Deep Learning - Final Project

How the Human Brain Makes Sense of Natural Scenes

Eleni Neti R.N : 2022202204018

Petros-Fotis Kamberi R.N. : 2022202204012

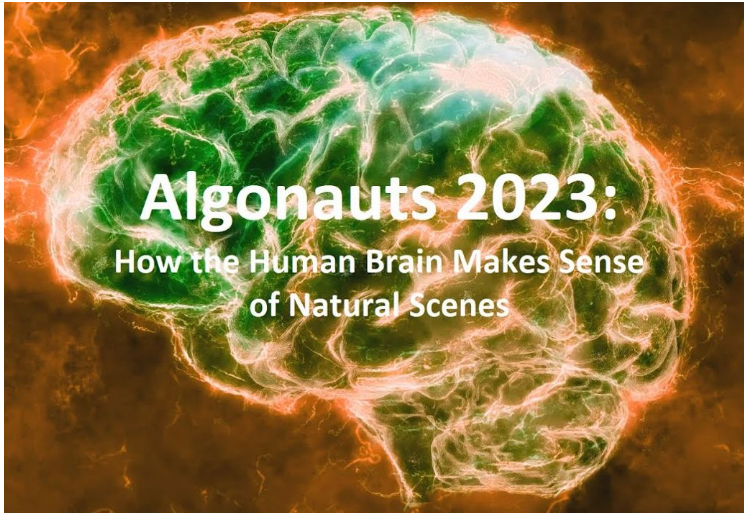
ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΛΟΠΟΝΝΗΣΟΥ
UNIVERSITY of the PELOPONNESE
ΔΗΜΟΚΡΙΤΟΣ
DEMOKRITOS

Project description

- Based on the **Algonauts 2023 challenge**.
- **Objective**:

  Understanding how the human brain works by predicting human brain responses to complex natural visual scenes.
- **Goal**:

  Develop computational models to accurately predict brain responses



The dataset

- **Natural Scenes Dataset (NSD)**

  A massive dataset of high- quality fMRI responses to ~73,000 different natural scenes.

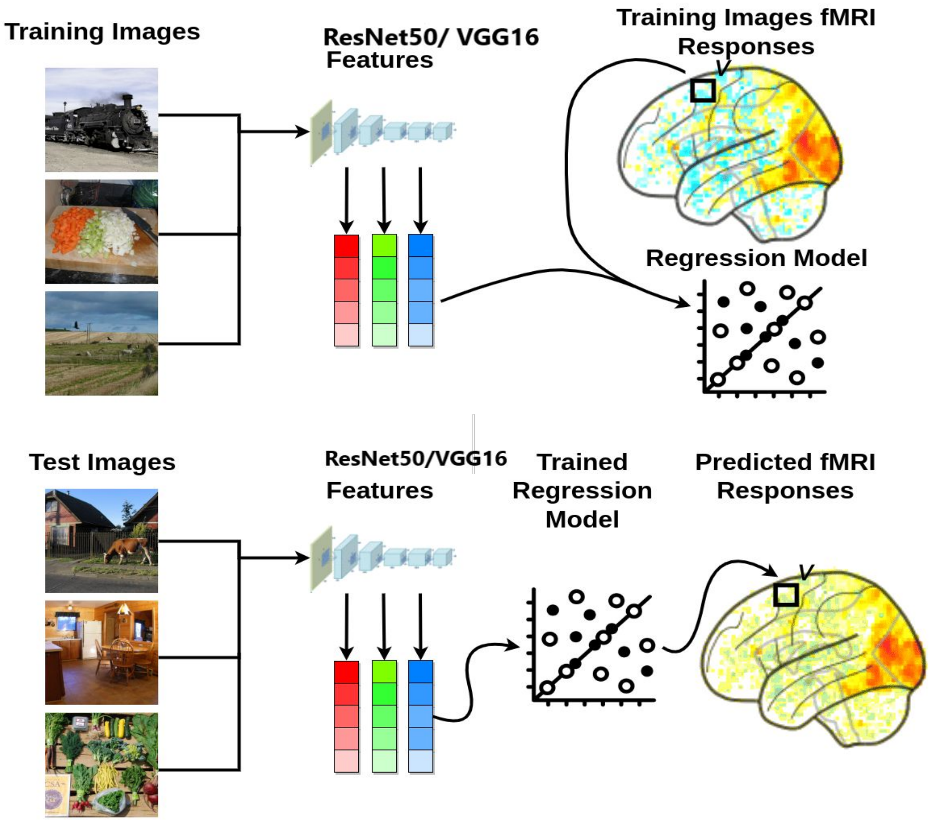
- **The experiment**

  Eight (8) individuals (subjects) where exposed to ~73.000 different naturalistic colored scenes during fMRI scanning sessions.

➢ We focus only on the data regarding the subject #1.

