Recognizing Brain States Using Deep Sparse Recurrent Neural Network

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Background

- Characterize and analyze the brain activity
- However the approaches were under the assumption of temporally stationary;
- Brain activities are under dramatic temporal changes at various time scales;
- For time series data: sliding windows; change point detection methods; Hidden Markov Model (HMM);
- RNNs can inherently acquire the temporal dependence of the sequential data, and is proposed here to model and recognize brain states in task fMRI data.

Dataset

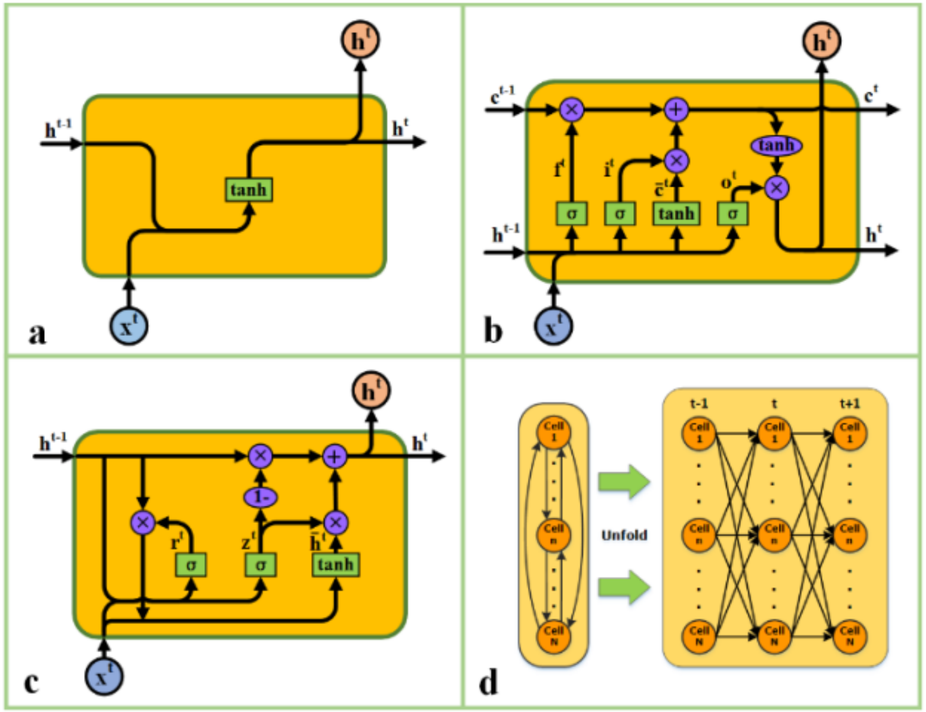
Table 1. Properties of HCP task-fMRI datasets

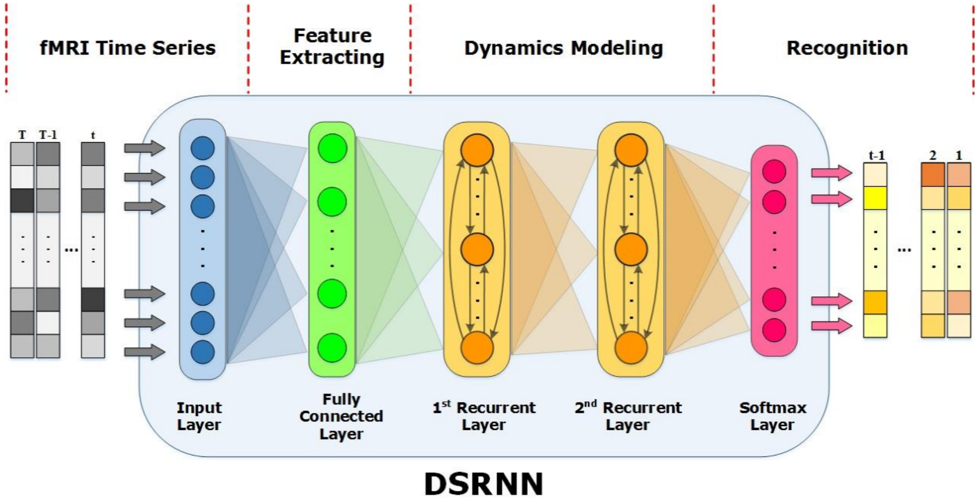
Task / Parameters	Working Memory	Gambling	Motor	Language	Social	Relational	Emotion
# of Frames	405	253	284	316	274	232	176
Duration (Min)	5:01	3:12	3:34	3:57	3:27	2:56	2:16
# of Task Blocks	8	4	10	8	5	6	6
# of Block Labels	3	3	6	3	5	3	3
Duration of Blocks(s)	25	28	12	See Text	23	16	18

