Brain Tumor Classification Through MR Imaging: A Comparative Analysis

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Abstract. Tumor in brain is one of the serious diseases throughout the world and it leads to death around 300 thousand people in 2020. Hence, Brain tumor diagnosis is a sensible and important task in clinical and medical field. Identification of illness, area, depth and severity of the disease are major challenges encountered before technological improvement in the clinical field. These major challenges are fulfilled few decades ago by acquiring images of human body parts with collaborations of electronic and mechanical devices. The familiar medical images are Magnetic Resonance Imaging (MRI) Scan, Computed Tomography (CT) Scan and Positron Emission Tomography (PET) Scan. Manual observation of aforementioned scans may lead error in the treatment. Hence, various image processing algorithms and pre-trained methods have been employed on medical images to identify the accurate location, area, depth and severity of the disease, which effectively improvise the treatment. The evolution process has several stages such as: preprocessing; segmentation; future extraction; and classification. Therefore, this work presents a detailed report of CNN based brain tumor classification methods through MR imaging scans. Finally, the performance measures of brain tumor classification methods have been presented and compared.

Keywords: Brain tumor · Diagnosis; Illness · Medical images · Classification

1 Introduction

Global Cancer Statistics 2020 announces, twenty million new incident cancerous cases and nearly 10 million new deaths are happened throughout the world in 2020. According to this, 2.5% deaths were due to brain tumor disease in 10 million cancerous death cases [1]. Hence, diagnosis of tumor in brain has been significant in the medical field. Disease detection, classification and severity estimation are prominent in diagnosis steps of tumor [2–15]. In disease diagnosis process; first capture the skeleton image of required human body part; familiarly it's named as medical image. Most familiar medical image types are X-ray, MRI scan, CT scan and PET scan [1–20, 22]. Out of this MRI scan is suitable to capture the soft tissues of the body part. Manual identification and classification of

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diseased/defected region may difficult, if raw medical image affected with noise and no variations in the intensity levels of diseased and non-diseased regions. It has been due to longer scan time by the sensors and age of the equipment also. Therefore, for accurate diagnosis of the particular disease, various automated algorithms and methods were designed [3–13]. Figure 1. Shows general flow of automated approach [2, 15]. First employ prepossessing scheme (noise removal) on raw medical image. Further, segmentation is employed on preprocessed image to locate/identify the Region of Interest (ROI). Image segmentation plays a vital role in the automation approach to differentiate diseased and non-diseased portions [21] for identifying the tumor/cancerous region and it helps to classify further. This information helps the diagnosis experts to treat patients effectively and accurately. The various segmentation methods are edge-based, threshold-based, region-based, cluster-based and watershed segmentation. Feature extractions are done from the extracted segmented portions of the image. Finally, classifier has to classify the disease based upon the extracted features. Now a days, CNN models are alternative for traditional algorithms/methods of image restoration, image dehazing [23, 24] along with classification.

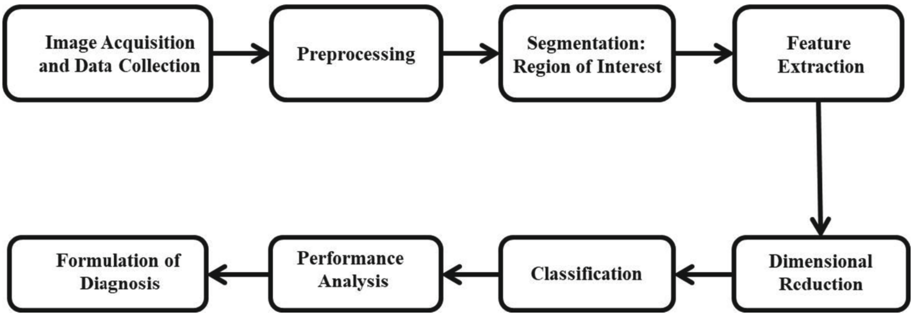

Fig 1. General flow of cancer detection system (Source: Chahal P K et al.[2] and P.R.Budumuru et al.[15]).

2 Related Work

S. Mohsen et al. (2023), proposed two intelligence models for the classification of tumor categories glioma and pituitary in brain. In these two models, VGG19 is first one and single-image super-resolution (SSIR) technique with ResNext101_32 × 8d is the second. Proposed SSIR technique based on GAN algorithm is employed on input MRI scan to produce high resolution images before classification. 344 layers in ResNext101_32 × 8d model includes, 104 layers each for batch normalization and convolution, 100 layers of ReLU, 33 bottleneck layers. Proposed VGG19 model in this work consists nineteen 2-D layers, in that three are fully connected layers and remaining 16 are convolution layers each of which is followed by max-pooling layers [3].