NSD experiment

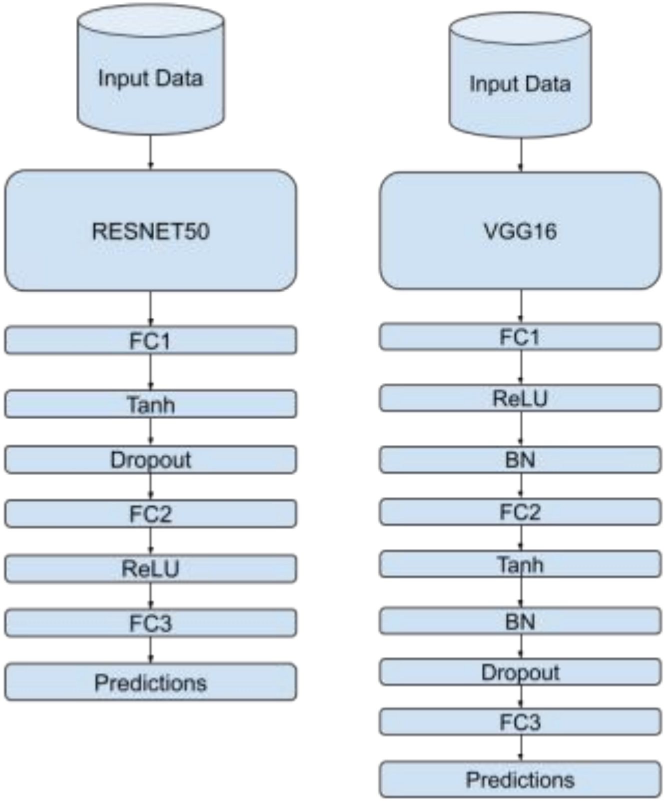
Outline of a Linearizing Encoding Model



- Extract **features** from images using a computer vision **pretrained model**, transforming the data format and reducing dimensionality.
- **Linearly map (via regression)** the computational model's **features** to **brain responses (voxel values)**, accounting for multiple features' contributions to each brain area.
- Apply the estimated mapping from the training data to **predict (i.e. encode) brain responses** for the test images.
- Compare the predicted brain responses to the withheld ground-truth data.

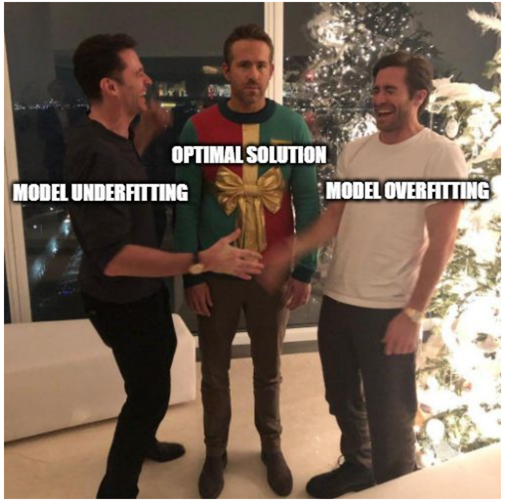
Transfer Learning

- Two models for each brain hemisphere: **ResNet50** and **VGG16**.
- **Last layer** of each pretrained model was **removed** and **three fully connected layers** were **added**.
- **Input**: pretrained model **features** of the input **images**.
- **Output**: **brain voxel values**.
- **Optional layers** included for enhanced expressiveness and flexibility.
- Model architecture allows for **customization** based on experimental requirements and optimization results.
- **Optuna** autoML tool used to determine transfer learning model architecture configuration.

