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Detection and Segmentation of Meningioma Tumors Using the Proposed MENCNN Model

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ABSTRACT

This paper develops a Meningioma Detection and Segmentation System (MDSS) using the proposed Meningioma Convolutional Neural Network (MENCNN) classifier. The main objective of this paper is to detect and locate the meningioma brain tumors using the proposed deep learning structure and segmentation algorithm. This proposed MDSS is designed with preprocessing of meningioma and healthy brain MRI images, feature computations and feature classification through the proposed MENCNN classifier and Meningioma Segmentation Algorithm. The noises in both meningioma and healthy brain images are removed using Mean Adaptive Filter (MAF) and the meningioma features are computed from the noise removed image. These meningioma features are classified by the proposed MENCNN classifier in order to obtain the classification results as either meningioma or healthy brain image. Finally, Meningioma Segmentation Algorithm (MSA) is proposed in this research work to segment the pixels belonging to the meningioma region. The proposed MDSS approach obtains 96.46% MSI, 97.75% MSR and 97.6% MSA on the set of meningioma images in Nanfang dataset. The proposed MDSS approach obtains 97.76% MSI, 98.03% MSR and 97.81% MSA on the set of meningioma images in Kaggle dataset.

1. Introduction

The growth of uncontrolled cells in human brain leads to tumor and it is considered as most dangerous diseases for all age groups irrespective of their sex. It affects all kind of age group persons around the world. Due to the tumor cells, the structure bond of the surrounding cells in the human brain may also get damaged. Sometimes, it may lead to death if it is properly untreated on time. Hence, its detection and earlier treatment is so important for the patients who are affected by brain tumors [4-7]. The brain tumors can be identified through its symptoms such as continuous vomiting, head ache, fatigue and memory loss problems. If the persons are affected by any kind of continuous symptoms, they must screen their brain region through the image scanning methods. The image scanning methods are categorized into Computer Tomography (CT) and Magnetic Resonance Imaging

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(MRI) and Positron Emission Tomography (PET). These image scanning methods are differentiated by its volume level of radiation to screen the various regions of brain [8-11]. The radiation is important for scanning the internal organs of the human body and also it affects the soft organ cell patterns due to its high level of intensity. In case of CT and MRI scanning methods, the volume level of radiation is moderate and it does not affect the other parts of the human body while scanning the brain region. In case of PET scanning method, the volume level of radiation is high to capture the fine tune variations in the human brain. Most of the tumors are clearly visible through either CT or MRI scanning method. If it is not visible through these image scanning techniques, then PET scanning method is preferred by radiologist. The brain images obtained through CT and MRI scanning methods are grey scale and the brain images obtained through the PET scanning method are RGB pattern to differentiate the fine tune variations between various regions of brain. The brain tumors are categorized with respect to various tissue or cell patterns as Glioma, meningioma and Glioblastoma [12-14]. Among these brain tumor types, meningioma is most crucial one which leads to immediate death in patients if it is timely treated by either radiation therapy or surgery. Therefore, its detection is most important than the other kind of brain tumors. Figure 1 shows the meningioma brain MRI where, the growth rate of the tumor cell is higher than the growth rate of the other cells in human brain.

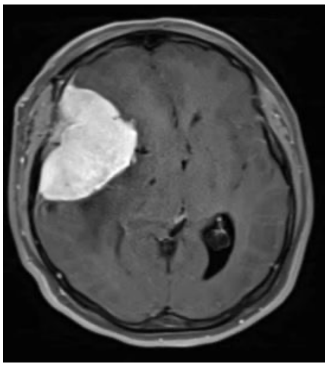


Fig. 1. Meningioma MRI

2. Literature Survey

Anagun *et al.*, [15] proposed meningioma brain tumor detection modeling approach using deep neural networking algorithm. This method used Sigmoid Activation function in the design of their internal layers to optimize the classification rate. The authors designed the proposed deep neural networks with respect to various numbers of neurons in Fully connected layers. The authors obtained 94.28% MSI, 95.06% MSR and 94.47% MSA for the brain images in Nanfang dataset and the authors obtained 94.39% MSI, 94.95% MSR and 94.29% MSA for the brain images in Kaggle dataset. Both dataset brain images were validated through the different validation algorithms in this work. Rahman *et al.*, [16] devised a methodology for the detection of brain tumors in brain MRI images. This method used uncertain algorithmic modeling for the effective classification of tumor cells from the non-tumor cells. This non-linear systematic approach for the classification of pixels relating to abnormal category, were verified through different dataset brain images in this work. The authors obtained 94.29% MSI, 94.05% MSR and 94.82% MSA for the brain images in Nanfang dataset and the authors obtained 93.28% MSI, 94.64% MSR and 93.37% MSA for the brain images in Kaggle dataset. Both dataset brain images were validated through the different validation algorithms in this work. Amin *et al.*, [7] reviewed much more meningioma detection models using various machine learning approaches with various tumor region segmentation methods. The authors discussed the main limitation of each existing method in terms of various parameters. Jhaveri *et al*., [12] stated the brain tumor detection and classification algorithm. The methodologies stated in this work were compared in terms of various reference papers.

