International Journal of Enhanced Research in Science, Technology & Engineering
ISSN: 2319-7463, Vol. 11 Issue 5, May-2022, Impact Factor: 7.957

Brain Tumour Detection using Convolutional Neural Network

D. Swathi[1], Rayavaram Pragnasree[2], M. Priya[3], B. Swetha[4], Mr. N. Chidambaram[5]

[1,2,3,4] B.E (ECE) Panimalar Engineering College, Chennai
[5]Assistant Professor, Panimalar Engineering College, Chennai

Problem Statement:

The brain tumors, are the most common and aggressive disease, leading to a very short life expectancy in their highest grade.

However the huge amount of data generated by MRI scan thwarts manual classification of tumor vs non-tumor in a particular time. .

Hence trusted and automatic classification scheme are essential to prevent the death rate of human.

The automatic brain tumor classification is very challenging task in large spatial and structural variability of surrounding region of brain tumor. In this work, automatic brain tumor detection is proposed by using Convolutional Neural Networks (CNN) classification.

Objective:

To detect brain tumour using MRI images by CNN.

ABSTRACT

Brain tumor means the aggregation of abnormal cells in some tissues of the brain. Brain tumor can be cancerous or noncancerous. The most common types of brain tumors are Glioma, Meningioma and Pituitary tumor. Early detection of tumor cells plays a major role in treatment and recovery of patient. Diagnosing a brain tumor usually undergoes a very complicated and time consuming process. The MRI images of various patients at various stages can be used for the detection of tumors. There are various types of feature extraction and classification methods which are used for detection of brain tumor from MRI images. Tumour segmentation is an important step in the pipeline in the analysis of this pathology. Manual segmentation is often inconsistent as it varies between observers. Automated segmentation has been proposed to combat this issue. We investigate the role of CNNs to segment brain tumours by firstly taking an educational look at CNNs and perform a literature search to determine an example pipeline for segmentation. Convolutional Neural Network image classification algorithm helps in detecting the tumor at early stage with high accuracy. We proposed A Convolutional Neural Network architecture for detection of tumor which gives high accuracy.

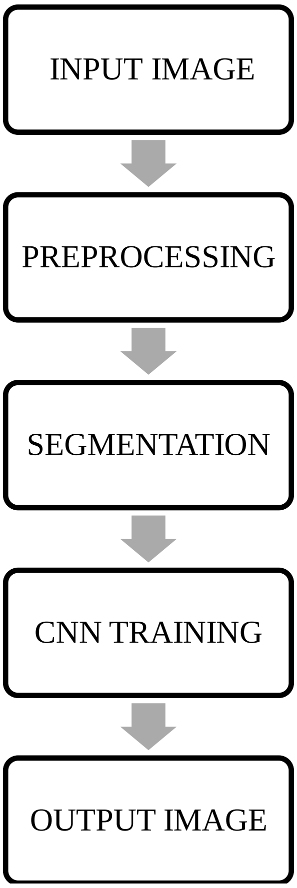
LITERATURE SURVEY:

Title	Authors	Method Used	Disadvantage
Pattern Descriptors Orientation and MAP Firefly Algorithm based Brain Pathology Classification using Hybridized Machine Learning Algorithm	**B. DEEPA , M. MURUGAPPAN ,(Senior Member, IEEE) M.G. SUMITHRA ,(Senior Member, IEEE) MUFTI MAHMUD, (Senior Member, IEEE), and MABROOK S. AL-RAKHAMI5**	**Map firefly Algorithm**	High Probability of being trapped in local optima because they are local search algorithms

