Segmentation of Brain Tumours from MRI Images Using CNN

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Abstract. Identification of brain tumours in the early stage is key to proper treatment and diagnosis It can be classified as malignant or benign based on the aggressiveness of the tumour. To diagnose a patient, an MRI imaging device is used to obtain scans of the brain. Due to the large quantity of data produced, radiologists must perform the tedious task of going through each MRI image to identify the brain tumour's location, size, and origin. This process is prone to human error and is also time-consuming. Therefore, this paper proposes a methodology to accurately diagnose and segment the brain tumours from the MRI images using Convolutional Neural Networks (CNN) specifically U-NET architecture.

Keywords: Machine learning, Biomedical Image Segmentation, Brain Tumours, Convolutional Neural Networks.

1 Introduction

Brain tumours occur due to an abnormal division of cells in the brain. Some of the main symptoms of brain tumours are fatigue, difficulty in coordination, speech difficulties, confusion, seizures, headaches, nausea or vomiting, issues in vision etc. They can be classified as primary and metastatic brain tumours. Primary is when cancer originates from the brain and does not transmit to any other parts of the body. Metastatic brain tumours are when cancer proceeds to the brain from some other part of the body. Tumours can also be benign which means non–cancerous or malignant which means the brain tumour is cancerous in nature [1].

There are many kinds of Brain Tumours depending on location, origin, size etc. Some of the common types of Brain Tumours are:

1. Glioma – originates from the brain and it is a common type of brain tumour. The tumour arises from the aggressive division of glial cells that surround neurons. These can be malignant or benign depending on the spread rate. About 33 % of brain tumours are gliomas.

2. Meningioma – This is also a very common brain tumour that originates from the brain and 30% of brain tumours and meningiomas. It originates in the meninges which consist of the layer of tissues that surround and cover the brain just under the skull. Most Meningiomas are benign but some can be persistent and return even after treatment [2].

3. Gliosarcoma – These tumours are connected with other supportive tissues. They are mostly benign but can spread to other areas. They are also usually aggressive and resistant to chemotherapy [2].

To detect and diagnose a patient with brain tumours usually, MRI imagining devices are utilized as they provide better results with respect to soft brain tissue as compared to other types of imaging devices. The MRI device makes use of the hydrogen molecules present in our body and as per the principles of electromagnetic imaging, any moving charge has its own magnetic field. Therefore, an MRI device with the help of powerful magnets and external radiofrequency and sensors connected to a computer can obtain images of the brain. To analyse these images radiologists, must sift through numerous MRI sequences to precisely diagnose the origin, type and size of the brain tumour in the patient. The various MRI sequences are T1, T1C, T2 and Flair. Each sequence provides additional information about the tumour [3].

To avoid manual MRI image segmentation of brain tumours the proposed methodology uses a Deep Learning model to segment and classify the data. Neural Networks are a set of supervised learning algorithms that mimics the human brain in the way it operates. The nodes simulate the neurons in the brain and the connections between them act like synapses in the brain. It comprises of 3 main layers input, hidden and output layers. Neural Network becomes a Deep Learning model when it has several hidden layers in it. Specifically, Convolutional Neural Networks (CNN) are achieving great results in the field of biomedical image processing and computer vision. An image is considered as input in the form of a matrix of pixels. The model makes use of filters for example of size 3x3 and slides them across images for automatic extraction of features. For each pixel, a value is computed using a convolutional operation. This process drastically reduces the number of inputs and weights required [4]. The output of the convolution operation is passed to an activation function which determines the presence of the essential feature required. In a similar manner, the number of layers implemented can be increased to check the presence of nuanced features [5].

This paper aims to solve the tedious task of manual segmentation of brain tumours from MRI images. This process can be automated by using CNN. In the Literature survey, this model had the greatest accuracy among all the other segmentation methods. It was also found that using a less complex CNN can decrease the computational overhead of training a Deep Learning (DL) model as well as increase the accuracy compared to other Machine Learning algorithms. The issue of diagnosing brain tumours with variable sizes, shapes and structures can also be achieved [5].

2 Related Work

The first study [6] proposed an approach for the segmentation of brain tumours using a thresholding algorithm which classifies voxels above a specific threshold as containing tumours. The proposed method can be condensed into 3 stages. The first stage is pre-processing which improves the quality of the MRI image by using techniques such as morphological and pixel subtraction operations. The second stage is the segmentation stage which is a threshold-based segmentation. Its main function is to transform grey-scale images into binary images. The third stage is the image filtering stage which uses a median filter to eliminate noise from the images. Finally, this approach has a success rate of 94.28 % and an overall accuracy of 96% [6].

