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Certain Investigations on Brain Tumor Localization, Segmentation and Classification Approaches with Research Recommendations for Refinement

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Abstract: Brain tumor diagnosis, a gradual process indulges several techniques; aid the classification of brain tumor. The diagnosis procedure comprises, pre-processing, localization, feature extraction, segmentation and classification. Deep Learning (DL) algorithms support every diagnosis and classification process. Depending on the dataset used, the authors decide the Machine Learning (ML) algorithms either separately or fuse the algorithms and procedures to attain foolproof classification. The paper's objective is to throw light on the procedures adopted in brain tumor detection and classification processes. The paper focuses on the conservative and contemporary approaches of the past two decades namely, (a) Threshold-based approaches, (b) Active-Contour Model-based approaches, (c) Bounding Box-based approaches, (d) Clustering-based approaches, (e) Genetic Algorithm-based Clustering approaches, (f) Texture-based Segmentation approaches, (g) Optimization-based approaches, (h) Phase Stretch Transform-based approaches and Hybridized-conventional approaches for optimum performance. Apart from the procedures of the prevailing algorithms, the performances of those methods were discussed in a precise manner, such as the dataset adopted, suitable ML models with its architecture and distinct performance metrics along with their significance and pitfalls. To conclude, the findings of the existing methods provide valuable insights for researchers in terms of research recommendations and opportunities for refinement, specifically in relation to brain tumor processing stages.

Keywords: Benign, brain tumor enhancement, classification, feature extraction, segmentation, tumor localization

1. Introduction (Heading 1)

A human body is built by trillions of cells. These cells grow and multiply in the human body by the process called cell division. The old cells are replaced by the new one regularly. The old or abnormal cells sometimes multiply which they shouldn't and form as lump or tumor in any part of the body. Thus, development of abnormal cells in the tissues of the human body is termed as tumor. The tumor(s) occur in any part of the body and need not be always cancerous. Tumors are determined cancerous or non-cancerous only by clinical experts after several medical examinations. In the initial stage, a clinician use imaging technology namely - x-ray (Computed Tomography (CT)), Magnetic Resonance Imaging (MRI), Ultrasound (US), Positron Emission Tomography (PET), Single-Photon Emission Computed Tomography (SPECT), and optical imaging for screening tumor [1].

Information millennium offer humanity with technologies like Artificial intelligence, Internet of Things and more [2]. Machine learning in Artificial Intelligence involves the neural network and DL technology. The application of deep learning is commonly seen in oncology and speech recognition. The common application of DL in healthcare is prediction of potential cancerous tissues from the tumor images. The deep learning algorithms process the brain images and support clinical practitioners in identifying the tumor stage and classification. Technically,

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the process of identification and classification has several sub stages. Each stage is enunciated as follows:

The brain images in imaging mostly MRI cannot be used by deep learning algorithms as such. The MRI brain images may contain non-affected portion of human brain or even the affected portion may not be clear. With respect to brain tumor disease the dimensions of tumor region are essential accurately for the treatment. Hence, the MRI brain images need processing before applying algorithms. The process of removing the unnecessary facts, increasing the brightness, enhancing the tumorous tissue with color or only with grey color is called Pre-processing. The removal of artefacts from the brain image - Denoising is carried out by filters. In general, denoising filters are classified as spatial domain filtering and Transform domain filtering [3]. Image enhancement comprise, techniques like linear contrast enhancement, Histogram equalization, Principal Component Analysis, Density slicing, Band rationing, Intensity Hue transformation are utilized [4].The data obtained in Segmentation is selected, combined and reduced as important features in terms of color, thickness, dimension, formulation without losing any of the information as a mechanism named as Feature extraction [5]. Researchers can choose any of the following Feature extraction techniques upon their convenience. Local Binary Pattern, GLCM, Haralick Features, Gabor Texture, Learning Vector Quantization, Principal Component Analysis and many more [6].

The last phase after extracting the features is tumor classification. Brain tumors are either Benign or Malignant. The usage depends on the dataset handled by the researcher. Some of the common classifiers are Linear regression, Naïve Bayes, Decision trees, Random Forest (RF), Neural Network (NN), Kernel Nearest Neighbor (K-NN), Support Vector Machine (SVM), Quantization technique [7].

2. Brain Tumor Segmentation and Classification: Essence of Existing Approaches

The following section comprises of detailed essence of existing methods concerning brain tumor segmentation and classification.

Parasuraman Kumar and Vijay Kumar [8] suggested segmentation and classification of tumor by means of Ensemble classifier to be influential and effective. Manifold phases of proposed method include pre-processing through filtering algorithm, segmentation through Fuzzy C-Means algorithm, Feature extraction by Gray Level Co-occurrence Matrix (GLCM) and automatic brain classification through Ensemble classification vis-à-vis SVM, Feed Forward Artificial Neural Network (FFANN) as well as Ensemble Classifier (EC) Learning Method. Comparison of Ensemble classifier with aforesaid classification method regarding accuracy, sensitivity, precision and F1 score exhibited 91.17%, 95.47%, 94.17% and 94.81% respectively, of Ensemble classifier as superior to other classification techniques.

Malathy and Kamali [9] ascertain clustering algorithms to detect tumor region effectively and identify the level of criticality. To achieve the goal, apart from median and mean filters, Discrete Wavelet Transform is used additionally to eliminate the multiplicative noise obtained from the filters. Although K-Means and FCM algorithms were used for the purpose of study, the results of FCM is comparatively more effective than K-Means, as the FCM algorithm explored tumor affected pixels which were not enlisted earlier.

Kannan and his team [10] proposed a novel threshold approach to detect brain tumor by means of Neuro Fuzzy technique. Manifold phases of this technique are: (a) pre-processing – RGB image to gray scale image conversion, re-sizing the image, (b) Decomposition of gray image into multiple sub bands through Dual Tree Complex Wavelet Transform for investigating the texture in an image, (c) GLCM extracts the features from sub-bands, (d) Image classification via Adaptive Neuro-Fuzzy Inference System (ANFIS) and (e) Segmenting the classified image using Otsu thresholding. Comparison of the performance measures in concern with sensitivity, specificity and accuracy of the proposed approach with other prevailing methods proved proposed system superior.

Yasmeen Khan and Anshul Bhatia [11] presented Active Contour (AC) based tumor segmentation on various datasets. During the pre-processing phase, denoising was done to extricate the artefacts in the input image followed by skull removal process. Later, AC algorithm was used to spot the variations in the input image such as healthy and abnormal tissue (tumorous) regions. Xiangrui and his team [12] proposed an improved AC based approach for segmenting tumor in brain images. Inner relationship between the neighboring pixels was used to minimize the noise effect through anisotropic spatial information.Rui Liu and his team [13] suggested an integration of Concurrent Self Organizing Map (CSOM) with AC model, referred as SOAC to segment the tumor region(s). As the single modal MRI brain image lacks the distinction between the healthy and unhealthy brain tissues, authors suggested multi-modal information for highlighting the tissue regions through Global Difference Images (GDI). Reorganizing the GDI and MRI images, brain tumor(s) are detected and segmented by SOAC approach. When evaluated on BRATS 2013 and BRATS 2015 dataset, SOAC approach resulted in improved segmentation results.