Variable structure based control for the chemotherapy of brain tumor	MUHAMMAD ZUBAIR, IFTIKHAR AHMAD* (MEMBER IEEE), YASIR ISLAM AND SAFDAR ABBAS KHAN	Variable structure based control	Disadvantage: difficulty in developing a more complete computa- tional HVS model
A YOLOv3 Deep Neural Network Model to Detect Brain Tumor in Portable Electromagnetic Imaging System	AMRAN HOSSAIN,(Member, IEEE), MOHAMMAD TARIQUL ISLAM , (Senior Member, IEEE), MOHAMMAD SHAHIDUL ISLAM, (Graduate Student Member, IEEE), MUHAMMAD E. H. CHOWDHURY	YOLO v3	Comparatively low recall and more localization error compared to Faster R_CNN
An Efficient Classification of MRI Brain Images	MUHAMMAD ASSAM , HIRA KANWAL, UMAR FAROOQ , SAID KHALID SHAH , ARIF MEHMOOD , AND GYU SANG CHOI	DWT(Discrete wavelet transform)	**Shift sensitivity, poor directionality, and lack of phase information.**
Digital Object Identifier 10.1109/ACCESS.2020.3016627 Hybrid Segmentation Method With Confidence Region Detection for Tumor Identification	KHURRAM EJAZ , MOHD SHAFRY MOHD RAHIM , USAMA IJAZ BAJWA , HUMA CHAUDHRY3 , (Member, IEEE), AMJAD REHMAN , (Senior Member, IEEE), AND FARHAN EJAZ	Hybrid segmentation with confidence region detection	Not possible to determine how many regions are required for a reasonable segmentation
Machine Learning and Deep Learning Approaches for Brain Disease Diagnosis: Principles and Recent Advances	PROTIMA KHAN1,, MD. FAZLUL KADER 1,, (Senior Member, IEEE),S. M. RIAZUL ISLAM 2,*, Member, IEEE), AISHA B. RAHMAN1 , MD. SHAHRIAR KAMAL1 ,MASBAH UDDIN TOHA 1, AND KYUNG-SUP KWAK 3	Machine learning and deep learning	It's very costly depending on the system used, the number of detectors purchased
Quantum Neural Networks: Current Status and Prospects for Development	M. V. Altaiskya , N. E. Kaputkinab , and V. A. Krylo	Quantum neural network	The greatest challenges involved with constructing quantum computers is controlling or removing quantum decoherence.
A hybrid method for MRI brain image classification	Yudong Zhang a , Zhengchao Dong b,c , Lenan Wu a , Shuihua Wan	Hybrid method of image classification	Not possible to determine how many regions are required for a reasonable segmentation

Two fully-unsupervised methods for MR brain image segmentation using SOM-based strategies	A. Ortiz a, J.M. Górriz b,∗, J. Ramírez b, D. Salas-González b, J.M. Llamas-Elvirac	SOM based strategy	Does not build a generative model for the data
A unidirectional 3D antenna for biomedical microwave imaging based detection of abnormality in human body	Md. Amanath Ullah1 • Touhidul Alam1,2 • Mohammed Shamsul Alam2 • Salehin Kibria1 • Mohammad Tariqul Islam1	3D antenna	Some designs such as metal 3D printed antennas are expensive to manufacture.

BLOCK DIAGRAM



MODULE DESCRIPTION:

MODULE 1:

INPUT IMAGE

Here, we are giving the collected dataset as input to the system.
MODULE 2:

The aim of pre-processing is an improvement of the image data that suppresses undesired distortions or enhances some image features relevant for further processing and analysis task

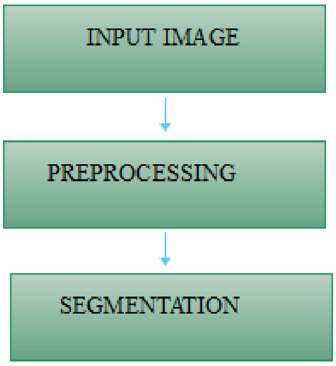
INPUT IMAGE ←

PREPROCESSING

MODULE 3:

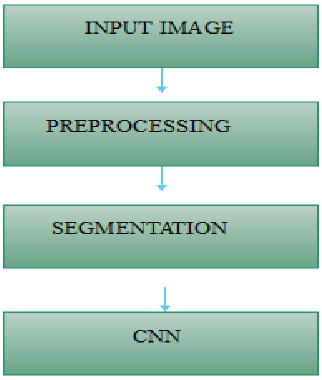
International Journal of Enhanced Research in Science, Technology & Engineering
ISSN: 2319-7463, Vol. 11 Issue 5, May-2022, Impact Factor: 7.957

Image segmentation is a method in which a digital image is broken down into various subgroups called Image segments which helps in reducing the complexity of the image to make further processing or analysis of the image simpler.