This study [7] provided an approach that enhanced the DL algorithm which is a kernel-based CNN with M-SVM. In the pre-processing stage, the LoG and CLAHE methods are used to detect the edges of images. They are also used to remove unwanted noise and parts of the background from the MRI images. Feature extraction is done using the SGLDM method. It is rooted in the spatial dispersal of levels of Gray in the regions of interest which focused on the construct, site, and overall shape of the tumour in the image. The M-SVM algorithm is used to classify the image as either ordinary or unusual. The images in the unusual class are passed as input to the kernel-based CNN which isolates the tumour in the image. Finally, this segmented image is classified as either malignant or benign [7].

This paper proposed [8] a two-step verification method for brain tumour image segmentation wherein 2 algorithms are used. The Watershed algorithm and SIFT together are called as Watershed-matching algorithm. Brain tumour image segmentation is done using the classical watershed algorithm. SIFT is used to match the segmented brain tumour image to the original image. This is the first verification step. Next, the volume of the tumour is calculated to differentiate between benign and malignant tumours. The area of the tumour is calculated and on detection of white pixels greater than 500, the tumour is classified as being in the critical stage else the initial stage. Hence the paper uses a two-step verification process for brain tumour image segmentation [8].

This paper [9] detailed an improved approach to brain tumour image segmentation using the Fuzzy C Mean algorithm and multiobjective optimization. The Fuzzy

Clustering algorithm is used to cluster a set of data points so that it has more similarity with one group than the other. Segmentation of brain tumours from MRI images is done using Fuzzy C Means and Genetic Algorithm. To extract objects from the background Thresholding segmentation is done. Finally, classification is performed by using an ensemble of Decision trees [9].

In this paper [10] a novel Dominant Gray Level Based K-Means Algorithm is used as opposed to a standard K-Means Algorithm which randomly chooses k number of pixels as the centroid. The proposed methodology first uses pre-processing techniques to convert red, green, and blue images of the MRI Brain image dataset to grayscale images. The algorithm is utilized to discover the probabilities of individual pixels. In this K-Means clustering algorithm, the top 16 pixels with the highest probabilities are chosen as centroids initially [10].

In [11] the aim was to perform automatic brain tumour segmentation in MRI images using contour-based algorithm , less computational costs and a texture. The first stage is the detection of tumour slices. This is done by creating a histogram for each hemisphere of the brain and determining which hemisphere would likely contain tumours. Feature extraction is done using AM-CWT and DT-CWT and other statistical techniques. Feature selection is done using a modified Regularized Winnow Algorithm. Finally, the tumour region is segmented by using an active contour model Skippy Greedy Snake Algorithm [11].

In [12] a Multi-Atlas Based Adaptive Active Contour Model was used in MRI and CT images for brain tumour image segmentation. The method utilizes theoretical information for the segmentation of brain tumours. It consists of reference images and label maps. The STAPLE algorithm is used to combine the label maps into a more accurate brain tumour contour. Active contour models are classified as either edge or region-based models. The proposed AELR active contour model is implemented using the DRLSE algorithm [12].

In [13] multi-modality MRI imaging scans were used to perform brain tumour image segmentation. Firstly, feature extraction is performed on pre-processed images. All the features combined are given as input to the RF Classifier to predict five classes namely background, enhancing tumour , non-enhancing tumour, oedema and necrosis, Finally, the class labels are used to calculate three regions hierarchically - active tumour, enhancing tumour and complete tumour [13].

This study [14] presented a comparison of various dimensionality reduction PCA Algorithms such as PPCA, EM-PCA, GHA and APEX with two clustering algorithms K-Means and Fuzzy C-Means Algorithm. PCA is essential to decrease the complexity of the image dataset as well as combat the curse of dimensionality issue. It was observed that PPCA achieved the best results out of all the clustering methods and the combination of EM-PCA and the PPCA with the K-Means algorithm obtained the best results for clustering and segmentation [14].

This research paper [15] focussed on the identification, segmentation, and early detection of brain tumours by using feature extraction methods such as DWT, GLCM and Probabilistic Neural Networks as a classifier. The first stage is the pre-processing of images which included Segmentation and Region growth. The feature extraction is executed by using DWT for extracting coefficients of wavelets and GLCM for extraction of statistical features. Finally, the images are given as input to the PNN for the grouping of abnormal and normal brain tissues. The location of the tumours are also identified [15].

