Significant CC400 Functional Brain Parcellations Based LeNet5 Convolutional Neural Network for Autism Spectrum Disorder Detection

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Significant CC400 Functional Brain Parcellations Based LeNet5 Convolutional Neural Network for Autism Spectrum Disorder Detection

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Abstract. Machine learning and computer vision have opened new pathways to investigate imaging data captured from different sensors. Numerous application areas are getting benefit from these advancements and one of these areas is medical imaging. Despite rapid advancements in machine learning based medical condition diagnosis systems (CADs), some ailments and disorders are hard to diagnose/classify due to the absence or the lack of consensus on biomarkers for specific disorders, like the Autism Spectrum Disorder (ASD). In this study, the challenging problem of classification of ASD using the magnetic resonance imaging (MRI) data is tackled. Hence, we propose an interpretable deep neural network based approach for ASD detection from MRI images. Our proposed explanation method is based on the selection of four regions of interest from the MRI images. The four significant CC400 functional brain parcellations are then concatenated and fed to a LeNet-5-based convolutional neural network to predict ASD. The performances of the proposed approach are evaluated on ABIDE dataset and promising results are achieved. Three augmented datasets are considered and an accuracy of 95% is achieved by using LeNet-5 which outperforms VGG16 and ResNet-50. The achieved accuracy outperforms also the existing deep neural networks based approaches on ABIDE dataset. The use of the four significant CC400 functional brain parcellations makes our approach more interpretable and more accurate.

Keywords: Deep learning · Convolutional Neural Network · Autism Spectrum Disorder · ABIDE I · MRI images

1 Introduction

Autism Spectrum Disorder (ASD) is a neurodevelopmental disorder that is perceived by a lack of emotional intelligence and social interaction. It is also

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recognized by repetitive, exaggerated, extreme and stigmatized behaviour [1]. This syndrome is not a rare condition, but a spectrum with several disabilities. According to DSM-IV APA (American Psychiatric Association) and ICD-10 WHO (World Health Organization 1993), behavioral and social characteristics is used to distinguish and to define ASD [2,3]. WHO reports, ASD affects one child in 160. An ASD subject has an abnormal social interaction with a limited enjoyment and interests in specific tasks and activities, and a limited of verbal and nonverbal communication skills. Children with ASD can improve their quality life, improve their social skills and reduce communication problems with an early diagnosis during childhood. However, ASD is difficult to diagnose because there is no medical test, like a blood test, to find the disorder. Regarding that, a lot of people are not diagnosed until they are teenagers or adults. This delay in diagnosis may affect the life of the ASD person and it delays to get help and needed health care services.

Magnetic-resonance Imaging (MR) examination provides a powerful tool for studying brain structural changes in people with ASD. In fact, MRI is a non-invasive technique universally used to study the brain and its structure thanks to regional network(s). Thus, subtle variations in neural patterns/networks are disclosed using this technique and new and relevant biomarkers can be defined for ASD. MRI scans are further divided into: (1) functional MRI (f-MRI) and (2) structural MRI (s-MRI) [4]. fMRI is a non-invasive technique for measuring brain activity and identifying changes associated with blood flow. Combining fMRI alongside with deep learning have been found to be the most essential and fruitful tool to yield significant results [5].

In this paper, a new and explainable deep learning-based approach is proposed to detect ASD from MRI images and evaluated on ABIDE dataset. The proposed approach is based learning deep patterns from significant CC400 functional brain parcellations for ASD detection. In addition to the high performance of our proposed approach, it offers an accurate ASD decision support system with interpretability ability for more trust in machine learning approaches. The paper is organized as follows: in the next Sect. 2, the literature review is presented, then the proposed approach is presented (refer to Sect. 4). After, experimental setups and achieved results are discussed in Sect. 5. The last Sect. 6 dispense our conclusion and our planned future work.

2 Related Work

Numerous approaches have been proposed in the literature for the detection of psychological and neurodevelopmental disorders [6,7]. Among these approaches, several ones are reported for ASD detection from MRI images. Brain activation patterns are recorded using fMRI of 17 adults diagnosed with high functioning autism (HFA) and 17 normal adults as control group [7]. These 17 adults who participated in the experiment were scanned while they imagined 16 social interaction scenarios. Authors presented machine learning technique based on Gaussian Naive Bayes (GNB) classifiers to classify autistic and control group.