Data acquisition parameters:
220 mm FOV, in-plane FOV: 208×180 mm2, flipangle=52, BW=2290 Hz/Px, 2×2×2 mm3 spatial resolution, 90×104 matrix, 72 slices, TR=0.72s, TE=33.1ms.

Preprocessing:
- Skull removal;
- Motion correction;
- Slice time correction;
- Spatial smoothing;
- Global drift removal;
- 4X4X4 mm^3 down sampling.

Model





Basic recurrent cell unit (a):

$$\boldsymbol{h}^t = \tanh(\boldsymbol{U}\boldsymbol{h}^{t-1} + \boldsymbol{W}\boldsymbol{x}^t + \boldsymbol{b})$$

LSTM (b):

$$\boldsymbol{h}^t = \boldsymbol{o}^t \odot \tanh(\boldsymbol{c}^t)$$

$$\boldsymbol{o}^t = \sigma(\boldsymbol{U}_o\boldsymbol{h}^{t-1} + \boldsymbol{W}_o\mathbf{x}^t + \boldsymbol{b}_o)$$

$$\boldsymbol{c}^t = \boldsymbol{f}^t \odot \boldsymbol{c}^{t-1} + \boldsymbol{i}^t \odot \tilde{\boldsymbol{c}}^t$$

$$\boldsymbol{f}^t = \sigma\left(\boldsymbol{U}_f\boldsymbol{h}^{t-1} + \boldsymbol{W}_f\mathbf{x}^t + \boldsymbol{b}_f\right)$$

$$\boldsymbol{i}^t = \sigma(\boldsymbol{U}_i\boldsymbol{h}^{t-1} + \boldsymbol{W}_i\boldsymbol{x}^t + \boldsymbol{b}_i)$$

$$\tilde{\boldsymbol{c}}^t = \tanh(\boldsymbol{U}_c\boldsymbol{h}^{t-1} + \boldsymbol{W}_c\boldsymbol{x}^t + \boldsymbol{b}_c)$$