Wang, Lin, Jianguo and Li [14] suggested the localizing of brain tumors based on AC models. The integration of K-Means clustering and gray scale properties were used to recognize the tumor's dominant slice followed by initial contour of tumor region(s). Multi threshold approach with morphological operations were adopted to determine the initial contour and applying AC model on initial contour localized the exact tumor boundaries. When evaluated on AANLIB dataset, this approach resulted in significant tumor segmentation results.

Aung, Khaing and Tun [15] suggested a unification of level set approach and AC model to segment the tumor region(s). In the first stage, initial mask was created to identify the tumor region, such that, the Region of Interest (RoI) and healthy tissues were distinguished properly. This initial mask along with the curve evolution formed due to level set approach and region-based AC model paved the path to absolute localization and segmentation of tumor region(s) in the image. When evaluated on images collected from Mandalay General Hospital, the present method resulted in improved segmentation results.

Shivani and Rahul [16] profess efficient and automatic tumor segmentation is achieved in fast bounding box algorithm. The proposed method enhances the converted greyscale MRI image initially by Median filter to remove artefacts (if any) and diagnose the edges accurately. Skull detection converts greyscale image into binary image. Joshi and Shah [17] assert tumor detection along with edema from MRI brain images is efficient when Bounding Box (BB) algorithm is used. Rajiv and Pushpakumar [18] assert integration of Masked Marker Controlled Watershed Algorithm and Split-up boundary box technique segment, classify and detect tumor efficiently from MRI brain images. Like other techniques, the pre-processing phase enhances the image, converts to 8-bit greyscale image and filters for noise removal after skull stripping. The 8-bit greyscale image obtained thus is processed further through Masked Marker Controlled Watershed (MMCW) algorithm.

Maya and Meenakshy [19] claim combination of Histogram, Thresholding and K-Means Clustering to segment brain tumor region from MRI brain images. The proposed combined algorithm segments the brain tumor in 8 steps. Chong Zhang and his team [20] claim integrated clustering methods followed by morphological operations segments brain tumor effectively. Adaptive Wiener Filter denoised MRI images and the brain surface is extracted by morphological operation. The tumor area is segmented by K-means++ clustering integrated with Gaussian Kernel based Fuzzy C-Means (FCM) algorithm.Hrosik and his team [21] proposed an approach by integrating Firefly algorithm (FA) and K-Means clustering, and detected brain tumor in primary stages like metastatic, glioma, adenocarcomp, sarcoma and metastatic bronchogenic carcinoma from SPECT, PET and MRI images. The Firefly-based segmented tumor images are fine-tuned by K-Means clustering using Otsu's criterion fitness function. Further, the outcomes of the integrated approach when compared with the existing approaches in the field – K-Means, Galactic Swarm Optimization (GSO), Real-coded Genetic Algorithm (RGA), K-Means GSO, K-Means FA in terms of root mean square error, peak signal to noise ratio and structural similarity index metric yielded surpassed other methods.

Mohan, Giri and Aswin [22] adopted dual clustering approach to segment the tumor portion from the MRI imagery. Dual Clustering Approach in this study was accomplished in two phases. The initial phase classified the image as Hue, Saturation or brightness and additionally based on the classification threshold evaluation, identification of low grey areas and threshold evaluation and computation of threshold for the bright areas respectively. The second phase creates bitmap based on the largest threshold value.Deepak and his team [23] presented K-Means clustering and Threshold segmentation detects brain tumor efficiently from MRI brain images. The input image is pre-processed by Median filter for artifact removal and image sharpening and enhancement. The image is further segmented by unsupervised clustering technique, K-Means. The greyscale image obtained is altered into binary format by Threshold segmentation thus highlighting the tumor area.

Bhaskarrao, Arun and Thethi [24] ascertain Genetic Algorithm (GA) to segment and classify brain tumor area from the emerging resonance images powerfully to aid medical treatment. Kiruthika, Feroz and Merlin [25] claim brain tumor detection and segmentation by means of GA is commanding than other methods. The input images obtained from MRI imagery are edge extracted and pre-processed by Gabor filter for noise removal. The denoised images are segmented by Gabor Wavelet Transform, followed by feature extraction where the images are enhanced through Locust GA to locate the tumor region accurately. The normal and abnormal tissues are classified by Locust-based GA. Detection of tumor on trained and tests data set with other techniques such as ANN, CNN, Fuzzy, and SVM revealed the advantage of genetic based classifier in computational time.

Chithambaram and Perumal [26] investigated and ascertained GA-based SVM classifier and Artificial Neural Network (ANN) segmented brain tumor accurately from the brain images of the patients. The intensity and texture of the tumor are vital for this study, Content based Active Contour model marks the tumor region of T1 weighted images and saved it as ROI images. Next, to enable Feature selection using GA through SVM and ANN, the intensity and texture features in ROI are removed to form dataset. Finally, classification by GA based SVM classifier and further refined by Artificial Neural Network yields a compatible and favorable output thus aiding the medical community in treatment.

Sharma and Mukharjee [27] worked on tumor segmentation from MRI images by means of GA and ANN Fuzzy Inference System (ANNFIS). This approach pre-processed the MRI images for quality enhancement. The vital features in the images were extracted and evaluated by GLCM technique. Among the extracted features, features relevant for the study were deduced and computed by GA to input ANFIS classifier. The performance measure of ANFIS and GA method with respect to Sensitivity, Specificity and Accuracy are evaluated and compared with other classifiers such as DWT and SOM, DWT and Principle Component Analysis (PCA) with KNN, Second order and ANN, Texture combined with ANN, FCM, K-Means proved its effectiveness.

Huang, Yang and Chen [28] segmented brain tumor on the basis of Texture, Intensity and Edge from the brain images effectively. From the sliced sub-images of MRI images, the intensity and texture features were extracted by Gaussian Markov random field model. Kernel Fischer Discriminant Classifier (KFDC) examined the sub-image to be a tumor or not by mapping. Upon tumor confirmation, segmentation carried out after refining the tumor contour. The execution time of the proposed method is comparatively less than traditional methods.

Li and Xiong [29] put forth the combination of Tamura Texture feature and SVM classifier model segment the tumor area accurately as all the characteristic feature of the brain image studied in detail. Roughness, Contrast, Directionality and gray scale are evaluated. The uniform sampling method of SVM classifier classifies the tumor and non-tumor area. Further the morphological operations on tumor affected area helps segment the tumor region. The results compared with SVM model without texture feature outperformed the later.

Sompong and Sartra [30] segment brain tumor via GLCM cellular automata-based texture feature. Tumor portion is segmented after the identification of intensity and texture features via GLCM, 8GLCM and GLCMCA. Further the texture features obtained are segmented by Tumor-cut and Active Contours based on Local Gaussian Distribution. The Dice co-efficient and Jacquard co-efficient of both the algorithms proved TC using texture image works best for edema segmentation and so also LGD than intensity images.