Irmak *et al*., [17] designed meningioma tumor detection and segmentation systematic system using deep Convolutional neural network modeling approach. This method used optimized frame work model to identify the region of pixels belonging to tumor and these segmented set of tumor pixels were diagnosed into different severity levels in this working procedural model. The authors obtained 93.86% MSI, 94.64% MSR and 94.27% MSA for the brain images in Nanfang dataset and the authors obtained 93.28% MSI, 93.67% MSR and 93.57% MSA for the brain images in Kaggle dataset. Sajjad *et al*., [18] graded the tumor types based on their affected region of volumes in human brain through the deep learning model. The proposed deep learning model was designed with less number of layering flow and hence they consumed less memory during their classification of brain images. The authors obtained 93.37% MSI, 93.85% MSR and 93.29% MSA for the brain images in Nanfang dataset and the authors obtained 92.06% MSI, 93.69% MSR and 92.47% MSA for the brain images in Kaggle dataset.

Bahadure *et al*., [1] used Support Vector Machine (SVM) for detecting the region of pixels belonging to tumor and they were optimized through different optimization algorithm in this work. John *et al*., [2] computed textural patterns from the source brain MRI images and these textural pattern features were classified and analyzed by Discrete Wavelet Modeling algorithm. Çinar *et al*., [3] designed a hybrid CNN modeling approach for the classification of meningioma images. The authors obtained 95.3% of tumor classification rate. Shree *et al*., [4] decomposed the regions of brain images using Discrete Wavelet Transform (DWT) and the decomposed sub bands were classified through the probabilistic neural network classification model to obtain the higher classification rate. Table 1 shows the summary of existing meningioma detection methods.

Table 1
Summary of existing meningioma detection methods

Methods	Limitations
Anagun *et al*., [15]	Low sensitivity and specificity
Rahman *et al*., [16]	High meningioma tumor detection time
Amin *et al*., [7]	Low level of segmentation accuracy
Jhaveri *et al*., [12]	High level of complexity
Irmak *et al*., [17]	Low sensitivity and specificity
Sajjad *et al*., [18]	Low level of segmentation accuracy
Bahadure *et al*., [1]	High meningioma tumor detection time

