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Detection and analysis of disease from brain MRI image

Pragati , Research Scholar, Institute of technology & management, Aligarh(U.P)

ABSTRACT

Now a day's tumor is second leading cause of cancer. Due to cancer large no of patients are in danger. The medical field needs fast, automated, efficient and reliable technique to detect tumor like brain tumor. Detection plays very important role in treatment. If proper detection of tumor is possible then doctors keep a patient out of danger. Various image processing techniques are used in this application. Using this application doctors provide proper treatment and save a number of tumor patients. A tumor is nothing but excess cells growing in an uncontrolled manner. Brain tumor cells grow in a way that they eventually take up all the nutrients meant for the healthy cells and tissues, which results in brain failure. Currently, doctors locate the position and the area of brain tumor by looking at the MR Images of the brain of the patient manually. This results in inaccurate detection of the tumor and is considered very time consuming. A tumor is a mass of tissue it grows out of control. We can use a Deep Learning architectures CNN (Convolution Neural Network) generally known as NN (Neural Network) and VGG 16(visual geometry group) Transfer learning for detect the brain tumor. In this paper, the design and implementation of a tumor detection system using two CNN models is considered. Digital image processing and Deep Learning technologies enable us to develop an automatic system for the diagnosis/detection of various kind of diseases and abnormalities. The tumor detection system may include image enhancement, segmentation, data augmentation, features extraction and classification; all these steps are discussed in details in the above sections. To work on CNNs, powerful GPU based system are required to speed up the process, lot of processing is carried out and also lot of RAM is required to process the images for testing. CNNs have also some options such as optimization technique selection, Number of Epoch, Batch size, iteration and learning rate. These options are tuned to get the optimal results from the CNN model. Learning rate is used to update the weights and bias in training phase, learning rate changes the weights. One Epoch is when the model see all images in training, as the training data maybe of very big sizes, the data in each Epoch is divided into batch sizes. Every epoch has a training and test session, after each Epoch the weights are updated according to the learning rate, optimization algorithms are used to update the learning of a CNN adaptively. When the best weights for training are computed, the model is said to be trained. All the experimental work is carried out in MATLAB simulation tool.

Keywords: Deep Learning, MATLAB, CNN, Brain Tumor, Tumor Detection, Magnetic Resonance Imaging, Digital Image Processing.

INTRODUCTION

Medical image analysis is an excited and challenging research field from the last two decades, it has many varieties of applications in different research areas that are related to health of not humans only but also animals. Medical images are very useful for study, diagnosis, and patient treatment plans. The biomedical image acquisition is done from the radiology department of a hospital, biomedical images are different from other 2-D and color medical images. The radiology unit of a hospital consists of different kind of machines i.e. Magnetic resonance imaging, Magnetic resonance angiography,

Positron emission tomography, Computed tomography, X-ray and ultrasound machine. The constructed images using these biomedical imaging may have some issues of noise, low illumination, blurness or sharpness, to overcome these issues first of all we apply some basic Digital images processing techniques to enhance the quality of images of the obtained images. These enhanced images are further processed for region of interest segmentation (Yi and Zhijun 2010), calculation of tumor and other anatomical structures sizes in 2D and 3D, classification the types of images or to classify the type and stage of a tumor and visualization of tumor in 3D and 4D space using volume rendering computer graphics algorithms. These four operations are now days the hot research topics for researchers working on medical image processing and computer vision technologies (Enhancement 2002). The brain is considered as the main organ of the central nerve system, which is protected a hard bone called the skull. The volume of the human brain on average is 1260 cubic millimeters which weights around 1.3-1.5 Kg, the CNS system consists of billions of neurons, blood vessels and glial cells which allow insulation between the neurons. The brain consists of gray matter, white matter and cerebrospinal fluid. The colour of WM appears light pinkish which is covered by GM, the colour of GM is gray because it doesn’t contain myelin sheath. Due to the change in colour these regions can easily be distinguished from one another. The human brain is surrounded by fluid called cerebrospinal fluid that flows through the brain and entire spinal cord. Tumors are muscular which is a kind of soft tissues is, tumors are actually the growth of abnormal tissues with the body. In the living organism, new cells are produced which replaces the old dead cells in case of human suffering from tumor, the cells of the tumor don’t die which increases in the body. Tumors are life threatening if aren’t diagnosed and treated on time. Benign and malignant are the two classes in which tumor can be divided, i.e., benign tumors are considering as non-cancerous tumor which are smaller in size, have a slow in growing rate, and do not affect the boundary normal cells. The malignant on the other hand are considered cancerous which has a very fast-growing rate and also affects the surrounding normal cells. In biomedical imaging MR imaging is an important and popular modality that construct 3D images of human soft water containing cell grids, MRI machine can create single as well series of volumetric images which help the medical doctors (i.e. Radiologist, surgons) in patients disease diagnosis and treatment planning. In our research work, we will also investigate and explain different segmentation methods, image segmentation improves the accuracy of tumor type identification by removing the unwanted region from the tumor regions.

OVERVIEW OF BRAIN AND BRAIN TUMOR

Main part in human nervous system is human brain. It is located in human head and it is covered by the skull. The function of human brain is to control all the parts of human body. It is one kind of organ that allows humans to accept and endure all type of environmental condition. The human brain enables humans to do the action and share the thoughts and feeling. In this section we describe the structure of the brain for understanding the basic things [4].

