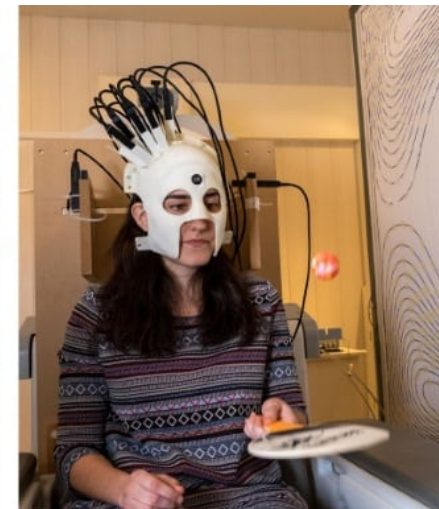
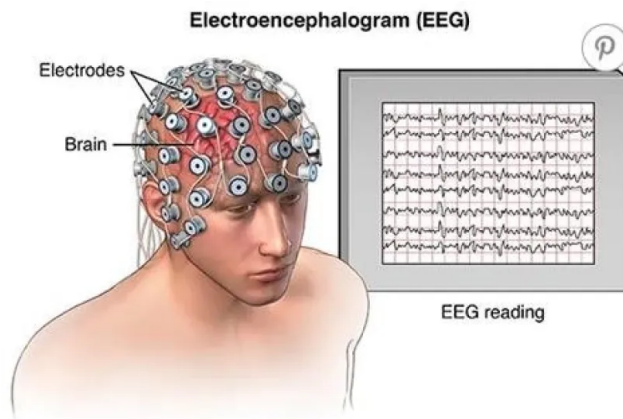
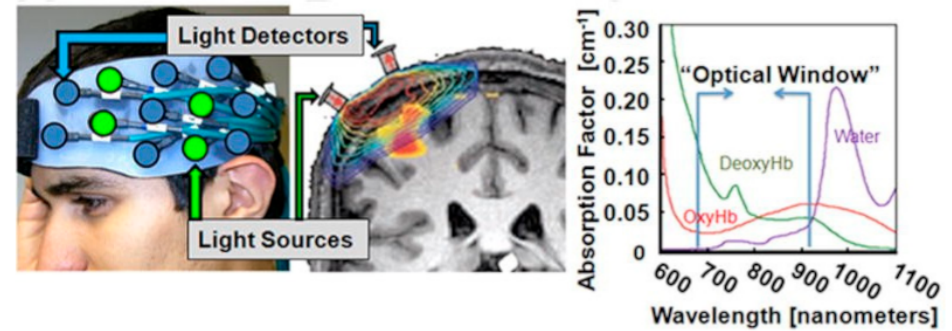
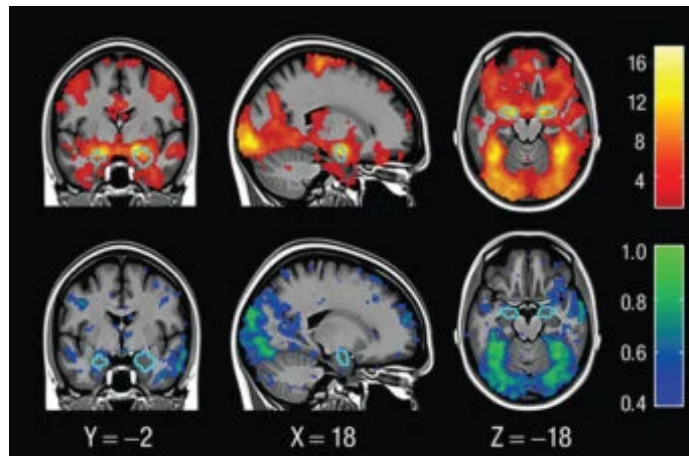


# Improving Multi-Voxel Pattern Analysis with Modern Convolutional Neural Network Architecture

蕭翔允, 鄭九彰, 簡志宇

2024/06/17

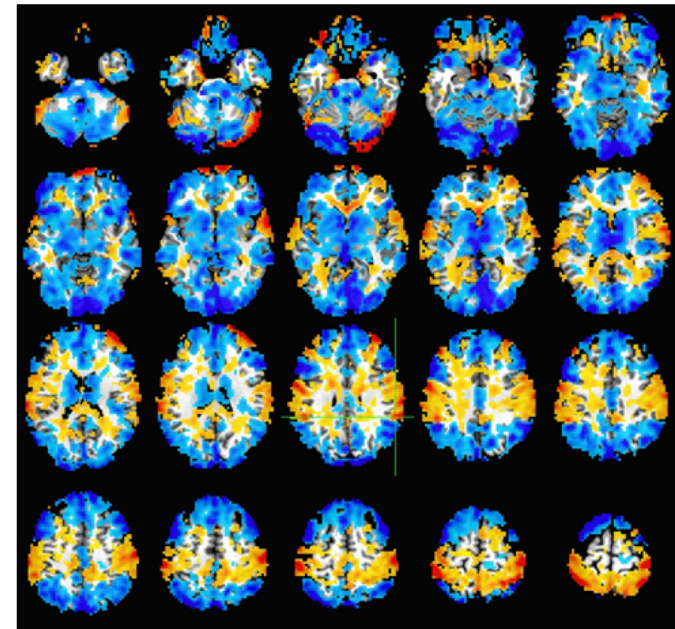
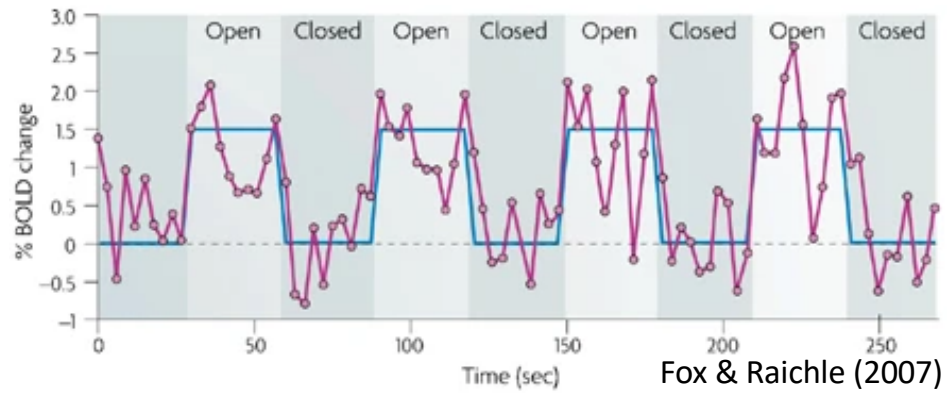
# Searching for Physical Signals of Psychological Processes





# Functional MRI

- Non-invasive brain activity detection
- High temporal resolution



# Data Source



OpenNEURO

 Files

 Download

 Derivatives

 Metadata

README

## Collaborations and deceptions in strategic interactions revealed by hyperscanning fMRI

### Aims:

The current study aims to investigate the neural mechanisms of interpersonal collaborations and deceptions, with an Opening Treasure Chest (OTC) game under the fMRI hyperscanning setup.



Prof. 陳德祐



Prof. 龔俊嘉



Prof. 翁明宏

[openneuro.org/datasets/ds004103](https://openneuro.org/datasets/ds004103)

# Collaborations and deceptions in strategic interactions revealed by hyperscanning fMRI

Siao-Shan Shen, Jen-Tang Cheng, Yi-Ren Hsu, Der-Yow Chen, Ming-Hung Weng, Chun-Chia Kung  
doi: <https://doi.org/10.1101/2021.07.11.451985>



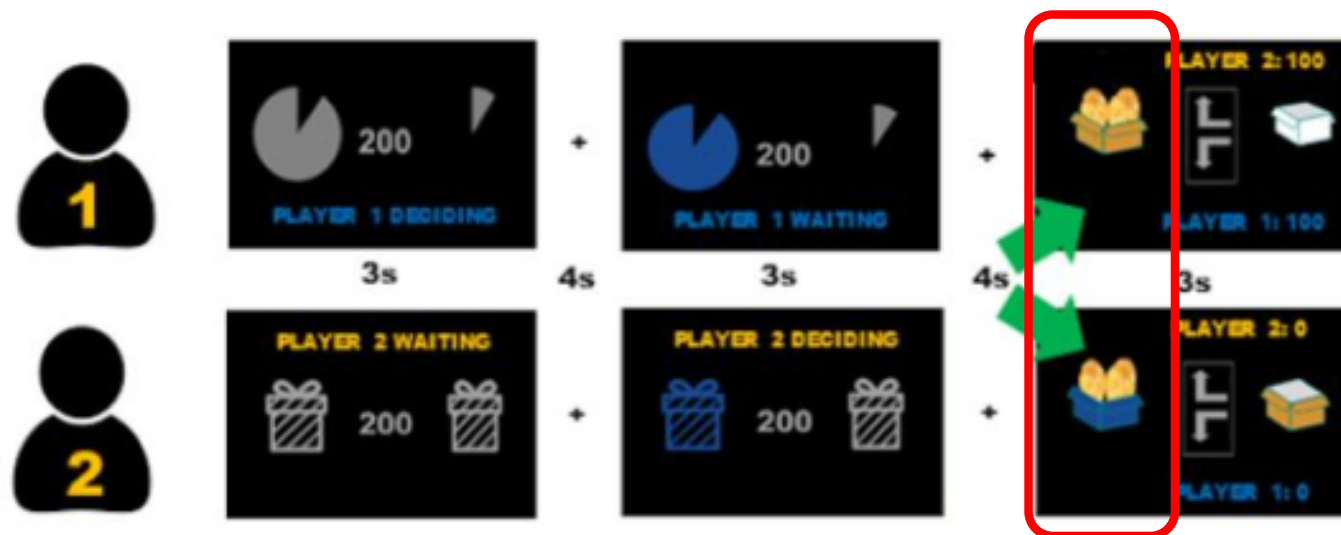
# Collaborations and deceptions in strategic interactions revealed by hyperscanning fMRI

Siao-Shan Shen, Jen-Tang Cheng, Yi-Ren Hsu, Der-Yow Chen, Ming-Hung Weng, Chun-Chia Kung  
doi: <https://doi.org/10.1101/2021.07.11.451985>



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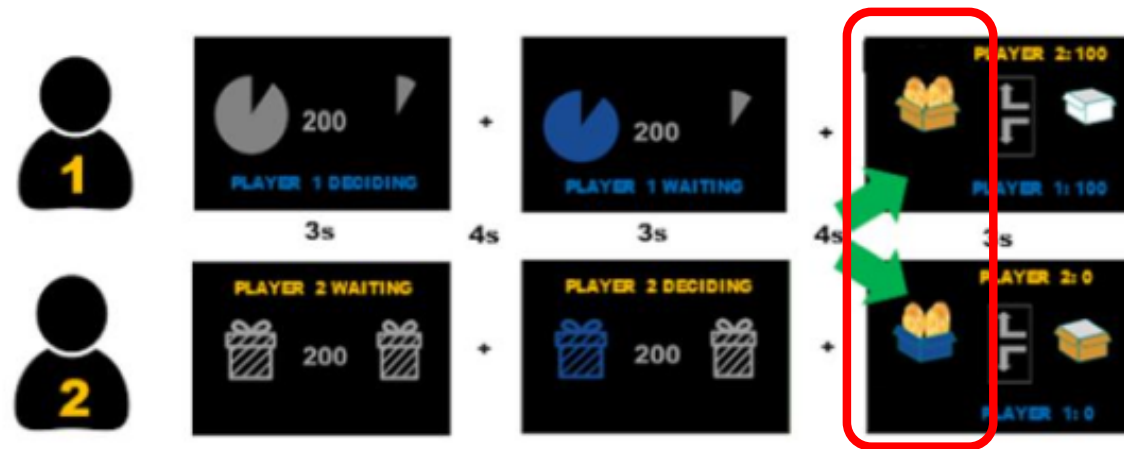




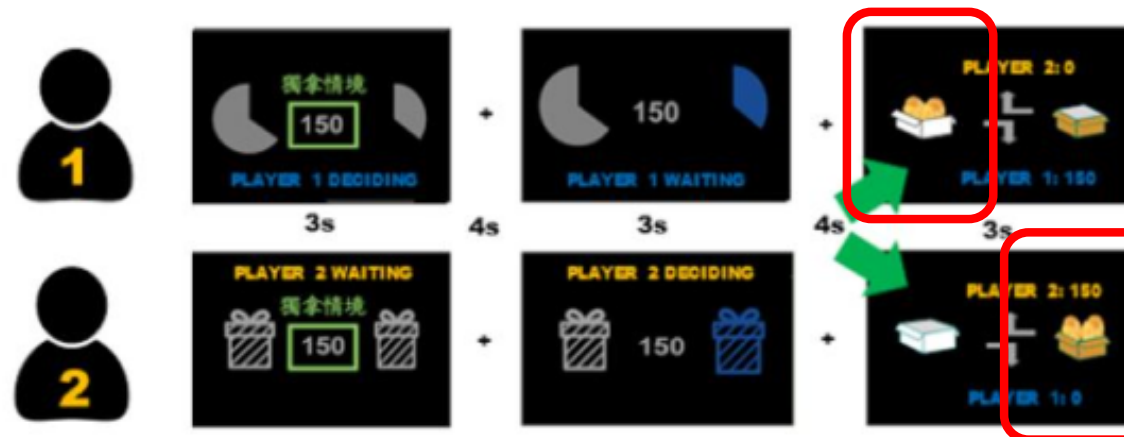
# Collaborations and deceptions in strategic interactions revealed by hyperscanning fMRI

Siao-Shan Shen, Jen-Tang Cheng, Yi-Ren Hsu, Der-Yow Chen, Ming-Hung Weng, Chun-Chia Kung  
 doi: <https://doi.org/10.1101/2021.07.11.451985>

Cooperation



Competition

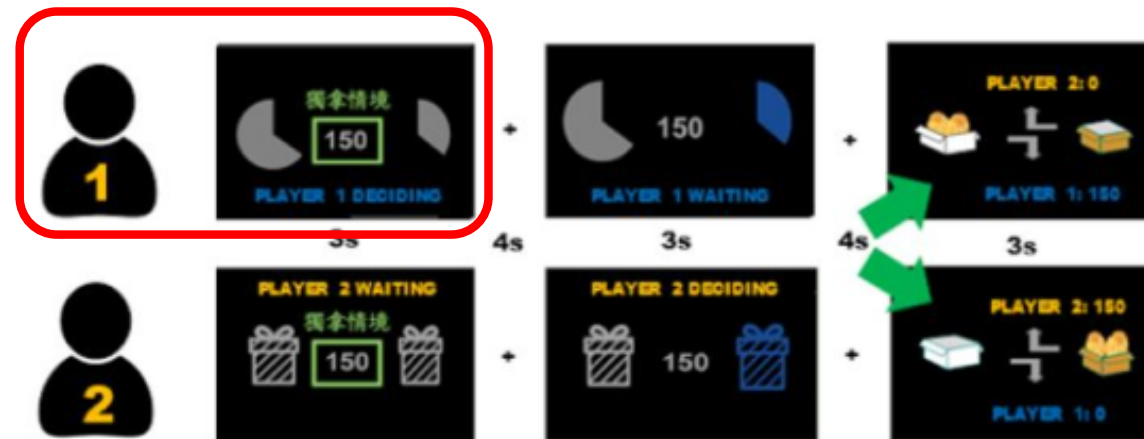


# Major Goal

Cooperation

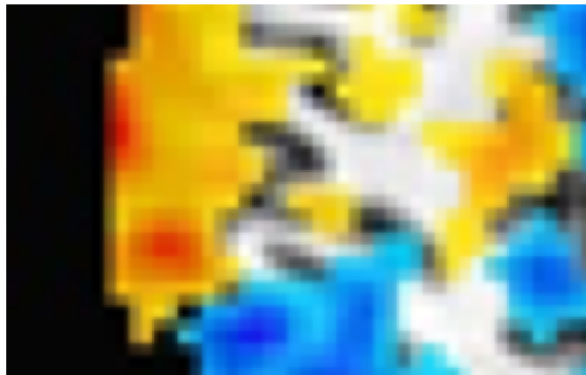
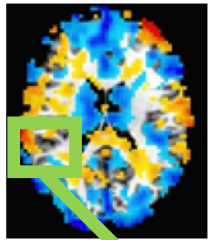


Competition



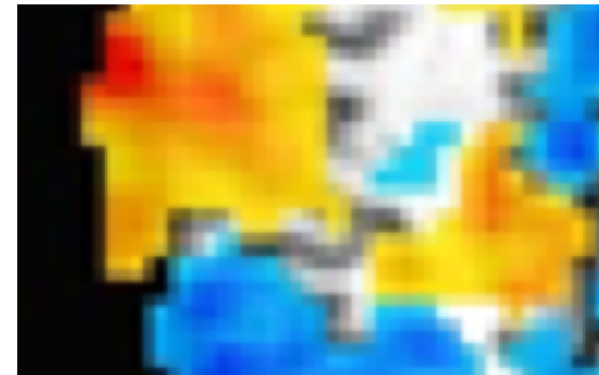
# Region of Interest Analysis

- Averaging a dataset will make it less informative.



