DEVELOPMENT OF DEEP LEARNING TECHNIQUES FOR IMAGE PROCESSING IN MEDICAL FIELD

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Abstract

Magnetic Resonance Imaging (MRI) aims to identify a tumor at earlier stages of the disease, when treatment can be more successful. Despite the existence of screening programmes worldwide, the interpretation of MRIs is affected by high rates of false positives and false negative. Recently deep learning has been playing a major role in the field of computer aided diagnosis. One of its applications is the reduction of human judgment in the diagnosis of diseases. Especially, brain tumor diagnosis requires high accuracy, where errors in judgment may lead to disaster. For this reason, brain tumor classification is an important challenge for medical applications. Currently several methods exist for tumor classification but they all lack high accuracy. Here we present an artificial intelligence (AI) system that is capable of surpassing human experts in predicting if an MRI contains or not a brain tumor. To assess its performance in the clinical setting, we treated a representative dataset from the department of radiology of the University of Athens. We show an absolute accuracy of 76.8% in predicting if an MRI contains a cancer or a general non-tumor pathology.

INTRODUCTION

Brain tumors can threaten human life directly. If the tumor is detected at an early stage, the patient's survival chance increases. Distinguish if there's a tumor or not inside a magnetic resonance image (MRI) depends on the doctor's experience and knowledge [5], moreover, is a very hard and time consuming task even for the most experienced ones. Besides MRIs there are many medical imaging modalities used for the analysis and cure of various diseases but MRI is advantageous over other modalities due to its high spatial resolution and the excellent capability of discrimination of soft tissues and for this reason is widely used by radiologists in order to determine the existence of tumors or the specification of the tumors [4]. Since MRI is very efficient in providing detailed and finer description of human brain tissues, it is mostly preferred by medical experts for diagnostic purpose as well as research oriented activities [7]. The rich information provided by MRI about the human brain soft tissues has brought dramatic improvement in both qualitative and quantitative analysis of human brain structure [8] but on the other hand, the task becomes harder and highly time consuming. For this reason, using an automated and flawless working tumor classification system based on MRIs images is extremely important to aid radiologists to classify correctly brain tumors.. Artificial intelligence (AI) in medical imaging is a potentially disruptive technology. An understanding of the principles and application of deep learning techniques is an essential foundation to weave design solutions that accommodate ethical and regulatory requirements and to craft AI-based algorithms that enhance outcomes, quality, and efficiency. Moreover, a more holistic perspective of applications, opportunities, and challenges from a programmatic perspective contributes to ethical and sustainable implementation of AI solutions. Numerous computer-aided diagnosis (CAD) systems have been recently presented in the history of medical imaging to assist radiologists about their patients. For full assistance of radiologists and better analysis of magnetic resonance imaging (MRI), multi-grade classification of brain tumor is an essential procedure. Recent works on computer-aided medical diagnosis provide improved performances owing to the advent of deep learning concepts. Deep learning strategies have been extensively used in the medical image analysis of breast cancer studies [1, 2] and lung cancer diagnosis [3]. The increase in the number of images for studying the pathological characterization of the human brain, a higher accuracy can be achieved. But, there are many limitations in manual inspection such as lack of reproducibility, long processing time and inaccuracies in the diagnosis. In order to achieve more accuracy in diagnosis, improve the quality of treatment and reduce the computation time, many automatic algorithms have been proposed and developed [12–15]. In [6], emphasis was placed on the latest trend of deep learning techniques in this area. State-of-the-art algorithms, with an emphasis on deep learning methods, were argued. In our work a CNN-based deep learning model was designed to extract features from brain MRI and successfully applied to the considered brain tumor classification problem. The advantage of CNN-based classifier systems is that they do not require manually segmented tumor regions and provide a fully automated classifier.

PROPOSED METHODOLOGY

The proposed methodology is composed of three main stages: data preprocessing, classification and heatmap generation for discriminative localization. In the data preprocessing stage, denoising and normalization operations were employed in order to prepare the input images for the classification. In the classification stage, a fine tuned CNN based on InceptionV3 model [16] is combined with a feedforward neural network to classify both MRIs and radiomics [20] features as: Non-Tumor pathology and Tumor pathology. In the last stage, we use the class activation mapping technique [17] on the trained CNN to localize the regions that contribute to discriminate these classes, with the claim that if an MRI contains a defection, it will be localized without a prior specification on its position.

