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Study of Brain Region Segmentation Using Convolutional Neural Network

Sachin Singh and Asmita Das[1]
[1]Corresponding Author Department of Biotechnology, Delhi Technology University
Main Bawana Road,Delhi-110042
Email: asmitadas1710@dce.ac.in, asmita1710@gmail.com

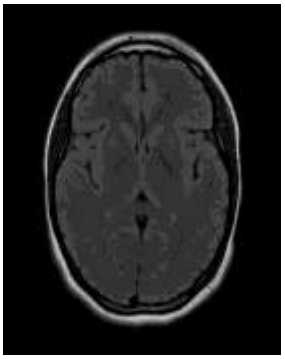
Abstract-*Magnetic Resonance Imaging (MRI) is used in medical imaging for detection of tumours and visualize brain tissues.This is done manually by expert radiologist and this takes good amount of time. The traditional method of MRI evaluation of tumour depends greatly on qualitative features,like density of tumour,growth pattern etc. Brain Region Segmentation is important in neuroimaging application, for example, alignment of images, surface reconstruction etc.The previous methods depends upon the qualitative features and is very sensitive to errors. Noise and errors need to be reduced and efficiently delineated, very less work is done in automatic tumour detection using deep learning methods and there is lot of areas which can be explored. The deep learning method is very much different from the machine learning method. The machine learning method uses algorithms to input data, learn from given data, and make decision based on the experience or learning whereas the deep learning can learn and make decisions on its own. Deep learning has a capability of learning from data that is unstructured or unlabeled. In deep learning, the algorithms try to learn using method of feature extraction which is very different and makes the model fully automatic, here we don't require any handcrafted feature. In traditional method we need to develop feature extractor for different problem, so we use deep learning which reduces effort of developing different feature extractor for different problem.*

In one of method of 2-D patch extraction could achieve accuracy of 88% where the network architecture is inspired by VGG Network, high grade and low grade network differs in number of convolutional layer preceding a max-pooling layer. In other,they have used encoder-decoder type neural network and achieved accuracy of 87.2%. In a single forward pass, previously discussed patch based technique are slow as network predicts only centre pixel of patch. In the present study, we have used supervised learning to learn the features from the input images and found that Convolutional Neural Network can achieve good accuracy.In CNN, the network in starting phase learns low level feature like lines or edges and then slowly learns the high level features. The present method achieved accuracy of 90-94% which is a good achievement in this field. MICCAI-BRATS challenge 2015 dataset is utilized in the present study. In present method, there are total of 245 MRI images which are further divided into 110 image for training the network and 145 images for testing the data.

Keywords:*Magnetic Resonance Imaging, neuroimaging, convolutional neural network,MICCAI-BRATS challenge.*

1. 1. Introduction

Brain is a complex organ which consists of huge number of working cells.Tumour which starts in the tissue of brain called primary brain Tumour.It can be further divided into malignant containing cancerous cells and tumour with no cancer cells called benign.The malignant tumour has rapid and uncontrolled growth which can lead to death [1]. So they are further divided in HGG (High Grade Glioma i.e malignant tumour) and LGG (Low Grade Glioma i.e Benign Tumour).



"Figure 1. MRI image of brain,the idea behind technique is different tissue under similar magnetic feld shows different behavior when exposed to radio waves."

tumour is among dangerous diseases human face,less than 20% of brain tumor patients survive beyond five years of their diagnosis.Brain tumour are main reason for death in children and young generation. Brain tumours are Gliomas,we typically refer to them as brain tumours.They affect the central nervous system or they usually are in brain and this is the serious illness which has a survival rate less than 2 years [2].The patient are typically monitored by MRI imaging,it is non-invasing and non-ionising radiation is used.The idea behind imaging is that you can visualize the tumour non-invasively and by looking at tumour and measuring its size,doctor use that as a marker for figuring out if tumour is progressing or responding to medication.So segmentation or delineating the pixels corresponding to tumour is important.It is typically done manually by expert radiologist ,however it can be very time taking and if there is very large patient and want to do meta analysis than it is not possible.So in order to augment the radiologist effort, brain region segmentation is an important step in medical image application .The accuracy of already previous methods relies on the geometry of image,so if it fails then chance of success decreases. In order to avoid this, it is deep learning algorithm that can effectively segment the glioma and can be very valuable.The network learns the connectedness and shape of brain and the performance of Convolutional Neural Network(CNN) resuts is very close to ground truth results given by experts. The challenges in Brain Tumour Detection are the traditional method of MRI evaluation of tumour depends greatly on qualitative features,like density of tumour,growth pattern and acellular composition etc [3], the methods in use are slow and costly,so there is need for method which is fast and cost effective for early detection of tumour so that many lives can be saved, the methods in use require expert radiologist and if there are large number of patients and we will not be able to do meta-analysis, the manual diagnosis requires several hour of concentration from radiologiost,therefore,it is exposed to human error.

