# Deep Learning in Medical Imaging: fMRI Big Data Analysis via Convolutional Neural Networks Department of **Scientific**

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### Abstract

This paper aims at implementing novel biomarkers extracted from functional magnetic resonance imaging (fMRI) images taken at resting-state using convolutional neural networks (CNN) to predict relapse in heavy smoker subjects. In this regard, two classes of subjects were studied. The first class contains 19 subjects that took the drug N-acetylcysteine (NAC), and the second class contains 20 subjects that took a placebo. The relapse data was assessed after 6 months past the treatment. The data was pre-processed and an undercomplete auto to extract salient features that could differentiate the pre and post treatment images. Finally, the extracted feature matrix was fed into robust classification algorithms to classify the subjects in terms of relapse and non-relapse.



### **Data Acquisition**

### **Data Preprocessing**

- 3.0 T Intera MRI. scanner, Philips Health care with a SENSE 32-channel receiver head coil • 39 subjects: 19 NAC, 20 placebo
- 200 3-dimensional temporal images of BOLD signal
- Anatomical MRI of size

The pre-processing stage include:

- Motion Correction
- Segmentation
- Realignment
- Temporal Slice Timing
- Smoothing

Figure: (a) ROC curves for classification using XGBoost employing leave-one-out cross-validation. The lighter curves demonstrate the ROC for each fold, the red curve illustrates the mean value of the lighter curves, and the shaded gray area shows the confidence interval of the classification. (b) ROC curves for classification using various machine learning algorithms including DT, RF, KNN, SVM, QDA, AdaBoost, and XGBoost employing leave-one-out cross-validation.

#### Table: Classification metrics for several machine learning algorithms employing leave-one-out cross-validation.

Classifier	F1 Score	Precision	Recall	AUC
DT	$0.68 \pm 0.02$	$0.68 \pm 0.02$	$0.67 \pm 0.03$	$0.55 \pm 0.04$
RF	$0.79 \pm 0.01$	$0.68 \pm 0.01$	$0.93 \pm 0.02$	$0.62 \pm 0.04$
KNN	$0.72 \pm 0.02$	$0.69 \pm 0.01$	$0.75 \pm 0.03$	$0.54 \pm 0.03$
QDA	$0.78 \pm 0.01$	$0.67 \pm 0.01$	$0.94 \pm 0.02$	$0.55 \pm 0.05$
SVM	$0.80 \pm 0.0$	$0.66 \pm 0.0$	$100.0\pm0.0$	$0.57 \pm 0.04$
XGBoost	$0.90\pm0.01$	$0.86\pm0.01$	$0.95 \pm 0.02$	$0.92\pm0.02$
AdaBoost	$0.80 \pm 0.01$	$0.69 \pm 0.01$	$0.94 \pm 0.01$	$0.68 \pm 0.04$

## $240 \times 240 \times 220$ • Functional MRI of size $80 \times 80 \times 37$



Co-Registration



Figure: (a) Axial MRI slice of anatomical scan of brain of a subject with size of  $240 \times 240 \times 220$ . (b) Axial MRI slices of pre-treatment and post-treatment functional scans with size of  $80 \times 80 \times 37$ through 200 snapshots.

#### Autoencoder

### **Feature Extraction**

#### Mapped Features



### Conclusions

Computing

The outstanding performance of the XGBoost along with the mapped extracted features using convolutional neural networks on a brain template can be considered significant enough to suggest that there is a difference in the resting-state fMRI images of a smoker that undergoes the smoking cessation treatment compared to a smoker that receives a placebo. This would open new avenues to implement novel biomarkers to focus on specific part of the brain (i.e. mesolimbic system) to discover the relation between the reward system of the brain and addiction in depth.





Figure: The general schematic structure of an autoencoder, mapping an input x to reconstruction x' via code h. The two essential components are: (1) encoder f which maps the input x to h, and (2) decoder which maps h to x'.

Layer Type Output Shape Params.  $80 \times 80 \times 37$ Input Image 0 Conv2D 5,344  $80 \times 80 \times 16$ MaxPooling2D  $40 \times 40 \times 16$  $\left( \right)$ Conv2D  $40 \times 40 \times 8$ 1,160MaxPooling2D  $20 \times 20 \times 8$ 0 584 Conv2D  $20 \times 20 \times 8$ MaxPooling2D  $10 \times 10 \times 8$ 0 Conv2D 584  $10 \times 10 \times 8$ UpSampling2D  $20 \times 20 \times 8$ 0 Conv2D  $20 \times 20 \times 8$ 584 UpSampling2D  $40 \times 40 \times 8$ 0 UpSampling2D  $80 \times 80 \times 8$ 02,701 Conv2D  $80 \times 80 \times 37$ 10,957 Total Parameters

Figure: The mapped extracted features by the developed autoencoder from a subject from the non-relapse class. The highest intensity that is indicated in red was seen close to the mesolimbic system which is in agreement with the previously published results.

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