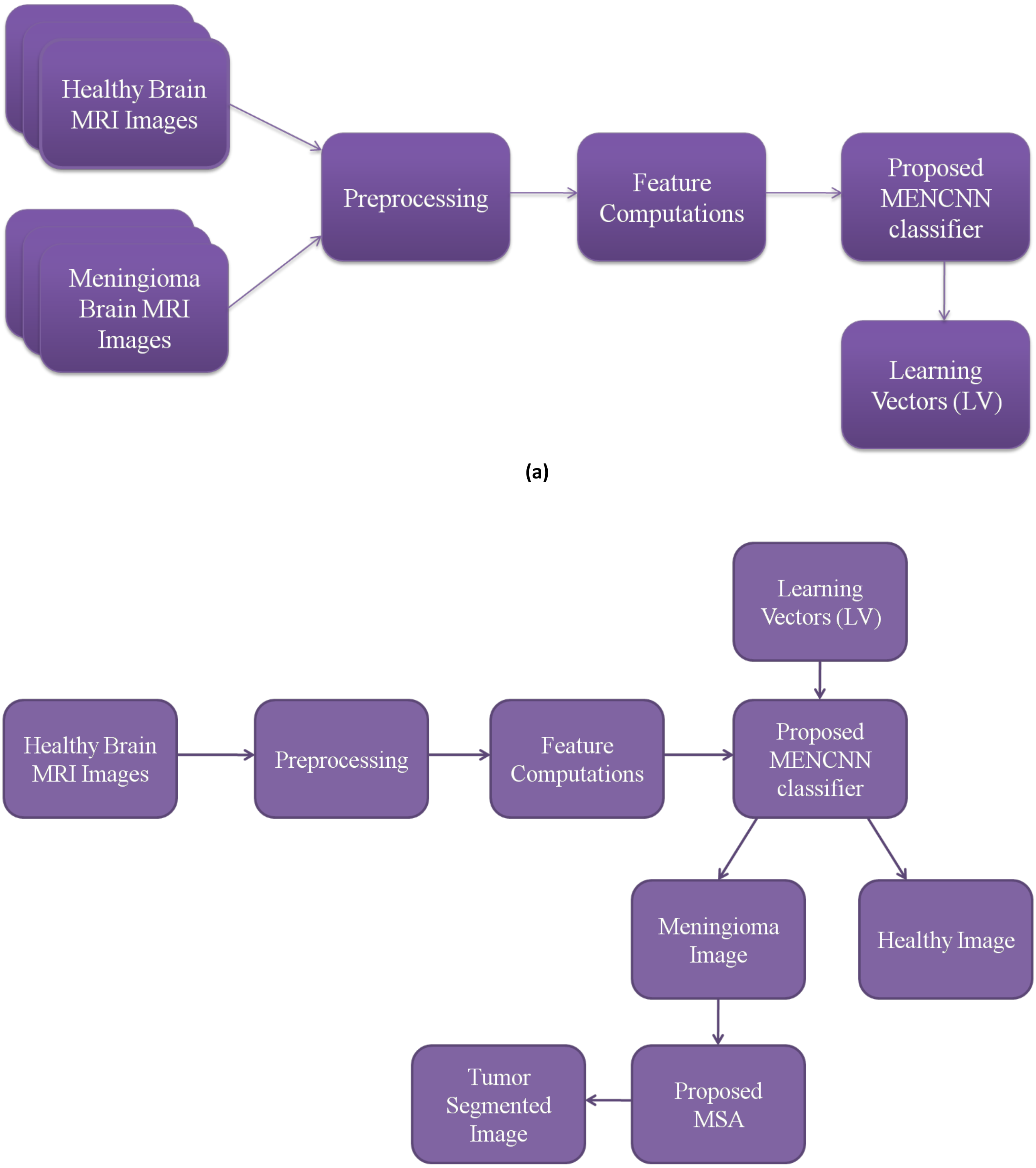
The novelty of this paper is stated as follows.

- A novel deep learning Meningioma Detection and Segmentation System (MDSS) is designed in this paper.
- MENCNN classifier is proposed in this paper with minimal number of internal resources.

3. Proposed methods

This paper develops a Meningioma Detection and Segmentation System (MDSS) using the proposed MENCNN classifier. This proposed MDSS is designed with preprocessing of meningioma and healthy brain MRI images, feature computations and feature classification through the proposed MENCNN classifier and Meningioma Segmentation Algorithm. The noises in both meningioma and healthy brain images are removed using Mean Adaptive Filter (MAF) and the meningioma features are computed from the noise removed image. These meningioma features are classified by the proposed MENCNN classifier in order to obtain the classification results as either meningioma or healthy brain image. Finally, Meningioma Segmentation Algorithm (MSA) is proposed in this research work to segment the pixels belonging to the meningioma region.

Figure 2 (a) shows the proposed Meningioma Learning System (MLS) and Figure 2(b) shows the proposed Meningioma Classification System (MCS).



(b)

Fig. 2. (a) Meningioma Learning System (MLS) (b) Meningioma Classification System (MCS)

3.1 Preprocessing and Feature computations

In this paper, Mean Adaptive Filter (MAF) (Nyhof *et al.*, [19]) is applied on the source brain images to detect and remove the noise variations in the image. This filter has the kernel size of 3*3 and it is applied on the image on non-overlapping procedure. The average value of this kernel window is computed and it is replaced with the center pixel in 3*3 kernel window. The edge pixels in the brain image are restored during the image denoising method in this work. This improves the quality of the brain images which also optimize the brain tumor classification rate. Further, the Grey Level Co-occurrence Matrix (GLCM) features (Vimal *et al.*, [20]) are computed with respect to 45 degree angle of orientation. From this constructed GLCM, energy, contrast, correlation and inertia features are computed and they are stored in a matrix which is fed to the next classification module in this paper.

3.2 Deep Learning Classification Architectures

In this paper, conventional LeNET architecture (Alzubaidi *et al.*, [21]) and the proposed MENCNN architecture are used for the classification of meningioma images. The conventional LeNET architecture is shown in Figure 3, which consists of two Convolutional layers $Clayer1\ and\ Clayer2$ and two pooling layers $Poollayer1\ and\ Poollayer2$ and three Fully Connected Neural Networks (FCNN).