H. A. Hafeez et al. (2023), come up with a low-grade and high-grade glioma type brain tumor classification model with CNN consisting of less number of layers, size and learnable parameters. This work has been designed in two ways; Feature extraction done by separately with resnet18, squeezenet, alexnet, and proposed CNN. Further, classification has been done with SVM classifier. Second approach is extraction and classification both are done by aforementioned CNN models used in first approach [4].

Assam, M et al. (2021), presented a four-step hybrid model with various stages pre-processing, feature extraction, feature reduction and classification for tumor classification in brain through MRI scans. Median filter, being one of the state-of-art and traditional method used to remove fixed valued impulse noise and unnecessary structures such as skull and scalp, it's a main block in pre-processing stage, further it converted to colored image. Feature extraction has been done in stage-2 with discrete wavelet transform (DWT). Feature reduction and optimal characteristics set is generated in the third stage with the help of color moments (CMs). Image classification is done by passing the reduced optimal characteristic set through various classifiers; FF-ANN, RSwithRF and RSwithBN [5].

Rehman, A et al. (2020), in this framework, three studies were conducted for classification of brain tumor using three popular CNN architectures (AlexNet, GoogleNet, and VGGNet). Each study investigated on MRI brain tumor dataset Figshare and explores it with transfer learning methods freeze and fine-tune. Chance of over-fitting is reduced by increasing the data set samples by employing augmentation on MRI slices [6].

Ali, M et al. (2020), proposed straight forward ensemble method for segmentation of tumor by processing the image through two individual networks 3D CNN and a U-Net. These two networks trained individually with BraTS-19 challenge dataset and estimate the segmentation maps which considerably differed from each other in sub-regions tumor segmentation. Final prediction of tumor segmentation is achieved by ensemble these two individual segmented maps [7].

Kumar, S. and Mankame, D.P., (2020), discussed the tumor classification based on the optimized deep learning mechanism in which fuzzy deformable fusion model used for the segmentation of the images. The statistical features are used to classify the tumor by deep convolutional neural networks (DCNN). Dolphin Echolocation Sine Cosine Algorithm (Dolphin-SCA) is also implemented in this work for the segmentation. BRATS and SimBRATS databases were used for the validation of this network [8].

Hasan, S.K. and Linte, C.A (2018), proposed a deep learning U-Net CNN model for characterization and segmentation of tumor in brain MR images. In this method, up-sampling with nearest neighbor algorithm is introduced instead of de-convolution component in the U-net model. Segmentation accuracy is improved by extracting low grade tumors with the help of data augmentation performed on dataset by employing elastic transformation. This frame work trained with BRATS 2017 MR dataset of 285 patients affected with glioma [9].

Seetha, J. and Raja, S.S., (2018), proposed an automatic classification of tumor in brain using CNN. Manual classification of tumor from the MRI data is challenging at particular times. So, low complexity CNN system proposed by training the last layer of the network and considered a pre-trained model brain data set for classification. Hence, validate with training accuracy and computational time; it examines with support vector machine (SVM) and deep neural networks (DNN) [10].

Selvapandian, A. and Manivannan, K., (2018), implemented tumor detection in brain with contourlet transform of non-sub sampled (NSCT) and neuro fuzzy inference adaptive system (ANFIS). Image enhancement is done with NSCT by combining low and high frequency sub-bands of MR image and extracted features from enhanced image are used to classify the normal and glioma type tumor images with ANFIS [11].

Bahadure, N.B et al. (2017), investigated Berkeley wavelet transformation (BWT) on brain MR images to extract the tumor region in segmentation process. The appropriate features are extracted from the segmented tissues by employing very well-known classifier support vector machine (SVM) [12].

Gopal, N.N. and Karnan, M (2010), proposed a two-stage intelligent system to recognize tumor tissues in brain MRI. In this system design optimization is employed along with Fuzzy c Means Clustering for segmentation. The adopted optimizing methods are Genetic Algorithm (GA) and Particle Swarm Optimization (PSO). In this, Preprocessing and Enhancement are the methods in the first phase; segmentation and classification are the methods in second phase [13].

