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A DEEP LEARNING APPROACH FOR SEMANTIC SEGMENTATION IN BRAIN TUMOR IMAGES

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Abstract:
In medical technology, Magnetic Resonance Imaging (MRI) has been used widely for detection of tumors and diagnosing various abnormalities in tissues. In scientific research, a major role has been played by the active development in the computerized segmentation of medical image. Based on fast decision making, the doctors can take required treatment easily. In the information technology, the segmentation of brain tumor is a key point. By analysing the radiation therapy treatment, tumor growth, computer-based surgery, developing the growth models of tumor, and treatment responses, the segmentation of brain tumor is motivated. For segmentation of brain tumor, a deep learning-based framework is presented. To achieve the robust performance through a majority rule, deep learning based semantic segmentation architecture is used for segmentation of tumor that can improve the performance effectively.

INTRODUCTION

Medical imaging is utilized the processes and techniques for creating the human body images for different purposes of clinical activities such as diagnosis of medical procedures or medical science subsuming the investigation of normal anatomy and function [1]. In medical field, an invaluable tool is diagnostic imaging. The imaging modalities such as digital mammography (MM), computer tomography (CT), magnetic resonance imaging (MRI), etc. provide an effective mapping of the anatomy of a subject noninvasively.

For a word neoplasm, the tumor is used as a synonym and it is formed with the cells based on an abnormal growth. Tumor is not mandatorily related to the cancer.

Three different types of tumor include:

1) Malignant
2) Pre-Malignant
3) Benign

A benign tumor is a kind of tumor which doesn’t able to expand abruptly and not affecting the neighboring healthy tissues and non-adjacent tissues [2]. The common example of benign tumors is the moles.

Premalignant Tumor is a disease and a precancerous stage. It leads to cancer if not treated properly.
Malignant is another type of tumor that grows gradually and the death of a person results ultimately. A severe progressing disease describes by a medical term known as malignant which is also used to describe the cancer.

MAGNETIC RESONANCE IMAGING (MRI)

As ionizing radiation is not incorporated, magnetic resonance imaging (MRI) is a non-invasive imaging method which provides three dimensional data about the anatomy of human soft tissue [4]. In the process of diagnosing brain disease like Epilepsy, Schizophrenia, Multiple Sclerosis, and others, the images of MRI are playing significant role.

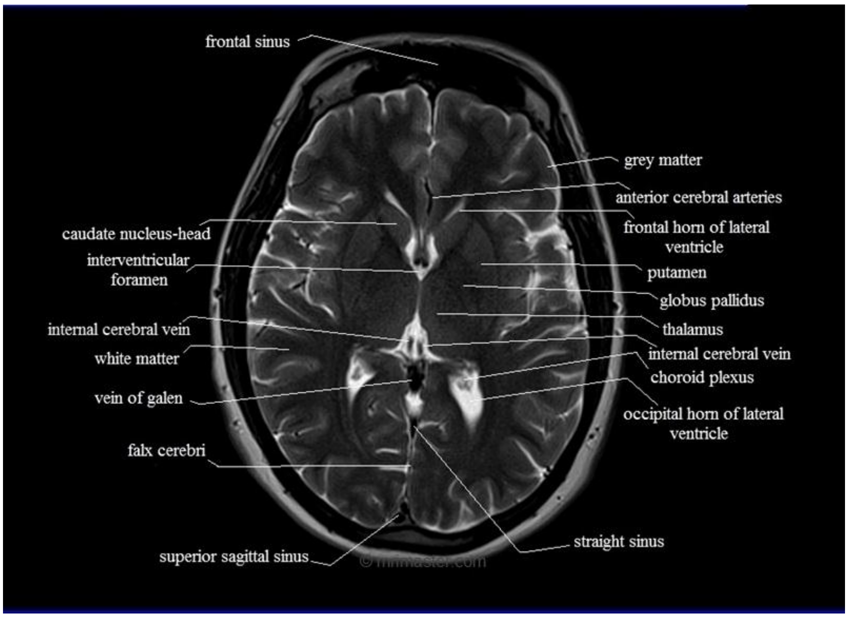

Fig.1 Brain MRI image

To diagnose the brain disorders, a significant role is played by segmenting the brain tissues into cerebrospinal fluid (CSF), gray matter (GM), and white matter (WM). For providing the treatment for multiple sclerosis, the white matter lesions' quantification requires. For diagnosing the Epilepsy and Schizophrenia, different tissue classes with volumetric analysis is crucial. The precision of segmentation analysis reduces by manual segmentation which is time consuming and liable to intra and inter-observer variability. However, an invaluable tool is considered as an accurate, automatic, and robust tissue segmentation method in the diagnosis of neurodegenerative diseases.

