AUTOMATIC INTERPRETATION MODEL OF RADIOGRAPHIC BRAIN IMAGE AND ITS APLICATION IN THE PYTHON METHODS: A SURVEY

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Abstract

Investigation and analysis of diseases caused by brain abnormalities and disabilities using the image of the brain is very helpful to the doctor in the quality of reading medical images so that a clinical diagnostic decision model is generated to determine the diagnosis and appropriate treatment steps for all patients with effective and accurate. The application machine learning of python programming language technology is used to design and develop software application models to analyze and explore knowledge of the patient's brain abnormalities image and facilitate the use of many advanced learning machines, pattern recognition and multivariate statistical techniques on brain imaging data for applications such as mutli-voxel pattern analysis, decoding, predictive modeling, functional connectivity, brain parcellations and connectomes. Clinical diagnostic decision making in brain imaging has been improved by functional magnetic resonance imaging (MRI) systems, serving as second readers to detect suspicious nodules for diagnosis by a radiologist. Brain Image analysis and interpretation is generally a process where digital brain image processing is utilized to process digital brain images in order to extract significant statistics or information from the medical images. The machine learning interpretation process enables to analyze and visualize medical images with python and machine learning neuroimaging technology of numerous modalities. A brain image interpretation is basically analyzed from the perspective of its machine learning, segmentation, edge detection, registration and morphology or motion analysis. Each method is discussed and analyzed through its applications, advantages, limitations and results.

Keywords: Nilearn, Automatic Brain Image Interpretation, Functional Brain Image Processing, Python Brain Imaging Application

1 INTRODUCTION

Brain analysis and interpretation generally focuses on anatomical analysis and functional analysis of brain organ structures that have high complexity and complexity and complexity in medical imaging data, it is generally difficult to obtain analytical solutions or simple equations to represent objects such as lesions and deep anatomy medical imaging data. Functional magnetic resonance imaging of brain tasks requires "learning from the example" for accurate data representation and knowledge, which is the focus of machine learning. Thus, machine learning in medical imaging has become one of the most promising areas of cultivation. The current machine learning plays an important role in the field of medical imaging, including the diagnosis of computer help, image segmentation, image registration, image fusion, image therapy, image annotation, and image data retrieval.(Codella et al., 2015)

Research on machine learning methods applied to the brain image analysis process becomes very challenging and popular. The classification method for the brain image analysis process performed functionally or structurally aims to further analyze normal or particular neurodegenerative abnormalities. Research and development of automatic detection procedures based on Magnetic Resonance Imaging (MRI) and other medical imaging techniques are in great demand in clinical medicine. It is important to note that this technique is intended to help clinicians with more statistical evidence for diagnosis, but is not intended to replace other existing diagnostic procedures.

In this paper will review the application of python technology applied to help the process of medical personnel as clinical decisions and researchers related to brain neurological knowledge, brain sensors, brain fluids, brain oxygen, brain bone structure, brain electrical system and physiological and psychological behavior the human brain

2 PYTHON TOOL FOR BRAIN IMAGING

2.1 Dataset

TABLE 1. NeuroImaging datasets
(Source:http://nilearn.github.io/modules/reference.html#module-nilearn.datasets)

No.	Name of Function
1	fetch_atlas_craddock_2012([data_dir, url, …])
2	fetch_atlas_destrieux_2009([lateralized, …])
3	fetch_atlas_harvard_oxford(atlas_name[, …])
4	fetch_atlas_msdl([data_dir, url, resume, …])
5	fetch_coords_power_2011()
6	fetch_atlas_smith_2009([data_dir, mirror, …])