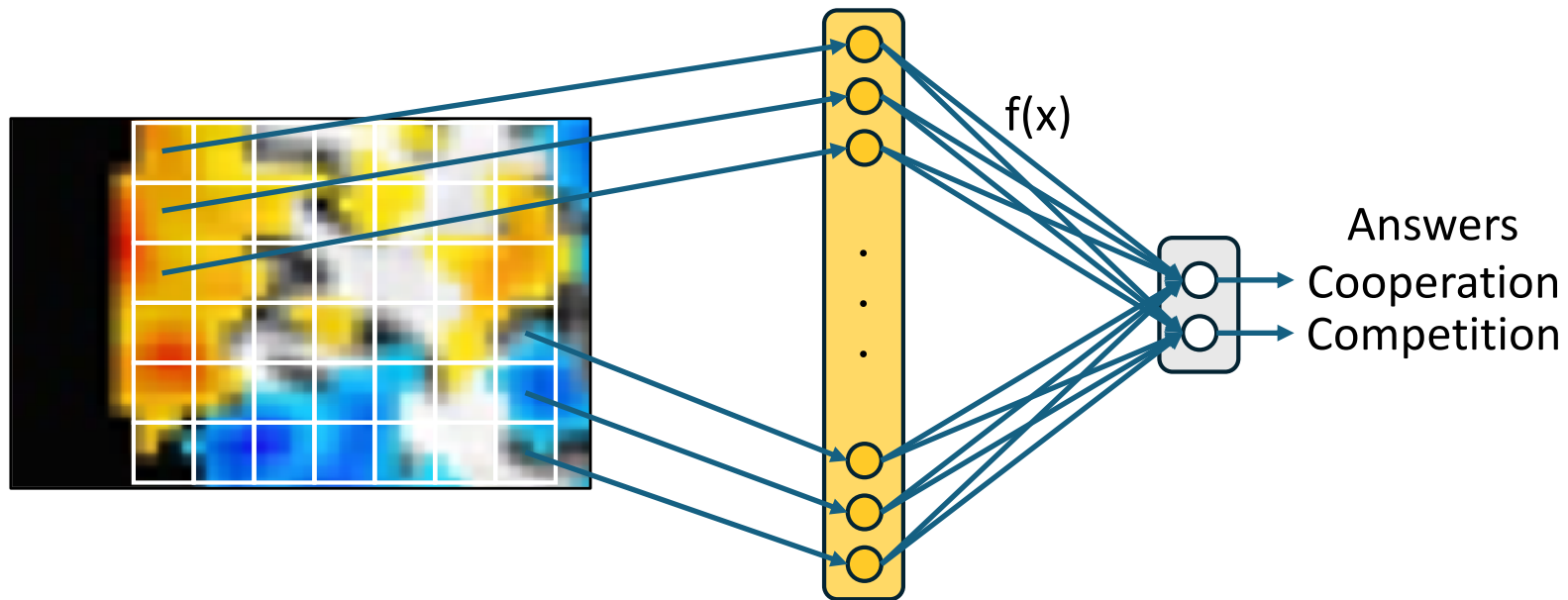
Mean Intensity

0.31

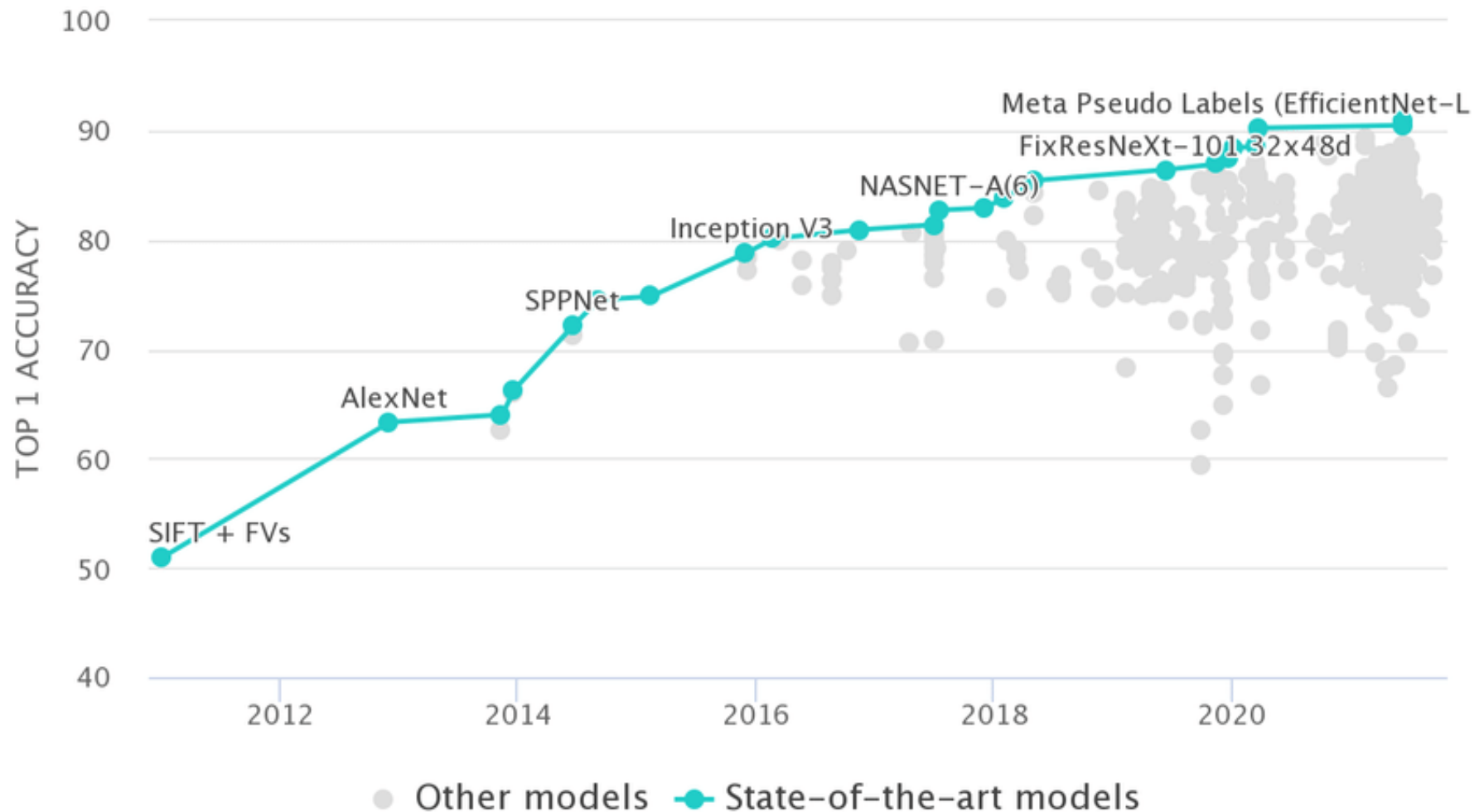


# Multi-Voxel Pattern Analysis

- Machine Learning based Image Classification
- Empirical, Data-driven, Self-adaptive



# Progress of Image Classification





# Explore of CNN-MVPA



Contents lists available at [ScienceDirect](https://www.sciencedirect.com)

Artificial Intelligence In Medicine

journal homepage: [www.elsevier.com/locate/artmed](http://www.elsevier.com/locate/artmed)



## 3D-CNN based discrimination of schizophrenia using resting-state fMRI

Muhammad Naveed Iqbal Qureshi<sup>a,b,c,d,1</sup>, Jooyoung Oh<sup>e,f,1</sup>, Boreom Lee<sup>g,\*</sup>

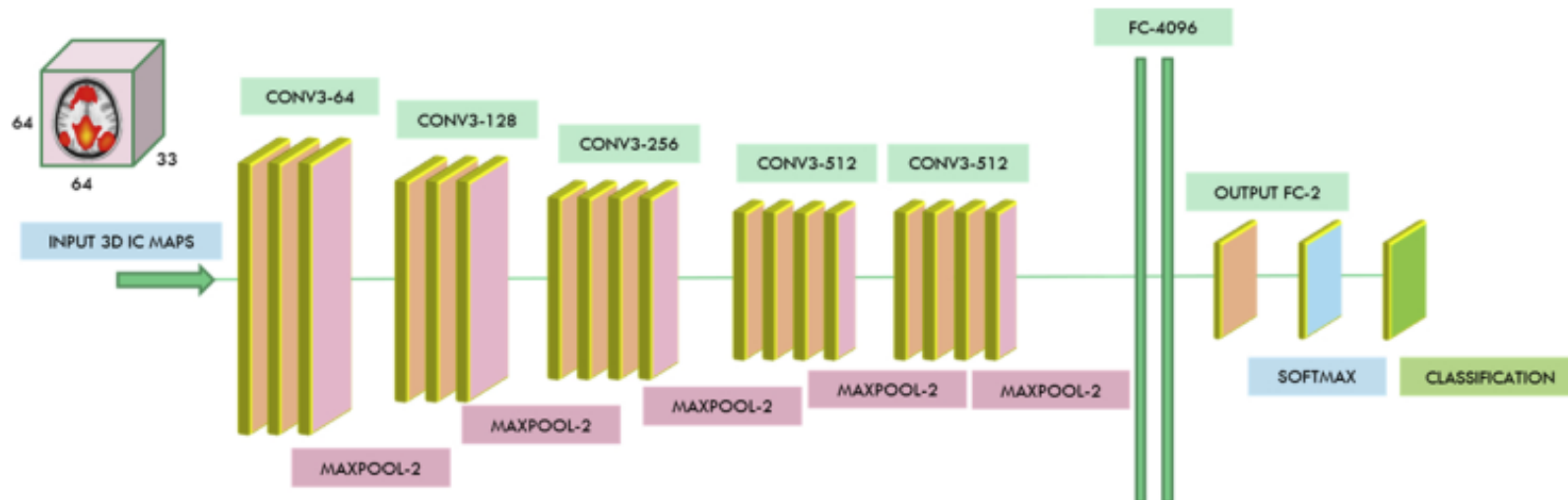


Fig. 2. VGG-Net based 3D-CNN architecture.

# Explore of CNN-MVPA (2)



Contents lists available at [ScienceDirect](https://www.sciencedirect.com)

NeuroImage

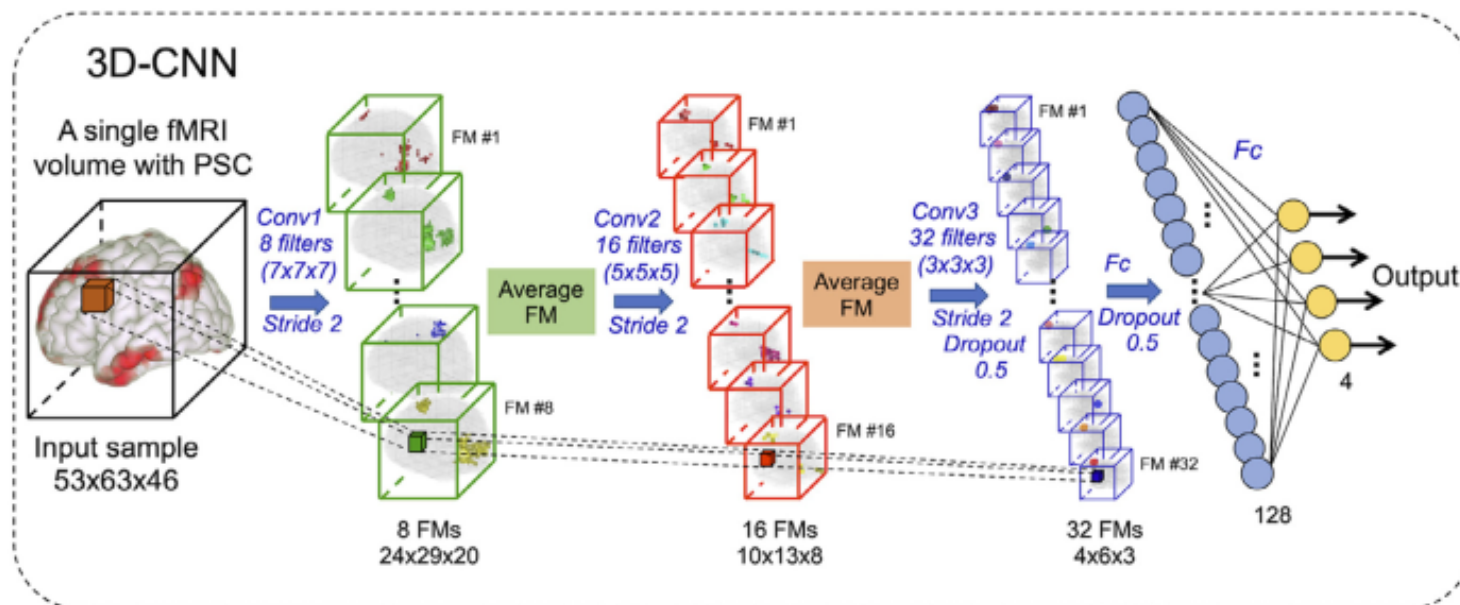
journal homepage: [www.elsevier.com/locate/neuroimage](http://www.elsevier.com/locate/neuroimage)



fMRI volume classification using a 3D convolutional neural network robust to shifted and scaled neuronal activations



Hanh Vu, Hyun-Chul Kim, Minyoung Jung, Jong-Hwan Lee\*



# Explore of CNN-MVPA (3)



Contents lists available at [ScienceDirect](https://www.sciencedirect.com)

Medical Image Analysis

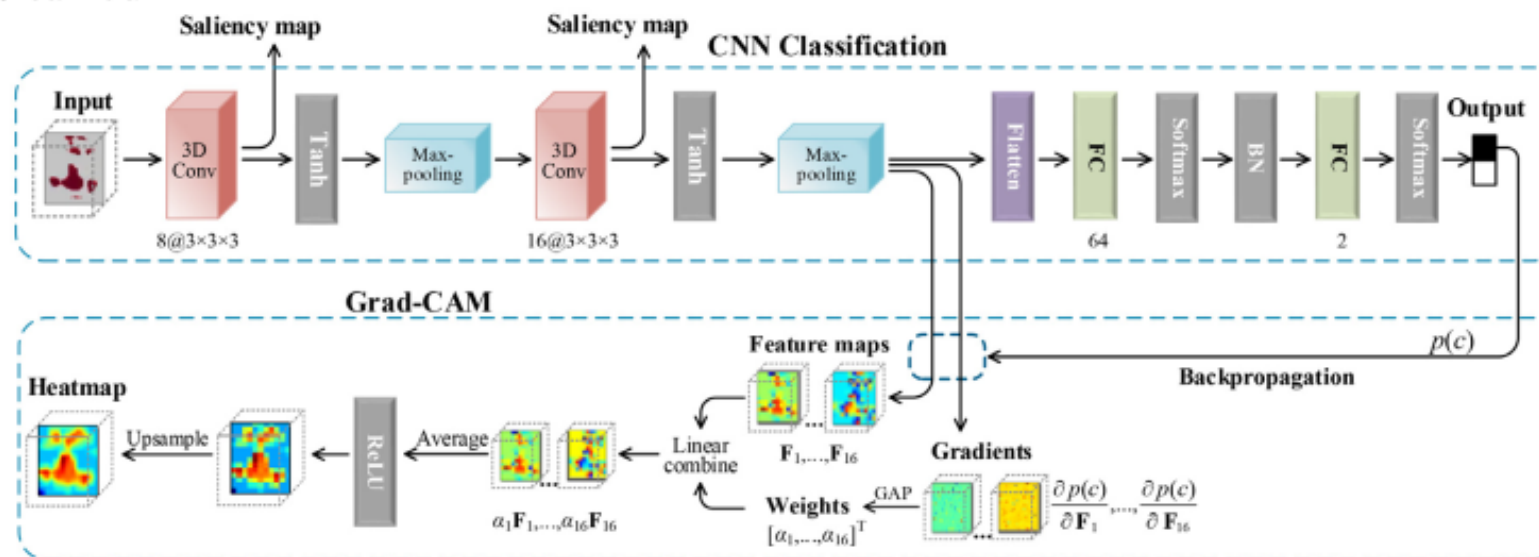
journal homepage: [www.elsevier.com/locate/media](http://www.elsevier.com/locate/media)



