Combining TernausNet and Attention Aware Faster RCNN For Brain Tumor Segmentation And Classification In MRI Images

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Abstract

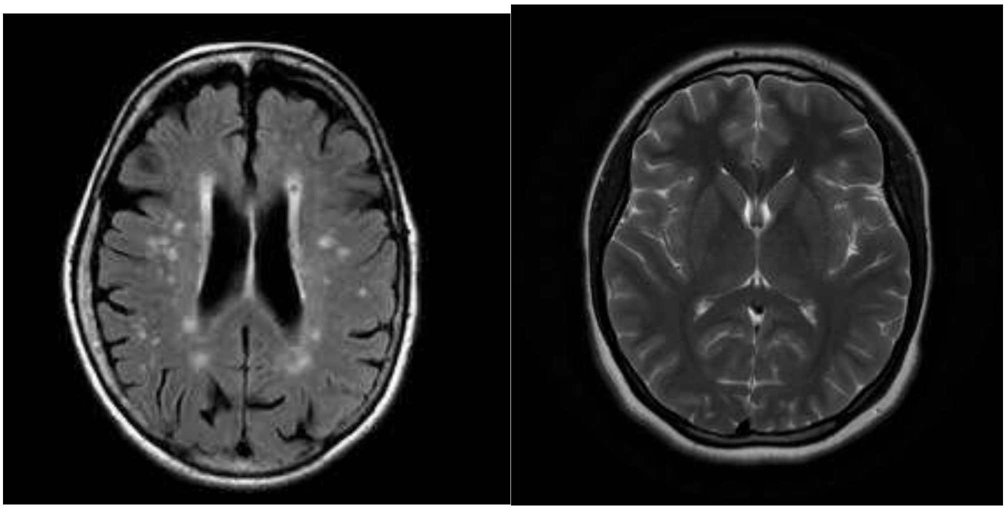
currently, brain tumor segmentation and classification in MRI images based on conventional preprocessing, feature extraction and classification methods are not sufficient. For instance, previous methods have the issues of huge loss of information, not suited for large volume of data and also contain white Gaussian noise. This paper proposes Brain tumor Segmentation and Classification (BORSTAL)-MRI for accurate classification of the brain tumor classes. The proposed brain tumor segmentation and classification model has four steps. In the first step, the proposed model uses Multi-Stage Preprocessing, in which artifacts are removed by performing intensity redistribution, noise removal, and contrast enhancement, respectively. This step produces the final outcome with respect to clear blurriness and smoothen image. In the second step, TernausNet based brain tumor segmentation is performed which is better as compared to the existing deep learning algorithms (CNN, U-Net, etc.). In third step, three types of features are extracted as Color, Texture, and Shape. These features are extracted using Faster R-CNN algorithm and finally this algorithm is used for classification into three classes as: High Tumor, Low Tumor, and No Tumor. The proposed model is implemented using MatlabR-2020a in which various performance metrics are computed as follows: PSNR, SSIM, MSE, Error Rate, Foreground Precision, Background Precision, Dice Similarity, Accuracy, Specificity, Sensitivity and AUC. The comparison results show that the performance of the proposed BROSTAL –MRI model receives higher performance than the previous methods.

Keywords: Brain Tumor Segmentation, and Classification, TernausNet, Deep Learning, MRI image dataset, and Faster CRNN

Introduction

Detecting brain tumor is a crucial task in current medical applications since differentiate abnormal tissues from normal brain tissues is a challenging [1]. This is due to irregular shape and diffused image boundaries in the tumor surrounding area [2]. In order to overcome the issues, preprocessing and data augmentation tasks are carried out into the brain tumor segmentation and classification [3]. However, preprocessing tasks are various such as intensity normalization, contrast enhancement, morphological erosion and dilation, and so on [4]. Previous works does fail to improve the quality of input image by using preprocessing.

Brain tumor was segmented using various techniques and some of the techniques are follows: Clustering (K-means, Fuzzy C-means and Potential Field Clustering), Region of Interest (Region Growing), Active Contour (level set) and machine learning algorithms [5] [6]. These works produces the overlapped segments for brain tumors that do not accurately determine the tumor area [7]. However, tumor segmentation is a key role in tumor classification that stability and accuracy must be higher [8]. In this case, ground truth image was compared with the actual segmentation image [9].



(a) (b)

Fig.1 Sample MRI images (a). Acquisition error in intensity (b). High complex shape of brain tumor

In deep learning, convolutional neural network is the most dominant networks for brain tumor classification [10] using MRI images. The sample set of MRI images is shown in fig 1. It can be useful for significant feature extraction in brain tumor classification and it classifies the tumor type accurately [11]. In CNN, convolutional layer performs the feature extraction and extracts the most relevant feature values from segmented part of tumor region [12]. The most important type of features is intensity, shape, texture and so on [13]. Some of the previous works have used texture and morphological oriented features from the segmented tumor for correctly identify the tumor into two classes as Benign or Malignant [14]. Here, texture features are extracted by using Gray Level Co-occurrence Matrix (GLCM) algorithm and Local Binary Pattern (LBP) and Histogram of Gradients (HoG) [15]. Brain tumor classification is a noteworthy task in brain tumor segmentation and classification which predicts whether the given image is belongs to cancerous tumor or not. The integration of CNN and Generative Adversarial Network (GAN) was found to be effective in detection of brain tumor and classification of tumor into several classes [16]. The optimization based extraction of features and classification of tumor from the input images was found to achieve better accuracy in classification [17]. The uncertainties in detection of tumor from the input images were predicted to achieve appropriate detection and classification [18]. Several approaches focused on detection of particular type of tumor from the input MRI images and performed grading of disease in order to determine the severity [19]. The integration of several deep learning networks by means of transfer learning was found to achieve increased accuracy in multi-class classification of brain tumor [20]. However, these approaches eventually increased the complexity and time consumption in classification of tumor. In particular, an effective approach with minimal complexity in classification of brain tumor from the input MRI images is still in demand. Table 1 represents the rank level of brain tumor.

Table.1 Rank level of brain tumor

Rank Level	Tissue Status
I	Slowly harmless growing
II	Normal venomous tissue
III	Medium growing abnormal tissues
IV	Highly growing abnormal tissues
V	Fast growing abnormal tissues

1.1 Research Aim and Objectives

This work focuses on both brain tumor segmentation as well as classification for MRI images. The main aim of this research is to design an effective architecture for improving segmentation and classification accuracy and reduces the classification error. The research issues undertaken for brain tumor segmentation and classification are follows:

- One of the important evolving problems of MRI image is that varied intensity ranges in the image acquisition process over variety of devices.
- The tumor area does not have a static size or shape. Tumors appeared anywhere in the brain region and have irregular shapes and lesions. Further, it might be overlapped with the healthy tissues and hence brain tumor segmentation becomes complex.
- MRI images contain *White Rician Noise* that due to the motion of human during image acquisition.
- The large size of tumors or abnormal tissues over the brain may change the brain structure which makes huge complexity for early diagnosis of tumor area.
- Brain tumor classification demands high level feature extraction i.e. multiple features such as color, shape, texture and spatial information must be taken into account for effective and early classification.

Many researchers are concentrate brain tumor detection and classification however detection accuracy is still low due to absence of essential features, noisy images and poor segmentation. This paper is primarily motivated by the following research issues.

- **High Complexity in Feature Extraction & Selection:** Machine learning aided classification was ineffective when individual feature extraction and selection for massive number of MRI images.

- **Absence of Essential Preprocessing:** Due to image at poor quality, various issues must be undertaken i.e. noise, weak object boundaries, inhomogeneous object region, weak contrast and many other artifacts (irregular shape, size and color).

- **Patch based Segmentation and Classification:** However, feature extraction and classification are performed in patch based processing. This result higher overlapping between features a vector that does not suit for accurate disease diagnosis.

In order to address the aforementioned issues in this paper, we have the following research contributions.

1.2 Research Contributions

In this paper, we have three contributions for addressing the primary issues of brain tumor segmentation and classification that are follows.

- We presented multi-stage preprocessing methods for improving the quality of input image. In this step, noise, blurriness, low contrast, low SNR and inhomogeneous in intensity. In the first step, intensity redistribution is implemented. For image normalization in terms of intensity, the Dynamic Intensity Specific Variance (ISV) is proposed. This ISV metric is dynamic and changed according to the input image. The value of ISV metric is adaptive and adjusted according to different input images. Here, image quantization is implemented in which distance between intensity values are considered for intensity adjustment. White Rician noise from the MRI image is removed using fuzzy connected twin filters such as Wiener Filter and Bilateral Filter. Finally, contrast enhancement is performed in which adaptive based CLAHE (A-CLAHE) algorithm is proposed. In this step, contrast is maximized and blurriness is minimized. As a result, the efficiency of the proposed approach is improved in brain tumor segmentation and classification.

- Brain tumor segmentation is performed using TernausNet which is a good segmentation method that performance is higher than the deep learning methods. With the use of TernausNet, tumor regions are accurately segmented with three layers as Down Block, Up Block and Soft Max Layer. Segmentation accuracy is very high since Ternaus Net that accurately segments tumor areas and further it improves the edge boundaries of image pixels.

- We proposed faster R-CNN that fixes the disadvantages of traditional CNN and machine learning in accurate brain tumor segmentation. It improves the accuracy and speed (fast training and testing). Training process can update once for all network layers and it does not require disk storage for feature caching.

- In feature extraction, three of types of features are extracted that are Color, Texture and Shape using Faster R-CNN algorithm and then the extracted features are increases the classification efficacy in terms of accuracy. Our proposed segmentation and classification algorithms reduce the number of false positive rate and the performance of segmentation and classification process has improved.

1.3 Paper Organization

The rest of this paper is organized as follows; Section II describes the literature survey related to brain tumor detection and classification. Section III explains the research problems which are existed in the previous works. Section IV illustrated the proposed BORSTAL-MRI research methodologies which explain the detail explanation of proposed system with pseudocode and mathematical representation. Section V explains the experimental analysis of the proposed and existing approaches. And Section VI represents the conclusion of the proposed work which includes future work also.

Literature Survey

In this section describes the concept of existing works which is related to brain tumor segmentation and classification using MRI images. It explains the research gaps in designing the efficient brain tumor detection and classification, which is explained in table 2. Brain tumor detection and segmentation was proposed and it's implemented via intensity adjustment [21]. In this work, k-means and fuzzy c-means clustering and active contour level set method was proposed for segmentation. In order to improve the segmentation, intensity enrichment and edge detection was focused in this paper. Then features are extracted namely, mean, intensity level, standard deviation, entropy, skewness, kutosis, IDM, DM, and correlation and these features are forwarded to SVM classifier which is classified into two classes as Normal and Abnormal. Limitation: Over segmentation is possible when use active contour based level set method. This should find accurate gradients to derive the contour, lack of segmentation and classification accuracy due to the weak edges and presence of noise. Active contour model was proposed for segmentation that segments the tumor part [22]. The initial level of contour for active contour model was detected using circular region around the tumor region. Before that, median filter was used to remove noisy pixels and replaces with the neighbor pixels. Further, background minimization was executed for performing morphological reconstruction (Erosion and Dilation). According to the tumor shape, circular region's radius was determined. For this, authors presented Radius Contraction and Expansion (RCE) technique which selects the initial level of contour model. Then, fuzzy c-means algorithm was used for edge pixels optimization since the active contour model boundary was determined. Gliomas brain tumor segmentation and classification was proposed [23]. CNN was proposed in this paper which extracts multiple features and visualize the outputs by means of features learning. CNN considers both local and global contextual data for segmentation and then detection. This work process the input image based on patches and also deals with the overfitting issues. Firstly, post processing step includes the skull portion and small false positives are removed. The performance was evaluated in terms of dice score coefficient (DSC), specificity and sensitivity. Limitation: The rate of accuracy for CNN is very low which does not concentrate on shape of the human brain and also structure is unpredictable. Unprocessed MRI images give poor segmentation and classification results due to loss of effective pixels and image quality was affected.

Authors [24] proposed a mesh free fractional partial differential equation using super diffusive model that locates the tumor regions more precise way. The proposed mesh free approach was applied for solving the dependency between meshes. Gaussian smoothing function was used to normalize the boundaries. For performance evaluation, three metrics are used such as Dice Coefficient, Jaccard Index, and Hausdorff Coefficient. However, Mesh free model induces high complexity that not suited for large number of images. It required choosing the arbitrary order for segmentation. This is not possible in Fractional Calculus Approach. Brain tumor detection was executed in MRI images [25]. For that purpose, abnormal tissues are segmented for the examination of disease over the brain tumor. There are four phases of works involved in this paper as follows Image Enhancement, Tumor Area Initialization, Masking Tumor Extraction and Region Refinement. For image enhancement, histogram equalization was applied which purpose is to normalize the intensity values and improves the contrast level. There are two classification methods are used for brain tumor detection as SVM and neural network. Based on the performance obtained, the proposed neural network has improved classification performance. Limitation: Feature extraction complexity is very higher, which increases the processing time. In neural network, classes are imbalanced in terms of random processing. This work was based on image patches and also patches sizes and overlapping patches are not focused in this paper. Glioma Tumor was determined using deep learning [26].

