Glioma Detection and Segmentation Using Deep Learning Architectures

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Abstract

Glioma is the primary type of brain tumors which occurred in both human brain regions and spinal cord. It can be cured if it is detected on time by the current scanning methodologies. In this paper, effective Computer Assisted Artificial Methods (CAAM) using deep learning architectures are proposed to differentiate the pixels belonging to Glioma tumors and the pixels belong to non-Glioma tumors. The LeNET and AlexNET deep learning structures along with morphological segmentation procedures are applied on the brain images to detect and locate the tumor pixels in Glioma images. The experimental results are carried out on BRTAS 2019 and BRATS 2020 dataset brain Magnetic Resonance Imaging (MRI). The experimental results of this work are extensively analyzed and compared with similar existing studies.

Keywords: Glioma, tumors, CAAM, deep learning, CNN, morphological;

1. Introductions

Glioma is the severe type of the brain tumor which is formed over the region of the nervous system of the brain in the human body. This type of tumor can be occurred in either spinal cord or stem of the brain tissues in the brain. There may be different kind of Glioma found from the last two decades. These types of Glioma tumors can be differentiated by the systematic study of symptoms over the long period of tumor detection interval rate. Among the series of systematic symptoms, headache and seizures are the common symptoms in all types of Glioma types [1-3]. The Glioma tumors can be treated by lot of different methods in medical field. Among them, radiation therapy and chemotherapy are very important for treating the tumor pixels in brain. Though these methods are effective in nature for treating the Glioma tumors, the severity levels of the side effects due to these Glioma tumor treating methods are high due to the level of radiation used in these methods. Hence, alternate methods are required to overcome the radiation effect on the brain regions [4-5]. These alternate methods include surgery and molecular therapy. The surgery is the process of removing the tissues belonging to the Glioma tumors in the brain and other regions such as spinal cord also. This surgery method requires accurate Glioma tumor tissues identification. The manual identification of tissues belonging to Glioma type of tumor is quite complex due to its extreme tissue intensity and illumination levels. Therefore, an effective Computer Assisted Artificial Methods (CAAM) is required to differentiate the pixels belonging to Glioma tumors and the pixels belonging to non-Glioma tumors. The various types of CAAM is illustrated in Fig.1.