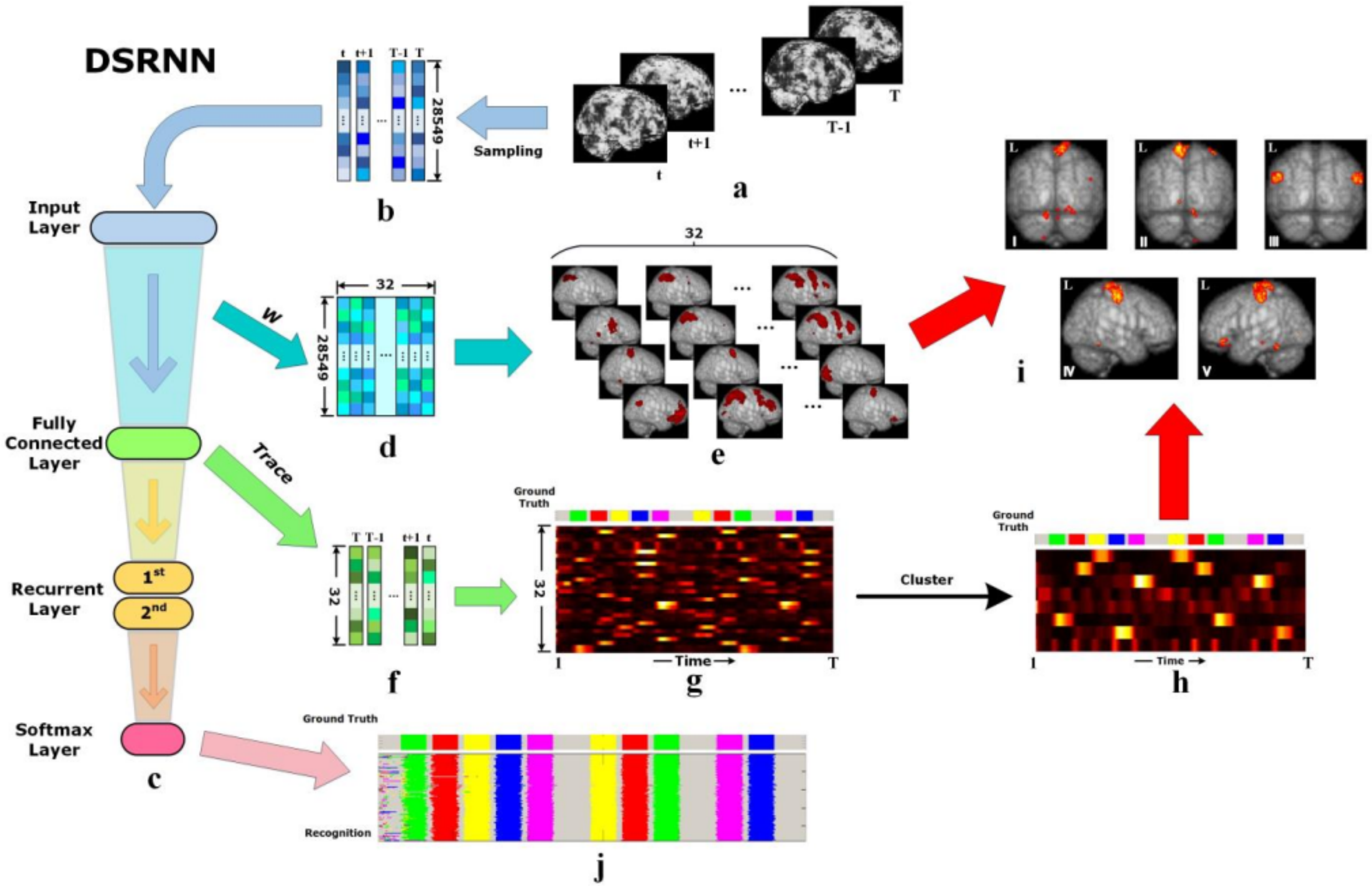
GRU (c):

$$\boldsymbol{c}^t = \boldsymbol{f}^t \odot \boldsymbol{c}^{t-1} + \boldsymbol{i}^t \odot \tilde{\boldsymbol{c}}^t$$

$$\boldsymbol{f}^t = \sigma\left(\boldsymbol{U}_f\boldsymbol{h}^{t-1} + \boldsymbol{W}_f\mathbf{x}^t + \boldsymbol{b}_f\right)$$

$$\boldsymbol{i}^t = \sigma(\boldsymbol{U}_i\boldsymbol{h}^{t-1} + \boldsymbol{W}_i\boldsymbol{x}^t + \boldsymbol{b}_i)$$

$$\tilde{\boldsymbol{c}}^t = \tanh(\boldsymbol{U}_c\boldsymbol{h}^{t-1} + \boldsymbol{W}_c\boldsymbol{x}^t + \boldsymbol{b}_c)$$



Task	Train	Test
WM	240	240
GAMBLING	320	320
MOTOR	320	320
LANGUAGE	300	300
SOCIAL	320	320
RELATIONAL	320	320
EMOTION	400	360