This study [16] aimed to implement Deep Learning Neural Networks to distinguish between ordinary brain tissues and different types of tumour tissues using brain MRI scans. In the recommended approach image segmentation is achieved using the Fuzzy C-Means algorithm. Feature extraction is done using DWT and dimensionality is reduced using PCA. Finally, the classification of the brain tumours is done using Deep Neural Networks (DNN) [16].

This [17] research paper focused on the fusion of various MRI sequences to provide an accurate analysis of the brain tumour. They are combined using DWT and Daubechies wavelet kernel into a single MRI image. Next PDDF is performed for noise reduction and global thresholding. Lastly, the images are classified using a CNN which consisted of 23 layers. These layers include - convolutional, batch normalization, Rectified Linear Unit function, max pooling for downsampling, fully connected and SoftMax layers to detect images with the presence of tumours [17].

The central idea of this study [18] was to improve the existing CNN model by using the BAT algorithm which is used for the automatic segmentation of brain tumours from images. An optimized loss function is used to attain this. The two phases of this model are pre-processing and segmentation. A hybrid CNN model is used and the Loss function is optimized by making use of the BAT algorithm [18].

In [19] prior knowledge is introduced in the CNN model. The information given was that most of the tumour regions in the images are of left-right symmetry. This prior knowledge is ignored by most of the existing CNN models. Therefore, by using DCSNN brain tumour image segmentation is performed by using multiple symmetric masks in the layers. The model is computationally efficient as it took only 10.8 s to segment an image. There are many stages in the proposed method.

The first stage is data pre-processing. Next is the baseline network which integrates a bottom-up and top-down pathway. The DCSNN takes four modal MRI images, so the Left-Right Similarity Mask (LRSM) presents a broad asymmetrical situation of four MRI sequences. The DCSNN is a five-classification task model. Finally, post-processing is done to remove segments with sparse voxels [19].

Research paper [20] aimed to present a CNN model that is less complex and has greater picture clarity and accuracy. The backpropagation method is used to classify brain tumours. The objective is to check if the model can classify test cases effectively into regular or irregular classes. To achieve this the final layer was executed only in the training phase. The convolutional layers consider the local spatial constructs in the previous layers. The forward pass is when multiple layers of neurons are interlinked in a way that each consecutive layer just relays the information from the previous layer which is what takes place in a feed-forward network. The Backward pass is when the weight or bias is modified, and the shift is propagated backwards all throughout the network for changing the weights and biases. The last layer consists of a soft-max function [20]. Table 1. shows a summary of all of the various algorithms that can be used for brain tumour image segmentation.

Table 1. Different methods used for brain tumour image segmentation

References	Problem Statement	Dataset	Algorithm	Advantage	Performance Measure Value
[6]	To achieve clear segmentations of brain tumours that can be used by a medical professional to gain more insight about the tumours to aid with their diagnosis.	TCIA (The Cancer Imaging Archive, 2017)	Thresholding Algorithm	Easy and efficient implementation	96%
[7]	Difficulty in brain tumour segmentation in an MRI image due to non-uniform boundaries of tumours and location of tumours in the brain.	Not mentioned	Laplacian of Gaussian filtering method (LoG) with Contrast Limited Adaptive Histogram Equalization (CLAHE),	Effective segmentation increased accuracy and low time complexity.	84 %

			Convolutional Neural Networks (CNN) with Multiclass-Support Vector Machine (M-SVM)		
[8]	Issues with diagnosing brain tumours present in the soft tissues of the brain as biopsy of tumour tissues are required which is time-consuming as well as prone to errors.	BRATS 2012 dataset	Watershed Algorithm and SIFT (Scale-Invariant Feature Transform) Algorithm	Computationally less complex and non-invasive.	98.5 % accuracy
[9]	Challenges regarding accurate segmentation of MRI images of brain tumours due to spatial and structural differences. Hard to isolate a region of interest.	DICOM MRI database	Fuzzy C-Means algorithm, Genetic Algorithm and Decision Trees	Improvement in the centre of cluster detection and increased convergence time.	92 %
[10]	Addresses the issue of selecting a random point as centroids for clustering which results in imprecise brain tumour image segmentation.	MRI Brain image Database	Dominant gray level-based K-Means Clustering Algorithm	Able to characterize regions with increased accuracy and less computational complexity.	95.37 %
[11]	The huge computational cost issue with implementation of existing techniques for the automatic detection of brain tumours is addressed.	NCI-MICCAI, 2013 database	Regularized Winnow, k-NN Classifier and Skippy Greedy Snake Algorithm	Increased Segmentation Accuracy, and reduced computational costs.	93.82 %
[12]	The difficulties with respect to exact delineation and the introduction of interobserver and intraobserver variability of brain tumours in radiotherapy.	Shandong Cancer Hospital and Institute (Shandong, China) in 2019	Simultaneous truth and performance level estimation (STAPLE) and the distance regularized level	Time-saving and accurate segmentation.	87.19 %