This paper was focused on severity levels computation for Glioma tumor namely, low grade and high grade. Firstly, region of interest (RoI) extraction was implemented in preprocessing step. The deep points were computed using distance function and then segmentation was invoked. Later, feature extraction was carried out by means of Information Theory. Then the classification was implemented using Deep Convolutional Neural Networks (DCNN) and training of DCNN was improved by Fractional Jaya whale Optimizer algorithm. Limitation: Segmentation was not completely suited for irregular shape and size of MRI images since it only computes the distance between pixels and does not group the similar pixel values in to a one group. DCNN based segmentation reduces accuracy since pooling operation downscales the feature size which tends to lose detailed information of image.

Brain tumor classification was implemented using hybrid feature extraction methods that uses regularized extreme learning machine [27]. Intensity normalization was implemented in this paper that range between 0 and 1. Then brain feature extraction was executed using hybrid PCA based normalized GIST descriptor. After feature extraction, brain tumor classification was implemented using RELM classifier that classifies the input into two classes as benign or malignant. Limitation: This paper does not include the spatial information of brain tumor in segmentation. Tumor boundary was not accurately segmented in this paper. In particular, in case of more thickness in input image, then boundary segmentation a based edge was not preserved. Authors [28] proposed brain tumor segmentation with different set of methods such as lesion enhancement by Weiner Filter, lesion segmentation by potential field clustering, feature extraction by LBP and GWT and classification by multiple classifiers. In lesion enhancement, Weiner Filter removes noisy pixels and enhances the region. Then potential field algorithm groups the subset of pixels and morphological operations were applied to refine the tumor segmentation areas. Next step towards segmentation is the feature extraction and then multiple classifiers are proposed for extracted feature classification. Limitation: Overall execution time is high and processing at massive size of brain tumor dataset was not possible. Selection of potential value is difficult and further local and global spatial information is not included in segmentation.

Brain tumor area was identified and classified for MRI images by means of deep learning algorithms [29]. The proposed architecture consists of Preprocessing, Skull Stripping, Segmentation, Morphological Extraction (area extraction and decision making), Feature Extraction (Mean, Entropy, Contrast and Energy) and SVM based Classification (normal and abnormal tissues). However, tumor size affects the segmentation accuracy and classification accuracy. This paper resolves this issue and also suitable for variant tumors MRI images. Limitation: This method does not suited for dynamic range of intensity images and it is very sensitive to the noise. The limitation of the proposed method is that it is very much sensitive to the noise and difficult to choose the kernel parameters in SVM. Brain tumor segmentation was performed for multimodal MRI images based sparse subspace clustering algorithm [30]. This algorithm was used to segment the non-overlapped edges in MRI image. For that sparse subspace clustering was applied to cluster data of the same class into the same subspace. The working flow of the proposed clustering is follows: (1). Input data collection, (2). Sparse Coefficient, (3). Similarity Matrix Computation and (4). Clustering Results. In order to evaluate the segmentation performance, Dice Coefficient, Jaccard, Precision and Recall are computed. However, cluster based segmentation is a time consuming task which results high complexity since weights must be optimized in this work. Authors [31] integrates various segmentation methods for brain tumor classification. They are region of interest (ROI), region growing and morphological operation (dilation and erosion). The proposed algorithm work was divided into several steps such as preprocessing (noise reduction), fuzzy c-means (region growing), and morphological edge detection (image enhancement). Shape based feature extraction was used for tumor segmentation. Limitation: This paper considers shape based features that does not sufficient for accurate tumor segmentation. FCM based segmentation does not effective. In FCM, number of clusters must be predefined and determine the membership cutoff values and clusters are very sensitive to noise and initial centroids assignment is very complex.

Table.2 Summary of related work

Reference	Concept	Algorithm	Features	Limitations
[21]	Brain tumor is detected by performing segmentation using intensity adjustment	Active contour SVM	Color, texture, shape, contrast	• Lacking segmentation and classification accuracy
[22]	Brain tumor segmentation using active contour	Active contour	Edge information	• Poor segmentation because Active contour does not consider the edge information of the images
[23]	Gliomas brain tumor segmentation using deep learning	CNN		• Poor segmentation and classification • CNN does not concentrate the shape of brain which reduces accuracy.
[24]	Brain tumor detection and segmentation using super diffusive model	Gaussian smoothing	Texture	• High complexity due to large number of images
[25]	Brain tumor detection is performed using MRI images	SVM and neural network	Color, texture, shape	• High latency during feature extraction and classification due to proposed SVM.

[26]	Glioma tumor detection using deep learning method	DCNN	Handcraft features	• Poor segmentation accuracy due to not considering the irregular shape of brain
[27]	Brain tumor detection using hybrid feature extraction model using machine learning algorithm	Hybrid PCA based GIST descriptor RELM	Spatial features	• Poor segmentation because of not considering the spatial information of brain tumor.
[28]	Brain tumor segmentation and detection using machine learning approach	LBP GWT	Texture	• High execution time • Poor segmentation due to lack of local and global spatial information
[29]	Brain tumor identification and classification using deep learning methods.	SVM	Color, texture, shape, contrast	• Not suitable for dynamic range of intensity images • Difficult to select kernels in SVM thus increase high latency
[30]	Brain tumor segmentation using clustering methods	Sparse subspace clustering	Texture	• High complexity due to perform clustering
[31]	Brain tumor segmentation and classification using MRI images	Modified fuzzy C-means	Shape	• Poor segmentation due to consider only shape features • High complexity for assigning initial centroid values during clustering.
[32]	Brain tumor segmentation and classification using DCNN and SVM	DCNN SVM	Color	• High computational complexity
[33]	Glioma grades prediction using deep learning approach	DNN DWT	Texture, shape	• Poor feature extraction because of not considering spatial information
[34]	Brain tumor segmentation and classification using SegNet	SEGNET	Spatial	• Less classification accuracy lack of features • For Multi-Segnet it takes high latency
[35]	Brain tumor segmentation and classification using k means clustering	K-means clustering SVM	Texture	• Boundary values are not informative due to the presence of noise

DCNN with fusion supported SVM algorithm was used for brain tumor segmentation and also classification [32]. Firstly, DCNN was used to train and learn the feature map, which was differentiates the image space to the tumor marker space. Trained features are forwarded to SVM for classification. Before going to segment brain tumors, data preprocessing tasks are invoked such as image registration, skull removal, and intensity normalization and offset correction. The proposed DCNN model was trained using feature extraction, forward propagation, reverse regulation, and multiple iterations. The performance was evaluated for segmentation results. However, DCNN produces high computational complexity i.e. O (N) and SVM integration requires O (logn) which increases complexity and computational processes. Authors [33] presented about the Glioma Grades Prediction by Wavelet radiomic features and deep learning algorithms i.e. deep neural network (DNN). The processes that are taken into account are Tumor Segmentation, Feature Extraction, Analysis and Classification. The DNN algorithm was integrated to the transformation such as Discrete Wavelet Transform (DWT) for powerful feature extraction. Grow Cut algorithm was used for tumor segmentation. Then, DWT was used to extract first order features, textural features and radiomic features by wavelet analysis. Finally, brain tumors classified. However, DWT based feature extraction does not focus on spatial information. However, DWT gives poor directional selection when extracting the diagonal features and also wavelet filters are real and separable. Compression time is longer and lack of shift invariance that means of small shifts in inputs causes major variations. Brain tumor disease detection was focused [34]. In particular, Glioma disease was predicted from the brain images. Firstly, this paper removes unwanted artifacts. For this purpose, fully convolutional neural network (SEGNET) was proposed which classifies four kinds of 3D modalities such as Flair, T1, T1ce and T2. Then, bias correction was introduced in this paper by using N4ITK algorithm. A decision tree based segmentation approach was proposed for segmentation and then pixel intensity and other related features are extracted from multi-modal MRI images. However this work focuses on intensity feature extraction only, which does not improve classification accuracy. Further, Segnet algorithm was used which are many times used for multiple feature extraction. Time consumption by Multi-Segnet is very high. Rough K-means Clustering Algorithm was used for brain tumor segmentation [35]. Before that, Gabor Wavelet Transform (GWT) was used for feature extraction. Then, oppositional fruit fly algorithm was used for optimal feature selection and modified kernel SVM algorithm was used for classification by two classes as Tumor and Non-Tumor. In the segmented image, the maximum accuracy rate was achieved i.e. 0.997. Limitation: when the points over the boundaries are not informative due to the presence of noise, then SVM will not work well. And in that case, it can be a computationally expensive operation.

Problem Statement

Accurate classification of brain tumor from the input MRI images is a crucial task due to differentiation of complex features. The existing approaches performed several classification techniques to accomplish the objective but those approaches possess specific problems which degraded the classification accuracy. The problems encountered in those approaches are as follows, brain tumor area was segmented using hybrid method (confidence region and contour detection) [36]. This method handles intensity variation issues and segments the tumor areas correctly. The major problems are defined as follows,

- Different artifacts presented (motion and blurring effects) in input image, which must be removed to improve the segmentation accuracy. Further, local noise, and intensity inhomogeneity problems affects the segmentation performance.
- However, the main intention for segmentation is to minimize the number of false positives that helps to diagnose the tumor areas and classify the disease accurately. This paper gives higher false positives. Further, inaccurate segmentation leads to higher classification time.

Brain tumor (Perilous Disease) was predicted, which damages human brain and also causes death [37]. This paper proposes Grab Cut method for segmentation. The main problems are listed as follows,

- Segmentation accuracy is very less since Grab Cut method incorporates irrelevant pixels in resulting segmented image. Further, grab cut require optimum user specified bounding box around the tumor area to be segmented and it only estimates the intensity distribution of the tumor image.
- Machine learning classifiers slower in brain tumor classifications due to high loss in training and validation.
- Normalization of intensity must be presented to eliminate the inhomogeneity issue.

K-means clustering algorithm was presented in which three different clusters such as Dark Cluster, Medium Cluster and Bright Cluster [38]. The main problems are defined as follows,

- Region growing method does not segment the tumor area completely, which must choose the optimum seed point for segmentation.
- It does not suit for effective segmentation when the input image is under noise, large slice thickness, anatomic complexity and variability and differentiates thin structure which consists of noise.
- In case of blurring in borders, it does not remove the noises when processing in patches. However, patch based processing does not take the complete patches of image details. Hence, this subject to low accuracy in tumor segmentation.

Brain tumor segmentation was proposed using hybrid deep autoencoder concept [39]. The major problems are defined as follows,

- MRI image contains of many artifacts such as blurriness, intensity inhomogeneity and low contrast. Hence, performing noise removal doesn't enhance the quality and also reduces the segmentation efficiency.
- Deep Autoencoder eliminates the important information from the input features. It is more sensitive in validation due to input errors in training set. Further, it waste a lot of time and also adds more complexity for producing the classification values.

Brain tumor classification was implemented in MRI images [40]. For that purpose, convolutional neural network was used to classify the input images into three classes as Meningioma, Glioma and Pitutary. The major problems of this research are defined as follows,

- This work does not suit for large number of patients. CNN was not providing the early diagnosis results. Since, tumor area must be segmented for classification. Lack of segmentation leads to huge misclassification rates. Further, CNN does not learn the temporal dependence among pixels. Training time is very high and also expensive and also testing process was very slow
- Lack of preprocessing steps such as intensity normalization, contrast level enhancement, morphological corrections decreases the segmentation accuracy and classification accuracy.

The proposed BORSTAL-MRI model is proposed to overcome the issues of the existing model to provide accurate detection of brain tumor using MRI images. (1).We presented multi-stage preprocessing methods for improving the quality of input image and White Rician noise from the MRI image is removed using fuzzy connected twin filters such as Wiener Filter and Bilateral Filter. (2). our proposed segmentation and classification algorithms reduce the number of false positive rate and the performance of segmentation and classification process has improved. (3). Segmentation accuracy is very high since Ternaus Net that accurately segments tumor areas and further it improves the edge boundaries of image pixels. (4). We proposed faster R-CNN that fixes the disadvantages of traditional CNN and machine learning. It improves the accuracy and speed (fast training and testing). (5).Training process can update once for all network layers and it does not require disk storage for feature caching. (6).We perform intensity redistribution, image quantization, noise filtering and contrast enhancement by using Dynamic Intensity Specific Variance Method, Unweighted Pair Grouping Method with Arithmetic Mean (UPGMA), Fuzzy based Wiener and Bilateral Filter and Adaptive CLAHE, respectively. (7).We focus on segmentation, feature extraction and classification by pixel based processing. This results accurate performance than patch based processing (8).MRI image artifacts are removed such as intensity inhomogeneity, blurriness and low contrast issues are addressed in this work. (9). We proposed faster R-CNN which provides fast training and testing results for n number of images. The region proposal network was fed into Faster R-CNN that taken into account a feature map and generates the anchors and classification layer classifies the feature vectors into three classes as High grade I tumor, Low Grade II tumor, and No tumor.