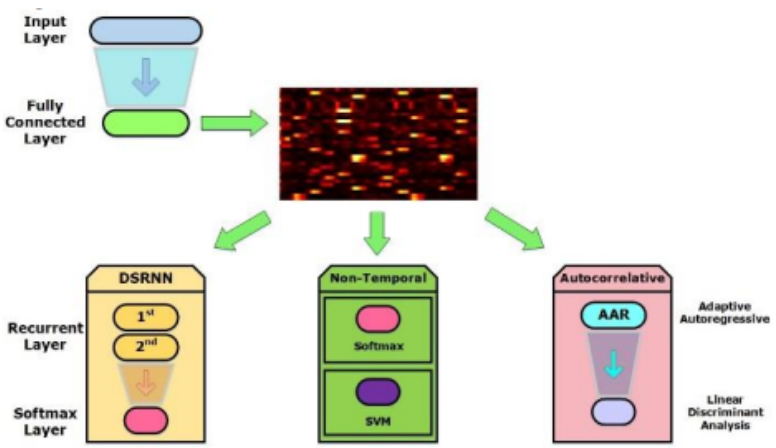
Loss function:

$$J(\boldsymbol{W}, \boldsymbol{b}) = CE(\boldsymbol{y} \| \hat{\boldsymbol{y}}) + \beta \|\boldsymbol{O_{Full}}\| + \lambda \|\boldsymbol{W_{Full}}\|$$

sparse

$$Accuracy = \frac{N(Labels_{Rec} == Labels_{GT})}{Sequence\ Length}$$

Results



AAR: $$y_t = a_{1,t}y_{t-1} + a_{2,t}y_{t-2} + \cdots + a_{p,t}y_{t-p} + x_t,$$

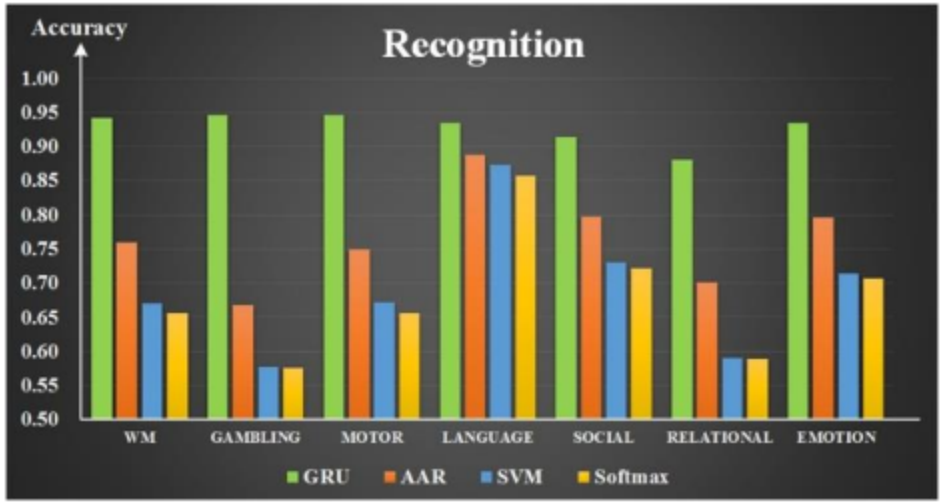


Fig. 5. Brain state recognition accuracies of seven tasks.