Image processing is relevant to the signal processing concept that involves the output can be either a set of parameters or characteristics corresponding to the image and the input is an image like photographs. In the segmentation process, representation of an image is changed by partitioning the digital image into multiple regions for easy analysis. For locating objects and boundaries in images, image segmentation utilizes. However, image segmentation has been improved by integrating various techniques and algorithms [6]. For solving a problem of an image segmentation effectively, these methods have been integrated with domain knowledge as there is no general solution for the challenges of image segmentation.

By providing the anatomical structures delineation and other regions of interest, image segmentation is considered as an essential role in the application of medical imaging. Several approaches are available in the literature regarding medical image segmentation. Based on one of the two intensity properties values such as similarity and discontinuity, algorithms of image segmentation have been developed generally. With the abrupt changes in intensity like image edges, the partitioning of an image is made by the approach in the first category [7]. According to a set of predefined criteria, the similar regions are partitioned from an image in the principle approaches of second category which includes the examples such as region growing, thresholding, merging, and region splitting.

Owing to the intensity presence in inhomogeneity that causes by variations in illumination occurs in real-world images often or imaging devices imperfection, a uniform intensity assumes in intensity-based segmentation algorithms which caused by misclassification of the pixels of various regions [8]. As the prolonged tails of each object's intensity distribution causes the misclassification, the accurate extraction of desired objects is difficult by their respective distributions of intensity. Since most of the representative algorithms are region-based that rely on interested object's intensity homogeneity, it's often a tough task for segmentation of images accurately with the inhomogeneity of intensity distributions.

The challenges in the design of effective segmentation algorithm depend on the type of segmentation method employed for segmentation and on the characteristics of the medical images. The type of segmentation algorithm used can be either region based or edge based algorithms. Intensity homogeneity in the region of interest is the requirement for accurate segmentation in region based algorithms [9]. Strong edges are the main requirement for accurate segmentation in edge based methods. It is a great challenge to design a segmentation algorithm for medical images with intensity inhomogeneity for region based models and to design a segmentation algorithm for medical images with weak edges for edge based models.

When compared to the traditional techniques, the better fusion results have been provided by the deep learning-based method. Different types of convolutional neural network models have been proposed since 2012 such as U-Net, FCN, DenseNet, Residual Net, GoogleNet, VGG, ZFNet, and AlexNet. For object detection, image segmentation and classification, and tracking tasks, these models have been provided the state-of-the-art performance and a new context for image fusion as well [10-11]. For this, four major reasons are included such as: the advanced features in neural networks is the major success of deep learning than the traditional machine learning that helps to learn high-level features from data incrementally. These features eliminate the domain expertise domain and difficult extraction of features. The problem is solved in an end to end manner.

The implementation of deep learning-based methods have been attempted in medical image field for medical image segmentation in the pancreas, lung, brain, multi-organ, and prostate because of the success in deep learning. A medical image segmentation is an essential section and requires for diagnosis, monitoring, and treatment in medical image analysis [12]. The label is assigned to each pixel of images which is the main objective of the technique. Two different phases like declining different anatomical structures and detection of unhealthy tissue or areas of interest in this method. By comparing with the traditional methods, superior performance has been achieved with the deep learning-based methods in the medical image segmentation.

LITERATURE SURVEY

Salem Saleh Al-amri et al. [13] was made an attempt for investigating the image segmentation methods based on five threshold techniques such as visual technique, Edge Maximization Technique (EMT), Histogram Dependent Technique (HDT), P-tile method, and Mean method. The efficient method is selected for image threshold segmentation techniques by comparing with one another. To select the base guesses for image threshold segmentation, these methods have been implemented on three satellite images.

Shanhui Sun Christian Bauer et al. [14] was focused on presenting the fully automated approach for lungs image segmentation in CT datasets. For segmenting the lungs with cancer masses robustly, the technique was designed specifically that includes three processing steps. Primarily, an algorithm of a ribcage detection which uses for initializing the model-based segmentation method. Secondly, an approach of robust active shape model matching implements for segmenting the lungs outline roughly. Third, the matched model outline adapts further for image data based on an optimal surface finding approach.

Li Minxia et al. [15] was designed defect extraction based on image segmentation. A technique of new wavelet adaptive threshold denoising was proposed based on the wavelet analysis and optimization of genetic algorithm. For enhancement of local contrast, the multi-scale morphological algorithm has been designed. By using the digital subtraction algorithm, the extraction of defect regions and simulation of background have been accomplished. The extraction of defect region can be achieved by the methods automatically based on the experimental results. To extract the flaw feature parameter, it is a good foundation and always a best choice.