3 Performance Measures

True Positive (T_p), True Negative (T_n), False Positive (F_p) and False Negative (F_n) are the words used in the evaluation parameters of tumor classification methods such as Accuracy, Sensitivity, Specificity [3–6, 8, 10–14]. Hence, these metrics are formulated from Eq. (1) to (3). Dice coefficient [7, 9] is another metric formulated as Eq. (4) to evaluate the similarity between predicted tumor pixels with ground truth pixels.

$$Accuracy(A) = \frac{Number\ of\ faithful\ detections}{Number\ of\ all\ assessments} = \frac{T_p + T_n}{T_p + T_n + F_p + F_n} \tag{1}$$

$$Sensitivity(Sen) = \frac{Number\ of\ true\ positive\ detections}{Number\ of\ all\ positive\ assessments} = \frac{T_p}{T_p + F_n} \tag{2}$$

$$Specificity(Spec) = \frac{Number\ of\ true\ negative\ detections}{Number\ of\ all\ negative\ assessments} = \frac{T_n}{T_n + F_p} \tag{3}$$

$$Dice\ Coefficient\ (DSC) = \frac{2 * |X \cap Y|}{|X| + |Y|} \tag{4}$$

where X : *set of* predicted pixels, Y : ground truth

4 Dataset Description and Evolution of Brain Tumor Classification Methods

Dataset summary and performance evaluation of each method discussed in previous section summarized in Table 2. Table 3 compare the detection accuracy of methods described in [3–6, 11, 12] and [13] evaluated on non- BRATS datasets and Table 4 compare the detection accuracy of methods described in [4, 8] and [11] evaluated on BRATS datasets.

Table 1. Summary of Brain Tumour Classification Methods using MRI Scans

Author(s), Year and Source	Methodology
[3] S. Mohsen et al. 2023 IEEE Access	Pituitary and glioma type tumor classification has been carried out by intelligence systems, single image super-resolution (SISR) technique with classification networks ResNext101_32 × 8d and VGG19 SISR method developed in two stages; generator is in first stage and discriminator in the second stage. Hence, it produces the super resolution image of size 256x256x3 from low and high-resolution images of same size. The entire process has been done on required input medical MRI scans of pituitary and glioma. Classification is done with CNN's such as ResNext101_32 × 8d and VGG19 after SISR method
[4] H. A. Hafeez et al. 2023 IEEE Access	It's a 12-layer CNN model to classify the grade I – II (low) and grade III – IV (high) glioma type brain tumor. In this, N4ITK [14] method was applied in the preprocessing stage to remove bias field distortion in MRI images. Further, feature extraction and classification done by proposed CNN
[5] Assam, M., et al. 2021 IEEE Access	Pre-processing: Median filter Features extraction: Discrete Wavelet Transform (DWT) Features Reduction: Color Moments (CMs) Classification: Individual classifier: FF-ANN (Feed Forward – ANN) Hybrid Classifiers: RSwithRF (Random Subspace with Random Forest) RSwithBN (Random Subspace with Bayesian Network)
[6] Rehman, A., et al. 2020 Circuits, Systems, and Signal Processing	Three studies have been conducting with different CNN's namely AlexNet, GoogleNet and VGGNet to classify the meningioma, glioma, and pituitary types
[7] Ali, M., et al. 2020 IEEE Access	It's a combination of 3D-CNN and U-Net, both are trained individually and finally ensemble the individual outputs of these two networks

(*continued*)

Table 1. (*continued*)