2. Materials and Methods

Data is a part of segmentation challenge which is conducted every year as a part of medical imaging conference called MICCAI-BRATS workshop 2015.This is publicly available dataset,it is multicentric because MR imaging is grayscale values or contrast that you see in values and some of artifacts and shading that you get in the images,vary from scanner to scanner and from hospital tohospital.So it is important to get data from different scanners or different centres,like different hospitals,so that your network generalize well to some new data from different hospitals.We use Brats data which contains MRI scan of tumour,generally gliomas,which is aprimary brain malignant stage tumour.The size of data file is almost 3 GB and for downloading the file go to “Medical Segmentation Decathon” website and select the download link.There are total of 245 MRI images which are further divided into 110 image for training the network and 145 images for testing the data.

Non Local Mean Filter is used for image denoising which calculates weighted average of pixels and finding similarity with the target pixel. The tool used is FSL and BET brain extraction uses the input image and gives the denoised image.The modification to image is done edge detection for identifying horizontal and vertical edges.For ex-if image size is n*n in grayscale,we apply f*f filters also called kernel and perform convolutional operation i.e element wise multiplication and obtain (n-f+1)*(n-f+1) edge detector image .Padding is done to reduce shrinkage of image and minimize the information loss.The pixels in the corners of image are used less while the pixels in middle are used more which can result in the loss of information.

The MRI data is a sequence of 3D volume of multiple sequences and we combine them into single 3D volume .Once we combine image for single slice and then we define boundaries of tumour using voxels also called pixels in 3D.This is done by breaking whole volume of images into subvolume and its is fed to segmentation model and result is aggregated.The training set is labeled and MRI data after preprocessing is given to CNN .The 3D volume of image is converted to 1D using 3D filters and each unit in 1D array is neuron which is given to fully connected network and output is obtained.After comparing the ouput and target output,the loss function is calculated and using backpropagation algorithm weights are optimized to get the desired ouput.

3. Results and Discussion

3.1 RELATED WORK

This was one of the winning entries in 2016 BRATS competition [S. Pereira May 2016 pp1240-1251]. The CNN were trained on 2D patches of MRI used to predict class of centre pixel. There was separate network of high grade glioma and low grade glioma. There was lot of preprocessing done like histogram matching in which intensity is made unform throughout. The classification task is done so it also make use of loss function which is calculated and alongwith label we can predict the results [1].Training is done with patches of size 33*33 extracted from MRI images and input to network to predict class of centre pixel

of patch. The network architecture is inspired by VGG Network, high grade and low grade network differs in number of convolutional layer preceding a max-pooling layer. The low grade glioma network has higher dropouts in fully connected layer than high grade network.Testing is done for patches of size 33*33 extracted from MRI image input to trained network. Patches were fed to trained network based on grade of lesion. The network to predict class of centre pixel of patches and connected components analysis is performed to reduce false positive.The above method was able to obtain dice similarity coefficient metric (0.88, 0.83, 0.77) for the challenge data set.Also, it secured first position by online evaluation platform.One of method used encoder-decoder type CNN fully convolutional neural network [Alex V Sep 2017 (pp. 216-225) Springer,Cham]. In a single forward pass, previously discussed patch based technique are slow as network predicts only centre pixel of patch. So inference time is reduced by either predict class associated to subset of pixels in image or patch or predict class of all pixels in image in a sinlge forward pass.Network accepts input of 240*240 and predicts class associated to all 240*240 pixel in one pass. The network has encoder which consists of convolutional layer and max-pooling layer, also it has decoder which consists of transposed convolutional layer. The skip connection made use in network to combine low level high resolution feature and high level low resolution features. In testing, axial slice of brain are fed to be used to train the network. The coonected components ate used to reduce the false positive. A single forward pass, generates segmentation mask for entire, slice of brain.The result obtained were good, dice score when using validation dataset 0.87 for whole tumour, 0.81 for core substructure and 0.72 for enhanced region. One of better method used 2-D Tiramisu-103 for segmentation of brain tissue [Shaikh M Sep 2017 (pp. 309-219) Springer,Cham]. Tiramisu-103 is a semantic segmentation network with dense block, transition Down and Transition Up. Training and Testing regime similar to U-Net. The postprocessing using connected components and Conditional Random Fields. The Transition Down layer has batch normalization, ReLU layer followed by 1*1 convolutional layer, dropout of 0.2 and max-pooling layer of 2*2 whereas Tansition Up layer 3*3 convolutional layer with stride 2. The dense block which consists of series of convolutional layer and each layer receives features learnt in the preceding layer as the input. The memory explosion maintained by learning a small number pf feature per layer growth rate (k=4). Transition Down is used to reduce the spatial dimension of the features and used in downsampling path of the network. Transition Up comprises of transposed convolution and used to increase the spatial resolution of the feature maps.The result obtained has accuracy of almost 0.85 and dice score 0.85-0.87 for whole tumour, and 0.79 for enhanced tumour. The building block of 3-D tiramisu is similar to 2-D variant [K. Kamnitsa et al 2016 pp 18-22]. The convolutional oprations are 3-D in nature and input to network is a 64^3 patch, stratified sampling from all classes to circumvent class imbalance. The 3-D connected components and CRF are postprocessing techniques utilized.The method used Deep Medic which is a 3-D convolutions aid in providing greater context to the network about the lesion. The memory requirement which is restricted by patch based technique is overcome. The training comprises of dual pathway – Local features at high resolution and Global features at low resolution. Local features learnt from patches of size 25^3 while global feature is learned from patches of size 51^3. The larger patches are resized to 19^3 and fed to the network. Network comprises of residual connections and global and local pathways are fused after a series of convolution. The network predicts the center 9^3 voxels of the input patch.In testing, during inference since network is fully convolutional the patches for larger sizes can be used for fasten the prediction time. 64 patches are extracted from MR volumes with a stride of 32. The stride was found to be useful for boundary voxels in the patches. Segmentations generated with stride seemed to be more smoother than un-strided approach. CRF was additionally done to smoothen the prediction made by the network. We discuss a completely programmed cerebrum tumor division strategy dependent on Deep Neural Networks (DNNs) [M. Prastawa Dec 2015 pp. 1993-2024]. The proposed systems are custom fitted to glioblastomas (both low and high evaluation) envisioned in MR pictures. These tumors have practically any sort of shape, size, and difference. Here, we give a depiction of various model decisions that we've seen as essential for acquiring serious execution. We present a novel CNN design which varies from those generally utilized in PC vision. Our CNN abuses both neighborhood includes just as increasingly worldwide logical highlights all the while. Likewise, unique in relation to most customary employments of CNNs, our systems utilize a last layer that is a convolutional usage of a completely associated layer which permits a 40 overlay accelerate. At long last, we investigate a course engineering where the yield of a fundamental CNN is treated as an extra wellspring of data for a resulting CNN. Results provided details regarding the 2013 BRATS test dataset uncover that our design improves over the as of now distributed best in class while being more than multiple times quicker.

