

Predicting Patient Characteristics given MR images with Deep Learning - Team 1

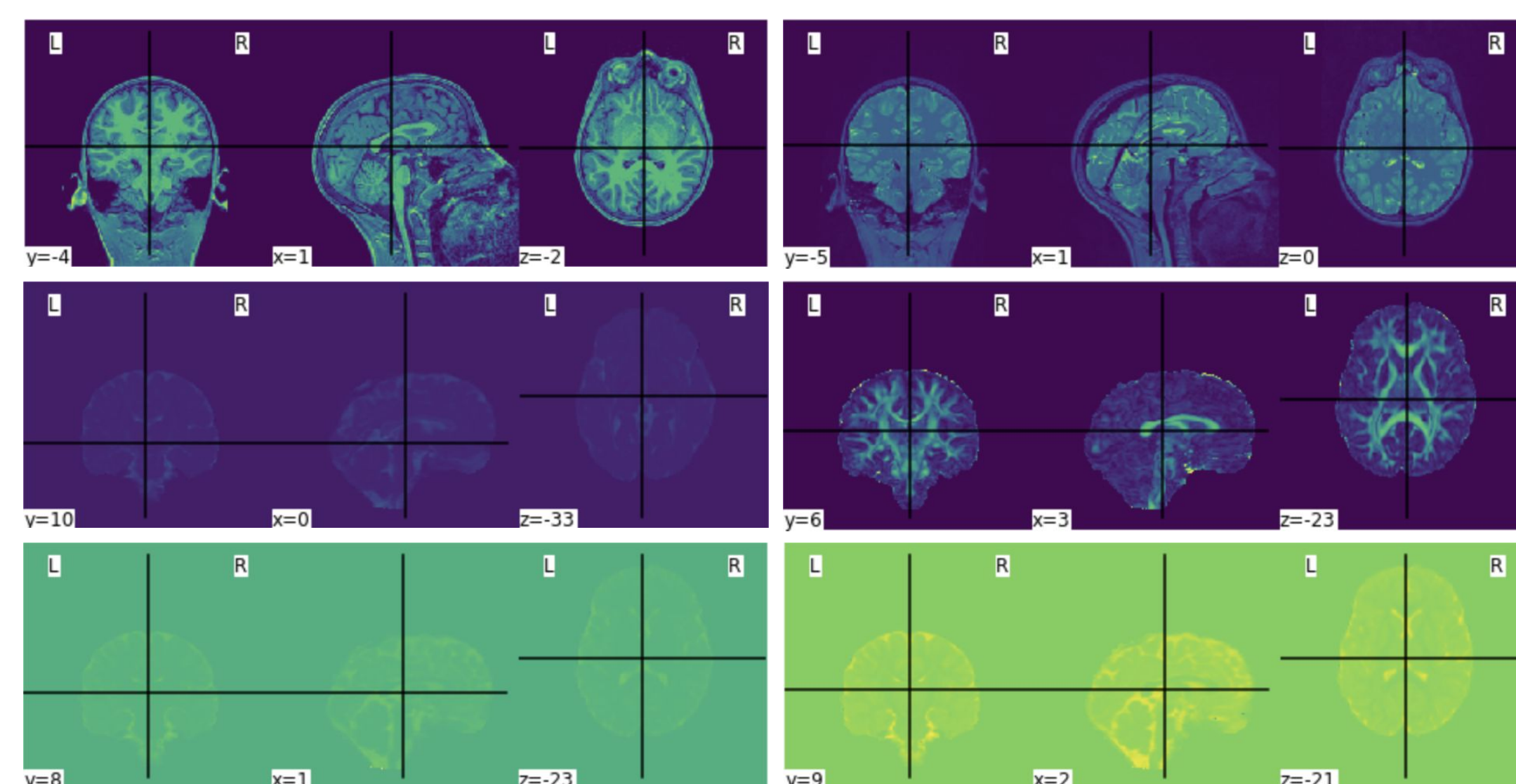
Project Description

The goal of this project is to explore the connection between human cognitive characteristics and neuroanatomical differences seen in brain images. This is done by working towards predicting human cognitive and non-cognitive features using MRIs as input data.

