Journal of the Arkansas Academy of Science

Volume 72 Article 11

2018

Deep Learning-based framework for Autism functional MRI Image Classification

Xin Yang
Southern Arkansas University, xinyang@saumag.edu

Saman Sarraf
The Institute of Electrical and Electronics Engineers, samansarraf@ieee.org

Ning Zhang
Middle Tennessee State University, ningzhang0123@gmail.com

Deep Learning-based framework for Autism functional MRI Image Classification

Cover Page Footnote
None

Deep Learning-based framework for Autism functional MRI Image Classification

X. Yang[1*], S. Sarraf[2,3], and N. Zhang[4]

[1]*Department of Math & Computer Science, Southern Arkansas University, USA*
[2]*Department of Electrical and Computer Engineering, McMaster University, Hamilton, Ontario, Canada*
[3]*The Institute of Electrical and Electronics Engineers, IEEE*
[4]*Computational Science Ph.D. Program, Middle Tennessee State University, USA*

[*]Correspondence: XinYang@saumag.edu

Running Title: Deep Learning for Autism fMRI Image Classification

Abstract

The purpose of this paper is to introduce the deep learning-based framework LeNet-5 architecture and implement experiments for functional MRI image classification of Autism spectrum disorder. We implement our experiments under the NVIDIA deep learning GPU Training Systems (DIGITS). By using the Convolutional Neural Network (CNN) LeNet-5 architecture, we successfully classified functional MRI image of Autism spectrum disorder from normal controls. The results show that we obtained satisfactory results for both sensitivity and specificity.

Introduction

The human brain is the most complex organ of human beings, which could include 100 billion neurons with more than a trillion connections. Although technology has been developing, humans are constantly exploring the mysteries of the brain, we still cannot prevent or treat brain disorders such as Autism Spectrum Disorder (ASD), Alzheimer's disease, stroke, and so on. In order to make breakthroughs in brain disease treatment and prevention, many academic institutions and scientists have conducted a lot of research studies in these fields (Olivito *et al.* 2017; Igelström *et al.* 2016; Dajani and Uddin 2016). Among all these research studies, neuroimaging technique has become the most commonly used imaging technique for the study of the human brain. The most commonly used neuroimaging techniques include Magnetic Resonance Imaging (MRI), functional Magnetic Resonance Imaging (fMRI), Positron Emission Tomography (PET) and so on (Poldrack *et al.* 2011). These neuroimaging techniques can provide us insights into the neural characteristics of the human brain and also help the diagnosis and prevention of many diseases. However, the analysis of neuroimaging data is extremely complicated, which requires the raw image preprocessing and efficient statistical analysis. Therefore, the main purpose of this paper is to implement the deep-learning based framework for the functional MRI image classification. The deep-learning framework is a very efficient learning framework for image analysis.

During the past decade, autism spectrum disorder (ASD) prevalence rate has increased dramatically. ASD is a neutrally based psychiatric disorder which is characterized by the impaired development of social interactions and communication skills. Although strong genetic factors are suspected, ASD continues to be diagnosed using symptom-based clinical criteria, and its etiology remains unestablished. Social and communicative impairments are the core symptoms of ASD, and a lot of research indicates that these impairments are associated with functioning and connectivity of cortical networks (Olivito *et al.* 2017; Igelström *et al.* 2016; Dajani and Uddin 2016). Recent epidemiological studies have shown that the incidence of autism is increasing. Although many researchers are currently studying ASD, no one has applied deep learning to classify ASD functional MRI images. In this work, we implement a deep-learning based framework for Autism Spectrum disorder fMRI image classification. Further research in this area could provide helpful information in gaining a better understanding of the neuronal pathology of autism in children.

Problem Statement and Related Work

Artificial Neural Networks have been introduced since the 1940s (Heaton 2015). However, because of limited computing power, people were not aware of the advantages of Artificial Neural Networks. With the development of advanced computing power, people began to recognize its superiority. Because Artificial Neural Networks can efficiently recognize patterns, they have been widely applied in many fields, such as speech recognition (Lippmann 1987; Lang *et al.* 1990; Fels and Hinton 1993), image classification (Rowley *et al.* 1998; Lawrence *et al.* 1997), and disease diagnosis (Khan *et al.* 2001; Kato *et al.* 2007; Petrosian *et al.* 2001). The accuracy of these works is highly dependent upon the feature extraction stage, which is a traditional analysis step for pattern analysis and classification (Rawat and Wang 2017).