Author(s), Year and Source	Methodology
[8] Kumar, S. and Mankame, D.P., 2020 Biocybernetics and Biomedical Engineering	It's a optimized Deep-CNN model trained with Dolphin-SCA Preprocessing: Non-Local Means (NLM) filter is used to remove artifacts in the different modalities of medical MR images Segmentation: To Extract ROI from the preprocessed image, employed a fuzzy deformable model with Dolphin Echolocation based Sine Cosine Algorithm (Dolphin-SCA) Feature Extraction: Feature vector has built with statistical parameters such as mean, variance, and skewness being extracted from segmented regions. Power LBP model has been adapted to extract useful features to train the classifier Classification: Deep CNN has been trained with Dolphin-SCA
[9] Hasan, S.K. and Linte, C.A., 2018 2018 IEEE Western New York Image and Signal Processing Workshop, IEEE	An improved version of Conventional U-net model by introducing up-sampling with nearest neighbor algorithm instead of de-convolution component and employing elastic transformation named as Nearest-Neighbor Re-sampling Based Elastic-Transformed to increase the segmentation accuracy
[10] Seetha, J. and Raja, S.S., 2018 Biomedical & Pharmacology Journal	It's a low complexity CNN based brain tumor classification method. In this, only last layer of the network has been trained and classification steps are done by a pre-trained model brain dataset. These two changes were made in traditional CNN for reducing computation time and performance improvement
[11] Selvapandian, A. and Manivannan, K., 2018 Computer Methods and Programs in Biomedicine	It is a fusion based glioma brain tumor classification approach. Low and high frequency sub-bands of input MR image scan are the components of fused image. Decomposing of sub-bands from input image has been done in spatial domain with the help of Pyramid Filter Banks (PFB) and Directional Filter Banks (DFB). Further, extracted features from fused image trains the classification approach and ANIFS classifier identifies the non-glioma and glioma images
[12] Bahadure, N.B., et al. 2017 International Journal of Biomedical Imaging	Tumor segmentation being done by Berkeley Wavelet Transformation (BWT). Features that are intensity and texture have been extracted from segmented image by employing GLCM, SFTA and IBF along with area of the tumor and dice coefficient similarity index are the two more features. PCA is used to select optimized relevant features. Finally, SVM is used for the brain tumor classification

(*continued*)

Table 1. (*continued*)

Author(s), Year and Source	Methodology
[13] Gopal, N.N. and Karnan, M., 2010 2010 IEEE International Conference on Computational Intelligence and Computing Research	It's a two-stage intelligent tumor detection system Stage 1: Preprocessing and Enhancement, Stage 2: Segmentation and Classification. Methods involved in this, Fuzzy C-Means Clustering Algorithm (FCA) with optimization tools Particle Swarm Optimization (PSO) and Genetic Algorithm (GA). In this, the overall detection accuracy is sum of accuracy of tumor pixels (75%) and position accuracy (25%)

Table 2. Summary of Brain Tumour Classification Methods using MRI Scans

Reference Number	Dataset	Performance Evaluation
[3]	Kaggle Dataset: It consists 1800 brain MRI images, out of these 900 images of each glioma tumor and pituitary tumor. They were resized to 224 x 224 and increase this dataset by three times with the help of data augmentation methods rotation, width and height shift. Further, dataset has to divide with 75% for training VGG19 and 85% for training ResNext101_32 × 8d	Testing Accuracy (%) a. VGG19: 99.89 b. SISR + ResNext101_32 × 8d: 100
[4]	BRATS 2017, BRATS 2018 and BRATS 2019 Dataset BHVB has been developed by acquiring 159 high grade and 176 low grade glioma MRI scan images from B V Hospital, Bahawalpur, Pakistan	a) Deep learning Method + SVM Classifier Testing Accuracy (%) BRATS 2017: 97.87 BRATS 2018: 97.67 BRATS 2019: 89.77 BHVB: 98.89 b) CNN Model Testing Accuracy (%) BRATS 2017: 97.85 BRATS 2018: 97.15 BRATS 2019: 97.15 BHVB: 97.99
[5]	70 T2-weighted standard image dataset (Normal: 45 and Abnormal: 25)	Testing Accuracy (%) a) DWT + RSwithRF: 97.14 b) DWT + RSwithBN: 95.71 c)DWT + CMs + FF-ANN: 95.83
[6]	Figshare dataset: It contains 3064 various types of brain tumor MRI scan images in which, meningioma: 708, glioma: 1426 and pituitary: 930	Testing Accuracy (%) a) AlexNet: 97.39 b) GoogleNet: 98.04 c) VGG16: 98.69

(*continued*)

Table 2. (*continued*)