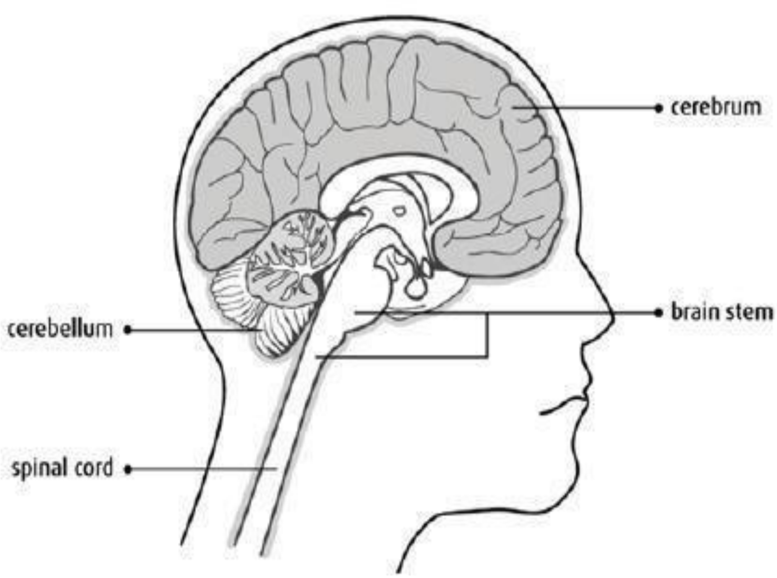

Fig.1: Basic Structure of human brain [5]

The brain tumors are classified into mainly two types: Primary brain tumor (benign tumor) and secondary brain tumor (malignant tumor).The benign tumor is one type of cell grows slowly in the brain and type of brain tumor is gliomas. It originates from non neuronal brain cells called astrocytes. Basically primary tumors are less aggressive but these tumors have much pressure on the brain and because of that, brain stops working properly [6]. The secondary tumors are more aggressive and more quick to spread into other tissue. Secondary brain tumor originates through other part of the body. These type of tumor have a cancer cell in the body that is metastatic which spread into different areas of the body like brain, lungs etc. Secondary brain tumor is very malignant. The reason of secondary brain tumor cause is mainly due to lungs cancer, kidney cancer, bladder cancer etc [7].

MAGNETIC RESONANCE IMAGING (MRI)

Raymond v. Damadian invented the first magnetic image in 1969. In 1977 the first MRI image were invented for human body and the most perfect technique. Because of MRI we are able to visualize the details of internal structure of brain and from that we can observe the different types of tissues of human body. MRI images have a better quality as compared to other medical imaging techniques like X-ray and computer tomography.[8]. MRI is good technique for knowing the brain tumor in human body. There are different images of MRI for mapping tumor induced Change including T1 weighted, T2 weighted and FLAIR (Fluid attenuated inversion recovery) weighted shown in figure.

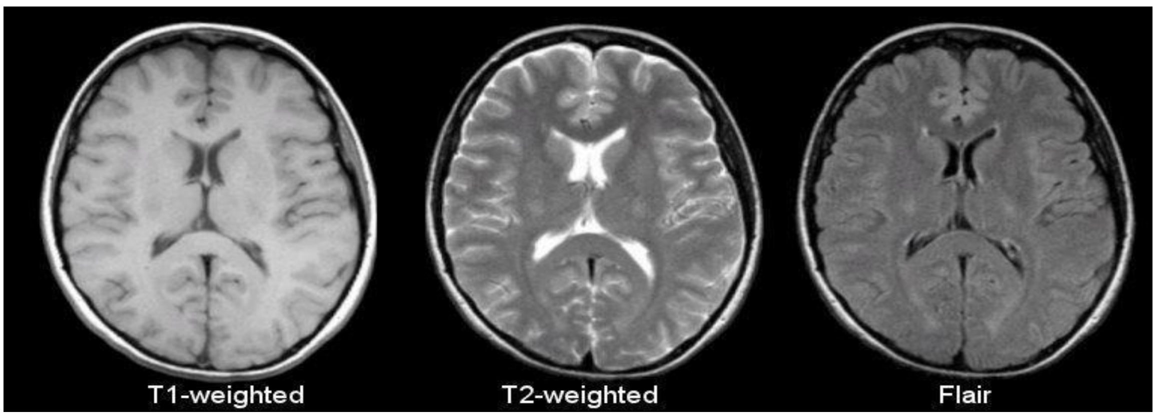

Fig 2: T1, T2 and Flair image [9]

The most common MRI sequence is T1 weighted and T2 weighted. In T1 weighted only one tissue type is bright FAT and in T2 weighted two tissue types are Bright FAT and Water both. In T1 weighted the repetition time (TR) is short in T2 weighted the TE and TR is long. The TE an TR are the pulse sequence parameter and stand for repetition time and time to echo and it can be measured in millisecond(ms)[9]. The echo time represented time from the centre of the RF pulse to the centre of the echo and TR is the length of time between the TE repeating series of pulse and echo is shown in figure.

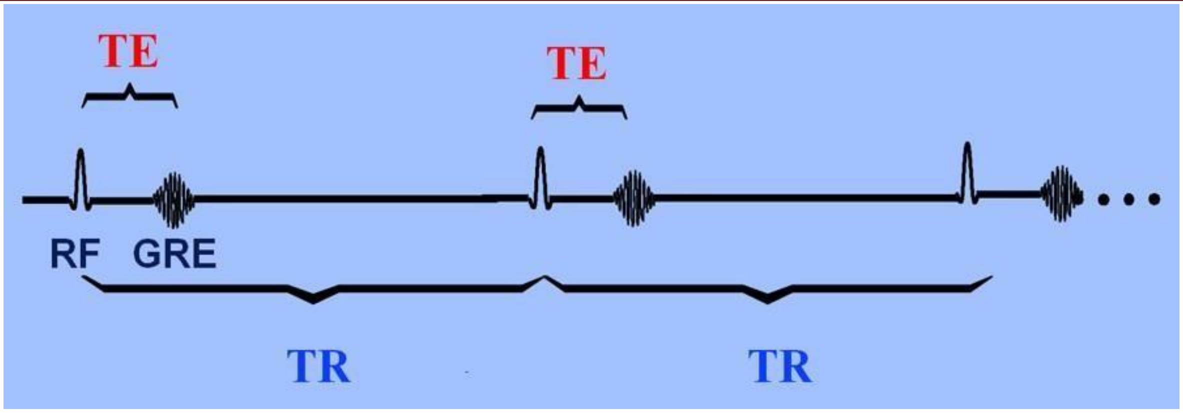

Fig. 3: Graph of TE and TR [10]

The third commonly used sequence in the FLAIR. The Flair sequence is almost same as T2-weighted image. The only difference is TE and TR time are very long. Their approximate TR and TE times are shown in table.

Fig.4: Table of TR and TE time [9]

	TR (msec)	TE (msec)
T1-Weighted (short TR and TE)	500	14
T2-Weighted (long TR and TE)	4000	90
Flair (very long TR and TE	9000	114

1.1 APPLICATION

- The main aim of the applications is tumor identification.
- The main reason behind the development of this application is to provide proper treatment as soon as possible and protect the human life which is in danger.
- This application is helpful to doctors as well as patient.
- The manual identification is not so fast, more accurate and efficient for user.
  To overcome those problem this application is design.
- It is user friendly application.

