Brain Tumor MRI Image Segmentation using Convolution Neural Network

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Abstract

A lump or development of abnormal cells in your brain is known as a brain tumour. There are several varieties of brain tumours. Some brain tumours are benign (noncancerous), while others are malignant (malignant). The greatest grade of glioma, the smallest brain tumour yet recognised, has an extremely poor prognosis. Thus, a crucial step in enhancing the quality of life for cancer patients is treatment planning. Multi-sequence MRI techniques for segmenting brain tumours are not standardised in clinical practise, necessitating the employment of a flexible segmentation strategy that makes the most use of all available MRI data. In order to precisely and successfully segment a tumour, we present an autonomous segmentation approach based on convolutional neural networks (CNN) that explores tiny kernels while also being effective against overfitting. Due to the smaller number of weights in the network, using tiny kernels enables the creation of a more complex architecture. To discover force markers from the training set, we employed depth normalisation as a pre-processing step. Later, supervised image classification using CNN is performed. Additionally, it accurately segments the tumour in the MRI picture.

Keywords: Convolution Neural Networks, Tumor, MRI, Image Segmentation.

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1. Introduction

A lump or development of abnormal cells in your brain is known as a brain tumour. There are several varieties of brain tumours. Some brain tumours are benign (noncancerous), while others are malignant (malignant). Primary brain tumours are those that start in the brain; secondary (metastatic) brain tumours are those that start in other regions of the body and spread to the brain. A brain tumor's rate of growth might vary significantly. Your nervous system's ability to operate depends on the development pace and location of a brain tumour. The sort of brain tumour you have, as well as its size and location, all affect your treatment choices.

Our body's control system is the brain. Brain tumours, which are both deadly and minor, are caused by the aberrant development of unusual tissues in the brain and its surrounding area. They are divided into two categories based on how they work. moderate and fatal primary and secondary brain cancers, respectively. Secondary brain tumours are brought on by the invasion of cancerous cells into the brain from other organs like the lungs or breast. More than any other malignancy, brain tumours are more likely to kill children and individuals under the age of 40.

Once diagnosed, gliomas decrease a person's life expectancy. For them to have a better chance of survival, treatment must be started right away. Brain tumours are diagnosed using MRI, X-ray, and CT scan; MRI is the only one of them that doesn't hurt the human body because it doesn't emit any radiation. Many other segmentation methods have been proposed, however we chose to segment the tumour using a supervised Convolutional Neural Network (CCN) of deep learning with the use of MRI data. This provides a precisely and effectively segmented picture for subsequent diagnosis [6] [9].

2. Related Works

Multiple slices throughout the 3D anatomical perspective make up an individual's brain Magnetic resonance imaging (MRI) scan. It is so difficult and time-consuming to manually segment brain tumours from magnetic resonance (MR) pictures. Additionally, an automatic categorization of brain tumours using an MRI scan is non-invasive, avoiding biopsy and improving the safety of the diagnosis procedure. The scientific community has worked extremely hard since the turn of the millennium and the late 1990s to develop an automated brain tumour segmentation and classification approach. There is therefore a wealth of research in the field that focuses on segmentation utilising deep learning, classical machine learning, and region growing techniques [8].

Similar projects have been completed in the field of classifying brain tumours according to their different histological types, with outstanding performance outcomes. The aim of this study is to present a thorough assessment of three recently suggested, key brain tumour segmentation and classification model methodologies, namely, region growth, shallow machine learning, and deep learning, taking into account state-of-the-art methods and their performance. The established works included in this review also address technical topics including feature extraction, datasets, pre- and post-processing procedures, strengths and drawbacks of various approaches, and metrics for measuring the performance of models [8].

From a database of imaging data, the qualitative information on brain shape is extracted automatically. It is quick and enables chartreading across a huge database [1]. Unwanted brain lumps may be found using a deep network and probabilistic neural network technique. When segmenting the tumour, ConvolutionalNeural Networks (CNN) with 3x3 and 7x7 are employed [7]. The training sets are subjected to Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA), which reduces the number of features employed. Nonlinear vs linear approaches were contrasted using the Support Vector Machine (SVM) classifier [3].

Feature extraction is used to extract the visual information from a picture, while feature selection is used to analyse the data and narrow down the feature sets. It provides decent accuracy. To find diseased brain cells, edge-based segmentation and watershed segmentation are used [2]. 150 T1 weighted MRI scans are tested to determine if the tumour is fatal or not. It is proposed to use a computer-aided, programmed segmenting approach [5]. It integrated the feature enlargement and described the area of interest in the image.

The images are then divided. After segmentation, the tested picture that contains subgroups is labelled. Following that, a tumour is found. Convolutional Neural Networks (CNN) are employed in this technique to segment the brain tumour. When compared to other approaches, it computes and detects the tumour fairly quickly. The tumour is segmented automatically and deep figures are used in the MRI scans. The picture must first go through preprocessing, then CNN classification and segmentation, and finally post-processing. In figure 1 using the flowchart, the procedure is depicted.

