International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

Classification and Diagnosis of Meningioma Brain Tumors Using Centric Convolutional Neural Networks

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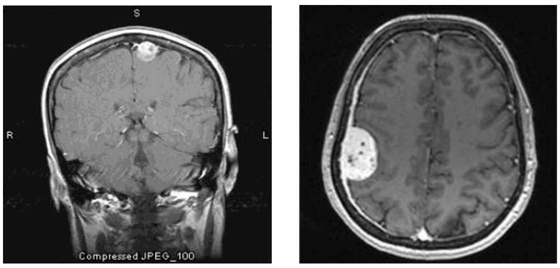
Submitted: 22/07/2022 **Accepted**: 25/09/2022

Abstract: The abrupt changes in brain cells creates tumor region in human brain. The detection of brain tumors on time saves the human life. Even though there are lots of brain tumors available, meningioma is most important which causes immediate death. Therefore, its detection is important at an earlier stage. The main objective of this article is to develop the meningioma brain tumor detection system using deep learning methods in MRI brain images. The conventional methods detected meningioma brain tumors with low tumor segmentation accuracy. Hence, there is a need for developing the meningioma detection system with high tumor segmentation accuracy. This article proposes a Centric based deep Convolutional Neural Network (CCNN) architecture for detecting the meningioma brain tumor images from the healthy case brain images. The proposed method uses Dual Tree Complex Wavelet (DTCWT) for decomposing the brain image and the features are derived from these decomposed sub bands. Further, these features are classified using CCNN classifier, which detects the meningioma brain image from the healthy brain images. The segmented tumor regions are computed from the classified meningioma image using morphological method and these segmented tumor regions are used to estimate the severity levels of the meningioma tumors using the proposed CCNN architecture. This proposed meningioma brain tumor detection approach using CCNN classifier model is tested on publicly available datasets Nanfang University (NU) and Kaggle. This proposed method obtains 98.93% Sensitivity Index Rate (SEIR), 99.02% Specificity Index Rate (SPIR), 99.16% Accuracy Rate (AR), 99.06% Precision Rate (PR) and 98.95% F1-Score (FS) for NU dataset images. This proposed method obtains 98.89% SEIR, 98.74% SPIR, 99.05% AR, 98.93% PR and 98.91% FS for Kaggle dataset images. From the quantitative analysis of the experimental analysis, it is concluded that the proposed CCNN method provides optimum results for meningioma brain tumor detection system with other similar state of the art methods.

Keywords: *brain, classifier, meningioma, segmentation, tumors.*

1. Introduction

Tumors are the most dangerous diseases in patients around the world. Most of the tumors are life killing diseases. Hence, the earlier detection of the tumor is most important to save the life of the patient on time. The tumors are occurred in various parts of the human body due to number of reasons. These tumors are mostly belonging to the human organs such as brain, liver, lung, and breast and cervical (Goyal et al. 2021 [1]). Among these tumors, brain tumors are most important due to severity levels. Due to the fluid level increase in blood vessels of the cells in brain regions, the cells become abnormal, this leads to tumor. This abnormal tumor cells also affect the nearby cells in the brain regions (Veeramuthu et al. 2019 [2]). Depends upon the size and growth rate, the tumors in brain are categorized into various types such as Glioma, Glioblastoma and meningioma. Among these types of tumors in brain, meningioma is most dangerous and leads to sudden death (Hossain et al. 2019 [3]). Therefore, this article proposes a computer aided meningioma tumor detection methodology. This tumor detection methodology is based on soft computing methods such as machine learning approach and deep learning approach. The implementation of machine learning approaches for the detection of tumor brain images consumes more computational time period and also requires more number of image samples in both healthy and tumor images categories (Győrfi et al. 2021 [4]). These limitations are resolved by implementing the deep learning approaches for the tumor image detection process. In this article, the deep learning structure is modified with respect to the centric method which consumed less computational time period for the classification of brain images than the existing deep learning approaches. This article also categorizes the severity levels of the meningioma brain tumors. Fig. 1(a) shows the meningioma brain MRI image in mild case and Fig.1 (b) shows the meningioma brain image in advance case.



(a) **(b)**

Fig. 1. (a) Meningioma-mild case (b) Meningioma- advance case.

This article is formatted into five sub sections, section 2 states the conventional meningioma brain tumor detection approaches,

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section 3 proposes a CCNN structure for meningioma image detection, section 4 states the experimental results and section 5 states the conclusion of this article.