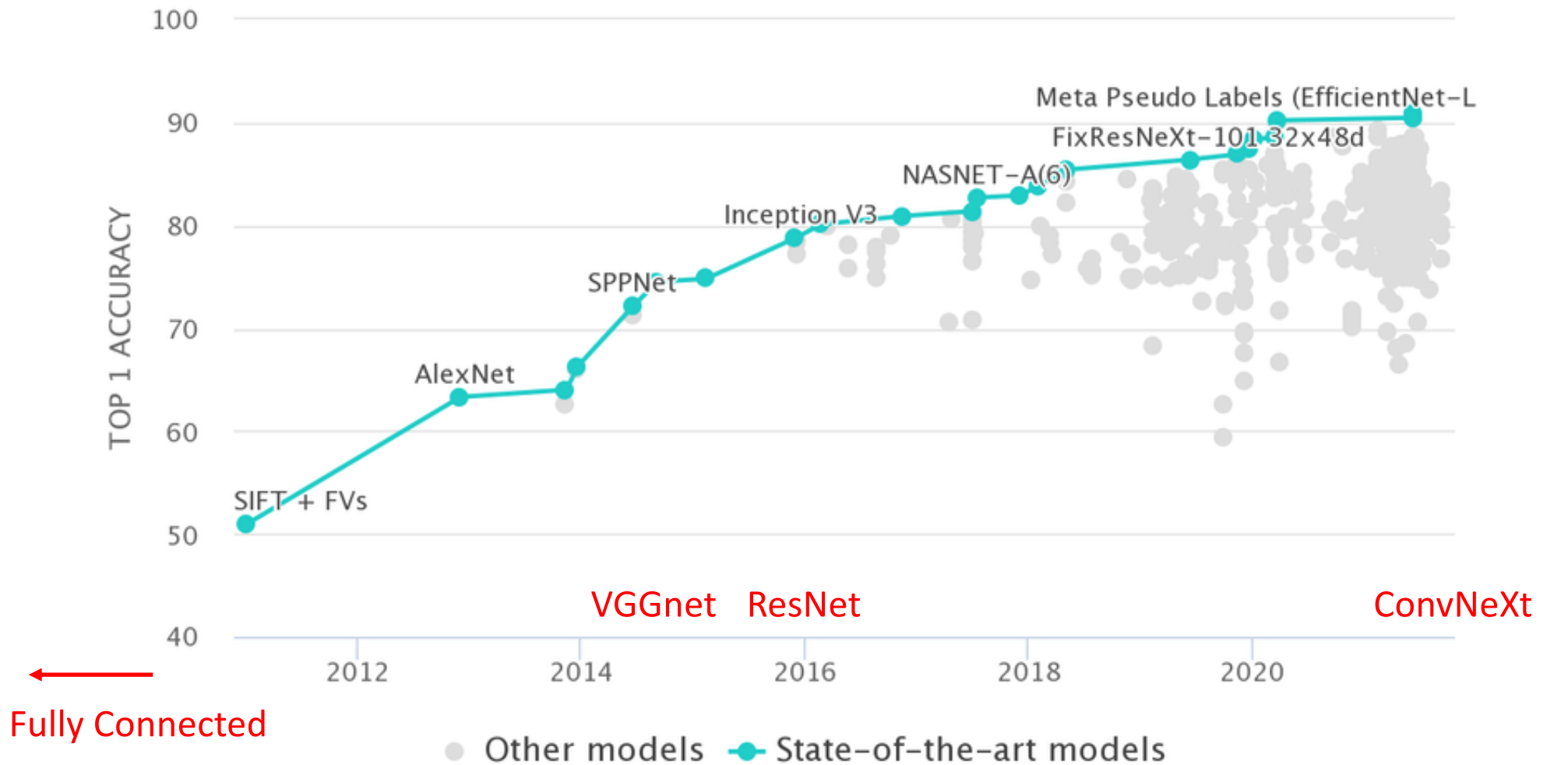
SSPNet: An interpretable 3D-CNN for classification of schizophrenia using phase maps of resting-state complex-valued fMRI data



Qiu-Hua Lin<sup>a,\*</sup>, Yan-Wei Niu<sup>a</sup>, Jing Sui<sup>b</sup>, Wen-Da Zhao<sup>a</sup>, Chuanjun Zhuo<sup>c</sup>,  
Vince D. Calhoun<sup>d</sup>

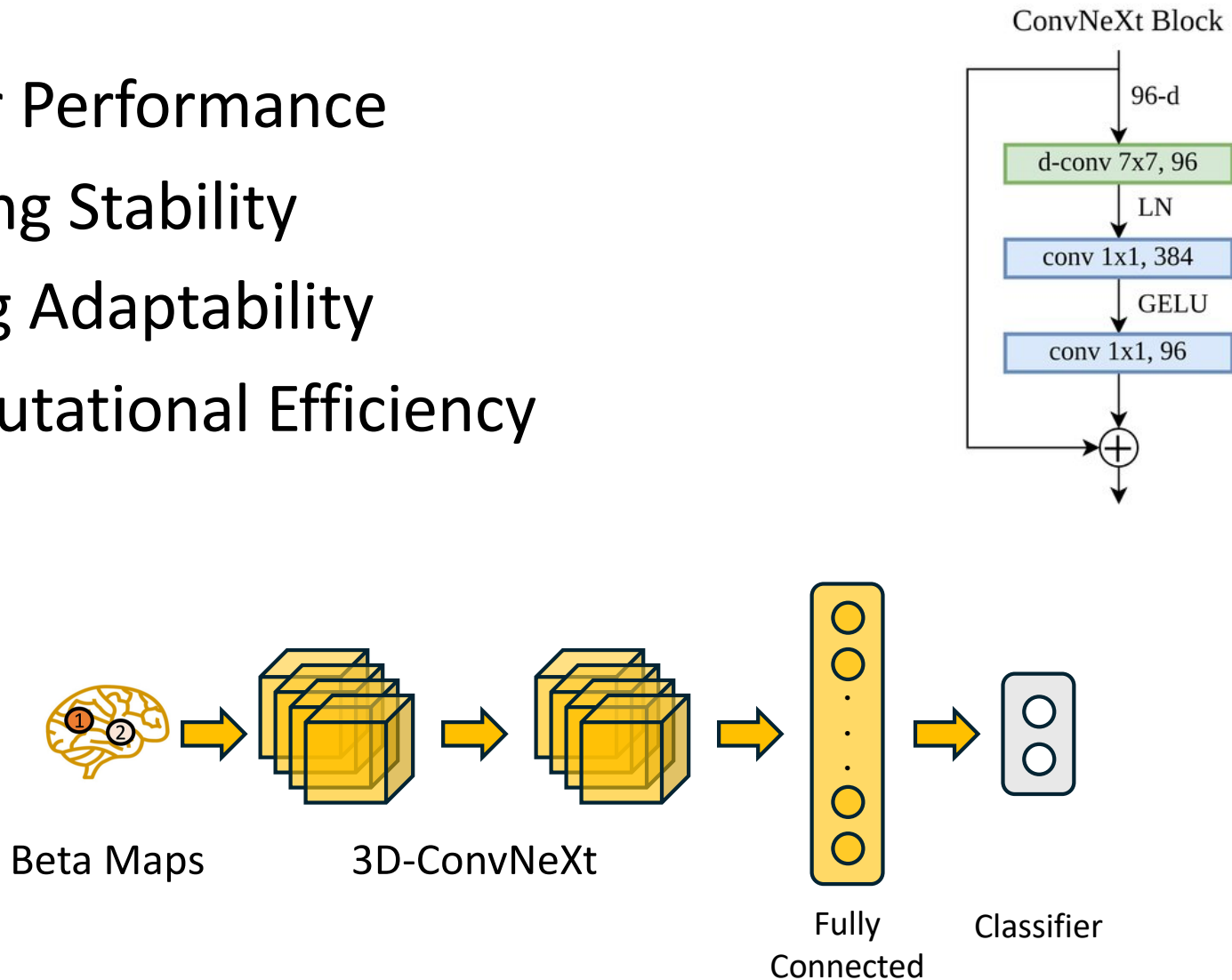


# Progress of Image Classification



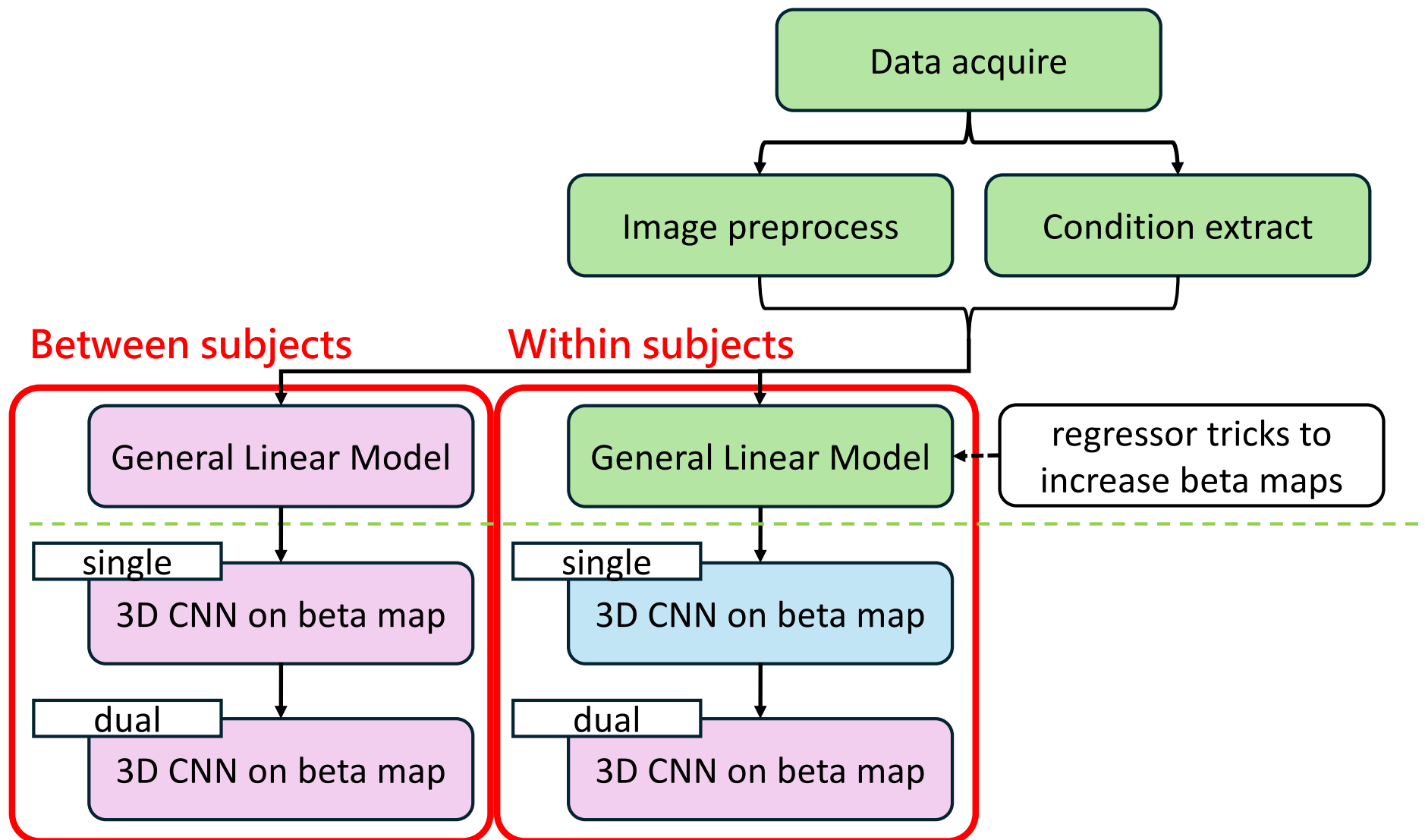
# The ConvNeXt Model

- Better Performance
- Training Stability
- Strong Adaptability
- Computational Efficiency