Hemalatha, Suresh and Sunil [31] proposed a combination of Kernel Fuzzy C-Means, Extreme learning Machine algorithm and Artificial Bee Colony (ABC) algorithm to segment medical images. The proposed technique is based on patterns and optimization of membership scaling function. Lakshmi and Sreenivasulu [32] proposed an automatic brain detection technique by adopting Swarm based optimization technique on T1 weighted MRI images. The proposed technique enhances the image by median filtering in pre-processing and GLCM on filtered images extracted vital features of the image. At last, SVM classified the tumor area from MRI images and the outcome was compared with other surviving methods in the scenario. Ultimately, the projected technique proved robustness in segmentation.

Sheshathri and Sukumaran [33] ascertained a Hybrid Clustering method, combining Ant Colony and Particle Swarm Optimization (HCACOPSO) method to segment the tumor area from brain image. Gaussian filter pre-processed the input color image and extracted RGB components from the image. HCACOPSO algorithm constructs clusters and segmented the tumor accurately and improved PSNR values.

Gopal and Karnan [34] diagnosed brain tumor by Clustering algorithms - Fuzzy C Means fused with optimization tools such as GA and Particle Swarm Optimization (PSO) algorithm. The pre-processing phase of the proposed method utilized tracking algorithm for removing artefacts and enhanced the image by median filter. The segmentation of enhanced image was by FCM along with metaheuristic algorithms such as GA and PSO. The outcome of the algorithm was compared with other methods to prove efficiency.

Ilioudis and his team [35] detected the edges on Synthetic Aperture Radar (SAR) images (widely in remote sensing) through Phase Stretch Transform Algorithm. Generally, the SAR images are thick and it was overthrown by localization kernel. The smoothened image was denoised further to yield the best outcome in PST. Experimental results on Coherent Change Detection Challenge dataset from AFRL and BC dataset included in RADARSAT-2 from Vancouver proved that PST performed well in detecting edge information and further thresholding and morphological operations on edge information extracted the edges effectively from the SAR images.

Asghari and Jalali [36] identified a unique method to detect edges from the images by nonlinear frequency dispersion operation often termed as Dispersive Phase Stretch Transform (DPST). Application of localization kernel smoothened the image and passed for 2D phase transformation with several Strength and Warp parameters. Kartika and Widhia [37] applied PST to identify and segment Optic Discs (OD) for the treatment of Diabetic Retinopathy. The three-phase approach – Preprocessing, Segmentation and Evaluation encompass several sub-processes in every phase. Before reaching the transformation phase, the Drishti-GSI dataset images were channel extracted, contrast stretched and filtered. To segment OD, the resultant images of PST were further processed by Thresholding and morphological techniques. Apart from segmentation, the result was validated finally based on Positive Predictive Value of 97.74%.

Thida, Soe and Khin [38] analyzed the edge detection techniques - PST and Canny algorithm methods on MRI images by evaluating the PSNR and MSE values. Upon analyzing the techniques on two different MRI images, the PST technique showed better result than Canny with PSNR and MSE values of 28.09 and 101.8, respectively.

Kamble and Kokare [39] catered a favorable method to extract the blood vessels rapidly in the treatment of Diabetic Retinopathy. The retinal images were cropped and enhanced initially. Consequently, the images were transformed through the dispersive property of PST with precise falsehood. Ying Tong [40] combined Non-Sub-sampled Shearlet Transform (NSST) and PST for image enhancement in visual sensor network. The application of NSST on four standard images decomposes them into multi scalar and multi directional coefficients among which high coefficients were used for processing. PST transforms the original image for extraction of features in the form of map. Based on Local Standard deviation (LSD) of every pixel, the high LSD pixels were further enhanced for several decomposition levels. Finally, to achieve the result inverse NSST transformation was applied. The author used for the purpose of study.

Sherlin and Murugan [41] ascertain Optimized Binarization Technique (OBT) with adaptive filter segment the tumor with better accuracy than other techniques. Initially the converted gray scale image was pre-processed by thresholding technique using adaptive filter. The features were extracted by PCA algorithm and were optimized by SVM. Finally, the Random Decision Forest (RDF) algorithm classifies the image either as normal or abnormal image. The results when compared with RDF, PCA, and OBT algorithm yielded best duration and 90% accuracy in OBT model.

Thejaswini, Bhavya and Kushal [42] claim Adaptive Regularized Kernel based Fuzzy C-Means Clustering (ARKFCM) to segment brain tumor successfully. Collected images were pre-processed by CLAHE, Wiener2 and Median2 filters. ARKFCM clustering algorithm segment the tumor region and the features of region of interest are extracted quantitatively by first order and second order statistic features. The SVM classifier detects the tumor region and the ANN Back Propagation algorithm classifies tumor as Benign and Malignant. The performance analysis of the proposed model with that of surviving methods showed superiority of 91.4% accuracy and 0.12 Bit error rate in the proposed method.

Wu, Lin and Chang [43] suggested a color-based KMC approach to segment the tumor region from input MRI brain images. Initially, the input grayscale image was subjected to pseudo color translation (R, G and B values) and color space translations (CIELab color model). Later, the KMC approach followed by histogram clustering was applied to distinguish the colored textured regions thereby differentiating the tumor region tissues from the normal brain tissues.

Logeswari and Karnan [44] presented a soft computing-based technique for detecting and segment the tumor in the input brain image. During the pre-processing stage, median filter was used to denoise the input image. The Hierarchical Self Organizing Map (HSOM), an extended and improved version of traditional SOM, was used to segregate the homogeneous pixels namely, color, textures, intensity and range values, present in the input brain image. Investigational results concluded that, among many possible neighborhood pixel combinations, 3 x 3 sized neighborhood pixels window resulted in significant tumor detection than the other neighboring pixels (5 x 5, 7 x 7, 9 x 9 and 11 x 11) window combinations.

Marshkole, Bikesh and Thoke [45] suggested a brain tumor segmentation using shape and texture features and classification based on Linear Vector Quantization (LVQ) method. Initially, the RoI (that is, the tumor region) was identified in the input brain image. The shape and texture features of input image were extricated using Fourier Descriptor Coefficients and Haralick Invariant Moments, respectively. Later, LVQ uses these features to categorize the brain tumors as benign and malignant tumors. Upon evaluation with 80 MRI brain images, the LVQ-based classification method resulted in 85% of classification accuracy.

Sachdeva, Vinod, Gupta, Niranjan and Ahuja [46] suggested a tumor segmentation method using Content-based AC (CBAC) model. The segmentation process initiated with the estimation of intensity and texture characterization followed by the edge-map generation. Later, the tumor contour was identified through the static and dynamic motion field estimation methods.

Hamamci and his team [47] suggested the Cellular Automata (CA) based segmentation of tumor in the input MRI brain image. Initially, the maximum Volume of Interest (VoI) regarding the tumor was marked manually to locate the tumor location in the input image. Later, CA algorithm was iterated twice to determine the seeds of the tumor and background regions, respectively.