Proposed Work

Our work resolves the problems that are discussed in the aforementioned studies related to the brain tumor segmentation and classification in MRI image. The key goal of this work is to enhance the image quality and to attain high accuracy in segmentation and classification. The processing of our proposed work is depicted with four different layers as depicted in fig 2. To accomplish mentioned goal, we carried out four consecutive processes that are,

- Multi-Stage Preprocessing
- TernausNet based Segmentation
- Feature Extraction and Classification

Multi-Stage Preprocessing

Primarily, we perform preprocessing since MRI images contains many artifacts such as high white Rician noise, blurriness, low contrast, low Signal to Noise Ratio (SNR) and Intensity Inhomogeneity. These problems are overthrow in this step by executing three level of preprocessing.

Intensity Redistribution

At first, Intensity Redistribution is performed where intensity value of the pixel in the input images is normalized into the fixed value. In this step, intensities of all most similar neighbors are aggregated to form a normalized intensity. For normalizing the intensities "Dynamic Intensity Specific Variance" is proposed in this research.

The intensities of the pixels in the input image are found to be scattered in nature. The brain MRI images possess three major tissue features namely cerebrospinal fluid, grey matter, and white matter respectively with three different intensities which are represented as

$$In = \{In_1, In_2, In_3\} \quad (1)$$

The difference between these intensities is formulated as,

$$dif_{1,2} = In_1 - In_2 \quad (2)$$

$$dif_{2,3} = In_2 - In_3 \quad (3)$$

$$dif_{1,3} = In_1 - In_3 \quad (4)$$

The intensity specific variation weights to a finite value which can be represented as,

$$W_{ISV} = 2^{3\times s(dif_{1,2})+s(dif_{2,3})+s(dif_{1,3})} \quad (5)$$

$$s(z) = \begin{cases} 0, z > 0 \\ 1, z < 0 \\ 2, z = 0 \end{cases} \quad (6)$$

Similarly, the weight function of intensity difference variations can be computed as,

$$W_{IDV} = 2^{2-s(dif_{1,2})-s(dif_{2,3})-s(dif_{1,3})} \quad (7)$$

The ISV metric can be computed from the above equations which is represented as,

$$ISV(In) = W_{ISV} \times W_{IDV} (8)$$

This ISV metric is dynamic and changed according to the input image. Then Image Quantization is performed minimize the number of intensity values in an image. In this stage, the relationship between two pixels is evaluated. Based on the similarity deviation between pixels, the quantization is performed. The relationship function between the nodes can be formulated as,

$$\mathcal{R} = \{\mathcal{R}_i | \forall i \in \mathcal{L}\} (9)$$

Where, $\mathcal{L}$ denoted the lattice in which the pixels are present. The distance between the two pixels can be formulated as,

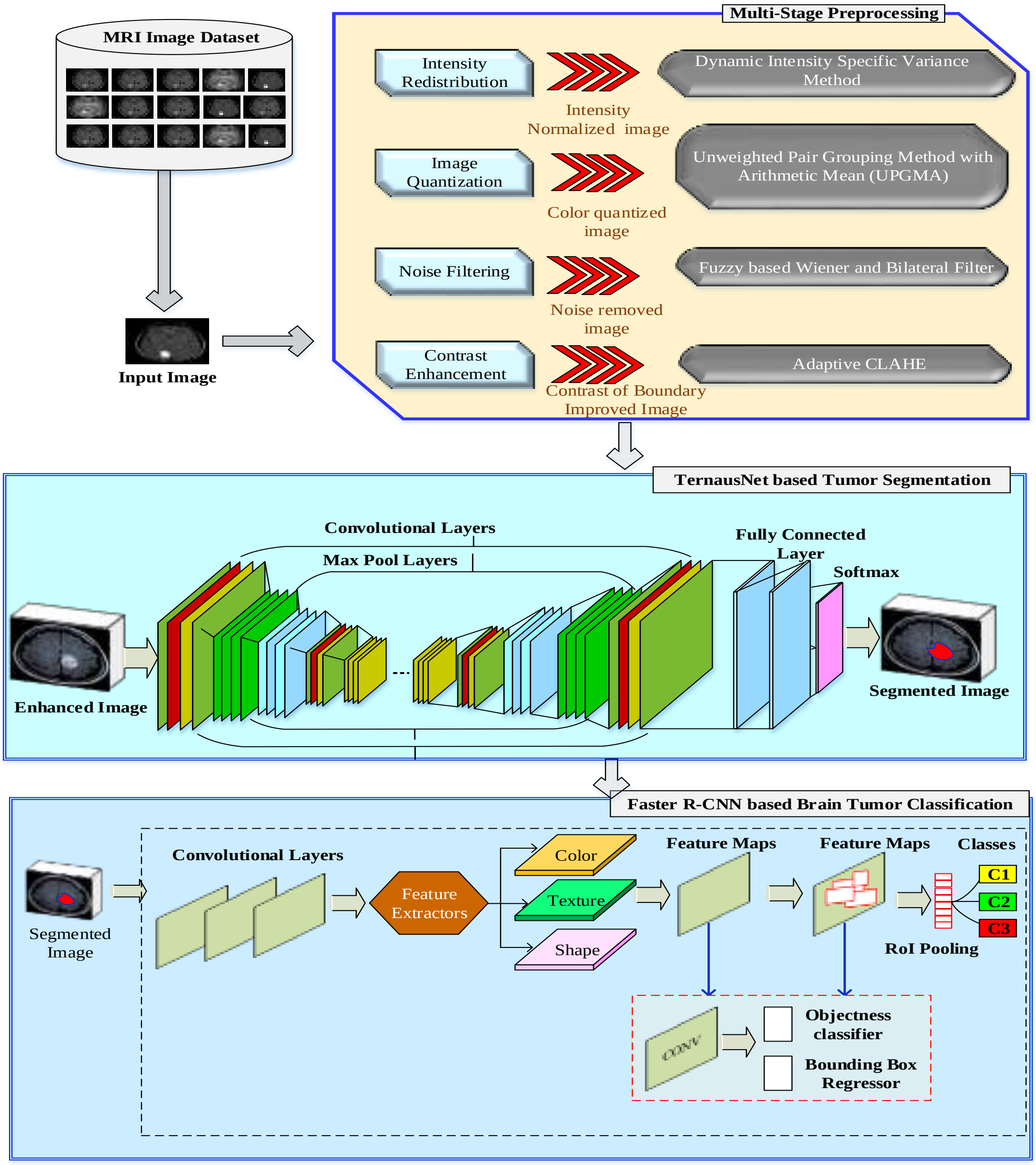


Fig.2. Proposed BORSTAL-MRI Model

$$D = \sqrt{(q_2(i,j) - q_1(i,j))^2 + (p_2(i,j) - p_1(i,j))^2} \quad (10)$$

Where $(p_1(i,j),\ q_1(i,j))$ and $(p_2(i,j),\ q_2(i,j))$ be the coordinates of the two pixels respectively. The intensity values are replaced with the center values and create a new intensity. Fig.3 (a) and (b) depicts the intensities of pixels before and after normalization.

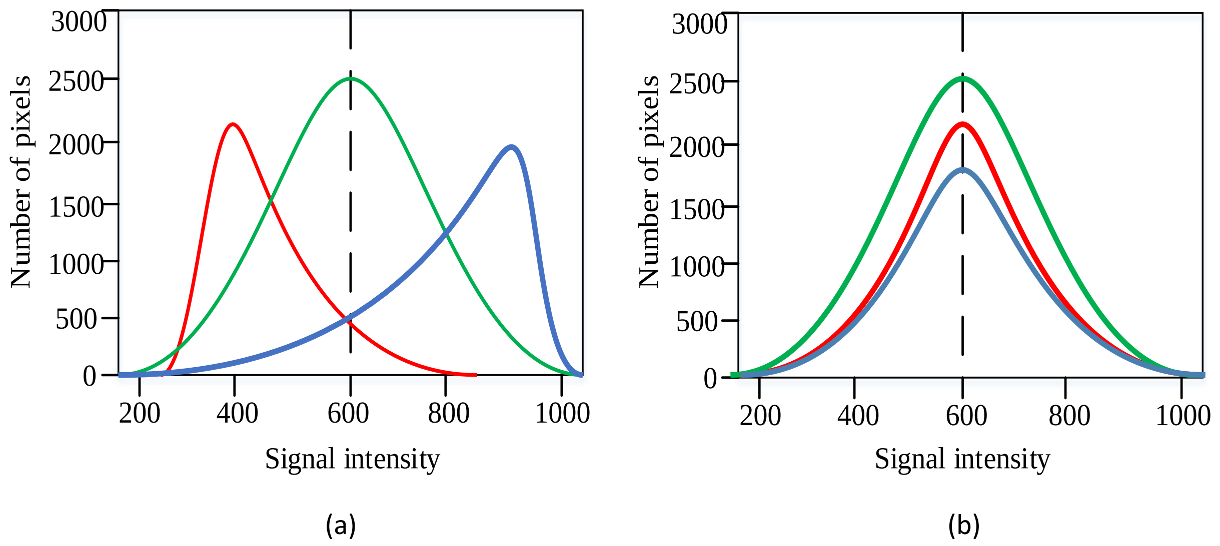


Fig.3 (a) pixel intensities before normalization, (b) pixel intensities after normalization

Noise Removal

Noise Removal is performed to removing the white Rician noise which adopts Fuzzy based Wiener and Bilateral Filter algorithm. Initially the wiener filter is proposed to simultaneously reduce the noise and blur in the input image which can be formulated as,

$$\mathcal{H} = \frac{G^*}{|G|^2+U} \quad (11)$$

Where $U = {}^{1}/_{SNR}$ (12)

The notations, $G$and G^* denote the function of degradation and its complex conjugate respectively. The output image is then fed into the bilateral filter in order to perform smoothing of image by removing the noise and preserving the edges. This can be formulated as,

$$Bf(M) = \frac{1}{W}\sum_{q\in N(p)} GSD(\|P-Q\|)PVD(|Mp-Mq|)Mq \quad (13)$$

Where PVD and GSD denote the on pixel value difference and Gaussian spatial distance respectively. The fuzzy based restoration of noise free image is performed to achieve preservation of details. The fuzzy membership function is constructed as a trapezoidal model which can be represented as,

$$Fz(a;u,v,x,y) = \begin{cases} 0\,, if a \le u \\ \frac{a-u}{v-u}, if u \le a \le v \\ 1, if v \le a \le x \\ \frac{y-a}{y-x}, if x \le a \le y \\ 0, if y \le a \end{cases} \quad (14)$$

Where a denotes the input vector, u, v, x, y denote the scalar parameters used to locate the feet and shoulder of the trapezoidal model. These parameters can be formulated as,

$$u = t_1 \times min\{\lambda_i, \lambda_g\} \quad (15)$$

$$v = t_2 \times max\{\lambda_i, \lambda_g\} \quad (16)$$

$$x = t_3 \times v \quad (17)$$

$$y = t_4 \times x \quad (18)$$

Wheret_1, t_2, t_3, t_4 denote the adaptable parameters and λ_i *and* λ_g represent mean of neighborhood in pixel i and mean of image containing noise. Here, fuzzy weight is adaptively changed based on the noise estimated. In addition, it also smoothen the image with the aid of the Noise Variance metric.

Contrast Enhancement

Contrast Enhancement is the final stage of pre-processing which is carried out by Adaptive based CLAHE (A-CLAHE) algorithm. It enhances the contrast and also removes blurriness of the image. The A-CLAHE overcomes the limitations of conventional CLAHE algorithm in which the block size and clip limit is adaptively changed based on the information such as edge details from the image. The process of bilinear interpolation for A-CLAHE is shown in fig 4. The stages involved in enhancement of contrast using A-CLAHE are as follows,

Stage-I: Initially, the output image obtained from the noise removal process is partitioned into non-overlapping regions of equal sizes. These regions are referred into three groups' namely inner region, border region and corner region respectively based on the position.

Stage-II: Compute histogram for each region and perform clipping of histogram based on the clip limit which is determined adaptively in order to compute the cumulative distribution function.

Stage-III: The implementation of bilinear interpolation is carried out to perform mapping of grid points in each pixel based on the computed cumulative distribution function.