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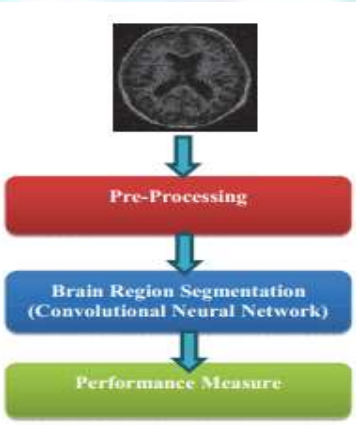
3.2 METHODOLGY

Deep Learning is one of the machine learning algorithm, it gains from the information picture utilizing either directed or unsupervised learning approach. In this,we have administered learning approach utilizing Convolutional Neural Network utilized for precise mind area division. So,typically not one image is acquired but volumes are acquired.It is the image volumes basically 3D-arrays,each image is 3D-array (240*240*155). This is the in-plane size and is in form of slices. Multiple image are acquired and each image volume corresponds to what is known as sequence.Each sequence corresponds to a separate kind of grayscale contrast in the image. So multiple different types of contrast are possible using MR images so for typical glioma imaging session,you will typically acquire about for such sequences. Every MR image is actually a volume and you will acquire about 4 such 3-D arrays per patient for diagnosing gliomas. The constituent of glioma are edema(collection of fluid), nerosis(dead cells),enhancing tumour(breakdown of blood brain barrier),non-enhancing tumour [4]. So this is why we need 4 such 3D-arrays because certain components of tumour are seen much more clearly in certain sequence.MRI images are taken from publicly available dataset MICCAI, a fully automated system for brain region segmentation by using deep learning techniques.There are three stages- pre-processing, Segmentation via Convolutional Neural Network, Perfomance Measure.



"Fig. 2 Steps involved in tumour detection starting from

denoising of MRI image in preprocessing and then this image is input to our network

for segmentation and performance via confusion matrix is calculated."

A.Preprocessing

The MR image are preprocessed to improve the quality of image for segmentation. In this,we use Non Local Mean Filter is utilized for picture denoising which computes weighted normal of pixels and discovering likeness with the objective pixel [5]. The tool used is FSL and BET brain extraction uses the input image and gives the denoised image.If you consider intensity of 100 or some anatomy in brain,which has intensity of 100,you want to match across all dataset so use histogram matching. It consist of three step-

Step 1: The weighted mean non-local pixel is used to remove data redundancy for the patces of noise image and noise free pixel is generated.The intensity ,NL[u(x_i)]of the noisy pixel u(xj) in the search window Vi is given by

$$NL(u(x_i)) = \sum_{x_j \in v_i} w(x_i, x_j) u(x_j) \qquad (1)$$

Where, M is the radius of the pursuit window Vi, (w (xi, xj), is the weight apportion to the loud worth u(xj) to set up the power u(xi) at voxel xi.

Step 2: The weight finds the similarity between intensity of close patches N_i and N_j concentrate on vowel x_i and x_j is estimated by the weight such that w(x, xj)∈[1,0]).

Step 3: The weight based on Euclidean distance between neighborhood patches is given by,

$$w(x_i, x_j) = \frac{1}{2} \exp\left[- \frac{\|u(N_i) - u(N_j)\|_2^2}{\square^2} \right] \qquad (2)$$

Where,

$$\sum_{x_j \in v_I} w(x_i, x_j) = 1$$

is an effective method to reduce the noise and it takes less time. Using Non Local Mean (NLM) filter(as shown in fig 2),there is no loss of information from the input image.When different sequences the MRI are combined then it is necessary that they are all having same alignment which is done in this preprocessing of image.