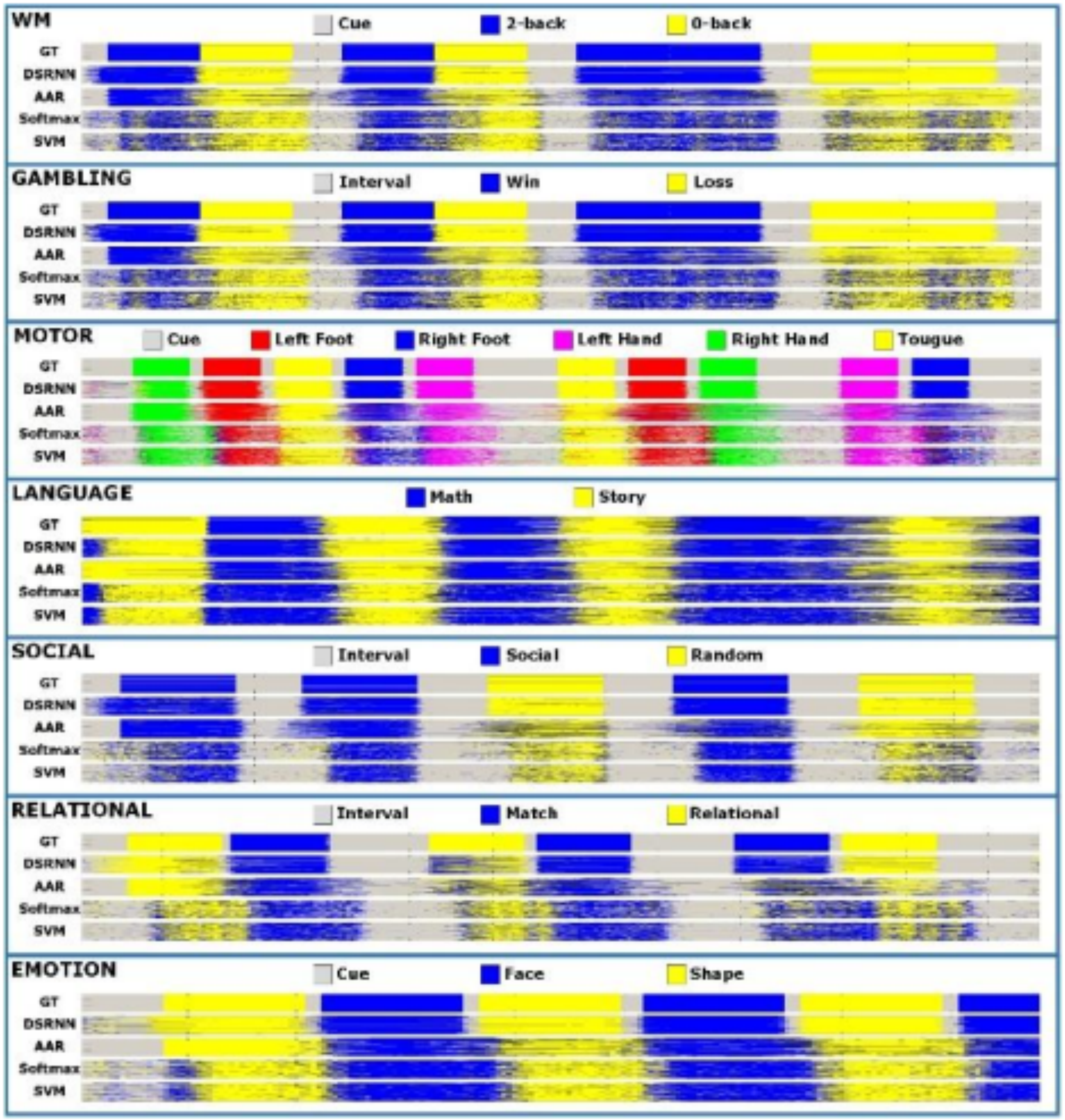


Fig. 6. Brain state series of seven tasks. In each subgraph, five state series

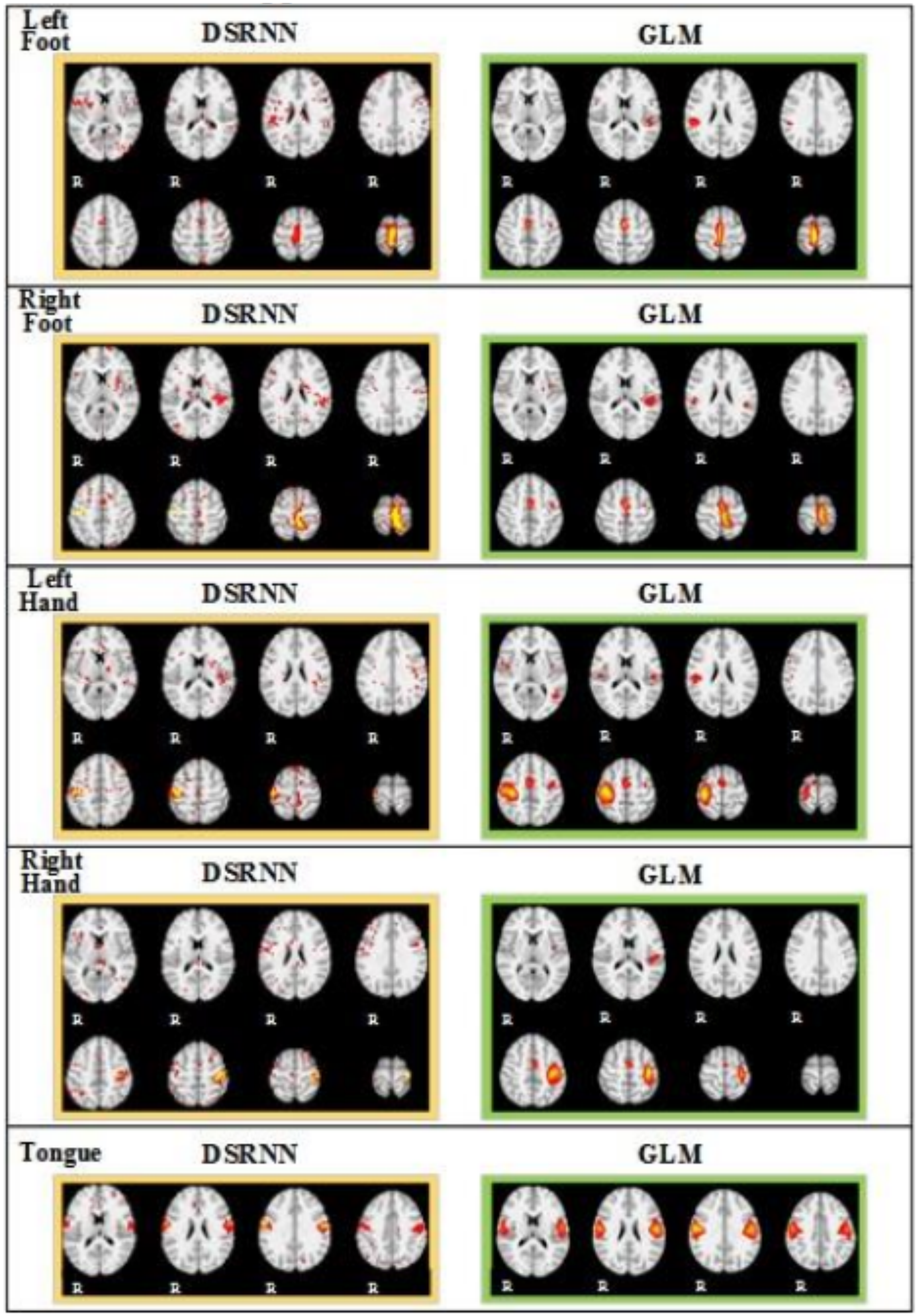
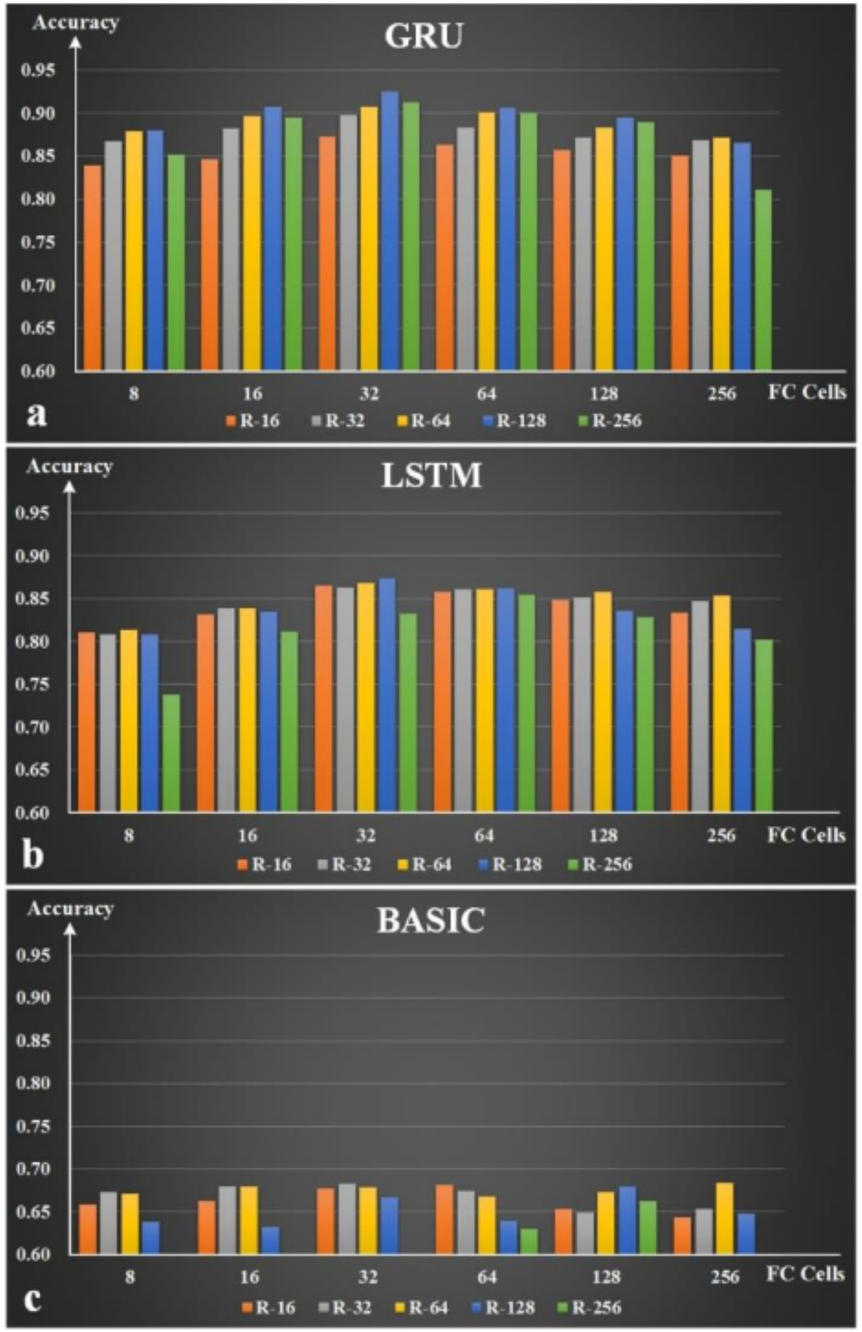
