Brain tumour detection and segmentation using Deep Neural Networks

Abstract

Detecting brain tumour using segmentation approach is highly critical in cases where the survival of the patient will depend on the accuracy of tumour detection and timely diagnosis. Gliomas are commonly prevalent in populations; they have an irregular shape and ambiguous boundaries making them difficult to detect. Brain tumour detection automation remains a major challenge because of its significant variations in its structure and intensity and detection is a complex process. The research report presents a deep neural network-based approach to evaluate the use of convolution neural network (CNN) algorithm for its utilisation in detecting brain tumours early. The report will acquire data from MRI images from the MedPix website. The MRI images are subject to a sequence of processes. At the first stage, pre-processing and noise is filtered from the chosen image. Removal of noise will improve the quality of the image. This is followed by skull uncovering, a significant process in image analysis to remove no-brain tissues in the MRI image. Subsequently, the image is segmented using the Berkeley wavelet transform to detach the tumour area in the MRI image. Image segmentation has the potential to determine tumour location, boundaries and propose an approach to contain a tumour. Following segmentation, the feature extraction processes will involve the use of fast Fourier transforms to extract the features of the tumour area in the image. Lastly, the CNN algorithm is applied to label the MRI image as normal or abnormal. CNN's are used for their ability to specify different forms of multi-layer perceptrons, and they are oriented to realise visual modalities from the raw image pixels. The project will also involve a minimum level of pre-pressing before feeding MRI images to CNN. Finally, the image is evaluated based on key performance measures such as accuracy, sensitivity and precision.

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Introduction

Image processing in disease diagnosis refers to the visualisation of medical images and analysing them under the given considerations. In the area of medical image processing accurate detection, location, and size of a tumour play an important role in the diagnosis of a brain tumour. The most widely used techniques in diagnosing brain tumour are magnetic resonance imaging (MRI) and computed tomography (CT Scans) scanning. There are many different processes involved in image processing. As a first step image processing involves noise identification and removal, filtering and the next step is segmentation. Hence, image processing to detect brain tumours involves the steps of noise removal from the image, segmentation of the image, feature extraction and lastly image classification (Malashree & Thomas, 2016). A brain tumour is understood as the abnormal growth of cells in an uncontrolled manner in the brain. Brain tumours can occur from brain cells, blood vessels, nerves, that come out from the brain. Tumours can damage the brain by inducing inflammation, exert pressure on parts of the brain and increase the pressure inside the skull. Tumours are not easy to detect because each a tumour can be of different shape, size location and with varying intensity (Verma et al., 2013). Manual detection of a tumour is very time consuming and manual detection depends on the observer's ability to locate the shape, size and location of a tumour in the brain (Deshmukh & Ghongade, 2014).

In the area of medical image processing, data generated is too high and hence difficult to interpret all data and analyse them manually. The MRI technique produces images of human tissues in a non-invasive manner to reveal the structure, metabolism and function of tissues and organs. MRI is very versatile and flexible in diagnostic radiology and can also join high-quality anatomical images with functional information (Peni & Tjahyaningtijas, 2018). In clinical studies MRI attracts more attention for brain tumour diagnosis especially Gliomas, are brain tumours with the highest mortality rate and is widely prevalent (Bauer et al., 2013). The brain tumours (neoplasms) can be graded into Low-Grade Gliomas (LGG) and High-Grade Gliomas (HGG) with varying intensity. It is important to note that even under treatment patients do not survive on the average of over 14 months after diagnosis, to note MRI is especially useful in the detection, location and size of a tumour (Pereira et al., 2016).

In the case of brain tumour segmentation, many different techniques were developed explicitly as parametric or non-parametric probabilistic models for the data involved in the study. The models usually include a likelihood function which corresponds to the observations and a prior model. Since neoplasm is an abnormality, they can be segmented as outliers in normal tissue. However, this outlier is subject to shape and the connectivity constraints (Sumithra & Malathy, 2017). Other segmentation approaches rely on probabilistic atlases. In brain tumours, the atlas is determined at the time of segmentation for its variable shape and location of the neoplasm. To improve the atlases, tumour growth models are used as an estimate of its mass effect. The neighbourhood of the voxels (a 3D equivalent of the pixel) will provide information that is useful for achieving fine segmentation through Markov Random Fields (MRF). In addition to MRF, many other techniques such as random forests (RF), support vector machines (SVM) classifiers and so on are used in brain tumour segmentation, as found in the literature. Many of these approaches generalise unseen data, but it is explicitly difficult to translate prior knowledge into an appropriate probabilistic model. There is a class of methods which learns a distribution directly from the data (Pereira et al., 2016).

According to Heba Mohsena et al., (2018), SVM along with neural networks are widely used for their good performance in brain tumour segmentation over the past decade. More recently, deep learning (DL) models which are a technique in machine learning and has deep architecture has the potential to efficiently represent complex relationships without the need for a huge number of nodes. Also to note, the problem of brain tumour segmentation is addressed using convolutional neural networks (CNN) due to its success in object recognition of 2D images, and CNN systems are readily available (Zikic et al., 2016). The manual segmentation of a tumour in MRI images is a difficult problem because two pixels can have similar features but different output labels. To overcome this problem, deep learning based techniques especially CNN's for image segmentation are tailored for pattern recognition tasks. Neural networks are successfully applied in medical image analysis, image segmentation and tissue classification. Recently DNNs (deep neural networks) algorithms are widely used inaccurate detection and diagnosis of brain tumours from MRI images (Hussain et al., 2018).