2. Literature Survey

Sahar Gull et al. (2021) [8] used CNN classification architecture for the classification of brain MRI images into its abnormality detection process. The internal feature regions from the brain images were categorized into multi class regions in this work. The authors obtained 95.81% SEIR, 95.48% SPIR, 94.29% AR, 94.29% PR and 95.94% FS on NU dataset and also obtained 98.89% SEIR, 98.74% SPIR, 99.05% AR, 95.93% PR and 98.91% FS on Kaggle dataset. Sharif et al. (2020) [9] applied Extreme Machine Learning (EML) classification approach for the classification of brain image for its detection of abnormality regions. The triangular fuzzy median filtering was applied on the source image to enhance the internal pixel regions for improving the tumor detection accuracy. The Candidate's lesions features and similar texture features were computed and classified by the EML algorithm. The authors obtained 94.87% SEIR, 94.28% SPIR, 95.37% AR, 95.94% PR and 96.04% FS on NU dataset and also obtained 98.89% SEIR, 98.74% SPIR, 99.05% AR, 95.93% PR and 98.91% FS on Kaggle dataset.

Jasmine Hephzipah et al. (2020) [10] utilized feature optimization algorithm for optimizing process of the computed feature set. Then, Adaptive Neuro Fuzzy Inference System (ANFIS) classifier model was used to classify the optimized patterns from the source brain image. The authors obtained 95.98% SEIR, 96.48% SPIR, 96.29% AR, 95.38% PR and 96.38% FS on NU dataset and also obtained 96.38% SEIR, 96.19% SPIR, 95.49% AR, 95.29% PR and 95.29% FS on Kaggle dataset. Amin et al. (2019) [12] decomposed the brain image into sub band regions using Discrete Wavelet Transform (DWT). Further, the texture and non-linear features were computed from the decomposed brain regions and these features were classified using CNN classification process to find the brain image belonging to healthy or abnormal category. Kathirvel et al. (2017) [11] detected and diagnosed the brain tumors from the source brain images using ANFIS classification process. The authors used morphological process to locate the tumor regions in the brain. The authors obtained 95.96% SEIR, 95.57% SPIR, 96.39% AR, 96.87% PR and 96.35% FS on NU dataset and also obtained 96.39% SEIR, 96.67% SPIR, 95.96% AR, 95.25% PR and 96.48% FS on Kaggle dataset.

The following points are inference from the related works,

- Most conventional methods used machine learning approaches for meningioma detection process.
- The tumor segmentation quantitative results are not optimum.
- DWT based meningioma detection methods exhibits losses during the decomposition process.

These limitations are resolved by the CCNN method stated in this paper for meningioma detection process.

3. Proposed Methodologies

The novel CCNN architecture is proposed in this paper for the detection and classification of meningioma brain Magnetic Resonance Image (MRI) images. The proposed method uses Dual Tree Complex Wavelet (DTCWT) for decomposing the brain image and the features are derived from these decomposed sub bands. Further, these features are classified using CCNN classifier, which detects the meningioma brain image from the healthy brain images. Fig. 2 (a) shows the Meningioma image detection – training method and Fig. 2 (b) shows the Meningioma image detection – testing method.

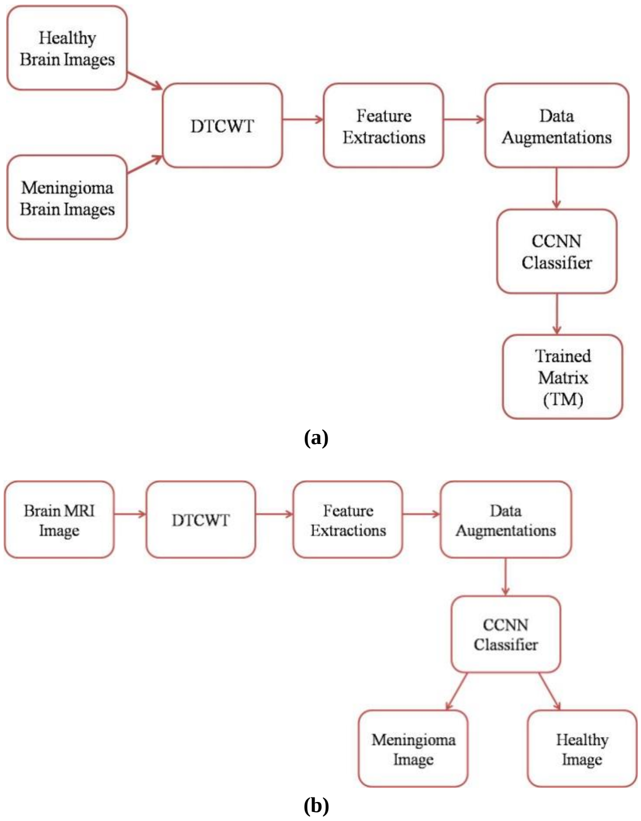

Fig. 2. (a) Meningioma image detection – training method (b) Meningioma image detection – testing method.

