A DETAILED ANALYSIS ON MEDICAL IMAGE PROCESSING TECHNIQUES USED FOR BRAIN TUMOR DETECTION AND CLASSIFICATION

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ABSTRACT

Detection and classification of tumor portions from the brain images are the challenging and demanding tasks in the field of medical imaging applications. Because, the earlier prediction of tumor is highly essential for the patients to provide proper treatment at the time. So, an automated tumor detection system can be more useful for the medical experts to identify the growth and structure of tumor region. For this purpose, there are different types of medical image processing techniques are developed in the existing works. The main aim of this work is to present the comprehensive survey for analyzing the techniques used for detecting the brain abnormalities. Also, it objects to investigate the operating characteristics, working nature and performance of various image processing techniques. Typically, the preprocessing techniques are mainly used to filter the noisy contents for improving the quality of images with increased contrast. Specifically, the feature extraction models are used for extracting the high level feature attributes and patterns from the filtered image. Then, the optimal numbers of features are selected with the help of optimization techniques by estimating the objective function based on the best fitness value. Here, the importance of using segmentation approaches is to partition the image into collection of pixels, which are helpful for locating the tumor, affected regions. Finally, the classifiers are used for predicting the output label as normal or tumor-affected by training the samples based on the optimal features. For experimental validation, there are different measures have been used to evaluate the performance results of these techniques.

Keywords: *Brain Tumor, Magnetic Resonance Imaging (MRI), Segmentation, Feature Optimization, BRATS Dataset, Deep Learning and Machine Learning Techniques.*

1. INTRODUCTION

Brain tumor is defined as the group of abnormal cells present in the nervous system, which affects the normal functionality of brain by destroying the cells and increasing the inflammation [1, 2]. Also, the brain tumor is one of the most dangerous and dreadful types of cancer, and if the growth is more than 50%, the tumor affected patient could not be recovered. Moreover, the brain tumors [3-5] are generally classified into the types of primary and secondary, in which the primary tumor is categorized into benign and malignant types. This type of tumor does not spread to the other parts of body, but it cause serious health issues to the body. Then, the malignant tumor is more dangerous and life threatening disease, which spreads on other parts of the body. So, it is more essential to detect the brain tumors in an earlier stage to provide an appropriate treatment for patient recovery. For this purpose, there are different types of imaging modalities [6] have been utilized in the recent days, which includes Magnetic Resonance Imaging (MRI), Computed Tomography (CT), ultrasound, and x-ray. These modalities helps to predict the abnormal growth and exact location of tumor exist in the brain neural system. When compared to the other imaging modalities, the MRI is one of the most extensively used tool for accurately visualizing the characteristics of the brain structure [7]. The major benefits of using this modality are listed as follows:

- It helps to accurately identify the nervous syndromes.
- It exactly recognizes the vascular malfunctions and flowing blood.

- Also, it does not require any ionizing radiation effects for image scanning.

Moreover, the automated brain tumor detection and classification system [8, 9] plays a vital in the recent days, because which helps to accurately detect the tumor affected regions in fast manner. Due to this fact, the medical experts are highly recommend an automatic brain tumor detection system for providing an earlier diagnosis treatment to the patients. For this purpose, most of existing research works [10, 11] developed an automatic segmentation and classification techniques for the accurate identification of brain tumors. For instance, the machine learning based classification techniques are widely used for classifying the medical images as normal or abnormal. Also, the general brain image segmentation and classification system comprises the following stages:

1. Dataset collection
2. Image Preprocessing
3. Segmentation
4. Feature Extraction
5. Feature Selection/Optimization
6. Classification

The previous studies are highly focusing on analyzing the types of techniques used for MRI brain tumor detection, which are mostly related to image segmentation and classification algorithms. But, this work investigated the recent techniques used for completely processing the medical images from preprocessing to classification. Also, it examines the working methodology and operations of each algorithm with its distinct advantages and disadvantages. In addition to that, the performance analysis and results of the recent state-of-the-art models have been validated and compared by using the distinct measures. The major objectives behind this work are listed as follows:

- To scrutinize the medical image processing techniques used for developing an automated tumor detection system.
- To study the operating characteristics and working principles of the image processing techniques with its benefits and demerits.
- To analyze the list of parameters used for evaluating the performance of brain tumor detection and classification systems.