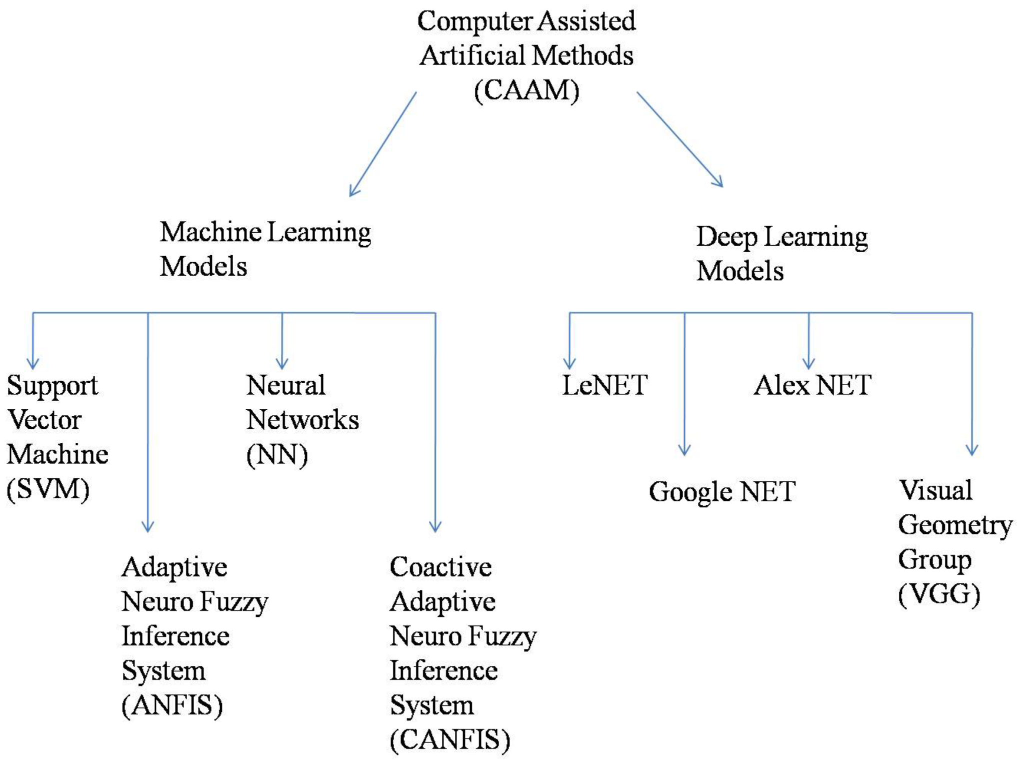


Figure 1 CAMM types

This paper applies various CNN architectures for the detection process of Glioma brain tumors. This work divides the entire paper into five sections. The introduction of the Glioma tumors are given in section 1, the existing methods are discussed in section2, section 3 proposes Glioma brain tumor detection system using various CNN architectures , section 4 is the simulation of the proposed work with respect to various CNN architectures and the final conclusion with future works are stated in section 5.

2. Literature Survey

Sahar Gull et al. (2021) developed the customizable CNN architecture for the process of detecting the tumor set of pixels in brain images. This developed method used global threshold technique to locate the non tumor related pixels from the pixels being related with tumor. Then, Google Net CNN architecture was established for training the threshold pixels in the brain images. The authors tested the developed brain tumor pixel segmentation method with the help of the brain images in BRATS 2018, 2019 and 2020 dataset. This method achieved 96% of accuracy rate for BRATS 2018 dataset images and 97% of accuracy rate for BRATS 2019 dataset images and 98% of accuracy rate for BRATS 2020 dataset images respectively. The results were compared with respect to gold standard brain images which were acquired through the radiologist from the recognized health care centers. Methil et al. (2021) provided a solution for the brain images having illumination problems. The illumination issues in the brain images reduced the detection accuracy of the tumor pixels in the brain images. In order to solve this illumination issues in the brain images, this paper used histogram equalization algorithm for improving the illumination level of each pixel in the brain images. The highly illuminated pixels in the brain images now fed into the classifier which trained and classified the system of brain tumor detection network. The work was regulated by varying the set of illumination static points in the source brain images. Sharif et al. (2020) learned and trained the non-linear pixel pair in source brain image to train the extreme machine learning algorithm. The static pixel features were derived from the trained labels and the mapping between the constructed labels were optimized through this EML algorithm. The developed training approach of the brain tumor detection system was analyzed through the series of testing and validation process to verify the level of accuracy and based on the validation behavior of this system.

Özyurt et al. (2020) detected the cluster pixels in source brain images by clustering the image into various set of non-overlapping regions. The detected cluster pixels in each clustered regions in the brain images were trained by the CNN system for the identification of pixels belonging to abnormal pattern in brain images. This method was tested with only high contrast brain images as the drawback of this developed brain tumor detection system. The authors obtained 96.1% of Tumor Detection Rate (TDR) for the high contrast brain MRI images. Swati et al. (2019) devised transfer learning method for the prediction and level synthesis of various pixel coordinates. The initial training rate of the transfer learning function was found through the threshold function and then the value of the obtained training rate of the transfer function was varied based on the population estimation index rate in this work. The parameters obtained through the transfer learning process were regulated by the fine tuning function. This work was evaluated by the standard validation approaches in this tumor pixel detection algorithm.

Based on the existing algorithms for Glioma detection, deep learning methods are preferred in this paper to identify the Glioma images, as illustrated in Fig.2.