The research report focuses on dilieanating the brain tumour in MRI images through deep learning architecture to classify a tumour as malignant and pre-malignant conditions. This classification will increase the remedy probabilities and at the same time improve patient’s durability, early diagnosis and as well as provide radiologists with an accurate diagnosis. The objectives of this research are:

1- Data Acquisition: the gathered MRI images available from MedPix website.

2- Image Processing: the paramount function of image pre-processing is to boost the quality of MRI images comprise of grey level conversion, resizing of an image and median filtering for noise removal. All of these steps to increase the quality of MRI images.

3- Skull Uncovering: Skull Uncovering is a significant process in Image Analysis for removing whole non-brain tissues in MRI images such as fat, skin and skull.

4- Image Segmentation: Image Segmentation using Berkeley wavelet transform is to detach out tumour area in MRI image. Utilising segmentation, it is potential to distinguish tumour location, boundaries and plan surgical approach.

5- Feature Extraction: to increase the precision of the classifier, features will be extracted using Fast Fourier Transform such as contrast, difference entropy, maximum probability, perimeter, tumour area and Normalized radial length.

6- Classification using Convolutional neural networks: classification specifies a label to an MRI image normal or abnormal. CNN's have different forms of multi-layer perceptrons; they are oriented to realise visual modalities, straightway from raw image pixels. In this project, a minimal pre-processing will perform before feeding MRI images to CNN's.

7- Appraisal matrices for MRI images analysis system: the system will be evaluated by using several key performance measurements such as accuracy, sensitivity and precision

Literature Review

The chapter provides a review and summary of brain tumour detection studies. The reviews were made from existing studies related to brain tumour detection using MRI and other techniques.

Related work on Brain Tumor Detection

According to Sontheimer (2015), brain tumours are not quite common, but they are most fatal for the individual. It is a form of cancer which affects the nervous system in the brain and is usually caused by uncontrolled cell proliferation. Further brain tumours are classified based on their origin and the degree of its intensity. Brain tumours can be classified into grades of I to IV based on their aggressiveness. Brain tumours due to their uncontrolled growth of cells can exert pressure on the brain, and manual detection of brain tumours is time-consuming and depends on the ability of the observer to detect the shape, size and location of a tumour (Shivani et al., 2014). However, a technique such as MRI and CT scan has been developed to detect tumors, and these techniques support the approach for tumour removal and treatment. It may be noted the brain is made up of the cerebrum also known as the cortex and is the largest part of the brain. The cerebrum functions thought, and action and are further divided into right and left hemispheres and are responsible for different functions. The cerebellum is responsible for control movement, balance and complex actions in the body and is also known as the little brain. The brain stem controls blood pressure, body temperature and breathing and controls and other basic functions. The brain stem joins the brain with the spinal cord and forms the midbrain, medulla, and pons (Malashree & Thomas, 2016). The brain tumour segmentation in MR image is shown in figure 1.

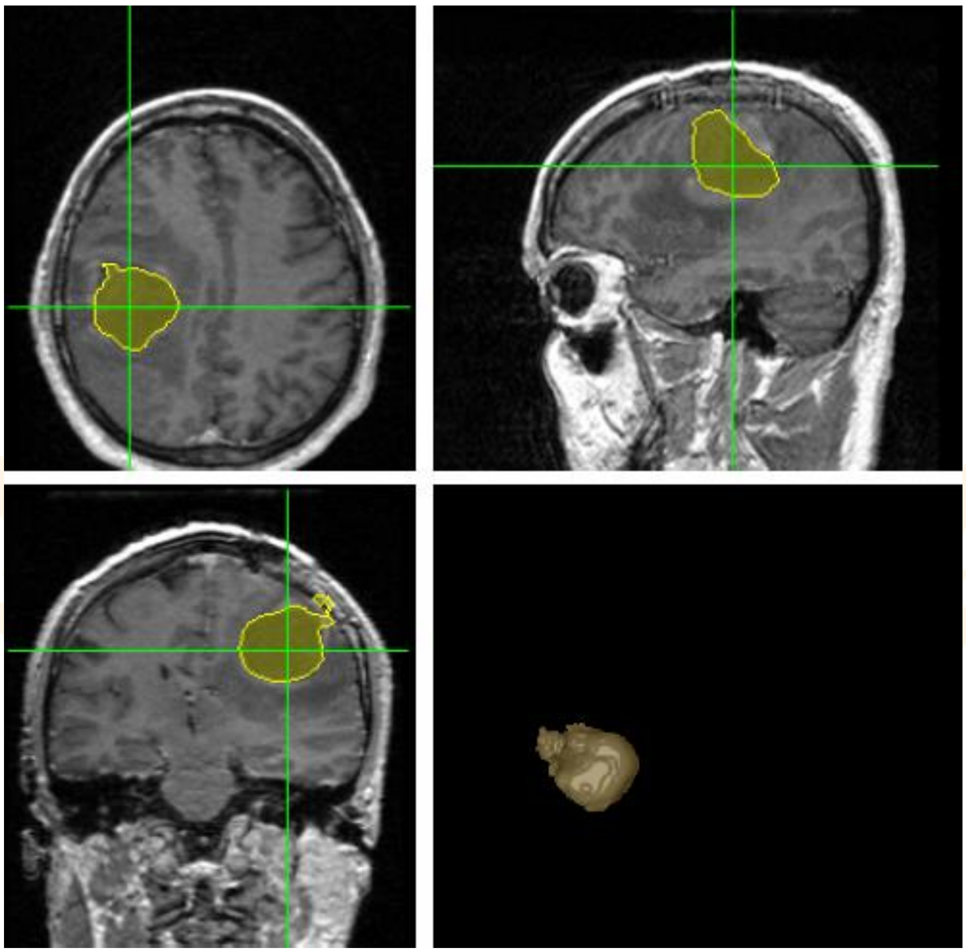

Figure 1: Brain tumour segmentation in MR imaging (Yu et al., 2012)