Taruno and his team [48] claim Electrical Capacitance Volume Tomography (ECVT), a sensor network 4D volumetric imaging technique to identify the brain abnormalities caused by brain tumor. The comparative study of CT /MRI scan images with ECVT images of tumor affected brain showed a pattern of low brain activity, as the signals are blocked by the tumor in reaching the cortex region (in tumor region detected by CT / MRI). The ECVT system design includes 3 major elements wherein data acquisition for capacitance measurement, a helmet like sensor to acquire signals and a PC to control data acquirement and image enhancement.

Halder, Giri and Halder [49] proposed a technique using 20 tumors affected T2 weighted images to depict the tumor region labeled by Object Labeling Algorithm. Enhancement of images is carried out in pre-processing via Noise removal and Morphological opening. The binary images are built by Threshold approach preceded by K-Means to segment the MRI image. The proposed K-Means followed by Object Labeling Algorithm (OLA) technique proved the percentage of accuracy to be more when compared with K-Means followed by threshold approach and FCM- K means with respect to the ground truth values.

Leung, Chen, Kwok and Chan [50] assert that a modified Generalized Fuzzy Operator detected the borderline of tumor effectively than Contour Detection Method with respect to frontal brain tumor. By the transformation of higher gray level pixel to 1 the edges are identified accurately by the modified GFO in the single instance considered for the study.

Iftekharuddin and his team [51] exploit two fractal feature extraction methods, one using Piecewise-Triangular-Prism-Surface-Area (PTPSA) and the other one, a combination of fractal and wavelet analysis via fractional Brownian motion framework to segment and classify brain tumor from MRI images. Out of 204, T1, T2 and FLAIR MRI images, Self-Organizing Map algorithm segmented the tumor accurately and SVM classifier classified the tumor region with the average accuracy of 95%.

Vijay and Subhashini [52] propose brain tumor segmentation from magnetic resonance images by K-Means Clustering under unsupervised approach as the training data set and preprocessing is minimal. The 100 MRI images were enhanced via Morphological image processing. K-Means clustering method yielded 95% accuracy when compared with other clustering algorithm like Fuzzy Means.

Debnath Bhattacharyya and Tai-Hoon Kim [53] claim percentage of accuracy to be more by using three sets of algorithms – conversion of 24-bit color image to 256 gray color image, image detection algorithm, edge detection algorithm to detect tumor region from MRI brain images. Among the 12 images considered the observation of 1 image upon execution of aforesaid 3 algorithms show the brain tumor detection clearly.

Natarajan and his colleagues [54] presented threshold operation technique in image processing to detect tumors from MRI brain images. The preprocessing of MRI brain images involved grayscale conversion via HE, application of high pass and median filter to enhance the histogram image, segmenting via Threshold operation (conversion into binary image), applying Morphological operations to identify the boundaries (to ease tumor removal), and finally image subtraction wherein the image after tumor extraction is subtracted from the original image.

Shubham and his team [55] proposed an auto search high-performance neural architecture, Learning-by-Self-Explanation (LeaSE) for classifying brain tumors from MRIs. Amin and team [56] devised a new technique to detect brain tumor employing ensemble transfer learning model and Quantum variational classifier. Ghada Saad and his research team [57] developed a hybrid algorithm for detecting brain tumor fusing KNN and SVM algorithm. KNN identified, segmented and extracted the brain tumor region whilst SVM categorized the tumor as benign or malignant. The proposed hybrid algorithm tested on the MRI brain dataset of 306 images revealed 95.6%, 97.5%, 93.7% of accuracy, sensitivity and specificity respectively dethroning other algorithms.

Soheila Saeedi and team [58] proposed machine learning technique based on deep learning comprising three stages namely pre-processing, feature detection and classification. The pre-processing stage resized (80*80 pixels), rotated to 90 degrees and finally flipped the 3264 images dataset thus enhancing to 9792 images. The features based on shape, intensity and model were extracted by 2D CNN and auto encoder CNN. The ML classifiers algorithms such as SVM, Logical Regression (LR), Random Forest (RF), Nearest Neighbor (NN), Stochastic Gradient Descent (SGD), and Multilayer Perceptron (MLP) were used to diagnose the tumors accurately. Further, the classification of images into glioma, pituitary, menigngioma and no tumor images were done. The performance was evaluated based on accuracy, Recall, precision and F-Measure. The result proved proposed 2D CNN accuracy was 96.47% and that of auto encoder was 95.63%. Moreover, among the ML classifiers, KNN achieved 86% accuracy.

Patel and his research team [59] presented the multi-class brain tumor segmentation using Graphical Attention Network (GAN) and multi parametric MRI. GAN integrates graphical neural network-based MRI's Regional Adjacency Graph (RAG) that studies tumor and the attention mechanism to model the spatial relationships between pixels in the MRI images. Ashok Babu and his team members [60] integrated Convolutional Neural Network, Artificial Bee colony and thresholding to segment and classify the tumor in MRI. Hossain and Islam [61] proposed Sensor-based Portable Microwave Brain Imaging System (SMBIS) using Lightweight Deep Learning Models to segment and classify tumors. The SMBIS implemented a 3D antenna sensor in its architecture and collected microwave brain images and reconstructed microwave (RMW) brain images which included healthy and unhealthy (single and double tumor) brain imagesMitrabinda, et.al., [62] made an effort to improve the accuracy of diagnosing brain tumor utilising Fused Layer Accelerator. The study involved an insight on light weight deep learning approaches. Suchismita, D and his team members [63] developed two layered ensemble brain tumor segmentation architecture to segment tumor based on multiple parameters of MRI brain tumor images. Ranit, S., and Gopinath, B [64] detected and classified brain tumor into three types Glioma, Meningioma, and Pituitary using CNN architectures like EfficientNetB0, ResNet50, Xception, MobileNetV2, and VGG16. The model was demonstrated on dataset of 3264 images which were augmented and pre-processed to increase data size.

The trial revealed EfficientNetB0 with eminent accuracy of 97.61%.

3. Experimental Results and Discussions

Table 1 illustrates the significance of the contemporary and existing brain tumor segmentation and classification approaches.