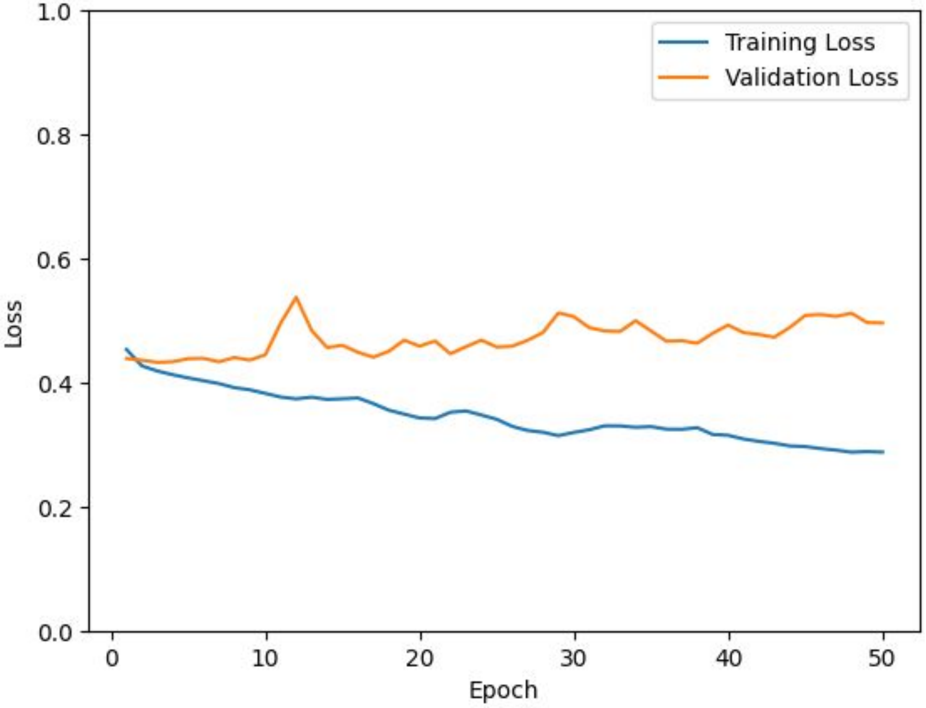


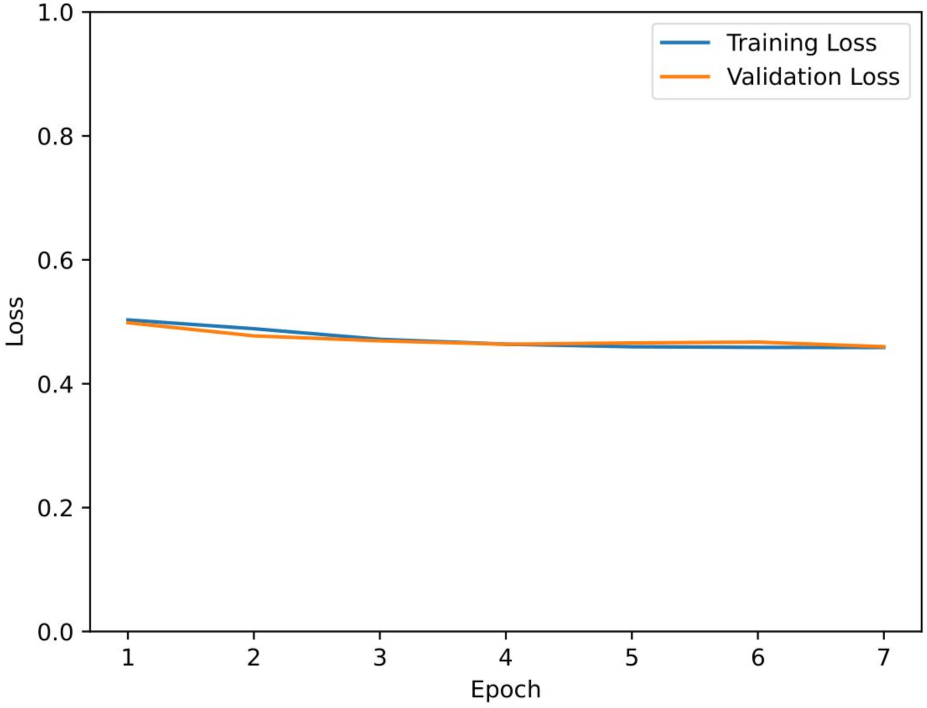
Mitigating Overfitting

- **Batch Normalization** to normalize layer inputs and reduce overfitting.
- **Dropout** was applied to randomly drop units during training and improve generalization.
- **Early stopping** was implemented based on validation loss. Training halts if no improvement in validation loss for **three consecutive epochs**.
    - Validation loss comparison considers two significant decimal digits to ensure meaningful improvement before resetting early stopping counter.
- **Optuna** optimized **learning rate**, and **weight decay** hyperparameters and chose the **optimizer** to further overfitting.



Before and After using Mechanisms for Mitigating Overfitting





Evaluation - Metrics

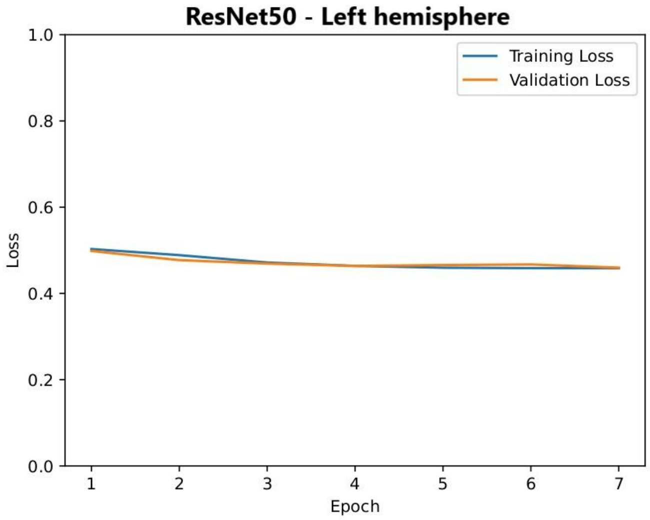
Evaluation metrics: Calculated R2 (where higher is better) score, as well as RMSE, MAE, and Smooth L1 scores (where lower is better) to quantitatively assess the model's performance

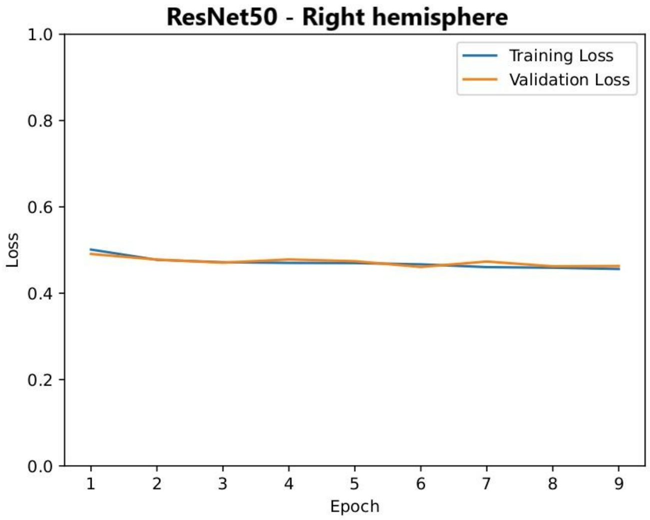
RESNET50 based Model	
LH RMSE	0.6769
LH R2	0.0799
LH MAE	0.5354
LH Smooth L1 Loss	0.2162
RH RMSE	0.6789
RH R2	0.0690
RH MAE	0.5373
RH Smooth L1 Loss	0.2175

VGG16 based Model	
LH RMSE	-0.0014
LH R2	-0.0014
LH MAE	0.5619
LH Smooth L1 Loss	0.2352
RH RMSE	0.7201
RH R2	-0.0412
RH MAE	0.5719
RH Smooth L1 Loss	0.2424

Evaluation - Learning Curves (RESNET50 based model)

Learning curves: Plotted the train and validation loss over epochs to analyze the model's learning dynamics and identify underfitting or overfitting.