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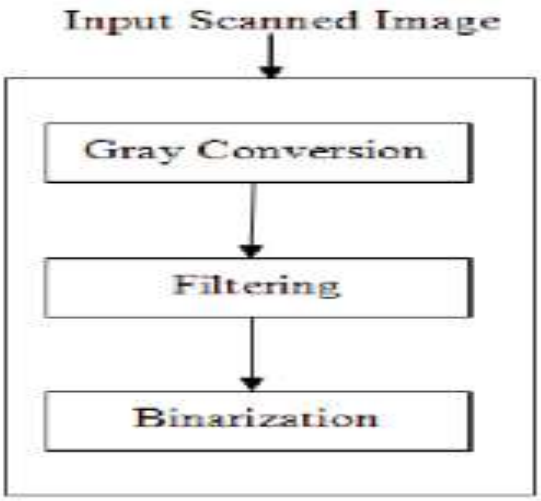


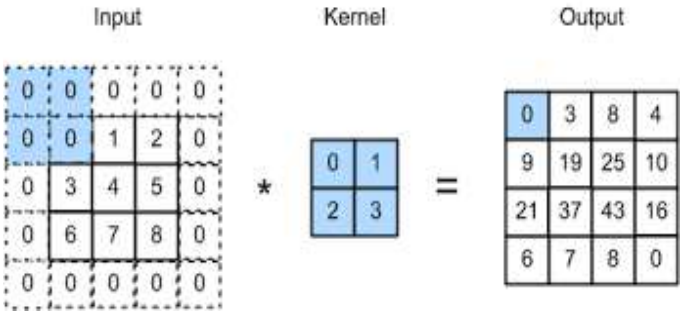
"Fig. 3. Preprocessing of image is done through three step (A) remove noise by non-local

mean filter algorithm (B) converting coloured pixel to grayscale and

(C) applying filtering and binarisation for intensities as input."

The denoised image is then converted to grayscale and filters are applied for brightness,curvature,intensities etc and finally each intensities value in matrix is binarized to produced a processed image for input to our CNN [6]. The modification to image is done edge detection for identifying horizontal and vertical edges. For ex-if image size is n*n in grayscale,we apply f*f filters also called kernel and perform convolutional operation i.e element wise multiplication and obtain (n-f+1)*(n-f+1) edge detector image. Padding is done to reduce shrinkage of image and minimize the information loss [7]. The pixels in the corners of image are used less while the pixels in middle are used more which can result in the loss of information. Padding is done as shown in Fig. 4.

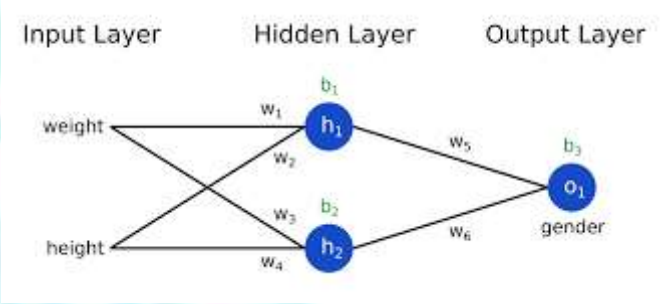
The MRI data is a sequence of 3D volume of multiple sequences and we combine them into single 3D volume. Once we combine image for single slice and then we define boundaries of tumour using voxels also called pixels in 3D. This is done by breaking whole volume of images into subvolume and it is fed to segmentation model and result is aggregated. The training set is labeled and MRI data after preprocessing is given to CNN. The 3D volume of image is converted to 1D using 3D filters and each unit in 1D array is neuron which is given to fully connected network and output is obtained. After comparing the ouput and target output, the loss function is calculated and using backpropagation algorithm weights are optimized to get the desired output.



"Fig. 4. Padding is applied to reduce the information loss from corners of image"

B. Convolutional Neural Network

How Neural Network works?



"Fig. 5. It shows a simple neural network having input neurons and hidden

layers which are initially given weights and inputs to calculate desired

output using optimsation algorithms."

As shown in fig 5, we are using supervised learning every input is associated with a label which is predicted by input layer. The input is given to the input layer and initially weights are assigned and output is calculated. Now the difference between output and target output is calculated and weights are optimized which are again fed back to network to calculate our desired output [8].This is the iterative process and features are extracted accordingly.

The traditional machine learning approach used two step-

- Feature Extraction-In this,the engineers manually extracted features called handcrafted images and represented them as vector.

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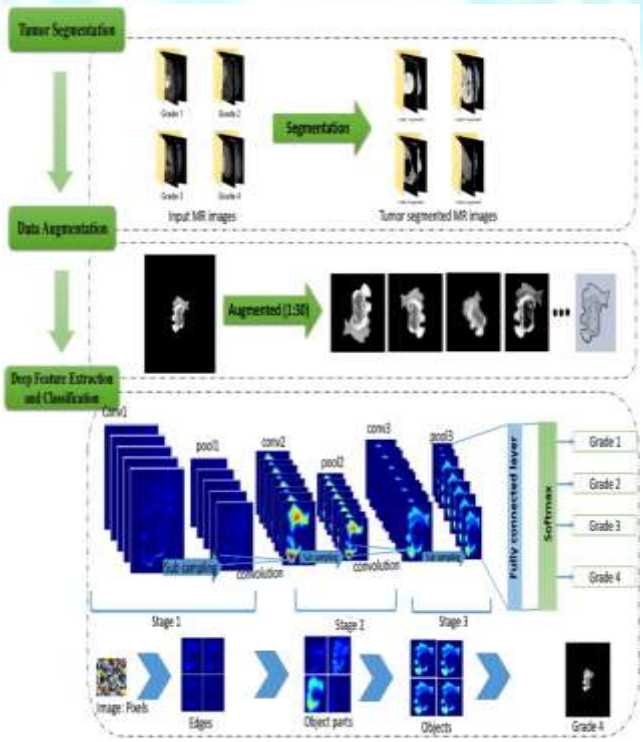
- Classifier- Using this classification was done by SVM or k-means algorithm.