Table 1. Significance of Existing Approaches

Ref. No.	Procedure Adopted	Significance of the Approach	Database & Evaluation Parameters
[8]	Pre-processing through filtering algorithm, segmentation through Fuzzy C-Means algorithm, Feature extraction by GLCM and automatic brain classification through Ensemble classifier	Ensemble classifier is compared with SVM, Feed forward ANN to prove superiority	Scores of Ensemble classifier Precision: 94.17% F1 Score: 94.81% Accuracy: 91.17% Sensitivity: 95.47%
[9]	Median and mean filter, DWT for pre-processing, K-Means and FCM clustering algorithms for tumor detection	FCM compared with results of K-Means	Magnetic resonance images FCM outperformed K-Means
[10]	Gray scale conversion for pre-processing, Decomposition using Dual Tree WT, GLCM for feature extraction, Classification by ANFIS, Segmentation through Otsu thresholding	Usage of algorithms in every phase, increased the performance	Training: 15 real-time human brain images Testing: several images
[11]	Pre-processed with denoising algorithm and skull removal technique. AC algorithm to detect healthy and tumor tissue region segmentation		MRI images of 3 datasets Dataset1: 91.45% Dataset2: 98.13% Dataset3: 97.9%
[12]	Noise removal with anisotropic spatial information, HMM random fields, Tissue identification by multi variant t-distribution (AC algorithm)	2D and 3D clinical and synthetic images depicted more accuracy	Images from Brain Web and Internet Brain Segmentation Repository Increased accuracy by 3% than other methods < 1 sec for 2D image (256 X256) <300 sec for 3D image (256 X256 X171)
[13]	Pre-processing with GDI to highlight affected tissues, segmentation by SOAC technique	Both BRATS 2013 and 2015 were tested	Dice score: 0.9142(Mean) 0.9298(Median) Specificity:0.9794 Sensitivity:0.915
[14]	From AANLIB images , K-Means and gray scale recognized tumor slices, multi threshold with morphological operations to identify initial contour and AC model to detect exact boundaries		Dataset from medical repository
[15]	Mask creation to distinguish RoI and healthy tissues, Level set approach and region based AC model for localization and segmentation		Images from Mandalay General Hospital
[16]	Pre-processing by median filter, Skull detection, Tumor region detection through Fast Bounding Box algorithm and tumor classification by Graphical plot		NIL

[17]	Preprocessing, BB algorithm to compute BC score, and thresholding to identify tumor with edema		NIL
[18]	Pre-processing includes greyscale conversion and skull stripping, MMCW algorithm for segmenting, Split up boundary box technique for fine tuning segmented image, classification using graphical plot of greyscale intensities		NIL
[19]	Pre-processing by median filter, binary image conversion using Histogram and thresholding, and segmentation by morphological operations and K-Means clustering technique		30 MR images of 10 patients from AANLIB database
[20]	Adaptive Wiener filter for denoising and segmentation and extraction by K-Means clustering clubbed with Gaussian Kernel and Fuzzy C-Means algorithm,	Extracted tumor region tuned by morphological operation and median filter	MR FLAIR images from BRATS 2012 images of 20 patients. Mean value of 100 images: Dice:0.9256 Sensitivity:0.9460 Specificity:0.9941 Recall:0.9087
[21]	Pre-porcessing, Segmentation by Firefly algorithm and tuned by K-Means clustering with Otsu's criterion fitness	Results compared with K-Means, GSO, RGA, K-Means GSO, K-Means FA to show superiority	Havard Whole Brain Atlas images
[22]	Image classification and threshold evaluation, bitmap creation, white and black pixel classification, evaluation of segmentation accuracy, Mean Square Error.	Comparison of result with FCM, KFCM, SKFCM, KFCM-F, GKFCM to prove superiority	NIL
[23]	Pre-processing by median filter, image segmentation by K-Means, Binary format conversion by Threshold segmentation		NIL
[24]	Pre-processing by skull stripping, Computation and Identification of maximum segmentation score using Watershed, Fuzzy C-Means, DCT, BWT, improvisation of feature extraction by morphological operation and GLCM, tumor tissue classification by GA	Tumor classification is more effective	Samples from 15 patients with 9 slices per patient. Accuracy: 92.03%, Specificity: 91.42%, Sensitivity :92.36%, Dice similarity index coefficient : 93.79%
[25]	Preprocessing by Gabor filter, segmentation by GWT, feature extraction by Locust GA	In terms of computational time, Locust GA is better than other classifiers ANN, CNN, Fuzzy, SVM	Accuracy: 67.25% Specificity: 71.34% Sensitivity: 69.05%
[26]	Content based Active Contour Model identify RoI, Feature selection and extraction by GA through SVM and ANN		428 MR images from 30 different patients at MRI, SRM,PGIMER, Trichy Tamilnadu, India, (Jan 2016–May 2017) Accuracy of GA-ANN is 94%.

[27]	Pre-processing, Feature extraction by GLCM, Deduction by GA and ANFIS	Performance metrics compared with DWT, SOM, DWT and PCA with KNN to prove efficiency	Dataset: http://mouldy.bic.mni.mcgill.ca/ brainweb/ Accuracy: 98.67% Specificity: 95.3% Sensitivity: 96.6%
[28]	Pre-processing, Image slicing, Intensity and feature extraction by Gaussian Markov Random model, Tumor determination by KFDC, Tumor area segmentation by contour model	Less processing time when compared with traditional techniques	Dataset: Images from Tianjin Medical University General Hospital
[28]	Tamura texture Feature for feature evaluation, SVM classifier for tumor classification, segmentation using morphological operations	Outperformed on comparison with SVM without texture feature	2013 BRATS dataset (of 30 patients) Scores: Dice: 88.07 with a Standard Deviation (SD) of 14.00 Sensitivity: 97.69 with a SD of 5.45 PPV: 85.64 with a SD of 13.42
[30]	Identification of intensity and texture features by GLCM, 8GLCM and GLCMCA, Feature segmentation by Tumor-cut and Active contours on Local Gaussian Distribution		Dataset: Images of 30 glioma patients from VSD BRATS dataset 2013; DSC: 91.89% and JC:85.08%
[31]	Segmentation by Kernel Fuzzy C-Means, Extreme learning Machine algorithm and ABC algorithm		Dataset: BRATS; Average accuracy of segmentation: 97.03%

[32]	Pre-processing by median filtering, feature extraction by GLCM, SVM classifier for tumor area classification		NIL
[33]	Pre-processing and RGB component extraction by Gaussian filter, Cluster construction and segmentation by HCACOPSO		Accuracy: 97%, 96%, 99%
[34]	Pre-processing by tracking algorithm and median filter, Segmentation by Fuzzy C-Means, GA and PSO	Efficiency proved by comparing with conventional methods	Dataset: 120 MRI images Accuracy and error rate of PSO: 92.3% and 0.1273%
[35]	SAR images were denoised, Edge detection by PST algorithm and tuned by thresholding and morphological operations	Synthetic Aperture Radar (SAR) images were used for the study	Dataset: CCDC from AFRL, C-Band data from BC dataset
[36]	Pre-processing by localization kernel, Edge detection by DPST, Optimum edge detection by thresholding and morphological operation technique		NIL
[37]	Pre-processing by channel extraction, contrast stretching and filtering, Segmentation of Optic Discs by Thresholding and morphological operations	Result validation by +ve predictive value of 97.74%	Dataset: 50 images from Drishti-GSI Positive Predictive Value score: 97.74%
[38]	PST and Canny algorithm for edge detection, PSNR and MSE value computation		Canny algorithm scores:

			MSE: 102.7 PSNR: 28.05
[39]	Pre-processing by image cropping and enhancement, Transformation of images by dispersive property of PST with precise falsehood, falsehood removal by pre-determined threshold value	Accuracy of 94.78% and 94.21% in Blood vessel identification	Dataset: DRIVE, STARE Average accuracy: 94.78 % DRIVE and 94.21% on STARE
[40]	Image decomposition into multi scalar and directional coefficients by NSST, high LSD pixels were enhanced by decomposition		Images used: 4 EPI and CII of Lena: 2.52 and 1.08 Barbara:3.12 and 1.36 Car : 2.64 and 1.29, and radar image: 2.42 and 1.36
[41]	Preprocessing using thresholding and adaptive filter, feature extraction by PCA and SVM, Random decision forest for tumor classification	90% accuracy attained in OBT algorithm	NIL
[42]	Pre-processing by CLAHE, Wiener2 and Median2 filters, segmentation by ARKFCM, feature extraction by first and second order	91.4% accuracy attained	Dataset: 94 images Accuracy: 91.4% Sensitivity: 98% Specificity: 78% Bit error rate: 0.12

	statistic features, tumor detection by SVM classifier, tumor classification by ANNBP algorithm		
[43]	Pre-processing by pseudo color translation and CIELab color model, identification of tumor region by KMC and histogram clustering technique	Significant result in differentiating WM, GM and CSF brain tissues	NIL
[44]	Pre-processing by median filter, application of HSOM to extract homogeneous pixels	3X3 sized neighborhood pixel window detected tumor better than other window sizes	Dataset: KMCH, Coimbatore
[45]	RoI identification, Shape and texture feature extraction by FDC and HIM, classification of brain tumor by LVQ	85% classification accuracy	Dataset: 80 images
[46]	segmentation process by estimation of intensity and texture characterization and edge-map generation. Identification of tumor contour by	Significant improvement in identifying homogeneous and heterogeneous tumors	Dataset: 428 real images of 45 patients from PGIMER, Chandigarh

	static and dynamic motion field estimation methods		
[47]	Maximum VoI identification manually, Iterated CA algorithm twice to determine seeds and background region, CA based seeded algorithm segmented necrotic region of the tumor		Datasets: Synthetic datasets from Utah, Harvard Brain Tumor Repository, CyberKnife radiosurgery treatment in Anadolu Medical Center (ASM), Kocaeli, Turkey Computation time: 1 s to 16 minutes depending on volume of tumor ranging 0.5 to 32cc
[48]	ECVT 4D volumetric imaging technique showed low brain activity in tumor region		Real images from 5 patients
[49]	Image enhancement by noise removal and morphological opening, segmentation by K-Means and Object Labeling algorithm	Percentage of Accuracy is more when compared K-Means +Thresholding and FCM + K-Means	20 images; Accuracy: >99.55 and <100%
[50]	Detection of tumor borderline by GFO for frontal brain tumor – accurate edge identification by transforming higher gray level pixel as 1		1 frontal tumor image Error rate: 2%
[51]	Feature extraction by PTPSA and Fractal + wavelet analysis, Segmentation of tumor by SOM algorithm and	Average accuracy of 95%	204 brain images from St. Jude Children's Research Hospital Accuracy based on data used for testing: 1/3 of data : 95.6%

	classification by SVM classifier		½ of data : 91.9%
[52]	Image enhancement by morphological processing, segmentation by K-Means clustering	95% accuracy attained than Fuzzy means	100 images Execution time for RGB and Lab images : 1.875 sec & 6.75 sec
[53]	Gray scale image Conversion, image detection and edge detection	Combination showed more accuracy	12 images
[54]	Pre-processing through HE and median filter, Segmentation by thresholding, Edge detection by morphological operation and tumor extraction		NIL
[55]	Learning-by-Self-Explanation a multi-level optimization technique comprises two models – explainer and audience model		3264 MRI images Accuracy: 90.6% AUC :95.6%
[56]	Feature extraction from InceptionV3 model, score vector acquisition using SoftMax, Tumor classification by Quantum variational classifier, Tumor analysis by SegNetwork		Global accuracy in Kaggle- 98.2%; one local dataset – 99.9% and BRATS - 99.7%
[57]	Hybrid algorithm using KNN - identified, segmented and extracted the brain tumor region SVM classified the tumor as benign or malignant		306 brain images Accuracy- 95.6% Sensitivity- 97.5% Specificity- 93.7%
[58]	Pre-processing, feature extraction by 2D CNN and auto encoder CNN, Tumor diagnosis and Classification by MLs : SVM, RF, LR, NN, SGD, MLP		3264 brain images; Accuracy of 2d CNN-96.47%; autoencoder-95.63%; KNN-86%
[59]	Graphical attention network (GAN) and multi parametric MRI.		BRATS 2020 dataset; Dice score >6%

		Hausdorff distance >50%
[60]	Denoising by Curvelet Transform; Tumor region extraction by ABC + Thresholding; Feature extraction by BWT;CNN model for classification	BRATS 2013 and 2015 dataset.2015 shows superiority Accuracy-98.07% Specificity-95.61% Sensitivity-99.6% DSC-0.9934
[61]	SMBIS using Lightweight DL Models to segment and classify tumors MsegNet and BINet were used	MsegNet IOU and Dice score:86.92% and 93.10% BINet classifier mean accuracy:89.33 %and 98.33 fir raw RMW and RMW images
[62]	Fused Layer Accelerator using InceptionResNetV2, EfficientNetV1 and MobileNetV2 and the attention modules	EfficientNetV1 showed more accuracy
[63]	Two layered ensemble brain tumor segmentation architecture which includes Basic encoder-decoder model, U-Net model and SegNet Model	Multimodal BRATS 2017 dataset of 210 patients
[64]	Brain tumor detection and classification through CNN architectures EfficientNetB0, ResNet50, Xception, MobileNetV2, and VGG16	3264 MR brain images; EfficientNetB0 showed superiority with accuracy of 97.61%

Figure 1 demonstrates the comparative performance of various Ensemble Classifier models compiled from [8]. Figure 2 displayed the performance of three different datasets on Active Contour based segmentation on the basis of evaluation metrics summarized from [12]. Figure 3 demonstrate the comparative performance of various evaluation models depicted from [13]. Figure 4 exposes the Recall, Sensitivity, Specificity and Dice metrics of certain Clustering algorithms compiled from [20]. Figure 5 discloses the comparative performance of KNN, ANFIS Classifier algorithms against GA in terms of performance metrics illustrated from [24]. Figure 6 reveals the comparative performance of Hybrid Genetic, CNN classifier and Threshold region algorithm. The experiments show Hybrid Genetic algorithm performed amicably than the other algorithms compiled from [25]. Figure 7 depicts the comparison of Performance Metrics Accuracy, Sensitivity, and Specificity of Classifier Algorithms and some fused Classifier Algorithms [27]. Figure 8 exhibits the edema segmentation on the basis of Texture and Intensity of MRI images using Dice similarity and Jaccard co-efficients [30]. The observations reveal Texture based segmentation outperformed in both the co-efficient values. Figure 9 reveals the comparative accuracy values of certain hybrid segmentation methods [31]. Figure 10 shows the performance of Fuzzy C-Means algorithms when combined with GA and PSO in terms of accuracy [34]. The accuracy value is higher when FCM combined with PSO. Figure 11 depicts the MSE and PSNR values of three different images out of which two were MRI images and the other one was an image of a building [38]. Figure 12 displays the execution time taken by different Clustering algorithms and the superiority attained by K-Means Clustering technique in terms of execution time [52].