7	fetch_atlas_yeo_2011([data_dir, url, …])
8	fetch_atlas_aal([version, data_dir, url, …])
9	fetch_atlas_basc_multiscale_2015([version, …])
10	fetch_atlas_allen_2011([data_dir, url, …])
11	fetch_coords_dosenbach_2010([ordered_regions])
12	fetch_abide_pcp([data_dir, n_subjects, …])
13	fetch_adhd([n_subjects, data_dir, url, …])
14	fetch_haxby([data_dir, n_subjects, …])
15	fetch_icbm152_2009([data_dir, url, resume, …])
16	fetch_icbm152_brain_gm_mask([data_dir, …])
17	fetch_localizer_button_task([n_subjects, …])
18	fetch_localizer_contrasts(contrasts[, …])
19	fetch_localizer_calculation_task([…])
20	fetch_miyawaki2008([data_dir, url, resume, …])
21	fetch_nyu_rest([n_subjects, sessions, …])
22	fetch_surf_nki_enhanced([n_subjects, …])
23	fetch_surf_fsaverage5([data_dir, url, …])
24	fetch_atlas_surf_destrieux([data_dir, url, …])
25	fetch_oasis_vbm([n_subjects, …])
26	fetch_megatrawls_netmats([dimensionality, …])
27	fetch_cobre([n_subjects, data_dir, url, verbose])
28	fetch_neurovault([max_images, …])
29	fetch_neurovault_ids([collection_ids, …])
30	get_data_dirs([data_dir])
31	load_mni152_template()
32	load_mni152_brain_mask()

2.2 Python For Image Processing

2.2.1 Scikit-Image

Scikit-image is a collection of algorithm for image processing. The scikit-image SciKit (toolkit for SciPy) extends scipy.ndimage to provide a versatile set of image processing routines(Van Der Walt et al., 2014)

2.2.2 Nilearn (Machine Learning for Neuro-Imaging in Python)

Nilearn is a Python module for fast and easy statistical learning on NeuroImaging data.

3 FUNCTIONAL MAGNETIC RESONANCE IMAGING OF BRAIN (FMRIB) MODEL

The process of interpretation and analysis of the functional magnetic resonance imaging of brain (FMRIB) required the process of classification of image objects such as plotting process, decoding process, connectivity process, image manipulation process and Brain Image Advanced processing.

3.1 Floating Process

In the process of interpretation of functional magnetic resonance imaging of brain (FMRIB) an important method is how to present visually the volume of brain images so that can analyzed the image of the brain in a systematic way. Here is a python machine learning method for visualizing brain volumes with the help of the nilearn module and displayed with the help of Nifty data visualization.