Pu J et al. [16] has been considered a shape “break-and-repair” strategy for segmentation of medical image and implemented for human lung and pulmonary nodules. The problems caused by the regions in segmentation were eliminated and determined with implicit surface fitting based on RBFs in this approach. In a unified framework, the most essential feature of the method is to segmenting the depicted anatomical structures on medical images within a single pass. This strategy robustness, generality, and feasibility have been described and the results of preliminary assessment are fostered in image segmentation.

KimmiVerma et al. [17] was researched the software utilization based on image segmentation and edge detection technique that provides the edge pattern and brain segment and the 68 brain tumor itself. The review of image segmentation and edges has been provided in this research with an emphasis of revealing the benefits and drawbacks of techniques for medical imaging applications. In different imaging modalities, the image segmentation usage is demonstrated in addition to the encountered difficulties in each modality.

P. Sadaphal et al. [18] was described the proof of principle of an innovative computational algorithm that identified the Ziehl-Neelsen (ZN) stained acid-fast bacilli (AFB) successfully in digital images. The possible ‘TB objects’ have been recognized by the color-based, multi-stage, and automated Bayesian segmentation that removes the artifacts based on color-labeled objects and shape comparison as ‘possible’, ‘definite’, or ‘non-TB’ and bypassing the calibration of photo micrographic images. The challenges were included low depth of field, extreme stain variation, and superimposed AFB clusters. In the developing countries in which the fluorescent unaffordable and inaccessible, this novel technique offers the TB electronic diagnosis and allowing the wider application.

H. Costin [19] was demonstrated a semi-automated and supervised technique using a rule based fuzzy system for medical image segmentation. A rule-based linguistic demonstration of the objects relevant to the Region of Interest utilizes for the application by the fuzzy system which allows the system to make the edge detection-based segmentation. A symbolic representation determines for each input image at the system entry and fuzzy rules have been implemented. For further analysis, the rule satisfies for those only among all points of interest (candidate points for contour detection). The contour points' position is yielded by the system finally.

Long et al. [20] was determined that one of the first deep learning works using a fully convolutional network (FCN) for semantic image segmentation. The convolutional layers include in an FCN (Figure 7) that allows to generate a segmentation map of the same size and take an image with arbitrary size. For managing the non-fixed sized output and input, the existing architectures of CNN have been modified based on the replacements of all fully-connected layers with the fully-convolutional layers. Rather than the scores of classification, a spatial segmentation map results by the model.

Chen et al. [21] was improved a semantic segmentation algorithm using the integration of fully connected CRFs and CNNs (Figure 10). For accurate object segmentation, the responses are not localized enough that are from the deep CNNs' final layer owing to the invariance properties that helps to achieve good CNNs for high-level activities like classification. The outputs at the final CNN layer with a fully-connected CRF are integrated for restricting the property of poor localization in the deep CNNs. This model is showed that the localization of segment boundaries at a higher rate of accuracy than the previous existing techniques.

Hung et al. [22] was proposed a framework using an adversarial network for semi-supervised semantic segmentation. By considering the spatial resolution, the differentiation of predicted probability maps from the distribution of ground truth segmentation is made possible by designing an FCN discriminator. Three kinds of terms include in this model's loss function such as: semi-supervised loss based on the confidence map i.e. the discriminator's output, adversarial loss of the discriminator network, and cross-entropy loss on the segmentation ground truth.

K Kamakshaiah et al [23], proposed recognition of objects such as fishes has drawn more attention while submerged pictures are showing some difficulty due to their poor picture quality which also includes rough background surfaces when compared to general images. Medicines prepared from fishes help in curing different diseases to reduce the health issues in the present world (for example, rheumatism problems, gel for wounds, bandages, etc). In our proposed method we are projecting a deep neural network that supports recognition of fishes to acquire their count, species and medical usage.

Existing method

Existing block diagram:

The following figure shows the existing system block diagram. The figure contains MRI input image, Fuzzy c means (FCM) clustering and result blocks. In FCM c will be selected by manually, by selecting the c value the membership will be updated along with the cluster centers.