These features include an array of **fluid intelligence scores** which capture different human skills and abilities, as well as phenotypes such as **gender, age, race** and **height**. The outcome of this project can help neuroscientists better understand the causes and progression of certain cognitive and behavioral characteristics that can affect people's lives.

Data

The dataset contains **10,000 patients**, each has 6 different MRI types associated and participated in a detailed survey collecting cognitive and non-cognitive information. [1]



Input

Cognitive:

- 10x fluid intelligence scores

Non-cognitive:

- Age
- Gender
- Race
- Parental income
- ...

Output

Figure 1. Input data (6 different MRI) and targets for deep learning model for one patient

Architectures

The base architecture (DenseNet) layers receive input from every preceding layer.

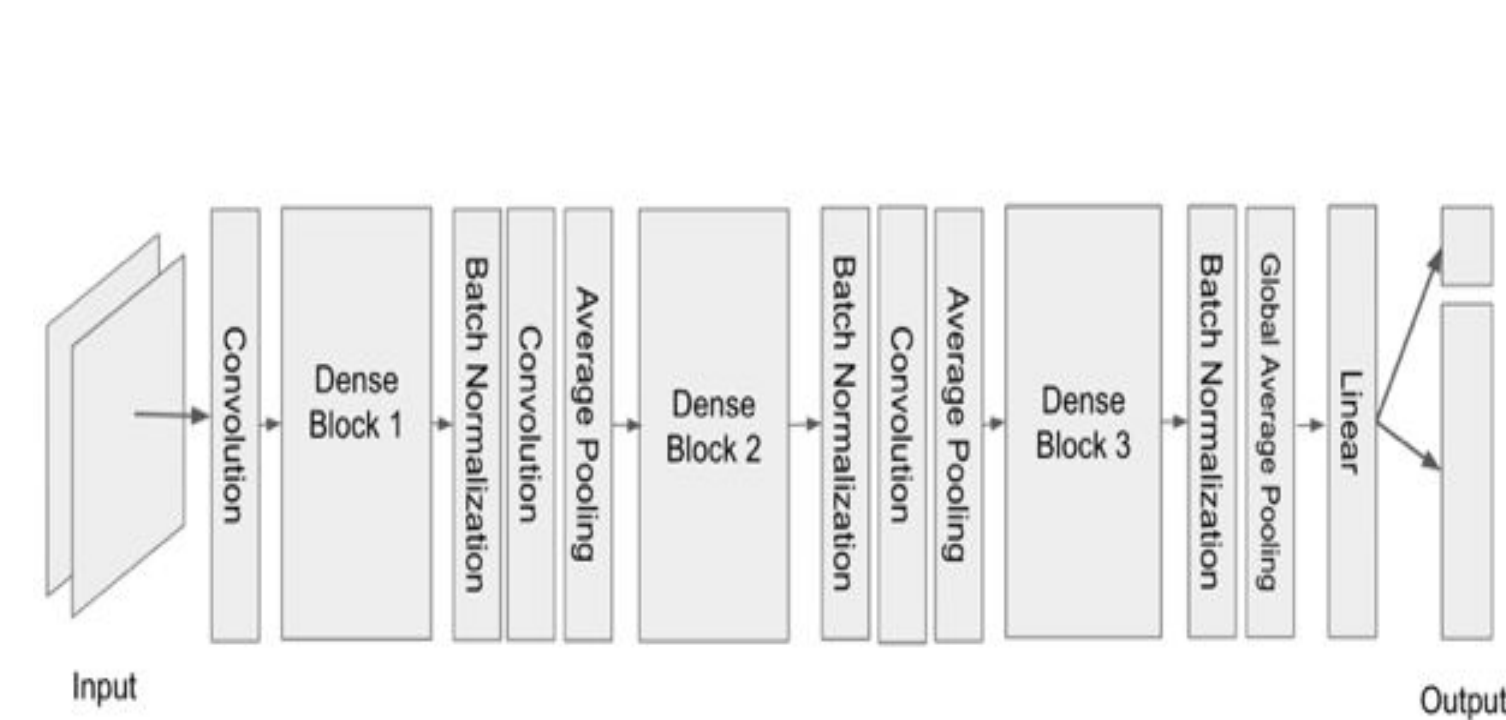


Figure 2 a. 3-D DenseNet Architecture

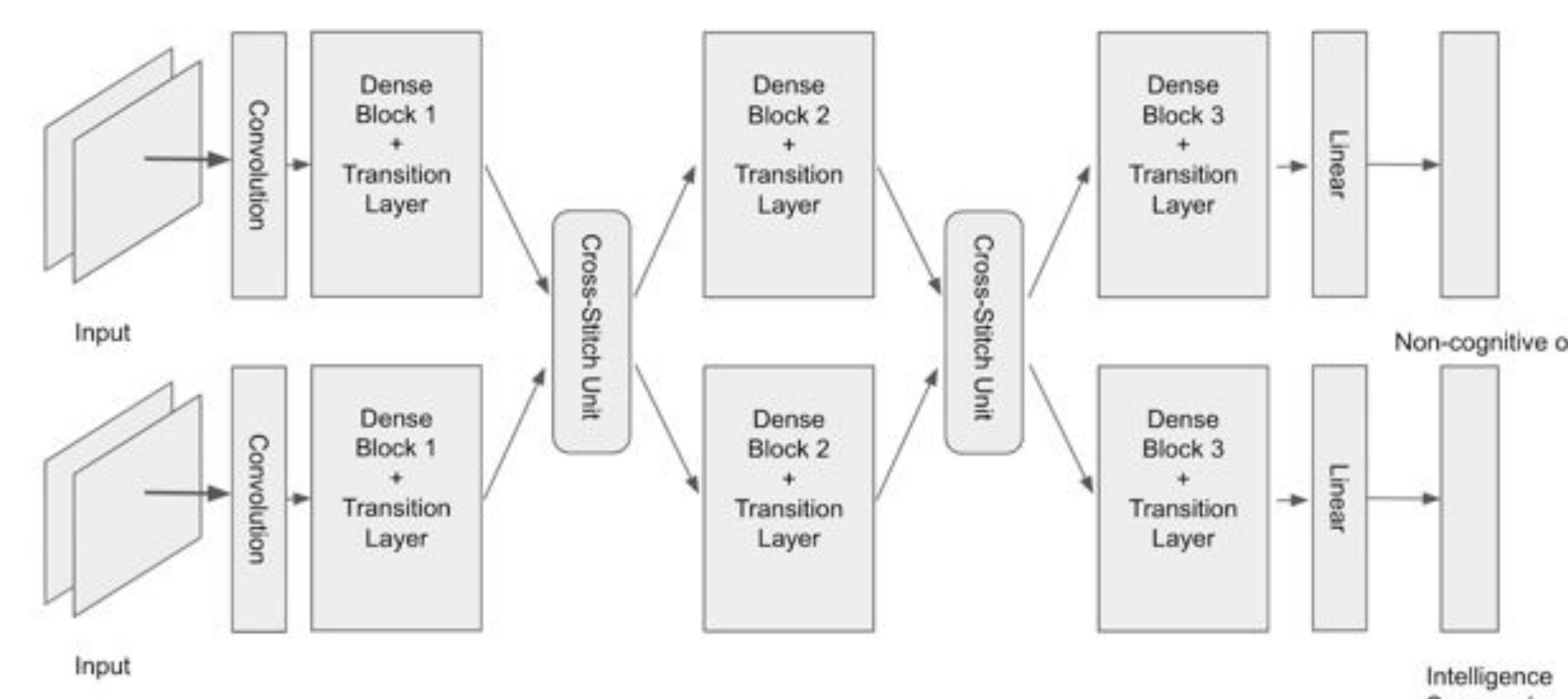


Figure 2 b. Two Tower 3-D DenseNet Arch. with cross-stitch units

Experiments

In order to reduce computational requirements for the original 256^3 -dim. images, various **cropped and downsampled** (128^3 & 64^3) combinations were experimented with.

Autofocus layers of varying dilation rates (0,2,4,6) were introduced in the DenseNet model by replacing 3^2 Kernels, each layer learning spatial areas to focus on.