			set evolution (DRLSE) Algorithm		
[13]	Usage of multi-modality images to classify brain tumours.	MICCAI BraTS 2013	Random Forest Classifier Algorithm	Multi-modality MRI images are used to give an accurate account of the location and size of the tumour and increase classification accuracy.	88% - complete tumour region, 75% - core tumour region and 95% - enhancing tumour region
[14]	In image segmentation increase in the number of features selected leads to a curse of dimensionality problem and affects the overall performance of the algorithm.	Dataset of T1w MRI images were obtained from a patient who suffered from a brain tumour	Conventional Principal Component Analysis (PCA), Probabilistic Principal Component Analysis (PPCA), Expectation Maximization Based Principal Component Analysis (EM-PCA), Generalize Hebbian Algorithm (GHA) and Adaptive Principal Component Extraction (APEX) algorithms, K-Means and Fuzzy C-Means Algorithms.	Comparison of various PCA algorithms in combination with FCM and K-Means Algorithm, less time consuming and less complex image data.	Error rates for 512x512 images for PCA -3.7993, EM-PCA - 3.7430, PPCA - 3.7991 , GHA - 4.7339 AND APEX - 4.5778
[15]	Difficulty in identification, segmentation, and discovery of affected areas in brain tumour MRI images at an early stage.	Digital Imaging and Communications in Medicine (DICOM) dataset	Discrete Wavelet Transform (DWT), Gray-Level Co-Occurrence Matrix (GLCM)	Fast and high accuracy in the detection of brain tumours at early stages.	95% accuracy

			and Probabilistic Neural Networks (PNN)		
[16]	Issues differentiating between normal brain tissues and other specific brain tumour tissues.	Dataset obtained from Harvard Medical School Website	Fuzzy C-Means (FCM), Discrete Wavelet Transform (DWT) and Deep Learning Neural Networks Algorithms	Differentiate between different types of brain tissues and able to identify complex relationships in the dataset.	96.97 %
[17]	Single MRI sequences do not provide enough information for accurate diagnosis of the type, shape, and severity of brain tumour	BRATS 2012, BRATS 2013, BRATS 2015, BRATS 2013 Leader board and BRATS 2018	Discrete Wavelet Transform (DWT), Daubechies wavelet kernel, PDDF, Global Thresholding Algorithm and Convolutional Neural Networks (CNN).	More information is provided due to the fusion of 4 MRI sequences, High Accuracy, and Large data set.	0.97 ACC - on BRATS 2012 Image, 0.98 ACC - BRATS 2013 Challenge, 0.96 ACC - BRATS 2013 Leader board, 1.00 ACC - BRATS 2015 Challenge and 0.97 ACC - BRATS 2018 Challenge datasets.
[18]	The structure of tissues adjacent to the tumours is changed by the tumour mass effect. Therefore, an Improved CNN model is required which produces optimized MRI images.	Brain Tumour Segmentation Challenge 2015 database (BRATS 2015)	Enhanced Convolutional Neural Networks (ECNN) and BAT Algorithms	Increased accuracy compared to that of a regular CNN model.	92 %
[19]	The changing nature of brain tumours with respect to size, shape and location affects the accuracy of segmentation	BRATS 2015	Deep Convolutional Symmetric Neural Network (DCSNN)	Complex function mapping achieved which learns features by itself, less computation time.	0.852 dice similarity index
[20]	A Less complex CNN model with high accuracy and speed	Radiopaedia 2013 and BRATS 2015	Convolutional Neural Network (CNN)	Training data are not corrupted by outliers, are less	97.5 % accuracy

	complex and have high accuracy

3 Proposed Work

The Brain tumour Image Segmentation is done using T1w MRI scans and using the RSNA MICCAI PNG Dataset from Kaggle which consists of training and testing data [21]. The Algorithm used is Convolutional Neural Networks specifically U-NET architecture. This is done by using Transfer Learning. The U-NET model has been trained on the BraTs 2020 Dataset [22]-[24].

The U-NET model is specifically used for biomedical image segmentation. The advantage of using this algorithm is that it can be trained end to end using very few images compared to other CNN architectures. It is U-shaped and symmetric and works by using an encoder – a decoder path or is also known as a contracting and expansive path. The encoder half works by reducing the spatial dimensions of the image as it passes through each layer [25-28].