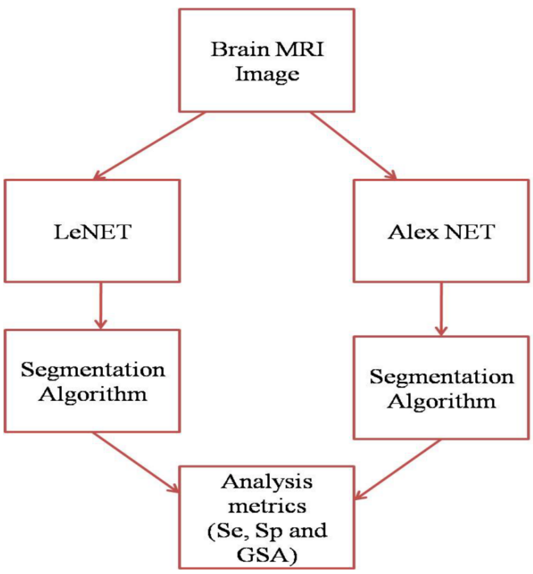


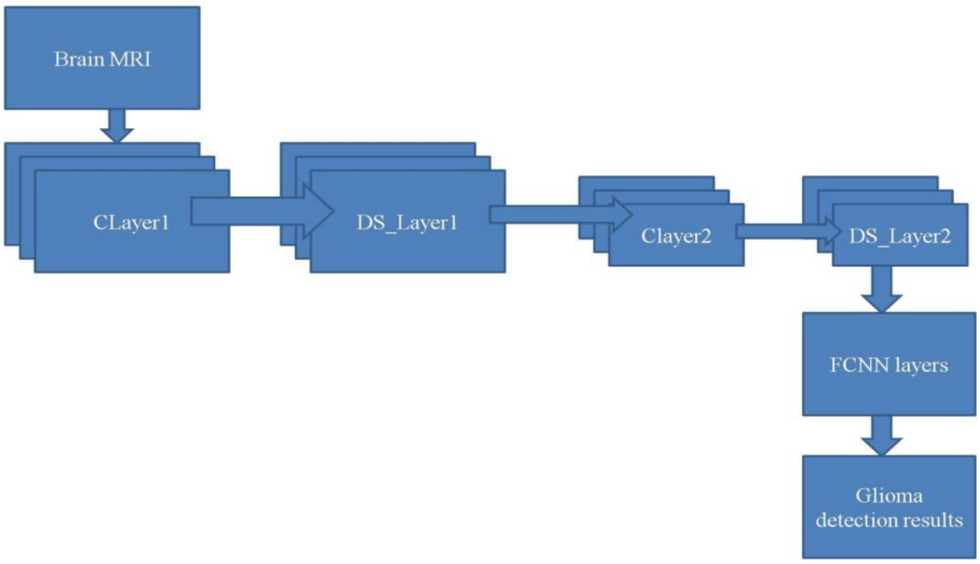
Figure 2 Methodologies for Glioma detection