Convolutional Neural Network(CNN) is one of the neural network which is used in image processing, classification, egmentation etc. It is end to end learning process and completely automatic as there is no human interference [9]. As already discussed,we give four 3-D images per patient for diagnosis. We use size of 240 by 240 by 155 by 4 where first three dimension are height,width and depth for input image and we use denoised image as an input for CNN.We have 7*7 convolutional layer followed by polling layer 4*4 again followed by 3*3 convolutional layer and 2*2 polling layer and finally we have softmax function and fully connected layer to get the desired result.The neural network used is shown in fig 4.

When we train the model,weight are updated to optimise the network.The feautures are used to predict the labels for unseen images. CNN extracts features directly from image unlike backpropagation neural network [10]. The input data given to the information layer predicts the label,CNN computes speck result of weight,input and include predisposition.The pooling layer is added to make down sampling i.e decrease the connections.There are three stages of CNN to learn the features

- Design the network and apply softmax.
- Train the network with input images.
- Extract the desired features.



"Fig.6 Network architecture of CNN having different layers (A) convolutional layer to reduce size of image (B) pooling layer to retain maximum intensity in images (C) fully connected

layer to give 1D input to each neuron and apply softmax function to classify output."

Different Stages in Feature Extraction-

i. **Convolutional Layer**-In this input image is given and we apply filters to reduce the size of image.Data are grouped according to feature i.e data having same feature are placed in one group.For ex-if we are giving 6*6 input image apply filters then we get 3*3 output image which is then given to ReLU layer.We have designed two phase training procedure that allows us to handle improper tumour labels.The input images given to network make the network optimise the weight so that weight can be adjusted and it can learn features for identifying the tumour for a unseen image.The features can be extracted in terms of brightness,texture,curvature and shape which is then classified using training set and classifier like SVM or random forest and performance parameters are calculated [11]. The convolutional layer is the inside structure square of a CNN. The layer's limits involve a ton of learnable channels (or bits), which have a little open field, yet loosen up through the full significance of the data volume. During the forward pass, each channel is convolved over the width and stature of the data volume, enlisting the spot thing between the sections of the channel and the information and conveying a 2-dimensional order guide of that channel. Consequently, the framework learns channels that authorize when it recognizes some specific kind of feature at some spatial circumstance in the input.Stacking the establishment maps for all channels along the significance estimation outlines the full yield volume of the convolution layer [12]. Each segment in the yield volume can thusly be deciphered as a yield of a neuron that looks at a little region in the data and offers limits with neurons in a comparative establishment map.

ii. **ReLU Layer**-In this we consider all positive value which are contributing towards the feature and all negative value is converted to zero.So,we are taking only those intensities which will help in extracting the features and neglecting value which will not support much in feature extraction.

iii. **Pooling Layer**-In this,the output from ReLU layer is taken and

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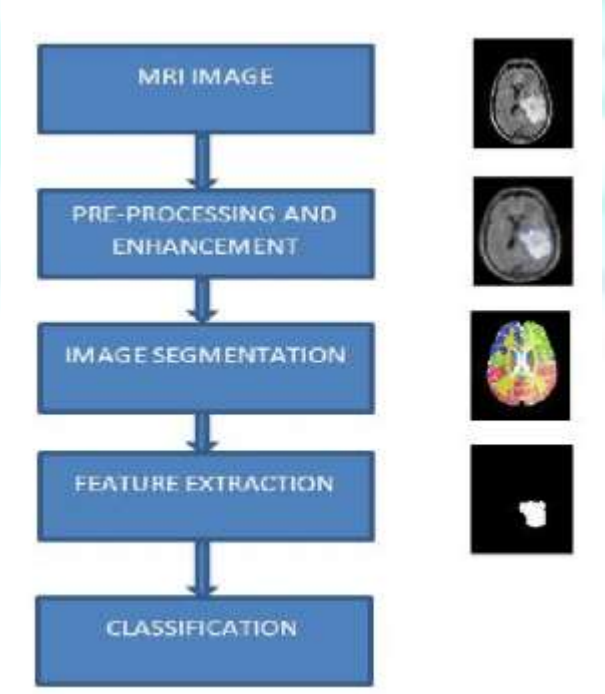
is reduced to by taking maximum intensity in different region which is contributing to greater extent so they will be retained [13].These three operation will be repeated depending upon type of convolutional network. Instinctively, the specific area of an element is less significant than its unpleasant area comparative with different highlights. This is the thought behind the utilization of pooling in convolutional neural systems. The pooling layer serves to logically lessen the spatial size of the portrayal, to decrease the quantity of boundaries, memory impression and measure of calculation in the system, and thus to likewise control overfitting

iv. **Flattening Layer**-This is simple added to reduce all 2-D and 3-D image to 1-D so that all will be used as an input to network.

v. **Fully Connected Layer-**In this,the output from flattening layer is taken and each output is fed to one neuron and all are connected further to get desired output.A softmax classifier is used to separate the classes –normal(no tumour) and abnormal(contain tumour).