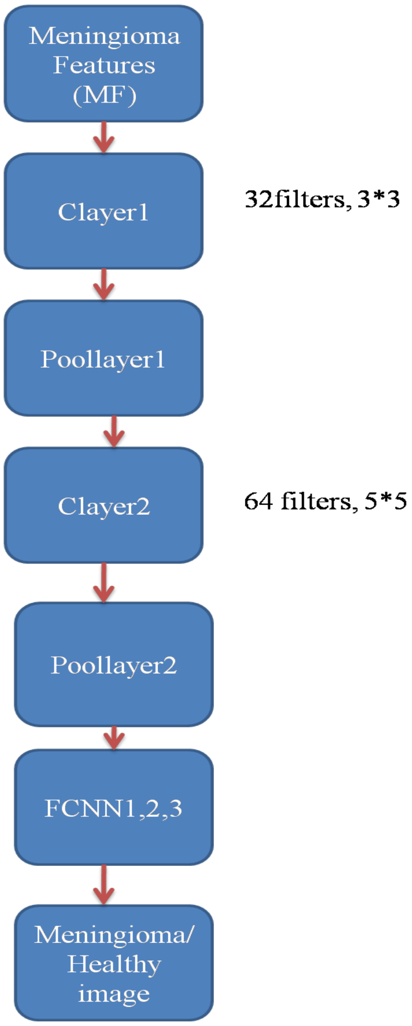


Fig. 3. Conventional LeNET architecture

These internal layers are mathematically modelled using the following equations for the design of conventional LeNET architecture.

$$Clayer1 = Convolution\ (MF, 32\ Filters, 3 * 3) \tag{1}$$

$$Poollayer1 = Maxpooling\ (Clayer1, 2 * 2 \tag{2}$$

$$Clayer2 = Convolution\ (Poollayer1, 64\ Filters, 5 * 5) \tag{3}$$

$$Poollayer2 = Maxpooling\ (Clayer2, 2 * 2) \tag{4}$$

$$FCNN\ layers = \{\ FCNN1, FCNN2, FCNN3\} \tag{5}$$

The proposed MENCNN architecture is the modification and extension of the conventional LeNET architecture model, which is shown in Figure 4, which consists of four Convolutional layers $Clayer1\ , Clayer2, Clayer3\ and\ Clayer4$ and four pooling layers $Poollayer1\ , Poollayer2, Poollayer3\ and\ Poollayer4$ and two Fully Connected Neural Networks (FCNN1 and FCNN2). In this paper, Max pooling layer is used in the proposed CNN structure. These internal layers are mathematically modelled using the following equations for the design of proposed MENCNN architecture.