1.2 OBJECTIVE

- To provide doctors good software to identify tumor and their causes.
- Save patient's time.
- Provide a solution appropriately at early stages. • Get timely consultation.

1.3 MOTIVATION

The main motivation behind Brain tumor detection is to not only detect tumor but it can also classify types of tumor. So it can be useful in cases such as we have to sure the tumor is positive or negative, it can detect tumor from image and return the result tumor is positive or not. This project deals with such a system, which uses computer, based procedures to detect tumor blocks and classify the type of tumor using Convolution Neural Network Algorithm for MRI images of different patients.

2. LITERATURE SURVEY

Paper-1: Image Analysis for MRI Based Brain Tumor Detection and Feature Extraction Using Biologically Inspired BWT and SVM

• Publication Year: 6 March 2017

- **Author**: Nilesh Bhaskarrao Bahadure, Arun Kumar Ray, and Har Pal Thethi
- **Journal Name:** Hindawi International Journal of Biomedical Imaging
- **Summary:** In this paper using MR images of the brain, we segmented brain tissues into normal tissues such as white matter, gray matter, cerebrospinal fluid (background), and tumor-infected tissues. We used pre-processing to improve the signal-to-noise ratio and to eliminate the effect of unwanted noise. We can used the skull stripping algorithm its based on threshold technique for improve the skull stripping performance.

Paper-2: A Survey on Brain Tumor Detection Using Image Processing Techniques

- Publication Year: 2017

- **Author:** Luxit Kapoor, Sanjeev Thakur
- **Journal Name:** IEEE 7th International Conference on Cloud Computing, Data Science & Engineering
- **Summary:** This paper surveys the various techniques that are part of Medical Image Processing and are prominently used in discovering brain tumors from MRI Images. Based on that research this Paper was written listing the various techniques in use. A brief description of each technique is also provided. Also of All the various steps involved in the process of detecting Tumors, Segmentation is the most significant.

Paper-3: Identification of Brain Tumor using Image Processing Techniques

- **Publication Year:** 11 September 2017
- **Author:** Praveen Gamage
- Journal Name: Research gate
- **Summary:** This paper survey of Identifying brain tumors through MRI images can be categorized into four different sections; pre-processing, image segmentation, Feature extraction and image classification.

Paper-4: Review of Brain Tumor Detection from MRI Images

- Publication Year: 2016
- **Author:** Deepa, Akansha Singh
- **Journal Name:** IEEE International Conference on Computing for Sustainable Global Development
- **Summary:** In this paper, some of the recent research work done on the Brain tumor detection and segmentation is reviewed. Different Techniques used by various researchers to detect the brain Tumor from the MRI images are described. By this review we found that automation of brain tumor detection and Segmentation from the MRI images is one of the most active Research areas.

Paper-5: An efficient Brain Tumor Detection from MRI Images using Entropy Measures

- **Publication Year:** December 23-25, 2016
- **Author:** Devendra Somwanshi , Ashutosh Kumar, Pratima Sharma, Deepika Joshi
- **Journal Name:** IEEE International Conference on Recent Advances and Innovations in Engineering
- **Summary:** In this paper, we have investigated the different Entropy functions for tumor segmentation and its detection from various MRI images. The different threshold values are obtained depend on the particular definition of the entropy. The threshold values are dependent on the different entropy function which in turn affects the segmented results.

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3. EXITING WORK & PROPOSED WORKFLOW

3.1 OVERVIEW OF EXITING WORK

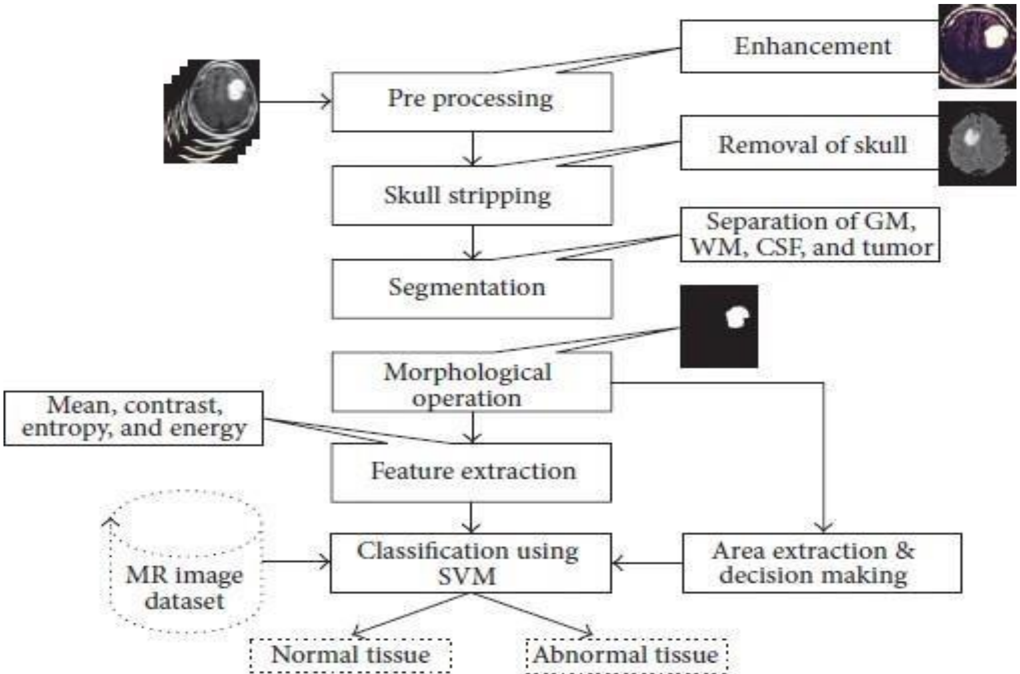

Fig.5.Existing work flow of brain tumor detection. [12]

In the first stage, there is a computer based procedures to detect tumor blocks and classify the type of tumor using Artificial Neural Network Algorithm for MRI images of different patients.