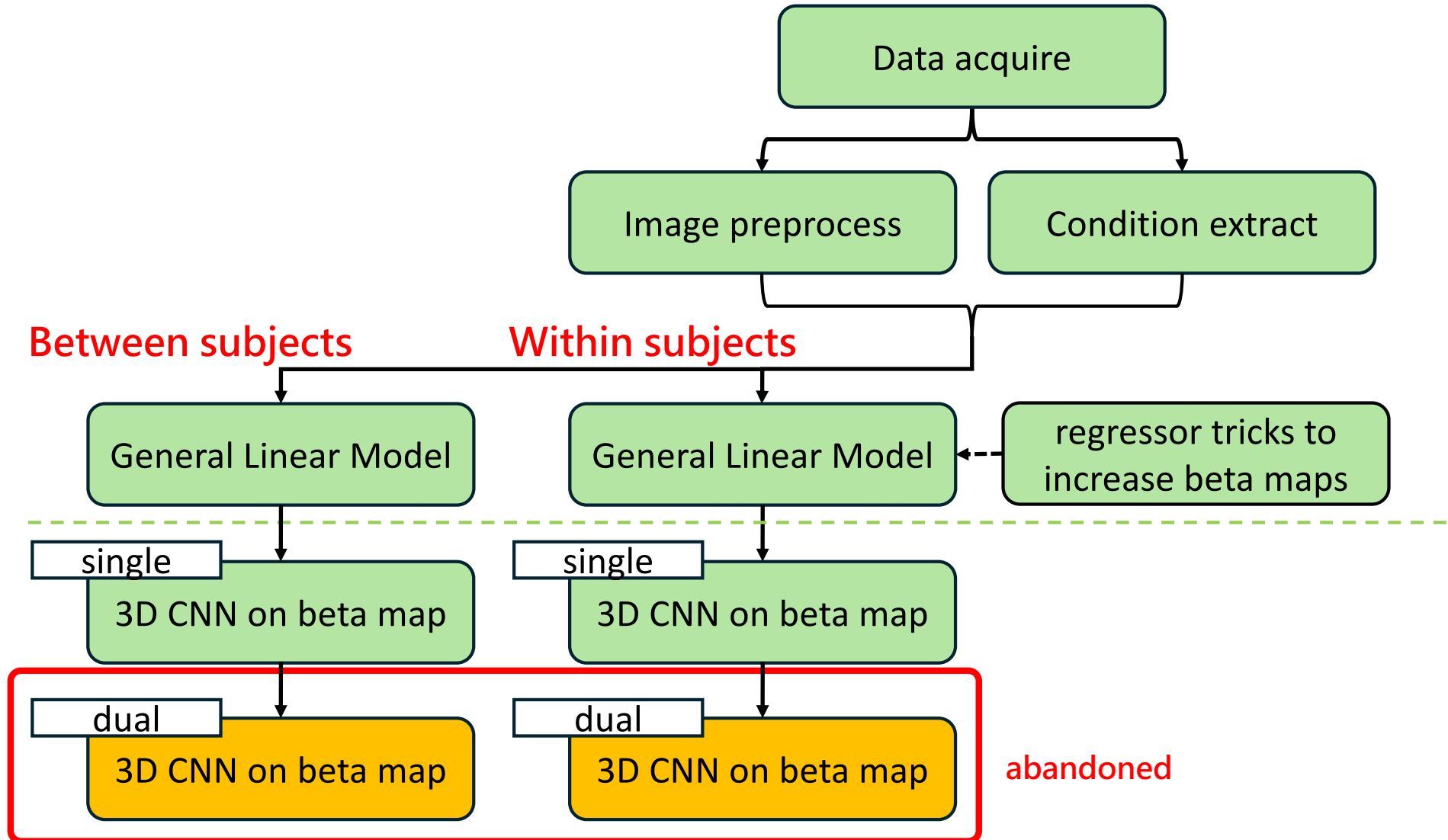




# Roadmap



# Roadmap



# Major Goal

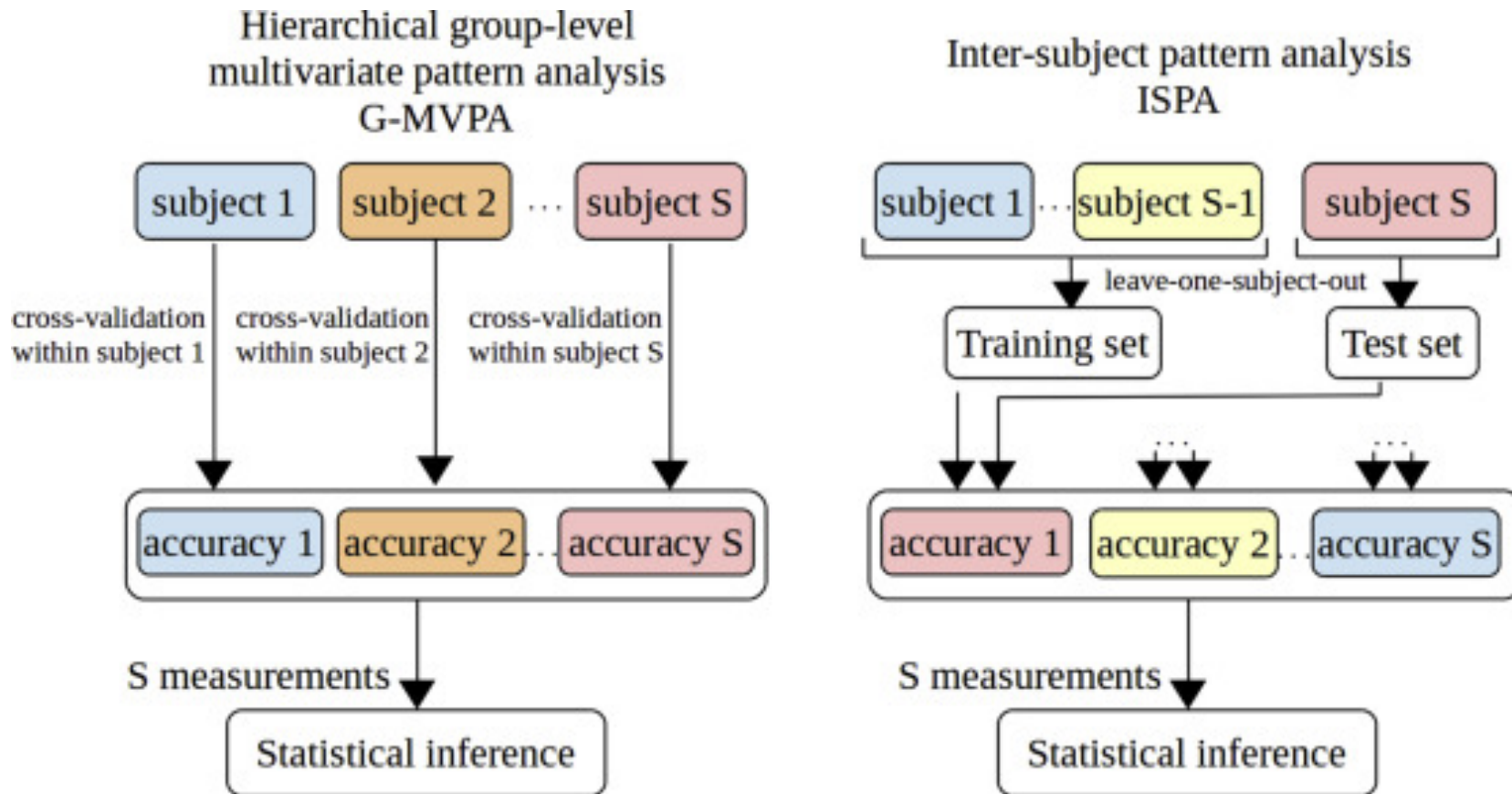
Cooperation



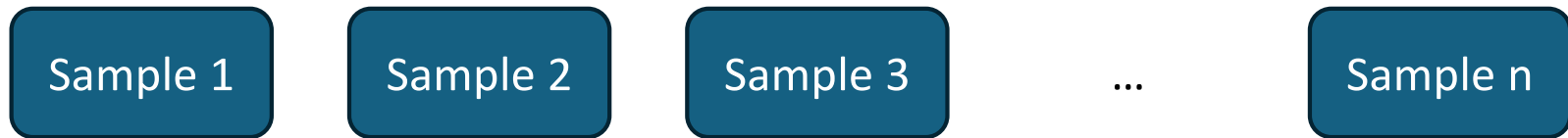
Competition



# Within/Between-Subject Scheme

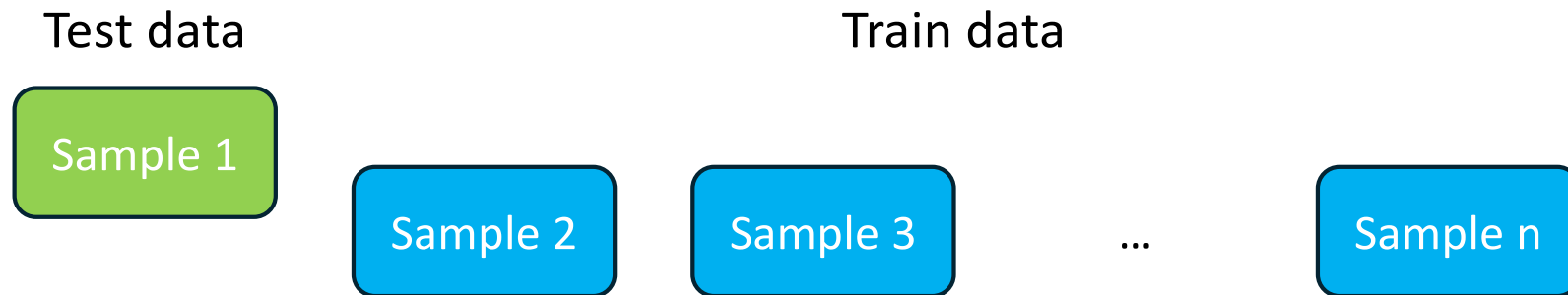


# Leave-One-Out Strategy

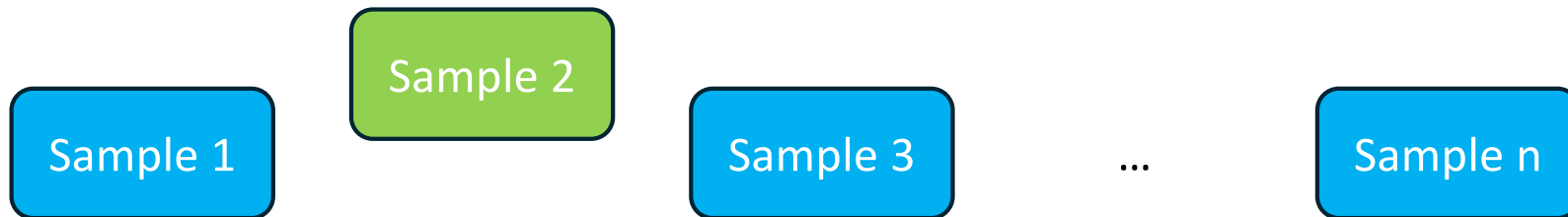




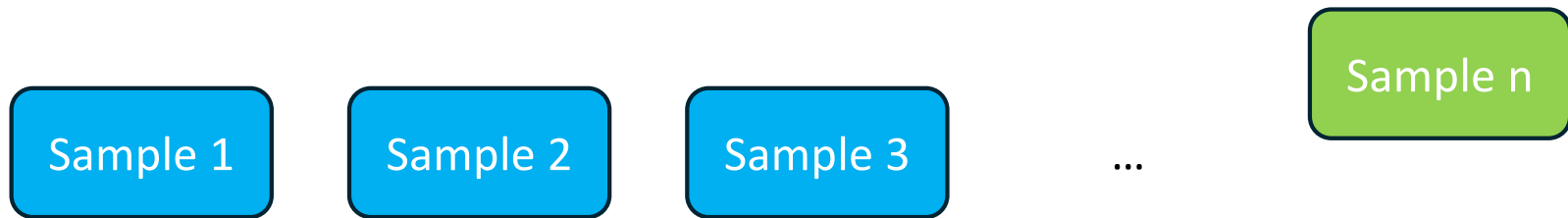
# Leave-One-Out Strategy



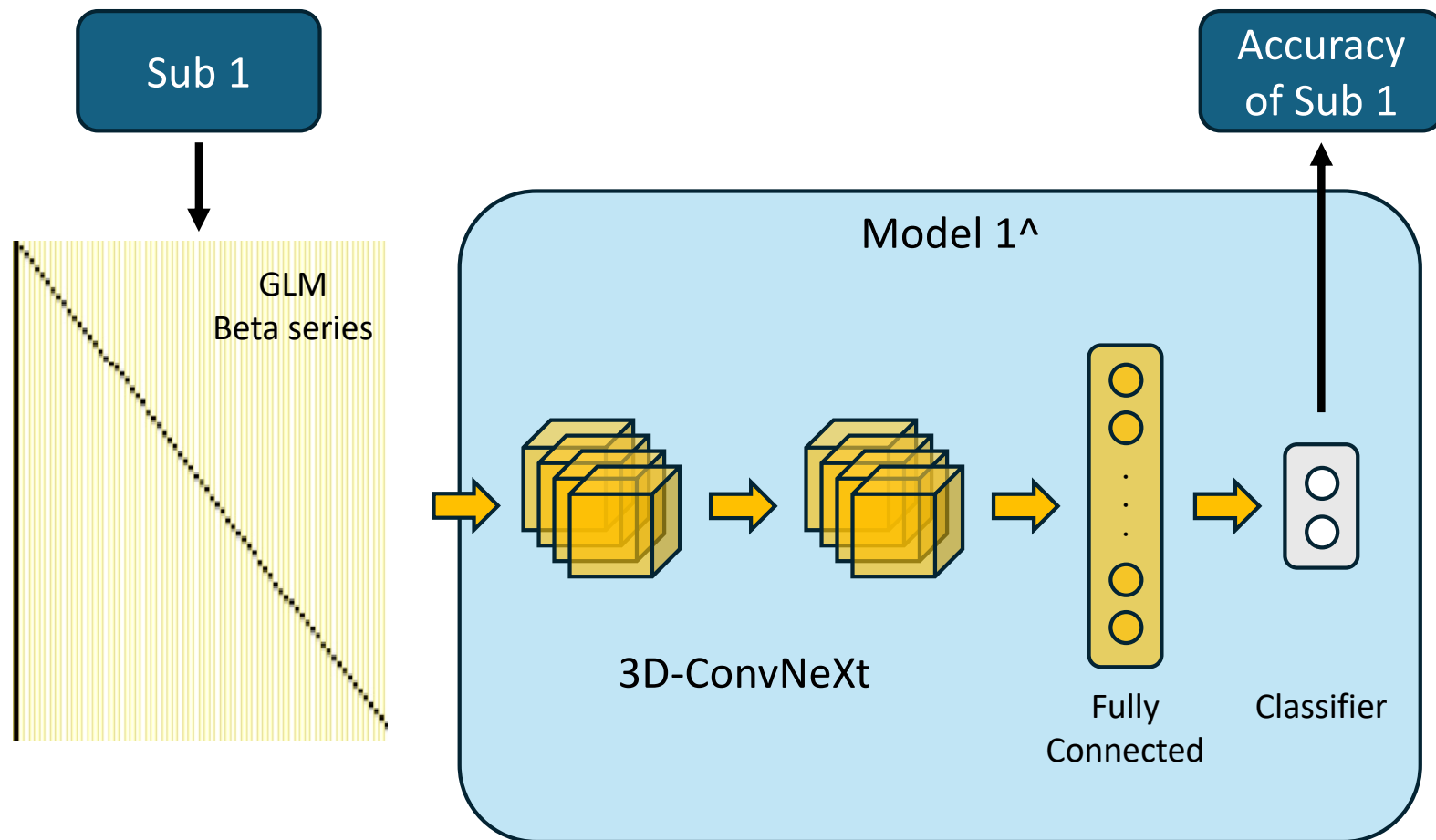
# Leave-One-Out Strategy



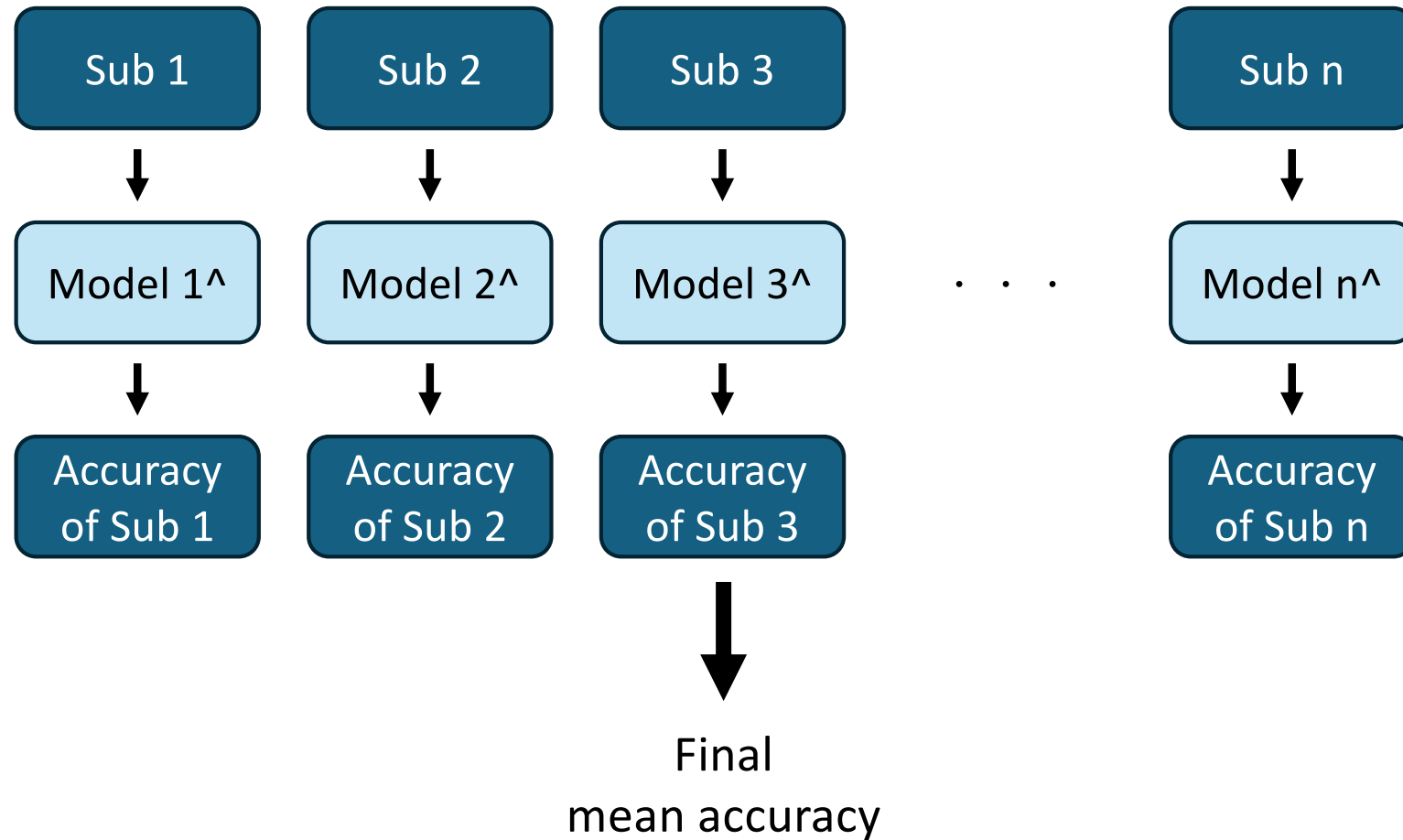
# Leave-One-Out Strategy



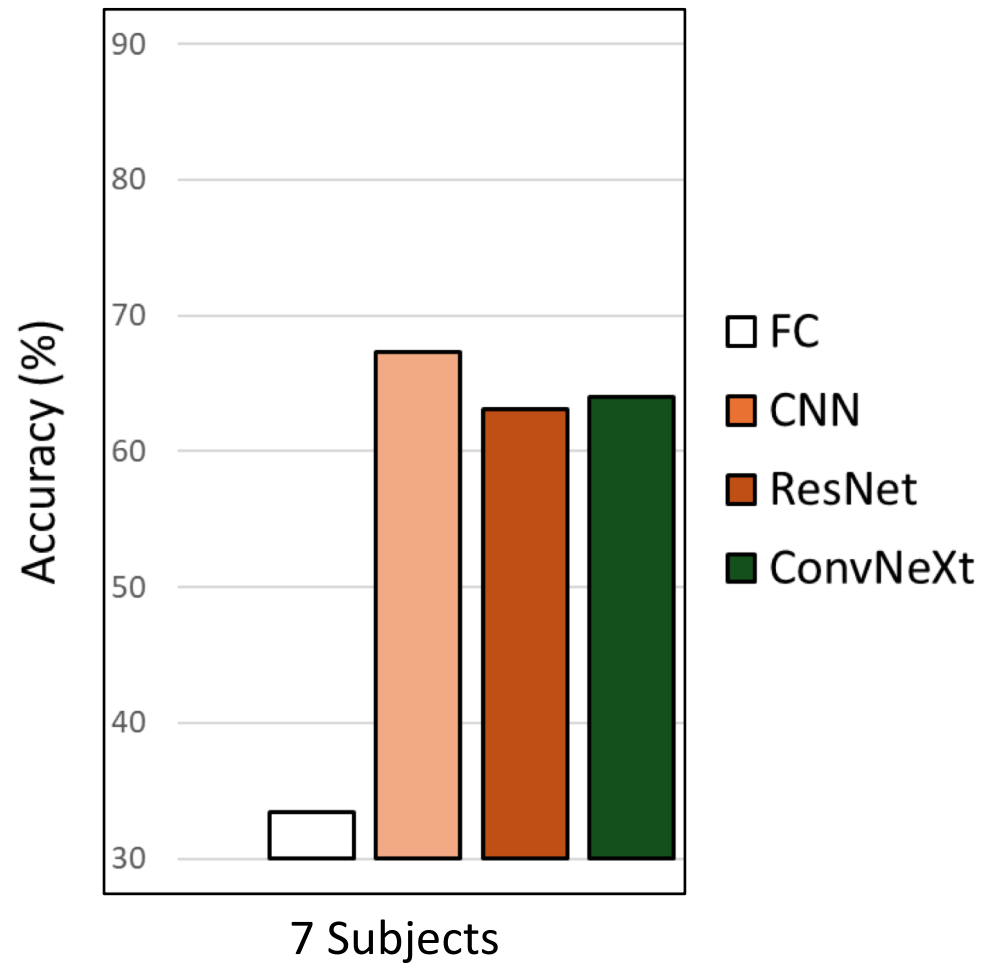
# Within Subject Test



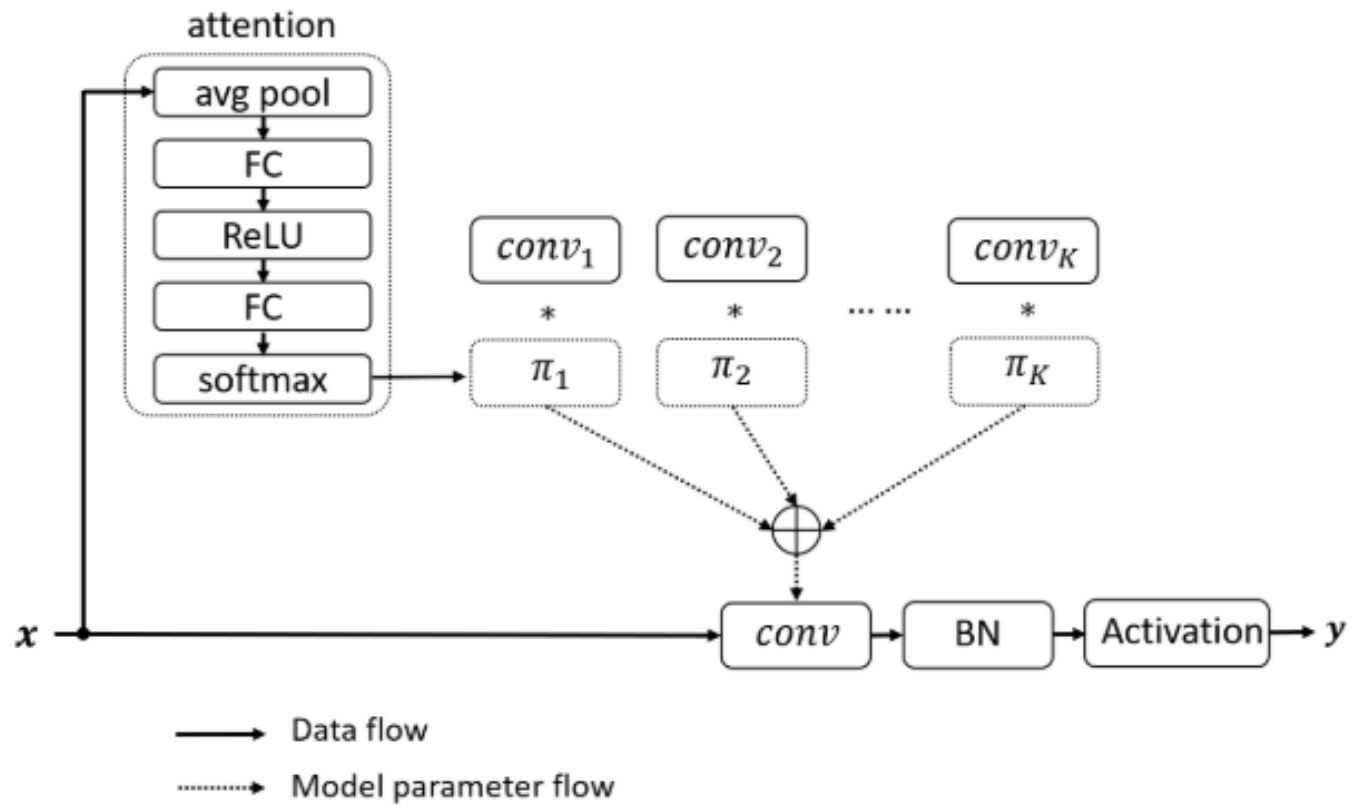