Kleesiek et al., (2016) explain that MRI is critical for neuroimaging workflows, and currently non-enhanced T1 weighted images show good results, but the challenge of other modalities and pathologically altered tissue is difficult to detect. The authors present an architecture for 3D convolutional deep learning to address the challenge. The approach trains the system to handle an arbitrary number of modalities that include contrast-enhanced scans. Further, this is applied to MRI data consisting of four channels namely non-enhanced and contrast-enhanced T1w and T2w and FLAIR contrasts using a challenging clinical dataset that contains brain tumours (N=53). The proposed approach showed significant performance by outperforming six commonly used tools with mean Dice score of 95.19. The proposed method also was demonstrated on publicly available datasets namely IBSR, LPBA40, and OASIS with N=135 volumes. The results showed the highest average Dice scores, for IBSR it is 96.32, and LPBA40 the score was 96.96 and for OASIS the second best Dice score of 95.02 was achieved. From this experiment, it was shown that by adjusting the cut off threshold for generation of binary masks from CNN probability output is used to enhance the sensitivity of the method. The method is useful for large-scale studies and clinical trials.

Brain tumour diagnosis is done using MRI, a non-invasive technique and provides good soft tissue contrast and widely used by radiologists. MRI makes use of radio frequency together with a magnetic field to obtain images of the human body without the use of ionising radiation. In addition, the CT scan makes use of a series of x-rays at different angles of the required part to get a perfect image (Verma et al., 2013). The MRI image of the brain is shown in figure 2.

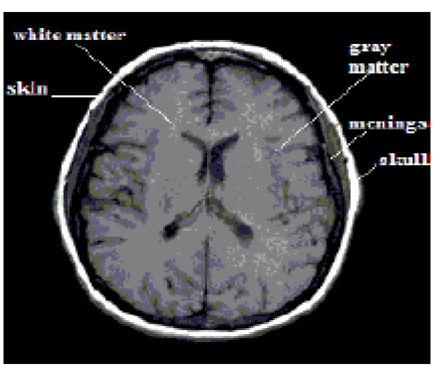

Figure 2: MRI image of the human brain (Malashree & Thomas, 2016)

The methods involved in MRI and CT scan are as follows:

Image pre-processing: In this step, the noise in the image is filtered. MRI technique makes use of a medium filter for noise removal whereas CT images use high-level filters for noise removal. Noise is usually developed in images due to thermal effects and variations in the source signals, and noise in modern MRI scan is less compared to a CT scan (Greenspan et al., 2016).

Segmentation: According to Costin (2013), the segmentation in image processing is classified as edge based methods, region-based and pixel based methods. The edge detection methods recognise edges that are often non-continuous. In order to segment an object in the edge detection method in the image, closed region boundaries are required in the image. The edges are the boundaries which lie between the chosen object. In the case of region-based segmentation, regions are formed either by associating or disassociating neighbour pixels and works by the principle of homogeneity. Here neighbouring pixels in a region possess similar characteristics and dissimilar to the pixels in the other region. In the region-based method, each pixel is compared with its neighbouring pixel to verify similarly in terms of colour, texture, shape and grey level. If the pixel matches it is added to the region and the region is developed.

Feature extraction: Feature extraction is a form of dimensionality reduction in image processing. Here, if the input data is too large for the algorithm to process and if the input data is notoriously redundant, the data will be transformed into a reduced set of features. The input data will be transformed into a set of features. This is helpful to detect a brain tumour for its location and helps in the prediction of next stage Feature extraction includes knowledge related to contrast, energy, entropy, shape, colour, and so on (Subashini & Sahoo, 2013).

Image classification: Classification is the final step in medical image visualisation obtained from MRI or CT scan technique. After the noise is removed from the image, they are segmented and clustered to extract the area that is not part of the normal patient, the resulting signals from feature extraction are used in detecting the type of a tumour or the location of the brain affected due to the formation of a tumour. The image is finally classified from the MRI or CT scan.

CT scan along with MRI imaging is crucial for treatment planning of various clinical applications. CT scan is used in radiotherapy and also in PET attenuation correction. At the same time, CT radiation can cause side effects to patients. Hence, MRI is much safer and does not involve much radiation. Hence, MR imaging of the subject case for radiotherapy planning is highly emphasised. In one study, a data-driven approach is proposed to address the challenging problem of MRI brain imaging and CT scan (Nie et al., 2017). The authors trained a fully convolutional network to generate a CT image from a given MR image. In order to model the relationship, from MRI to CT for producing realistic images, the authors proposed an adversarial training method and a function for image gradient difference loss. Further, a model named as AutoContext model is applied to implement the context-aware generative adversarial network. Through this method, the authors were able to predict CT scan images from the given MRI images accurately, and this approach also performed better compared to other methods (Nie et al., 2017). Figure 3 shows the original image, resized and grey scale image for both MRI scan and for CT scan.