3. Proposed Work

For the system to produce correct results, several training sets are put into it. To obtain contrast, pre-processing enhancement of the input MRI picture is performed. Each configuration of the training set and testing picture is subjected to the depth normalisation approach. Each arrangement's histogram is compared, and patches within each group are standardised. To adjust the magnetic field non-linearities that might affect tissue types with identical intensity scales across various patients, bias field correction is carried out. The following steps make up pre-processing: First, denoising Identification of the tissues in an MRI is challenging due to noise.

De-noising is used to separate tumour from healthy brain tissue so that the area of interest (ROI) may be found and processed further. Wavelets, Non-Local Means, and Anisotropic Diffusion Filtering (ADF) are some of the several de-noising methods. The most popular approach overall continues to be ADF. Skull-stripping: The technique that clears up the distinction between tissues is the removal of the scalp, skull, and meninges from soft brain tissue. Due to the great accuracy of this approach, we can improve pre-surgical planning, tumour identification effectiveness, designing of neural surfaces, and brain cytology. Correction of bias fields It eliminates the impact of magnetic field nonlinearities on tissue types with comparable scales of intensity across various participants. c. Normalizing the intensity This crucial phase involves classification and grouping.

Anatomy-vigorous normalisation is utilised to improve the MRI and remove tumor-related confounding factors. And for all of the patches, the mean depth value and standard deviation are completed. Each collection of patches should be systematised so that it has a zero mean and unit fluctuation.

Isolating aberrant tissues from normal brain tissues is one of the most important challenges in any method for detecting brain tumours. It's interesting to note that the field of brain tumour analysis has successfully applied medical image processing ideas, notably on MR images, to automate the fundamental procedures, such as extraction, segmentation, and classification for close tumour diagnosis. Because of its non-invasive imaging capabilities, MR has received increased attention in research. Because tumours may vary in their sizes, locations, and forms, computer-aided diagnostic and detection systems are growing more difficult and are still an unsolved problem [9].

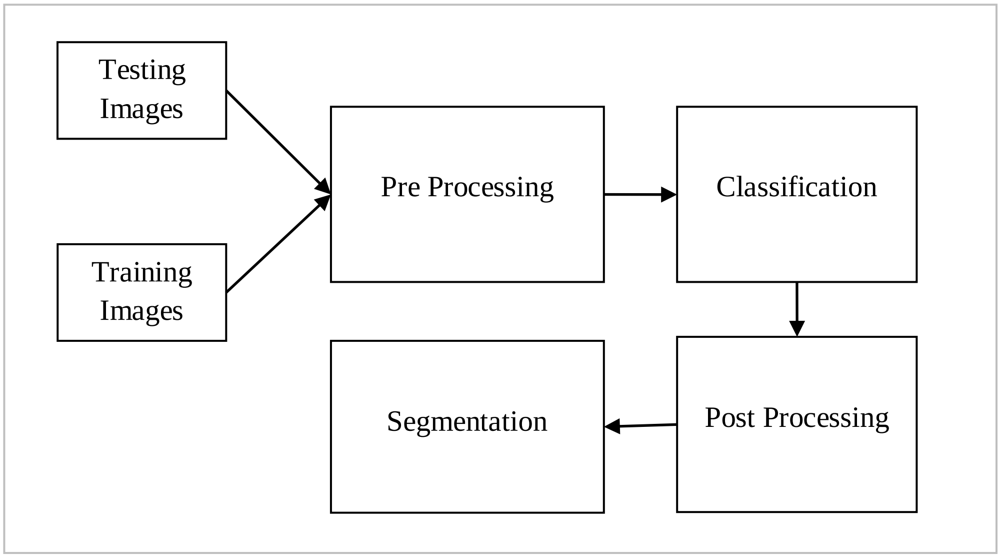

Fig.1: Flow diagram

Previous research in the fields of medical image processing and soft computing has produced notable reviews and analyses of automatic brain tumour detection methods that centre on segmentation, classification, and their combinations. The merits and challenges of the various brain tumour detection methods for MR images are discussed in the paper in order to identify different forms of brain tumours. The most recent segmentation, classification, and detection methods are also provided, with an emphasis on the benefits and drawbacks of the various medical imaging modalities.

The work in [9] examines numerous segmentation/classification strategies that are effective for the early identification of a variety of brain disorders and attempts to assist researchers in determining the key features of different types of brain tumours. The paper discusses the most pertinent methodologies, methods, and associated preferences, limitations, and potential pitfalls for MR image-based brain tumour diagnosis. The present state of the art with regard to various tumour kinds might be summarised in an effort to aid researchers in determining new directions.

4. Convolutional Neural Networks

Convolutional neural networks are used to extract picture features. Unlike fully connected (FC) layers, convolutional layers may be trained more easily and are less susceptible to overfitting since they have different kernels for maps with the same attributes. Usually, a non-linear actuation function is applied to each neural network's output. Convolutional layer stacking abstracts characteristics as depth increases, starting with edges for the first layer and moving on to motifs, components, and objects for later levels. It includes the following techniques: First, initialization The weights of the neural network are established and convergence is accomplished in this stage. The activation mechanism Data is converted nonlinearly.