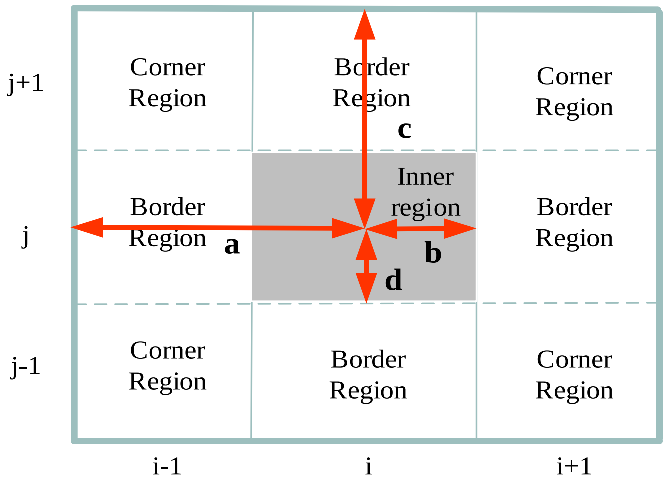


Fig.4 Bilinear interpolation for A-CLAHE

The clip limit γ can be computed as,

$$\gamma = \frac{NP_x}{GL}\left(1 + \frac{\beta}{100}(Sl_{max} - 1)\right) \quad (19)$$

Where Sl_{max} denote the maximum slope of the transformation and β denote the clipping coefficient. The number of pixels and grey scale is denoted as NP_x and GL respectively. After mapping of transformed value of the pixel Pt_{new} is expressed as,

$$Pt_{new} = \frac{d}{c+d}\left(\frac{b}{a+b}m_{i-1,j-1}(Pt_{old}) + \frac{a}{a+b}m_{i,j-1}(Pt_{old})\right) + \frac{c}{c+d}\left(\frac{b}{a+b}m_{i-1,j}(Pt_{old}) + \frac{a}{a+b}m_{i,j}(Pt_{old})\right)$$
(20)

Where $m_{i,j}$ denote the pixel's mapping function in the region of(i,j). This distributes the histogram equally in the image thereby achieving enhanced quality. By performing these processes in preprocessing improves the quality of the MRI brain image. As a result, efficiency of the upcoming processes i.e. segmentation and classification is increased.

Pseudocode: Pre-processing

1. Input: Brain MRI images $\{img_1, img_2, \ldots\ldots img_n\}$
2. Output : Preprocessed image
3. Begin
4. {
5. For every image do
6. // Intensity redistribution
7. Determine the initial intensities (In) of pixels
8. Compute W_{ISV} and W_{IDV}using eqn () and eqn()
9. Calculate the ISV metric using eqn ()
10. Perform intensity normalization from pixel similarities
11. //Noise removal
12. Initialize the degradation function
13. Execute wiener filtering based removal of rician noise
14. Compute PVD and GSD to adopt bilinear filtering
15. Compute u
16. Compute v
17. Compute x
18. Compute y
19. Perform smoothening by computed fuzzy weights
20. //Contrast enhancement
21. Partitioning of image into equal regions CR, IR, BR
22. Determine the dynamic clip limit using eqn ()
23. Perform bilinear interpolation
24. Compute new pixel Pt_{new} by using eqn()
25. end for
26. }
27. Return the enhanced image

B. TernausNet Based Segmentation

We propose novel algorithm named TernausNet which performs better in tumor segmentation compared to the existing CNN algorithms. TernausNet accurately segments the tumor region with the aid of three layers that down block, up block and soft max layer. It follows semantic segmentation which understands the MRI image in pixel level. The combination of U-Net with VGG11 encoder is known as TernausNet. The

U-Net architecture consists of path contraction for capturing the context which enables the precise localization of the preprocessed images. The contraction path includes the architecture of convolutional layer, alternating convolution and pooling operation and downsampling which is perfumed in down block. Each step in the path contraction includes the feature map upsampling monitored by convolution which is performed in upblock. For localization upsample features are combines with high resolution features from the skip connection. Then the output provided as mask imaged which shows the class of every pixels. For improving the performance of the traditional U-Net we proposed pre-trained encoders. TernausNet is includes the modified U-Net which means it relatively simple pre-trained VGG11 encoder architecture. The proposed VGG11 encoder includes 7 convolutional layers each convolution layer perform based on the ReLU activation function. It includes five max pool layers each layer reduces the feature map by 2. Every convolutional layer has 3×3 kernels. First convolutional layer provides 64 channels and then the next layers provide double of the first layer until reach 512. For constructing encoder we need to remove the fully connected layer and replace with a single convolution layer of 512 channels. The upsampling process is performing at 5 times with 5 max pooling.

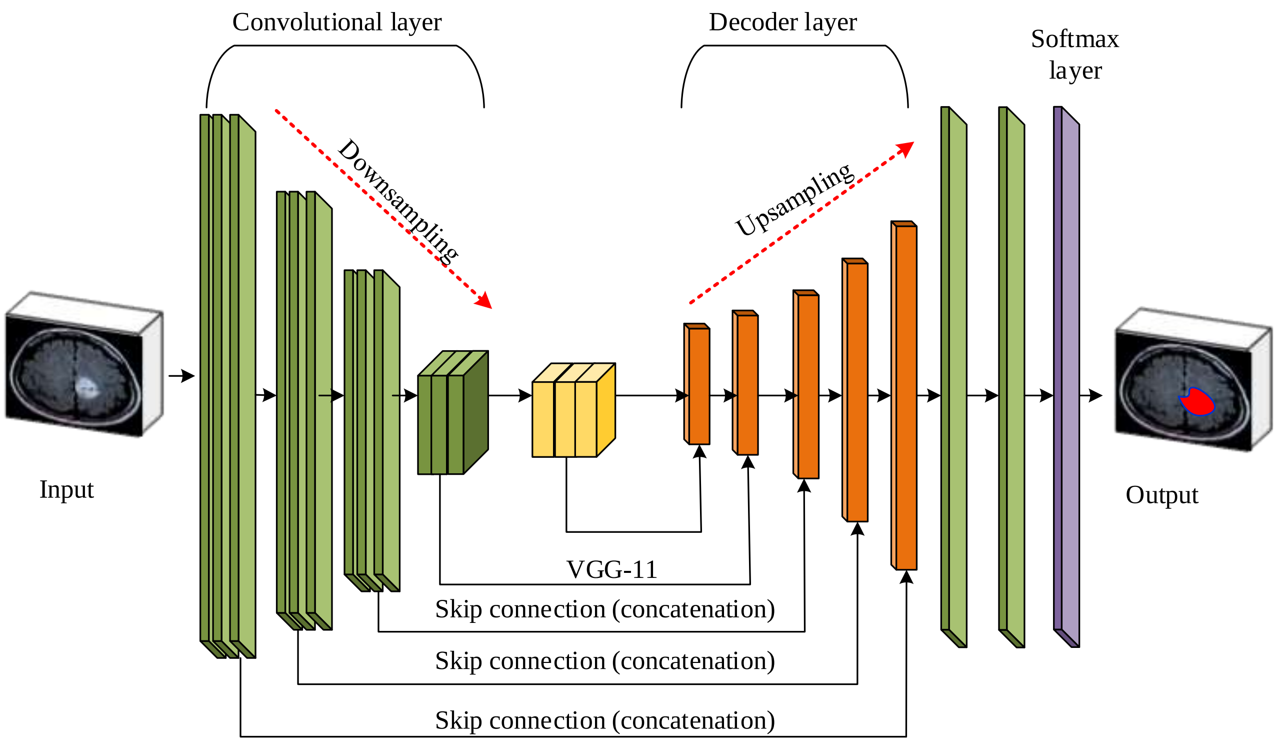


Fig.5 Architecture of TernausNet

Finally the softmax layer provides the segmented image for brain tumor. Hence, proposed TernausNet attains higher accuracy in segmentation compared to the patch level segmentation algorithm. The jaccard index is used as the evaluation metric. It is used to measure the similarity between the finite amount input images sets. For example we consider two sets such as C and D which is defined as follows,

$$J(C,D) = \frac{|C \cap D|}{|C \cup D|} = \frac{|C \cap D|}{|C| + |D| - |C \cap D|} \quad (21)$$

Each and every images consist number of pixels, the last expression to discrete the object which is defined as follows,

$$J = \frac{1}{n} \sum_{i=1}^{n} \left(\frac{x_i \hat{x}_i}{x_i + \hat{x}_i - x_i \hat{x}_i} \right) \quad (22)$$

Where x_i represent the binary value of the pixel and $\hat{x}_i$ represent the predicted probability. Hence we consider image segmentation process with respect to the pixel of the images. Then we calculate the loss function for binary segmentation. Binary cross entropy which is defined as follows,

$$\rho = -\frac{1}{n}\sum_{i=1}^{n}(x_i \log \hat{x}_i + (1 - x_i)\log(1 - \hat{x}_i))(23)$$

Then the loss function is calculated as follows,

$$L = \rho - \log J(24)$$

By minimizing the loss function we have increased the predicted or segmented region from the images. The objective of the proposed TernausNet is to detect the segment or affected area. For different loss function the threshold value is different from zero to one. Then multiply 255 for every pixel in an output images then we get a block and white segment image. The segment image represents the affected area which means the tumor region. Fig 5 represents the architecture of the proposed TernausNet.

C. Feature extraction and Classification

In feature extraction, three types of features are extracted that is Color, Texture and Shape. This way of feature extraction increases the classification efficacy in terms of accuracy. The features extraction is performed by using the ResNet based Feature Pyramid Network (Res-FPN) which utilizes the integrated feature semantic mapping to obtain an attention map in order to balance the original features. The proposed algorithm performs better compared to other machine learning algorithm. Finally, the Region Proposal Network (RPN) based bounding box formation is implemented to classifies brain tumor into three classes as Highly Tumor, Low Tumor and No Tumor. The accuracy of classification is improved by implementing a CR loss function which optimizes the size of the bounding boxes.

The purpose of implementing ResFPN is to identify the complex features of tumor from the hierarchical placement of CNN. The top-down and bottom-up approaches were adopted to generate the feature maps of tumor with diffrenent sizes. These feature maps are then fused to obtain the semantic information. The number of convolutional layers in ResFPN is assumed to be NC and the outputs of the convolutional layers be denoted as $\{Cn_2, Cn_3, Cn_4, Cn_5\}$ and the features extracted from those layers be denotes as $\{Fn_2, Fn_3, Fn_4, Fn_5\}$. The fusion of these feature maps is carried out which can be formulated as,

$$F_I = \frac{1}{NC}\sum_{nc=nc_{min}}^{nc_{max}} F_{nc} \quad (25)$$

This fused feature map is then fed into the attention block in order to eliminate the unwanted information which affects the classification. The attention block comprising of a multilayer perceptron is implemented to extract the texture information and shape information to construct the attention map. The attention map can be formulated as,

$$A_m = (1 + TI_m \otimes SI_m) \otimes F_I \quad (26)$$

The output obtained from the attention map is represented as $\{Am_2, Am_3, Am_4, Am_5\}$ which is further concatenated with the output of convolutions layers $\{Cn_2, Cn_3, Cn_4, Cn_5\}$ to obtain the final output $\{Kn_2, Kn_3, Kn_4, Kn_5\}$ which comprises of the enhanced feature set. The above obtained final output is utilized as the input for the proposed RPN to achieve the 4k and 2k output of regression and classification layers respectively. The CR loss function for the regrassion and classification layers is expressed as,

$L^T = \frac{1}{N_{cf}} \sum_i L_{cf}(Kn_i, Kn_i^*) + \mu \frac{1}{N_{rg}} \; Kn_i^* L_{cr}(h_i, h_i^*)$(27)

Where $L_{cr}(h_i, h_i^*) = S_{nc1}(h_i, h_i^*) + \frac{Rc(b_i, b_i^{gt})}{Rc_i'}$(28)

The $L_{cr}(h_i, h_i^*)$ denote the center point of rectangle loss function in which h_i and h_i^* denote the predicted anchor box and grounf truth anchor box coordinate vectors respectively. The $S_{nc1}(h_i, h_i^*)$ denote the smooth loss and $Rc(b_i, b_i^{gt})$ denote the center point of rectangle. The feature maps generated by the RoI pooling are led into the fully connected layer and softmax layer for future classification of tumor which is shown in fig 6.