Proposed approach achieved average recognition accuracy of 97%.
Sabuncu et al. [8] employed three different machine learning algorithms i.e. Support Vector Machine (SVM) [9], Neighborhood Approximation Forest (NAF) [10] and Relevance Vector Machine (RVM) [11] to analyze different neurological disorders, which include Alzheimer, schizophrenia, autism, attention deficit and hyperactivity disorders. Authors conducted machine learning experiments on structural MRI (s-MRI) data (s-MRI presents morphological features of brain) collected from 2800 individuals, gathered from six publicly available datasets[1]. Study conducted by Sabuncu et al. achieved average recognition accuracies of 59%, 70% and 86% for Autism, Schizophrenia and Alzheimer respectively using 5-fold cross-validation learning strategy.

Recent studies are based on deep learning algorithms that uses large brain imaging datasets for ASD detection. A transfer learning strategy is performed in [1]. Another Convolutional Neural Networks (CNN) based approach is proposed in [3] by using parallel filters to study the brains regions. In order to analyze MRI images, some researchers employed Convolutional Neural Networks (CNN) which are special deep neural networks well suited for analyzing structures present in the images. Sherkatghanad et al. [12] proposed architecture for ASD detection based on CNN. They also used resting-state functional magnetic resonance imaging (rsfMRI) data from ABIDE dataset and an average accuracy of 70.22% is achieved. Apart from achieving recognition accuracy, Zeinab et al. have also graphically shown which areas of brain are significant/salient in detecting ASD. Huang et al. [13] proposed a graph based model for detection of ASD. Authors have used a three-layer deep belief network (DBN) [14], where DBNs are probabilistic generative models. Proposed model is tested using resting-state functional magnetic resonance imaging (rsfMRI) data from ABIDE dataset and 76.4% of mean accuracy is achieved.

3D CNN based approach is proposed in [15]. Researchers have also proposed models that exploit the time-series nature of rs-fMRI Data. One such model is proposed by Dvornek et al. [16]. They utilized long short-term memory (LSTMs) for ASD classification. Authors have conducted experiment using data from ABIDE-I dataset [17] and they have achieved accuracy of 68.5%. In another article by Dvornek et al. [18], different methodologies/scenarios were proposed that incorporated phenotypic data with resting-state functional magnetic resonance imaging (rsfMRI) into recurrent neural networks (RNN) for classifying ASD. Proposed model achieved average recognition accuracy of 70.1% on the ABIDE dataset [17] when raw phenotypic data was combined directly with the baseline RNN model.

More recently, researchers applied autoencoders to detect ASD and augmented datasets to achieve a strong trained classifier. One such framework is proposed by Eslami et al. [19]. They proposed a framework (ASD-DiagNet) for automatic detection of ASD using functional magnetic resonance imaging (fMRI) data. Their proposed method is based on application of autoencoders and single layer perceptron (SLP). For robust training of proposed architecture, authors not

[1] https://www.nmr.mgh.harvard.edu/lab/mripredict.

only used ABIDE dataset but also its augmented version (linear interpolation). By using autoencoders, proposed architecture was able to reduce feature vector, thus reducing time complexity of model training as well. Proposed architecture achieved average recognition accuracy of 82% on data from 10 sites. Another framework that utilizes autoencoders to detect ASD is proposed by Wang et al. [20]. Wang et al. [20] proposed multi-atlas feature representation based method. Multi-atlas feature representation was deduced by applying stacked denoising autoencoder (SDA). Classification of features was achieved using Multi-Layer Perceptron (MLP) and Ensemble learning method. Proposed architecture was tested on ABIDE dataset and a mean accuracy of 74.52% is achieved.

3 Motivations and Contributions

As shown in the previous section, deep learning is the new trend in ASD diagnosis from MRI images. Despite the high performances and the accurate predictions of deep learning-based approaches, they remain black boxes and we cannot fully explain their predictions. Healthcare is one the applications that impact human lives and interpretability is crucial in healthcare decision support systems. A model's output is not very meaningful or accountable if it can't be explained. To trust a system and to deploy it in real-world healthcare applications, we must be able to explain why it has given an output. To the best of our knowledge, no explainable deep learning-based approach have been proposed for ASD diagnosis from MRI images in the literature.

In this paper, we aim to reach high performances by leveraging high advances in deep learning, while having the ability to interpret and to explain the deep neural network predictions. Thus, the main contributions of this paper are:

- A new approach for MRI-based automatic ASD detection via deep learning,
- An explainable deep neural network-based approach for ASD decision support system,
- Investigate local brain regions based high-level descriptors for ASD detection,
- A comparative analysis of three deep neural networks for ASD detection,
- Study of the importance of data augmentation in the proposed framework,
- Our proposed achieves very promising results on ABIDE dataset.