Evaluation - Learning Curves (VGG16 based model)

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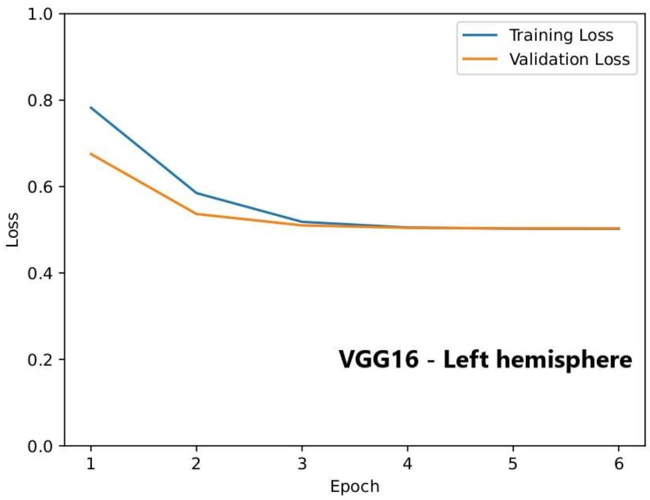
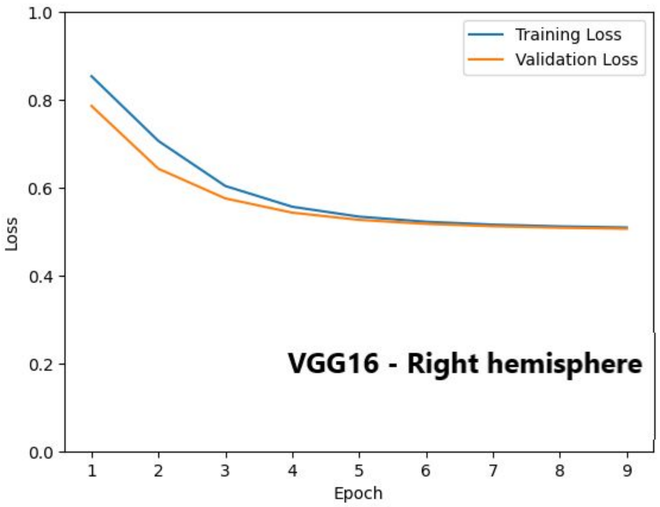
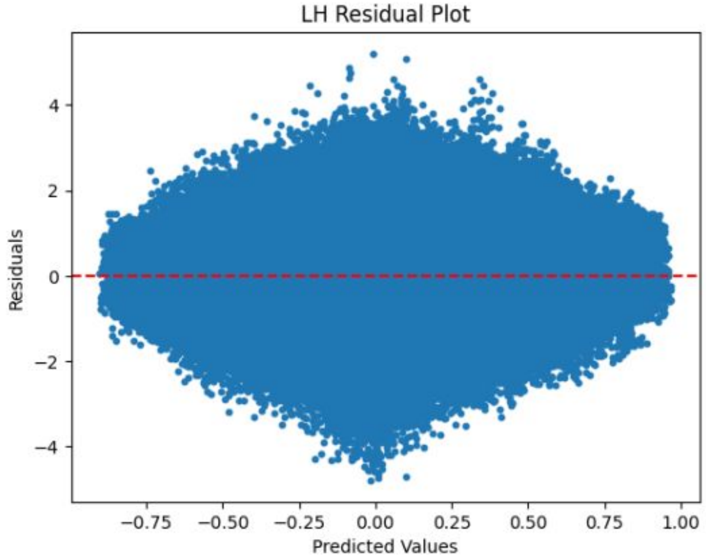
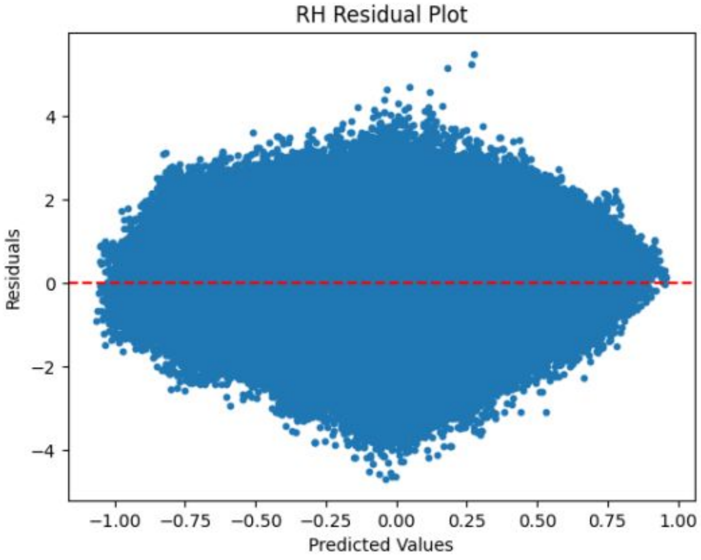




Evaluation - Residual Plots (RESNET50 based model)

Residual plots: Examined the differences between predicted and actual voxel values to assess the quality of the model's predictions and identify systematic patterns or biases.