$$Clayer1 = Convolution\ (MF, 256\ Filters, 5 * 5) \tag{6}$$

$$Poollayer1 = Maxpooling\ (Clayer1, 2 * 2) \tag{7}$$

$$Clayer2 = Convolution\ (Poollayer1, 512\ Filters, 7 * 7) \tag{8}$$

$$Poollayer2 = Maxpooling\ (Clayer2, 2 * 2) \tag{9}$$

$$Clayer3 = Convolution\ (Poollayer2, 256\ Filters, 5 * 5) \tag{10}$$

$$Poollayer3 = Maxpooling\ (Clayer3, 2 * 2) \tag{11}$$

$$Clayer4 = Convolution\ (Poollayer2, 512\ Filters, 7 * 7) \tag{12}$$

$$Poollayer4 = Maxpooling\ (Clayer4, 2 * 2) \tag{13}$$

$$Feature\ Vector\ (FV) = Integration\{Poollayer3, Poollayer4\} \tag{14}$$

$$FCNN\ layers = \{\ FCNN1, FCNN2\} \tag{15}$$

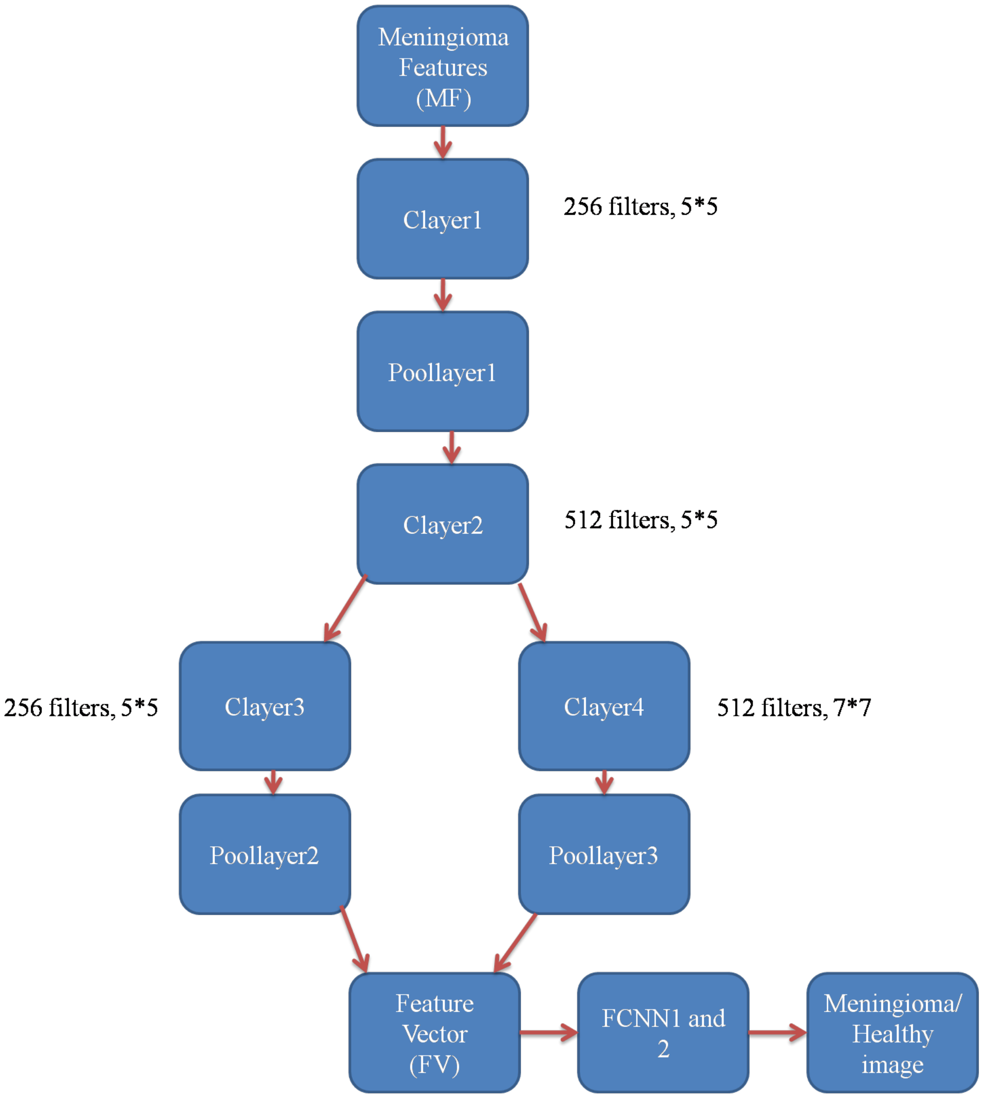


Fig. 4. Proposed MENCNN architecture

It is the process of locating the pixels in brain image which is belonging to tumor region. This segmentation process ends at the end of the pixels in the brain image and produces the segmentation results.

The meningioma segmentation algorithm is explained in the following steps.

Step 1:

Expand the outlier disk shaped boundary of each pixel in meningioma image using the below equations.

$$E1 = Open\ (M, disk, 2mm\} \tag{16}$$

Step 2:

Shrink the outlier disk shaped boundary of each pixel in meningioma image using the below equations.

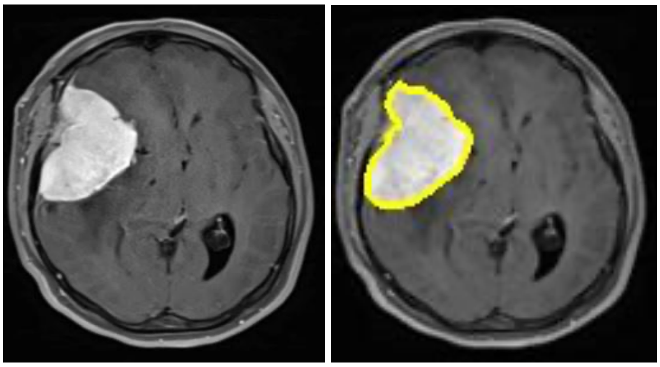
$$S1 = Close\ (M, disk, 2mm\} \tag{17}$$

Step 3:

Segregate the tumor pixel using the Expand & Shrink images using the following equations.

$$Tumor\ pixels = |E1 - S1| \tag{18}$$

Figure 5 (a) shows the source meningioma brain image and Figure 5(b) shows the segmented tumor image.