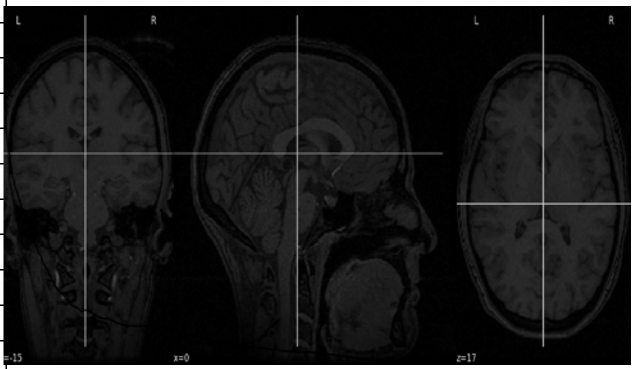


FIGURE.1 Fetch Data Process

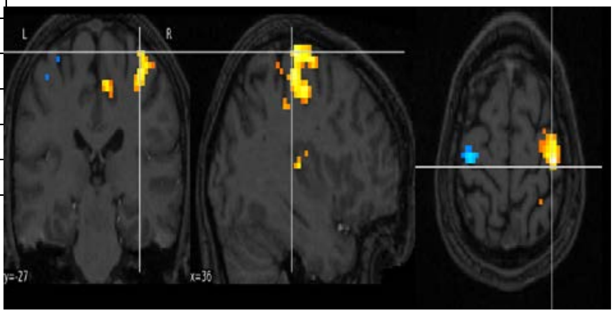


FIGURE.2 Visualization Process

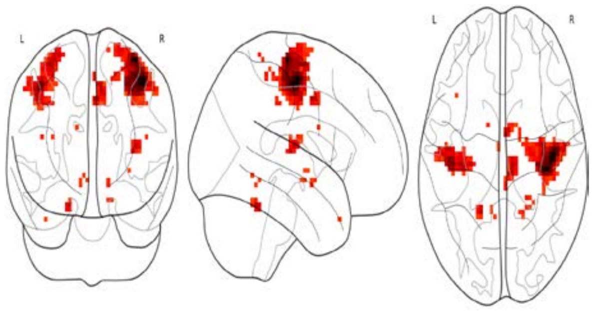


FIGURE.3. Extracting a brain mask process

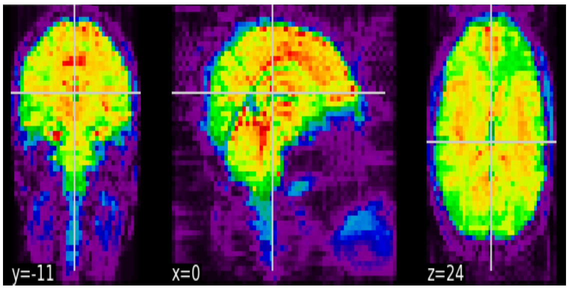


FIGURE.4. Applying the mask to extract the corresponding time series.

Visualization process on brain image of scanning in Figure 1,2,3,4 above machine learning divide into 4 process of plotting of brain image into: (1) Fetch data process; (2) Visualization Process, (3) Extracting a brain mask process, (4) Applying the mask to extract the corresponding time series.

By comparing the process running model image visualization speed can be generated figures show the comparison of the process in Fig.4 as shown in Fig.5

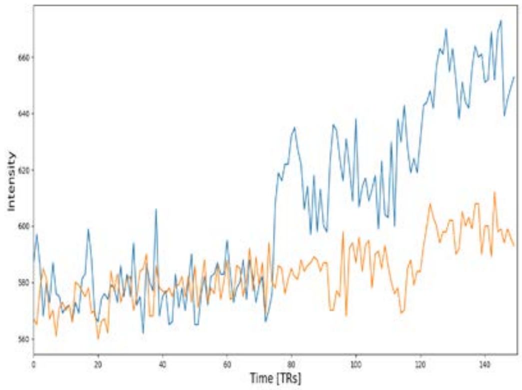


FIGURE.5 A Floating Point Of Two Voxel (timepoints, voxels)

3.2 Decoding Process

These regularize classification and regression problems in brain imaging. The results are brain maps which are both sparse (i.e regression coefficients are zero everywhere, except at predictive voxels) and structured (blobby). The superiority over methods without structured priors like the Lasso, SVM, ANOVA, Ridge, etc. for yielding more interpretable maps and improved prediction scores is now well established(Grosenick, Klingenberg, Katovich, Knutson, & Taylor, 2013)(Gramfort, Thirion, & Varoquaux, 2013)(Grosenick et al., 2013).

