Detection of Midline Brain Abnormalities using Convolutional Neural Networks

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Abstract

Patients with mental diseases have an increased prevalence of abnormalities in midline brain structures. The detection and study of these brain abnormalities in Magnetic Resonance Imaging requires a tedious and time-consuming process of manual image analysis. In this work, we explore, for the first time in the literature, an automated detection method based on CNNs. In particular, we compare different CNNs models to face this problem on a dataset of 861 subjects (639 patients with mood or psychotic disorders and 223 healthy controls) and obtain very promising results.

1 Introduction

Different studies have demonstrated that the prevalence of abnormalities in midline brain structures in patients with mental diseases is increased with respect to healthy patients [1]. Concretely, in this work, we focus on a variant cerebrospinal fluid (CSF) space formed between the leaflets of the septum pellucidum. This zone is called the cavum septum pellucidum (CSP) (see Figure 1). The presence of a CSP with a length from anterior to posterior part of the brain of around 1-1.4mm is considered normal anatomy of the brain, with an incidence of 60-80%[2], so a larger cavity will be considered as an abnormality.

Manually detecting this kind of abnormalities is a tedious task, and defining accurately the borders of this cavity can be quite controversial. Thus, a fully-automated method would help researchers and clinical professionals to study this abnormalities in detail. Up to our knowledge, there is not any work in the literature regarding this issue. In this work, we compare three different Convolutional Neural Networks (CNNs) to detect CSP slides-by-slide in Magnetic Resonance Images (MRI).

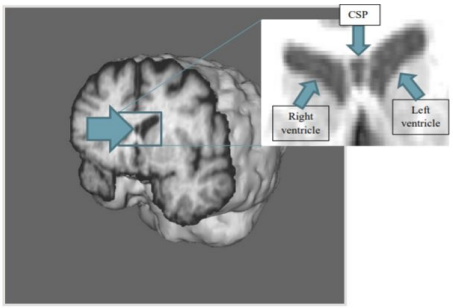

Figure 1: Cavum Septum Pellucidum (CSP) seen from the anterior part.

2 Data

In this study, the considered data consists in 861 subjects, from which 639 are patients with schizophrenia, bipolar disorder and other psychotic or mood disorders, and 223 healthy controls. In particular, we used T1-weighted MRI images. All subjects had been scanned with a 1.5 Tesla GE Signa scanner (General Electric Medical Systems) located at Sant Joan de Déu Hospital in Barcelona. A ground truth was created specifically for this study which contained 888 slices with CSP corresponding to 213 subjects and 26510 slices from subjects without CSP (highly unbalanced problem). All images were preprocessed with a pipeline that contained the following steps: Skull-stripping with FSL-BET (Brain Extraction Tool) software; Registration to transform all images with the same voxel coordinate which corresponds to the posterior genus with FNIRT (FMRIB's Linear Image Registration Tool); Segmentation of tissues with FSL-FAST (FMRIB's Automated Segmentation Tool) (Gray matter, white matter and CSF); Region of Interest definition: a volume of 50x30x30 voxels of the zone between ventricles (accorded with clinical experts from FIDMAG); Centering and scaling; Slicing to 2D images. Finally, to increase the number of samples of this CSP class (under-represented), we flip the image in both horizontal and vertical axes. This data augmentation procedure was consensuated with clinical experts from FIDMAG.

3 Methods

In this study, we compare two different 2D CNN models [5] implemented using the framework Keras[1] (in Python) to classify the ROI extracted slides-by-slide as with or without CSP. The first model stacks two Convolution layers with a kernel of 3x3 and an Activation layer which performs ReLu activations after every Convolutional layer at the beginning of the network, then a maxpooling layer with a 2x2 kernel, a dropout, then a flatten layer to reach 1D data, followed by two blocks of a Fully Connected, ReLu Activation and dropout.The final layer is a softmax activation layer. The first model is the simpler in terms of number of hyperparameters despite having more layers, it has 1,234,658 parameters. The second model is based on a more compact model, which has a single convolutional layer with a kernel of 3x3, followed by a max pooling layer and a dropout for regularization layer, which reduces the outputs until a binary classifier is obtained. Figure 2 shows the schema of the second model. In order to learn contextual information of the CSP, we propose to change the input of

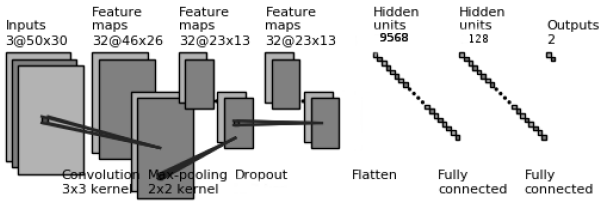

Figure 2: The second CNN model with 3 levels of zoom as input.

the second model by adding three different channels containing three different levels of zooming of the ROI. We expect this contextual information can help to better detect the CSP.

4 Results

In Table 1, we compare the results of the two models plus the variant of the second model. As can be seen, the results of the three methods are equivalent, although the last variant gives slightly better sensitivity and specificity. In Figure 3, we show qualitative results. As it can be seen in the examples, the definition of the CSP is not a simple task due to the fact that the boundaries are difficult to discriminate.

Our method is able to detect the presence of CSP from front to rear, in axial projection, of a MRI image. These approaches can classify almost perfectly slices where the CSP can be easily seen by an expert, like in the two first images in Figure 3. The main errors appear in slices where it is difficult to

[1] https://github.com/fchollet/keras

Table 1: Results

Method	Accuracy	Sensitivity	Specificity
CNN 1	0.97	0.98	0.97
CNN 2	0.98	0.98	0.98
CNN 2 (3 zoom levels)	0.98	0.99	0.99

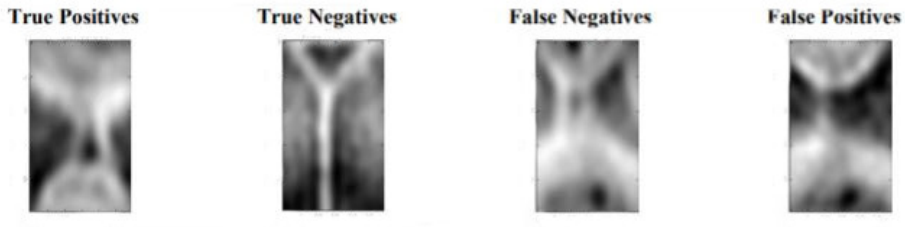

Figure 3: Qualitative results.

define the CSP even by an expert, like for example in the last image in Figure 3. In this FP example it is difficult to see if the CSP exists or not.

5 Conclusions

In this work, we studied, for the first time in the literature, the automatic detection of midline brain abnormalities in MRI slide-by-slide. For this propose, we compared three different approaches based on CNNs. The best approach reached 98% of accuracy. Despite having high accuracies, some false positives and false negatives are found in axial slices of the brain volume where it is anatomically impossible. This problem will be faced, in the further study, by using 3D semantic segmentation algorithms, such as the one in [3]. We expect the use of a 3D model will help to take into account spatial coherence information that can give robustness to results. We also plan to face the segmentation problem to obtain information of the volume of the CSP. For that we have a new ground truth of a subset of the data with the manually delineated borders and we will consider fully-convolutional networks such as the one presented in [4]. Up to our knowledge, there are no studies, in the literature, with such an amount of patients and studying the relation of this volume with mental disorders. Moreover, we can explore weighted minimizing functions that will take into account the unbalanced classes of the training set. Finally, we will integrate the best methodology to a public software to let researchers and clinical professionals conduct their own studies and incorporate this information in a translational manner to their patients.

References

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