Reference Number	Dataset	Performance Evaluation
[7]	BraTS2019 challenge dataset: In this dataset total 335 patients' information has been used for training. Out of these, 259 high-grade and 76 low-grade type glioma cases information. Validation process has been done with 125 cases of unknown grade	Dice Scores Enhancing Tumor(ET): 0.750 Whole Tumor(WT): 0.906 Tumor Core: 0.846
[8]	BRATS Database: It consists 65 tumor images of T1, Tlc, T2 and flair modalities. Out of which, 51 are high-grade glioma patients' information SimBRATS database: It's a simulated image dataset with 50 images of all four varieties as same as BRATS database. Out of which 25 high-grade and 25 low-grade glioma images	Testing Accuracy (%) BRATS database: 95.3 SimBRATS database: 96.3 Specificity (%) BRATS database: 0.953 SimBRATS database: 0.910 Sensitivity (%) BRATS database: 0.977 SimBRATS database: 0.992
[9]	BRATS 2017 MR dataset: 285 glioma patients' information is used for training and 146 patients' information for testing	Dice Similarity Coefficient (DSC): LGG: 0.8976 HGG: 0.8459 Intersection over Union (IoU): LGG: 0.8869 HGG: 0.826 LGG: Low-graded gliomas HGG: High-graded gliomas
[10]	Tumor images are accessed from Radiopaedia and BRATS 2015 dataset accessed for testing	Training Accuracy (%) CNN: 97.5
[11]	Low-grade and high-grade type brain tumor images of BRATS 2015 dataset sub-database has been used for training the classification stage alone. Brain MRI images from LeaderBoard and Challenge sub datasets also considered along with BRATS 2015 dataset have been for the evaluation of different performance metrics	Testing Accuracy (%) BRATS 2015 dataset: 99.30 LeaderBoard dataset: 95.9 Challenge dataset: 96.4 Specificity (%) BRATS 2015 dataset: 99.71 LeaderBoard dataset: 96.2 Challenge dataset: 95.1 Sensitivity (%) BRATS 2015 dataset: 70.25 LeaderBoard dataset: 92.3 Challenge dataset: 96.2

(*continued*)

Table 2. (*continued*)

Reference Number	Dataset	Performance Evaluation
[12]	DICOM Dataset: 22 infected brain tumor tissue images are considered Brain Web dataset: It has simulated three-dimensional MR imaging data of modalities T1-weighted, T2-weighted and proton density weighted. In this 13 out 44 are infected brain MR images Third dataset: It consists, 135 images of 15 patients collected from the expert radiologists	Testing Accuracy (%) SVM Classifier: 96.51 Specificity (%) SVM Classifier: 94.2 Sensitivity (%) SVM Classifier: 97.72
[13]	A Set of 120 MR images	Detection Accuracy (%) a. GA + FCM: 89.6 b. PSO + FCM: 98.87

Table 3. Testing Accuracy of Brain Tumor Classification Methods Tested on Brats Datasets

Reference	Alphabet [Method Name]	Accuracy (%)
[3]	a [VGG19]	99.89
[3]	b [SISR + ResNext101_32 × 8d]	100.00
[4]	a [Deep learning Method + SVM Classifier]	98.89
[4]	b [CNN Model]	97.99
[5]	a [DWT + RSwithRF]	97.14
[5]	b [DWT + RswithBN]	95.71
[5]	c [DWT + CMs + FF-ANN]	95.83
[6]	a [AlexNet]	97.39
[6]	b [GoogleNet]	98.04
[6]	c [VGG16]	98.69
[11]	a[Image Fusion + ANIFS]	96.40
[12]	a [SVM]	96.51
[13]	a [GA + FCM]	89.60
[13]	b [PSO + FCM]	98.87

Figure 2 and Fig. 3 show the bar graph representation of various methods corresponding reference number on X-axis and with their testing accuracy (%) on Y-axis. Most of the related works discussed in this paper were implemented with more than one methodology. Hence, represent the methods with alphabets a, b and c with method name in Table 3 and Table 4. Methods proposed by the models represented in Fig. 2, [3, 4] and [13] with two methods each, [5] and [6] with three methods each, [11] and [12] each one method. Performances of all these models were evaluated with different brain tumor

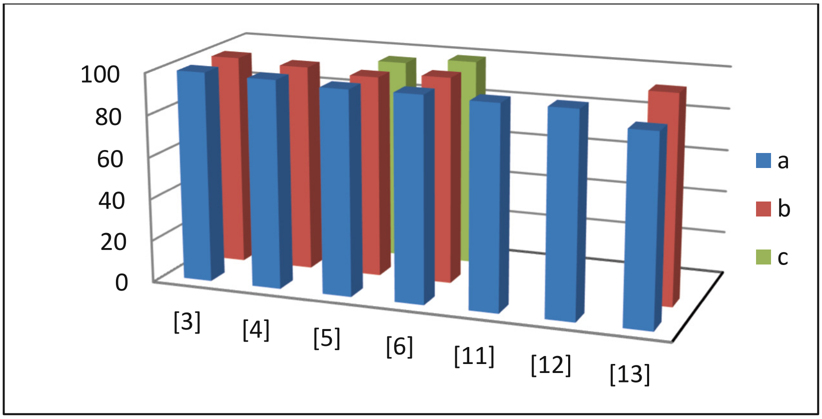

Fig. 2. Accuracy comparison of Brain Tumor Classification Methods tested on other than BRATS datasets