(a) **(b)**

Fig. 5. (a) Source meningioma brain image (b) Segmented tumor image

4. Results and Discussions

This paper uses brain MRI images in both meningioma category and healthy category from Nanfang and Kaggle datasets. The Nanfang dataset consist of 378 brain images which are categorized into 250 healthy brain images and 128 meningioma brain images [22]. The Kaggle dataset consist of 450 brain images which are categorized into 250 healthy brain images and 200 meningioma brain images [23]. All these brain images are having the image size of 256*256 after applying resize function on these brain images due to the various sizes of the brain images in these two different datasets.

In this research work, the proposed MDSS approach is significantly analyzed and evaluated using the following performance index.

$$\text{Meningioma Sensitivity Index (MSI)} = \frac{G_{TP}}{G_{TP}+G_{FN}} \tag{19}$$

$$\text{Meningioma Specificity Rate (MSR)} = \frac{G_{TN}}{G_{TN}+G_{FP}} \tag{20}$$

$$\text{Meningioma Segmentation Accuracy (MSA)} = \frac{G_{TP}+G_{TN}}{G_{TP}+G_{TN}+G_{FP}+G_{FN}} \tag{21}$$

where as, G_{TP} and G_{TN} are the correctly segmented meningioma pixels and non-meningioma pixels. G_{FP} and G_{FN} are the incorrectly segmented meningioma pixels and non-meningioma pixels.

These parameters are mostly used in many existing meningioma detection system and hence they are also used in this paper for fair comparisons. Table 2 is the results of proposed MDSS approach on Nanfang dataset brain images. The proposed MDSS approach obtains 96.46% MSI, 97.75% MSR and 97.6% MSA on the set of meningioma images in Nanfang dataset. On the other hand, Figure 6 shows the graphical analysis of proposed MDSS approach on Nanfang dataset.

Table 3 demonstrates the results of proposed MDSS approach on Kaggle dataset brain images. The proposed MDSS approach obtains 97.76% MSI, 98.03% MSR and 97.81% MSA on the set of meningioma images in Kaggle dataset.

Table 2
Results of proposed MDSS approach on Nanfang dataset

Meningioma image number	Performance index in percentage		
	MSI	MSR	MSA
1	96.2	97.3	97.3
2	96.8	97.1	97.2
3	96.9	97.9	98.6
4	96.4	97.6	98.3
5	96.3	98.3	97.6
6	96.9	98.6	97.2
7	95.9	97.1	97.7
8	96.3	97.9	97.4
9	96.2	98.1	97.2
10	96.8	97.6	97.5
Average	**96.47**	**97.75**	**97.6**

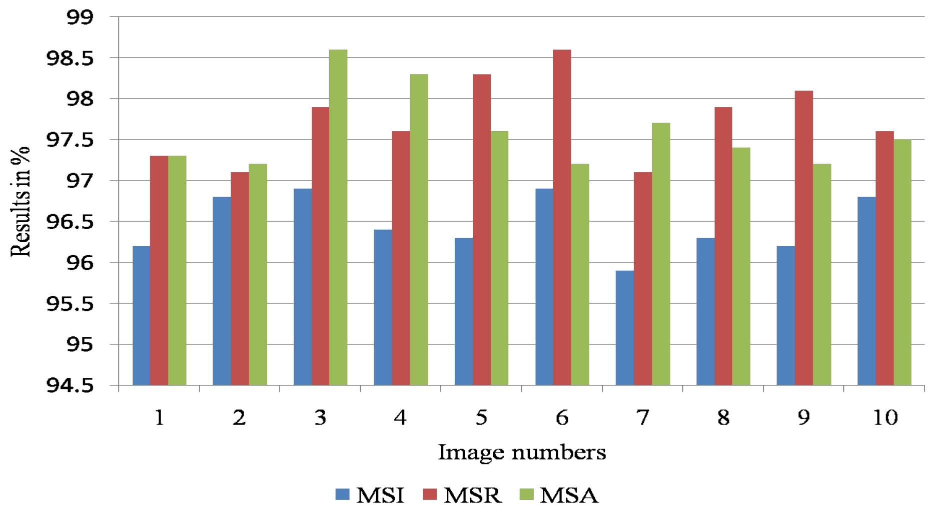


Fig. 6. Graphical analysis of proposed MDSS approach on Nanfang dataset

Table 3
Results of proposed MDSS approach on Kaggle dataset

Meningioma image number	Performance index in percentage		
	MSI	MSR	MSA
1	97.3	98.5	97.5
2	98.1	98.2	97.2
3	98.6	98.4	98.5
4	97.5	98.1	98.4
5	97.9	97.9	97.6
6	97.4	97.5	98.3
7	98.2	98.3	97.2
8	97.5	97.6	97.6
9	97.6	98.2	97.5
10	97.5	97.6	98.3
Average	**97.76**	**98.03**	**97.81**