"Fig. 7. The steps involved in feature extraction are input generation,training the network

and extracting the learned features like brightness,curvature etc and classifying them

as output data i.e which are tumour and non-tumour."

Data Normalisation is done by applying scaling,shifting and modifying the data and every pixel value is converted to ratio between 0 and 1 [14].The output y is calculated as,

$$y=w*x+bias \qquad (3)$$

where x=input pixel and w=optimized weight

The cross entropy function is used to calculate the error i.e difference between true output and obtained output and weight is updated accordingly and propagated backward to optimize the network and get better result [15].

C. Performance Measure

It is important to analyse our result both quantitatively and qualitatively to visualize and give numerical value to obtained outcome.The PSNR value is calculated to find the loss in the image pixel and it is found by,

$$PSNR=10\log_{10}(f_{max}^2/MSE) \qquad (4)$$

Where f_{max} is maximum possible pixel value of image and MSE is mean square error between constructed and original image.

The "confusion matrix" is created and and used to calculate all the parameters to show the result obtained.The segmentation result have error rate defined by false and true positive,false and true negative [16].The performance is then calculated in terms of this error rate which is given by,

Recall Sensitivity True positive rate (TPR)	$\frac{TP}{FN+TP}=\frac{TP}{P}$
False positive rate (FPR) False alarm rate	$\frac{FP}{TN+FP}=\frac{FP}{N}$
Specificity True negative rate (TNR)	$\frac{TN}{TN+FP}=\frac{TN}{N}=1-FPR$
Precision	$\frac{TP}{TP+FP}$
False negative rate (FNR)	$\frac{FN}{FN+TP}=\frac{FN}{P}$
Accuracy	$\frac{TP+TN}{P+N}=\frac{TP+TN}{TP+TN+FP+FN}$

"Table 1 Confusion matrix is calculated which gives relation between predicted and actual value,if predicted positive and actual positive both matches then we say true positive(TP) otherwise false positive(FP),calculate

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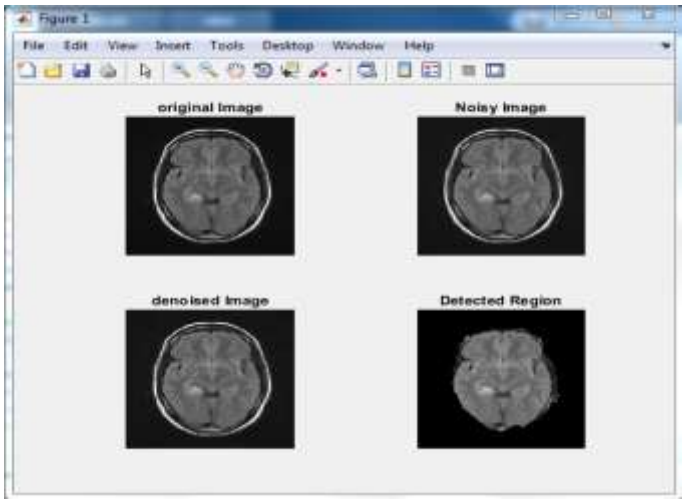
performance of classifier for test data whose true value are known."

The analysis of tumour by use of MRI is tough task, and the doctors depend on biopsy test for detection of every kind of cancer. Biopsy are time consuming and risk involved in specially in case of brain tumour and also they are susceptible to human error, therefore, deep learning techniques can be used to get desired and quick result. It saves both time and cost thus proving to be economical. We have decided to use MICCAI dataset for both training and testing. As metioned earlier, there are only 110 images in training phase and 145 images for testing. Noisy MRI image are firstly denoised using Non Local Mean Filter method and then denoised image are fed to CNN to train it iteratively with input pattern along with target labels. Trained CNN is then given unseen images and Performance Measure is important step in developing a segmentation algorithm.

Input Images	Denoised Image PSNR(db)	Sensitivity (%)	Specificity (%)	Accuracy (%)
Image 1	43.4950	0.8473	0.9884	0.9436
Image 2	43.3960	0.9545	0.9677	0.9436
Image 3	43.5087	0.8348	0.9968	0.9468
Image 4	43.4229	0.9586	0.9723	0.9678
Image 5	43.5086	0.9549	0.8545	0.8864

"Table 2. The table shows us performance measure of different input images which are multicentric and we calculate the psnr(signal to noise ratio),specificity,sensitivity and accuracy to check how our network is performing on different sets of data."

The proposed method uses BRATS database for evaluating the brain tumour segmentation . All brains in dataset have similar orientation. It would be ideal if you note we were unable to utilize BRATS 2014 dataset because of issue with both the framework playing out the assessment and nature of marked information.