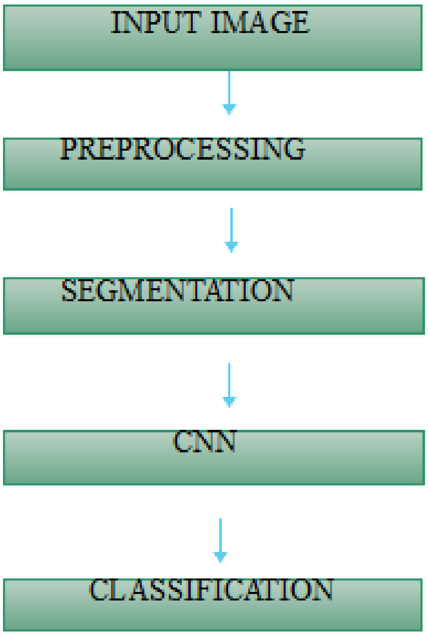
MODULE 4:

When it comes to Machine Learning, Artificial Neural Networks perform really well. Artificial Neural Networks are used in various classification task like image, audio, words.



MODULE 5:

Classification methods aim at identifying the category of a new observation among a set of categories on the basis of a labeled training set. Depending on the task, anatomical structure, tissue preparation, and features the classification accuracy varies.

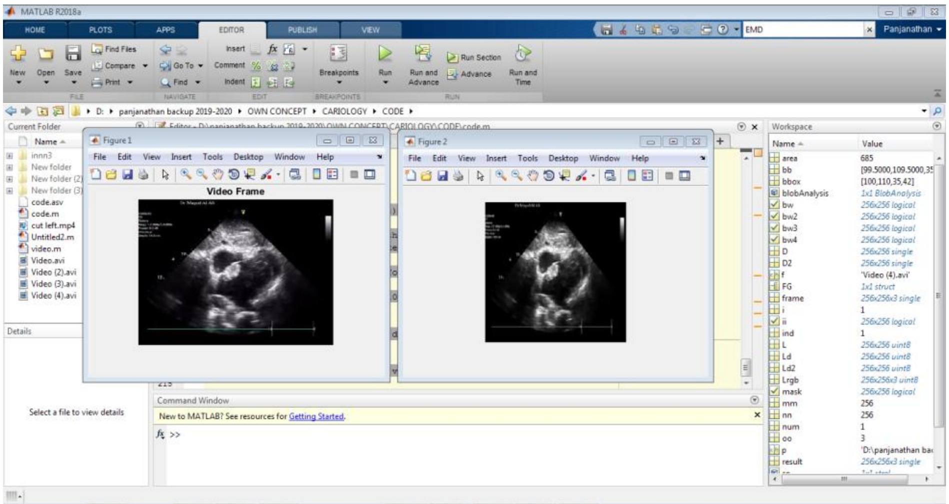


CODE:

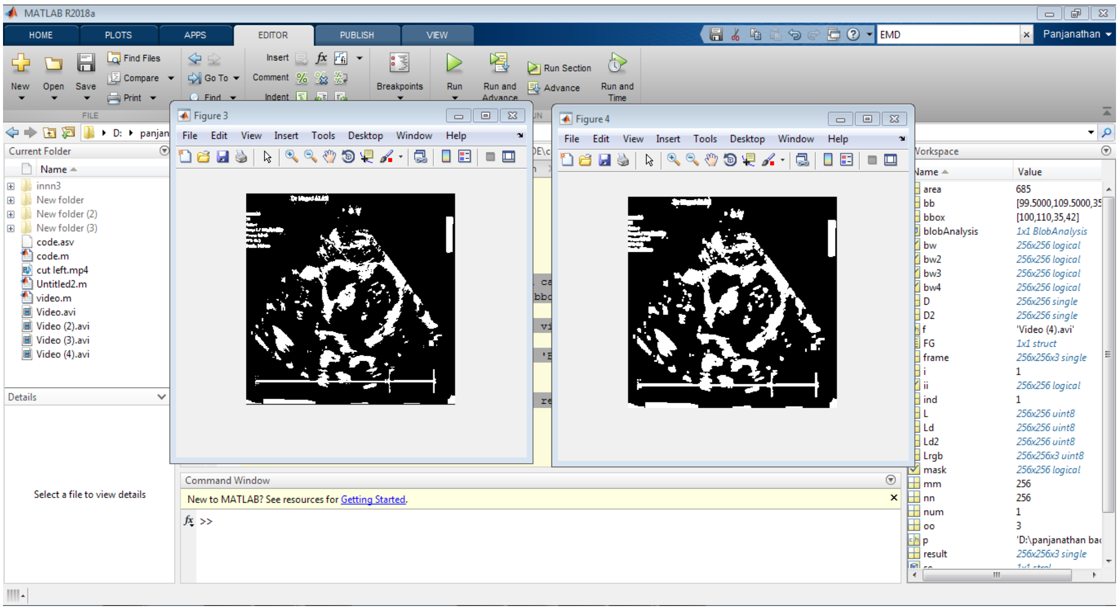
```
%%%%%%%%%% BRAIN TUMER CLASSIFICATION %%%%%%%%%%%%%%
clc;
clear;
close all;
warning off

%%%%% TRAIN THE DATASET IMAGES %%%%%
matlabroot='C:\Users\SPIRO-36\Desktop\MADLAB';
data1 = fullfile (matlabroot,' TRAINING IMAGES');
Data=image Datastore (data1,'IncludeSubfolders',true,'LabelSource','foldernames');
Validation Path = fullfile (matlabroot,'TESTING IMAGES');
imdsValidation = image Datastore (validationPath, ...
'IncludeSubfolders',true,' LabelSource','foldernames');
%% CREATE CONVOLUTIONAL NEURAL NETWORK LAYERS %%%%%%
%  layers=[imageInputLayer([255 255 3])
  %     convolution2dLayer(3,8,'Padding','same')
%     batchNormalizationLayer
%     reluLayer
%     maxPooling2dLayer(2,'Stride',2)
%     convolution2dLayer(3,16,'Padding','same')
%     batchNormalizationLayer
%     reluLayer
%     maxPooling2dLayer(2,'Stride',2)
%     convolution2dLayer(3,32,'Padding','same')
%     batchNormalizationLayer
%     reluLayer
%     maxPooling2dLayer(2,'Stride',2)
%     convolution2dLayer(3,64,'Padding','same')
%     batchNormalizationLayer
%     reluLayer
%     maxPooling2dLayer(2,'Stride',2)
%     convolution2dLayer(3,128,'Padding','same')
%     batchNormalizationLayer
%     reluLayer
%     maxPooling2dLayer(2,'Stride',2)
% %     convolution2dLayer(3,256,'Padding','same')
% %     batchNormalizationLayer
% %     reluLayer
% %     maxPooling2dLayer(2,'Stride',2)
%     fullyConnectedLayer(2)
%     softmaxLayer
%     classificationLayer];
options=trainingOptions('sgdm','MaxEpochs',50,'InitialLearnRate',0.00001,'Shuffle','every-epoch', ...
%     'ValidationData',imdsValidation, ...
%     'ValidationFrequency',30,...
%     'Verbose',false, ...
%     'Plots','training-progress');
%  convnet=trainNetwork(Data,layers,options);
%  save convnet.mat convnet
% %%% CLASSIFY VALIDATION IMAGES AND COMPUTE ACCURACY % % % % %
% YPred = classify(convnet,imdsValidation);
% YValidation = imdsValidation.Labels;
% accuracy = sum(YPred == YValidation)/numel(YValidation);
```