# Within Subject Test



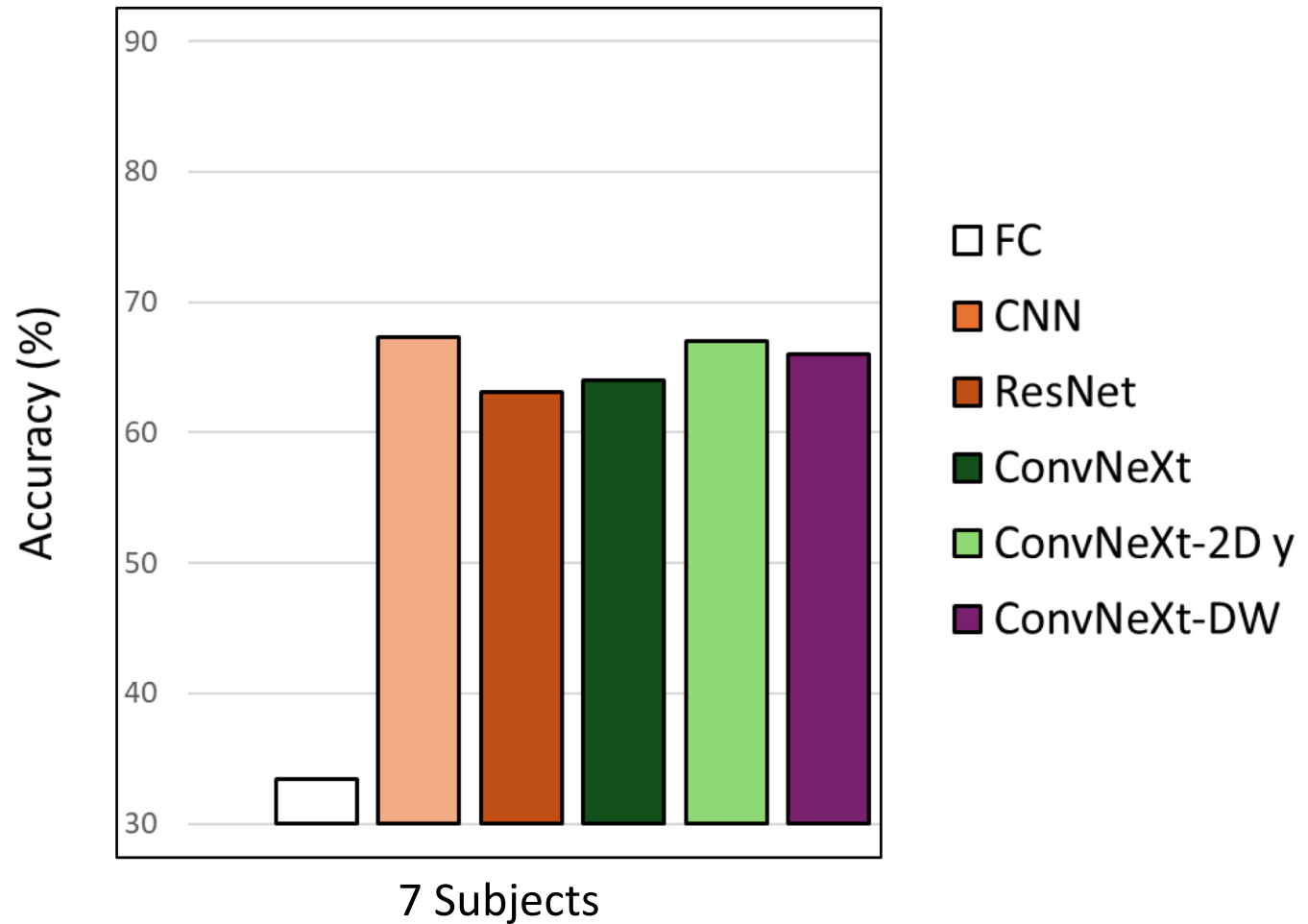
# Within Subject Test Results



# Dynamic Convolution

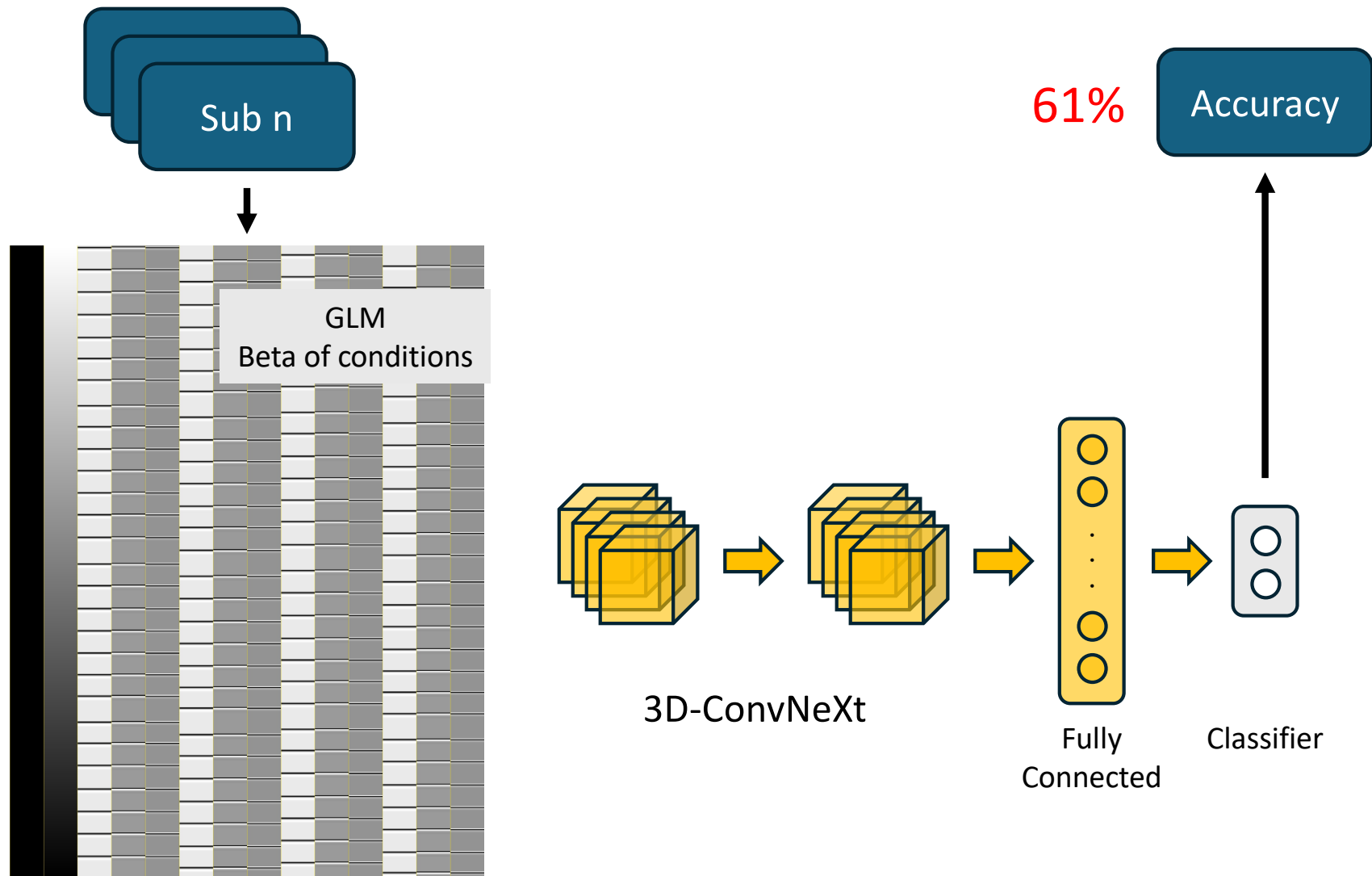


# Within Subject Test Results

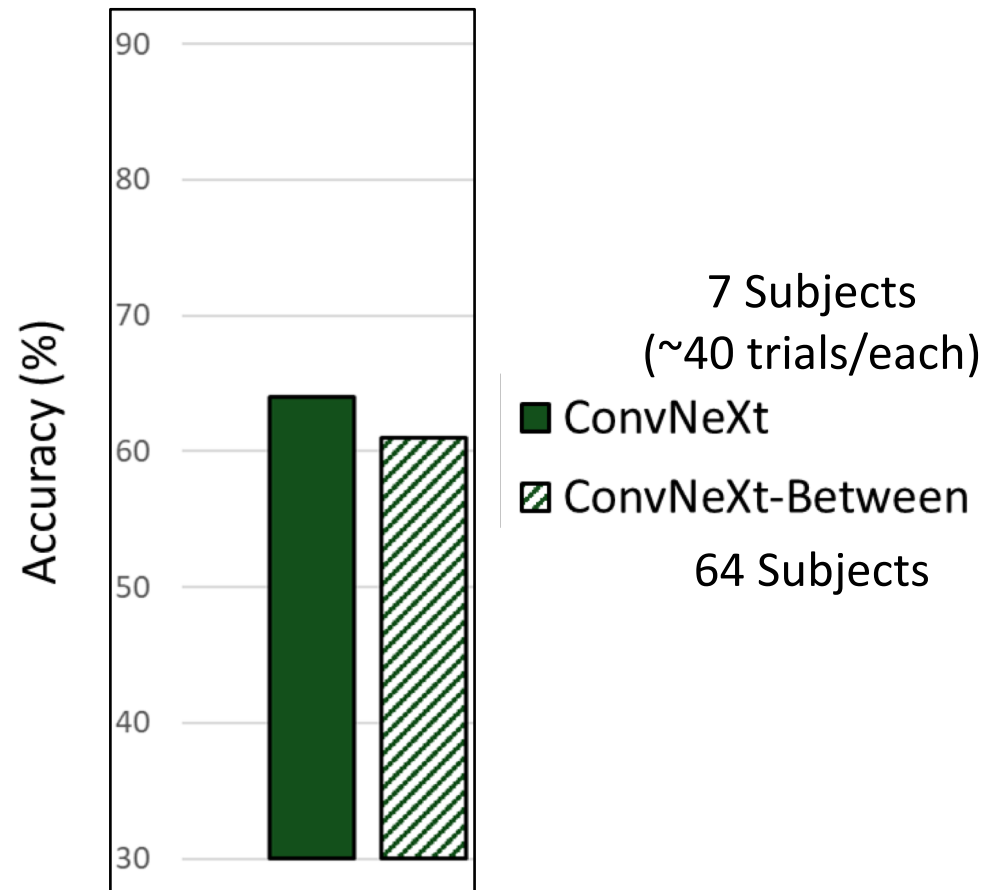




# Between Subject Test



# Between Subject Test Results



# Within/Between Pattern

- Within subject classification show promising result.
- Between subject pattern might be diverse.





Similar conclusion to:



NeuroImage  
Volume 97, 15 August 2014, Pages 271-283

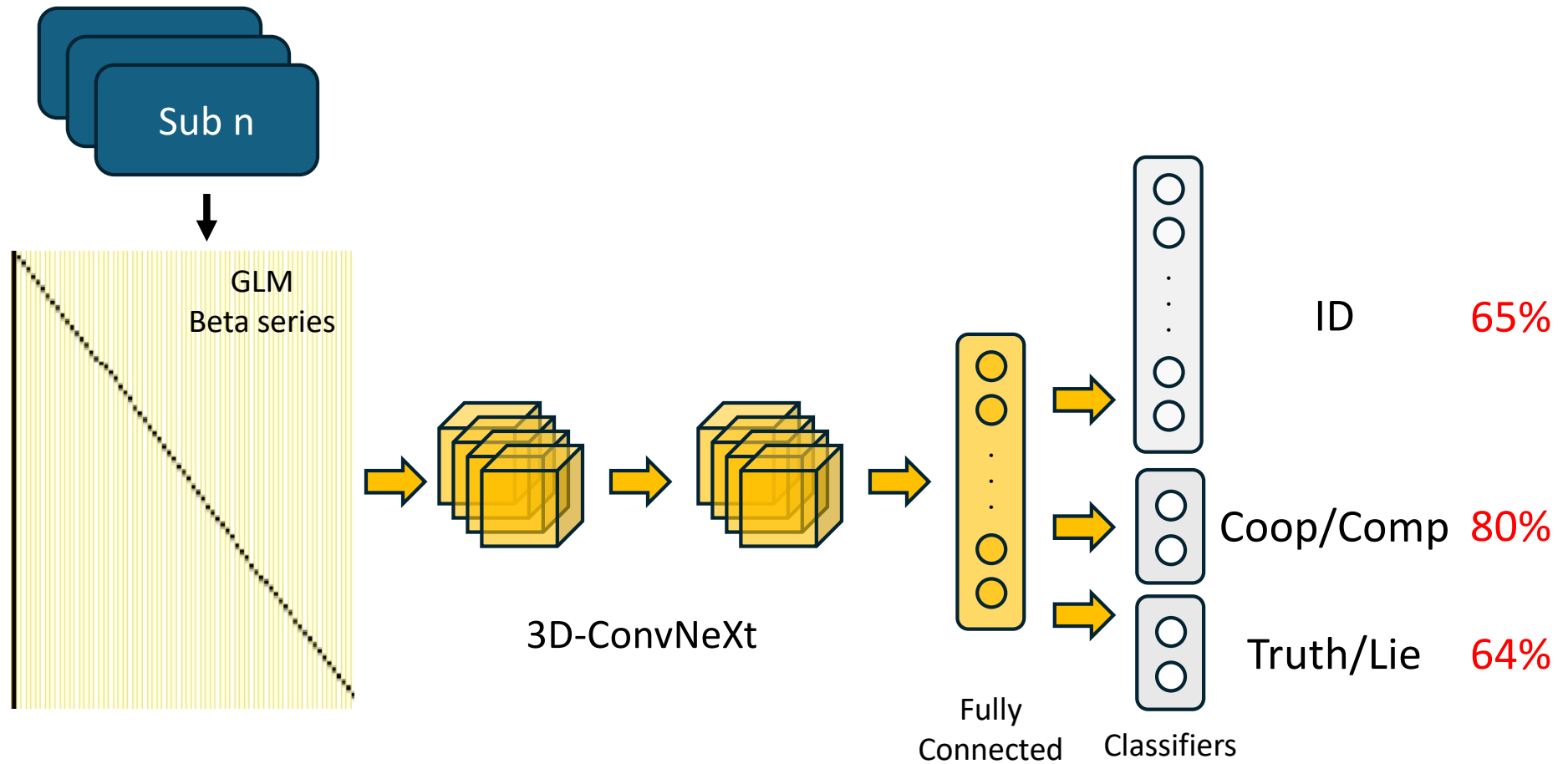


What do differences between multi-voxel and univariate analysis mean? How subject-, voxel-, and trial-level variance impact fMRI analysis