3.1. Dual Tree Complex Wavelet Transform (DTCWT)

The pixels in source brain image represents spatial domain format, which cannot be direct used to compute the features. Therefore, it is necessary to convert the spatial domain image into frequency domain image which is suitable for extracting the internal features from the image. Most of the researchers used Discrete Wavelet Transform (DWT), Contourlet and Gabor transforms, to transform the pixels from one domain to another. These transforms exhibits the losses during its reconstruction process (Khan et al. 2019). Hence, DTCWT is used in this article to transform the pixels into frequency domain format, which decompose the entire image into various sub bands. The source brain image x(n) is passed through the set of low and high pass filters which is designated at four consecutive stages as shown in Fig. 3. The decomposed coefficients in each stages of this DTCWT structure are stored in a matrix which has M rows and N columns.

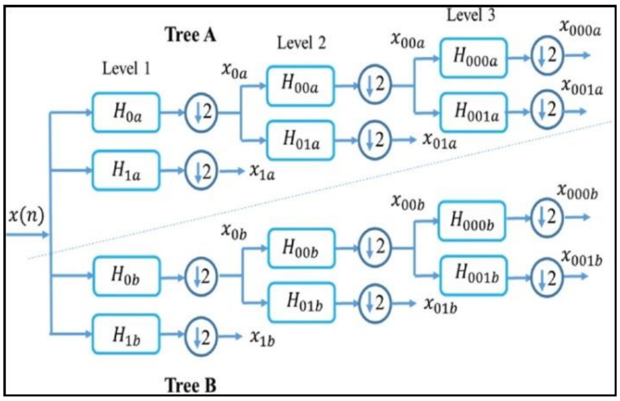

Fig. 3. DTCWT structure.

3.2. Feature Extraction and Data Augmentations Process

Features correlate the relation between the abnormal and normal pixel in a brain MRI image. Therefore, it is necessary to compute the features from both normal and abnormal brain images for the effective classification process. In this article, the following features are computed from the DTCWT sub band coefficient matrix D, with M numbers of matrix rows and N numbers of matrix columns.

$$Row\ Metric\ Index\ (RMI) = \sum_{i=1}^{M}\sum_{j=1}^{N}\frac{D(i,j)*i}{i+1} \quad (1)$$

Where, $D(i,j)$ is the coefficient value in the DTCWT sub band coefficient matrix D by row i and column j.

$$Column\ Metric\ Index\ (CMI) = \sum_{i=1}^{M}\sum_{j=1}^{N}\frac{D(i,j)*j}{j+1} \quad (2)$$

$$Energy\ Metric\ Index\ (EMI) = \sum_{i=1}^{M}\sum_{j=1}^{N}D^2(i,j) \quad (3)$$

$$Heuristic\ Metric\ Index\ (HMI) = \sum_{i=1}^{M}\sum_{j=1}^{N}\frac{D^2(i,j)}{i*j} \quad (4)$$

These features are computed from normal brain MRI image and stored in a matrix F1 and these features are computed from normal brain MRI image and stored in a matrix F2. These two matrixes are integrated into unique feature matrix F.

In order to increase the size of unique feature matrix F for the effective meningioma brain tumor classification system, the data augmentation process is used in this article. The data augmentation functions left flip rotate and a right flip rotate are used in this article to increase the size of the unique feature matrix F. Therefore, Data Augmented Matrix (DAM) is constructed by integrating feature matrix generated by left flip rotate, feature matrix generated by right flip rotate and source feature matrix. This DAM is now fed into the proposed CCNN classifier for the further classification process.