The remaining sections of this paper are structuralized as follows: the existing works related to the brain tumor segmentation and classification are surveyed in Section II. Then, the different types of image processing techniques are discussed with its operating principles, advantages and disadvantages in Section III. The results and discussions of the conventional methodologies are presented with its parametric estimations in Section IV. Finally, the obtainment of overall study is summarized with its future scope in Section V.

2. RELATED WORKS

This section reviews some of the conventional works related to the brain tumor segmentation and classification systems. Also, it examines the advantages and disadvantages of each technique with respect to its working operations and functions. This survey could be more helpful for identifying the suitable image processing techniques used to develop an automated brain tumor detection system.

Tahir, et al [12] developed an enhanced framework for accurately segmenting and classifying the brain tumor from the medical images. The main focus of this work was to improve the performance of classification by applying a combination machine learning techniques, which comprises the stages of image preprocessing, segmentation and classification. In which, the noise removal, contrast enhancement, and edge enhancement processes were performed during image preprocessing that helps to filter the image with good quality. Then, the Otsu thresholding based classification methodology was utilized to label the class of tumor. The key benefits of this work were increased accuracy, better prediction results, and simple design. However, it has the limitations of increased time consumption and inability to handle large dimensional datasets. *Jemimma and Vetharaj* [13] utilized a watershed segmentation technique for identifying the abnormalities from the MRI brain images. The main consideration of this work was to accurately segment the tumor affected regions by applying the Watershed Dynamic Angle Projection – Convolutional Neural Networks (WDAPP-CNN) mechanism. The working stages involved in this system were input image obtainment, segmentation, feature extraction, and classification. To evaluate the performance of this technique by using various performance measures, the BRATS dataset has been utilized in this work. The advantages behind this work were easy implementation, reduce computational time, and fast processing.

Arunkumar, et al [14] suggested an Artificial Neural Network (ANN) based classification approach for designing the fully automated brain tumor segmentation system. Here, the MRI brain image was taken as the input, where the quality enhancement and noise removal processes have been performed at the initial stage for increasing the detection accuracy of classification. Moreover, the Histogram of Gradient (HOG) descriptor algorithm was utilized to extract the histogram features based on the weighted gradient. Consequently, the Region of Interest (ROI) was plotted to filter the non-brain object based on the histogram threshold. In addition to that, the Hough circle transformation was applied to find the difference between the planes, which helps to reduce the global consistency error of segmentation. The merits of this paper were increased recognition accuracy, and exact object picking. Yet, it has the major issues of increased computational steps, and requires more time for training and testing datasets.

Amin, et al [15] implemented a score level fusion mechanism for developing an automated brain tumor segmentation and classification system. The main intention of this work was to exactly classify the benign and malignant tumor classes by using the CNN model. During the lesion enhancement, the gray scale conversion, linear transformation, log transformation, smoothening, and edge enhancement processes have been performed. Consequently, the global thresholding estimation and morphological operations were accomplished for segmenting the lesions. Finally, the CNN technique categorized the healthy and unhealthy lesions by estimating the score vector using an Alex net and Google net layers. *Sharif, et al* [16] employed a binomial thresholding and multi-features selection methods for segmenting the abnormal tissues from the MRI brain images. The stages involved in this detection system were image preprocessing, tumor segmentation, geometrical feature extraction, GA based optimization, and SVM classification. In which, the normal skull stripping was performed to extract the ROI, and the Gaussian filtering technique was utilized to remove the noise artifacts. Then, the tumor portion was segmented by applying the thresholding method, and the geometrical and texture features were extracted from the segmented region. After that, the GA was employed to select the best optimal features, and these features were fed to the SVM classifier for predicting the classified labels.

Tiwari, et al [17] presented a new review of methods for the identifying the most suitable mechanism used for MRI brain tumor image segmentation. Also, it conducted an experimental analysis for comparing the performance of different machine learning techniques such as Support Vector Machine (SVM), Self-Organizing Map (SOM), and other deep learning models. Moreover, it examines the efficiency of different optimization mechanisms include Particle Swarm Optimization (PSO), Genetic Algorithm (GA), Ant Bee Colony (ABC) optimization, Differential Evaluation (DE) and Bat algorithm. In paper [18], the GA based classification technique was utilized for improving the accuracy of automatic brain classification. Here, a combination of segmentation techniques have been utilized for enhancing the performance of this system, which includes the techniques of Berkeley Transformation (BT), Fuzzy Clustering Means (FCM) and Discrete Cosine Transformation (DCT). After segmenting the regions of image by using these techniques, varying features like contrast, mean, energy and entropy were extracted for decision making process. Based on these feature values, the normal and abnormal tissues have been segregated with the help of GA. Still, this work limits with the issues of high false positives, reduced robustness, and minimal accuracy in classification.