"Fig. 8. The original MRI image of patient is preprocessed and denoised image is

used as an input for convolutional neural network and segmentation is done

to detect the tumour region."

Different optimizer like Gradient Descent Optimisation which uses ADAM model and learning rate alpha and depends on time can be used to optimize the network more efficiently and fast. In Fig. 5.3,image 1 we can see we are getting accuracy 94.36% which is very good and it can be improved further by training our network to more and more data i.e image. We can see the input image is firstly denoised and denoised image is taken as input for the convolutional neural network which then produces the tumour detected image.Technique such as Markov Networks ,SVM can also be implemented in CNN to improve the classification task of our network get more accuracy. The data can be augmentated by applying rotation,shifting,brightness and zoom to improve the performance.

We assembled a profound CNN model that fragment MRI pictures utilizing pixel savvy order approach, numerous examinations were held during the tuning procedure of the model and their outcomes were utilized to improve the model execution. 0.94 and 0.92 accuracy for the images, we accept that these outcomes can be improved further with the utilization of post preparing strategies.

The given segment model has time issue to segment MRI imasges it takes around four minutes to portion a 240×240

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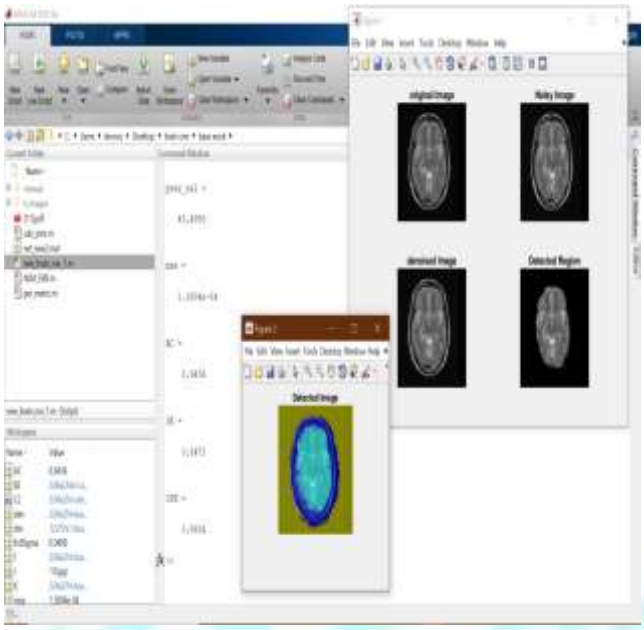
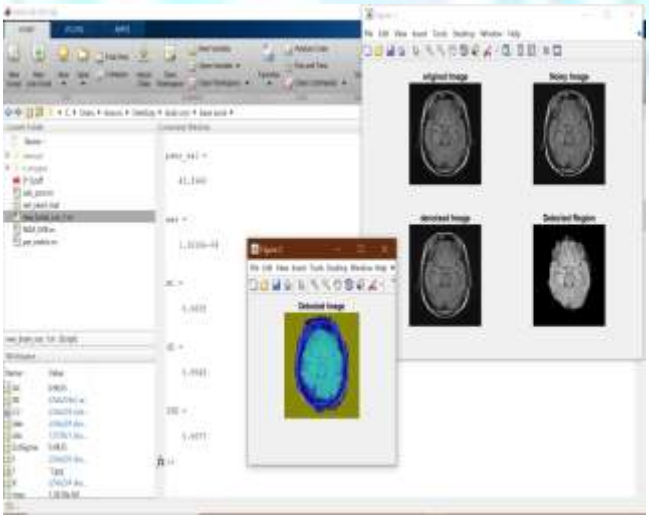
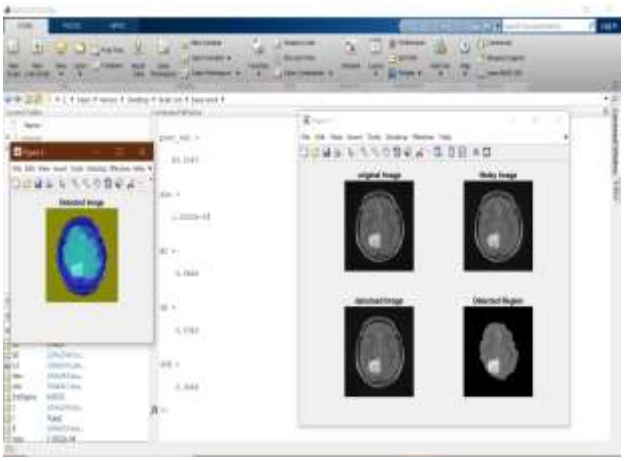
picture. It additionally performs inadequately in dividing pixels at the edge of the brain.



"Fig. 9. Result for image 1 obtained after applying deep learning algorithm and showing accuracy of 94.36% with specificity 98.84%."



"Fig. 10. Result for image 2 obtained after applying deep learning algorithm and showing accuracy of 96.35% with specificity 96.77%."



"Fig. 11. Result for image 3 obtained after applying deep learning algorithm and showing accuracy of 94.68% with specificity 99.68%."

"Fig. 12. Result for image 4 obtained after applying deep learning algorithm and showing accuracy of 96.78% with specificity 97.23%."