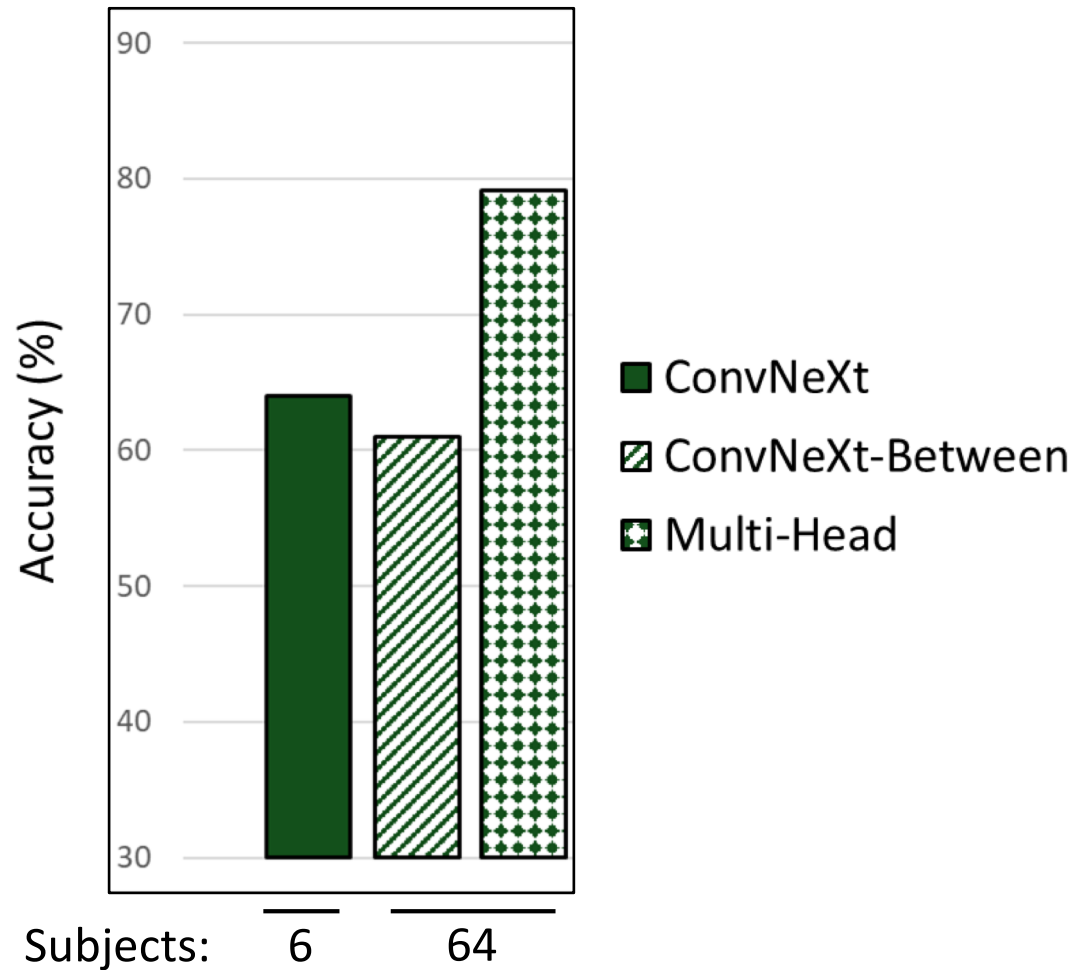
Tyler Davis<sup>a 1</sup>  , Karen F. LaRocque<sup>b 1</sup>  , Jeanette A. Mumford<sup>d e f</sup>,  
Kenneth A. Norman<sup>g h</sup>, Anthony D. Wagner<sup>b c</sup>, Russell A. Poldrack<sup>d e f</sup>

<https://doi.org/10.1016/j.neuroimage.2014.04.037>

# Multi-Head Structure



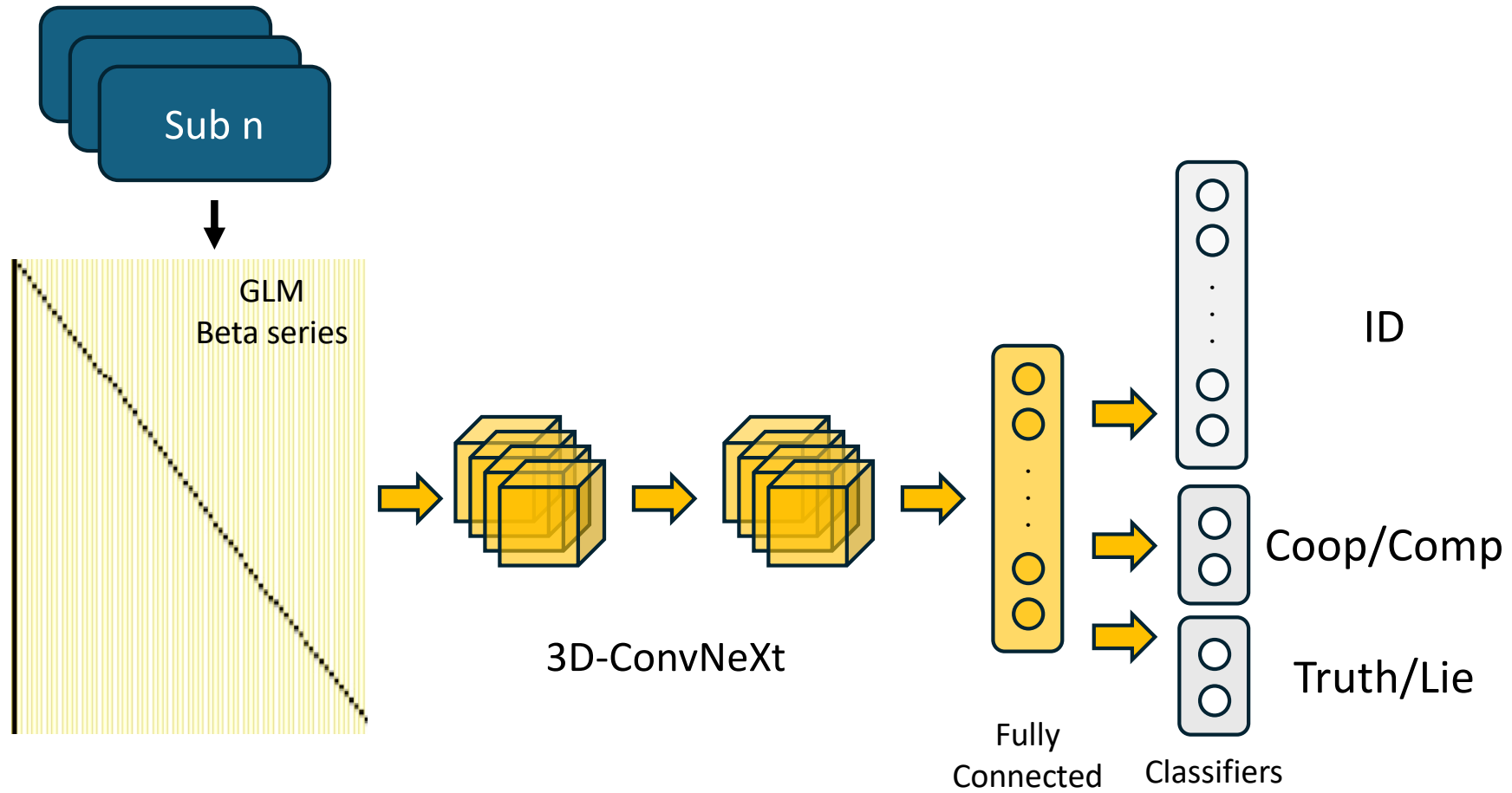
# Multi-Head Structure Performance



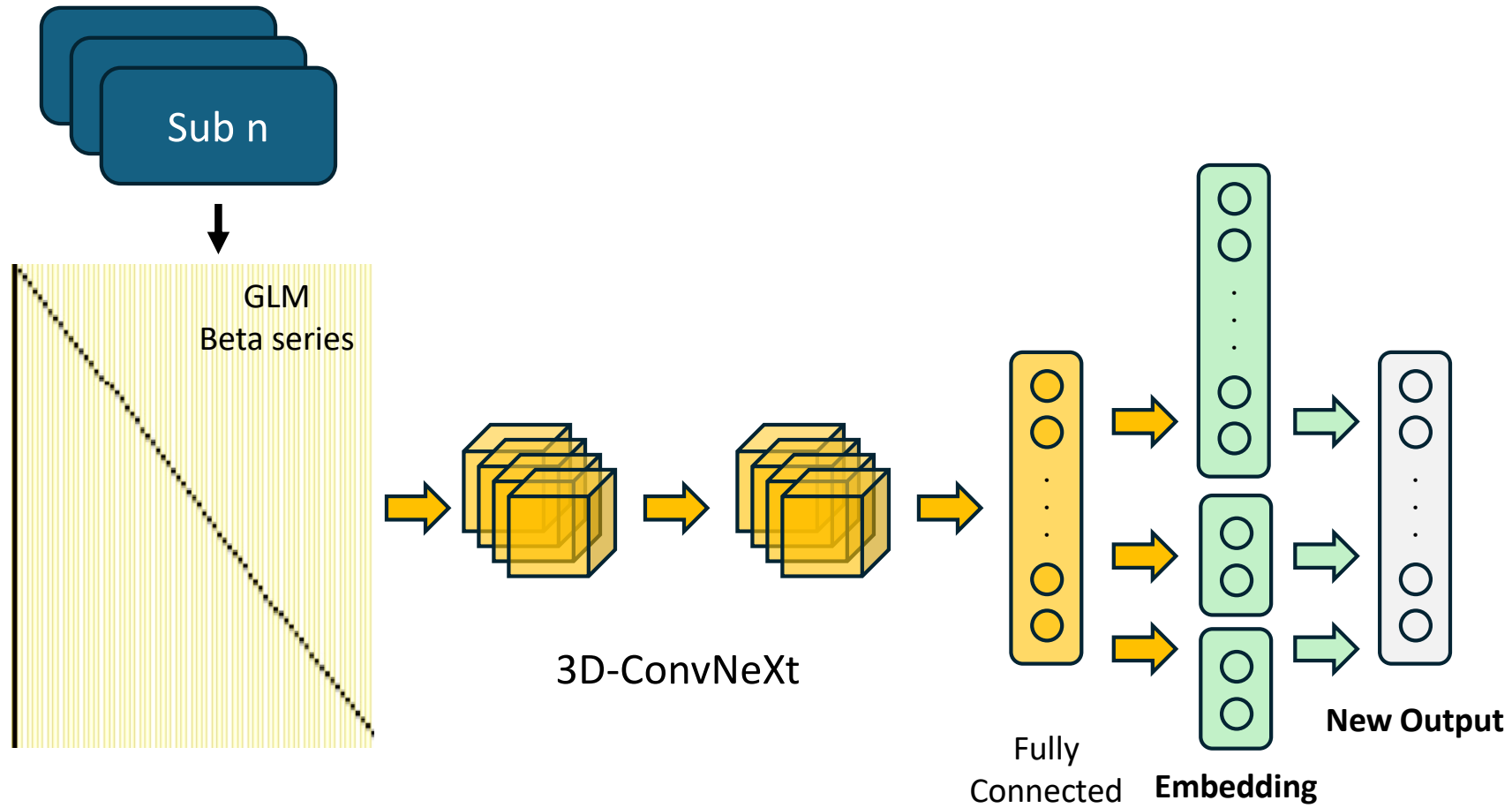
# Within/Between Pattern (2)

- Individual different can be detected with multi-head design.
- Multi-head structure can also handle several factors at once.

# Multi-Head Structure

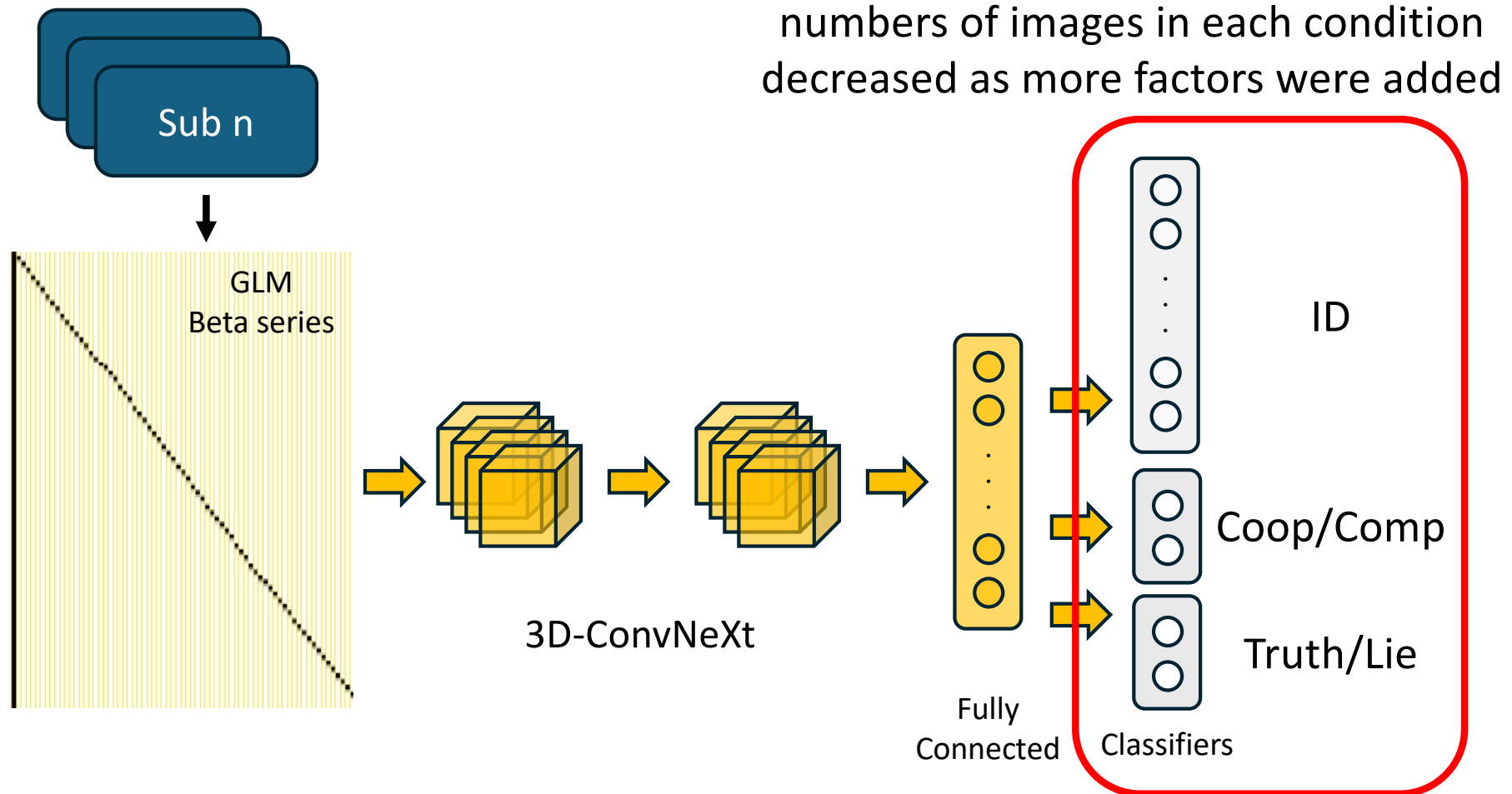


# Multi-Head for Embedding

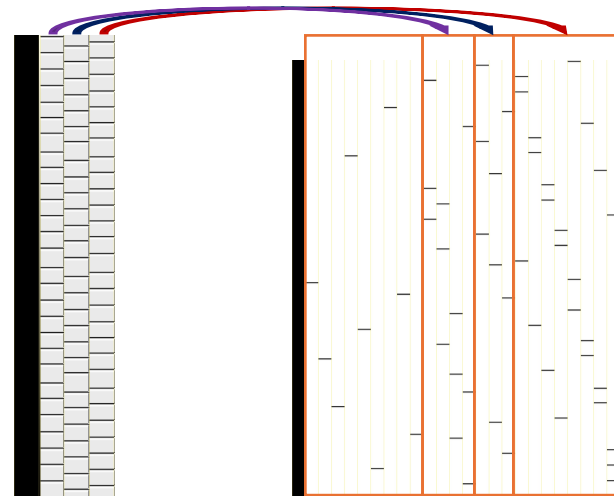
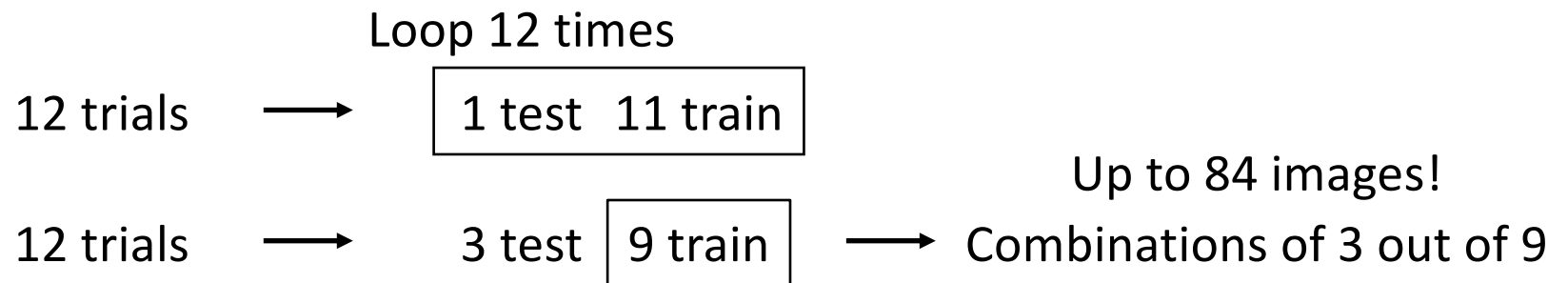