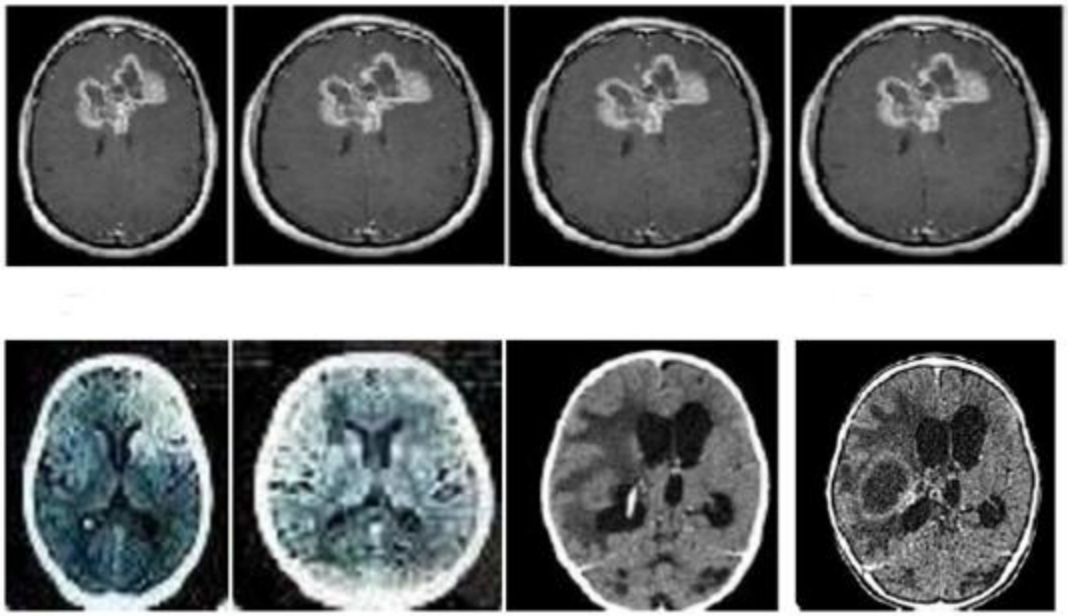

Figure 3: Original image, resized image, the grayscale image for the MRI scan above and CT scan below (Malashree & Thomas, 2016).

A Brief on the methods in brain tumour image segmentation

Brain tumour image segmentation can be broadly categorised as manual, semi-automatic and fully automatic methods depending on the level and need of user interaction.

<u>Manual segmentation:</u>

In manual segmentation, the radiologist will use multi-modality information provided by MRI images along with the anatomical and physiological knowledge. The radiologist would have gained knowledge through training and experience. In the manual procedure, the radiologist will go through multiple slices of images, one slice at a time to diagnose a tumour and the tumour regions are drawn manually. This is a time-consuming task, and the radiologist is dependent on the segmentation results which are a variable in terms of large intra and inter rates. Manual segmentation methods are used widely to evaluate the semi-automatic and fully automatic approaches (Pereira et al., 2016).

Semi-automatic segmentation:

In the case of the semi-automatic method, user interaction is needed for three purposes namely initialisation, intervention and feedback response and evaluation. Initialisation, in general, involves defining the region of interest (ROI) which contains the approximate tumour region. This is processed by the automatic algorithm. It must be noted that the parameters of pre-processing methods can be modified to fit the input images. Further to initialisation, algorithms that are automated are managed to obtain the desired result by the process of receiving feedback and by providing modifications in the response. In semi-automatic segmentation, the results can be evaluated and modified to repeat the process if it is not satisfactory (Jain et al., 2015).

Fully automatic segmentation:

In fully automatic brain tumour segmentation, user interaction is not needed. In fully automatic segmentation, the techniques of artificial intelligence and prior knowledge are combined to find solutions to the segmentation problem. It is important to note that automatic segmentation of gliomas is very challenging. This is because the tumour boundaries are unclear with irregularities and discontinuities thus posing a challenge to edge-based methods. Further, the MRI data obtained from clinical scans are complex. Also, automatic segmentation is classified as discriminative and degenerative methods. From literature, it may be found that discriminative methods implement the processing pipeline of pre-processing, feature extraction, classification and post-processing steps as mentioned earlier. Some of the segmentation methods include neural networks, support vector machines, k-means clustering, discrete wavelet transforms, and so on. Though these methods report good performance, new trends in automatic brain tumour segmentation involve the techniques of CNN and deep learning methods with good state of the art results (Isin et al., 2016).

Related work image segmentation

It may be noted that in medical image processing segmentation and feature extraction techniques are directly relevant in medical applications which are enabled by MRI and CT scan. It is important to note that MRI images are basically the pre-processing of brain tumour detection and diagnosis. Kharrat et al., (2009) introduced an efficient detection of a brain tumour from cerebral MRI images using a three-step methodology namely enhancement, segmentation and classification. The authors applied an enhancement process to improve the quality of images and to limit the risk of distinct regions in the segmented phase. Mathematical morphology is further adapted to increase the contrast in MRI images. The MRI images were decomposed by applying a wavelet transform in the segmented phase. Lastly, the k-means algorithm was implemented to extract the suspicious regions which are tumours. The experimental results on brain images proved the feasibility and performance of this approach.