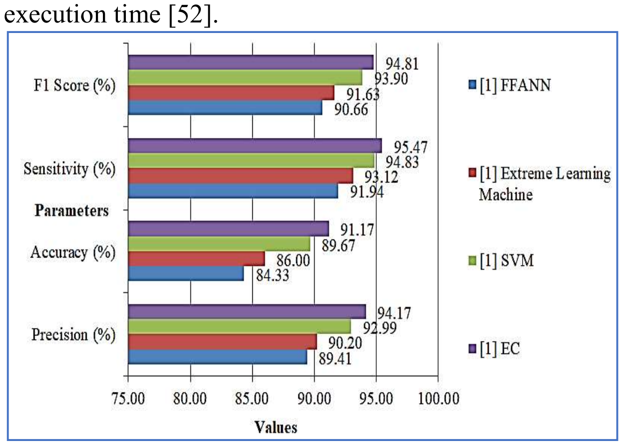

Figure 1. Performance comparison of various models

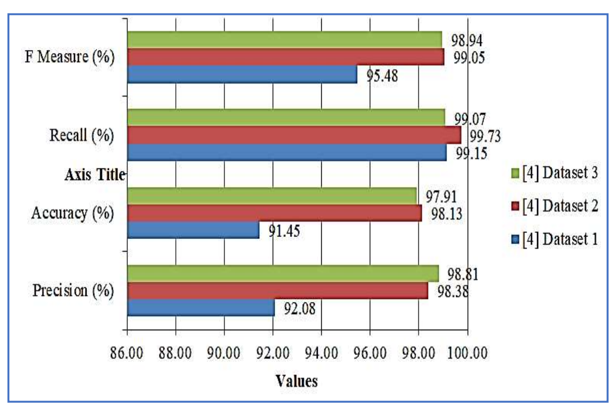

Figure 2. Performance comparison of various datasets

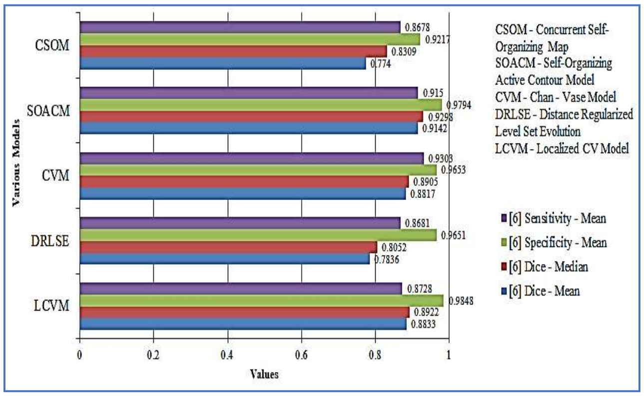

Figure 3. Evaluation summary of various models

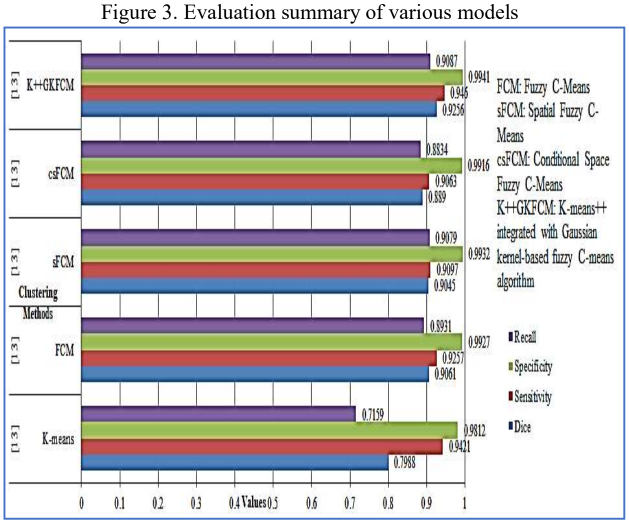

Figure 4. Performance comparison of various Clustering Algorithms

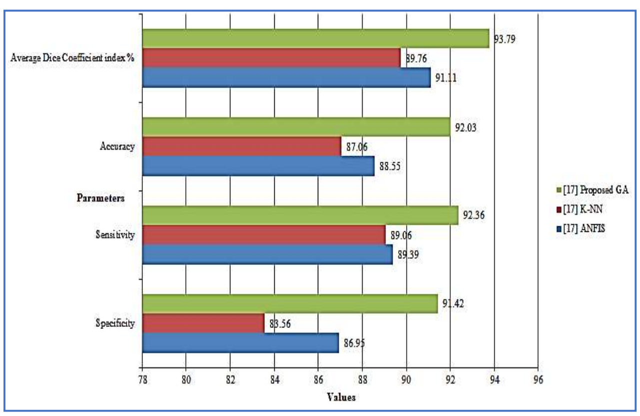

Figure 5. Performance comparison of distinct Classifiers

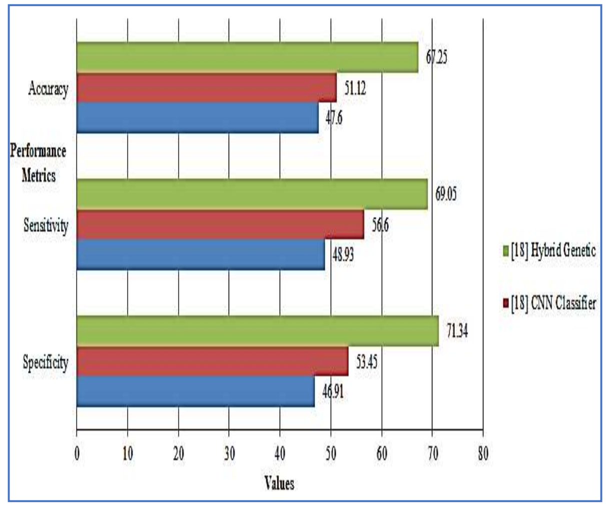

Figure 6. Performance comparison of Conventional and Hybrid CNN

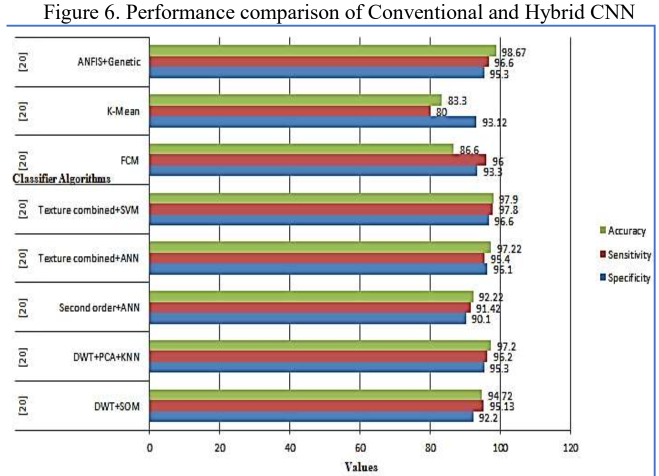

Figure 7. Performance comparison of various Hybrid Classifier Algorithms

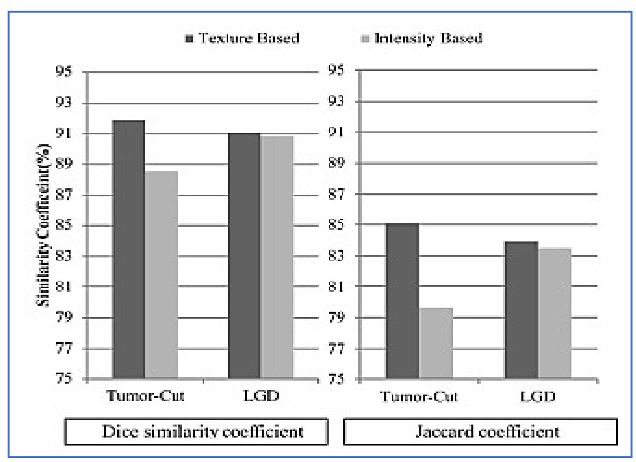

Figure 8. Performance summary of edema segmentation (Courtesy: Source [23])

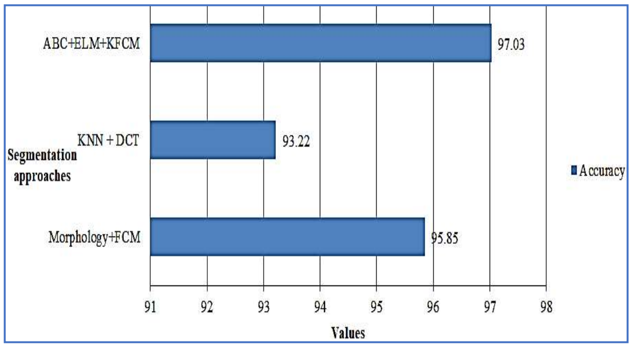

Figure 9. Comparative performance of Segmentation Approaches

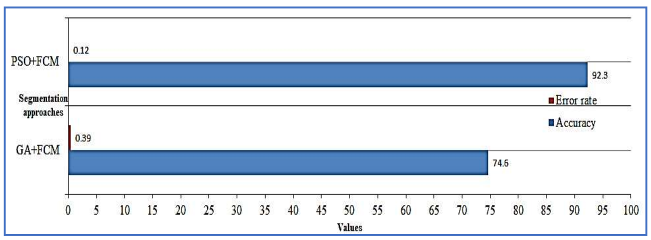

Figure 10. Performance of FCM-based Segmentation Approaches

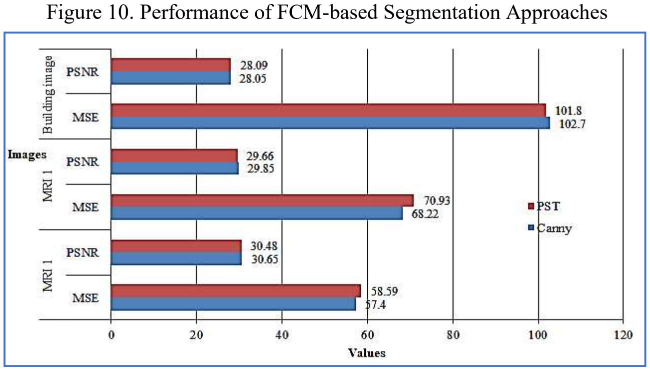

Figure 11. Comparison of MSE and PSNR values of Canny and PST Techniques

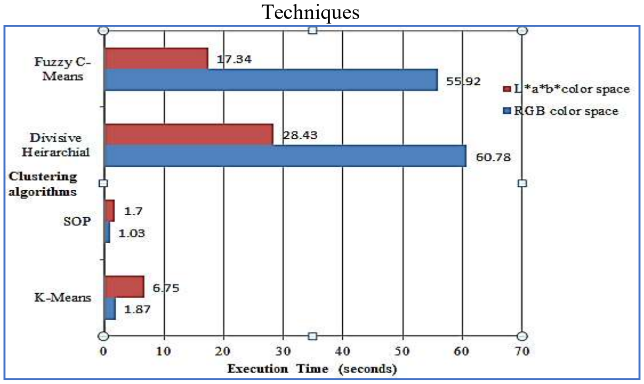

Figure 12. Comparison of execution time taken by Clustering Algorithms under RGB and L*a*b* Color Spaces.

4. SUMMARY OF THE FINDINGS

The subsequent section deals with the concise findings from existing studies concerning the image enhancement, localization, segmentation, feature extraction and classification processes.

- Ensemble classifier has significantly improved the classification accuracy than the traditional methods
- Denoising during the process has a greater impact in the tumor localization process.
- Integration of multi-threshold approach with morphological operations lead to better identification of tumor boundaries
- Fast BB algorithm is more efficient in localizing the RoI
- Integrating an optimal algorithm such as Firefly with K-Mean Clustering has greater efficiency
- Either the modified version or the integrated version of the traditional algorithms resulted in better classification or computation time.