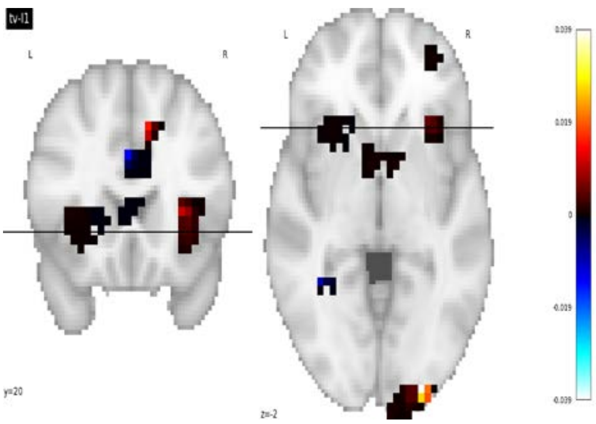


FIGURE. 6. Functional Brain Maping Clasification

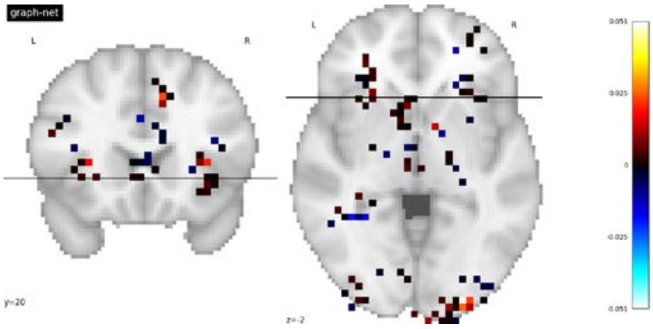


FIGURE. 7 Functional Brain Maping Intepretation Clasification

3.3 Functional Connectivity Process

Functional Connectivity is a set of connections representing brain interactions between regions. Here we show how to extract activation time-series to compute functional connectomes. Functional connectomes capture brain interactions via synchronized fluctuations in the functional magnetic resonance imaging signal.(Gael Varoquaux & Thirion, 2014)

Numerous studies have demonstrated that brain networks derive from neuroimaging data have nontrivial topological features, such as small-world organizations, modular structures and highly connected hubs. In these studies(Zalesky, Fornito, & Bullmore, 2012), the extent of connectivity between pairs of brain regions has been measured by some form of statistical correlation.

3.3.1 Functional connectivity matrices Running Test for group analysis of connectomes

This example compares different kinds of functional connectivity between regions of interest : correlation, partial correlation, as well as a kind called tangent. The resulting connectivity coefficients are used to discriminate ADHD patients from healthy controls and the tangent kind outperforms the standard connectivity kinds.

The following functions for floating matrices in the image :

```
# A useful matrix plotting function
import numpy as np
import matplotlib.pylab as plt

def plot_matrices(matrices, matrix_kind):
    n_matrices = len(matrices)
    plt.figure(figsize=(n_matrices * 4, 4))
    for n_subject, matrix in enumerate(matrices):
        plt.subplot(1, n_matrices, n_subject + 1)
        matrix = matrix.copy()  # avoid side effects
        # Set diagonal to zero, for better visualization
        np.fill_diagonal(matrix, 0)
        vmax = np.max(np.abs(matrix))
        plt.imshow(matrix, vmin=-vmax, vmax=vmax,
```

```
        cmap='RdBu_r', interpolation='nearest')
    plt.title('{0}, subject {1}'.format(matrix_kind,
n_subject)
```