3. Proposed Methods

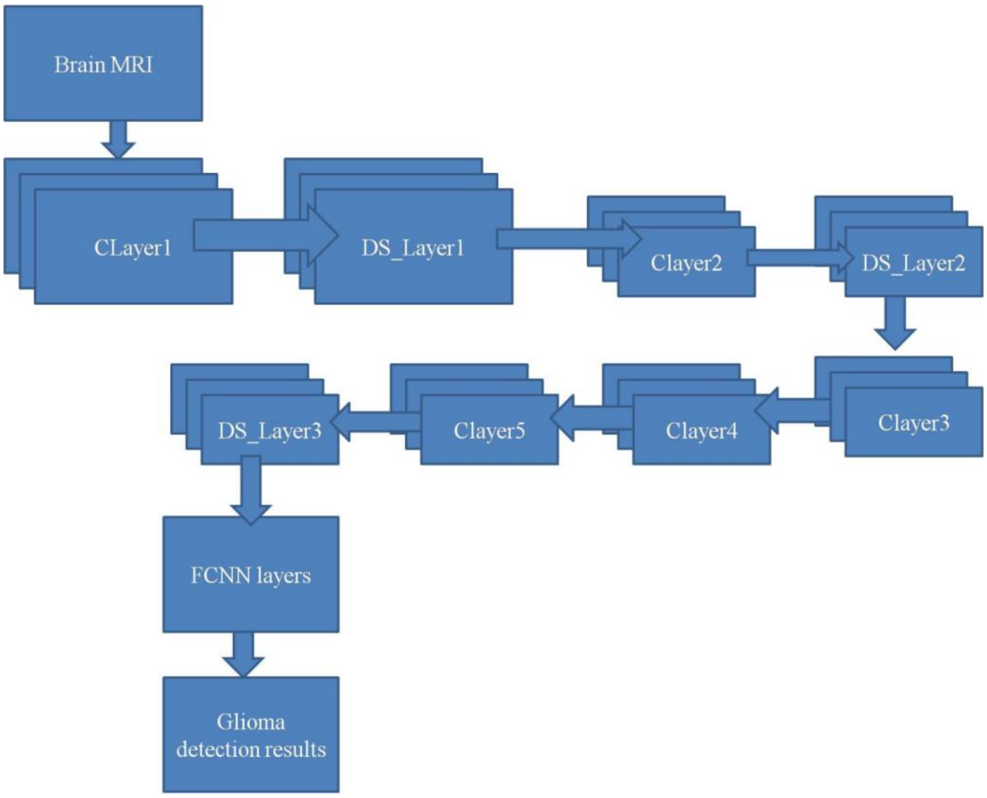
In this paper, deep learning structures LeNET and AlexNET methods (Kestrilia et al. 2019) are applied on the source brain images to detect the Glioma brain image category. The LeNET structure is depicted in Fig. 3(a) and AlexNET structure is depicted in Fig. 3(b) respectively. The deep leraning architecture in general methodology consists of Convolutional Layer (CLayer) and Down Sampling Layer (DS_Layer) and Fully Connected Neural Networks (FCNN) with different set of internal neurons in each layers. The LeNET structure used in this design consist of CLayer1 and CLayer2 with DS_Layer1 and DS_Layer2 and three FCNN layers as FCNN1, FCNN2 and FCNN3 respectively (as illustrated in Fig. 3a). The CLayer1 consists of 32 filters with 5×5 kernel and CLayer2 consists of 64 filters with 5×5 kernel. The size of convolution response from CLayer1 is high and hence DS_Layer is placed between two CLayers in this design. In this paper, Max DS_Layer is preferred than the Average DS_Layer due to its minimization of internal losses during the size reduction process. The internally assigned neuron counts for each FCNN layer is depicted in Table 1.

The Alex NET structure used in this design consist of five numbers of CLayers (CLayer1, CLayer2, CLayer3, CLayer4, CLayer5) with three numbers of DS_Layers (DS_Layer1, DS_Layer2 and DS_Layer3) and three FCNN layers as FCNN1, FCNN2 and FCNN3 respectively (as illustrated in Fig. 3b). The CLayer1 consists of 96 filters with 11×11 kernel and CLayer2 consists of 256 filters with 5×5 kernel . CLayer3 and CLayer4 consist of 384 filters with 3×3 kernel respectively and CLayer5 consists of 256 filters with 3×3 kernel.

The size of convolution response from CLayer1 is high and hence DS_Layer is placed between two CLayers in this design. The responses from CLayer5 are reduced by DS_Layer3 and the internal assigned neuron counts for each FCNN layer is depicted in Table 1. The neurons assigned in FCNN3 layer is two which corresponds to Glioma and Healthy brain images.



(a)



(b)

Figure 3 Deep learning CNN structures (a) LeNET (b) Alex NET

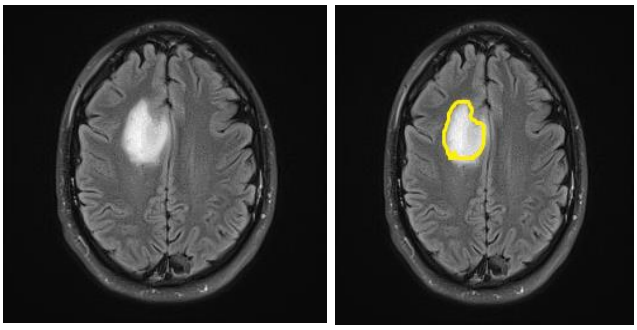
Table 1 Specifications of Deep learning CNN structures