CNN was proposed by LeCun *et al.* (1989**)**. They used backpropagation (LeCun *et al.* 1999) to train the architecture of the networks, and it has been successfully applied to the recognition of handwritten zip code digits provided by the US Postal Service. Their work has demonstrated that the Convolutional Neural Networks can directly deal with large low-level information rather than feature vector. This has overcome the traditional pattern analysis and classification challenges. Although the Convolutional Neural Networks achieved its initial successful application, it is difficult to implement, and it is really slow. As a result, it was not widely used until 20 years later due to the limitation of computing power.

In recent decades, the computational power of computers has increased dramatically, and neural networks have once again received widespread attention. In 2006, Chellapilla *et al.* first introduced GPUs (Graphics Processing Units) implementation of Convolutional Neural Networks. The GPUs contain parallel pipelines which speed up the computations (Chellapilla *et al.* 2006). In addition to improving computing power, some researchers have made some improvements to the original Convolutional Neural Network algorithm. The first application of maximum pooling was proposed by Huang *et al.* (2007). In 2012, Alex Krizhevsky *et al.* introduced deep convolutional neural networks to large-scale images recognition in the paper (Krizhevsky *et al.* 2012). They classified 1.3 million images in the LSVRC-2010 ImageNet training set into 1000 different classes, which yielded more accurate results than any previous algorithms. Since then, deep Convolutional Neural Networks have been applied to various fields with large-scale datasets (Oquab *et al.* 2014; Karpathy *et al.* 2014; Ji *et al.* 2013).

Because of the powerful analysis capabilities, deep neural networks have become one of the hottest topics in Pattern Recognition and Artificial Intelligence (Schmidhuber 2015). Large corporations and many research institutions are all paying attention to these fields. For a long time, people have always believed that computers are not intuitive at all. However, after a long period of research by scientists, this understanding has been challenged. In 2015, Google DeepMind developed a computer program called AlphaGo which plays the board game go. To capture the intuitive of the game, the AlphaGo combines advanced tree search with deep neural networks (Silver *et al.* 2016). In 2016, AlphaGo becomes the first computer program to beat a 9-dan professional Go player.

Although many researchers are currently studying ASD, no one has applied deep learning framework to classify ASD functional MRI images. The purpose of this paper is to introduce deep learning-based framework with LeNet-5 architecture and implement the experiments for functional MRI image classification of ASD. This efficient deep learning process will provide us some insights into the neuronal pathology of autistic children, and also help the diagnosis of the early stage of autism in children.

Overview of the LeNet-5 Architecture

Neural Networks consist of three types of layers: a convolution layer, a pooling layer, and fully connected layer. The convolution layer extracts feature from the original input images. It detects the same feature at all locations on the input image. The different feature detector in the layer can extract different types of local features (LeCun *et al.* 1989). The output from this layer is called a feature map. Once the features have been detected, the exact location is not so important. The pooling layer is used to reduce the spatial resolution of the feature maps. The pooling layer reduces the dimensions of the feature maps in the convolution layer.

In LeNet-5, the pooling layer is called the subsampling layer. The fully connected layer is the hidden layer of Artificial Neural Networks, which fully connects the features from convolution layer and pooling layer to produce the output for image classification. A typical convolutional neural network of LeNet-5 is shown in Figure 1. LeNet-5 has a total of 7 layers, excluding the input layer (LeCun *et al.* 1989). In our experiments, the input is a 64*64 color image. Layer C1 is a convolution layer with 20 feature maps. Each unit in each feature map is a convolution between a 5 by 5 neighborhood in the input image and a feature detector. 20 different feature detectors produce 20 feature maps. Layer P1 is a pooling layer with a stride of 2. The feature map from the C1 layer is connected to a 2 by 2 pooling filter; max pooling is implemented to reduce the spatial resolution of the feature maps. The max pooling reduces the dimension of the feature maps. Layer C2 is a convolution layer with 50 feature maps. Each unit in each feature map is a convolution between a 5 by 5 neighborhood in the P1's feature maps and a feature