Raju, et al [19] implemented a novel Harmony Crow Search (HCS) optimization incorporated with Support Vector Neural Network (SVNN) classification technique for detecting the abnormal tumor affected cells from the brain image. Here, the classifier was trained by estimating the optimal weight value of the features. Moreover, the Bayesian fuzzy clustering technique was utilized to segment the regions of the image slices. During the feature extraction, the scattering and wavelet transformation techniques have been applied with the information theoretic measures. However, this work comprises the major disadvantages of highly complexity, requirement of manual segmentation, and increased time consumption. *Mathew, et al* [20] utilized a combination of techniques for the detection and classification brain abnormalities, which includes median filtering, Otsu thresholding based segmentation, K-Means clustering, GLCM feature extraction, PCA based optimization, and SVM classification. Moreover, this work extracted various features such as contrast, entropy, energy, standard deviation, skewness and kurtosis for improving the accuracy of detection. Still, it has an increased number of computational steps, which leads to the high complexity of algorithm design. *Raju, et al* [21] suggested a hybrid active contour model incorporated with Deep Belief Networks (DBNs) for an automatic brain tumor classification. In order to integrate the functionalities of Bayesian fuzzy clustering with the active contour model, the

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laplacian correlation has been utilized. Moreover, the classifier predicts the output label into the classes of tumor or non-tumor, in which the tumor was categorized into the types of core, edema, and enhanced tumor.

Daimary, et al [22] employed a hybrid CNN technique for classifying the abnormal brain regions from the brain MRIs. The main intention of this work was to develop a hybridized architecture based on the fusion of U-Net and SegNet5 models. The main drawback behind this work was, increased computational complexity of algorithm design. *Ganesan, et al* [23] used a threshold based segmentation approach for identifying the brain abnormalities by computing the intensity of image. Here, the Discrete Wavelet Transformation (DWT) has been utilized to perform the image decomposition, which helps to increase the accuracy of classification.

Shah, et al [24] suggested a cascaded random decision forests model for segmenting the abnormal brain regions from the MRIs. Here, three different cascaded models have been utilized for enhancing the accuracy of segmentation, which includes complete tumor region extraction, tumor core extraction, and accurate tumor affected region segmentation. In order to validate the effectiveness of this model, the grade of tumor has been computed for the three cascaded segmented regions, where the tumor was categorized into the types of low grade and high grade. *Iqbal, et al* [25] developed an integrated deep learning based patch-wise image segmentation model for improving the classification performance of brain tumor detection. Here, the different classes of images have been validated for examining the efficiency of the suggested scheme. The advantage of this work was, it has the ability to handle the imbalanced imaging data with better performance outcomes. *Narmatha, et al* [26] implemented a hybrid optimization technique by incorporating the operating characteristics of fuzzy and brain storm optimization models for medical imaging applications. This work comprises the working modules of image obtainment, enhancement, feature extraction and classification. During brain-storming, the set of iterations have been accomplished to identify the suitable solution for segmentation. Here, the high level features like color, texture, shape and size were extracted and utilized at the time of classification.

Based on this review, it is studied that the conventional works limits with the problems of high difficulties in handling large type of datasets, inaccurate location identification, misclassified outcomes, and increased complexity in algorithm design.

3. BRAIN TUMOR SEGMENTATION AND CLASSIFICATION

Typically, there are different types of image segmentation and classification methodologies are used for the detection of brain abnormalities, in which the most extensively used medical image processing mechanisms [27-30] are discussed in this section with its operating characteristics, advantages and disadvantages. The general brain image processing system comprises the following operating stages:

- Image acquisition
- Preprocessing
- Segmentation
- Feature Extraction
- Optimization
- Classification

For developing an automated tumor detection system, there various brain imaging datasets such as BRATS, brain web, cancer imaging archive, and public repository MRIs are available in the present days. The BRATS dataset contains 3D MRI scanned images with the four different modalities of T1-weighted, T2-weighted, T1C-weighted, and Flair of high grade and low grade gliomas and, each having the size of $240 \times 240 \times 155$. Then, the brain web dataset comprises the 3D normal and multi-sclerosis images, which has moderating intensities, noises and thickness. The cancer imaging archive dataset contains the combination of T1-slicing images with the patients having benign and malignant tumor. At last, the public repository dataset contains large number of imaging sequences with the categories of normal, benign and malignant tumors.