4 Proposed Approach

As shown in Fig. 1, our proposed approach is constituted of four steps. After a preprocessing step, local Regions of Interest (ROI) are extracted and concatenated into one image. Then, data augmentation is performed to overcome over-fitting issue related to training Deep Neural Networks. Finally, the augmented data are fed a LeNet-5 based deep neural network. More details about the proposed approach are given in the following.

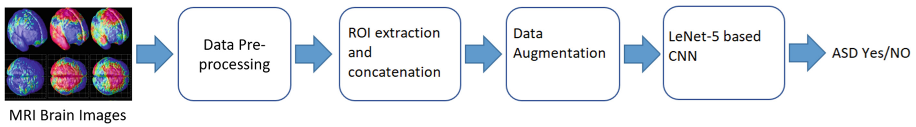

Fig. 1. The proposed approach for ASD detection

4.1 Preprocessing

The Preprocessed Connectomes Project (PCP) published preprocessed versions of the ABIDE dataset with several pipelines [21] using: (1) the NeuroImaging Analysis Kit, (2) the Data Processing Assistant for Resting-State fMRI (DPARSF), (3) the Configurable Pipeline for the Analysis of Connectomes (CPAC) and (4) the Connectome Computation System (CCS). In this work, We used the data processed through Configurable Pipeline for Analysis of Connectomes(C-PAC). The used C-PAC pipeline[2] is constituted of

- a resampling to RPI orientation,
- a slice timing correction,
- a motion correction,
- a global mean intensity normalization and standardization of functional data
- extraction of ROI time series.

In our work, the version that consider a data extraction with global signal regression and a band-pass filtering (0.01–10 Hz) is used.

4.2 Regions of Interest (ROI) Selection

It has been demonstrated that four brain areas are significant in the diagnosis of ASD subjects based on the CC400 functional parcellation atlas of the brain [3]. In the CC400 atlas, the whole brain is parcellated into 400 regions. These regions are called C326, C115, C247 and C188 with the centers of mass equal to (−22.5; −85.5; 31.0), (61.9; −36.3; 34.4), (−2.1; −43.0; −40.7) and (−27.6; −40.2; −17.6), respectively. The four ROI (See Fig. 2) quoted above are the regions of the brain with the most information to detect ASD. In this work, we extracted the four brain areas, We concatenated them into 2D images and then resized them to fit the input size of our deep neural network of 156 * 32.

4.3 Data Augmentation

Data augmentation is an essential step to overcome over-fitting and data scarcity problems when training deep neural networks architectures, it also improve the robustness of the proposed architecture against noise. A transformation-based technique is performed to generate new images. Five transformation functions are considered which rescale, zoom, shift and shear an original image.

[2] https://fcp-indi.github.io/docs/latest/user/quick.html#default-pipeline.

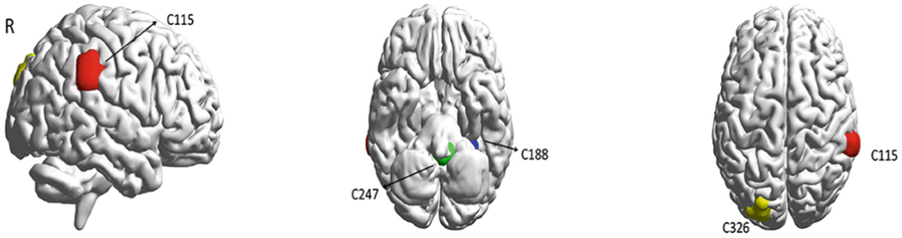

Fig. 2. The most discriminant and important regions of Interest for ASD classification, that are extracted, then concatenated and fed to the LeNet-5 based CNN. These regions are called C326, C115, C247 and C188 with the centers of mass equal to (−22.5; −85.5; 31.0), (61.9; −36.3; 34.4), (−2.1; −43.0; −40.7) and (−27.6; −40.2; −17.6), respectively.

Three expanded and balanced datasets are generated: **Dataset1** of 10k images, **Dataset2** of 30k images and **Dataset3** of 100k images. The performances of the proposed approach are evaluated in the three augmented datasets (refer to Sect. 5.3).

4.4 LeNet-5 Based Deep Neural Network for ASD Detection

The resulting 2D image from the previous steps are fed to LeNet-5 based deep neural network [22]. LeNet-5 is a CNN. It is one of the earliest CNNs, it was firstly implemented for digit images classification on MNIST dataset [22]. Afterwords, it has been applied to solve several problems and it has been demonstrated its high performances in classifying images like for example, for the classification of Alzheimer's disease using fMRI data [23], sleep apnea detection from a single-lead ECG signal [24], hyperspectral images classification or for the classification of pulmonary nodules of thoracic CT images [25] and also for efficient brain tumor segmentation in MRI images [26]. It has been shown that LeNet-5 can deal with small size datasets [22,27] and it requires small size of the input image like in our work. We have compared three famous and popular CNNs (VGG16, LeNet-5 and ResNet) and we found the LeNet-5 is the best performing CNN among them as described in Sect. 5.3.