The Encoder path is responsible for feature extraction. With each convolution operation, detailed features are extracted and the input size of the image is reduced. In the Encoder path, the convolutional operation takes place by convolving the input MRI scans using an n x n size filter to give an output feature map, Batch Normalization normalizes the output of the convolution layer that is it brings the mean to 0 and standard deviation to 1. Finally, the output from the Batch Layer is passed onto the Rectified Linear Unit Function (ReLU) Activation Function.

The Max Pooling Layer present in the Encoder Path is used to calculate the maximum value from each 2x2 size window of the feature map. The Convolution method which consists of the convolution layer is called multiple times with a different number of filters starting from 32, 64, 128 and 256.

The Decoder Path is responsible for the reconstruction of the segmented masks from the extracted features. In the Decoder path, the spatial dimensions of the image are increased, and the value of the number of channels is reduced. This also starts with the calling on the Convolution method with a different number of filters but in this case, the number of channels gradually decreases as opposed to Max Pooling where it gradually increased in number. Upsampling is done each time after the convolution method is called. It is done to preserve the input volume size at the end of each convolutional operation. The feature maps of the encoder are concatenated with the decoder so that the model can segment the brain tumours from the MRI scans using detailed and general features. Finally, the input is passed to the final convolutional layer with kernel size 1x1 and with the Sigmoid function as an Activation function.

In this project, the U-NET model is implemented by using the concept of Transfer Learning which is using prior knowledge of the model when solving one problem and using that information to solve a similar application. Fig 1. Gives an overview of the proposed methodology.

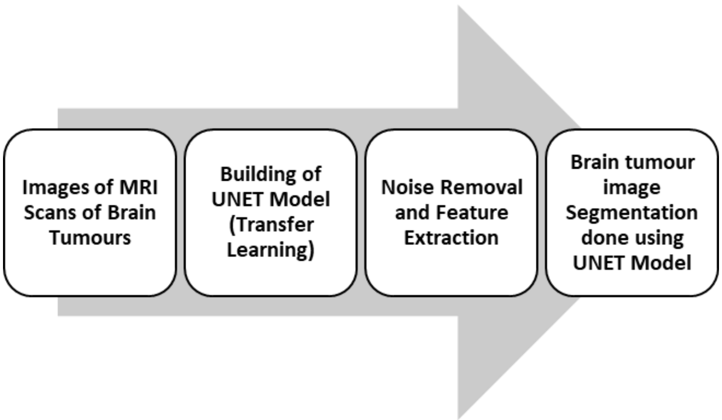

Fig. 1. Architecture Diagram

Brain Tumour Image Segmentation:

The prediction of the tumour is done by first resizing the image to 240 x 240 and then the model is used to predict the mask using the resized image and the dimension of the image is reversed by using the transpose method. The noise from the image is removed by using morphological functions in using OpenCV library. Opening which is Erosion followed by Dilation was performed to remove unnecessary minute objects from the image and to smoothen the boundary of the tumour. This function to predict the tumour is used in the find_tumour function which finds the path where the image on which the prediction should be made and passes it to the prediction function. It also returns the path to the tumour slice if the tumour pixel is greater than max_detected. Then a display function is used to display the image of the brain in grayscale and then the tumour in red.

4 Results Analysis

The model was able to predict accurately brain tumours as the accuracy of the U-NET model is 98%. The presence of a tumour in the MRI Scan was predicted by using a red mask as shown in Fig 2. The model was able to precisely segment tumours of varying boundaries and edges.

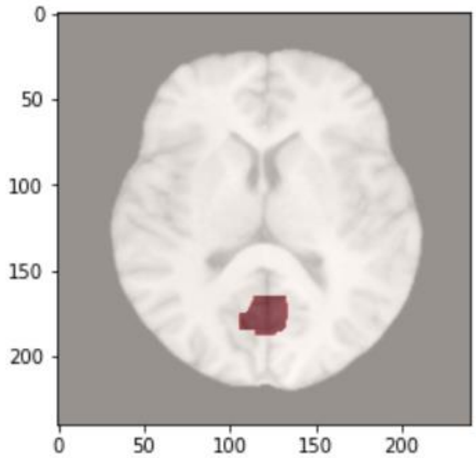

Fig. 2. Brain Tumour Image Segmentation using MRI Scans

5 Conclusion

In Conclusion, we find that Deep Learning architectures, specifically U-NET architecture is accurate in biomedical image segmentation. Using this method variable size, shape and structure tumours can be easily diagnosed. And there will be no requirement for manual segmentation by radiologists as well. In the future, the model can be further optimized by trying different loss functions and optimizers as well as testing the model on different modalities of MRI Scans.

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