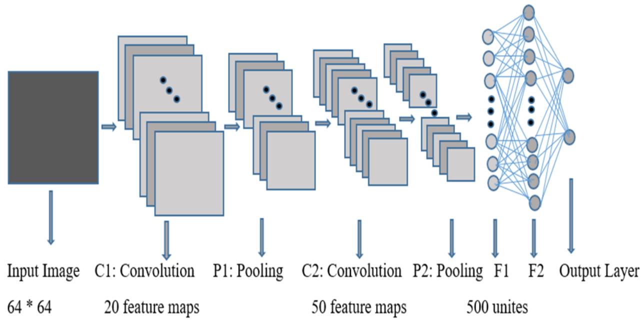


Figure 1: LetNet-5 Architecture

detector. Layer P2 is a pooling layer with a stride of 2. The feature map from the C2 layer is connected to a 2 by 2 pooling filter; max pooling is implemented to reduce the spatial resolution of the feature maps. Layer F1 contains 500 units and is fully connected to P2. As in artificial neural networks, units in F1 layer compute a dot product between their input vector and the weight vector, then pass through a rectifier activation function to produce the inputs for Layer F2. Units in Layer F2 also compute a dot product between their input vector and the weight vector (LeCun *et al.* 1989). Finally, the output layer passes through a soft-max activation function to get probabilities between 0 and 1 for each class. The class label with the highest probability is assigned to the corresponding input image.

Experiments Data Set

In this work, we implement a deep learning-based framework on a NVIDIA GPU platform. By using the CNN LeNet-5 architecture, we successfully classified functional MRI image of Autism Spectrum Disorder as being distinct from Normal Controls.

In our work, all fMRI data set are downloaded from an Image & Data Archive of ABIDE (Autism Brain Imaging Data Exchange) (https://ida.loni.usc.edu/). Initially, we downloaded 100 subjects in total from the Image & Data Archive: 50 controls and 50 autisms. However, in order to provide more meaningful analysis results, only 16 controls and 11 autisms from the 100 subjects group are qualified for our analysis after screening. The subjects were removed who has the wrong image information. And all subjects we used in this paper are collected under the same scanning protocol and parameters. The chosen subjects include both female and male, whose age is between 9 and 20.

The analysis of fMRI data is extremely slow due to its high dimensionality. For each subject, the scanner collects 64*64*29*210 images. There are 29 slices for each subject, the dimension of each slice is 64*64, and in total there are 210 time courses. To improve the efficiency of the data analysis process, we implement the NVIDIA Deep Learning GPU Training System (DIGITS). DIGITS can be used to train the deep neural network (DNNs) for image classification with high accuracy (https://developer.nvidia.com/digits). To train DNNs on GPU systems, we installed DIGITS in Ubuntu 16.0 under NVIDIA GeForce GTX 1060 and used LeNet-5 under deep learning framework Caffe.

Image Preprocessing

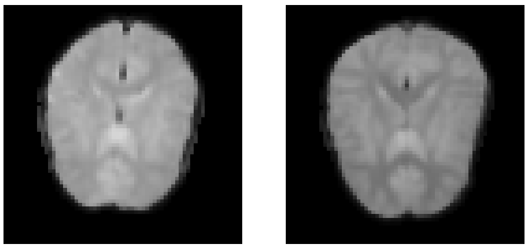
The analysis of fMRI data is incredibly complicated. First, it has particularly high dimensionality. Second, the data is interfered by other factors such as head movement, variability between individuals, and variability through time within individuals. Therefore, applying imaging preprocessing to fMRI data will provide more meaningful interpretation of the analysis results. The most common image preprocessing packages include SPM, FSL, AFNI, Brain and Voyager (Poldrack *et al.* 2011).

In our experiments, we use FMRIB Software Library (FSL) for the image preprocessing. The first step is brain extraction, to do this, we need to remove the skull from the anatomical scans (structural MRI) by using FSL BET brain extraction. The second step is fMRI data preprocessing; and this step is done by using FSL FEAT fMRI analysis. This step will register the fMRI data by using the extracted brain image from step 1, and the standard space we used here is MNI152_T1_2mm_brain. After the fMRI data have been preprocessed, the third step is to convert NII files to PNG images. The third step is done under OpenCV library in Python. When all NII files have been converted to PNG images, we can apply deep learning framework to these preprocessed PNG images (Sarraf and Tofighi 2016).