The LeNet-5 architecture used in this work has 6 layers, not counting the input, all of which contain trainable parameters (weights) as shown in Fig. 3. The six layers are two convolution layers followed by two average pooling layers, and two fully connected layers. Although the LeNet architecture is firstly designed for training a 28×28 MNIST dataset, our input is a 150×32 pixel image. The output layer of the LeNet-5 is a dense layer of size 2 for binary ASD detection with a sigmoid activation function. The bias and the weight matrices are learned through a training process. In our work, the classification is learned by optimizing the cross-entropy between the classification outcome (predicted labels) and the ground truth (true labels), instead of learning the gaussian connection as described in the original paper of [22], using the function defined by:

$$L = 1/N \sum_{i=1}^{n} (Y_i - \hat{Y}_i)^2 \tag{1}$$

where L is the average loss for all the training samples, $\hat{Y}_i$ is the predicted ASD label and Y_i is the real ASD label.

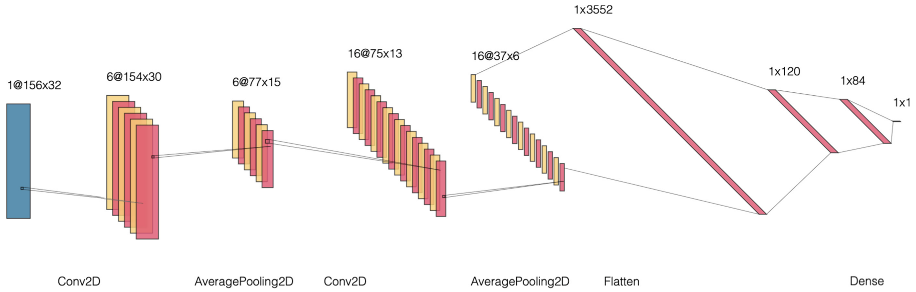

Fig. 3. Our Lenet-5 architecture used as final model

5 Results and Experiments

5.1 Dataset

The rs-fMRI images from Autism Brain Imaging Data Exchange (ABIDE-I) dataset [17] are used to evaluate the performances of the proposed approach. ABIDE is a collaborative consortium that provides neuroimaging data of control and ASD subjects with their phenotypic information. It is born from the collaboration between universities and laboratories around the world. It was built to have an easiest access to a large dataset of MRI images in order to have a better understanding of the disease. These images were collected and annotated across more than 24 brain imaging laboratories around the world. In this work, we use ABIDE-I dataset collected from 17 different imaging sites. It contains of 1112 subjects (539 autism subjects and 573 healthy control subjects).

5.2 Implementation Details

In this work, the choice of the optimal hyperparameters was done thanks to the model selection algorithm GridSearchCV[3] on 3, 4 and 5 fold cross-validations. A batch size of 32 is considered in all the experiments. The range of values that have been explored are: (1) Adam and Rmsprop for the optimizer, and 5, 10, 15, 25 and 40 for the number of epochs.

[3] GridSearchCV.

GridsearchCV uses an exhaustive search over specified parameter values for an estimator (the LeNet5 model for this work). The parameters of the estimator are optimized by cross-validated grid-search over a parameter grid. All the possible combinations of parameter values are evaluated and the best combination is retained.

The parameters of the final model are set to Adam for the optimizer, 25 for the number of epochs, 32 for batch-size, a momentum equal to 0.9 and a learning rate equal to 0.001. No fine-tuning is performed and three deep neural networks are trained from scratch as described in Sect. 4 using the three expanded datasets. For all experiments, the dataset is randomly divided into 80% for training, 20% for testing. In order to keep a balanced ratio between the labels, autistic and non-autistic subjects are first separated before performing the random split.

5.3 Performances

Performance Comparison of the LeNet-5 and Other Deep Neural Networks: The performances of the proposed approach have been evalutated using three popular deep neural networks (LeNet5, VGG16 and ResNet50). LeNet5 is a simple and an early convolutional neural network consisting of seven layers: 2 convolutional layers, 2 subsampling layers and 2 fully connected layers. VGG16 [28] is more deeper than LeNet5, it is formed of 13 convolutional layers, and 3 top fully connected layers. While ResNet50 is a deep residual neural network [29] designed to train deep networks with lower complexity. It consists of blocks of convolutional layers and residual shortcut connections.