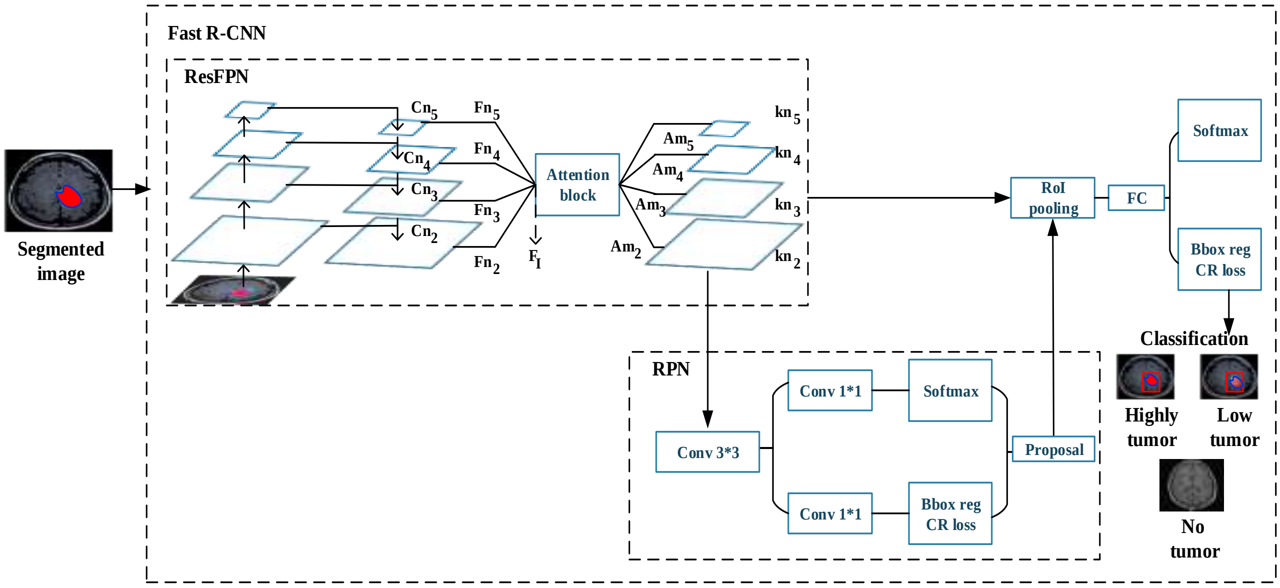


Fig.6 FRCNN based classification of brain tumorExperimental Study

The experimental analysis of our BORSTAL-MRI model is presented in this section. The experimental analysis proved that our proposed model achieves superior performance compared to the existing work. This section includes three sub sections such as simulation study, comparative analysis and research summary.

A. Simulation Setup

The simulation is conducted by matlab with version R2020a simulation tool. Table illustrates the system requirements which includes both software and hardware requirements.

Table.3 System Requirements

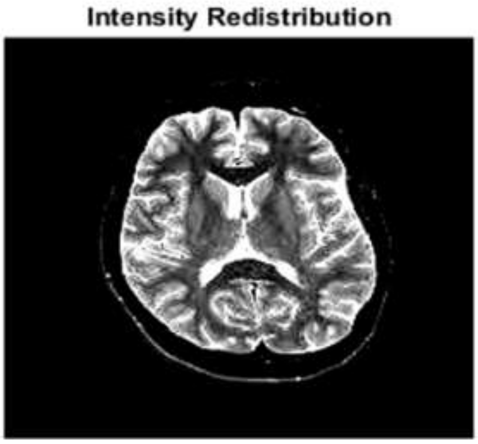
Software Requirements	Matlab	R2020a
	OS	Windows 10 pro

Hardware requirements	RAM	8GB
	CPU	Intel core
	Hard disk	1TB
	Processor	2.90GHZ

Fig 7 represents the process of preprocessing which includes intensity redistribution, image quantization, and noise filtering and contrast enhancement. In intensity redistribution we normalize the input image intensity by using the Dynamic Intensity Specific Variance method. Then image quantization we using Unweighted Pair Grouping Method with Arithmetic Mean to minimize the number of intensity values in an input image. And noise filtering we performed to remove the white rician noise by using Fuzzy based Wiener and Bilateral Filter algorithm. To enhance the contrast and remove blurriness of the image by using Adaptive based CLAHE (A-CLAHE).

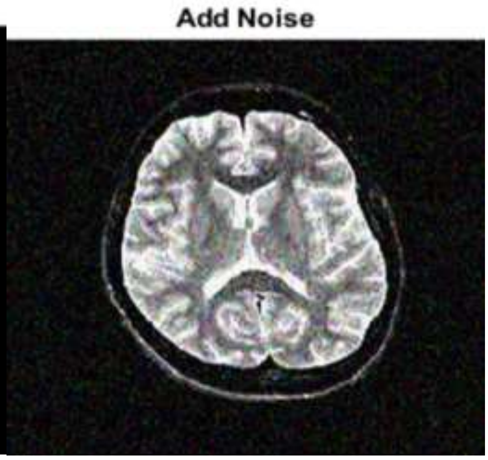
Fig 8 represents the architecture of proposed TernausNet which is used to segment the tumor region. This process is used to increase the performance of feature extraction and classification.

(a)

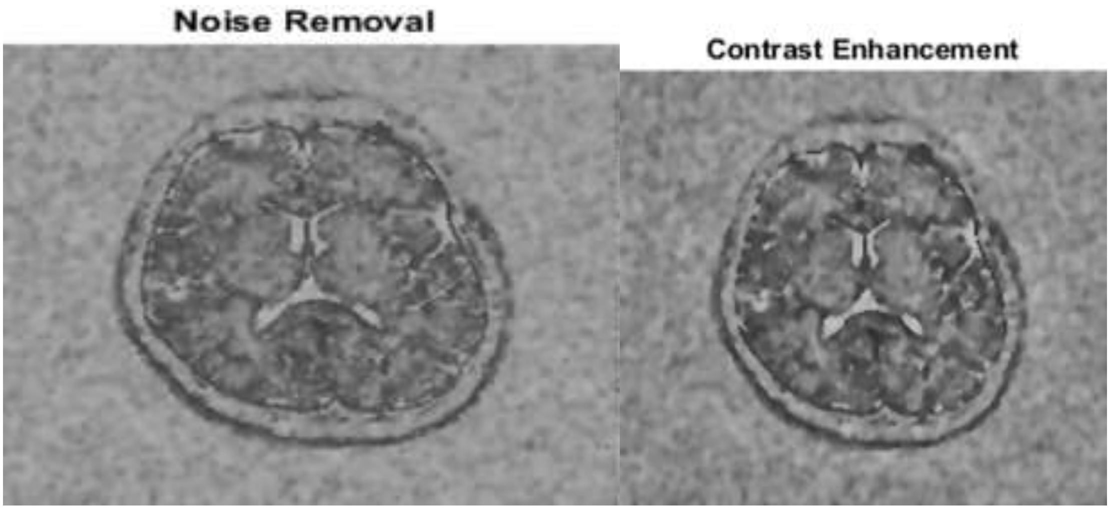


(b)

(c)



(d)



(e) (f)

Fig.7 Steps of preprocessing (a)Input image (b) Intensity redistribution (c) image quantization (d) add noise (e) noise removal (f) contrast enhancement.

Fig 9 represents the architecture of proposed Faster R-CNN which is used for feature extraction and classification. Here we extract color, shape and texture features for detecting the brain tumor in MRI images.Fig 10 represents the output of feature extraction process. The Faster R-CNN extract the color features such as variance, mean, standard deviation, skewness and kurtosis, and extract shape features such as area, perimeter, solidity, density, and extract texture features such as contrast, correlation, entropy, homogeneity and energy.