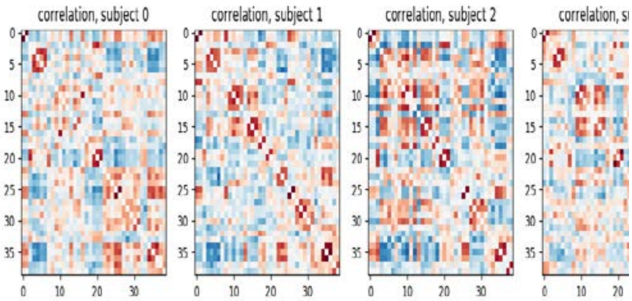


FIGURE8. Region signals extraction

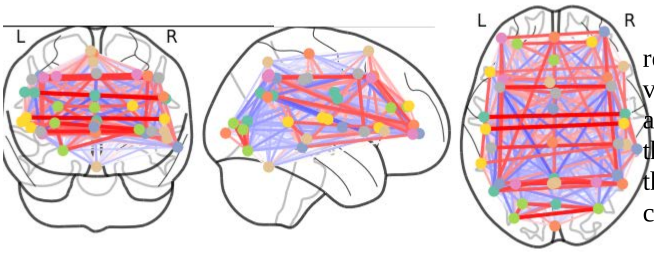


FIGURE9. Brain Mapping Region signals extraction

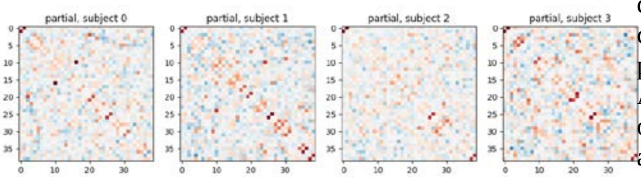


FIGURE. 10 tangent_matrices` model individual connectivities

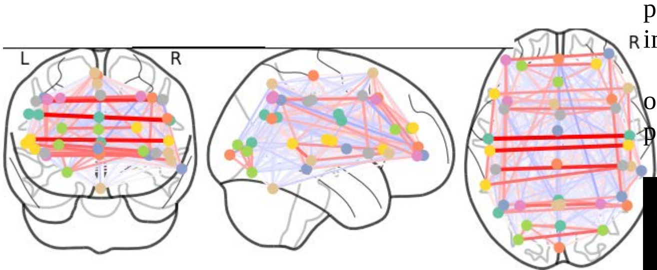


FIGURE 11 Brain Mapping Region signals extraction result

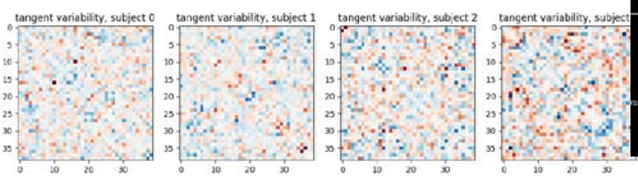


FIGURE. 10 tangent_matrices` model individual connectivities result

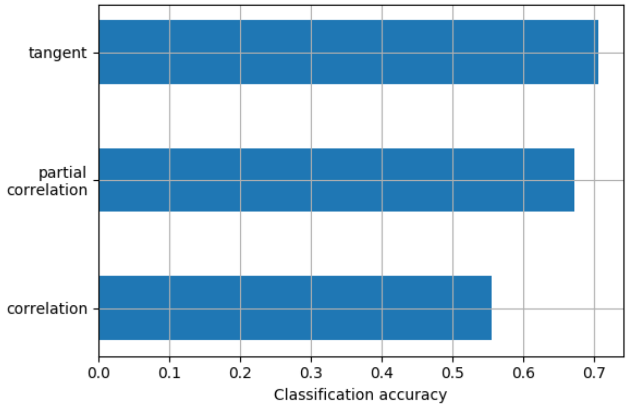


FIGURE.11 Connectivity classification scores

3.4 Image Manipulation Process

Investigation of features brain image characteristics required systematic observations from all object are in voxel images like gray-level appreance, border strength, and average position(Duta & Sonka, 1998). An image is the association of a block (array) of spatial data, with the relationship of the position of that data to some continuous space.

A Brain image is the association of a block (array) of spatial data, with the relationship of the position of that data to some continuous space. Therefore a brain image contains an array a spatial transformation describing the position of the data in the array relative to some space. An image always has 3 spatial dimensions. It can have other dimensions, such as time. A brain image has an array. The first 3 axes (dimensions) of that array are spatial. Further dimensions can have various meanings. The most common meaning of the 4th axis is time. The relationships of the first three dimensions to any particular orientation in space are only known from the image transform.

Here is a python model to describe the characteristics of brain images through the process of image processing manipulation.