Results

To make the experiments more meaningful, first, we combine both Autism and normal controls images into one folder. Then we randomly split all images to 4 folders. 110376 images (3-fold) are taken as the training dataset; there are 65100 NC images and 45276 AT images among them. 36793 images (1-fold) are taken as the testing dataset; there are 21700 NC images and 15093 AT images among them. We repeat this process five times with different random seed. Figure 2 shows image slice examples for both AT and NC. Table 1 and Table 2 summarize the training and testing results. The sensitivity and specificity for test data are listed in Table

2. Here NC means normal controls, AT means autistic subjects. We have applied 30 epochs for each training process, with a batch size of 100. The training loss results for training 1 are displayed in Figure 3. From Figure 4, we can see that the test data accuracy rate converges to 100% after 2 epochs. The training loss and test data accuracy rate figures for the other 4 training sets are similar to training 1.



AT slice NC slice

Figure 2: Autistic subject and Normal Control fMRI image slice

Table 1: Training data

Training Data	NC Count	AT Count	Training Time
Train1	65100	45276	10 min 1 sec
Train2	65100	45276	10 min 1 sec
Train3	65100	45276	10 min 7 sec
Train4	65100	45276	10 min 1 sec
Train5	65100	45276	9 min 56 sec

Table 2: Testing Results

Testing Data	NC Count	AT Count	Sensitivity	Specificity
Test 1	15093	21700	99.99%	100%
Test 2	15093	21700	99.98%	100%
Test 3	15093	21700	99.99%	99.99%
Test 4	15093	21700	99.99%	100%
Test 5	15093	21700	99.99%	100%

By using the CNN LeNet-5 architecture, we successfully classified functional MRI image of ASD from Normal Controls. The results listed in Table 2 show that we obtained satisfactory results for both sensitivity and specificity. Because of the high speed of the GPU implementation, the training model can be trained in a concise time even though the training data are large.

Figure 3: Loss function for training data

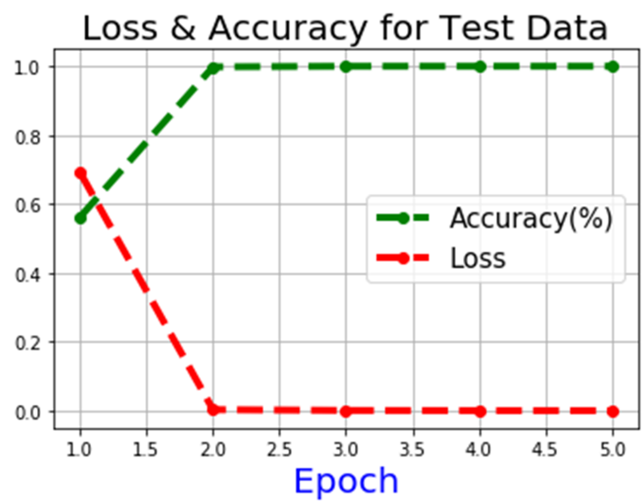


Figure 4: Loss function and classification accuracy rate for test data

Conclusion

Over the last several years, deep neural networks have played an increasingly important role in the field of pattern recognition and machine learning. In this paper, we implement CNN LetNet-5 architecture for autism fMRI image classification under the NVIDIA GPU platform. By using the CNN LeNet-5 architecture, we successfully classified functional MRI image of ASD from Normal Controls. The results in Table 2 demonstrate that we obtained satisfactory results for both sensitivity and specificity.

Although many researchers have studied functional connectivity of ASD, no one has applied deep learning framework to classify ASD functional MRI images. In this paper, we implemented slice-level image classification by using deep learning CNN. This study can help us the further research to locate the brain pathology of ASD subjects and identify the autism biomarkers, which will be our future work.

Literature Cited

Chellapilla K, S Puri, and **P Simard.** 2006. High performance convolutional neural networks for document processing. *In:* G. Lorette, editor. Tenth International Workshop on Frontiers in Handwriting Recognition, La Baule (France), (Universite de Rennes 1, Suvisoft. http://www.suvisoft.com) p 386-408.

Dajani DR and **LQ Uddin.** 2016. Local brain connectivity across development in autism spectrum disorder: A cross-sectional investigation. Autism Research 9(1):43-54

Fels SS and **GE Hinton.** 1993. Glove-talk: A neural network interface between a data-glove and a speech synthesizer. IEEE transactions on Neural Networks 4(1):2-8.

Heaton J. (2015). Encog: library of interchangeable machine learning models for Java and C#. Journal of Machine Learning Research 16:1243-1247.

Huang FJ, YL Boureau, and **Y LeCun.** 2007. Unsupervised learning of invariant feature hierarchies with applications to object recognition. *In* 2007 IEEE Computer Society Conference on Computer Vision and Pattern Recognition, CVPR'07. p 1-8.