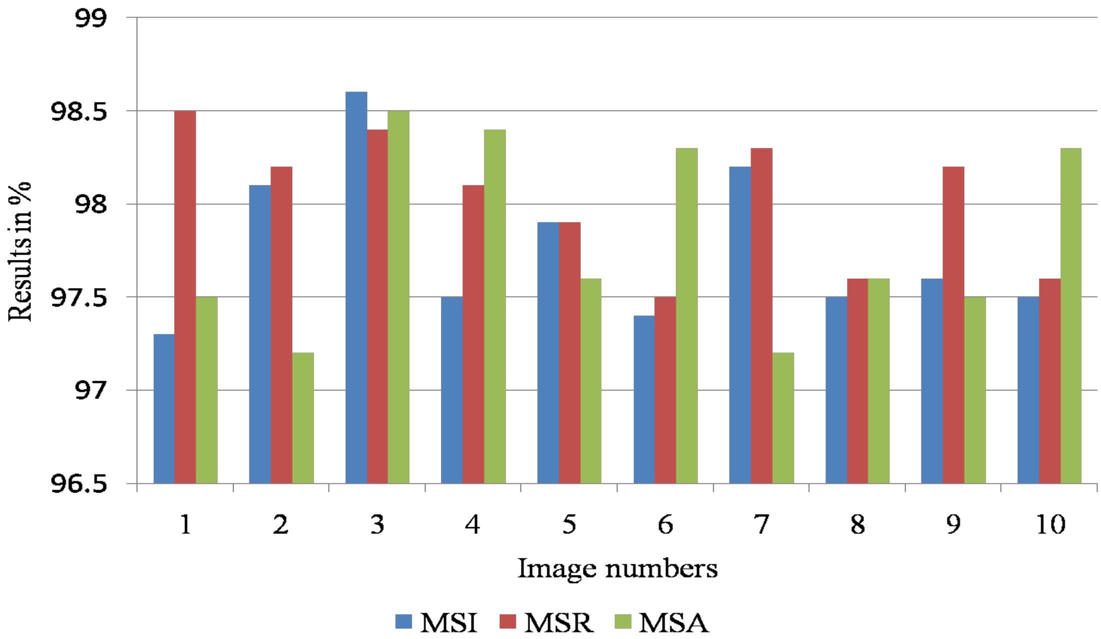


Fig. 7. Graphical analysis of proposed MDSS approach on Kaggle dataset

Figure 7 shows the graphical analysis of proposed MDSS approach on Kaggle dataset. Table 4 demonstrates the experimental results comparisons between different datasets with respect to MSI, MSR and MSA. The proposed MDSS approach obtained significant experimental results on the set of meningioma images from both Nanfang and Kaggle datasets.

Table 4
Results comparisons between different datasets

Parameters	Nanfang dataset	Kaggle dataset
MSI	96.47	97.76
MSR	97.75	98.03
MSA	97.6	97.81

Table 5 below shows the comparisons of proposed MDSS approach on Nanfang meningioma images with other existing approaches Anagun *et al.*, [15], Rahman *et al.*, [16], Irmak *et al.*, [17] and Sajjad *et al.*, [18].

Table 5
Comparisons of proposed MDSS approach on Nanfang meningioma images

Approaches	Performance index in percentage		
	MSI	**MSR**	**MSA**
Proposed work (in this research work)	**96.47**	**97.75**	**97.6**
Anagun *et al.*, [15]	94.28	95.06	94.47
Rahman *et al.*, [16]	94.29	94.05	94.82
Irmak *et al.*, [17]	93.86	94.64	94.27
Sajjad *et al.*, [18]	93.37	93.85	93.29

Figure 8 shows the graphical comparisons of proposed MDSS approach with others for the images in Nanfang dataset.