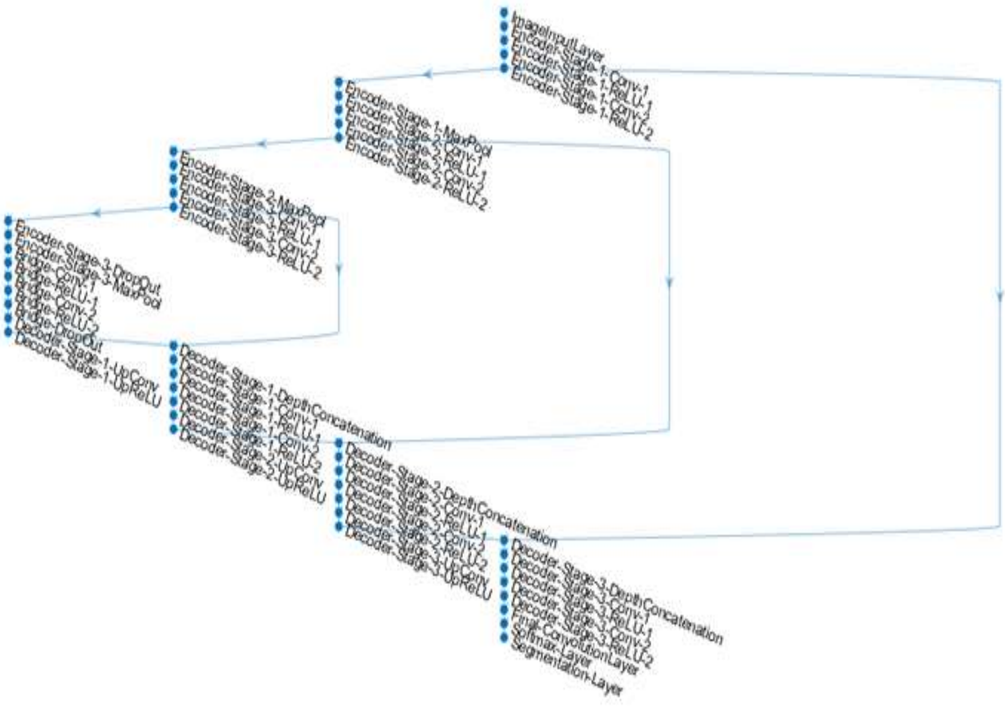


Fig.8 Architecture of TernausNet

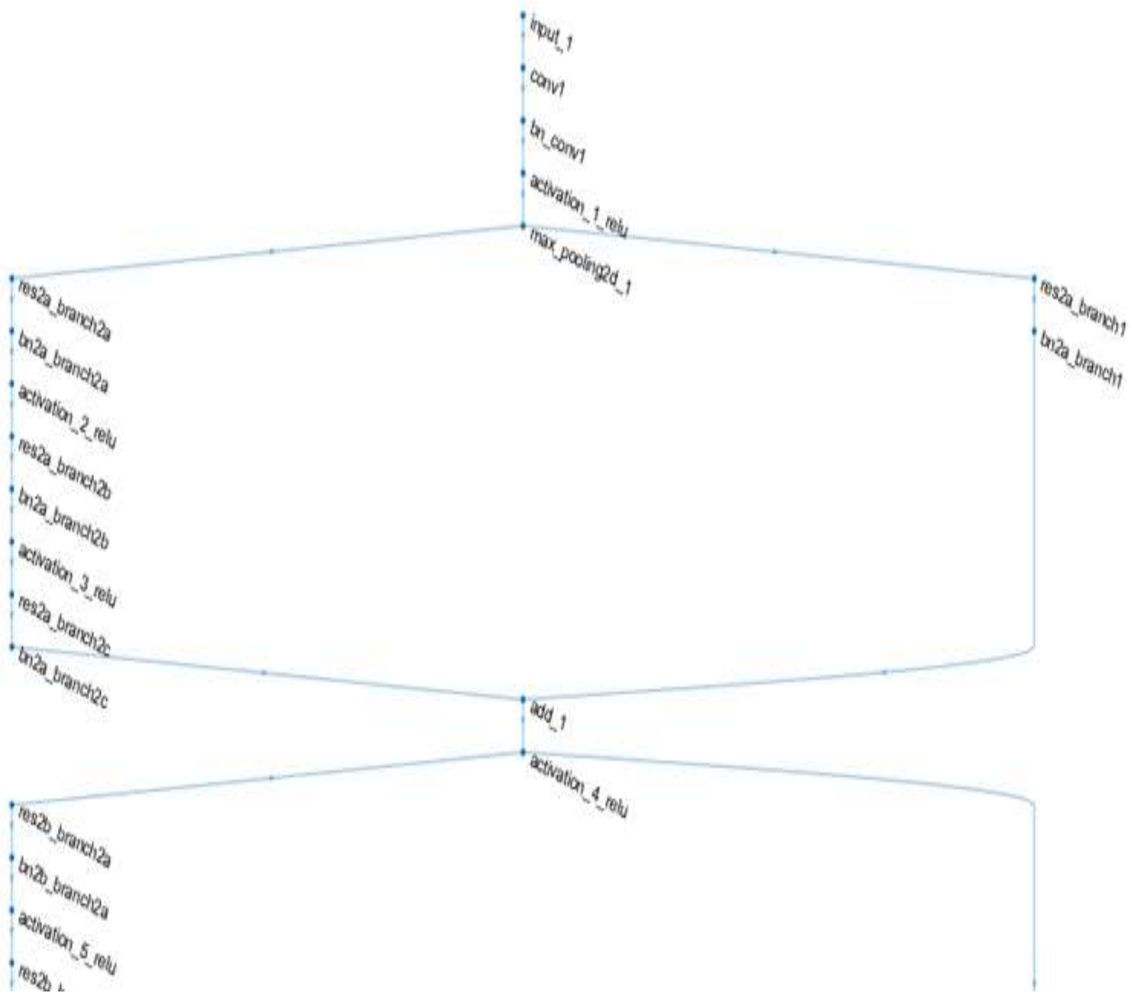


Fig.9 Architecture of Faster R-CNN

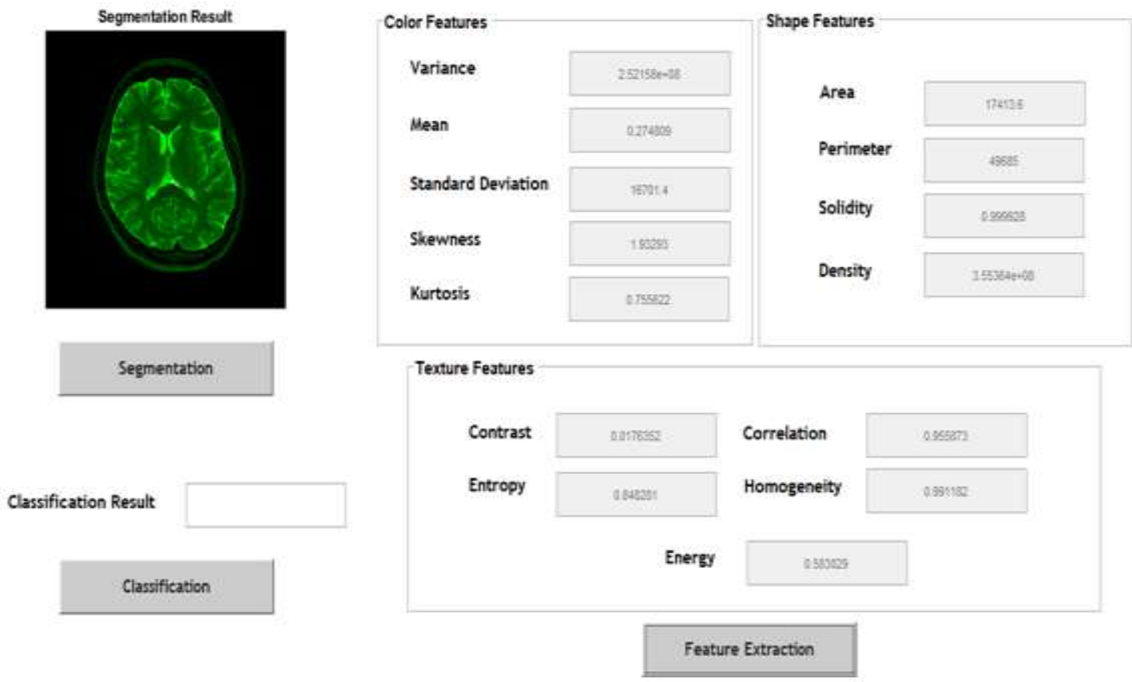


Fig.10 Result of feature extraction

B. Comparative Analysis

The Proposed BORSTAL-MRI model is evaluated by comparing with the existing approaches such as BTC-BFC [39], HSM-TI [36], and BTD-DL [37] in terms of performance metrics such as PSNR, SSIM, MSE, Error Rate, Foreground Precision, Background Precision, Dice Similarity, Accuracy, Specificity, Sensitivity, and AUC.

The proposed BORSTAL-MRI model is evaluated by BRATS 2013 dataset, which is available in BRATS. Thus dataset contains 4 MRI for training which is T1, T2, T1c and T2flair sequences for each patient. The dataset has many training images such as 10 Low grade gliomas (LGG), 20 high grade gliomas (HGG) three dimensional images which consist two 155 two-dimensional slices for each. The training images are used to provide the output labels. This dataset has four types of tumor images such as core tumor, necrosis, edema, enhancing tumor and non-enhancing tumor.

a. Impact of PSNR

This metric is used to calculate the value between the maximum possible signal power and noise corrupting power. It is used to evaluate the quality of the images. This metric is calculated as the function of MSE between original and received images. The PSNR value is calculated as follows,

$$PSNR = 10log_{10}\left(\frac{P_{Max}^2}{MSE}\right) dB \quad (29)$$

Where, P_{Max}^2 represent the image maximum pixel intensity value and MSE represent the mean square error.Fig 11 represent the comparison of proposed and existing PSNR values with respect to noise level. The figure shows that the proposed model achieves high PSNR compared to existing model, by removing White Rician Noise using fuzzy based wiener and bilateral filter for removing noise for both linear and nonlinear images respectively. The fuzzy weight is adaptively changed based on the presence of SNR. We integrate two filters for removing noise which increase image quality. A-CLAHE method is used to increase the contrast value of the images which also increase the quality of the images.

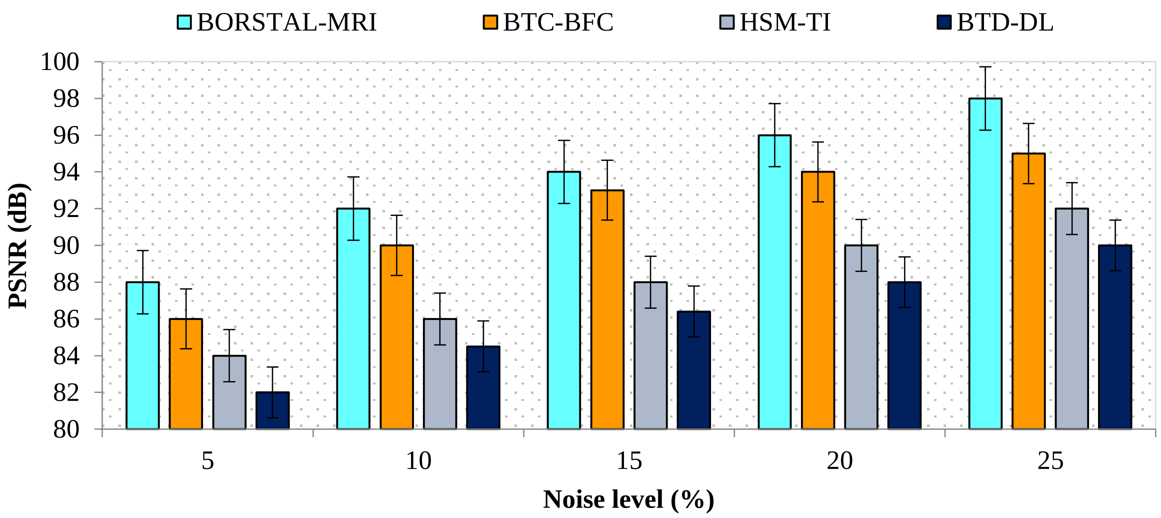


Fig.11 Noise level vs. PSNR

In our BOSTRAL-MRI method achieves high accuracy compared to existing methods. The proposed method achieves 10 db higher than BTD model and 8db higher than the HSM-TI model and 6db higher than BTC-BFC model.

b. Impact of SSIM

SSIM stands for Structural Similarity Index which calculates image quality degradation affected by preprocessing. It is used to calculate the similarity between two images. The SSIM measures the luminance, contrast and structure of the images for detecting the similarity. The value of SSIM is calculated as follows,

$$SSIM(u,v) = [s(u,v)^{\alpha}.t(u,v)^{\beta}.q(u,v)^{\gamma}] \quad (30)$$

Where, s represent local means and t represent cross covariance and q represent standard deviation for image u,v. Fig 12 represents the comparison of proposed and existing SSIM value with respect to noise level. From the comparison result the figure shows that our proposed BORSTRAL-MRI achieves high SSIM compared to existing work. In our BORSTAL-MRI method has high SSIM by performing four types of preprocessing, which improves the similarity value between two images. The SSIM value is calculated based on the luminance, contrast and structure. Here, A-CLAHE method is used for improving contrast and luminance of the images by reducing the noise from the images.

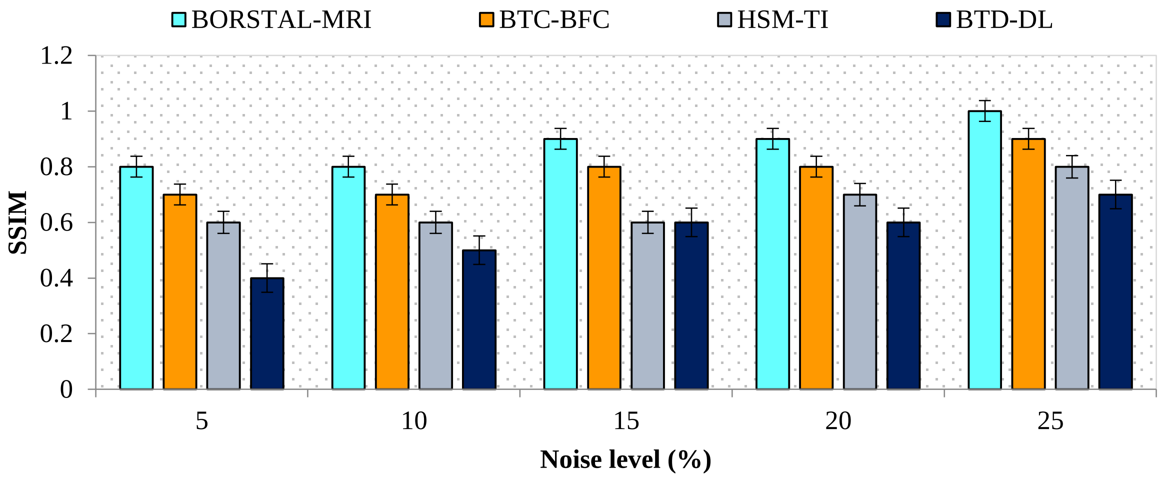


Fig.12 Noise level vs. SSIM

Hence our method has high similarity compared to other existing methods. Our BORSTAL-MRI increase 0.3%higher than BTD-DL and 0.2% higher than HSM-TI and 0.15% higher than BTC-BFC.

c. Impact of MSE

MSE stands for Mean Sqaure Error which is used to measure the image compression quality. It represents the cumulative error between the compressed image and original image. If the system has low MSE then it also has low error, thus improve the quality of the images which increase segmentation and detection accuracy.

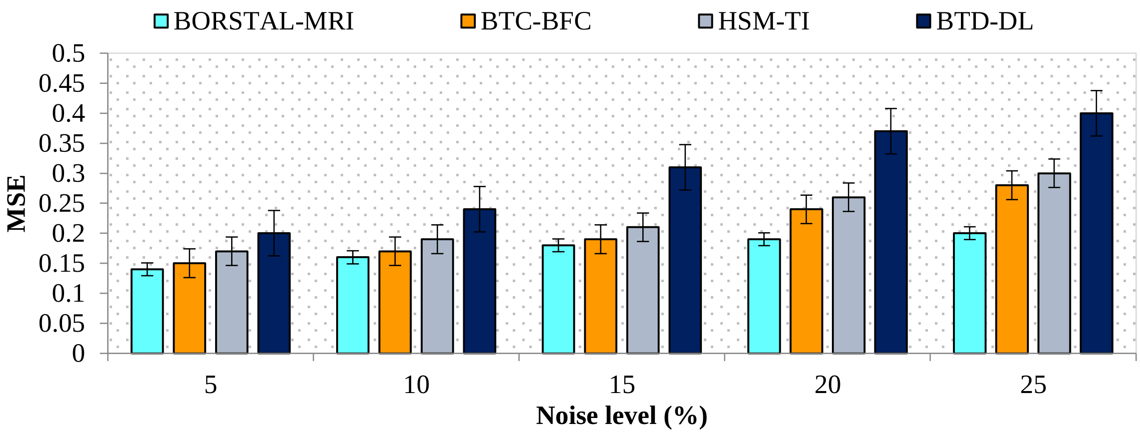


Fig.13 Noise level vs. MSE

Fig 13 represent the comparison of proposed and existing MSE values with respect to noise level. The figure clearly states the proposed BOSTRAL-MRI achieves high low MSE compared to existing models. Our BOSTRAL-MRI has low MSE by performing preprocessing, TernausNet based segmentation, feature extraction and classification. In preprocessing we performed intensity redistribution, image quantization, noise filtering and contrast enhancement. The overall preprocessing method improves the quality of the images thus increase segmentation accuracy. And segmentation is performing by TernausNet algorithm which accurately segments the tumor. This segmentation process increase segmentation accuracy compared to patch level segmentation algorithm. The segmentation process increases the detection accuracy by extract optimal features from the segmented region. Faster RCNN is used for feature extraction and classification, in which the color, textured and shape features are extracted for tumor detection. By this way we increase high accuracy and reduce cumulative error in brain tumor detection. The proposed BORSTAL-MRI reduces 0.2% compared to existing model.

d. Impact of Error rate

This metric is used to calculate the error rate in brain tumor detection. If the system has low MSE then it also has low error rate.