Internal layers	**Specifications**	
	LeNET	**Alex NET**
CLayer1	32 filters, 5 × 5 kernel	96 filters, 11 × 11 kernel
DS_Layer1	2 × 2 Max pooling	2 × 2 Max pooling
CLayer2	64 filters, 5 × 5 kernel	256 filters, 5 × 5 kernel
DS_Layer2	2 × 2 Max pooling	2 × 2 Max pooling
CLayer3	-	384 filters, 3 × 3 kernel
CLayer4	-	384 filters, 3 × 3 kernel
CLayer5	-	256 filters, 3 × 3 kernel
DS_Layer3	-	2 × 2 Max pooling
FCNN1	120	4096
FCNN2	84	4096
FCNN3	2	2

The Glioma images after classification process through the deep learning structures, morphological open and the morphological close using ‘diameter’ property laid on the Glioma images individually, which produces $Morp_{open_{image}}$ and $Morp_{close_{image}}$ respectively. The ‘diameter’ size in open and close function determines the accuracy level of tumor pixel segmentation. After number of iterations, the ‘diameter’ size is fixed in this paper for the segregation of the abnormal tissues in Glioma images more accurately. The tumor pixels ($I_{tumor\ pixels}$) are segmented using the following Equation.

$$I_{tumor\ pixels} = I(Morp_{open_{image}}) - I(Morp_{close_{image}}) \quad (1)$$

Fig. 4 (a) is the Glioma image and Fig.4 (b) is the tumor pixels located Glioma image.



(a) (b)

Figure 4 (a) Glioma image (b) Tumor pixels located Glioma image

4. Results and Discussions

In this paper, 200 Glioma image samples and 176 Healthy brain images are acquired from BRAT 2019 dataset [12]. Also, 125 Glioma image samples and 189 Healthy brain images are acquired from BRAT 2020 dataset [13]. The proposed Glioma detection method using LerNET and AlexNET are individually applied and tested on both BRATS 2019 and BRATS 2020 dataset to estimate the performance metrics as stated in the Equations (2-4).

$$Sensitivity\ (Se) = \frac{TRP}{TRP+FAN} \quad (2)$$

$$Specificity\ (Sp) = \frac{TRN}{TRN+FAP} \quad (3)$$

$$Glioma\ Segmentation\ Accuracy\ (GSA) = \frac{TRP+TRN}{TRP+TRN+FAP+FAN} \quad (4)$$

Whereas, TRP and TRN are the detected pixels belonging to tumor and healthy category correctly, FAP and FAN are the detected pixels belonging to tumor and healthy category incorrectly.

Table 2 is the Glioma detection analysis on BRATS 2019 dataset. The Glioma detection method using LeNET in this paper obtained 95.63% of Se, 94.56% of Sp and 94.4% of GSA. The Glioma detection method using Alex NET in this paper obtained 95.23% of Se, 95.19% of Sp and 96.1% of GSA.

Table 2 Glioma detection analysis on BRATS 2019 dataset

Glioma sequences	LeNET			Alex NET		
	Se (%)	Sp (%)	GSA (%)	Se (%)	Sp (%)	GSA (%)

G19_1	97.3	94.1	94.2	94.8	95.2	94.9
G19_2	96.1	92.9	96.1	92.9	94.9	95.2
G19_3	96.3	93.1	94.2	94.9	96.2	98.4
G19_4	95.9	94.2	94.5	95.1	94.8	93.8
G19_5	95.6	96.2	92.9	94.8	93.9	94.9
G19_6	95.2	91.2	94.1	93.9	95.8	97.2
G19_7	94.9	95.3	93.9	96.2	93.9	94.9
G19_8	96.1	98.2	96.1	96.4	95.8	96.4
G19_9	94.2	94.3	94.2	98.2	92.9	98.2
G19_10	94.7	96.1	93.8	95.1	98.5	97.1
Average	**95.63**	**94.56**	**94.4**	**95.23**	**95.19**	**96.1**

Table 3 is the Glioma detection analysis on BRATS 2020 dataset. The Glioma detection method using LeNET in this paper obtained 94.56% of Se, 95.32% of Sp and 96.53% of GSA. The Glioma detection method using Alex NET in this paper obtained 94.53% of Se, 95.32% of Sp and 97.88% of GSA.

