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Implementation of MRI Based Brain Tumor Segmentation Using Convolutional Neural Networks

Vasim J. Tamboli

Assistant professor, Dept. of Electronics Engineering, Padmabhooshan Vasantraodada Patil Institute of Technology, Sangli, Maharashtra, India

ABSTRACT: In recent times, MRI analysis for studies of brain tumors is getting attracted due to an ascending need for efficient and objective evaluation of large amounts of data in image form. Automatic brain tumor segmentation from MR images is a challenging work that involves different disciplines covering pathology, MRI physics, perception by radiologists, and intensity and shape based image analysis. There are many problems and challenges related to the segmentation of tumors in brain.

A tumor is a bunch of tissue that's situated by an accumulation of abnormal cells. Because of the age they die the cells in the human body and are replaced by new cells. Tumors can spread through the blood and lymphatic systems to surrounding tissues. Tumor cells grow, even though the body does not need them and unlike normal old cells, they don't die. As this process continues, the tumour continues to grow as increasing numbers of cells are added to the mass. Cancer is a disease in which cells, almost anywhere in the body, begin to divide uncontrollably. With cancer and other tumors, something disrupts normal cycle of cells.

The fundamental of tumor recognition and detecting together have different methods of acquiring and its applications are very useful for our medical life. Detection of tumor throughout the MR image need quality check as well as data at each pixel is needed to be very precise. By this system, we also be forwarded to prepare a classify the various kind of brain tumor and their threatening effects

KEYWORDS – Brain tumor, brain tumor segmentation, convolutional neural networks, deep learning and magnetic resonance imaging.

I. INTRODUCTION

Brain tumors can have any kind of size, shapes and may appear anywhere in the body. It may appear in different intensities in MR image. Some tumors also mislead and deform other structures and appear to change intensity of the nearby region in conjunction with edema. Manual segmentation is a not easy and time-consuming task for many human experts, which makes an automated method of segmentation of brain tumors desirable [2]. An automotive method has many possible applications it can be used for surgical planning, treatment planning and vascular analysis.

In the last decade, clinical neuro-oncology has significantly changed and evolved. Two novel, strong subspecialties, neuropathology and neuroradiology have emerged from the most important diagnostic disciplines, pathology, and radiology. Management as well as treatment has become multidisciplinary at modern clinical neurooncology centres, including neurosurgery, neurology including epileptology, radiation oncology, medical and pediatric oncology, psychological oncology and palliative care [3]. These disciplines are ideally cooperating under the umbrella of a Neuro-Oncology Center with standardised diagnostic and therapeutic procedures. Such structures are needed to face the growing challenges in neurooncology that stem from the vast heterogeneity of intrinsic brain tumors, increasing rates of systemic cancer involvement of the nervous system and the great risk of complications of the nervous system as major side effects of current cancer therapies [4].

II. LITERATURE SURVEY

Magnetic Resonance Imaging (MRI) is a process using potent magnetic fields. This causes no ionising radiation. Situations where MRI is used include checking for tumor or sarcoma in the region of the head and neck. There are other tests such as Laboratory tests, genetic testing. Laboratory testing is performed to the point where a patient is suspected of having a tumor. A blood sample is normally taken for monitoring blood counts. Genetic testing may be useful when

it comes to certain tumor cases. Genetic testing, however, cannot detect tumors, but can identify part of the genetic defects that indicate a predisposition to tumor development and thus detect a genetic susceptibility to tumor [2]. MRI allows distinctly different types of tissue contrast to be created by various periods of excitement and repetition, making it a very versatile tool for imaging different interesting structures. Due to the existence and presence of brain tumours, one sequence of MRIs is not adequate to fully segment the tumour, including all of its sub-regions. Several MRI sequences are used in current clinical routine for the treatment and delineation of tumor compartments (Drevelgas and Papanikolaou (2011)). These sequences include T1-weighted MRI (T1), T1-weighted MRI including contrast enhancement (T1c), T2-weighted MRI (T2) and T2-weighted MRI including fluid attenuated inversion recovery (T2FLAIR). Comparing any method against the real case would be ideal [2].

The final diagnosis of the tumor is based on the opinion of one pathologist. A general practitioner does a patient's clinical exam. The doctor also considers the background of the patient's family, and charts the most common tumor risk factors.

This is, however, a major, if not impossible, challenge in this field. In the absence of a well-accepted ground-truth, an expert will compare the current gold standard for assessment with the manual segmentations. However, this is an exceedingly time-consuming and tedious task it is not objective in addition. Mazzara et al. (2004) noted 20% \pm 15% intra-rater volume variability, and 28% \pm 12% inter-rater volume variability for manual segmentation of brain tumor images. Manual segmentation, however, is time consuming also subject to difficult characterization of inter- and intra-rater errors. So usually doctors use rough measurements for evaluation.

Here, Inter-rater is 'score homogeneity exists in rating given by judges' and Intra-rater is 'score consistency in rating given by same person across multiple instances'. Hence, they consider 12 to 28% error in their report. Making report and reducing error rate is bit time consuming.

However, this is a daunting challenge, as the form, structure and position of this abnormality is highly variable. The effect of tumour mass also alters the arrangement of normal surrounding tissues. MRI images can also present problems between the same sequences and the acquisition scanners, such as inhomogeneity strength or different ranges of intensities.