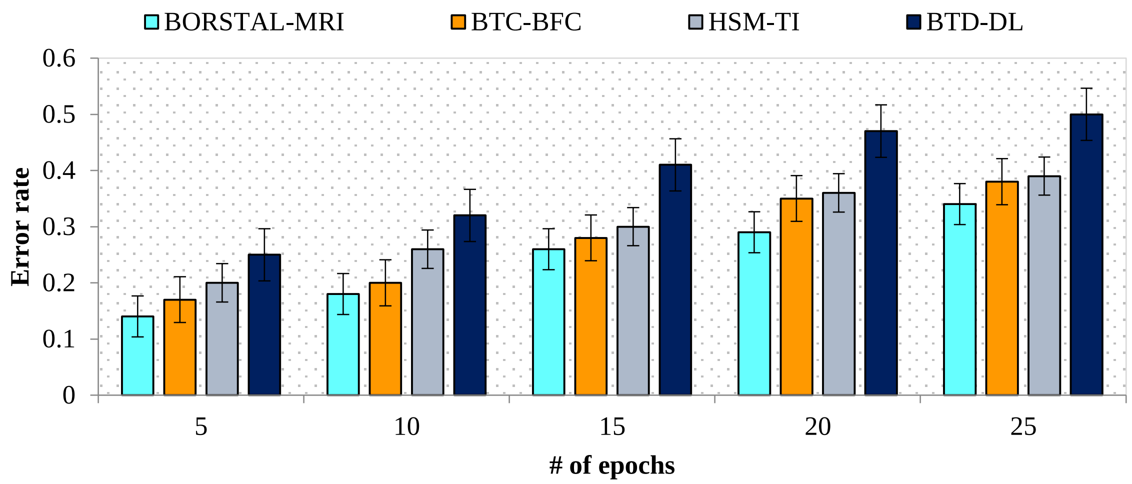


Fig.14 Number of epochs vs. error rate

Fig 14 represents the comparison of proposed and existing error rate with respect to number of epochs. The error rate is increased exponentially with the increasing number of epochs. Form the comparison result the proposed BORSTAL-MRI has less error rate compared to existing model. The error is occurring due to the presence of noise, blurriness, low contrast, and low intensity and without performing segmentation. In our work, performs preprocessing, segmentation, feature extraction and classification which increase detection accuracy. Segment the affected region and extract the features from the tumor region which reduces error rate. In existing work does not perform segmentation and the features are extracted from the images thus reduces detection accuracy and increase false positive rate and error rate compare to our proposed BORSTAL-MRI.

e. Impact of Foreground Precision

This metric is used to evaluate the correctness of obtaining foreground images during image segmentation and feature extraction. By extracting the features from the foreground is a challenging task because it is not uniform in shape, color and texture, because it has the reflection of camera flash and illumination changes in histograms. Fig 15 represents the comparison of proposed and existing model foreground precision with respect to number of epochs. The fig clearly states that the proposed BORSTAL-MRI model achieves high foreground precision compared to existing model, because we perform A-CLAHE method for contrast enhancement which increase contrast and remove blurriness and correct the illumination correction of the images. This process increases the foreground precision accuracy compared to the existing model. But existing model use some low quality images for brain tumor detection thus reduces foreground precision accuracy and increase false alarm rate. Our proposed BORSTAL-MRI achieves 0.34% higher than BTD-DL model and 0.26% higher than HSM-TI model and 0.12% higher than BTC-BFC.

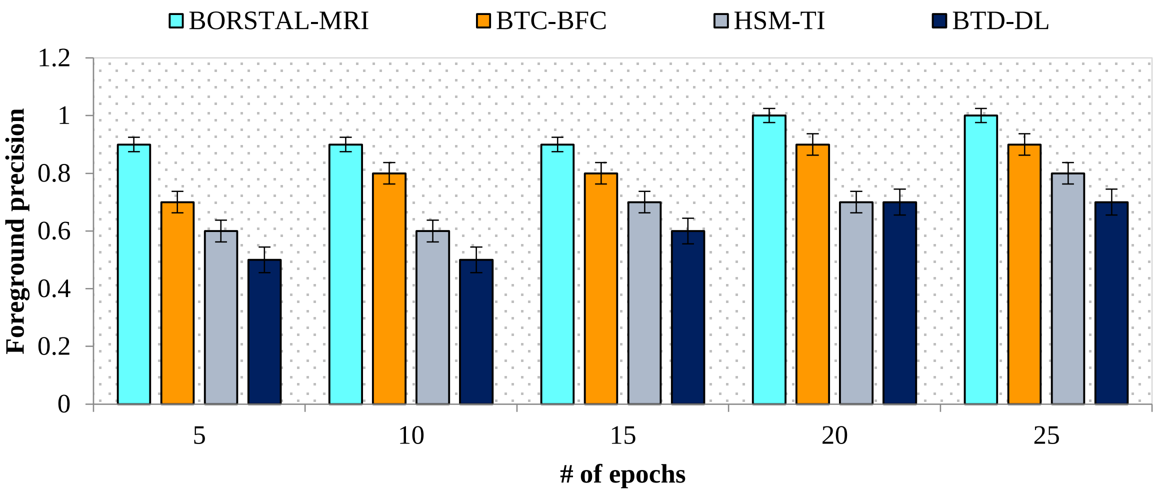


Fig.15 Number of epochs vs. foreground precision

f. Impact of Background Precision

This metric is used to evaluate the correctness of obtaining background images during image segmentation and feature extraction. It is more similar than the foreground images. If the similarity of foreground and background is high then the system has high background precision.

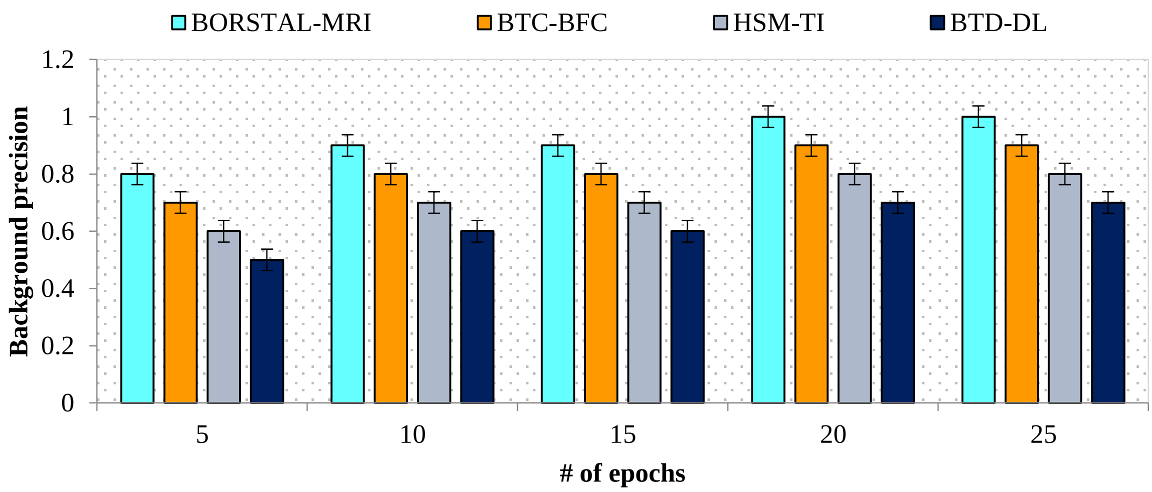


Fig.16 Number of epochs vs. background precision

Fig 16 represents the comparison of proposed and existing model background precision with respect to number of epochs. The fig clearly states that the proposed BORSTAL-MRI model achieves high background precision compared to existing model, because we perform A-CLAHE method for contrast enhancement which increase contrast and remove blurriness and correct the illumination correction of the images. The similarity is calculated between foreground and background images which increase the overall precision value of the proposed model. This process increases the background precision accuracy compared to the existing model. But existing model use some low contrast enhancement technique thus reduces the contrast and quality of the images which reduces the background precision accuracy and increase false alarm rate. Our proposed BORSTAL-MRI achieves 0.31% higher than BTD-DL model and 0.20% higher than HSM-TI model and 0.9% higher than BTC-BFC.

g. Impact of Dice Similarity

This metric is used to evaluate the spatial overlap index during segmentation. It is calculated based on overlap between two pair of segmentation result. This metric is used to evaluate the accuracy of segmentation results. If one system has high dice similarity then it has high segmentation accuracy.

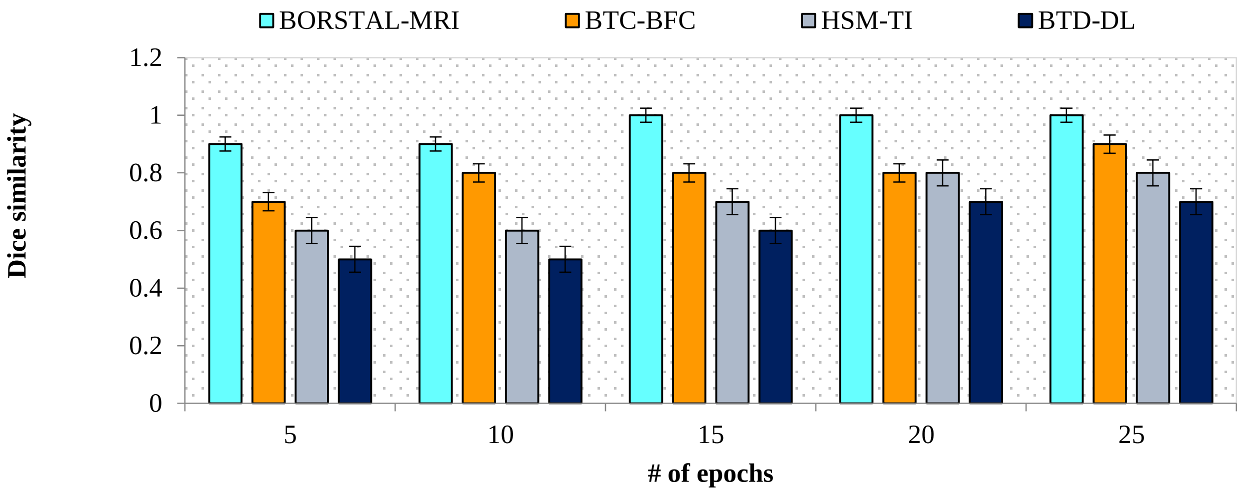


Fig.17 Number of epochs vs. dice similarity

Fig 17 represents the comparison of proposed and existing model dice similarity with respect to number of epochs. The comparison result shows that the proposed model achieves high dice similarity compared to existing work, which means the proposed work has high segmentation accuracy. For segmentation we proposed TernausNet algorithm which performs better than existing CNN method. Here, we perform pixel wise segmentation thus increase high segmentation because it segment the images into pixel by pixel. But existing work performs segmentation using patch wise manner thus reduces the accuracy compared to pixel level segmentation. In sometimes the patch wise segmentation missed the edge level of the region thus reduces segmentation accuracy and increase false alarm rate. In our proposed work perform pixel wise segmentation which covers all the pixels in the images that segment the affected region accurately which increase segmentation and detection accuracy.

h. Impact of Accuracy

This metric is used to evaluate the accuracy which represents the correctly classified samples from the total sample. It is calculated as follows,

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (31)$$

Where, TP represent true positive rate and TN represent true negative and FP represent false positive rate and FN represent false negative rate. Fig 18 represents the comparison of accuracy for both proposed and existing model with respect to number of epochs. From the comparison result the proposed BORSTAL-MRI model achieves high accuracy compared to existing work. Because we proposed efficient preprocessing for removing noise, blurriness, low intensity and so on, from the images for improving image quality. The preprocessed image has high quality it will be used for further process for brain tumor detection. The segmentation process is used to detect or segment the affected region thus increase feature extraction and classification performance. Segmentation improves the detection accuracy and reduces false positive rate. The features (color, shape and texture) are extracted from the segmented region for detecting brain tumor. For that we proposed Faster RCNN algorithm which improves the efficiency of the proposed work in terms of detection and classification accuracy. The proposed BORSTRL-MRI method improves 0.30 % high accuracy compared to BTD-DL model and 0.24% higher than HSM-TI and 0.16% higher than BTC-BFC model.