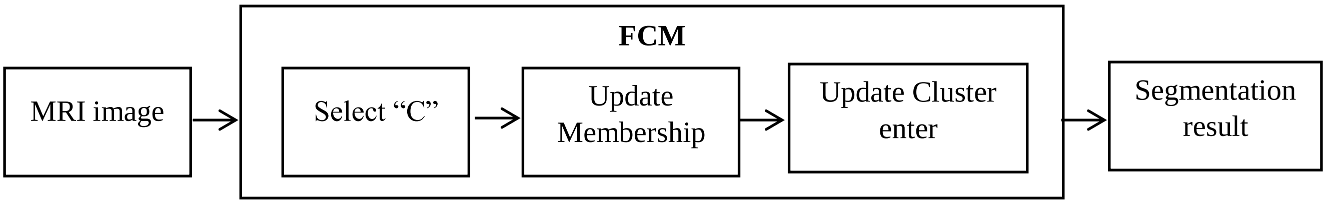

Fig 2. Brain tumor detection using FCM clustering

FUZZY C MEANS CLUSTERING ALGORITHM

One pixel allows in Fuzzy C means clustering algorithms that relates to one or more clusters [9, 10]. A collection of "C" fuzzy clusters is partitioned from a finite collection of pixels in accordance with some given criteria of FCM algorithm [3]. By using Fuzzy C-means Algorithms, the below objective function minimizes.

$$J(U, c_1, c_2, \ldots, c_c) = \sum_{i=1}^{c} J_i = \sum_{i=1}^{c} \sum_{j=1}^{n} u_{ij}^m d_{ij}^2$$

u_{ij} is between 0 and 1; m€ [1,∞] is referred to a weighting function, d_{ij} is the Euclidean distance between jth data point and ith centroids; and C_i is the cluster centroids I. Through the below objective function's iterative optimization, fuzzy partitioning of known data sample is processed.

$$u_{ij} = \frac{1}{\sum_{k=1}^{c} \left(\frac{d_{ij}}{d_{kj}} \right)^{2/(m-1)}} \qquad c_{ij} = \frac{\sum_{j=1}^{n} u_{ij}^m x_j}{\sum_{j=1}^{n} u_{ij}^m}$$

If $\max_{ij} \left\{ \left| u_{ij}^{(k+1)} - u_{ij}^{(k)} \right| \right\} < \varepsilon$, this iteration will be stopped. Here, k related to the iteration steps and ε is a termination criterion which is between 0 and 1. This process is converged to a local minimum or saddle point of J_m. The below-mentioned steps contain in the algorithm such as:

1. The number of clusters c and cluster centers is initialized to m>1 and $U=[u_{ij}]$ matrix, $U^{(0)}$.
2. The centers of vectors $C^{(k)} = [c_j]$ with $U^{(k)}$ is calculated at k-step.

$$c_j = \frac{\sum_{i=1}^{N} u_{ij}^m x_i}{\sum_{i=1}^{N} u_{ij}^m}$$

3. The membership function matrix $(U^{(k)}, U^{(k+1)})$ updates.

$$u_{ij} = \frac{1}{\sum_{k=1}^{c} \left(\frac{\| x_i - c_j \|}{\| x_i - c_k \|} \right)^{\frac{2}{m-1}}}$$

4. If $\| U^{(k+1)} - U^{(k)} \| < \varepsilon$, the updating of cluster centers is stopped; otherwise go to step 2.

Proposed System

Block diagram

The following figure shows the proposed block diagram. The block diagram contains input image, preprocessing, color feature extraction and semantic segmentation blocks. Input Brain tumor MRI image is pre-processed for block division. Block images contains tumor and non tumor parts, these blocks are fed to color feature extraction. Color features are processed by semantic segmentation. The trained model is saved into .mat file for further processing.

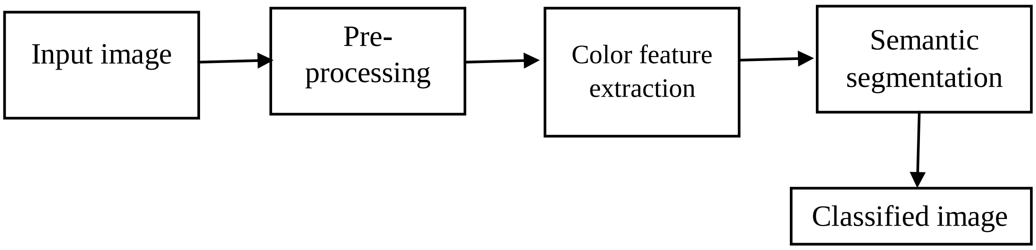

Figure 2. Proposed block diagram

In the fig 3, the proposed technique's block diagram is shown. In the block diagram of proposed system,

Pre-processing

In the experiment, the basic pre-processing techniques are used. The cropping and resizing of images is done with the use of suitable schemes of cropping (NDVI image) in order to fulfil the needs. To provide uniform intensity, the image is normalized later. The filteration of an image is also accomplished based on low pass filter.