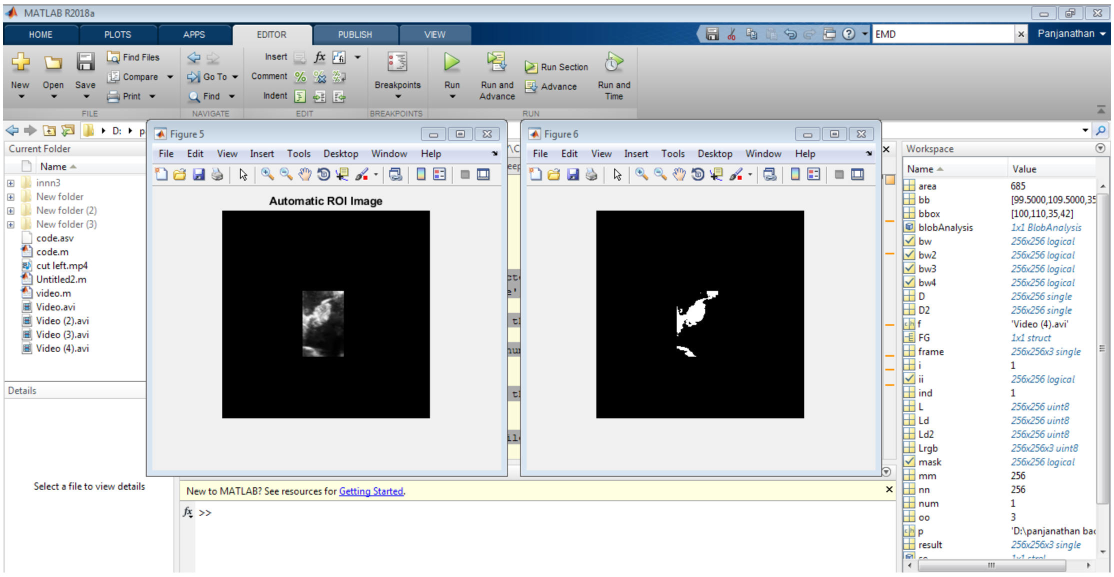
INPUT FRAME:



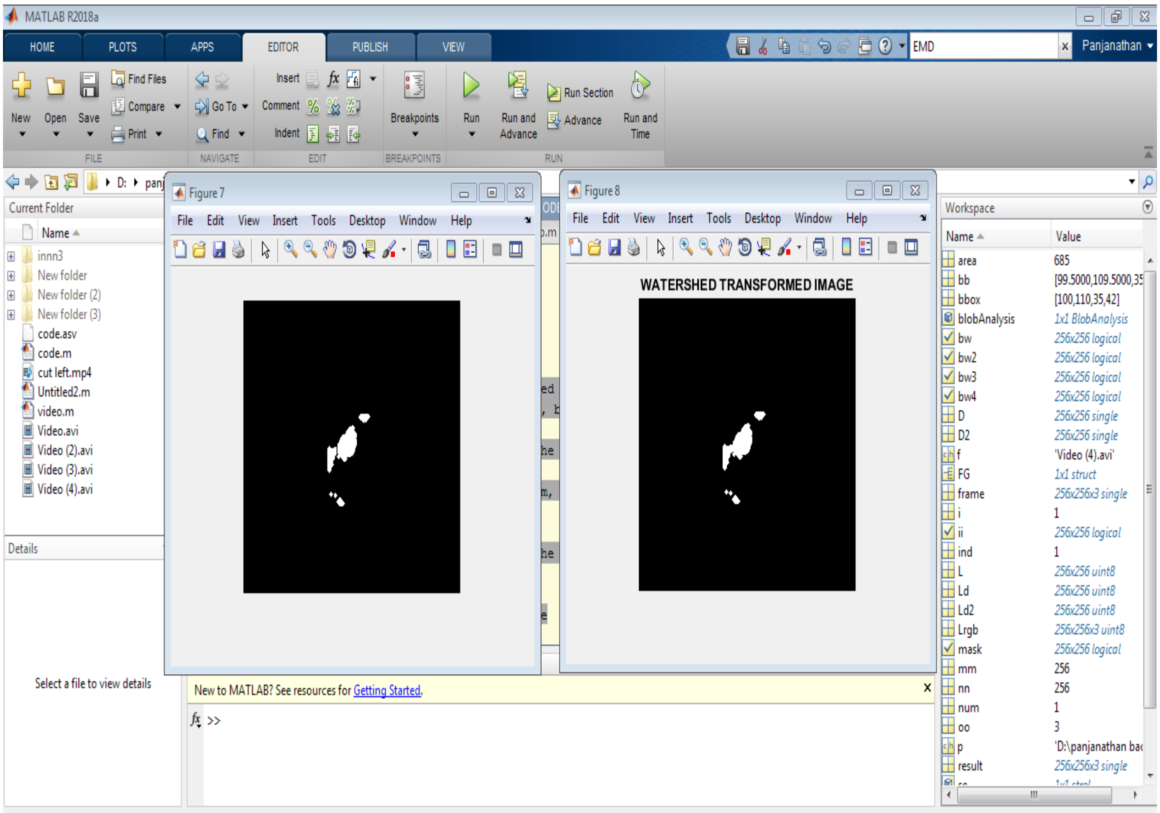
ADAPTIVE THRESHOLDING:



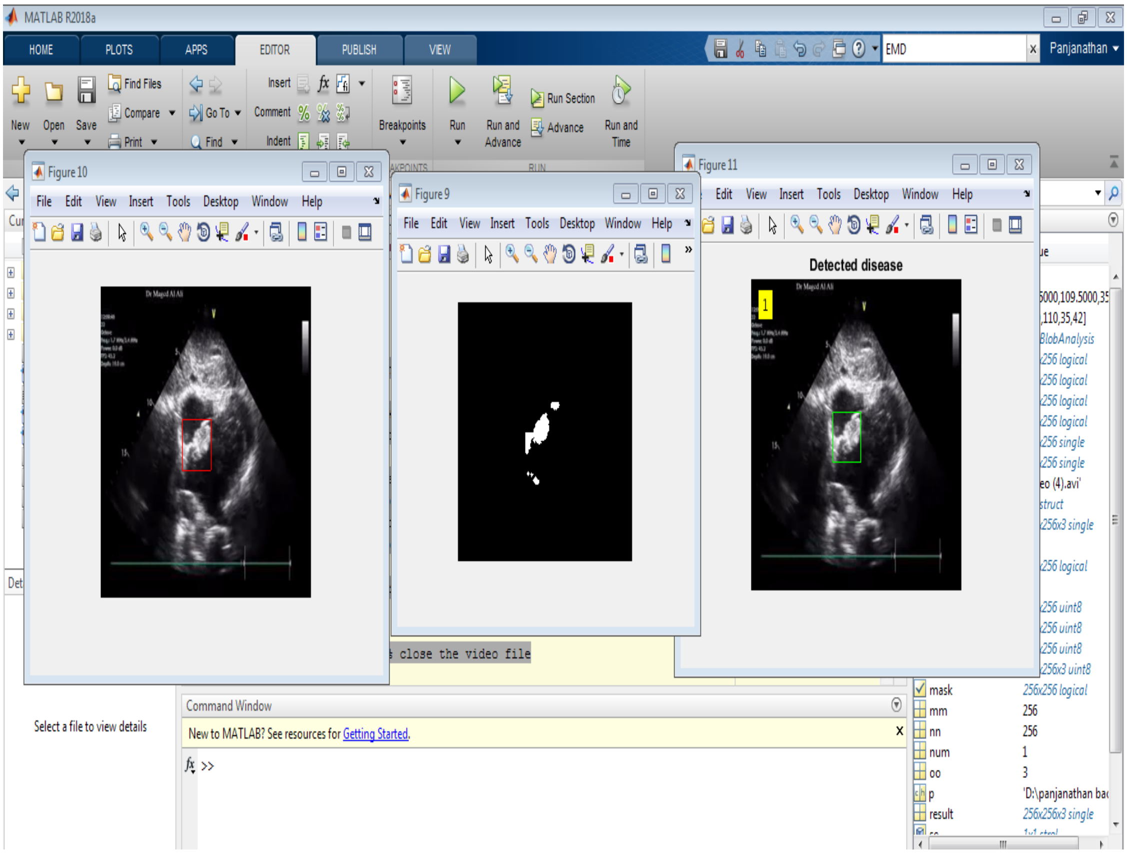
REGION BASED SEGMENTATION:



WATERSHED SDEGMENTATION:



FINAL OUTPUT CANCER DETECTED PARTS:



EXISTING SYSTEM	PROPOSED SYSTEM
EXISTING METHOD: Classical self-supervised networks suffer from convergence problems and reduced segmentation accuracy due to forceful termination. Qubits or bilevel quantum bits often describe quantum neural network models. In this article, a novel self-supervised shallow learning network model exploiting the sophisticated three-level qutrit-inspired quantum information system, referred to as quantum fully self-supervised neural network (QFS-Net), is presented for automated segmentation of brain magnetic resonance (MR) images. The QFS-Net model comprises a trinity of a layered structure of qutrits interconnected through parametric Hadamard gates using an eight-connected second order neighborhood-based topology. The nonlinear transformation of the qutrit states allows the underlying quantum neural network model to encode the quantum states, thereby enabling a faster self-organized counter propagation of these states between the layers without supervision. The suggested QFS-Net model is tailored and extensively validated on the Cancer Imaging Archive (TCIA) dataset collected from the Nature repository. The experimental results are also compared with state-of-the art supervised (U-Net and URes-Net architectures) and the self-supervised QIS-Net model and its classical counterpart. Results shed promising segmented outcomes in detecting tumors in terms of dice similarity and accuracy with minimum human intervention and computational resources. The proposed QFS-Net is also investigated on natural gray-scale images from the Berkeley segmentation dataset and yields promising outcomes in segmentation, thereby demonstrating the robustness of the QFS-Net model.	**PROPOSED METHOD:** Brain tumor is the collection or mass of abnormal cells in the brain or central spine canal. Our brain is enclosed by skull which is very rigid. Any growth inside such a restricted space can cause many problems for human. Brain tumors can be both cancerous (malignant) or noncancerous (benign). The pressure inside the skull increase when benign or malignant tumors grow. This will result in brain damage, and it can be life-threatening. A brain tumour usually appears in various locations with different dimensions and shapes. Brain tumors are categorized as primary or secondary. A primary brain tumor originates in our brain. Many primary brain tumors are benign. A secondary brain tumor, which is also known as a metastatic brain tumor, occurs when cancer cells spread to our brain from another organ, such as lung or breast. Early detection of tumor cells can save large number of human lives. Detecting the brain tumor and its stage undergoes a very complicating and time consuming process. The patient refers to MRI when some symptoms related to tumours have appeared. After examining the brain images, if tumor existence is suspected, the patient's brain biopsy comes into action. Biopsy is an invasive procedure and in some cases it may even take up to a month for a definite answer.
EXISTING TECHNIQUE : • **QUANTUM SELF SUPERVISED NETWORK**	**PROPOSED ALGORITHM:** • **CNN**
TECHNIQUE DEFINITION: This work focuses on a novel quantum fully self-supervised neural network (QFS-Net) characterized by qutrits for fast and accurate segmentation of brain lesions. The primary aim of the suggested work is to enable the QFS-Net for faster convergence and making it suitable for fully automated brain lesion segmentation obviating any kind of training or supervision. The proposed QFS-Net model relies on qutrits or three-level quantum states to exploit the features of quantum correlation. To eliminate the complex quantum backpropagation algorithms used in the supervised QINN models, the QFS-Net resorts to a novel fully self-supervised qutrit-based counter propagation algorithm.	**ALGORITHMDEFINITION:** The Convolutional Neural Networks (CNN) is one of the most famous deep learning algorithms and the most commonly used in image classification applications. In general, the CNN architecture contains three types of layers, which are convolutional layers, pooling layers, and fully connected layers. The CNN algorithm receives an input image that passes through the layers to identify features and recognize the image, and then it produces the classification result. The architecture of the CNN contains alternating convolutional layers and pooling layers, followed by a set of fully connected layers. The output of each layer in the CNN is the input of the following layer. The input of the CNN is image (width × height × depth), the width and the height are the dimensions of the images.