Table 3 Glioma detection analysis on BRATS 2020 dataset

Glioma sequences	**LeNET**			**Alex NET**		
	Se (%)	**Sp (%)**	**GSA (%)**	**Se (%)**	**Sp (%)**	**GSA (%)**
G20_1	93.8	94.9	95.8	94.2	95.3	96.1
G20_2	94.2	92.1	96.7	94.9	95.2	97.9
G20_3	94.9	94.8	96.3	94.1	97.1	98.4
G20_4	94.8	98.2	97.1	94.3	94.3	98.8
G20_5	93.9	96.4	95.9	95.1	95.2	98.2
G20_6	94.1	95.8	97.1	94.2	94.3	97.9
G20_7	94.9	94.7	96.8	94.9	94.9	98.3
G20_8	92.9	96.3	96.3	94.2	95.9	97.8
G20_9	94.2	94.2	97.2	94.3	96.1	97.3
G20_10	97.9	95.8	96.1	95.1	94.9	98.1
Average	**94.56**	**95.32**	**96.53**	**94.53**	**95.32**	**97.88**

Table 4 is the analysis of Glioma detection methods on BRATS 2019 and BRATS 2020 datasets in terms of metrics using ground truth samples.

Table 4 Analysis of Glioma detection methods on BRATS 2019 and BRATS 2020 datasets

Metrics	**BRATS 2019 dataset**		**BRATS 2020 dataset**	
	LeNET	**Alex NET**	**LeNET**	**Alex NET**
Se (%)	95.63	95.23	94.56	94.53

Sp (%)	94.56	95.19	95.32	95.32
GSA (%)	94.4	96.1	96.53	97.88

Table 5 and Table 6 are the comparative study of Glioma detection methods on BRATS 2019 and BRATS 2020 dataset images with other similar studies. In this work, the methodologies used in Sahar Gull et al. (2021), Sharif et al. (2020) and Swati et al. (2019) are evaluated on the same number of Glioma image samples which are used in this paper and the results are compared.

Table 5 Comparative study of Glioma detection methods on BRATS 2019

Methods	**Se (%)**	**Sp (%)**	**GSA (%)**	**Methods**	**Se (%)**	**Sp (%)**	**GSA (%)**
LeNET	95.63	94.56	94.4	**Alex NET**	95.23	95.19	96.1
Sahar Gull et al. (2021)	92.9	92.8	93.1	Sahar Gull et al. (2021)	92.9	92.8	92.9
Sharif et al. (2020)	91.7	92.1	92.9	Sharif et al. (2020)	93.1	91.7	92.1
Swati et al. (2019)	91.8	90.7	91.8	Swati et al. (2019)	92.8	93.2	90.9

Table 6 Comparative study of Glioma detection methods on BRATS 2020

Methods	**Se (%)**	**Sp (%)**	**GSA (%)**	**Methods**	**Se (%)**	**Sp (%)**	**GSA (%)**
LeNET	94.56	95.32	96.53	**Alex NET**	94.53	95.32	97.88
Sahar Gull et al. (2021)	93.1	92.9	92.8	Sahar Gull et al. (2021)	92.8	92.8	94.2
Sharif et al. (2020)	92.9	91.7	91.7	Sharif et al. (2020)	92.7	92.1	94.1
Swati et al. (2019)	92.1	90.5	90.6	Swati et al. (2019)	90.4	90.9	93.2

5. Conclusions

In this work, deep leraning structures LeNET and Alex NET are used to detect the Glioma images. The Glioma detection method using LeNET in this paper obtained 95.63% of Se, 94.56% of Sp and 94.4% of GSA for BRATS 2019 dataset images. The Glioma detection method using Alex NET in this paper obtained 95.23% of Se, 95.19% of Sp and 96.1% of GSA. The Glioma detection method using LeNET in this paper obtained 94.56% of Se, 95.32% of Sp and 96.53% of GSA for BRATS 2020 dataset images. The Glioma detection method using Alex NET in this paper obtained 94.53% of Se, 95.32% of Sp and 97.88% of GSA. The experimental results of both dataset are compared with Sahar Gull et al. (2021), Sharif et al. (2020) and Swati et al. (2019). The present deep learning structure will be customized in future to improve the experimental results for Glioma detection.

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