- Integrating ABC optimal algorithm with FCM (also) resulted in optimal solution.
- The PST based edge detection algorithm performed well than the threshold-based edge detection method and Canny-based edge detection method.
- The integration of the K-Means algorithm with OLA has higher accuracy than the traditional K-Means algorithm.

5. CONCLUSION

The main challenges in brain tumor detection and classification include the rapid growth of tumor size, the difficulty of tumor segmentation from brain due to fuzzy borders, and the optimization of feature extraction and selection for accurate classification of brain tumors. Different models have been implemented in the literature to address these challenges, including machine learning approaches that mainly use indigenous features and pre-determined features. However, when boundaries between healthy tissues and tumors are inexplicit, these methods may exhibit poor performances. In recent years, DL and quantum ML methodologies have been widely exploited for tumor localization and classification. Such techniques employ automatic feature learning to differentiate complicated patterns, which helps to improve the accuracy of tumor diagnosis. However, limitations still exist in the current machine/deep learning methods. Deep learning models necessitate high computing power and large memory, which can pose a challenge for some researchers.

To address these limitations, researchers have proposed several traditional classifiers, including RF, K-NN, and DT- based on Majority Voting Method. These classifiers have an advantage over DL algorithms as they need small datasets for training and incur low computational time complexity and cost. In addition, traditional classifiers can improve the performance of tumor diagnosis and classification. In conclusion, the paper's findings provide valuable insights for researchers in terms of research recommendations and opportunities for refinement, particularly in relation to brain tumor processing stages.

Conflicts of Interest

"The author(s) declare(s) that there is no conflict of interest regarding the publication of this paper."

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