Deep learning is a new and rapidly expanding field of machine learning. There are two properties to deep learning in general:

- (1) Multiple layers of non-linear units
- (2) Supervised / unsupervised learning of presentations of features on each layer

In 1980s, the past framework for deep learning was based on artificial neural networks (ANNs), while in 2006, the real effect of deep learning became straightforward. Since then, deep learning has been applied to a wide range of areas including automatic speech processing and recognition, image recognition and detection, natural language processing, and bio-informatics. Because of advances in high-throughput technologies, bio-medical data such as genomic sequences, protein functionality, and medical image have seen massive growth in the last decades. This flood of bio-medical big data requires more effective computational tools for storing, analyzing and interpreting such image or data [1].

In this paper we described normalization techniques of MRI. MR Images are changed by a distortion of the bias field that makes varying the intensity of similar tissues across the image. To get it right, we applied different techniques like histogram equalization, median filter, Adjust the contrast also mean and standard deviation, this gives us better results. As well as we implemented traditional pre-processing steps as crop the part of the image that contains only the brain, Resize the image and reduce intensity inhomogeneity.

III. PROPOSED MODEL

There are three main stages: pre-processing, classification via CNN and post-processing.

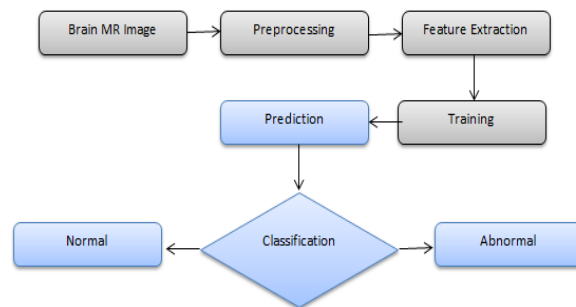


Fig. 1 Overview of the proposed approach.

A. Pre-Processing

MRI images are altered by the bias field distortion. This makes the intensity of the same tissues to vary across the image. To correct it, we applied mean and standard deviation, this gives us better results.

B. Convolutional Neural Network

CNN is easier to train and less prone to over fitting.

1. *Convolution*: The application of convolutional layers consists of convolving a signal or an image with kernels to obtain feature maps. The term convolution refers to the mathematical combination of two functions to produce a third function. It merges two sets of information. In the case of a CNN, the convolution is performed on the input data with the use of a filter or kernel (these terms are used interchangeably) to then produce a feature map.



Fig. 2 Result of Convolution process in CNN

2. *Activation Function*: It is responsible for non-linearly transforming the data. Rectifier linear units (ReLU), were found to achieve better results than the more classical sigmoid, or hyperbolic tangent functions, and speed up training.[]

3. *Pooling*: It combines spatially nearby features in the feature maps. This combination of possibly redundant features makes the representation more compact and invariant to small image changes, such as insignificant

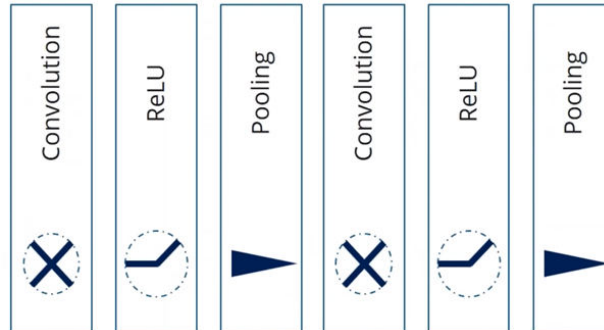


Fig. 3 Inner process in CNN

details, it also decreases the computational load of the next stages. To join features it is more common to use max-pooling or average-pooling.

IV. RESULTS

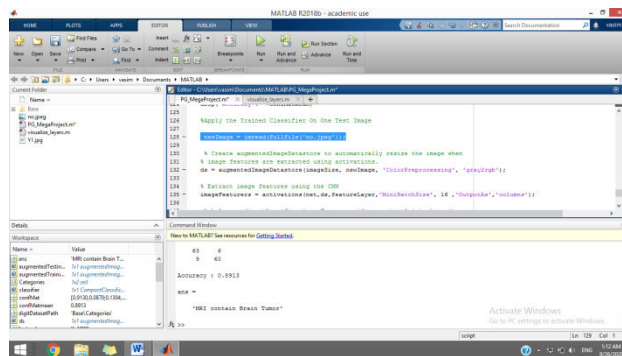


Fig. 4 Output for tumorous image

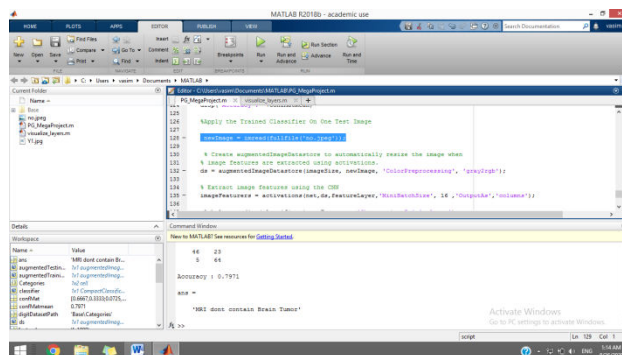


Fig. 5 Output for non-tumorous image

V. CONCLUSION

In summary, we propose a novel CNN-based method for the classification and segmentation of brain tumors in MRI images. We start by a pre-processing stage consisting of bias field correction, intensity and patch normalization. The CNN is built over convolutional layers with small kernels to allow deeper architectures.

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