Color feature extraction

Color is considered as an essential feature that perceives by humans while viewing an image. By comparing with the gray levels, the human vision system sensitives to information of color so it is used as the first parameter utilizes for extraction of feature.

In three-dimensional color spaces, colors are defined commonly. The color space models can differentiate as user oriented and hardware-oriented. According to theory of three-color stimuli, the hardware-oriented color spaces are implemented that include YIQ, CMY, and RGB.

For manipulation of colors, the technique provides by color spaces which define as a model to represent the color in terms of intensity values. In the retrieval system of color image, the following four models are utilized such as:

- The CIE lab color space
- The HMMD color space
- The HSV color model
- The RGB color model

The most common model i.e. RGB color space utilizes for computer images as the display of computer is used the primary colors combination (blue, green, and red) for displaying any perceived color. Three points are contained in each pixel in the screen that stimulates by blue, green, and red electron gun individually. The RGB space is not uniform perceptually so the dissimilarity of color in perception doesn't corresponding to the color distance in RGB color space. In prior to the feature extraction, the transformation of image data in RGB color space into other perceptual uniform space is preferred.

Semantic segmentation

In computer vision, a well-studied problem is a pixel-wise image segmentation. The classification of each pixel in the image is the task of semantic image segmentation.

From a predefined set of classes, the each pixel's classification in an image is the task of semantic image segmentation which is different from object detection. Because, the image segmentation doesn't forecast any bounding boxes around the objects. The image with a higher level understanding requires for performing the semantic segmentation. The available objects and the pixels that relevant to the objects should figure out by the algorithm. To gain a complete view of understanding, one of the important tasks is considered as semantic segmentation.

Medical images

To carry out the diagnostic tests, the body scans with automated segmentation can helpful for doctors. For an instance, the training of models can be made for tumor segmentation.

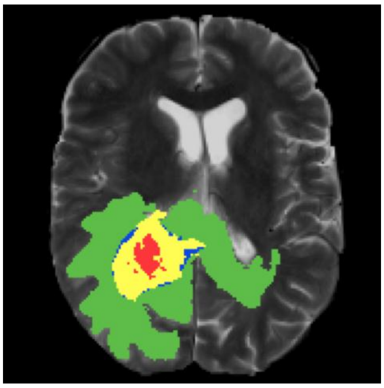

Fig 4. Tumor segmentation of brain MRI scan.

Convolutional neural networks for semantic segmentation

The deep CNNs has gained much popularity at peak level and became the *de facto* standard eventually for various types of computer vision and ML applications over the years. In sequential data processing involving Speech Recognition, Natural Language Processing, and even 1D signals, these are widely used furthermore.

Not similar to the traditional Artificial Neural Networks (ANNs), deep CNNs are providing a benefit of combining both classification tasks and feature extraction into a single body along with the achieving of efficient performance levels. CNN-based methods are learned to extract the "optimized" features from the raw data directly to overcome the problem at hand for improving the accuracy of classification whereas conventional Machine Learning (ML) methods have been performed specific pre-processing steps and utilize the hand-crafted and fixed features that are sub-optimal as well as needed a high computational complexity. For improving the classification performance significantly, the extraction of optimized features is the key characteristic that made CNNs will get much attention in the complicated engineering applications. As the modelling and creation of deep CNNs was made designed for 2D signals and was not applied for 1D signal signals specifically in case of data scarcity, the reign of conventional ML approaches was not challenging for 1D signals.

In this paper, the training samples is considered as a matrix $X = [x_1, x_2, \ldots \ldots x_N]'$ where xi represents the d-dimensional measurement space and N is the number of training samples. The real output target vector is denoted as $Y = y_{1,} y_2, \ldots \ldots y_N$ that is associated with **X**. A number of L layers in which *ml* feature signals are contained for each layer *l* (*l=1..L*) in a 1D-CNN and is performed both operations of subsampling and convolution. The assumption of subsampling factor (ss) equivalent to 2 (ss=2) is considered. In Figure 4.4, 1D-CNN with a general architecture is demonstrated.