- The second stage involves the use of different image processing techniques such as histogram equalization, image segmentation, image enhancement, morphological operations and feature extraction are used for brain tumor detection in the MRI images for the cancer-affected patients.
- This work iss introduced one automatic brain tumor detection method to increase the accuracy and decrease the diagnosis time.
- **Image Preprocessing:** As input for this system is MRI, scanned image and it contain noise. Therefore, our first aim is to remove noise from input image. As explained in system flow we are using high pass filter for noise removal and preprocessing.
- **Segmentation:** Region growing is the simple region-based image segmentation technique. It is also classified as a pixel based image segmentation technique since it is involve the selection of initial seed points.
- **Morphological operation:** The morphological operation is used for the extraction of boundary areas of the brain images. This operation is only rearranging the relative order of pixel value, not mathematical value, so it is suitable for only binary images. Dilation and erosion is basic operation of morphology. Dilation is add pixels to the boundary region of the object, while erosion is remove the pixels from the boundary region of the objects.

- **Feature Extraction:** The feature extraction is used for edge detection of the images. It is the process of collecting higher level information of image such as shape, texture, color, and contrast.
- **Connected component labeling:** After recognizing connected components of an image, every set of connected pixels having same gray-level values are assigned the same unique region label.
- **Tumor Identification:** In this phase, we are having dataset previously collected brain MRIs from which we are extracting features. Knowledge base is created for comparison.

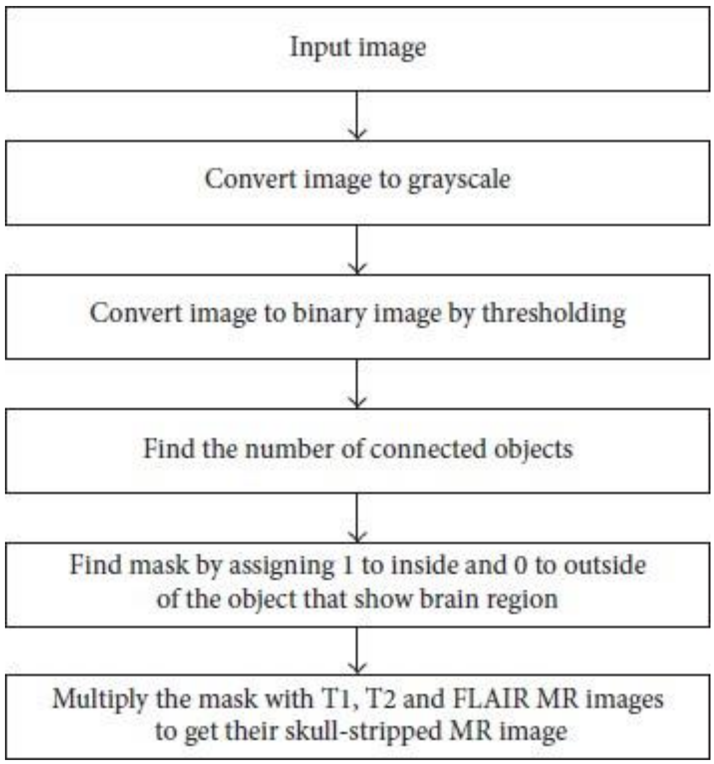

Fig. 6.Steps used in skull stripping algorithm.[12]

In the first step we can take image as input. In the image we used tumor in the image and only fat and water tissues in the images.

- In the second step convert image to grayscale
  - Signal to noise
  - Complexity of the code
  - Learning image processing
  - Difficulty of visualization
  - Color is complex
- Then we convert image to binary image by thresholding.

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Thresholding is the simplest method of image segmentation and the most common way to convert a grayscale image to binary image.

In thresholding we select threshold value and then gray level value .below the selected threshold value is classified as 0.and equal and greater then the threshold value are classified as 1.

- Find the number of connected object
- Find mask by assigning 1 to inside and 0 to outside of the object that show brain region.
- Multiply the mask with T1,T2 and FLAIR MR images to get their skull stripped MR image
- T1 & T2: weighted MRI
- FLAIR: fluid attenuated inversion recovery weighted MRI.

Types of MRI images

- T1: one tissue type is bright-FAT
- T2: two tissue types are bright-FAT and water

PROPOSED WORKFLOW

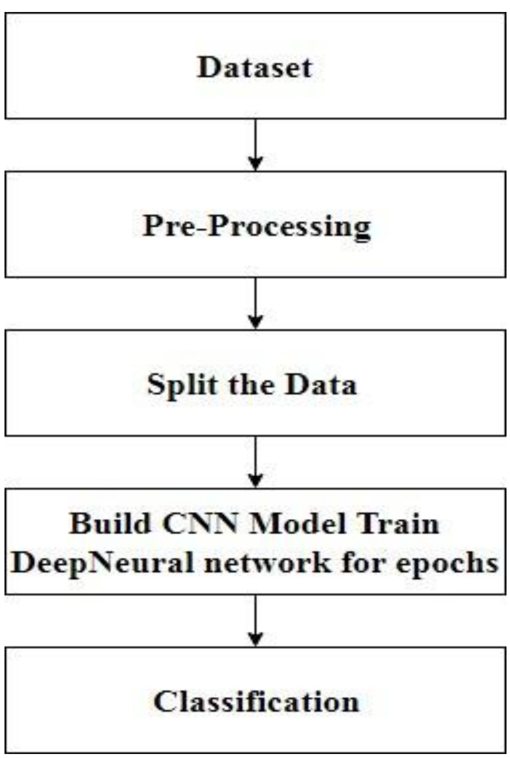

Fig. 7.Proposed work flow of brain tumor detection

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The proposed system has mainly five modules. Dataset, Pre-processing, Split the data, Build CNN model train Deep Neural network for epochs, and classification. In dataset we can take multiple MRI images and take one as input image. In pre-processing image to encoded the label and resize the image. In split the data we set the image as 80% Training Data and 20% Testing Data. Then build CNN model train deep neural network for epochs. Then classified the image as yes or no if tumor is positive then it returns yes and the tumor is negative the it returns no.