DRAWBACK:	Advantage:
• This process comes under normal machine learning techniques. • Here UNET and RseNet50 are used.	• The CNN also reduces the normal machine learning process like feature extraction and classification. • That is CNN= (feature extraction+ classification). • This process comes under deep learning. • Here a brain tumor stage of classification is done leads to advanced development when compared to existing technique.

APPLICATION:

- To support early detection, diagnosis and optimal treatment.
- Image segmentation plays an essential role in many medical applications.
- Low SNR conditions and various artifacts makes its automation challenging.
- To achieve robust and accurate segmentation.

HARDWARE REQUIREMENTS:

- Processor : Pentium Dual Core 2.00GHZ
- Hard Disk : 500 GB
- RAM : 4GB (minimum)
- Keyboard : 110 keys enhanced

SOFTWARE REQUIREMENTS:

- MATLAB 8.6 Version R2018a

ADVANTAGES:

Here the segmentation process is more accurately done.
Because of segmentation of MRI images leads to give an accurate classification.
This process comes under deep learning convolutional neural network

FUTURE ENHANCEMENT

[1]. In future, with more time and with more comprehensive research the proposed system can be made more accurate. Also new brain tumour disease detection algorithms can be added so as to give the doctor a wider variety of options to choose from.

[2]. REFERENCES:

[3]. JCS: An Explainable COVID-19 Diagnosis System by Joint Classification and Segmentation.by Yu-Huan Wu , Shang-Hua Gao, Jie Mei , Jun Xu , Member, IEEE, Deng-Ping Fan , Member, IEEE, Rong-Guo Zhang, and Ming-Ming Cheng , Senior Member, IEEE

[4]. Predictive modeling of Covid-19 data in the US: Adaptive phase-space approach by Vasilis Z. Marmarelis, Fellow, IEEE

[5]. Analysis and Predictions of Spread, Recovery, and Death Caused by COVID-19 in India by Rajani Kumari, Sandeep Kumar*, Ramesh Chandra Paonia, Vijander Singh, Linesh Raja, Vaibhav Bhatnagar, and Pankaj Agarwal

[6]. Weakly Supervised Deep Learning for COVID-19 Infection Detection and classification from CT Images SHAOPING HU1 , YUAN GAO 2,3, (Member, IEEE), ZHANGMING NIU3,4, YINGHUI JIANG4,5 , LAO LI4,5, XIANGLU XIAO3,5, MINHAO WANG4,5, EVANDRO FEI FANG6 , WADE MENPES-SMITH3 , JUN XIA7 , HUI YE8 , AND GUANG YANG 9,10, (Member, IEEE)

[7]. A Proactive and Practical COVID-19 Testing Strategy by KUAN SONG Gago Ltd., Beijing 100870, China SHIQI JIAO Gago Ltd., Beijing 100870, China QIANG ZHU Gago Ltd., Beijing 100870, China HUITAO WU Zhejiang Lab, Hangzhou 311122, China

[8]. L. Pellis et al., "Challenges in control of COVID-19: Short doubling time and long delay to effect of interventions," 2020, arXiv:2004.00117. [Online]. Available: http://arxiv.org/abs/2004.00117

[9]. F. Zhou et al., "Clinical course and risk factors for mortality of adult inpatients with COVID-19 in Wuhan, China: A retrospective cohort study," Lancet, vol. 395, no. 10229, pp. 1054–1062, Mar. 2020.

[10]. Y. Fang et al., "Sensitivity of chest CT for COVID-19: Comparison to RT-PCR," Radiology, vol. 296, no. 2, pp. E115–E117, Aug. 2020. [4] K. A. Erickson, K. Mackenzie, and A. Marshall, "Advanced but expensive technology. Balancing affordability with access in rural areas," Can. Family Physician Medecin de Famille Canadien, vol. 39, pp. 28–30, Jan. 1993.