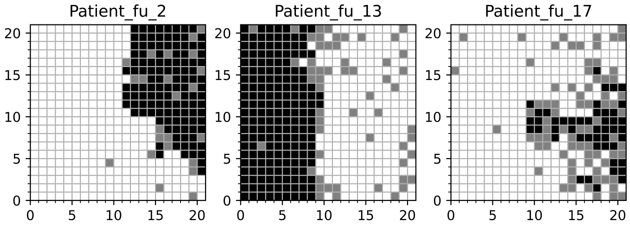

Figure: Patient ID = [2, 13, 17], follow-up stage

Appendix

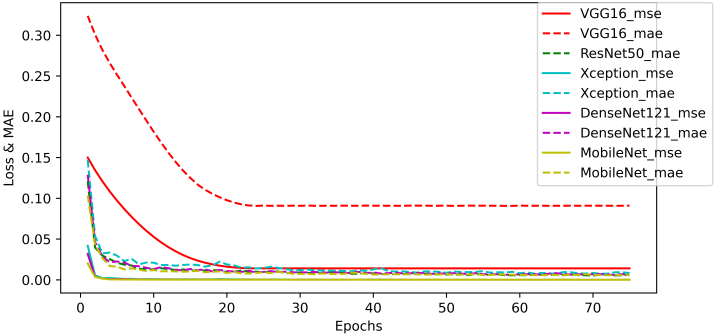

Figure: Loss and MAE during training process for Question 4

Appendix

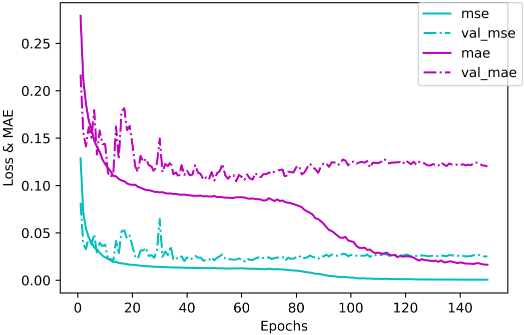

Figure: Loss and MAE during training process for 1D CNN model

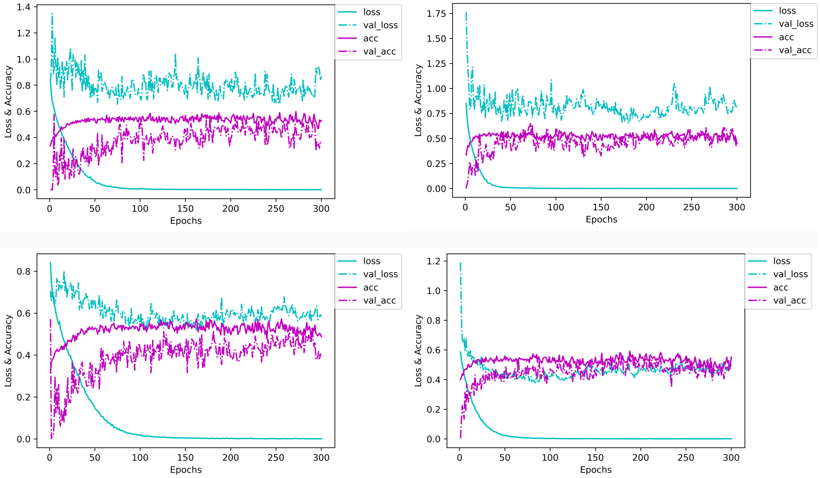

Figure: Performances of different cases of 3D CNN models for Question 3

Appendix

GCN: convolved signal matrix

$$\mathbf{Z} = \widetilde{\mathbf{D}}^{-\frac{1}{2}}\widetilde{\mathbf{A}}\widetilde{\mathbf{D}}^{-\frac{1}{2}}\mathbf{X}\Theta \tag{4}$$

A is the adjacent matrix, D is the degree vector, X is the input features, θ is the matrix of filter parameters.

Appendix

Mean Squared Errors

$$MSE = \sum_{i=1}^{n} \frac{(\hat{y}_{(i)} - y_{(i)})^2}{n} \tag{5}$$

Mean Absolute Errors

$$MAE = \sum_{i=1}^{n} \frac{|\hat{y}_{(i)} - y_{(i)}|}{n} \tag{6}$$

Appendix

R-Squared

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (y_{(i)} - \hat{y}_{(i)})^2}{\sum_{i=1}^{n} (y_{(i)} - \bar{y})^2} \tag{7}$$

Cross Entropy

$$CE(p, q) = -\sum_{i=1}^{n} p(i)\, log\, q(i) \tag{8}$$