3.1.1 Working of CNN model

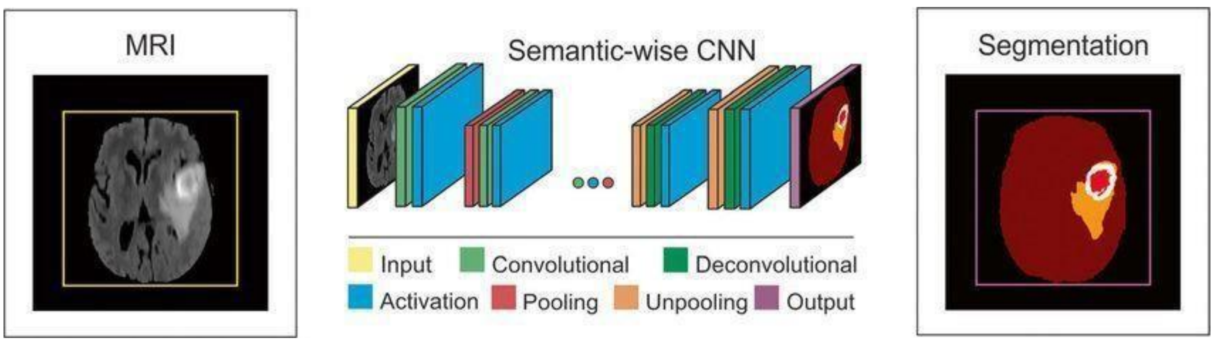

Fig.8.Working of CNN model for brain tumor detection [14] ➢ **Layer of CNN model:** o Convolution 2D
o MAX Poolig2D o Dropout o Flatten o Dense o Activation

- **Convolution 2D:** In the Convolution 2D extract the featured from input image. It given the output in matrix form.
- **MAX Poolig2D:** In the MAX polling 2D it take the largest element from rectified feature map.
- **Dropout:** Dropout is randomly selected neurons are ignored during training.
- **Flatten:** Flatten feed output into fully connected layer. It gives data in list form.
- **Dense:** A Linear operation in which every input is connected to every output by weight. It followed by nonlinear activation function.
- **Activation:** It used Sigmoid function and predict the probability 0 and 1.
- In the compile model we used binary cross entropy because we have two layers 0 and 1.
- We used Adam optimizer in compile model.
  Adam:-Adaptive moment estimation. It used for non convex optimization problem like straight forward to implement.

- ✦ Computationally efficient.
- ✦ Little memory requirement.

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3.1.2 Working of VGG16 model

Transfer learning is a knowledge- sharing method that reduces the size of the training data, the time and the computational costs when building deep learning models. Transfer learning helps to transfer the learning of a pre-trained model to a new model. Transfer learning has been used in various applications, such as tumor classification, software defect prediction, activity recognition and sentiment classification. In this, the performance of the proposed Deep CNN model has been compared with popular transfer learning approach VGG16.

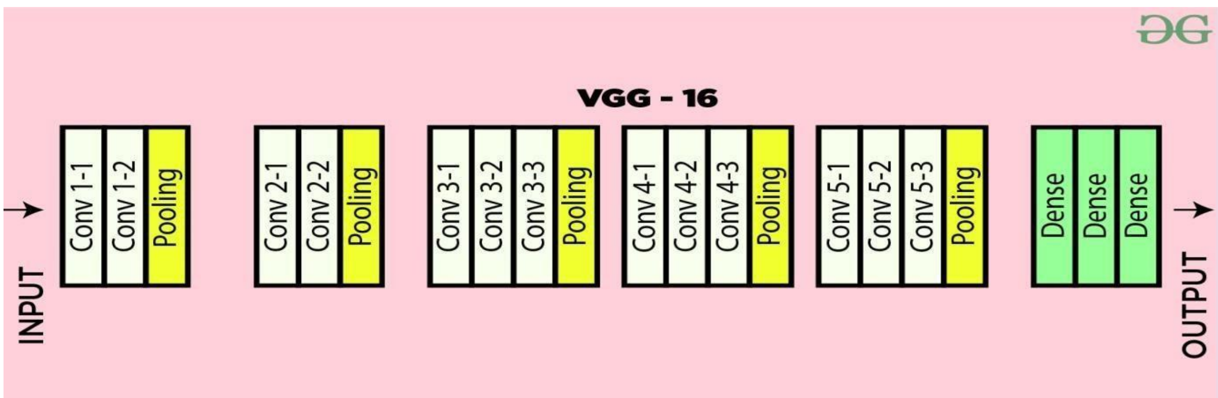

Fig.9. VGG16 layered architecture[20]

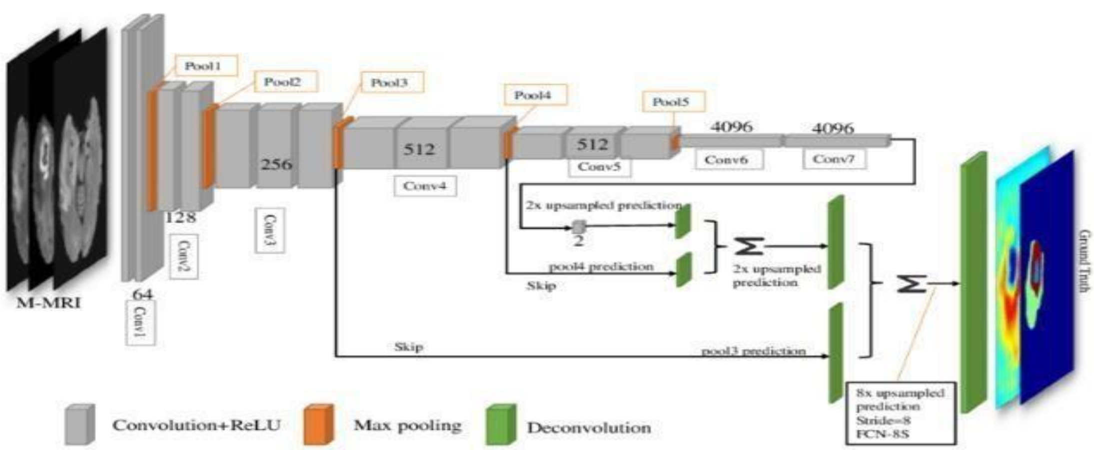

Fig.10.Working of VGG16 model for brain tumor detection [14]

VGG16 is a convolutional neural network. The input of the 1 convolution layer is of fixed size 224 x 224 RGB image. The image is passed through a stack of convolutional layers, where the filters are used with a very small receptive field 3×3 (which is the smallest size to capture the notion of left/right, up/down, center). In the configurations, it is also utilizes 1×1 convolution filters, and it can be seen as a linear transformation of the input channels. The convolution stride is fixed to 1 pixel, and the spatial padding of convolution. Input layer is the spatial resolution is preserved after convolution, i.e. the padding is 1-pixel for 3×3 convolution layers. Spatial pooling is carried out by five max-pooling layers, which follow the some convolution layers (not all the conv. layers are followed by max-pooling). Max- pooling is performed over 2×2 pixel window, with stride 2.