Kapse et al., (2015) explain that recent detection of a brain tumour in the MRI image is challenging because MRI images are used by experts. Image segmentation in tumour detection is a challenging task because of the high level of diversity in the presence or appearance of tumour tissues found in different patients and the similarity with usual tissues. The authors explored and presented a variety of algorithms to segment MRI images using different tools and methods to detect a brain tumour from MRI images accurately. From the literature, it was found that the fuzzy c-means (FCM) method were used for spatially coherent and noise-robust image segmentation (Cong et al., 2015).

Despotovic et al., (2015) in their study integrated spatial information of local image features with similarity measure and membership function to overcome the effect of noise. In addition, the introduction of anisotropic neighbourhood based on features of phase congruency allowed more accurate segmentation without image smoothing. The results prove that for segmentation, of both synthetic and real images the method efficiently preserved the homogeneity of regions and is more strong to noise than the elated FCM methods. In another study, the demand for automating tumour detection and segmentation process was explained due to the difficulty of brain tumour diagnosis, as tumours are of different sizes, shapes and appearance. Computer-Aided diagnosis of a brain tumour from MRI images is developed to overcome the difficulties in manual segmentation. This can be done through the introduction of the segmentation method to detect bias field image and classify the white matter and grey matter. This method took less time than the FCM algorithm (Mandlik & Salankar, 2017).

Abdel-Maksould et al., (2015) presented an efficient method for image segmentation using the k-means clustering technique which is integrated with the fuzzy c-means algorithm. This integration was followed by thresholding, and segmentation levels set stages to obtain the benefits of k-means clustering in the aspect of minimum compute time. On the aspects of accuracy, the fuzzy c-means provides good advantages. The authors compared the proposed approach to image segmentation with segmentation algorithms in terms of processing time, accuracy, and performance. The accuracy was evaluated through the comparison of the results with each processed image. Through the experimental results, the authors showed that their proposed approach is effective with a high number of segmentation problems, obtained good accuracy in reduced execution time.

Further studies were found on the use of different algorithms for the detection of a brain tumour and diagnosis. Sivaramakrishnan & Karnan, (2013) stated that the MRI scan is used to produce an image of any part of the body and is an efficient and fast technique to detect a brain tumour. In their method, an existing k-nearest neighbour was used in classifying a subject as normal or an abnormal image. The authors proposed a method for efficiently detecting brain tumour region from the cerebral image using FCM clustering and histogram. Based on the histogram the intensity values of the grey level images and the decomposition of the image are extracted using the principal component analysis (PCA) to reduce the dimensionality of the wavelet coefficient. The FCM clustering algorithm will detect the centroids of cluster groups along with brain tumour patterns got from MRI images, and the segmentation result showed the extracted tumour region.

It may be noted that image analysis focuses on methods to interpret the acquired images. In the domain of medical image analysis, segmentation and registration are the two main divisions, along with image enhancement, visualisation, quantification and modelling. Image segmentation also aims to partition the image into multiple segments. The segments can be chosen according to the affected area of interest, tissue types, functional areas, and so on. Also, segmentation plays an important role in medical image processing and diagnosis of a brain tumour through manual segmentation is time-consuming and there is a need for automatic segmentation (Peni & Tjahyaningtijas, 2018).

Brain image segmentation using Convoluted Neural Networks (CNN)

The process of image segmentation will partition a given image into mutually exclusive regions, and image segmentation is crucial for facilitating delineation, characterisation and visualisation of regions of interest in the given medical image. Despite extensive research in this area, the challenges in segmentation arise due to diverse image content, cluttered objects, image noise, occlusion, non-uniform object texture, and many other factors. Many algorithms and techniques have been developed, but this area of research still needs to develop an efficient and fast technique for the segmentation of medical images.

Zhang et al., (2015) explain that the segmentation of images obtained from infant brain tissue into white matter (WM) and grey matter (GM) and cerebrospinal fluid plays a significant role in early brain development related to health and disease. It was found that WM and GM showed identical levels of intensity in both T1 and T2 MRI thus posing a challenge for tissue segmentation. The authors propose a deep convolutional neural network (CNN) for segmenting isointense stage brain tissues using multi-modality MR images. CNN's are one of the types of deep models where trainable filters and local neighbourhood pooling operations are applied alternatively on raw input images to result in a hierarchy of increasingly complex features. Further, the information of multimodality from T1 and T2 along with fractional anisotropy (FA) images were used as inputs to generate the segmentation maps as outputs. The performance of this approach was compared with the commonly used segmentation methods on manually segmented isointense stage brain images. The results of this approach show that the proposed model performed better on infant brain tissue segmentation and this approach led to significant improvements in performance.

Havaei et al., (2017) presented a fully automatic brain segmentation based on deep neural networks (DNN). Based on the MRI images the networks were customised for both low grade and high-grade glioblastomas. Since tumours by nature can be found anywhere in the brain with almost any shape or size and contrast the authors exploited a flexible high capacity DNN from machine learning technique. The authors also provide different model choices which are required for gaining competitive performance. The training data was made by exploring different CNN architectures and were adapted to image data. In addition, the article also presents a novel CNN architecture which is different because it exploits both local features and global contextual features simultaneously. Compared to traditional uses of CNN, this proposed network use a final layer to implement a convolutional layer of a fully connected layer with 40 fold speed up. A 2-phase training procedure which allows for tackling difficulties related to an imbalance of tumour labels is described. Lastly, the article explores a cascade architecture in which the output of basic CNN is treated as an additional source of information for subsequent CNN. The results were reported using the 2013 BRATS test dataset.