Igelström KM, TW Webb, and MS Graziano. 2016. Functional connectivity between the temporoparietal cortex and cerebellum in autism spectrum disorder. Cerebral Cortex 27(4):2617-2627.

Ji S, W Xu, M Yang, and **K Yu.** 2013. 3D convolutional neural networks for human action recognition. IEEE transactions on pattern analysis and machine intelligence 35(1):221-231.

Karpathy A, G Toderici, S Shetty, T Leung, R Sukthankar, and **L Fei-Fei.** 2014. Large-scale video classification with convolutional neural networks. *In:* 2014 IEEE Conference on Computer Vision and Pattern Recognition CVPR’14. p 1725-1732.

Kato H, M Kanematsu, X Zhang, M Saio, H Kondo, S Goshima, and **H Fujita.** 2007. Computer-aided diagnosis of hepatic fibrosis: preliminary evaluation of MRI texture analysis using the finite difference method and an artificial neural network. American Journal of Roentgenology 189(1):117-122.

Kha, J, JS Wei, M Ringner, LH Saal, M Ladanyi, F Westermann, and **PS Meltzer.** 2001. Classification and diagnostic prediction of cancers using gene expression profiling and artificial neural networks. Nature Medicine 7(6):673.

Krizhevsky A, I Sutskever, and **GE Hinton.** 2012. ImageNet classification with deep convolutional neural networks. *In:* Advances in neural information processing systems. p 1097-1105.

Lang KJ, AH Waibel, and **GE Hinton.** 1990. A time-delay neural network architecture for isolated word recognition. Neural Networks 3(1):23-43.

Lawrence S, CL Giles, AC Tsoi, and **AD Back.** 1997. Face recognition: A convolutional neural-network approach. IEEE transactions on Neural Networks 8(1):98-113.

LeCun Y, L Bottou, Y Bengio, and **P Haffner.** 1998. Gradient-based learning applied to document recognition. Proceedings of the IEEE 86(11):2278-2324.

LeCun Y, B Boser, JS Denker, D Henderson, RE Howard, W Hubbard, and **LD Jackel.** 1989. Backpropagation applied to handwritten zip code recognition. Neural computation 1(4):541-551.

LeCun Y, P Haffner, L Bottou, and **Y Bengio.** 1999. Object recognition with gradient-based learning. *In* D.A. Forsyth *et al.* (editors). Shape, contour and grouping in computer vision. Lecture Notes in Computer Science 1681. Springer (Berlin, Heidelberg). p 319-345.

Lippmann R. 1987. An introduction to computing with neural nets. IEEE ASSP magazine 4(2):4-22.

Olivito G, S Clausi, F. Laghi, AM Tedesco, R Baiocco, C Mastropasqua, M Molinari, *et al.* 2017. Resting-state functional connectivity changes between dentate nucleus and cortical social brain regions in autism spectrum disorders. The Cerebellum 16(2):283-292.

Oquab M, L Bottou, I Laptev and **J Sivic.** 2014. Learning and transferring mid-level image representations using convolutional neural networks. *In:* 2014 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)’14. p 1717-1724.

Petrosian AA, DV Prokhorov, W Lajara-Nanson, and **RB Schiffer.** 2001. Recurrent neural network-based approach for early recognition of Alzheimer's disease in EEG. Clinical Neurophysiology 112(8):1378-1387.

Poldrack RA, JA Mumford and **TE Nichols.** 2011. Handbook of functional MRI data analysis. Cambridge University Press.

Rawat W and Z Wang. 2017. Deep convolutional neural networks for image classification: A comprehensive review. Neural computation 29(9):2352-2449.

Rowley HA, S Baluja, and T Kanade. 1998. Neural network-based face detection. IEEE Transactions on pattern analysis and machine intelligence 20(1):23-38.

Sarraf S and **G Tofighi.** 2016. Deep learning-based pipeline to recognize Alzheimer's disease using fMRI data. Future Technologies Conference (FTC); December 2016; San Francisco, CA: IEEE. p. 816-820.

Schmidhuber J. 2015. Deep learning in neural networks: An overview. Neural networks 61:85-117.

Silver D, A Huang, CJ Maddison, A Guez, L Sifre, G Van Den Driessche, and **S Dieleman.** 2016. Mastering the game of Go with deep neural networks and tree search. Nature 529(7587):484-489.