Three Fully-Connected (FC) layers are follow a stack of convolutional layers which has a different depth in different architectures and the first two have 4096 channels each, the third performs 1000-way ILSVRC classification and it contains 1000 channels one for each class. The final layer is the soft-max layer. The configuration of the fully connected layers is same in every network.

All hidden layers are equipped with the rectification (ReLU) nonlinearity. It is also noted that none of the networks (except for one) contain Local Response Normalization (LRN), such normalization does not improve the performance on the ILSVRC dataset, but leads to increased memory consumption and computation time.

4. DATASET, IMPLEMENTATION AND RESULT

4.1 : DATASET DETAIL

The dataset has 556 images with different types of tumor and also including images which has tissues of Fat or water.

1. DICOM Samples Image Sets, http://www.osirix-viewer.com/.[3]
2. "Brainweb:SimulatedBrainDatabase," http://brainweb.bic.mni.mcgill.ca/cgi/brainweb1.[4]

4.2 : TOOLS & TECHNOLOGY USED

Python: Python was the language of selection for this project. This was a straightforward call for many reasons.

1. Python as a language has a vast community behind it. Any problems which may be faced is simply resolved with a visit to Stack Overflow. Python is among the foremost standard language on the positioning that makes it very likely there will be straight answer to any question
2. Python has an abundance of powerful tools prepared for scientific computing Packages like NumPy, Pandas and SciPy area unit freely available and well documented. Packages like these will dramatically scale back, and change the code required to write a given program.This makes iteration fast.
3. Python as a language is forgiving and permits for program that appear as if pseudo code. This can be helpful once pseudo code given in tutorial papers must be enforced and tested. Using python this step is sometimes fairly trivial. However, Python is not without its errors. The language is

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dynamically written and packages are area unit infamous for Duck writing. This may be frustrating once a package technique returns one thing that, for instance, looks like an array instead of being an actual array. Plus the actual fact that standard Python documentation does not clearly state the return type of a method, this can lead to a lot of trials and error testing that will not otherwise happen in a powerfully written language. This is a problem that produces learning to use a replacement Python package or library more difficult than it otherwise may be.

- **Jupiter Notebook:** The Jupyter Notebook is an open-source web application that enables you to make and share documents that contain live code, equations, visualizations and narrative text. Uses include: data cleaning and transformation, numerical simulation, statistical modelling, data visualization, machine learning, and much more.
- **Noise Removal and Sharpening:** Unwanted data of element are remove using filter and image Can be sharpen and black and white gray scale image is used as a input.
- **Erosion and Dilation:** It is applied to binary image, but there are many versions so that can be work on grayscale images. The basic effect of the operator on a binary image is eroding away to the boundaries of regions for ground pixels.
- **Negation:** A negative is an image, usually it used on a strip or sheet of transparent plastic film, in negation the lightest areas of the photographed subject appear darkest and the darkest areas appear lightest.
- **Subtraction:** Image subtraction process is the digital numeric value of one pixel or whole image is subtracted from another image. The white part of tumor can be subtracted from another remaining part that is the black portion of the images.
- **Threshold:** Thresholding is a process of image segmentation. It converts the gray scale image into binary image.
- **Boundary Detection:** Total area or boundary can be form properly using boundary detection method. White part of tumor tissues can be highlighted and there proper boundary can be detected. It is useful method to calculate the size and shape occupy by tumor tissues.

4.3 : RESULTS • Give the label of the image

```
<built-in function dir>
/content/drive/My Drive/brain_dataset/yes
X_data shape: (235, 224, 224, 3)
y_data shape: (235,)
<built-in function dir>
/content/drive/My Drive/brain_dataset/no
X_data shape: (413, 224, 224, 3)
y_data shape: (413,)
```

Fig.11.Label of the image

These outputs in images are resized and give label name to all images.

• Split the Data

```
X_data shape: (330, 224, 224, 3)
X_data shape: (83, 224, 224, 3)
Y_data shape: (330,)
Y_data shape: (83,)
```

Fig.12.Split the image data

Fig 12. Contain Total 413 dataset images are divided into two parts 330 are in training part and 83 is the testing part.

• Train Data

```
Epoch 245/250
15/15 [==============================] - 48s 3s/step - loss: 0.4972 - accuracy: 0.7542 - val_loss: 0.5175 - val_accuracy: 0.8485
Epoch 246/250
15/15 [==============================] - 48s 3s/step - loss: 0.5008 - accuracy: 0.7374 - val_loss: 0.5198 - val_accuracy: 0.7879
Epoch 247/250
15/15 [==============================] - 52s 3s/step - loss: 0.4825 - accuracy: 0.7879 - val_loss: 0.5250 - val_accuracy: 0.7879
Epoch 248/250
15/15 [==============================] - 48s 3s/step - loss: 0.4977 - accuracy: 0.7407 - val_loss: 0.5130 - val_accuracy: 0.8182
Epoch 249/250
15/15 [==============================] - 48s 3s/step - loss: 0.4789 - accuracy: 0.7542 - val_loss: 0.5168 - val_accuracy: 0.8788
Epoch 250/250
15/15 [==============================] - 48s 3s/step - loss: 0.4849 - accuracy: 0.7441 - val_loss: 0.5262 - val_accuracy: 0.7879
WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/tensorflow/python/ops/resource_variable_ops.py:1817: calling BaseResourceVari
Instructions for updating:
If using Keras pass * constraint arguments to layers.
```

Fig.13.Train CNN image data

Fig . 13. Consist output of train the convolutional neural network. Train 330 samples and validate on 150 samples

• Test Data

```
scores=model.evaluate(xTest, yTest)
print("%s: %2f%%" %(model.metrics_names[1], scores[1]*100))

3/3 [==============================] - 2s 808ms/step - loss: 0.5499 - accuracy: 0.8072
accuracy: 80.722892%
```