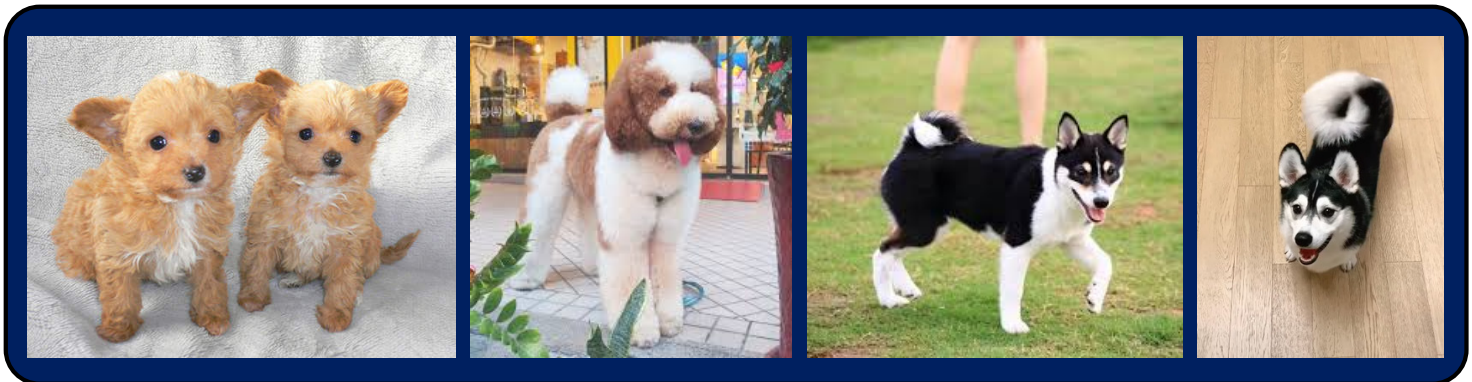
# Multi-Head Structure



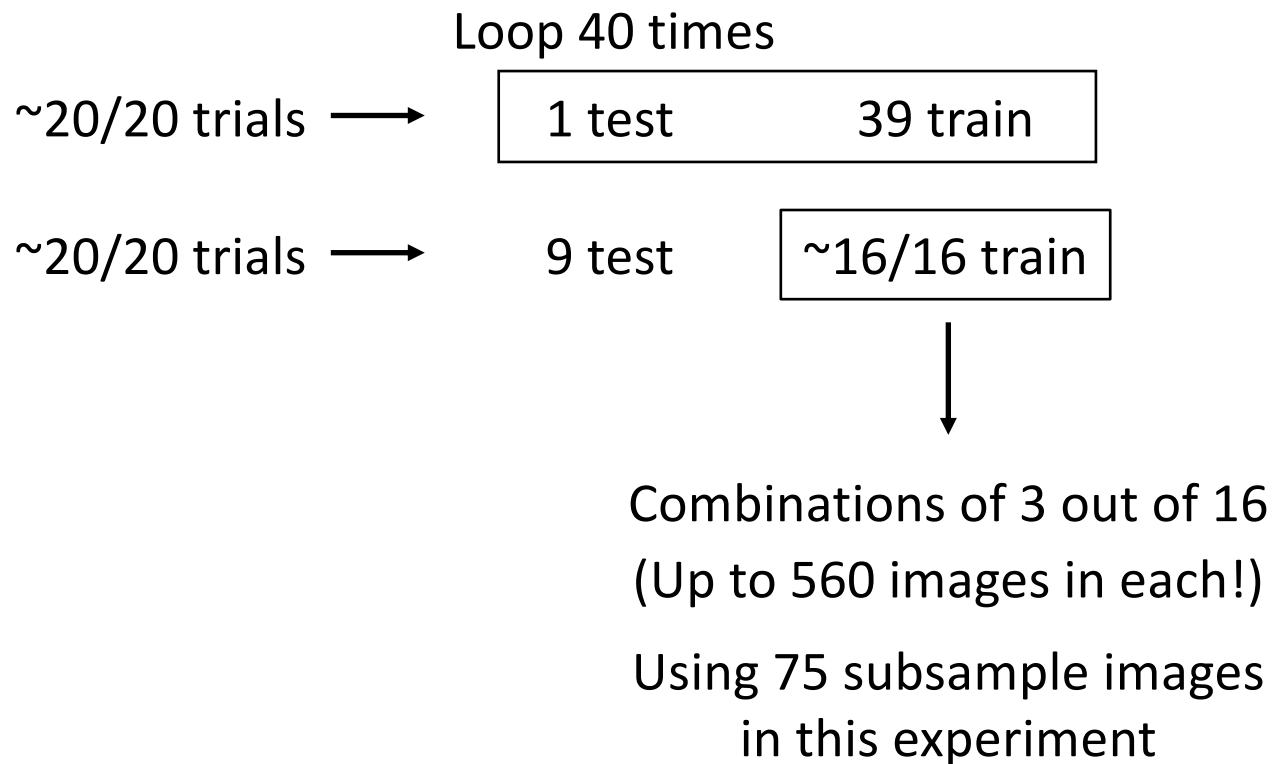
# Subsampling GLM Trick for Training Data



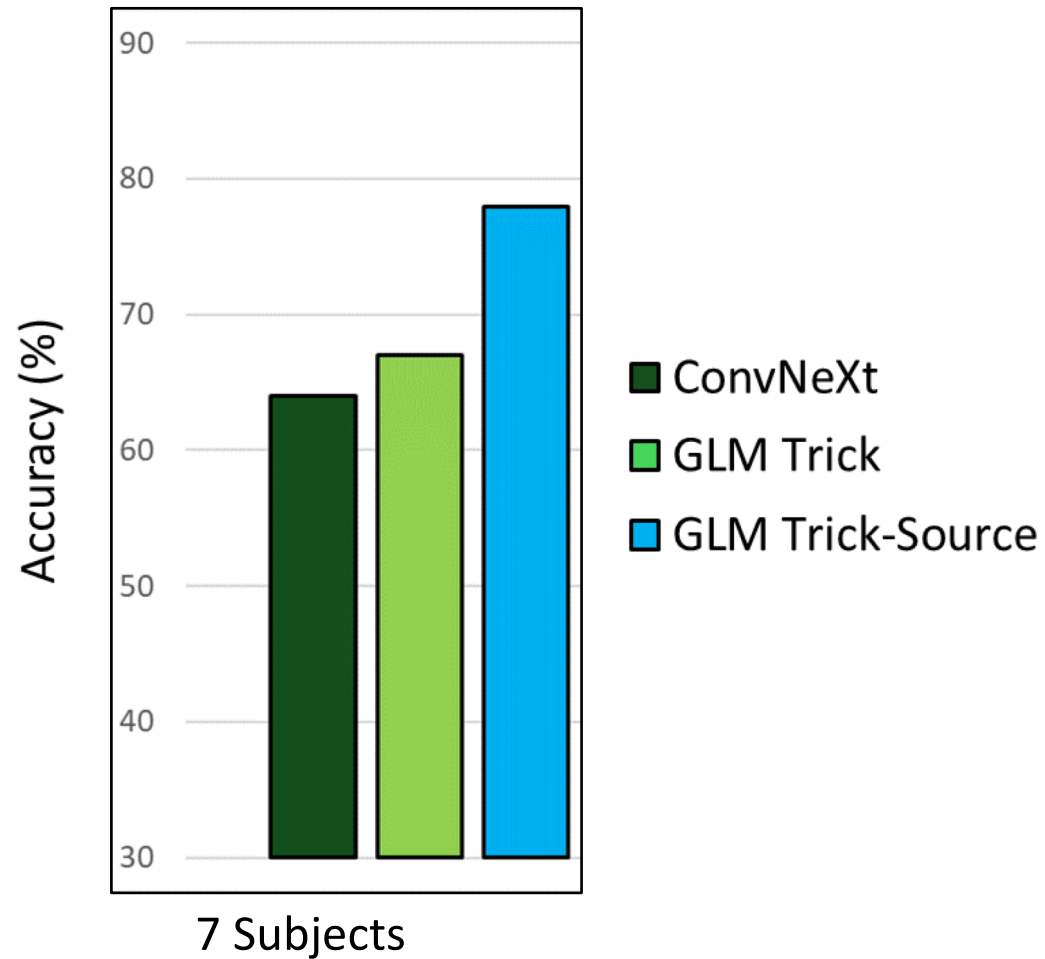
# Hybrid to Create More Sample



# Subsampling GLM Trick for Training Data



# Performance of Subsampling Trick

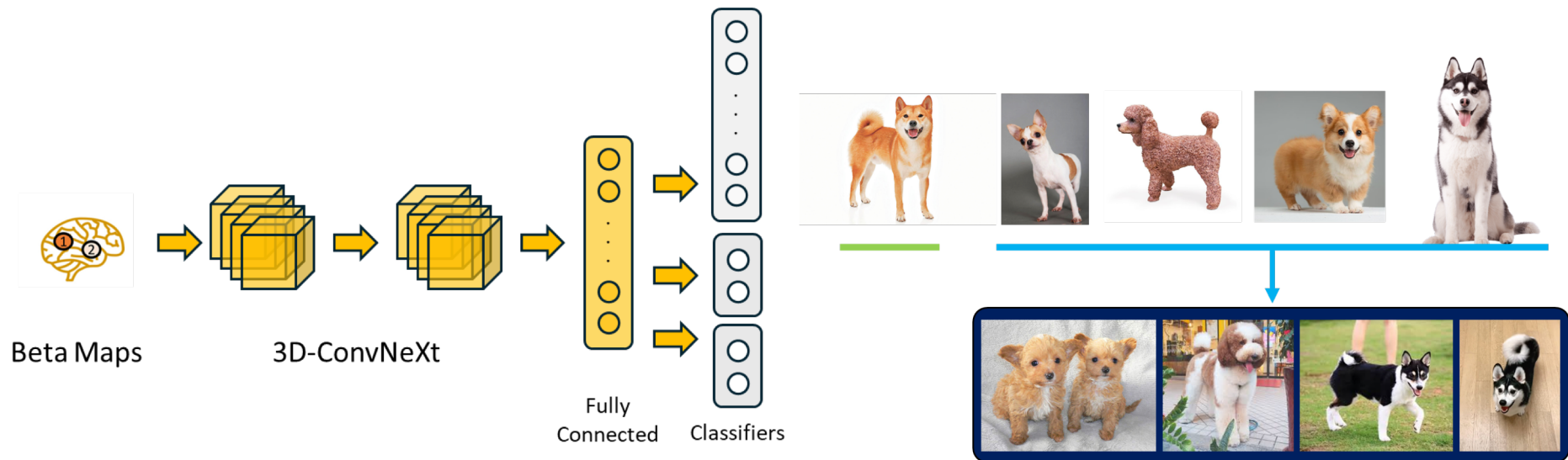


# Summary

- Introduce new CNN architecture for MVPA
- Apply multi-head structure for complex conditions
- Design a subsampling trick to increase training data
- Advanced models can detect more hidden patterns underlying brain activation.
- Additional techniques are needed to better visualize and interpret those models.

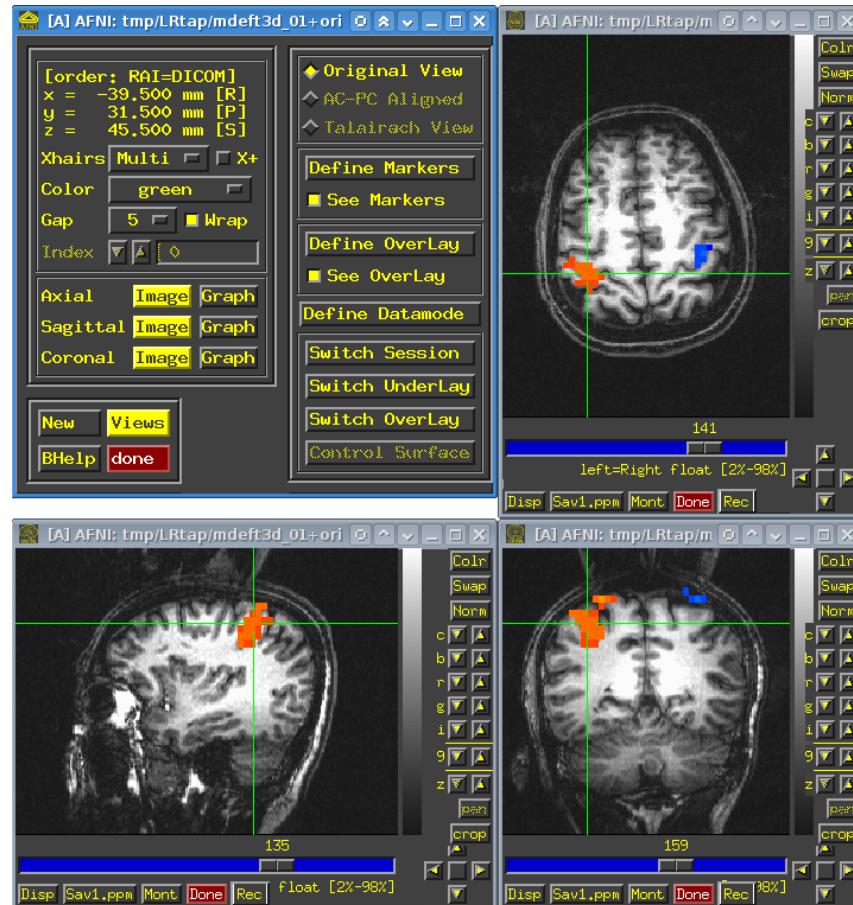
# Thanks for your time and attention

Any question or suggestion is welcome!!