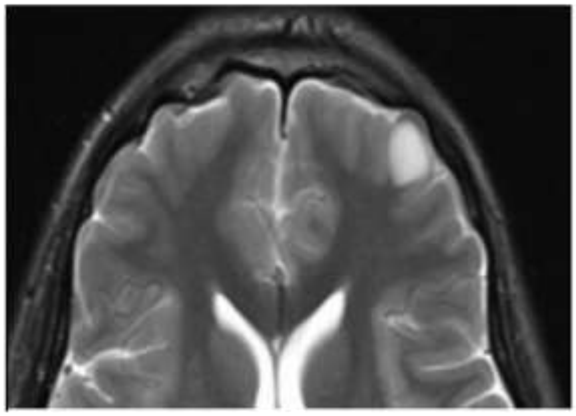

Fig. 2: Input Image

Convoluting close map elements can lessen the computational strain and decrease the likelihood of spotting irrelevant data. The terms average-pooling and maxpooling are commonly used. Max pooling performs better. Normalization stage allows for the management of model complexity by reducing overfitting. Next, in the field correction step, the size of the training steps might be increased, leading to inaccurate inputs. It might lessen overfitting as well. Then in the next step, the neural network's mistake is referred to as loss. Loss function must thus be decreased during training.

Fig. 3 : Output Image

Finally, the Post-Processing will be done by applying volumetric limitations and eliminating clusters whose threshold value is below a predetermined limit can prevent some small clusters, such as a tumour edge, from being mistakenly identified as tumours and deleted. Through the proposed method is tested with a sample image (Figure 2) and it produces the output image (Figure 3) through which the tumor is detected.

5. Conclusion

One of the most vital organs in the human body, the brain is necessary for the proper operation of all other bodily systems and must be safeguarded against illness. The algorithms for tumour identification have been becoming better over time, yet they still fall short. Each algorithm created to identify and categorise the tumour must be enhanced to attain the highest level of accuracy in order to obtain outstanding results from computer-aided detection to diagnose the disease. It is recommended to use an unique CNN-dependent methodology for segmenting brain tumours in MRI images. The pre-processing stage, which included a depth normalisation approach, was followed by CNN processing.

Convolutional layers in CNN enabled additional processing using just 3x3 bits. To segregate the brain tumour, data augmentation methodology is used. During post-processing, the minuscule healthy tissues were separated from the real tumour. When compared to the other approaches, the suggested CNN method took less computing time.

References

[1]. Guimond, Alexandre & Subsol, Gérard & Thirion, Jean-Philippe. (1997). Automatic MRI Database Exploration and Applications. IJPRAI. 11. 1345-1365. 10.1142/S0218001497000627.

[2]. Shakir Khan, V. Saravanan, Gnanaprakasam C. N, T. Jaya Lakshmi, Nabamita Deb, Nashwan Adnan Othman, "Privacy Protection of Healthcare Data over Social Networks Using Machine Learning Algorithms", Computational Intelligence and Neuroscience, vol. 2022, 8 pages, 2022. https://doi.org/10.1155/2022/9985933

[3]. Vinit Kumar Gunjan, Y. Vijayalata, Susmitha Valli, Sumit Kumar, M. O. Mohamed, V. Saravanan, "Machine Learning and Cloud-Based Knowledge Graphs to Recognize Suicidal Mental Tendencies", Computational Intelligence and Neuroscience, vol. 2022. DOI: https://doi.org/10.1155/2022/3604113

[4]. M. Nasor and W. Obaid, "MRI Tumor Detection and Localization by Multiple Threshold Object Counting Technique," *2018 International Conference on Computer and Applications (ICCA)*, 2018, pp. 158-161, doi: 10.1109/COMAPP.2018.8460322.

[5]. S. Handore and D. Kokare, "Performance analysis of various methods of tumour detection," 2015 International Conference on Pervasive Computing (ICPC), 2015, pp. 1-4, doi: 10.1109/PERVASIVE.2015.7087002.

[6]. C. P. S. Raj and R. Shreeja, "Automatic brain tumor tissue detection in T-1 weighted MRI," 2017 International Conference on Innovations in Information, Embedded and Communication Systems (ICIIECS), 2017, pp. 1-4, doi: 10.1109/ICIIECS.2017.8276094.

[7]. K. D. Mistry and B. J. Talati, "Integrated approach for bone tumor detection from MRI scan imagery," 2016 International Conference on Signal and Information Processing (IConSIP), 2016, pp. 1-5, doi: 10.1109/ICONSIP.2016.7857471.

[8]. Biratu ES, Schwenker F, Ayano YM, Debelee TG. A Survey of Brain Tumor Segmentation and Classification Algorithms. J Imaging. 2021 Sep 6;7(9):179. doi: 10.3390/jimaging7090179. PMID: 34564105; PMCID: PMC8465364.

[9]. Chahal, P.K., Pandey, S. & Goel, S. A survey on brain tumor detection techniques for MR images. Multimed Tools Appl 79, 21771–21814 (2020). https://doi.org/10.1007/s11042-020-08898-3.

[10]. K. Soni, et.al., "Brain Tumor MRI Image Segmentation using Convolution NeuralNetwork", Neuro Quantology, vol. 20, no. 7, 2022.