3.3. CCNN Classifications

In this article, the CCNN architecture is propose for the classifications of source brain MRI image into either meningioma or healthy image. This CCNN architecture is constructed with five numbers of Convolutional layers (C) and five numbers of Pooling layers (P) and two numbers of Dense layers (D). The DAM data is fed into both C1 and C2 simultaneously and this DAM data is convolved with the kernels of C1 and C2 layers. The C1 and C2 layers are designed with 32 numbers of filter banks and the size of each kernel in filter bank of these layers are 3*3. The filter bank responses of these layers are high and hence they are passed through the pooling layers to reduce the size of the filter bank responses. The responses from C1 layer is passed through P1 and the responses from C2 layer is passed through P2 layer respectively. In this article, Max pooling operation is executed in each pooling layers (Tiwari et al. 2020 [6]). The output responses from P1 and P2 are integrated into a unique matrix which is called as Integrated Metric Feature (IMF1). The P1 layer response if passed through C3 layer and their size is reduced by passing these responses through P3 layer. The P2 layer response if passed through C4 layer and their size is reduced by passing these responses through P4 layer. At the same time, IMF1 internal features are passed through C5 and P5 layers. The C3and C4 layers are designed with 64 numbers of filter banks and the size of each kernel in filter bank of these layers are 5*5. The C5 layer is designed with 128 numbers of filter banks and size of C5 layer is 7*7. Now, the response from P3, P5 and P4 layers are integrated into IMF2 and these internal features are passed through dense layers D1 and D2 consequently. The D1 layer is designed with 1024 neurons and the D2 layer is designed with 512 neurons. The D2 layer produces the classification responses as Meningioma or healthy. The entire proposed CCNN architecture is clearly illustrated in Fig. 4.

Table 1. Design specifications of CCNN architecture

Internal layers	*Specifications*
C1 layer	32 filters , 3*3
C2 layer	32 filters , 3*3
C3 layer	64 filters , 5*5
C4 layer	64 filters , 5*5
C5 layer	128 filters , 7*7
D1 layer	1024 neurons
D2 layer	512 neurons

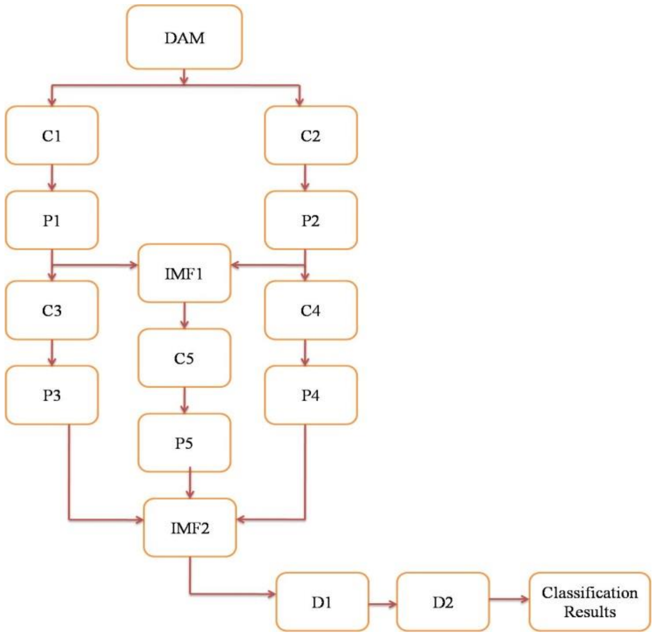

Fig. 4. Proposed CCNN architecture.

The morphological segmentation algorithm is used in this article to segment the tumor regions in classified meningioma brain images. The segmented tumor regions from Mild category and Advance category are trained by the CCNN classifier in training phase. In testing phase of the classifier, the segmented tumor regions from the test brain image are classified using the proposed CCNN classifier with trained segmented patterns. The response from this CCNN classifier is belonging to either mild or advance. Fig.5shows the tumor diagnosis system.

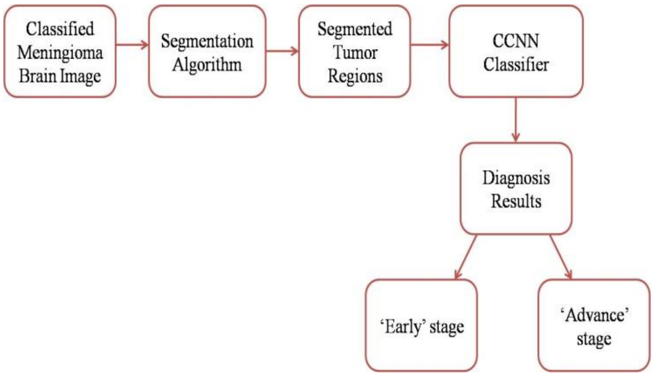

Fig. 5. Tumor diagnosis system.