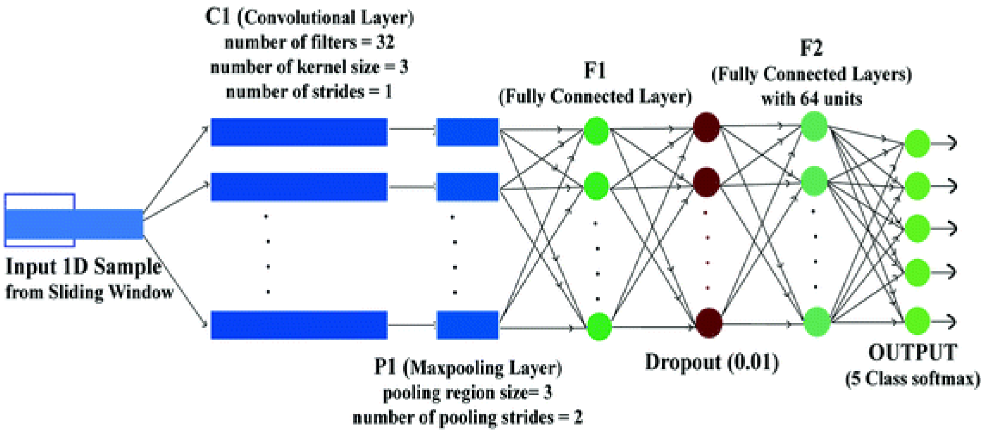

Figure 4. 4: Detail architecture of semantic segmentation

A proper 1D to 2D conversion is required naturally in the application of 1-D signal processing based on the direct utilization of a deep CNN. The researchers have been made tests on using deep CNNs for fault diagnosis of bearings. For representation of 1D vibration signals in 2D, different conversion techniques have been used for that purpose. The reshaping of the vibration signal into an $n \times m$matrix which is termed as “the vibration image” was done in a widely used method. Other technique was utilized that involves the computation of two vibration signals based two accelerometers. In a matrix form, two transformed signals were represented that can integrate into a conventional deep CNN in the improved Discrete Fourier Transform (DFT). The usage of such type of deep CNNs are having certain limitations and drawback for classification of satellite data and detection of different areas. A high computational complexity is posed by it that needs special hardware especially for training. For real-time applications on low-power or low-memory and mobile devices, 2D CNNs are not suitable. For achieving a capability of reasonable generalization, a massive size dataset is required for proper training of deep CNNs additionally. In many practical applications of 1D signal where the scarcity of labelled data is existed, this may not be a viable option.

Results and discussion

The training process requires set of layers and options. Reach the computational architecture of the neural network. When regression is not an easy thing to do, add a regression layer at the end of the network. Constructing a collection of layers requires the input image unique size.

Using increased image data to train a convolutionary neural network. Data increase helps prevent the network from overrunning and storing exact training picture information.

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Reach the computational architecture of the neural network. At the end of the network, a regression layer includes for problems with regression.

The training process includes generally two graphs which are accuracy and loss. If the training process reaches to maximum epoch the accuracy graph reach to 100% and the loss graph reaches to 0%.

In the both accuracy and loss graphs consists 3 lines. The thick line represents the training(smoothed). Thin line with dots represents the training and the dash line represents the validation.

By using semantic segmentation, the training process for face images is shown in figure 5.