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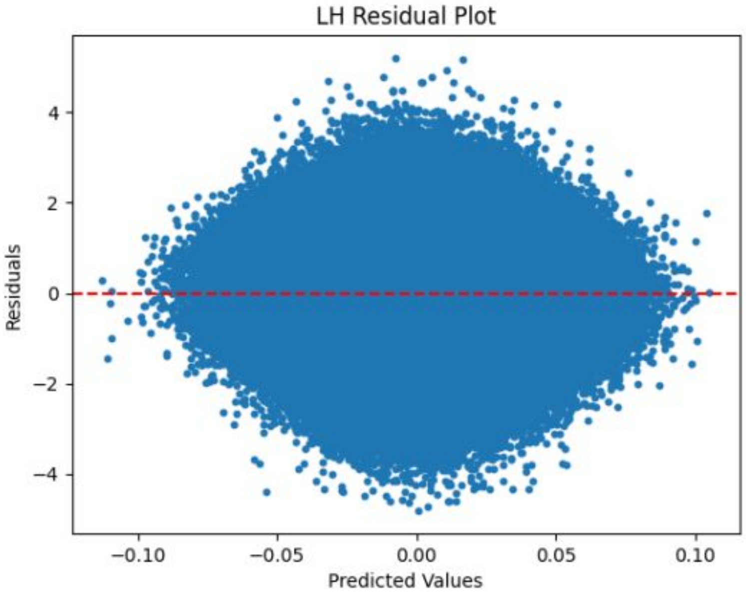
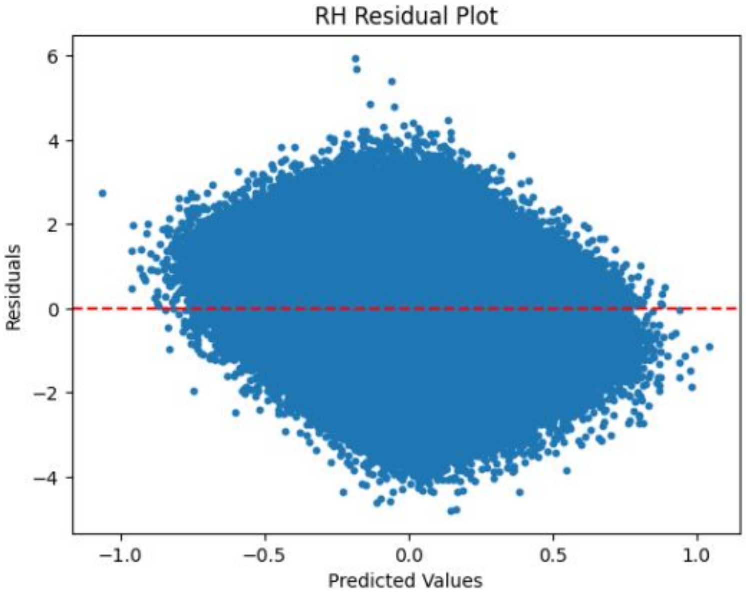