Kamnitsas et al., (2015) presented an 11 layer deep, 2-pathway, 3D CNN developed for segmentation of brain lesions. This system will segment pathology voxel-wise after a corresponding multi-model 3D patch at multiple scales is processed. The authors demonstrated that it is possible to train such deep and wide 3D CNN on a small dataset of 28 cases. The results showed promising on the task of segmenting ischemic stroke lesions, successfully achieving a mean Dice of 64% on ISLES 2015 training dataset. The authors claim that regardless of the data size, the network is capable of processing 3D brain volume in 3 minutes, thus making it applicable for automated analysis of larger similar studies.

Pim Moeskops et al., (2016) presented a method for automatic segmentation of MRI brain images divided into different tissue classes using a CNN. The network made use of multiple patch size and multiple convolutional kernel size to obtain multi-scale information about each voxel. This was done to ensure the proposed method obtained accurate segmentation detail and spatial consistency. This method is not dependent on explicit features but learns to recognise the information important for classification based on training data. The method proposed needs a single anatomical MR image only. The segmentation method is applied to different data sets, and the results showed accurate segmentation on all the datasets tested. Hence, the authors claim that automatic segmentation of MRI brain images is important for quantitative analysis in large-scale studies that include images obtained from all ages.

Shakeri et al., (2016) proposed a deep learning approach for the segmentation of sub-cortical structures of the human brain from MRI image data. The authors adapted state of the art fully CNN architecture to segment semantically the objects in natural images. The proposed approach was applied to the 2D image without aligning the image or the registration steps during tests. Further, the segmentation results were improved by the interpretation of CNN output potential of a Markov random field (MRF) which has the topology corresponding to a volumetric grid. The performance of the proposed pipeline was compared with a system using Random Forest pairs and with state of the art segmentation algorithms to show promising results on two datasets of MRI brain images.

Bao & Chung, (2015) propose a novel method for brain MR image segmentation using deep learning techniques to get preliminary labelling and graphical model to determine the final result. The authors made use of the specific architecture named multi-scale structured convolutional neural networks (MS-CNN). This MS-CNN is designed to gather discriminative features for every sub-cortical structure and will generate a label probability map for the target image. Since brain images are complex, the lack of spatial constraints exist between testing samples, initial results that were obtained with MS-CNN is not smooth. This problem was addressed with a dynamic random walker with the decayed region of interest to implement label consistency. By performing comprehensive evaluations using two publicly available datasets, the authors conducted experiments to show results obtained through the proposed method had better quality and segmentation efficiency.

Ganaye et al., (2018) focused on MRI image segmentation of cerebral structure using CNN as semantic segmentation is a rapidly evolving field in medical imaging. CNN's provide good performance by identifying effective high dimensional image features that describe only the patch content. The authors proposed a different method by introducing spatial constraints in the network to reduce inconsistencies in prediction. The method makes use of patch-based CNN which is trained and makes use of multiple scales to collect contextual information. Within the CNN spatial constraints were introduced by the use of distance to landmarks feature. The experiment demonstrated that the use of spatial information helps in reducing segmentation inconsistencies.

Milletari et al., (2016) proposed a method for segmentation of 3D images based on volumetric, and fully CNN. The CNN was trained on MRI volumes to depict prostrate and to predict segmentation for the entire volume at once. The training of CNN is made end-to-end. The authors introduced a novel objective function, which is optimised during training based on the Dice coefficient. This way the situation where there is a strong imbalance between the number of foregrounds and background voxels was dealt. In order to cope with a limited number of annotated volumes available for training, the authors augmented the data by applying random non-linear transformations and histogram matching. In addition, through experimental evaluation of this approach, the authors showed that good performance was achieved when using challenging test data and the process required only a small fraction of processing time.

Valverde et al., (2016) proposed CNN trained with 3D patches of candidate lesion voxels. This was done to address the challenge of automatic multiple sclerosis (MS) lesion segmentation in MRI imaging. The challenge arises mainly due to the small size and shape of the distribution, the heterogeneous shape of the lesions, overlapping tissue intensity distribution, and MR image artefacts. The authors used four anatomical MR images to demonstrate their method. The anatomical MR images include T1w, T2w, PD-weighted and T2-FLAIR-weighted. The presented method is based on deep learning of 3D patch from candidate lesion voxels.

Kamnitsas et al., (2017) proposed a dual pathway, 3D CNN with 11 layers deep to address the challenge of brain lesion segmentation. The proposed architecture is the result of an in-depth analysis of the shortcomings of the current networks proposed for brain lesion segmentation. The authors to resolve the computational burden of 3D medical scan images devised a dense training scheme. This training scheme joins the processing of neighbourhood image patches into a single pass through the network. At the same time, the scheme automatically adapted to the inherent class imbalance found in data. Further analysis was done for more discriminative 3D CNN. The authors employed a dual pathway architecture to process the input images at multiple scales simultaneously. This dual pathway architecture will incorporate both local and larger contextual information. For the purpose of post-processing of network's soft segmentation, a 3D fully connected conditional random field was used to remove false positives effectively. This pipeline is evaluated thoroughly on three challenging tasks that involve segmentation of lesion in multi-channel MRI patient data with traumatic brain injuries, brain tumours and ischemic stroke. The authors further improved the three applications with top performance on public benchmarks namely BRATS 2015 and ISLES 2015. This method is computationally efficient and can be adopted on a variety of research and clinical settings. The authors have also made the source code of this implementation publicly available.