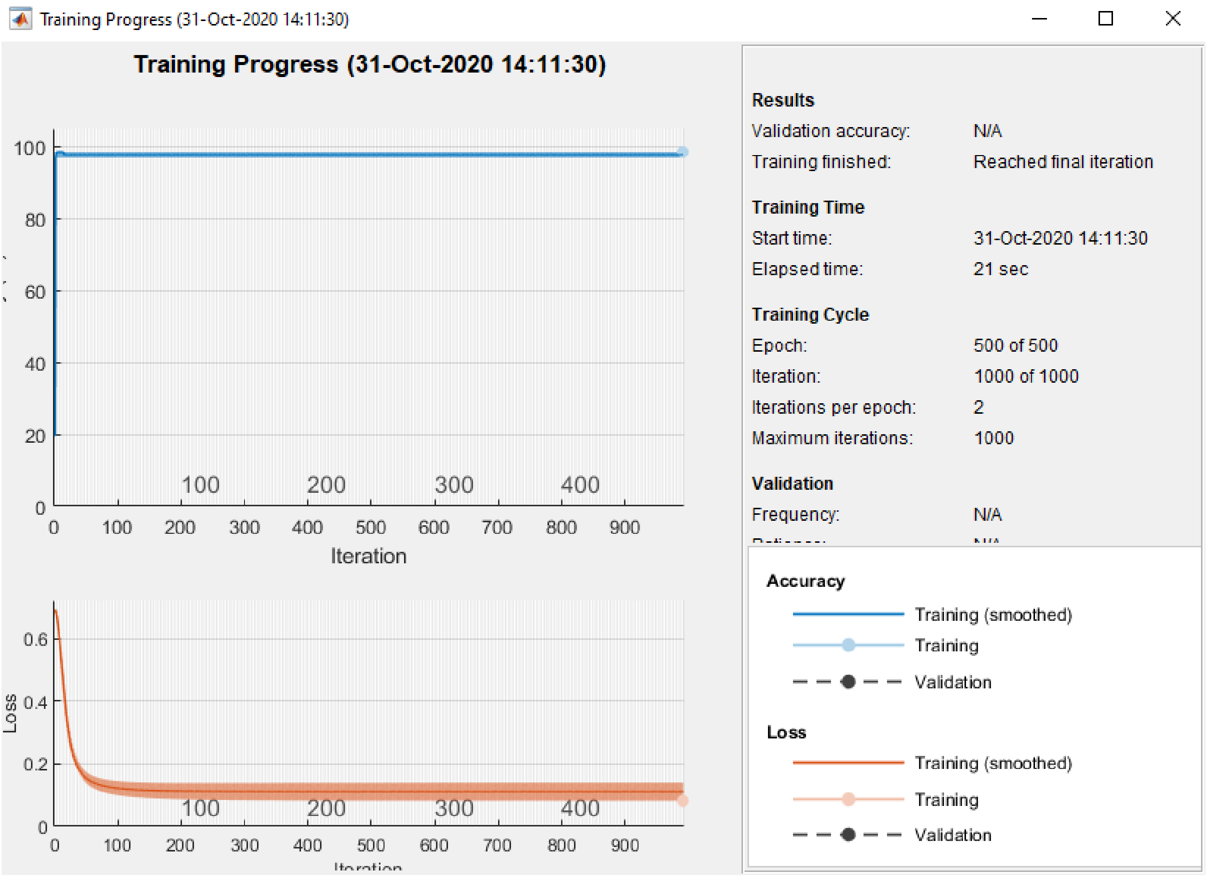
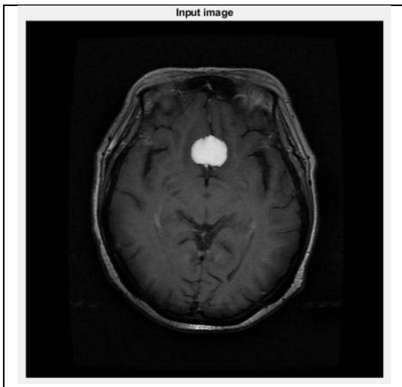
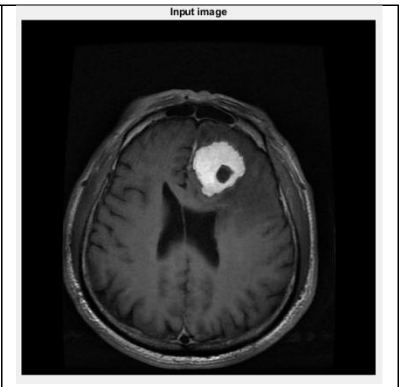


Fig 5. Training process

Figure 6 shows the different brain tumor images.

	
A. Input image	b. input image

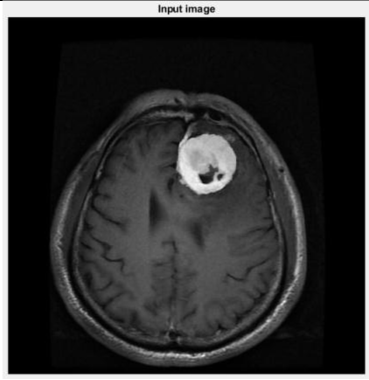
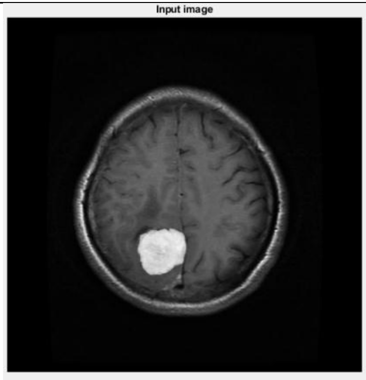
	
c. input image	d. Input image

Fig 6. Different tumor input images

Figure 7 shows the binarized image by mapping labels into original size, then get the binarized output.