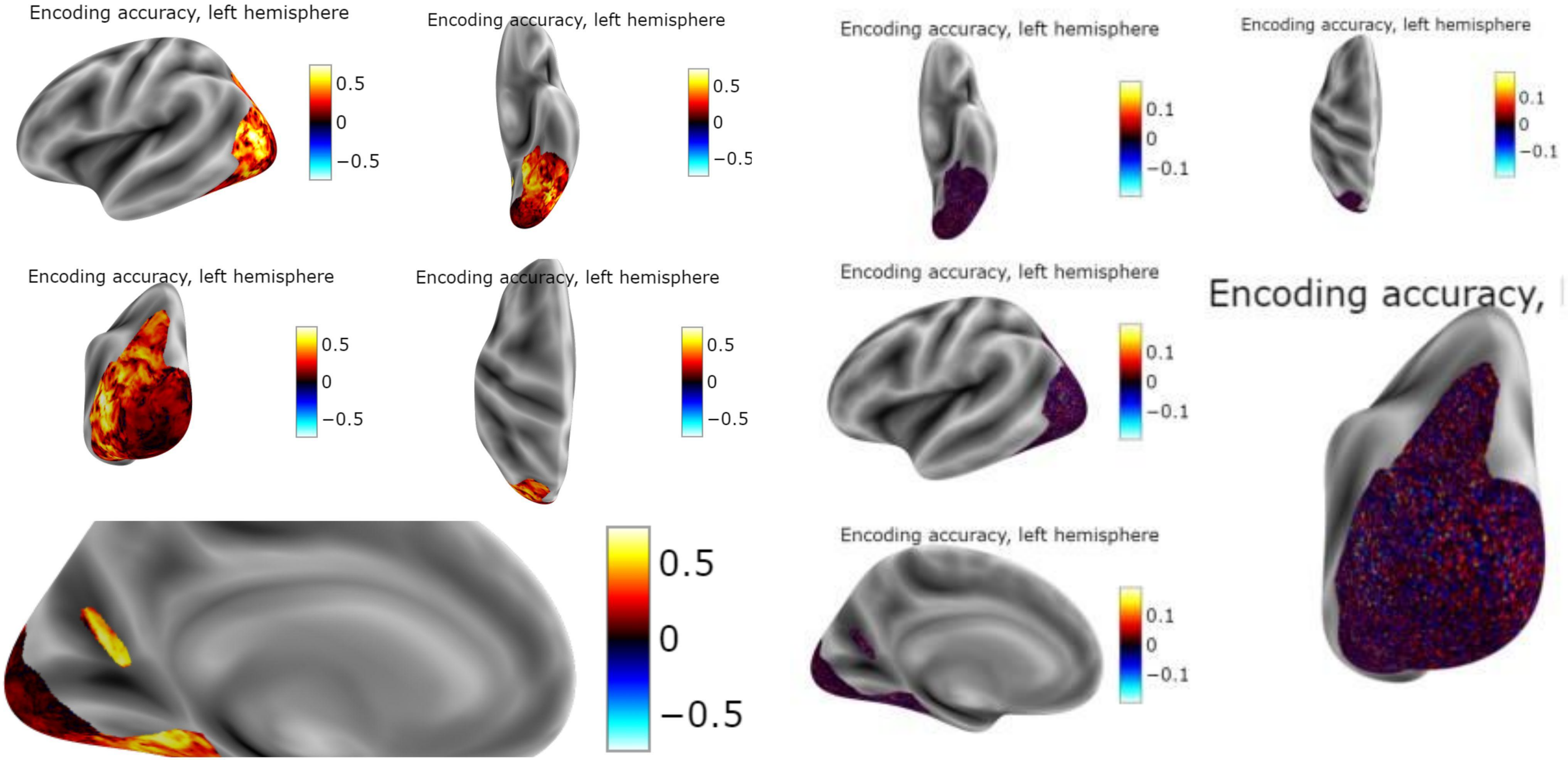


Evaluation - Brain Surface Heatmaps

Pearson correlation: Computed the correlation coefficient to measure the linear relationship between predicted and actual voxel values, indicating how well the model captured the underlying relationship.

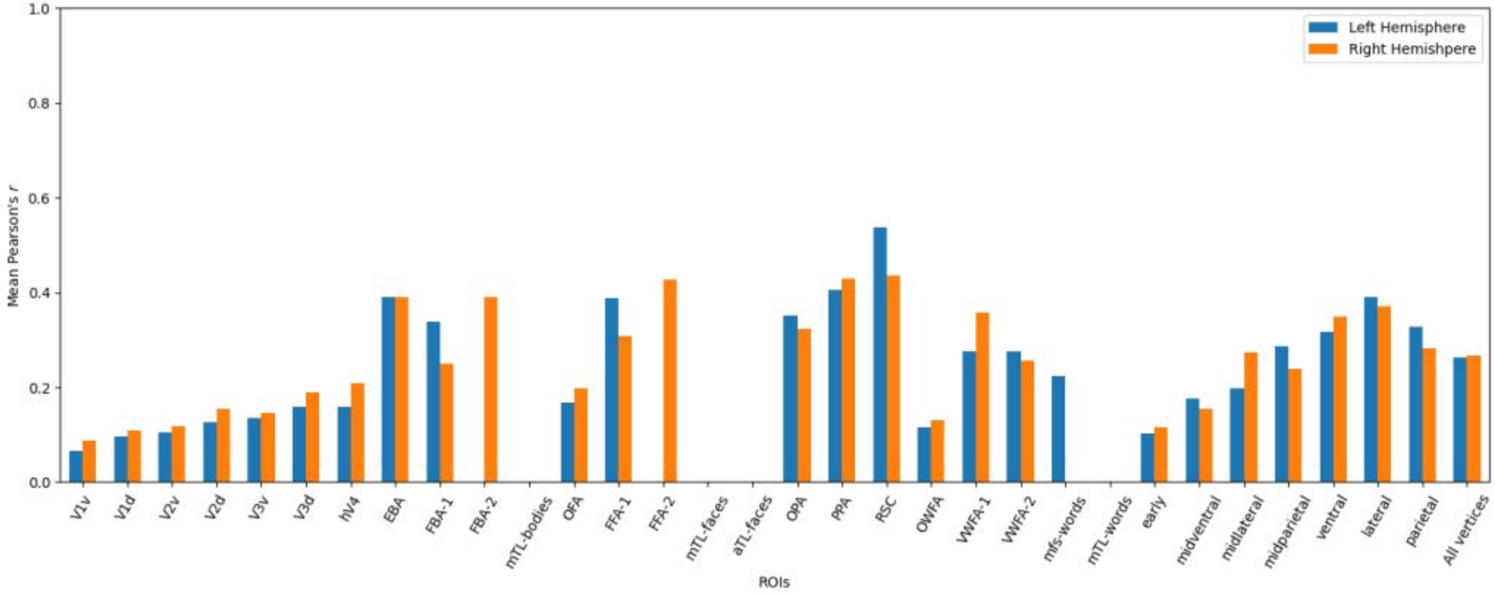
Heatmap visualization: Generated **brain surface maps** using **Nilearn** to visualize the predicted **voxel values as a heatmap**, providing spatial representation and identifying regions of accurate predictions.

Brain surface heatmaps (left: RESNET50 based model, right: VGG16 based model)



Evaluation - Regional Analysis (RESNET50 based model)

Regional analysis: Plotted Pearson correlation barchart for each **brain ROI** in the left and right hemisphere to evaluate the model's performance on specific brain regions, gaining insights into regional performance variations.