After image acquisition, the image preprocessing has been performed for enhancing the contrast, sharping the edges, improving the quality, reducing the blurring effects, and filtering the noisy contents. Then, the segmentation techniques are applied to segregate the brain region based on the weight functions or thresholds. Consequently, the higher order features like color, contrast, texture, and size are extracted from the segmented regions by applying the segmentation approaches. After that, the optimal number of features are selected by computing the best fitness values and weighting objective functions. Finally, the machine learning or deep learning classification techniques are used to predict the classifier label as whether normal or tumor affected with its types.

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A. *Image Preprocessing*

Generally, the medical images having more noisy contents due to the variations of image generation and patients movements at the time scanning [31]. The noisy image can affect the performance of classifier with high false positives and reduced accuracy levels. So, it must be eliminated before processing the image, and also it is one of the most essential task for the medical imaging applications. For this purpose, there are various filtering techniques [32] have been used for eliminating the noisy contexts and artefacts, which includes the types of mean filtering, median filtering, hybrid filtering, wiener filtering, and morphology based filtering. Also, it can be used to improve the quality of images by performing the contrast enhancement, blurring enhancement, and sharpening the images. Table 1 shows the operating characteristics of these filtering techniques with its benefits and demerits.

Table 1. Analysis Of Various Image Preprocessing Methods

Preprocessing Methods	***Operating Characteristics***	***Benefits***	***Demerits***
Median filtering	It can replace the value of center pixel with the median value its neighboring pixel.	• It efficiently reduces the salt and pepper noise. • Better edge and boundary preservation	•Increased complexity •Hightime consumption
Mean filtering	It filters the noisy contents by estimating the average value for all pixels.	• Fast response time.	Inaccurate edges and boundaries
Hybrid median filtering	It incorporates the functionalities of both mean and median filtering.	• Highly efficient for removing the speckle, Gaussian, salt and pepper noisy contents.	• Increased time consumption
Wiener filtering	It is highly used in the frequency domain applications. It helps to remove the white noisy pixels.	• Better normalization with removal of blurring effects.	• Low speed in processing • It is not suitable for all imaging applications
Morphology based filtering	It working based on the opening and closing operations of the morphological functions.	• Efficient in processing.	• High designing complexity

In paper [33], the MRI and patch preprocessing have been performed by estimating the mean intensity and standard deviation of all pixels of image. Based on this, the patches are normalized with the zero mean and unit variance sequences. In this work [34], the preprocessing is done by considering the input image as the reference image, based on this the skull region and other noise artefacts are eliminated by using the anisotropic filtering techniques. Moreover, it helps to preserve the structure of the image with strengthened edges. The median filtering [35] technique has been utilized to reduce the noisy contents with minimal computational complexity. Here, the histogram equalization is also used for improving the contrast of image by computing the intensity of image based on the probability density function.

B. *Feature Extraction*

Feature extraction is more helpful for extracting the high level of feature attributes from the brain image, which includes the shape, size, contrast, color and texture properties. These features are mainly used for improving the precision of brain detection system. There are different types of feature extraction techniques [36] are used for improving the medical image diagnosing system such as Gray Level Co-occurrence Matrix (GLCM), Discrete Wavelet Transform (DWT), Discrete Fourier Transform (DFT), Local Binary Pattern (LBP), Local Tetra Pattern (LTrP), Local Ternary Pattern (LTP), Local Discriminative Analysis (LDP), and some other pattern extraction approaches. In paper [37], the GLCM and DWT techniques are used for extracting both the wavelet coefficients and statistical features of the image. The different types of texture features extracted by using GLCM are as follows: energy, correlation, contrast, entropy, homogeneity, peak signal to noise ratio, and mean squared error. Here, the tractographic features [38] are extracted for accurately segmenting the tumor affected regions from the brain image. This work used the statistical feature [39] extraction approach for finding the spatial connections between the pixels of brain image.