From the above studies, it may be noted that brain tumour segmentation is crucial in image segmentation because early diagnosis of a brain tumour plays a role in treatment possibilities and also increase the survival rate of patients. Different image segmentation using CNN methods were explored and discussed for their efficiency and effectiveness in radiotherapy planning. Also during the past years, there has been an increase in the use of CNN in medical imaging applications. The CNN based segmentation is used in numerous applications from knee cartilage, to detection of Alzheimer disease to detection of brain-related problems and many more (Finzel, 2017).

Brain image segmentation using deep learning neural networks (DNN)

According to Ker et al., (2017) the potential of machine learning algorithms for image recognition has increased its use in medical diagnostic imaging. The authors provide a review of machine learning algorithms as applied to medical image analysis with the focus on convolutional and neural networks and emphasise the clinical aspects in this application area. Further, the significance of machine learning in the current medical big data scenarios has significant relationships within data which can be processed for insights using algorithms with complex features. The article covers key research applications and areas in medical image classification with emerging trends and future directions.

Mohsen et al., (2018) state that deep learning (DL) is a field under machine learning which has gained immense interest during the past year and is widely applied and proven to have the potential to learn and train data to handle complex problems. The authors use deep neural network classifier which is one of the DL architectures to classify states of 66 brain MRI image into 4 different classes namely normal glioblastoma, sarcoma and metastatic bronchogenic carcinoma tumours. Further, the classifier was combined with a discrete wavelet transform (DWT) which is a strong feature extraction tool along with principal component analysis (PCA). The results from evaluation showed good performance on all the performance measures.

de Brebisson & Montana, (2015) presented an approach to automatically segment MRI images of the human brain into anatomical regions. This approach is based on the deep artificial neural network which assigns each voxel in an MR image of the brain to its corresponding anatomical region. The input of this approach is the network capture information at various scales around the region (voxel) of interest. In this approach, 3D and orthogonal 2D intensity patches capture the local spatial context. Meanwhile, downscaled 2D orthogonal patches and distances to the regional centroids enforce the global spatial consistency. On the contrary, the technique does not require the registration of non-linear MR images. The dataset provided for MICCAI 2012 challenge was used to benchmark this model. The authors obtained competitive results to show the mean Dice coefficient of 0.725 with an error rate of 0.163 which shows the potential of the proposed approach. In fact, this is the first deep neural network model to tackle the anatomical segmentation of the human brain. The gliomas subregions of brain segmentation are shown in figure 4.

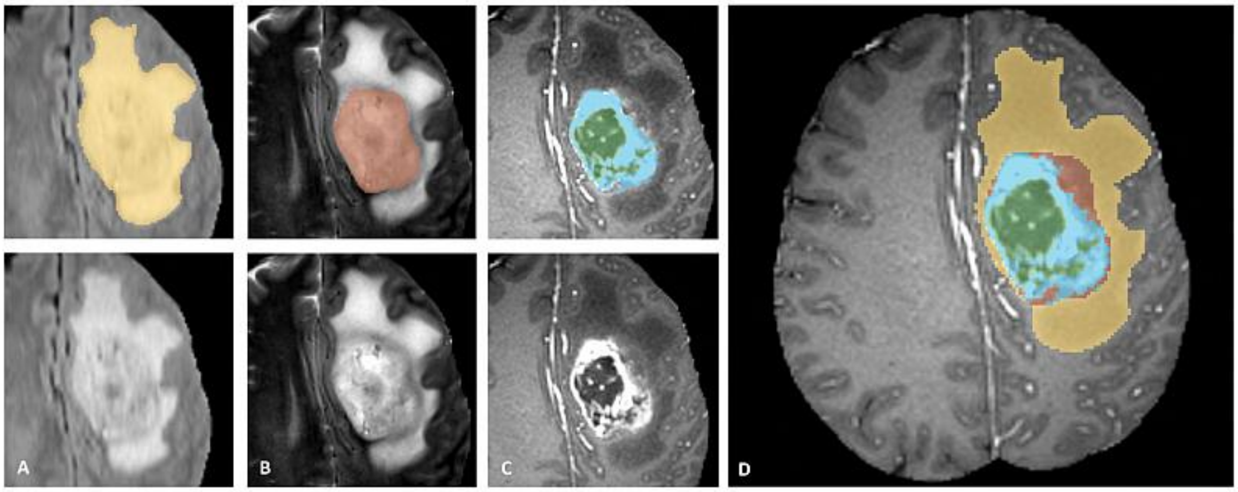

Figure 4: Brain tumour segmentation (braintumorsegmentation.org)

Tajbakhsh et al., (2016) explained that by fine-tuning a CNN which is already pre-trained for the use of a large set of labelled natural images, the difficulty of training DNN could be overcome. However, the major differences between natural and medical images are advised against the knowledge transfer. The authors in their article attempt to answer the question related to medical image analysis which reads a whether the pre-trained deep CNN's with adequate fine tuning be used to eliminate the need for training deep CNN from scratch. In order to address this question, the authors considered 4 specific medical imaging applications in three specialised area namely radiology, cardiology and gastroenterology. The method involved classification, detection and segmentation from the three imaging modalities, and the performance was investigated on how deep CNN's were trained from scratch and compared with pre-trained CNN's which were fine-tuned in a layer-wise manner. The experiment consistently demonstrated that the usage of pre-trained CNN with appropriate fine-tuning performed effectively compared to CNN trained from scratch. The fine-tuned CNN were more robust compared to the size of training sets than the CNN which were trained from scratch. Further, it was noticed that shallow tuning or deep tuning was the optimal choice for a specific application. The layer-wise fine tuning scheme offered a practical way to achieve the best performance for the application with the available amount of data.