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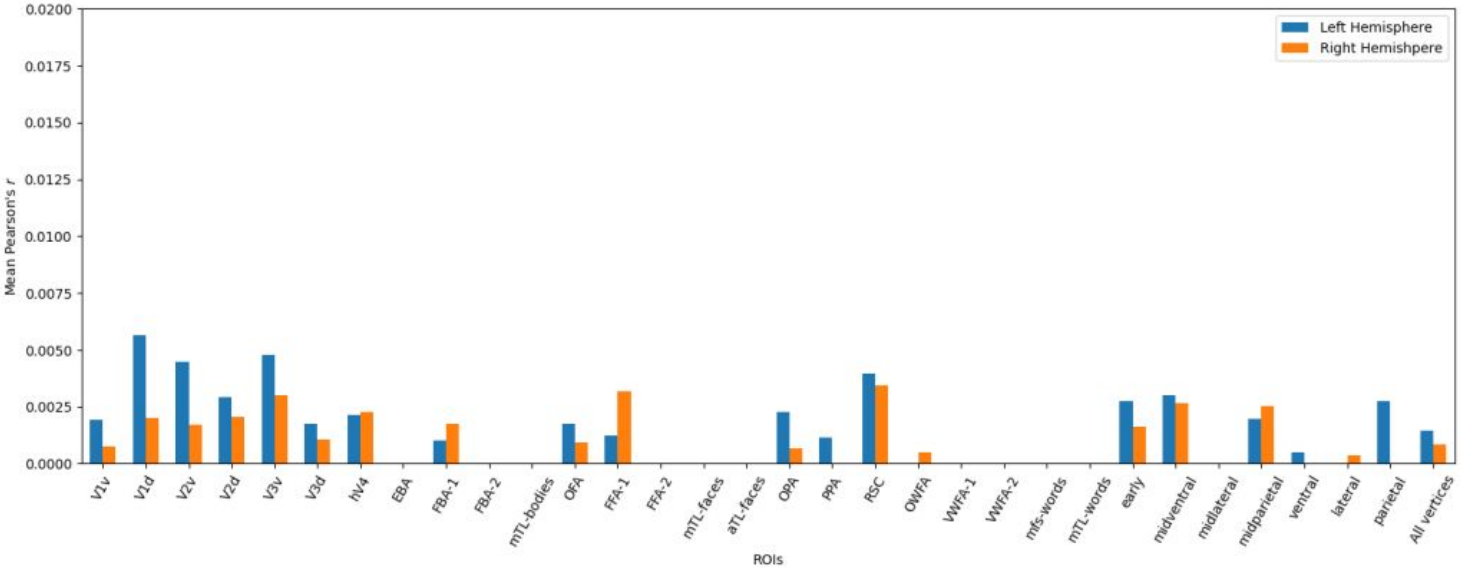
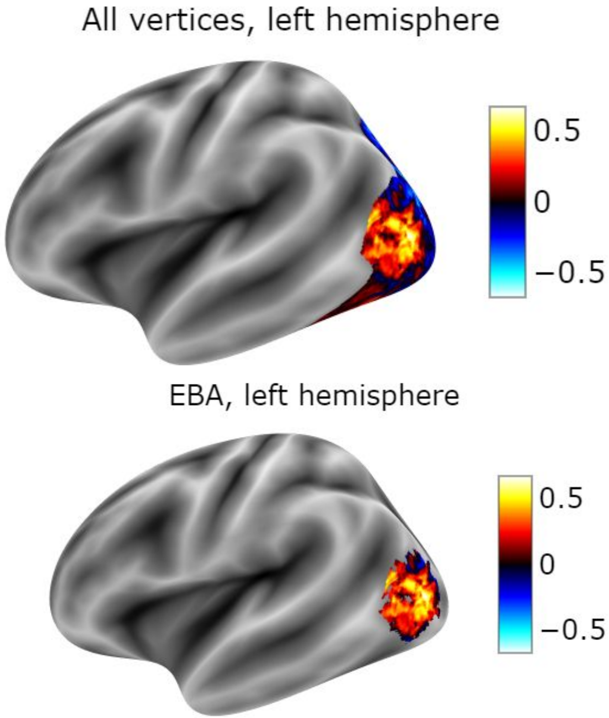


DEMO

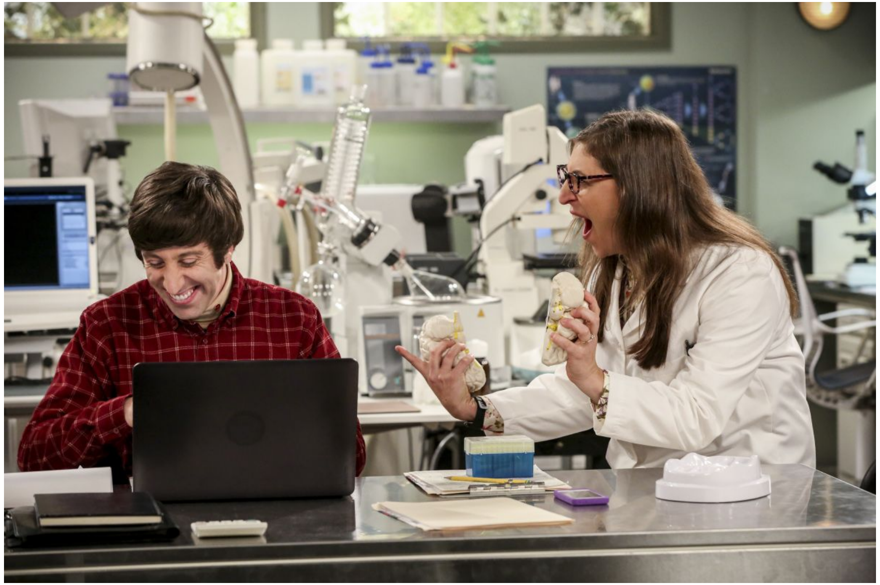
- Created a simple demo to showcase the model's capabilities.
- Applied the model on both **test images** from the dataset and **external images**.
- Generated visualizations that plot the input image alongside the predicted brain response for all examined vertices of the brain.
- Enabled the ability to selectively visualize the image with the brain response on specific regions of interest (ROIs) within the brain.