Multi-Head 3D-ConvNeXt

# Data Preprocessing





# Major Python Packages



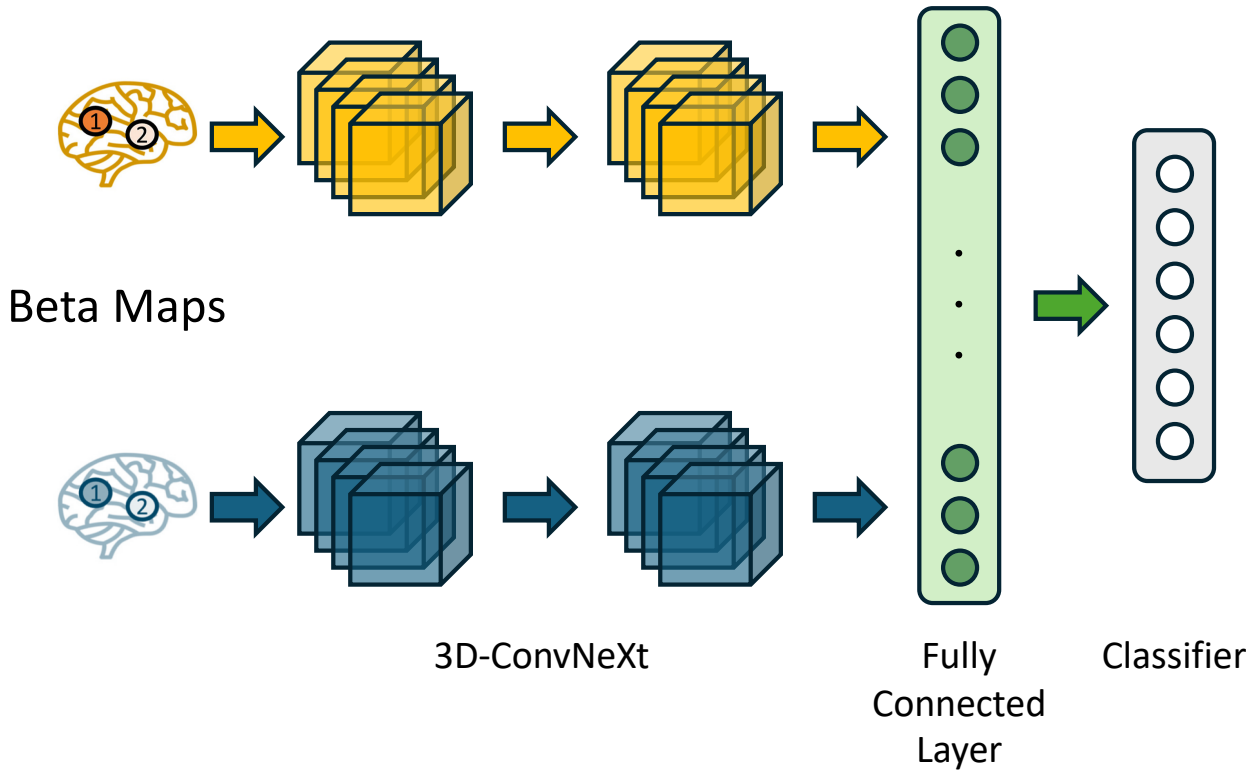
Major ANN programming tool



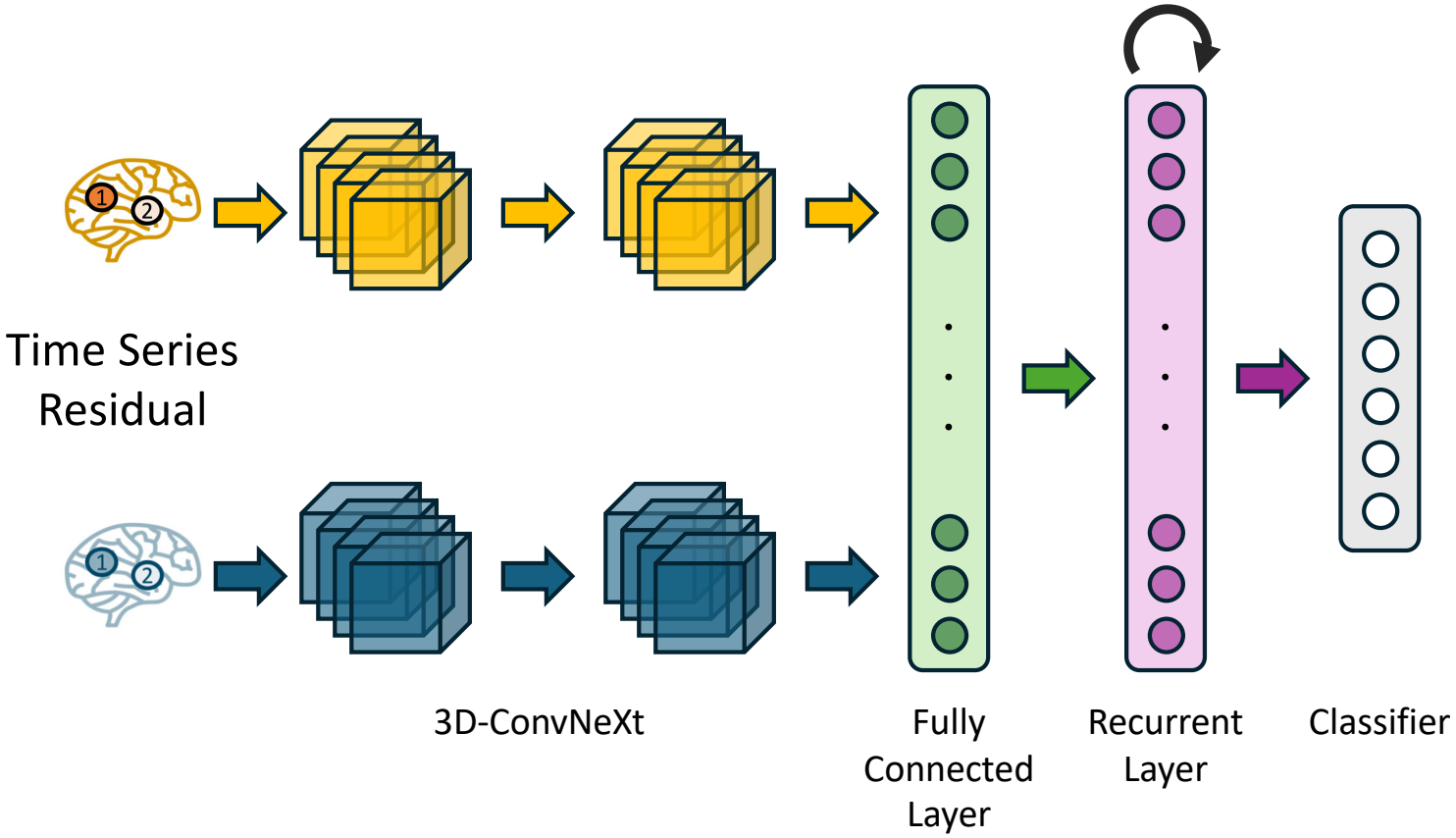
Designed for brain volumes analysis  
*\*Able to directly handle AFNI output!!*

Also provides statistical and  
machine-learning tools

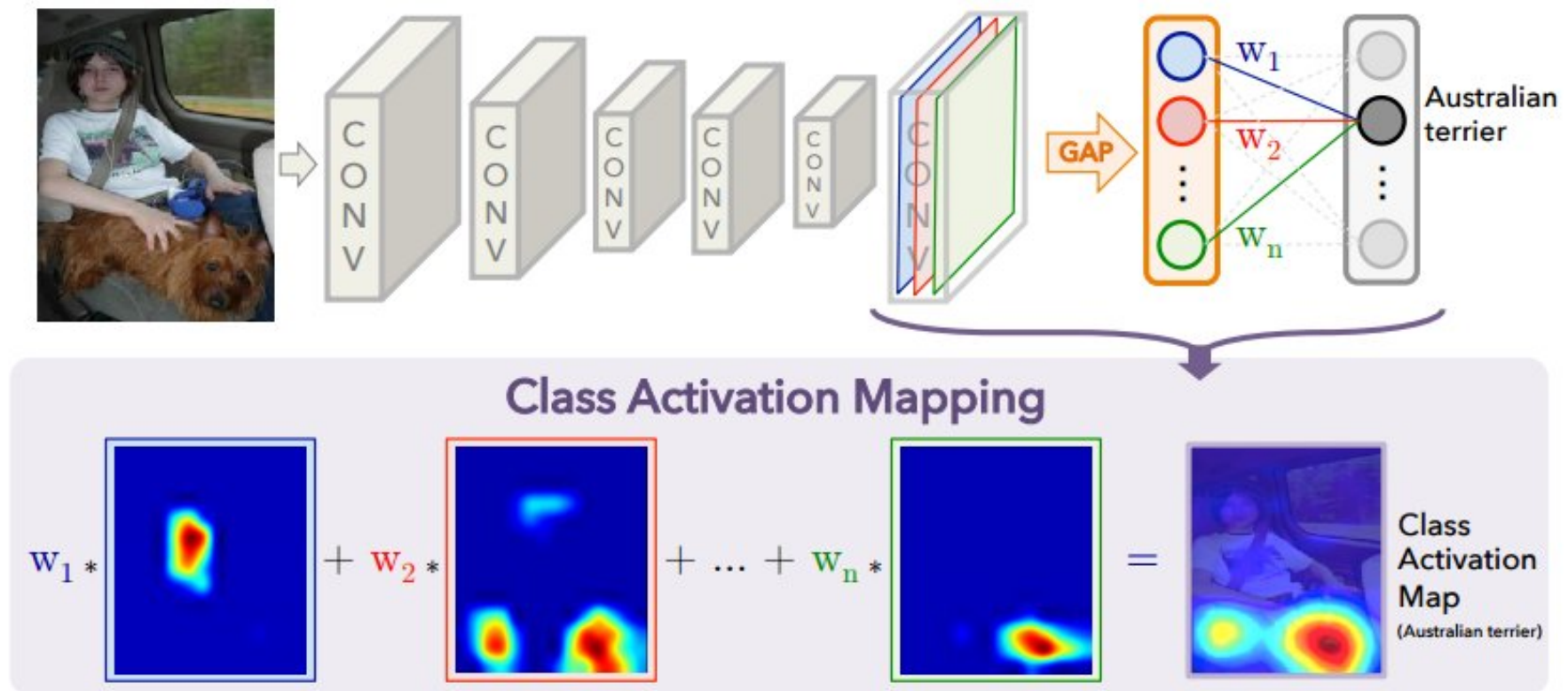
# Tentative Architecture



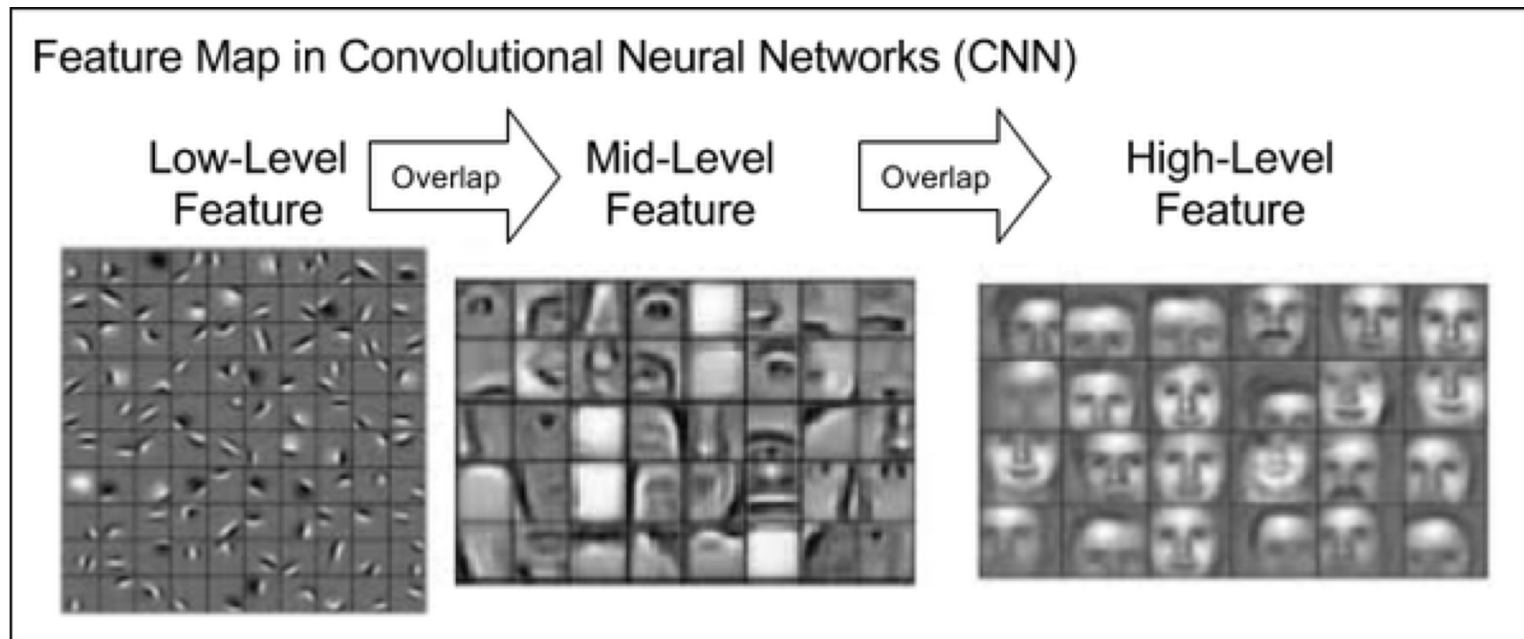
# Tentative Architecture



# CNN Heat Map



# CNN Feature Map



**Kolmogorov**



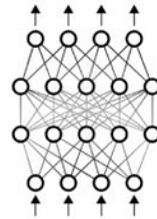
+

**Arnold**



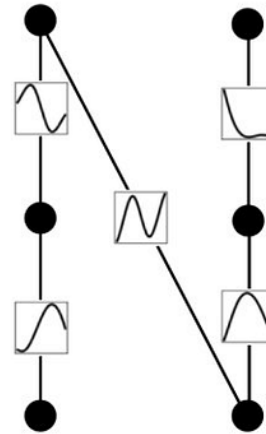
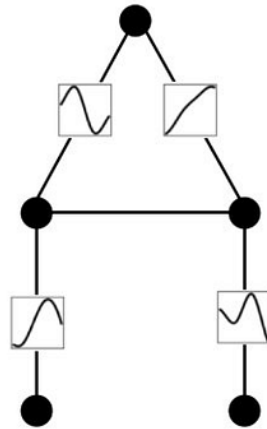
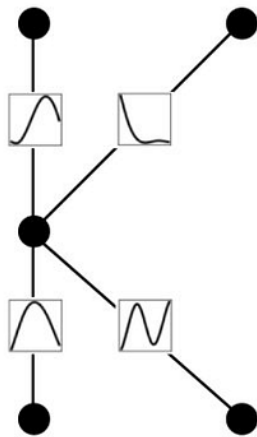
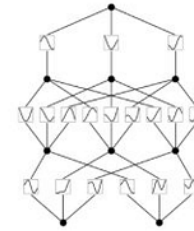
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**Network**



=

**KAN**



Mathematical

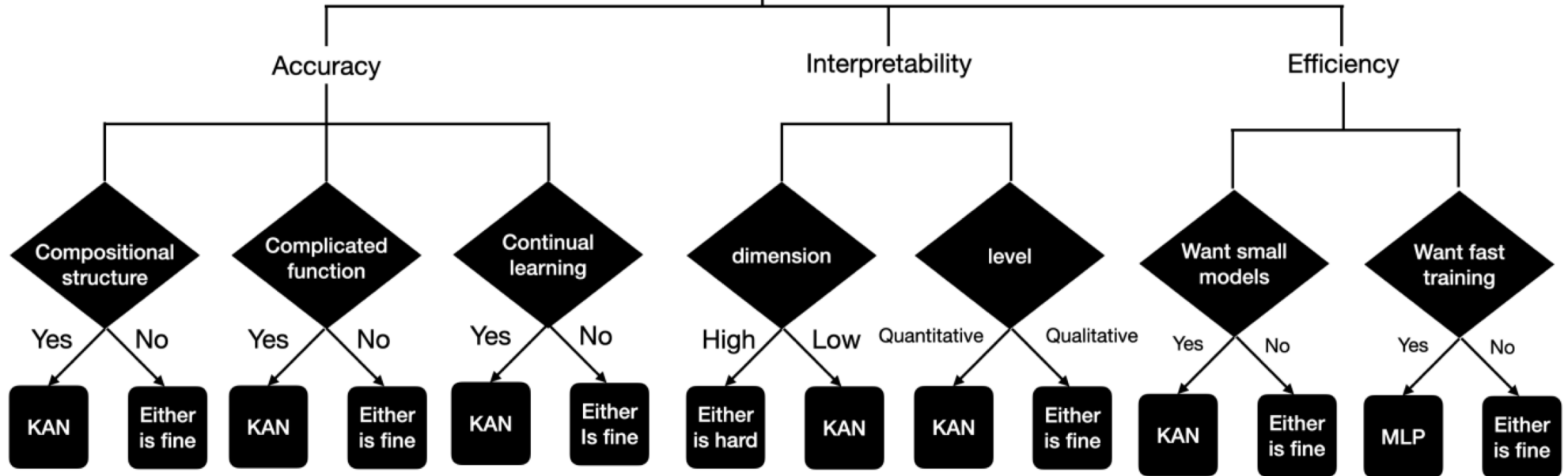
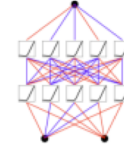
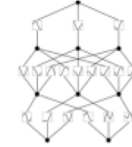
Accurate

Interpretable

# Kolmogorov-Arnold Networks (KANs)



Should I use KANs or MLPs?



```
class attention2d(nn.Module):
    def __init__(self, in_planes, ratios, K, temperature, init_weight=True):
        super(attention2d, self).__init__()
        assert temperature % 3 == 1
        self.avgpool = nn.AdaptiveAvgPool2d(1)
        if in_planes != 3:
            hidden_planes = int(in_planes * ratios) + 1
        else:
            hidden_planes = K
        self.fc1 = nn.Conv2d(in_planes, hidden_planes, 1, bias=False)
        self.fc2 = nn.Conv2d(hidden_planes, K, 1, bias=True)
```

```
self.weight = nn.Parameter(torch.randn(K, out_planes, in_planes//groups, kernel_size, kernel_size))
```

```
aggregate_weight = torch.mm(softmax_attention, weight)
```