4. Results and Discussions

This article uses MATLAB R2020 simulating software for implementing the proposed Meningioma brain tumor detection system using CCNN. In this article, two publicly available datasets Nanfang University (NU) (https://doi.org/10.6084/m9.figshare.1512427.v5) and Kaggle(https://www.kaggle.com/datasets/denizkavi1/brain-tumor?select=2) are used for evaluating the performance of the proposed Meningioma brain tumor detection system. The NU dataset [13] is made up of 571 meningioma brain images and 600 healthy brain images. The Kaggle dataset [14] is made up of 980 meningioma brain images and 1200 healthy brain images. In this article, 20% images in these dataset are used for training the proposed system and the remaining 80% of the brain images are used for testing the proposed system. Therefore, 114 meningioma images from NU dataset is used for training and the remaining 457 meningioma brain images are used for testing. The 120 healthy images from NU dataset is used for training and the remaining 480 healthy brain images are used for testing. Similarly, 196 meningioma images from Kaggle dataset is used for training and the remaining 784 meningioma brain images are used for testing. The 240 healthy images from Kaggle dataset is used for training and the remaining 960 healthy brain images are used for testing.

The performance measures are made on the proposed meningioma brain tumor detection system using the following metrics (Zhou et al. 2020).

$$Sensitivity\ Index\ Rate\ (SEIR) = \frac{TP}{TP+FN} \quad (5)$$

$$Specificity\ Index\ Rate\ (SPIR) = \frac{TN}{TN+FP} \quad (6)$$

$$Accuracy\ Rate\ (AR) = \frac{TP+TN}{TP+TN+FP+FN} \quad (7)$$

$$Precision\ (PR) = \frac{TP}{TP+FP} \quad (8)$$

$$F1-Score\ (FS) = \frac{2*TP}{2*TP+FP+FN} \quad (9)$$

Whereas, TP and TN correlate the correctly located tumor and non-tumor pixels, FP and FN correlates the wrongly located tumor and non-tumor pixels, respectively.

All these performance measures are measured in % with respect to the gold standard images available in the corresponding datasets.

Table 2 shows the performance measures of meningioma brain tumor detection system using CCNN on NU dataset. This proposed method obtains 98.93% SEIR, 99.02% SPIR, 99.16% AR, 99.06% PR and 98.95% FS on the meningioma brain images in NU dataset.

Table 2. Performance measures of meningioma brain tumor detection system using CCNN on NU dataset

Meningioma image orders	*Performance measures in %*				
	SEIR	*SPIR*	*AR*	*PR*	*FS*
1	97.8	97.9	99.6	98.5	99.1
2	98.5	98.4	99.8	99.7	98.3
3	99.2	99.4	99.5	99.3	98.8
4	98.9	99.3	98.9	98.2	99.1
5	99.5	99.7	99.5	99.6	99.3
6	99.3	99.2	98.9	99.3	98.7
7	99.2	98.6	98.6	98.7	98.9
8	99.8	98.9	99.2	98.9	99.1
9	98.6	99.5	98.7	99.3	98.9
10	98.5	99.3	98.9	99.1	99.3
Average	**98.93**	**99.02**	**99.16**	**99.06**	**98.95**

Table 3 shows the performance measures of meningioma brain tumor detection system using CCNN on Kaggle dataset. This proposed method obtains **98.89**% SEIR, **98.74**% SPIR, **99.05**% AR, **98.93**% PR and **98.91**% FS on the meningioma brain images in Kaggle dataset.

Table 3. Performance measures of meningioma brain tumor detection system using CCNN on Kaggle dataset

Meningioma image orders	*Performance measures in %*				
	SEIR	*SPIR*	*AR*	*PR*	*FS*
1	98.7	98.5	98.8	98.5	98.7
2	98.3	98.8	99.7	98.9	99.3
3	99.2	98.3	99.3	98.6	99.1
4	99.5	99.2	99.1	99.4	98.5
5	99.3	98.7	99.4	99.6	99.3
6	98.7	99.3	99.3	98.5	98.9
7	98.9	98.5	98.9	98.7	98.7
8	99.3	98.6	98.6	98.7	98.2
9	98.1	98.6	98.9	99.1	99.1
10	98.9	98.9	98.5	99.3	99.3
Average	**98.89**	**98.74**	**99.05**	**98.93**	**98.91**

Table 4 shows the comparative performance measures of the proposed meningioma brain tumor detection method on both NU and Kaggle datasets. From this comparative analysis between different meningioma brain image dataset, the proposed CCNN based meningioma brain tumor detection method provides superior tumor region segmentation results when compared with tumor segmentation results of the proposed method on Kaggle dataset.