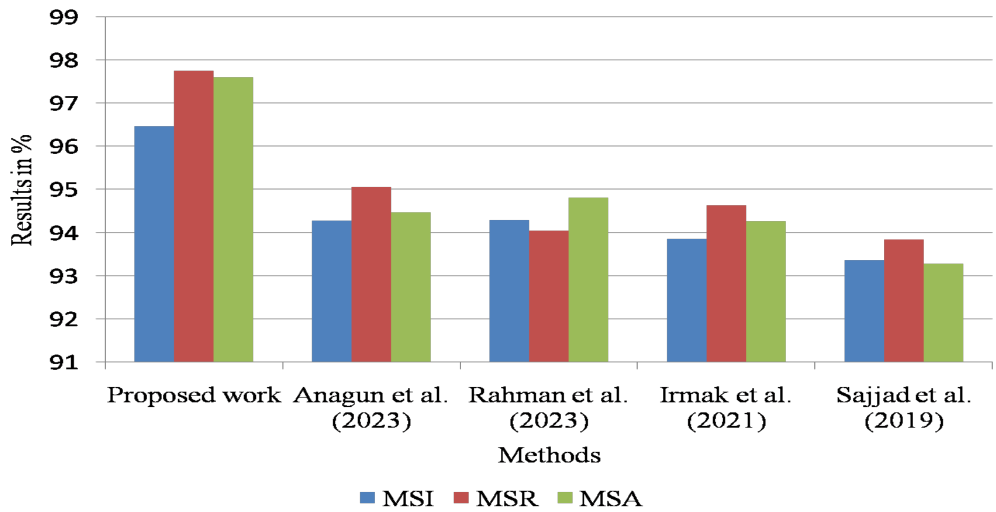


Fig. 8. Graphical comparisons of proposed MDSS approach with others for Nanfang dataset

Table 6 shows the comparisons of proposed MDSS approach on Kaggle meningioma images with other existing approaches Anagun *et al.*, [15], Rahman *et al.*, [16], Irmak *et al.*, [17] and Sajjad *et al.*, [18].

Table 6
Comparisons of proposed MDSS approach on Kaggle meningioma images

Approaches	Performance index in percentage		
	MSI	**MSR**	**MSA**
Proposed work (in this research work)	**97.76**	**98.03**	**97.81**
Anagun *et al.*, [15]	94.39	94.95	94.29
Rahman *et al.*, [16]	93.28	94.64	93.37
Irmak *et al.*, [17]	93.28	93.67	93.57
Sajjad *et al.*, [18]	92.06	93.69	92.47

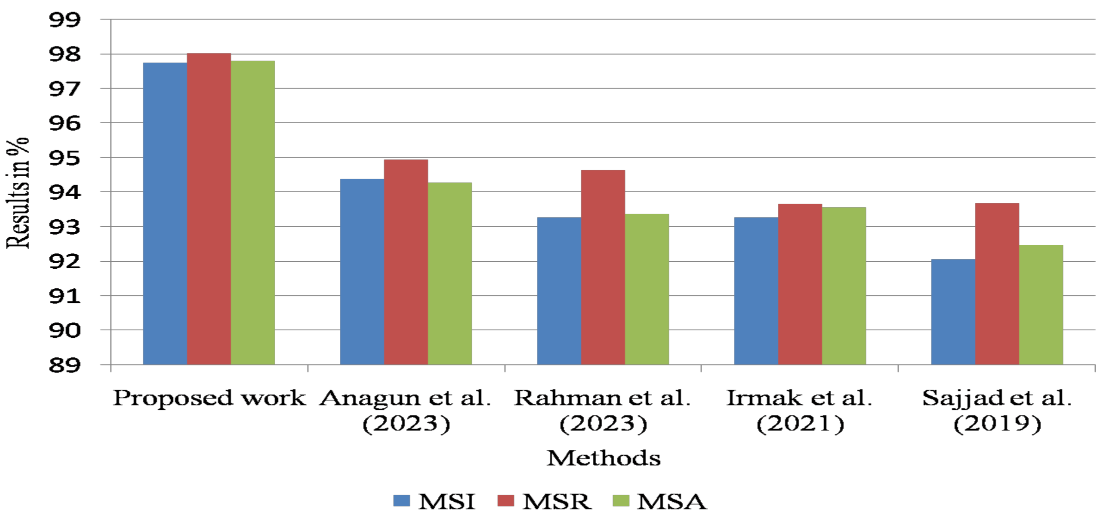


Fig. 9. Graphical comparisons of proposed MDSS approach with others for Kaggle dataset

Figure 9 shows the graphical comparisons of proposed MDSS approach with others for the images in Kaggle dataset.

5. Conclusions

In this article, a Meningioma Detection and Segmentation System (MDSS) is proposed using the proposed MENCNN classifier. The proposed MDSS approach obtains 96.46% MSI, 97.75% MSR and 97.6% MSA on the set of meningioma images in Nanfang dataset. The proposed MDSS approach obtains 97.76% MSI, 98.03% MSR and 97.81% MSA on the set of meningioma images in Kaggle dataset. From the effective analysis and comparisons between the experimental results of two different datasets, the proposed MDSS approach stated in this research work provided significant tumor segmentation results. This paper only detects the tumor regions and intended for any diagnosis process for clinical applications. In future, the proposed MDSS approach will be used for diagnosis the segmented tumor regions.

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