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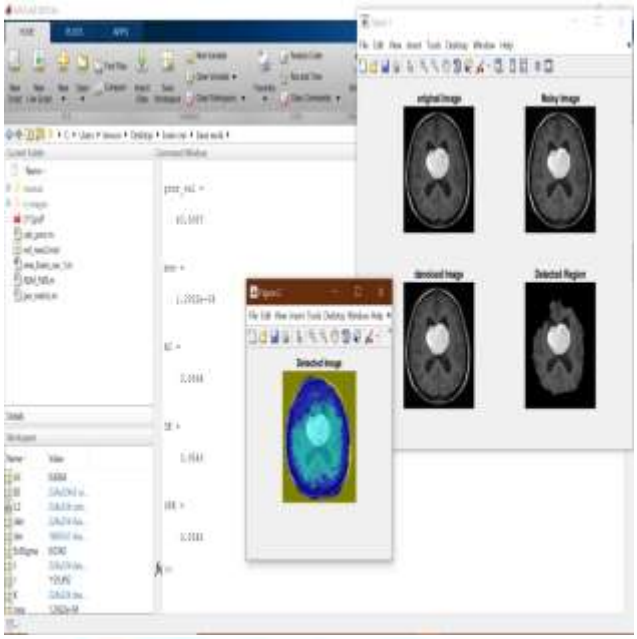

"Fig. 13. Result for image 5 obtained after applying deep learning algorithm and showing accuracy of 88.64% with specificity 85.45%."

The deep learning method is very much different from the machine learning method. The machine learning method uses algorithms to input data, learn from given data, and make decision based on the experience or learning whereas the deep learning can learn and make decisions on its own. Deep learning has a capability of learning from data that is unstructured or unlabeled. In deep learning, the algorithms try to learn using method of feature extraction which is very different and makes the model fully automatic, here we don't require any handcrafted feature. In traditional method we need to develop feature extractor for different problem, so we use deep learning which reduces effort of developing different feature extractor for different problem.

The present method achieved accuracy of 90-94%. The use of CNNs are spurred by the way that they can catch significant highlights from a image. The regular neural systems can't do this on their own they require handcrafted features. Another principle highlight of CNNs is weight sharing. Lets take a guide to clarify this. Let's assume you have a one layered CNN with 10 channels of size 5x5. Presently you can just figure boundaries of such a CNN, it would be 5*5*10 loads and 10 inclinations i.e 5* 5*10 + 10 = 260 boundaries. Presently lets take a basic one layered NN with 250 neurons, here the quantity of weight boundaries relying upon the size of pictures is '250 x K' where size of the picture is P X M and K = (P *M). Moreover, you need 'M' inclinations. For the MNIST information as contribution to such a NN we will have (250*784+1 = 19601) boundaries. Unmistakably, CNN is progressively effective as far as memory and multifaceted nature. Envision NNs and CNNs with billions of neurons, at that point CNNs would be less unpredictable and spares memory contrasted with the NN.

Regarding execution, CNNs outflank NNs on customary picture acknowledgment assignments and numerous different errands. Take a gander at the Inception model, Resnet50 and numerous others.

For a totally new issue CNNs are excellent element extractors. This implies you can separate helpful properties from a previously prepared CNN with its prepared loads by taking care of your information on each level and tune the CNN a piece for the particular assignment. Eg : Add a classifier after the last layer with names explicit to the errand. This is additionally called pre-preparing and CNNs are proficient in such assignments contrasted with NNs. Another favorable position of this pre-preparing is we abstain from preparing of CNN and spare memory, time. The main thing you need to prepare is the classifier toward the end for your marks.

4. Conclusions

The main objective was to build a solution that can segment brain tissues on various MRI images with good accuracy. So, we made study of MRI images, their various properties and how different tissues behave when exposed to radiowaves to have good understanding of problem. We made thorough study of previous method to come up with a better solution. In one of previous method of 2-D patch extraction could achieve accuracy of 88% where the network architecture is inspired by VGG Network, high grade and low grade network differs in number of convolutional layer preceding a max-pooling layer. In other,they have used encoder-decoder type neural network and achieved accuracy of 87.2%. In a single forward pass, previously discussed patch based technique are slow as network predicts only centre pixel of patch. In previous method, we need to develop feature extractor for different problem, so we use deep learning which reduces effort of developing different feature extractor for different problem. In the present study, we have used supervised learning to learn the features from the input images and found that Convolutional Neural Network can achieve good accuracy.In

CNN, the network in starting phase learns low level feature like lines or edges and then slowly learns the high level featuresAfter going through various methods and algorithm, CNNs was used in the approach .

In the work, Convolutional Neural Network(CNN) is used for detection of portion which contains tumour. The publicly available dataset from MICCAI was used in the work. The MRI images are preprocessed using histogram matching and Non-Local Mean Filter and Tumour is detected by using CNN. The advantage of deep learning method is no handcrafted features or human interaction is used,the network learns from itself. The network gives us the high accuracy of 90%-96%.In future, improve the accuracy by training with more number of muticentric images.Use of more hidden layers in our network to optimize the network more efficiently, identifying different tumour sub regions in i.e edema,necrotic and enhancing tumour regions.

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