Fig.14.Test CNN image Data

Fig 14. Consist output of convolutional neural network testing accuracy score 80.72%

• Train Data

```
model.save('braintransfer-VGG70.model')
scores=model.evaluate(xTest, yTest)
print("%s: %2f%%" %(model.metrics_names[1], scores[1]*100))

83/83 [==============================] - 42s 500ms/step
accuracy: 85.542166%
```

```
Epoch 65/70
20/20 [==============================] - 338s 17s/step - loss: 0.5633 - accuracy: 0.7473
Epoch 66/70
20/20 [==============================] - 329s 16s/step - loss: 0.5276 - accuracy: 0.7677
Epoch 67/70
20/20 [==============================] - 333s 17s/step - loss: 0.5474 - accuracy: 0.7382
Epoch 68/70
20/20 [==============================] - 329s 16s/step - loss: 0.5726 - accuracy: 0.7524
Epoch 69/70
20/20 [==============================] - 340s 17s/step - loss: 0.5436 - accuracy: 0.7598
Epoch 70/70
20/20 [==============================] - 326s 16s/step - loss: 0.5467 - accuracy: 0.7587
```

Fig.15.Test VGG16 image Data

Fig . 15. Consist output of train the VGG 16 Transfer Learning model. Train 330 samples and validate on 150 samples

• Test Data

Fig.16.Test VGG16 image Data

Fig 16. Consist output of VGG 16 testing accuracy score 85.54%

• Implementation: CNN model summary

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```
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_4 (Conv2D)            (None, 254, 254, 32)      896
_________________________________________________________________
max_pooling2d_4 (MaxPooling2 (None, 127, 127, 32)      0
_________________________________________________________________
dropout_5 (Dropout)          (None, 127, 127, 32)      0
_________________________________________________________________
conv2d_5 (Conv2D)            (None, 125, 125, 64)      18496
_________________________________________________________________
max_pooling2d_5 (MaxPooling2 (None, 62, 62, 64)        0
_________________________________________________________________
dropout_6 (Dropout)          (None, 62, 62, 64)        0
_________________________________________________________________
conv2d_6 (Conv2D)            (None, 60, 60, 128)       73856
_________________________________________________________________
activation_3 (Activation)    (None, 60, 60, 128)       0
_________________________________________________________________
max_pooling2d_6 (MaxPooling2 (None, 30, 30, 128)       0
_________________________________________________________________
dropout_7 (Dropout)          (None, 30, 30, 128)       0
_________________________________________________________________
conv2d_7 (Conv2D)            (None, 28, 28, 512)       590336
_________________________________________________________________
activation_4 (Activation)    (None, 28, 28, 512)       0
_________________________________________________________________
max_pooling2d_7 (MaxPooling2 (None, 14, 14, 512)       0
_________________________________________________________________
dropout_8 (Dropout)          (None, 14, 14, 512)       0
_________________________________________________________________
flatten_1 (Flatten)          (None, 100352)            0
_________________________________________________________________
dense_2 (Dense)              (None, 64)                6422592
_________________________________________________________________
dropout_9 (Dropout)          (None, 64)                0
_________________________________________________________________
dense_3 (Dense)              (None, 1)                 65
_________________________________________________________________
activation_5 (Activation)    (None, 1)                 0
=================================================================
Total params: 7,106,241
Trainable params: 7,106,241
Non-trainable params: 0
_________________________________________________________________
None
```

Table.1. CNN model summary table

• IMPLEMENTATION: VGG16 MODEL SUMMARY

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```
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
vgg16 (Model)                (None, 7, 7, 512)         14714688
_________________________________________________________________
flatten_1 (Flatten)          (None, 25088)             0
_________________________________________________________________
dropout_1 (Dropout)          (None, 25088)             0
_________________________________________________________________
dense_1 (Dense)              (None, 1)                 25089
=================================================================
Total params: 14,739,777
Trainable params: 25,089
Non-trainable params: 14,714,688
_________________________________________________________________
None
```

Table. 2. Transfer learning VGG16 model summary

• **IMPLEMENTATION: COMPARISON CNN ACCURACY WITH**
VGG16 ACCURACY

epochs	**CNN**	**VGG 16**
30	67.469877%	76.854917%
50	69.87952%	81.927711%
70	72.698794%	85.542166%

Table 3. Comparison table of CNN vs. VGG16

• IMPLEMENTATION: CNN VS. TRANSFER LEARNING(VGG16) ACCURACY CHART

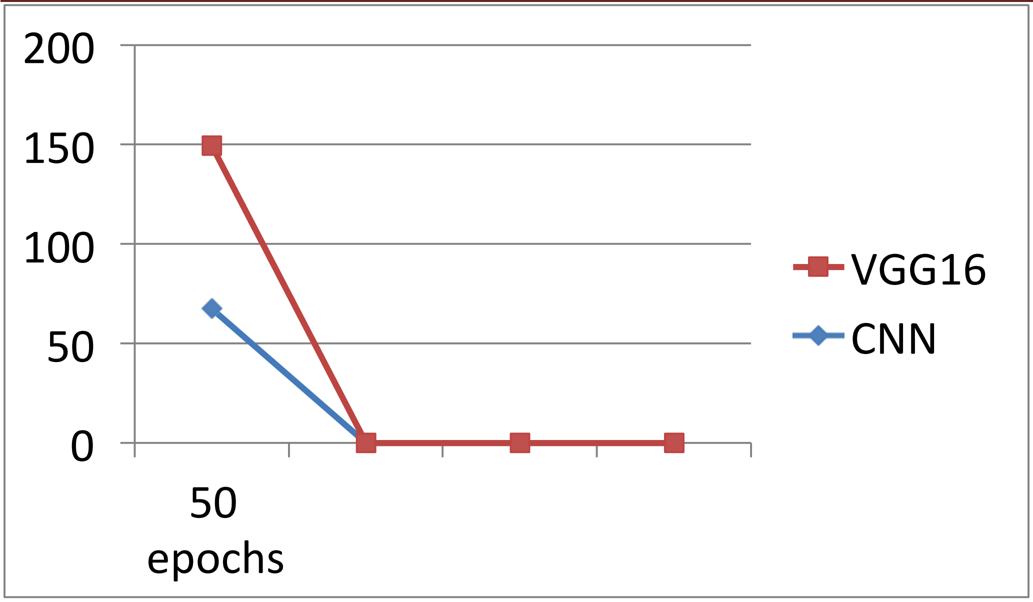

Fig.17. Chart of CNN vs. VGG16

5. CONCLUSION

In brain tumor detection we have studied about feature based existing work. In feature based we have study about image processing techniques likes image pre-processing, image segmentation, features extraction, classification. And also study about deep learning techniques CNN and VGG16.In this system we have detect the tumor is present or not if the tumour is present then model return's yes otherwise it return no. and we have compared CNN with the VGG 16 Model. The result of comparison VGG 16 is more accurate than CNN. However, not every task is said to be perfect in this development field even more improvement may be possible in this application. I have learned so many things and gained a lot of knowledge about the development field.