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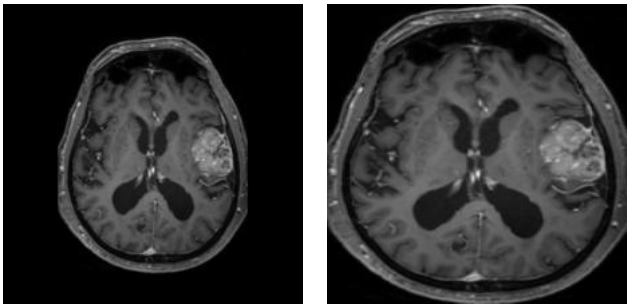

Figure 1: Crop Normalization

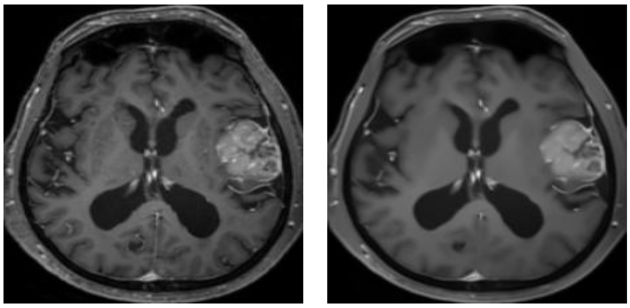

Figure 2: Non-Local Means Noise Removal

Data Set

Our dataset is composed by 1631 MR images in DICOM format, divided into three classes: 600 MRIs without any defection in it, labelled as "Normal"; 390 MRIs with a non-tumor pathology (Edema is one of the most common example), labelled as "Non-Tumor" and 641 MRis with at least one tumor inside, labelled as "Tumor". One of the main contribution of this work is that the MRIs in our dataset are heterogeneous with respect to the possible MRI acquisition modalities which are: T1, T2, Flair, Diffusion and Gadolinium. The idea of using different modalities for the MRIs in the dataset highly affects the overall accuracy of the model in a negative fashion but as drawback, an MRI can be classified irrespective of its acquisition modality.

Data Preprocessing

Data Preprocessing is that process in which the data gets transformed, in order to bring the raw features to such a state that can now be easily interpreted by the algorithms. In this work, several preprocessing steps that were involved:

Crop Normalization Is the approach of cropping an image according to extreme points in its contour. Fist of all, given an MRI, we compute the contour of the brain then, we find the coordinates of the farthest north, south, east, west points along the contour. With the coordinates of the extreme points along the contour, we can retain only the portion of the MRI which contains the brain and remove the unnecessary black background. This normalization can be seen as zooming in the region of the brain without losing information.

Reshaping Due to the fact that different acquisition modalities produce MRIs of different shape with different aspect ratio, we have to uniform the shape of the images in our dataset according to a preset format. Furthermore, our dataset is composed entirely of black & white images, which correspond of tensors of depth one while the classifier requires tensors of depth three. In order to adapt the dataset to the classifier requirements, we've build the required tensors by stacking three times the tensor associated to the MRI. At the end, an input images has the following shape: $299 \times 299 \times 3$.

Denoising & Normalization The reshaping process involves interpolation operations that inevitably add noise to the images in the dataset. In order to get rid off this additive noise, we used the non-local means algorithm [18] on the reshaped image. The non-local means algorithm replaces the value of a pixel by an average of a selection of other pixels values: small patches centered on the other pixels are compared to the patch centered on the pixel of interest, and the average is performed only for pixels that have patches close to the current patch. As a result, this algorithm can restore well textures, that would be blurred by other denoising algorithm. As last preprocessing step, we normalize the tensor associated to the image in order to have zero mean, unitary standard deviation and the values in the [0,1] range.

Classification of MRIs

For the classification stage, we used pre-trained deep convolutional neural network, the InceptionV3 model using the transfer learning technique as initialization for its weights.