C. Feature Selection

Generally, the feature selection approaches are mainly used for reducing the dimensionality of feature attributes, because increased number of features create high complexity and inaccurate classification results [40]. So, it is more important to select the optimal number of features by computing the fitness function based on the weight values. For this purpose, there are various optimization techniques [41] are used for improving the efficiency of feature selection. It includes the types of Principle Component Analysis (PCA), Particle Swarm Optimization (PSO), Genetic Algorithm (GA), Whale Optimization (WO), Gray Wolf Optimization (GWO), Ant Colony Optimization (ACO), Ant Bee Colony Optimization (ABO), Honey Bee (HB) optimization, fuzzy clustering based optimization, and some other multi-objective optimization mechanisms [42]. These techniques compute the objective functions based on the fitness value and weight value of the image particles for selecting the well-suited feature vectors. The optimal number of selected features are used by the classifier to train the detection system for improving the accuracy and efficiency measures. In paper [43], the stochastic optimization technique is used for choosing the optimal parameters with reduced cost function. This technique helps to accurately identify the tumor affected regions from the brain MRIs. Here [44], the WO technique has been utilized for selecting the features by updating the current position of whales based on the probability value. *Pereira, et al* [45] suggested a feature recombination algorithm for computing the spatial correspondence between the features, which helps to enhance the segmentation results.

D. Segmentation

Segmentation is an important stage of brain tumor detection system, which is mainly used to segregate the regions of image for locating the tumor affected pixels. Also, it helps to detecting the brain tumor from the human MRIs for providing an appropriate treatment and diagnosis. For simplifying the process of classification, there are various segmentation approaches have been used for medical imaging applications, which includes the watershed segmentation, active contour segmentation, region growing, thresholding, and other multi-objective segmentation techniques. In paper [46], the multi-class segmentation approach is used for processing the multi-modal brain MRIs with increased accuracy and efficiency. The authors [47] examined the use of both thresholding and region growing segmentation approaches for obtaining an increased classification efficiency of medical imaging diagnosis system. Thresholding based segmentation technique is highly suitable for processing the brain MRIs, due to their benefits of fast processing, easy implementation, and simplicity in nature. The intensity value of image pixels are estimated for determining the threshold value used for segmentation [48]. Similarly, the region growing is also one of the popular technique that helps to segregate the image regions based on the same intensity value. The main reason of using this approach is, it does not require any priory knowledge about the shape of image, so it can be more suitable for images with varying sizes. But, it requires the selection of seed points of each region of image, and it must satisfy the desired similarity principles [49], which are the major issues of using this technique. Table 2 describes the advantages and disadvantages of these segmentation approaches used for the brain tumor detection system.

Table 2. Merits And Demerits Of Various Segmentation Techniques

Methods	Benefits	Demerits
Watershed segmentation	• Enhanced capturing range of image. • It segments the image based on mathematical morphological operations.	• Results in over segmentation of image. • High complexity.
Active contour segmentation	• Efficient preservation of edges. • Better accuracy with the use of active contour models.	• It requires to identify the strong gradients of image for segmenting the regions. • It does not suitable for the images having weak

		boundaries and edges.
Region growing segmentation	• It accurately segments the regions of image with same properties.	• Not suitable for all images, due to the need of manual interaction at time of seed point estimation.
Thresholding segmentation	• It helps to exactly locate the edge pixels based on gradient magnitudes. • Increased accuracy.	• High computational complexity • Discontinuous edges