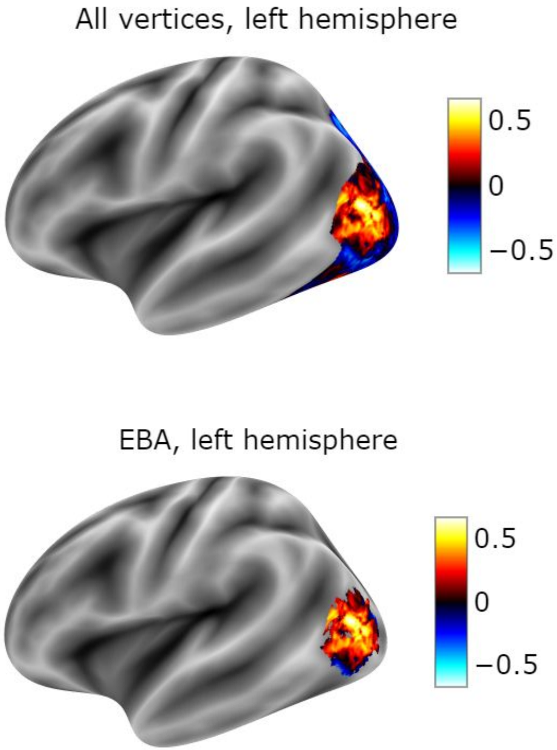
DEMO - Test image example

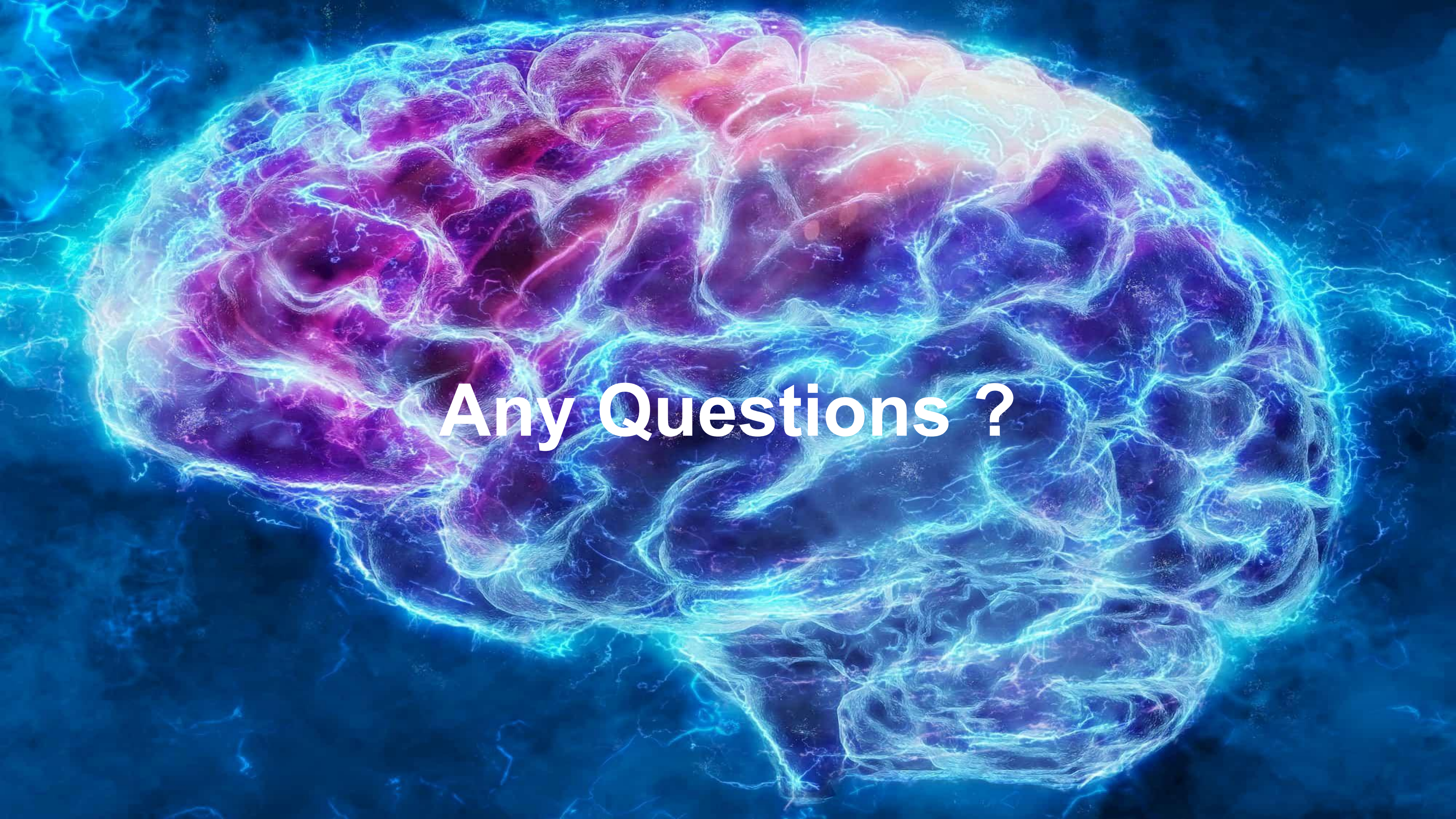
Test image: 25



DEMO - External image example






Any Questions ?


Thank You!