Model Our classification model is mainly based on the InceptionV3 model. It is a deep convolutional neural network from the Google Brain team and is a widely-used image recognition model that has been shown to attain greater than 78.1% accuracy on the ImageNet dataset. The model itself is made up of symmetric and asymmetric building blocks, including convolutions, average pooling, max pooling, concats, dropouts, and fully connected layers. Batch normalization is used extensively throughout the model and applied to activation inputs. In order to handle both images and raw vectors, before the classification we have concatenated the feature map that comes from the last layer of the convolutional model with the last layer of a feedforward model that process the radiomics features. After the concatenation another feedforward neural network cares about the non-linear mapping of the joint vector.

Transfer Learning as Weights Initialization In practice, it is almost impossible that a deep convolutional neural network is trained with success using random weights initialization. The main reason is that for a given task, there's no dataset with a sufficient number of data samples to overcome the random weights initialization. Alternatively, is has become quite a standard procedure to use the weights taken

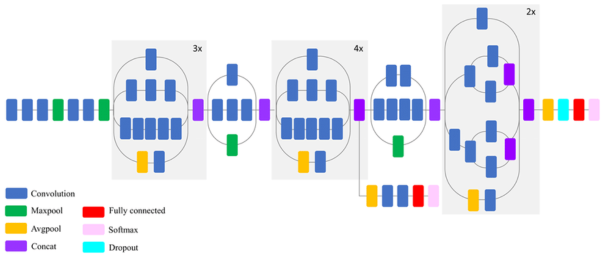

Figure 3: Model

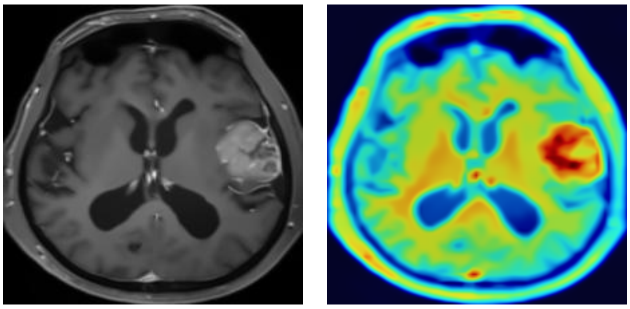

Figure 4: CAM applied to the denoised mri

from the same model trained on a huge dataset referring to this procedure as transfer learning. Intuitively, this technique consist in taking the information learned from a task for improving the learning process in a new similar task. In this work, we have initialized the weights of our model with the ones optimized for the classification of the ImageNet dataset.

Discriminative Localization

The final stage of this work is to apply the class activation mapping technique in order localize class-specific regions without specifying a priori where the class-related object is.

Class Activation Mapping Technique The class activation mapping technique, introduced by Zhou et al. [17] explicitly enables the convolutional neural network to have remarkable localization ability even if it is trained on a classification task rather than a detection task. It can be shown that the convolutional filters of the network behave as object detectors even if the location of the object is unknown at the time of the training. The core idea is to perform a global average pooling on the convolutional feature maps and use the result to identify the importance of the image regions by projecting back the weights of the output layer onto the convolutional feature maps. The final output is computed by a weighted sum of the last convolutional layer.

RESULTS & DISCUSSION

CONCLUSION & FUTURE DEVELOPMENTS

This paper presents an automatic framework to classify brain MRI images and localize eventual defections. In order to extract the correct features, several preprocessing techniques were involved: cropping the dark corners around the brain, Non-Local means noise removal and MRI normalization. For improving the performances of the classification, we used the transfer learning technique on InceptionV3 by initializing its weights with the ones optimized for the ImageNet classification task so it was possible to achieve such high accuracy even on such small and heterogeneous dataset. In order to tune the hyper-parameters of the last layers we adopt a modified version of the random search [19] which grants robustness to the useless hyper-parameters. After the classification, we used the CAM technique to localize defection for the MRIs classified as abnormal. The future possibilities of this work could be use data augmentation to introduce variations in the data sample which leads to have a model which generalize better the data and prevent overfitting. Another important improvement could be the training of the model including non-images data like: patients data, radiomics and clinical history; this could allow the users of the framework to analyse which features will affect the diagnosis.

REFERENCES

[1] M. Yousefi, A. Krzyzak, C.Y. Suen, Mass detection in digital breast tomosynthesis data using convolutional neural networks and multiple instance learning, Comput Biol. Med. 96 (2018) 283–293.

[2] McKinney, S.M., Sieniek, M., Godbole, V. et al. International evaluation of an AI system for breast cancer screening. Nature 577, 89–94 (2020).