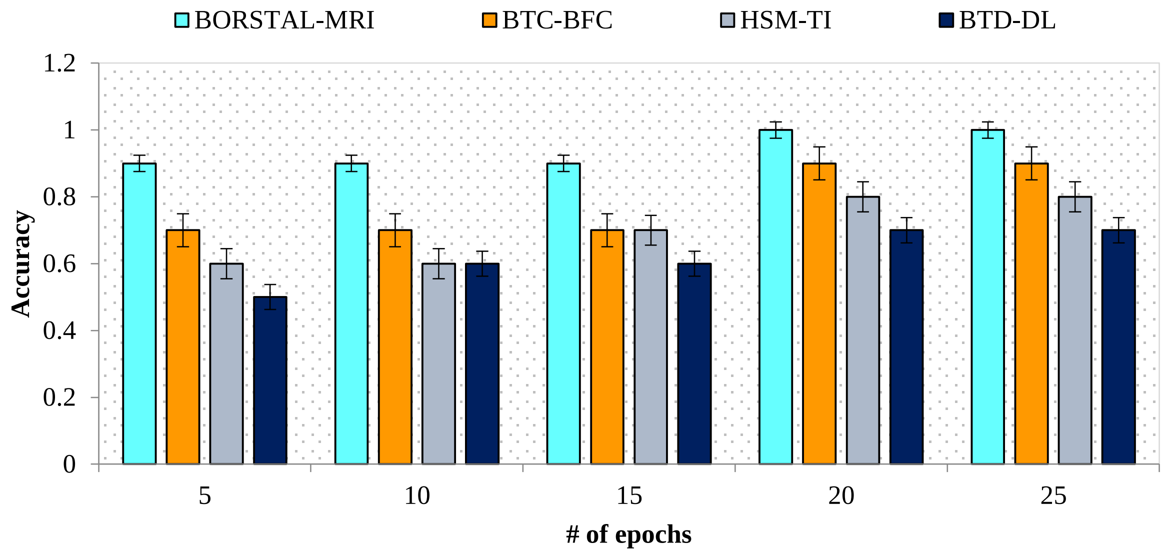


Fig.18 Number of epochs vs. accuracy

I. Impact of Specificity

This metric is used to evaluate the specificity. It represent the correctly classified negative instances form the positive and negative instances. The calculation of specificity is defined as follows,

$$Specificity = \frac{TN}{TN+FP} \quad (32)$$

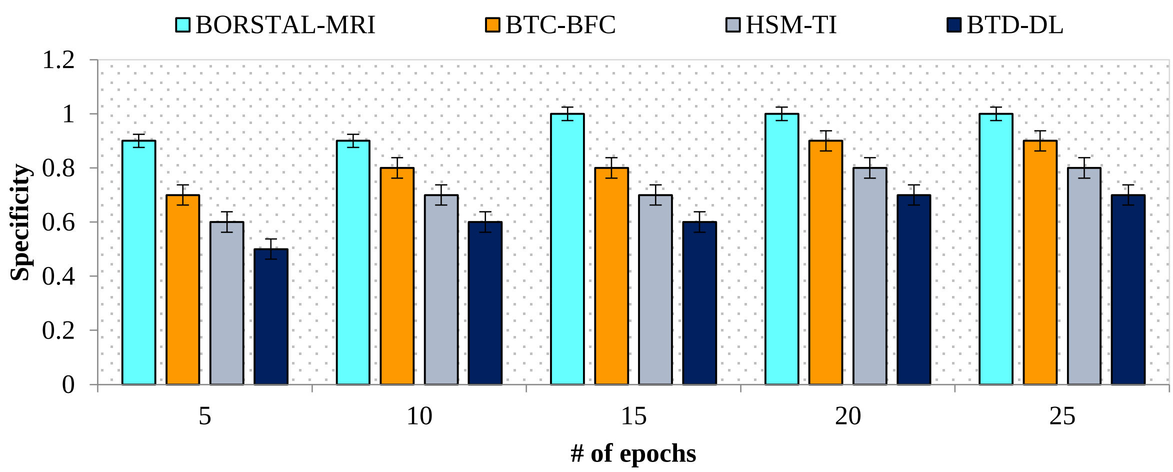


Fig.19 Number of epochs vs. specificity

Fig 19 represent the comparison of specificity of our proposed BORSTAL-MRI model and existing BTC-BFC, HSM-TI and BTD-DL model. The specificity value is increased exponentially with the increasing number of epochs. Form the comparison result our proposed BORSTAL-MRI achieves high specificity compared to other models. In our proposed work correctly classifies the negative samples by proposing preprocessing, TernausNet based segmentation, Faster RCNN based feature extraction and classification. In preprocessing we remove noise, blurriness and other artifacts presence in the image thus increase the quality of the image. The segmentation process reduces false negative rate because it detect the affected region, based on these region we extract the features thus increase classification and detection accuracy reduces false alarm rate and specificity rate. Our proposed BORSTAL-MRI model achieves 0.27% higher than BTD-DL model and 0.17% higher than the HSM-TI model and 0.11% higher than the BTC-BFC model.

j. Impact of Sensitivity

This metric is used to calculate the sensitivity value which represents the correctly classified positive samples from the positive and negative samples. The calculation of sensitivity is defined as follows,

$$Sensitivity = \frac{TP}{TP+FN} \quad (33)$$

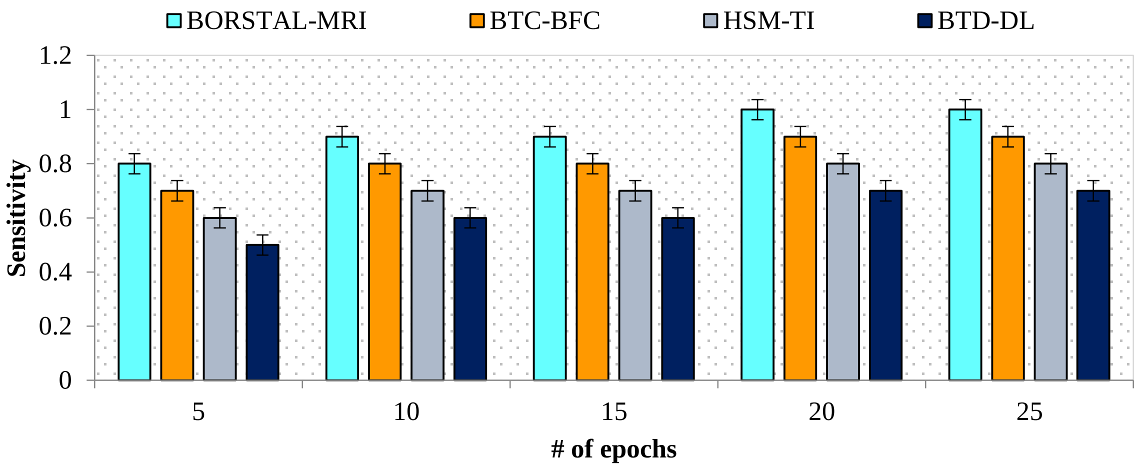


Fig.20 Number of epochs vs. sensitivity

Fig 20 represents the comparison of both proposed and existing model in terms of sensitivity. The figure shows that the proposed model achieves high sensitivity values compared to existing work. The BORSTAL-MRI model classifies the positive samples accurately by proposing TernausNEt based segmentation and Faster RCNN based feature extraction and classification. The TenausNet model performs better in brain tumor segmentation compared to existing CNN algorithms. It segments the MRI images in pixel level which helps to accurately segment the tumor region. Hence, proposed TernausNet attains higher accuracy in segmentation compared to the patch level segmentation algorithm. Based on the segmentation features are extracted thus improves the classification or detection accuracy. The segmentation process reduces the complexity during feature extraction. By this way we achieve high sensitivity and low false positive rate. BORSTAL-MRI improves 30% of BTD-DL model and 0.18% higher than HSM-TI model and 0.11% higher than BTC-BFC model.

j. Impact of AUC curve

This metric is used to evaluate the degree of separability. It is used to classify the images with brain tumor and without brain tumor (normal). The curve is plotted with respect to true positive rate and false positive rate.

Fig 21 represents the comparison of false positive rate and true positive rate for both proposed and existing model. The figure clearly state that proposed BORSTAL-MRL model achieves high true positive rate compared to exiting work. In our work performs preprocessing which increase the quality of the image thus reduces false positive rate and increase true positive rate. Generally MRI images have racian noise we need to remove it otherwise we cannot obtain accurate result thus increase high false alarm rate. Hence we remove the noise using fuzzy based weiner and bilateral filter thus reduces false alarm rate. In order to improve the detection accuracy we perform segmentation before feature extraction thus increase classification accuracy and true positive rate. By this way we achieves high true positive rate compared to other existing models such as BTD-DL, BTC-BFC, and HSM-TI.

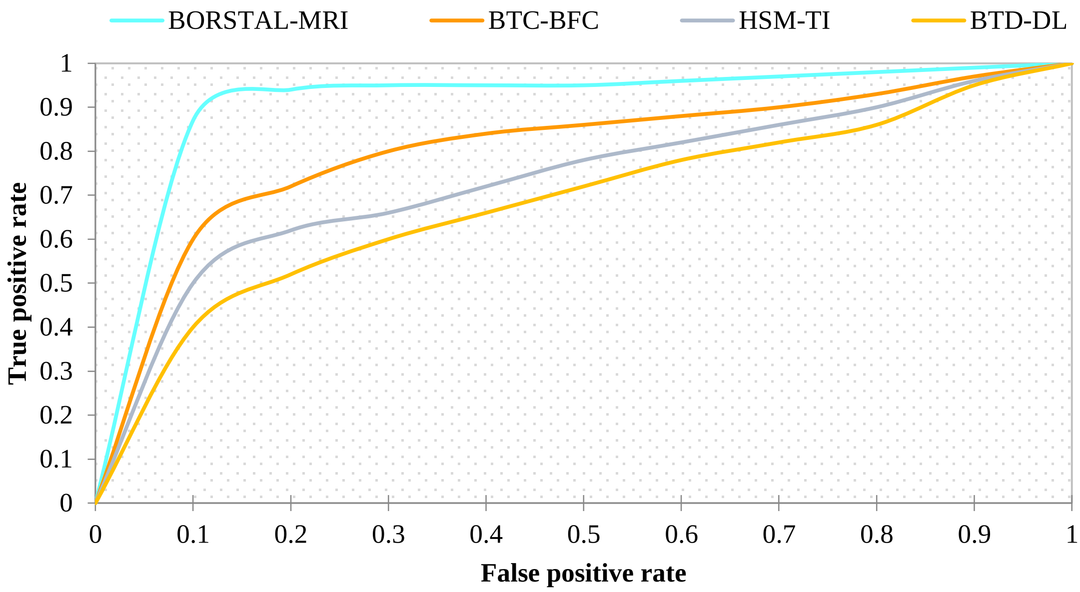


Fig.21 TPR vs. FPR

C. Research Summary

In this section summarizes how the proposed BORSTAL-MRL method improves the better performance compared to existing methods.

Table.4 Performance Analysis

Performance	**BORSTAL-MRI**	**BTC-BFC**	**HSM-TI**	**BTD-DL**
PSNR	93.6 ± 0.1	91.6 ± 0.2	88 ± 0.3	86.18 ± 0.5
SSIM	0.88 ± 0.01	0.78 ± 0.02	0.66 ± 0.03	0.56 ± 0.05
MSE	0.174 ± 0.001	0.206 ± 0.002	0.226 ± 0.003	0.304 ± 0.005
Error rate	0.242 ± 0.001	0.276 ± 0.002	0.302 ± 0.003	0.39 ± 0.005
Foreground precision	0.94 ± 0.01	0.82 ± 0.02	0.68 ± 0.03	0.60 ± 0.05
Background precision	0.92 ± 0.01	0.83 ± 0.02	0.72 ± 0.03	0.62 ± 0.05
Dice similarity	0.96 ± 0.01	0.81 ± 0.02	0.73 ± 0.03	0.61 ± 0.05
Accuracy	0.94 ± 0.01	0.78 ± 0.02	0.70 ± 0.03	0.62 ± 0.05
Specificity	0.95 ± 0.01	0.84 ± 0.02	0.76 ± 0.03	0.68 ± 0.05

Sensitivity	0.96 ± 0.01	0.85 ± 0.02	0.78 ± 0.03	0.66 ± 0.05

Fig.11-21 describe the performance of the proposed work in terms of PSNR, SSIM, MSE, error rate, foreground precision, background precision, dice similarity, accuracy, sensitivity and AUC with the use of combining TernausNet and Attention aware Faster R-CNN for brain tumor segmentation and classification. Table 4 represent the numerical analysis of the proposed and existing model performance in terms of as PSNR, SSIM, MSE, Error Rate, Foreground Precision , Background Precision, Dice Similarity, Accuracy, Specificity, Sensitivity , and AUC. It illustrates the average values of the performance metrics. From the comparison result our proposed model achieves high performance compared to existing methods.

Conclusion and future work

This paper presented an accurate brain tumor segmentation and classification approach known as BROSTAL for MRI images. The proposed model consists of three steps as multi-stage preprocessing, segmentation, feature extraction and classification. Firstly, MRI images are converted to normalized images by means of intensity normalization, denoising and contrast enhancement. Tumor area is segmented using TernausNet and then the most important and relevant features are extracted fast RCNN and finally, the brain tumors are classified. The tumor classification and segmentation accuracy of the proposed BROSTAL-MRI model is evaluated and compared for public database. The experiments are conducted with 70% training and 30% testing. The performance results demonstrated that the accuracy, precision, recall and ROC curve of the proposed BROSTAL-MRI is better than using BTC-BFC, HSM-TI, and BTD-DL methods. Furthermore, the experimental results showed that the proposed model has reached higher classification performance as compared with the state of the arts. We plan to apply the proposed model in order to solve another modality issue and perform the comparative study using some other deep learning algorithms.

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