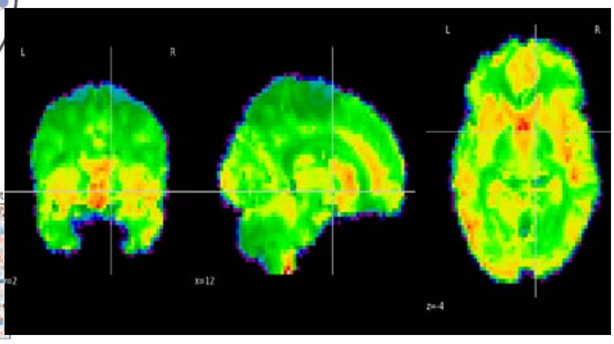


FIGURE.12 Brain Smoothing Model

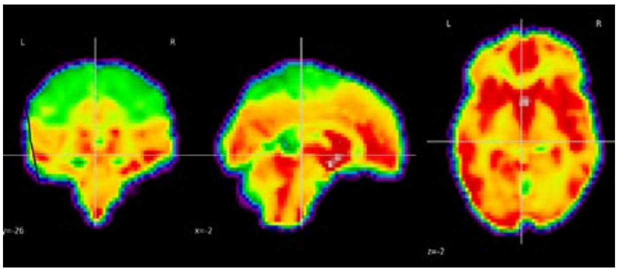


FIGURE.13 Brain Smoothing Model with spatial effect 1

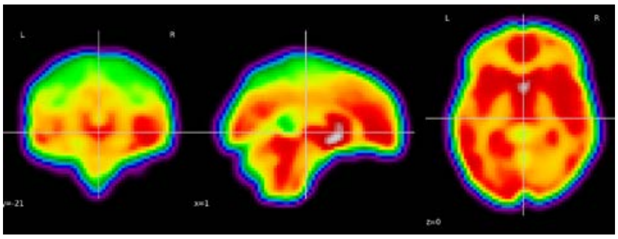


FIGURE.14 Brain Smoothing Model with spatial effect 2

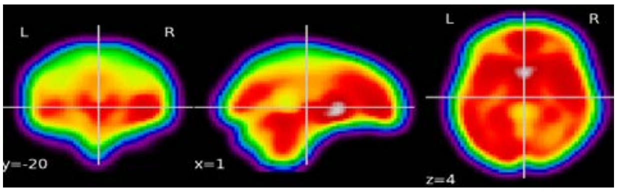
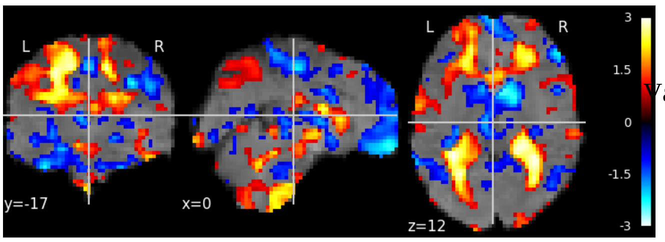


FIGURE.15 Brain Smoothing Model with spatial effect 3

3.5 Brain Image Advanced Processing With Spatial Independent Component Analysis (ICA)

Analytical method for extracting knowledge from brain features correlate each other to form functional networks for disease zone release to analyzed using independent spatial component analysis technique. Spatial Independent Component Analysis (ICA) is an increasingly used data-driven method to analyze functional Magnetic Resonance Imaging (fMRI) data(Varoquaux et al., 2010;Mensch, Varoquaux, & Thirion, 2016). Machine learning for Neuro-Imaging in Python (Nilearn) has introduced the use of multi-subject Independent Component Analysis (ICA) fMRI data for state-breaking to extract brain tissue in a data-driven way. The approach method used is 'Canica', which applies a multivariate random effects model across subjects.

The example here applies the scikit-learn ICA to resting-state data.



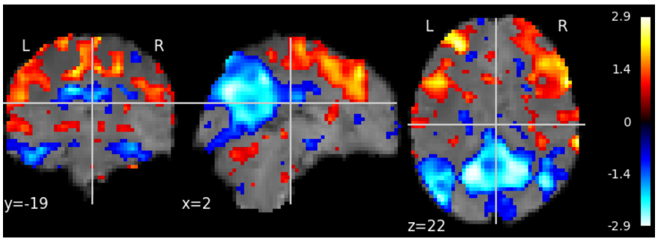


FIGURE.15 Applies The Scikit-Learn Ica To Resting-State Data

4 CONCLUSION

The application of classification methods in Machine learning for Neuro-Imaging in Python (Nilearn) can produce the quality of brain image so that the image of the brain arrangement function more clearly and facilitate in the process of analysis for medical experts or users of image data image of the brain.

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