As shown in Table 1, LeNet5 outperforms surprisingly VGG16 and ResNet50 with an accuracy of 65% on Dataset1. LeNet5 is the more shallow CNN among the tested ones. However, it outperforms the other ones. This is due to the small size of the input image ($156 * 32$) which represent the concatenation of the four significant CC400 functional brain parcellations. VGG16 and ResNet50 have close performances and they achieved the accuracy of 55% and 56% in MRI images classification for ASD diagnosis.

Importance of Data Augmentation. In order to overcome the lack of labeled datasets required to train deep neural networks, a data augmentation step is performed for MRI images generation as described in Sect. 4.3. The best performing deep neural network (LeNet5 according to our experiment in the previous section), is evaluated on three augmented datasets (see Table 1).

The data augmentation step is a crucial step in our proposed approach and without it an over-fitting problem is shown. To overcome it, the size of the training dataset must be increased. When increasing the size of the original dataset, the proposed LeNet5 based framework reaches an accuracy of 80% on Dataset2 and 95% on Dataset3. The more data is used for the training, the most accurate the LeNet5-based framework becomes. The best performing LeNet5-based framework has an F1-score equal to 0.95, a precision equal to 0.95 and a recall equal to 0.95.

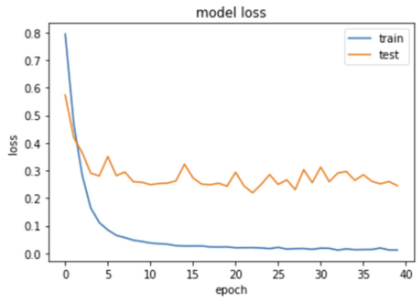

Fig. 4. Training and test loss in terms of training epochs of the LeNet-5 based CNN on Dataset 3.

The train and the validation sets in terms of number epochs of the proposed LeNet-5 based framework for binary ASD classification, is shown in Fig. 4. The proposed framework is not overfitting and training stops after 40 epochs when model performance stops improving.

The proposed method achieves significantly good performance on the augmented ABIDE dataset. Even with simple technique of expanding the training labels, the proposed deep neural network learns how to differentiate accurately between MRI images of control and ASD samples. Thus, the expansion of the labeled training dataset by generating new MRI images could significantly improves the performances of our approach and the achieved performance confirm the possibility of deploying the LeNet5 in a decision support system for ASD diagnosis.

Explainability of Our Proposed Approach: In addition to the high performances of our proposed approach, the output of DL can be explained by the different and the discriminant structure of the CC400 functional brain parcellations between healthy controls and ASD subjects. Only four brain areas are considered and features are learned from these regions of interest. By using our ASD decision support system, the clinician can justify his diagnosis by a disfunctioning in the C115, C188, C247, and C326 brain areas. More quantitative analysis of these brain regions could be performed.

Table 1. Proposed deep neural networks performances for ASD detection in term of accuracy based on different CNNs, and different dataset sizes

Dataset	Number images	VGG16	ResNet-50	LeNet-5
Dataset1	10 K	55%	56%	65%
Dataset2	30 K	–	–	80%
Dataset3	100 K	–	–	95%

Table 2. Comparison of different Deep learning approaches for autism detection disorder in terms of Accuracy

Method	Accuracy
Li et al. [1]	70.4%
Craddock et al. [30]	70%
Sherkatghanad et al. [3]	70.22%
Thomas et al. [15]	66%
Huang et al. [31]	76.4%
Ingalhalikar et al. [32]	71.35%
Jha et al. [33]	77.4%
Our proposed approach	95%

5.4 Comparison with State of Art Methods

Table 2 compares the performances of our LeNet5-based framework with existing state-of-the-art methods for ASD detection in terms of accuracy. Our proposed approach outperforms all existing approaches due to: (1) our data augmentation step, (2) the selection of the significant functional brain parcellations relevant in recognizing ASD and (3) the robustness of deep learning of ASD discriminating features.

6 Conclusion and Future Work

In this paper, a new deep learning based approach for ASD detection from MRI images is proposed. Four significant CC400 functional brain parcellations are extracted and concatenanted into one new input image. Then, the generated input image is fed to a LeNet5-based convolutional neural network. Promising results are achieved on ABIDE dataset that confirm the deployability of the proposed approach into an ASD decision support system. The proposed approach has the advantage of being interpretable and very accurate. The proposed deep learning solution will open new avenues in ASD detection from MRI images and it enables researchers and physicians to develop interpretable computer-aided diagnosis system. We demonstrated the importance of data augmentation on the performances of the framework. We plan for future works to evaluate our approach on others datasets and with different strategies of training.

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