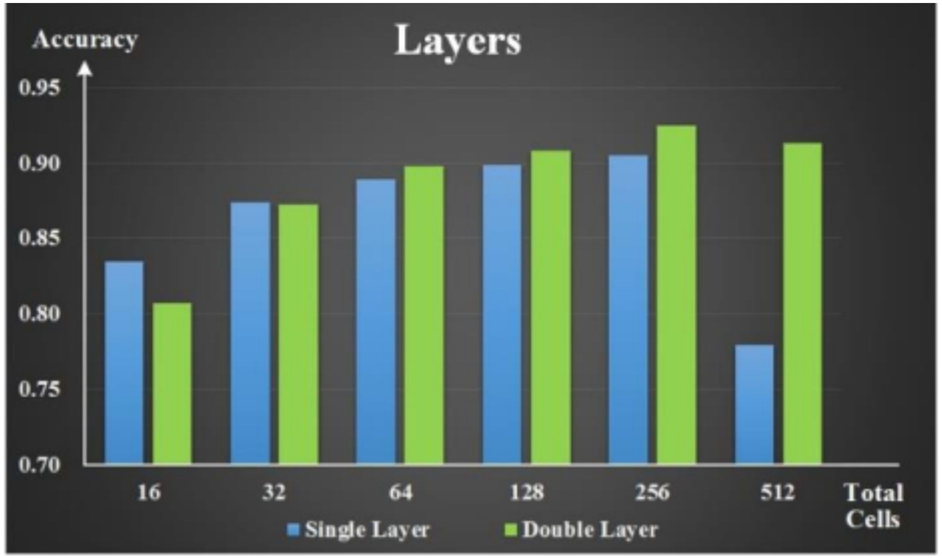
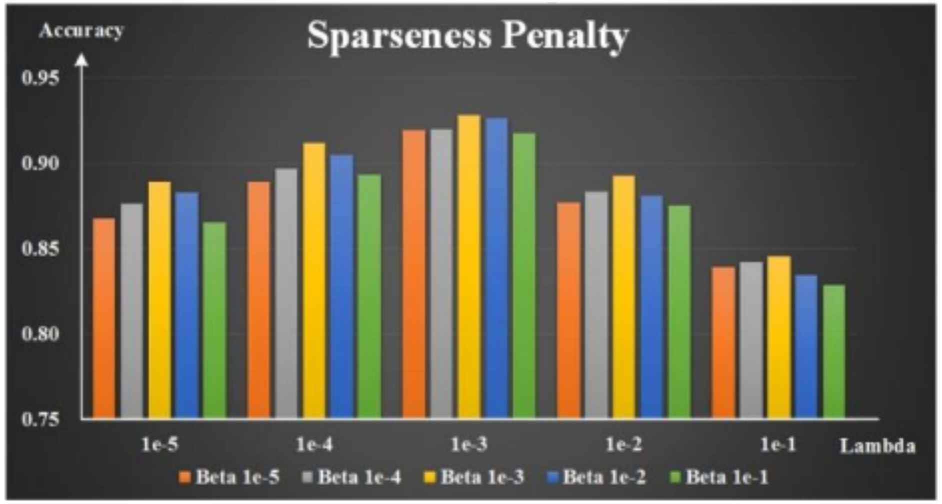
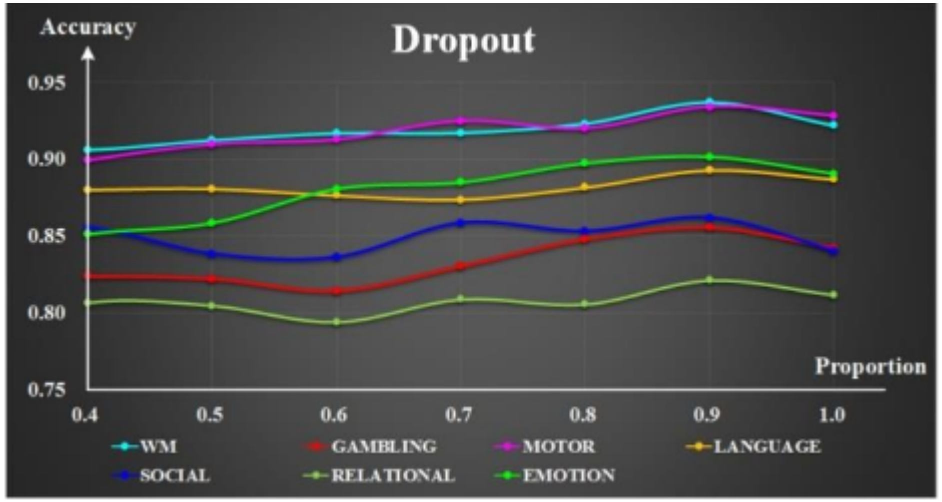


Fig. 7. Activation maps of motor task.




Layers
Accuracy
0.95
0.90
0.85
0.80
0.75
0.70
16
32
64
128
256
512
Total Cells
Single Layer
Double Layer


Sparseness Penalty
Accuracy
0.95
0.90
0.85
0.80
0.75
1e-5
1e-4
1e-3
1e-2
1e-1
Lambda
Beta 1e-5
Beta 1e-4
Beta 1e-3
Beta 1e-2
Beta 1e-1


Dropout
Accuracy
0.95
0.90
0.85
0.80
0.75
Proportion
0.4
0.5
0.6
0.7
0.8
0.9
1.0
WM
GAMBLING
MOTOR
LANGUAGE
SOCIAL
RELATIONAL
EMOTION