Kriegeskorte, (2015) state that recent trends in neural network models enable major strides in computer vision and other artificial intelligence applications. The article provides a framework for modelling biological vision and brain information processing through the application of deep neural networks. Chen et al., (2016) explored the deep residual learning of volumetric brain segmentation task. This was done to fully leverage the contextual representation for recognition of tasks from volumetric data which is not studied in the field of medical image computing, and the number of image modalities is in volumetric format. The authors provided two main contributions. First a deep voxelwise residual network known as VoxResNet was proposed. This network will borrow techniques from deep residual learning in 2D image recognition tasks and is extended into the 3D variant for handling volumetric data. Secondly, the authors proposed an autocorrect version of the VoxResNet by the integration fo low-level image feature appearance, implicit shape information and high-level context together to improve the volumetric performance further. The efficacy of this proposed method was corroborated b the extensive experiments on challenging benchmark brain segmentation from MRI images on the proposed method which deals with volumetric data. It was shown that the work has the potential of 3D deep learning to advance the recognition performance on volumetric image segmentation.

Dou et al., (2016) proposed an automatic method to detect cerebral microbleed (CMB) which is an important condition involving cerebrovascular disease and cognitive dysfunction of the brain. The article detects CMBs from MRI images by exploiting the 3D convolutional neural network (CNN). This method takes full advantage of the spatial contextual information in MR volume to extract more representative high-level features for CMBs and hence achieves a good amount of detection accuracy compared to earlier methods which make use of low-level descriptors or 2D CNN. To improve the detection performance a cascaded framework under 3D CNN for the task of CMB detection is proposed. The process will first exploit the 3D fully convoluted network strategy to retrieve the candidates of high probabilities of CMBs, followed by the application of a well trained 3D CNN discrimination model to determine CMBs from hard mimics. The proposed 3D fully convoluted network strategy has the ability to remove massive redundant computations and significantly speed up the detection process. The authors constructed a large dataset with 320 volumetric MR scans and performed detailed experiments to validate their proposed method and achieved a high sensitivity of 93.16%.

Havaei et al., (2016) explain that the segmentation of localised brain pathologies such as lesions or tumours is caused by multiple sclerosis and ischemic strokes. This creates the need for medical diagnosis, surgical planning and disease development along with other applications such as tractography. Over the years the developments in machine learning and deep learning in medical imaging area has obtained state of the art results from different datasets. More recently, the computer-aided diagnostics that make use of deep learning provide promising results in detecting brain tumours. The authors provide a survey of CNN methods in the article as applied to medical imaging with a focus on brain pathology segmentation. Discussions are provided on the characteristic peculiarities, and specific configuration and adjustments are suited to segment medical images. Also, the underlying intrinsic differences between deep learning methods with other machine learning methods are discussed.

Kodner et al., (2017) presented a framework for brain tissue segmentation based on Atlas of Classifiers (AoC). The AoC involves the use of a statistical summary of annotated datasets by taking into account the imaging data and the corresponding labels. Hence, it is more informative compared to the classical probabilistic atlas and more economical compared to other popular multi atlas approaches which need large memory consumption along with high computational complexity for each segmentation. An AoC is specifically considered as a spatial map for voxel-wise multinomial logistic regression (LR) function which is learned from labelled data. On convergence, the resulting fixed logistic regression weights represent the training dataset, and this dataset is huge. The LR output based on respective voxel wise feature requires the calculation of the segmentation of the new image. Also to note the AoC construction is not dependent on test images, thus providing the flexibility to train it on available labelled data and is used for the segmentation of images from different datasets. The proposed method is applied to publicly available datasets for segmenting brain MRI tissues, and results show similarities of commonly used methods. Results were promising for multi-modal, cross-modality MRI segmentation.

Xu et al., (2018) state that white matter (WM) lesion detection and segmentation prove to be of significant clinical importance, for the diagnosis and treatment of neurological conditions. CNN's have demonstrated their effectiveness on large lesion load segmentation, but are not useful in small deep WM and sub-cortical lesion segmentation. The authors to overcome this shortcoming propose a multi-scale supervised fully convoluted network for segmenting small WM lesions in 22 anaemic patients. The multiple scales enable the identification of small lesions while overcoming the problem of false alarms and multi-supervised scheme manages the unbalanced data much better. The performance of this method on test dataset achieved a Dice score of 0.78, which is efficient.

Litjens et al., (2017) explain that deep learning algorithms and in particular CNN's are the choice for analysis of medical images. The article reviews all the deep learning concepts which are specific to medical image analysis, and summaries are provided for over 300 contributions in this field, which mostly belong to the past year. Further, the authors also surveyed the use of DL for image classification, object detection, segmentation, registration, and other useful tasks. The article summarises the current state of the art techniques with critical discussions and directions for future research.

In summary, the chapter on literature review provides a discussion on brain tumour detection techniques, to highlight the importance of MRI brain image scan and CT scan. The segmentation of a brain tumour is provided as found from research journals. The methods involved in MRI and CT scan are provided in brief. The different methods of image segmentation of a brain tumour are discussed and explained for its importance. Secondary research related to image segmentation techniques and methods are reviewed and summaries provided. The chapter also provides review summaries of brain image segmentation of CNN and deep neural networks.

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