Table 4. Comparative performance measures

Performance measures in %	*Datasets*	
	NU dataset	*Kaggle dataset*
SEIR	98.93	98.89
SPIR	99.02	98.74
AR	99.16	99.05
PR	99.06	98.93
FS	98.95	98.91

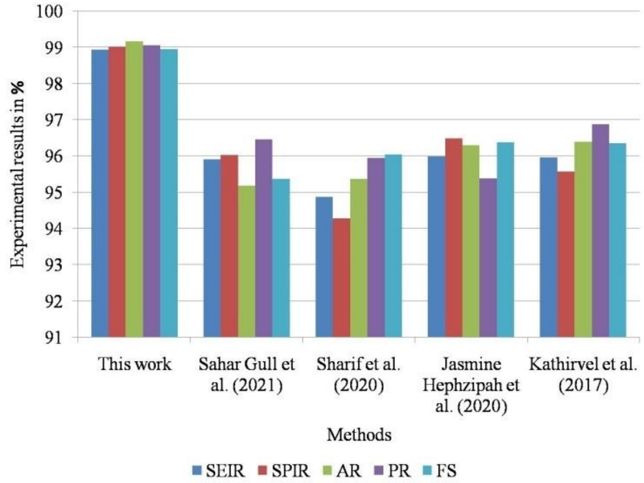

Fig. 6. Comparative analysis of proposed CCNN for meningioma tumor detection on NU dataset.

Fig. 6 shows the comparative analysis of proposed CCNN for meningioma tumor detection on NU dataset with respect to the experimentation results of Sahar Gull et al. (2021) [8], Sharif et al. (2020) [9], Jasmine Hephzipah et al. (2020) [10] and Kathirvel et al. (2017) [11].

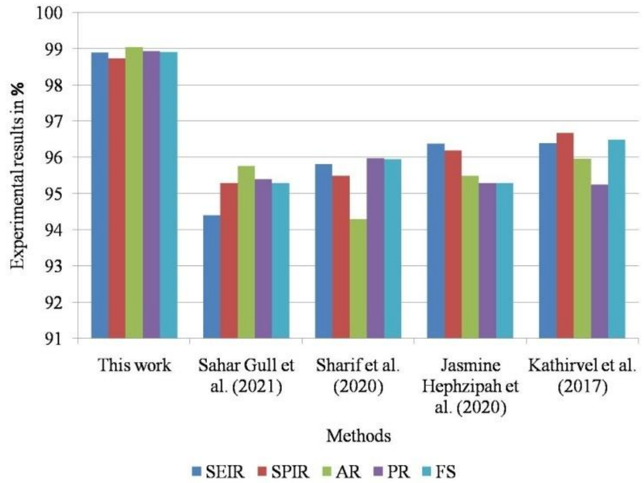

Fig. 7. Comparative analysis of proposed CCNN for meningioma tumor detection on Kaggle dataset.

Fig. 7 shows the comparative analysis of proposed CCNN for meningioma tumor detection on Kaggle dataset.

The proposed CCNN classifier detects 350 mild images over 357 mild images and obtains 98% of Meningioma Diagnosis Rate (MDR) for mild case. The proposed CCNN classifier detects 98 advance case images over 100 advance case images and obtains 98% of MDR for advance case. Therefore, the average MDR is 98% on NU dataset. The proposed CCNN classifier detects 691 mild images over 700 mild images and obtains 98% of MDR for mild case. The proposed CCNN classifier detects 252 advance case images over 260 advance case images and obtains 98% of MDR for advance case. Therefore, the average MDR is 97.8% on Kaggle dataset.

5. Conclusions

The detection of meningioma brain tumors are most important than other brain tumor types due to its severity levels. The conventional methods used machine and deep learning methods for the meningioma detection process, which obtained low tumor segmentation accuracy. Hence, the meningioma brain tumors are detected and diagnosed in this work using the proposed CCNN classification architecture which is the modification of the conventional CNN in this article. The proposed method is tested on two independent datasets NU and Kaggle using the gold standard images. This proposed method obtains 98.93% SEIR, 99.02% SPIR, 99.16% AR, 99.06% PR and 98.95% FS on the meningioma brain images in NU dataset. This proposed method obtains 98.89% SEIR, 98.74% SPIR, 99.05% AR, 98.93% PR and 98.91% FS on the meningioma brain images in Kaggle dataset. The future extension of this work is to implement the proposed approaches for the detection of stroke in brain images.

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