References

[1] L.Guo,L.Zhao,Y.Wu,Y.Li,G.Xu,andQ.Yan,"Tumordetection in MR images using one- class immune feature weighted SVMs," IEEE Transactions on Magnetics, vol. 47, no. 10, pp. 3849–3852,2011.

[2] R.Kumari,"SVMclassificationanapproachondetectingabnormalityinbrainMRIimages,"InternationalJournalofEngineeringResearchandApplications,vol.3,pp.1686–1690,2013.DICOM Samples Image Sets, http://www.osirix-viewer.com/.

[3] J. C. Buckner, P. D. Brown, B. P. O'Neill, F. B. Meyer , C. J. Wetmore,J. H Uhm, "Central nervous system tumors." In *Mayo Clinic Proceedings*,Vol. 82, No. 10, pp. 1271- 1286, October 2007.

[4] Deepa , Singh Akansha. (2016). - Review of Brain Tumor Detection from tomography. *International Conference on Computing for Sustainable Global Development (INDIACom)*

[5] R. A. Novellines, M. D. - *Squire's fundamentals of radiology*; Six Edition; UPR, 2004.preston, D. c. (2006). Magnetic Resonance Imaging (MRI) of the Brain and Spine from Basics. *casemed.case.edu* .

[6] Hendrik RE. (2005) Glossary of MR Terms from *American College of Radiology* .

.

[11].A. Demirhan, M. Toru, and I. Guler, "Segmentation of tumor and edema along with healthy tissues of brain using wavelets and neural networks," IEEE Journal of Biomedical and Health Informatics, vol. 19, no. 4, pp. 1451–1458, 2015.

[12] Nilesh Bhaskarrao Bahadure, A.K. (2017, March 6). Retrieved from https://www.hindawi.com/journals/ijbi/2017/9749108/.

[13] S. Mohsin, S. Sajjad, Z. Malik, and A. H. Abdullah, "Efficient way of skull stripping in MRI to detect brain tumor by applying morphological operations, after detection of false background," *International Journal of Information and Education Technology*, vol. 2, no. 4, pp. 335–337, 2012.

[14] Gavale, P. M., Aher, P. V., & Wani, D. V. (2017, April 4). Retrieved from https://www.irjet.net/archives/V4/i4/IRJET-V4I462.pdf.

[15] N. Gordillo, E. Montseny, and P. Sobrevilla, "State of the art survey on MRI brain tumor segmentation,"*Magnetic Resonance Imaging*, vol. 31, no. 8, pp. 1426–1438, 2013.

[16] Samantaray, M.(2016, November 3). Retrieved from http://ieeexplore.ieee.org/document/7727089/ .

[17] Nandi, A. (2016, April 11) Retrieved from http://ieeexplore.ieee.org/document/7449892/

[18] C. C. Benson and V. L. Lajish, "Morphology based enhancement and skull stripping of MRI brain images," in *Proceedings of the international Conference on Intelligent Computing Applications (ICICA '14)*, pp. 254–257, Tamilnadu, India, March 2014.

[19] S. Z. Oo and A. S. Khaing, "Brain tumor detection and segmentation using watershed segmentation and morphological operation," *International Journal of Research in Engineering and Technology*, vol. 3, no. 3, pp. 367–374, 2014.

[20] R. Roslan, N. Jamil, and R. Mahmud, "Skull stripping magnetic resonance images brain images: region growing versus mathematical morphology," *International Journal of Computer Information Systems and Industrial Management Applications*, vol. 3, pp. 150– 158, 2011.

[21] Akata, Zeynep et al. 2014. "Classification To Cite This Version : Good Practice in Large-Scale Learning for Image Classification."

[22] Algohary, Ahmad O, Ahmed M El-bialy, Ahmed H Kandil, and Nael F Osman. 2010. "Improved Segmentation Technique to Detect Cardiac Infarction in MRI C-SENC Images."

"BRAIN TUMOR CLASSIFICATION USING SPARSE CODING AND DICTIONARY LEARNING Institute for Information Processing , Leibniz University Hannover." 2014. : 2774–78.

[23] Cheng, Jun et al. 2015. "Enhanced Performance of Brain Tumor Classification via Tumor Region Augmentation and Partition." : 1–13.

[24] Deng, Wankai, Wei Xiao, He Deng, and Jianguo Liu. 2010. "MRI Brain Tumor Segmentation With Region Growing Method Based On The Gradients And Variances Along And Inside Of The Boundary Curve." 0(Bmei): 393–96.

[25] Enhancement, B Image. 2002. "Guest Editorial : Medical Image Computing at the Institute of Mathematics and Computer Science in Medicine , University Hospital Hamburg – Eppendorf." 21(7): 713–23.

[26] Joshi, Dipali M, and N K Rana. 2010. "Classification of Brain Cancer Using Artificial Neural Network." : 112– 16. Juan-albarracín, Javier, Elies Fuster-garcia, and José V Manjón. 2015. "Automated Glioblastoma Segmentation Based on a Multiparametric Structured Unsupervised Classification." : 1–20.

[27] Khotanlou, Hassan, Olivier Colliot, Jamal Atif, and Isabelle Bloch. 2009. "3D Brain Tumor Segmentation in MRI Using Fuzzy Classification, Symmetry Analysis and Spatially Constrained Deformable Models." Fuzzy Sets and Systems 160(10): 1457–73.