Table 4. Testing Accuracy of Brain Tumor Classification Methods Tested on Brats Datasets

Reference	Alphabet [Method Name]	Accuracy (%)
[4]	a [Deep learning Method + SVM Classifier]	97.87
[4]	b [CNN Model]	97.85
[8]	a [Proposed Dolphin-SCA based Deep CNN]	96.30
[11]	a [Image Fusion + ANIFS]	99.30

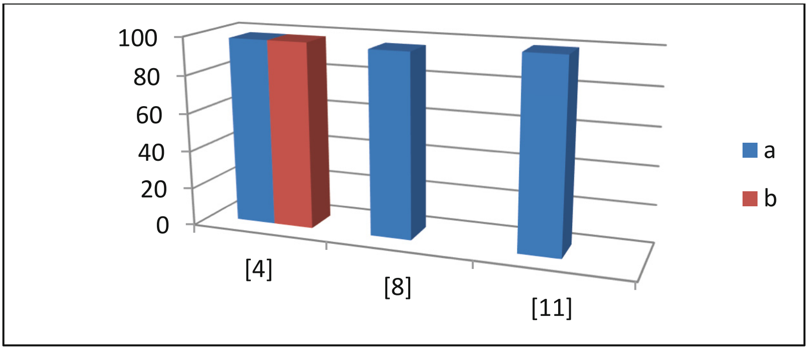

Fig. 3. Accuracy comparison of Brain Tumor Classification Methods tested on BRATS datasets

datasets. Figure 3 shown model [4] proposed with two methods and each one from [8] and [11]. These three models were tested with either of BRATS 2015, BRATS 2017, BRATS 2018, BRATS 2019 and SimBRATS database.

5 Conclusion

The availability of open-source image datasets of various diseases has enabled the automatic disease classification systems since past two decades. In this study the performance analysis of brain tumor classification methods through MRI scans has been analyzed. The intelligence systems proposed in [3–6, 8, 11, 12] and [13] are Deep-learning and CNN models. All these classify the various brain tumor types: meningioma; pituitary; low-graded and high-graded glioma. Tumor detection accuracy: In [3], SISR + ResNext101_32 × 8d achieves 100% on Kaggle Dataset. In [5], a hybrid classifier DWT + RSwithRF achieves 97.14% on standard dataset of 70 images. In [6], VGG16 achieves 98.69% on Fighshare dataset. SVM classifier [12] achieves 96.51% on dataset created with 135 images of 15 patients collected from expert radiologists. In [14], Particle Swarm Optimization with Fuzzy c Means Clustering (PSO + FCM) achieves 98.87% on a set of 120 images. Hence, all these methods performed well on various datasets in terms detection accuracy. In [4], Deep learning Method + SVM Classifier and CNN Model validated with BRATS 2017, BRATS 2018 and BRATS 2019 along with BHVB. It has been developed by acquiring images from Bahawal Victoria Hospital, Bahawalpur, Pakistan. Deep learning Method + SVM Classifier and CNN Model achieved 97.87%, 97.85% and 98.89%, 97.99% detection accuracies on BARTS 2017 and BHVB datasets in order. In [11], Image Fusion with ANIFS classifier validated with BRATS 2015, LeaderBoard and Challenge datasets. It achieved 99.30%, 95.9 and 96.4% of detection accuracies respectively. Proposed Dolphin-SCA based Deep CNN [8] achieves 96.3% on SimBRATS database. In separate datasets validation process, performance of super resolution image with ResNext101_32 × 8d model achieved highest detection rate of brain tumor type's pituitary and glioma. CNN model [4] classifies the Low grade and High-grade glioma brain tumor types efficiently with more than 97% detection rate on BRATS datasets 2017, 2018, 2019 and non-BRATS dataset. Image Fusion + ANIFS [11] outperformed on BRATS 2015 dataset for the classification of glioma type brain tumor.

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