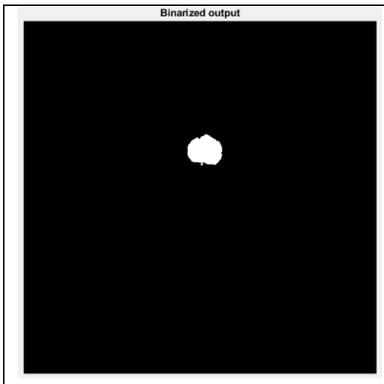
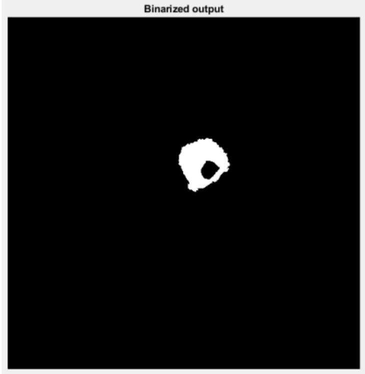
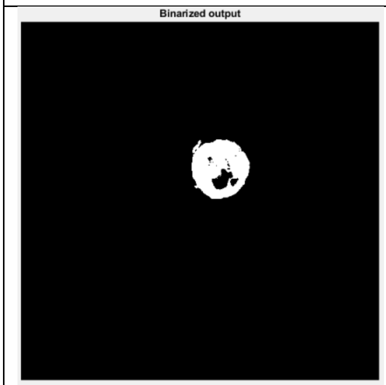
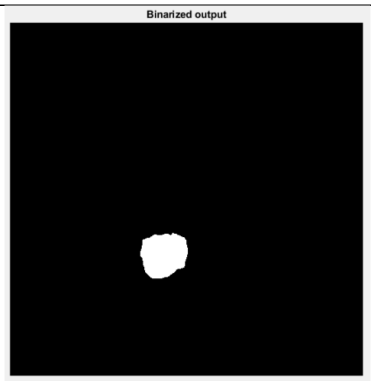
	
A. Binarized output	B. Binarized output
	
C. Binarized output	D. Binarized output

Fig 7. Different binarized output images

Figure 8 shows the semantic segmented images. Semantic segmentation generates colours automatically forregion of interest parts.

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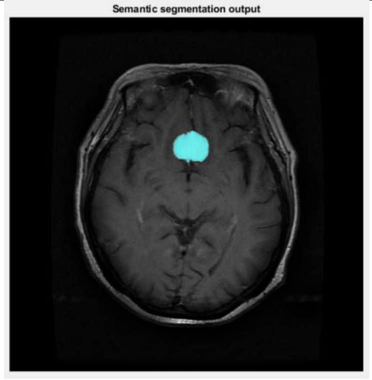
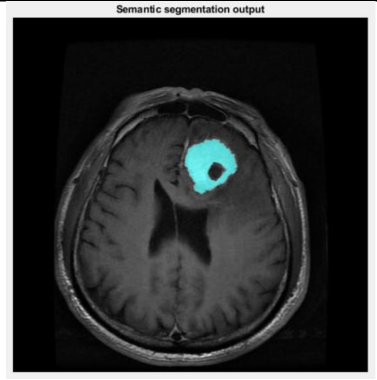
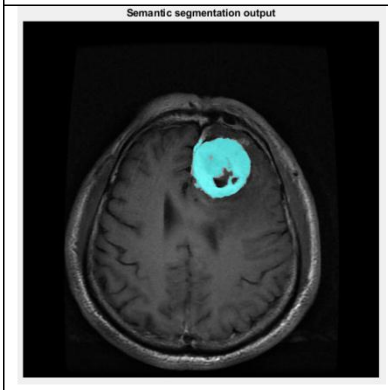


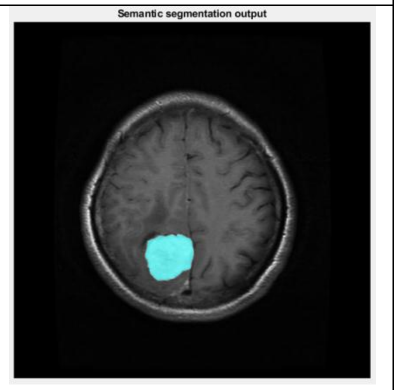
Semantic segmentation output 1



Semantic segmentation output 2



Semantic segmentation output 3



Semantic segmentation output 4

Fig 8. Different sematic segmentation output images

Conclusion:

Based on deep convolutional neural networks, an automatic brain tumor segmentation technique presents in this paper. To predict the brain tumors, an essential diagnostic tool is considered as MRI using segmentation technique. First, a MRI image is used to segment two different parts called tumor and non tumor parts for deep learning training method, then color features are extracted and trained for prediction of automatic brain tumor . For tumor segmentation, we used semantic segmentation architectures for robust performance.Different training strategies and network architectures will explore further for improving the results.

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