Multitask Architecture was refined to optimize parameter/information sharing between tasks with introduction of **Cross-Stitch layers**, and **Task Hierarchy** mechanism.

Results

The experiments show that phenotypes can be predicted from MRI, such as **gender** (92% acc.), **race/ethnicity** (74% acc.) or **age** (21% lift), but intelligence scores do not improve significantly. In addition, following trends can be observed:

- Smaller resolution (64x64x64) performs better than larger
- Deeper networks improve the accuracy
- T1&T2 or only T2 MRI as input tend to have the best performance, diffusional MRIs do not support the performance
- Refining multi-task strategies provides additional boost

In order to explain predictions and localize the region of the brain that contributed most to the predictions, two explainability methods – GradCAM and Occlusion Sensitivity, were used. The output was an importance mask where the brightness of each pixel corresponds to its importance.

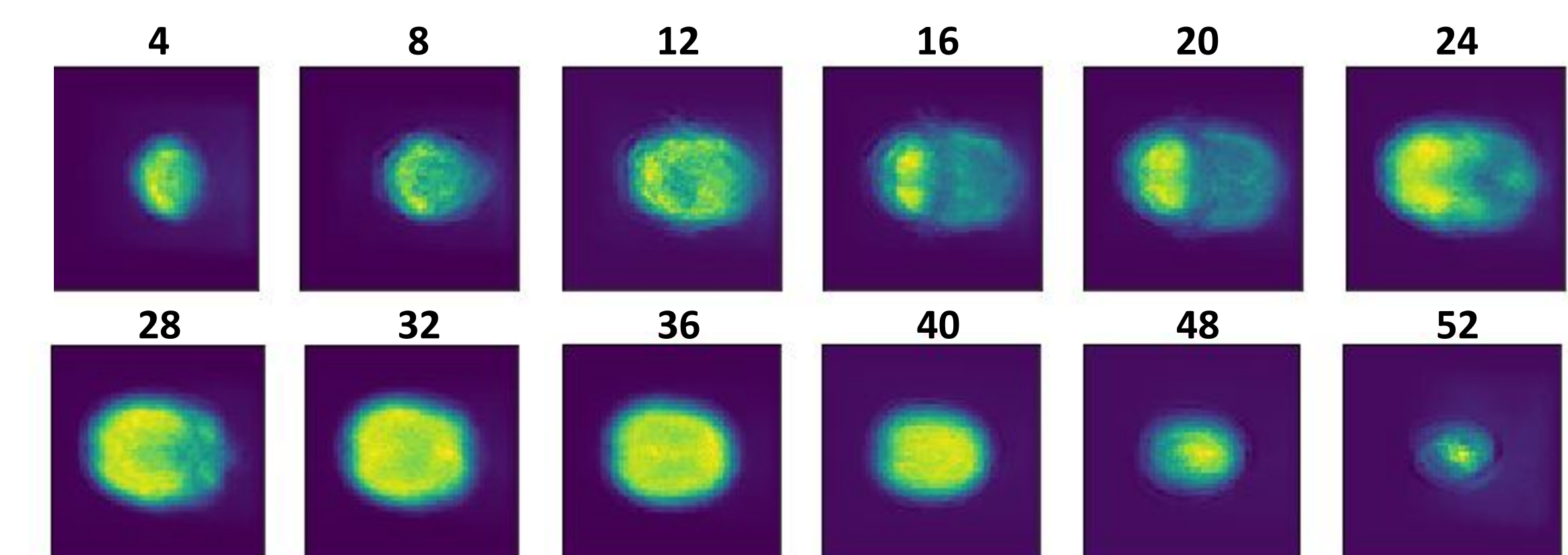


Figure 3. Visualizing GradCAM results for male brain. Each importance map is a different slice (title is slice in pixel)

Acknowledgements

We would like to thank Prof. Cha, Prof. Chen, Prof. Drinea and Seungwook Han for advising us on the project.

References

- [1] Mihalik A, et al. ABCD Neurocognitive Prediction Challenge 2019: Predicting Individual Fluid Intelligence Scores from Structural MRI Using Probabilistic Segmentation and Kernel Ridge Regression. Adolescent Brain Cognitive Development Neurocognitive Prediction. 2019.