[3] Y. Gu, X. Lu, L. Yang, B. Zhang, D. Yu, Y. Zhao, T. Zhou, Automatic lung nodule detection using a 3D deep convolutional neural network combined with a multi scale prediction strategy in chest CTs, Comput. Biol. Med. 103 (2018) 220–231.

[4] Pereira S, Pinto A, Alves V, Silva CA. Brain tumor segmentation using convolutional neural networks in MRI images. IEEE T Med Imaging 2016; 35: 1240-1251.

[5] Dandıl, Emre and Çakıroğlu, Murat and Ekşi, Ziya. Computer-aided diagnosis of malign and benign brain tumors on MR images. ICT Innovations 2014; 18-23 September 2017; Skopje, Macedonia. pp. 157-166.

[6] Ali Işın and Cem Direkoğlu and Melike Şah. Review of MRI-based brain tumor image segmentation using deep learning methods. Procedia Comput Sci 2016; 102: 317-324.

[7] M. Shenton, R. Kikinis, F. Jolesz, et al., Abnormalities of the Left Temporal Lobe and Thought Disorder in Schizophrenia, N. Eng. J. Med, vol. 327, (1992), pp. 604-612.

[8] L.M. Fletcher-Heath, L.O. Hall, D.B. Goldgof, F.R. Murtagh, Automatic Segmentation of Non Enhancing Brain Tumors in Magnetic Resonance Images, Artif. Intell. Med, vol. 21, no. 1-3, (2001), pp. 43-63.

[9] R.A. Lerski, K. Straughan, L.R. Schad, D. Boyce, S. Bluml, I. Zuna, MR Image Texture Analysis: an Approach to Tissue Characterization, Magn. Reson. Imaging, vol. 11, no. 6, (1993), pp. 873-887.

[10] H. K. Khan, A.S. Shah and M. A. Khan, Critical Evaluation of Frontal Image-Based Gender Classification Techniques, International Journal of Signal Processing, Image Processing and Pattern Recognition, vol. 9, no.10, (2016), pp. 313-324.

[11] Z. Ullah., M. Fayaz, and A. Iqbal, Critical Analysis of Data Mining Techniques on Medical Data, International Journal of Modern Education and Computer Science, vol. 8, no. 2, (2016), 42-48.

[12] C. A. Cocosco, A. P. Zijdenbos, and A. C. Evans, A fully Automatic and Robust Brain MRI Tissue Classification Method, Med. Image Anal., vol. 7, no. 4, (2003), pp. 513–527.

[13] A.S. Shah, M. N. A. Khan, F. Subhan, M. Fayaz, A. Shah, An Offline Signature Verification Technique using Pixels Intensity Levels, International Journal of Signal Processing, Image Processing and Pattern Recognition, vol. 9, no.8, (2016), pp. 205-222.

[14] J. Tohka, A. Zijdenbos, and A. Evans, Fast and Robust Parameter Estimation for Statistical Partial Volume Models in Brain MRI, NeuroImage, vol. 23, no. 1, (2004), pp. 84–97.

[15] V. Singh, Use of a Non-Stationary Markov Random Field in Brain Tissue Partial Volume Segmentation, M.S. thesis, Dept. Elect. Comput. Eng., McGill Univ., Montreal, QC, Canada, Feb. (2005).

[16] C. Szegedy, V. Vanhoucke, S. Ioffe, J. Shlens and Z. Wojna, Rethinking the Inception Architecture for Computer Vision, arXiv:1512.00567, (2015).

[17] B. Zhou, A. Khosla, A. Lapedriza, A. Oliva and A. Torralba, Learning Deep Features for Discriminative Localization, arXiv:1512.04150, (2015).

[18] A. Buades, B. Coll and J. -. Morel, "A non-local algorithm for image denoising," 2005 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR'05), San Diego, CA, USA, 2005, pp. 60-65 vol. 2.

[19] James Bergstra and Yoshua Bengio. 2012. Random search for hyper-parameter optimization. J. Mach. Learn. Res. 13, (2012), 281–305.

[20] Rizzo, Stefania et al.and Raimondi, Sara. 2018. Radiomics: the facts and the challenges of image analysis. European radiology experimental