E. Classification

The classification is the final stage of image processing system, which produces the classified label as whether normal or abnormal based on the selected features of the segmented output. Typically, the machine learning [50] and deep learning classifier are highly used for decision making, and also it predicts the data by training the classifiers. Table 3 depicts some of the highly used classification approaches for handling the medical images. Moreover, the machine learning methods are categorized into the types of supervised and unsupervised learning techniques. In supervised classification, the k-Nearest Neighbor (k-NN), Support Vector Machine (SVM), Relevance Vector Machine (RVM), Random Forest (RF), Neural Networks (NN), Artificial Neural Network (ANN), Recurrent Neural Network (RNN), Probabilistic Neural Network (PNN), and fuzzy systems are used. In unsupervised classification, the k-means clustering, Fuzzy C-Means (FCM) clustering, active contour models, geometric deformable models, and other hybrid mechanisms are used. In paper [51], the deep CNN technique is used for predicting the multi-grade brain tumors based on data augmentation. Here, the VGG-19 architecture model is employed for predicting the four different types of tumor grades by using the layers of convolutional, fully connected and softmax. In order to improve the efficiency of classification, there are various augmentation techniques such as edge detection, emboss, sharpening, and Gaussian blur removal are applied on the input images. The authors [52] utilized a k-means clustering technique incorporated with NN mechanism for increasing the accuracy of tumor detection. The main reason of using k-means clustering is to choose the optimal region by estimating the distance value between the pixels of image.

Table 3. Advantages And Disadvantages Of Classification Methods

Methods	***Benefits***	***Demerits***
Adaboost	1. Fast computation. 2. It does not require any prior knowledge. 3. Highly Adaptable.	1. The performance of this technique is highly depends on the data learning. 2. Increased failure ratio.
NN	1. Most suitable optimization results. 2. No overlapping estimations. 3. Constant and optimal solutions. 4. Simple to design.	1. It is not more suitable for complex optimization problems. 2. Inefficient results.
SVM	1. Reduced overfitting. 2. Highly robust. 3. Accurate classification.	1. High computational complexity. 2. Increased time consumption. 3. Slower in process. 4. Binary classification outcome.
K-Means	1. Easy to implement. 2. Fast computation. 3. Easy to understand the clustering process.	1. It is highly difficult to predict the cluster value. 2. The data ordering may affect the final result.
Ensemble classification	1. Improved prediction accuracy. 2. High efficiency.	1. Complicated design. 2. More complex to understand.

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FCM	1. Better convergence. 2. It does not require any supervision control.	1. Requires more time consumption. 2. Highly sensitive.
CNN	1. It has the ability to learn the complex features. 2. Capability of handling large datasets.	1. Requires more training data. 2. Increased computational complexity.

4. RESULTS AND DISCUSSION

This section presents the different types of performance indicators used for validating the effectiveness of medical imaging system. Also, the list of measures and their estimations are shown in Table 4, and an improved performance values of these measures ensure the efficient image processing techniques.

Table 4. Evaluation Parameters

Measures	***Calculations***
Accuracy	$Accuracy = \frac{TP+TN}{TP+TN+FP+FN}$
Sensitivity	$Sensitivity = \frac{TP}{TP+FN}$
Specificity	$Specificity = \frac{TN}{TN+FP}$
Jaccard	$Jaccard\_Similarity = \frac{TP}{TP+FN+FP}$
Dice	$Dice\_Overlap = \frac{2TP}{FP+2TP+FN}$
Precision	$\Pr ecision = \frac{TP}{TP+FP}$
Recall	$\text{Re}\,call = \frac{TP}{TP+FN}$
F1-measure	$F1\_Score = \frac{2\times \Pr ecision \times \text{Re}\,call}{\Pr ecision + \text{Re}\,call}$
Matthews Correlation Coefficient	$MCC = \frac{TP\times TN - FP\times FN}{\sqrt{(TP+FP)(TP+FN)(TN+FP)(TN+}}$
Error rate	$Error\_Rate = 1 - Accuracy$
Kappa coefficient	$Kappa\_Coeff = \frac{P_o - P_e}{1 - P_e}$
Where, TP – True Positives, TN – True Negatives, FP – False Positives, FN – False Negatives.	

In this study, the widely used BRATS dataset has been considered for validating the effectiveness of the existing image processing techniques. As shown in Table 5 and Fig 1, the performance of PSO, WSO, GSO, and FBSO techniques are validated by using the measures of sensitivity, specificity, accuracy, and F1-measure.

Table 5. Comparative Analysis Between The Optimization Techniques Using BRATS Dataset

Optimization Methods	Sensitivity	Specificity	Accuracy	F1-score
Particle Swarm Optimization (PSO)	87.77	78.38	84.33	89.66
Whale Swarm Optimization (WSO)	92.11	85.29	89.67	92.90
Glow Swarm Optimization (GSO)	89.60	79.78	86	90.63
Fuzzy Brain Storm Optimization (FBSO)	92.90	87.88	91.16	93.81

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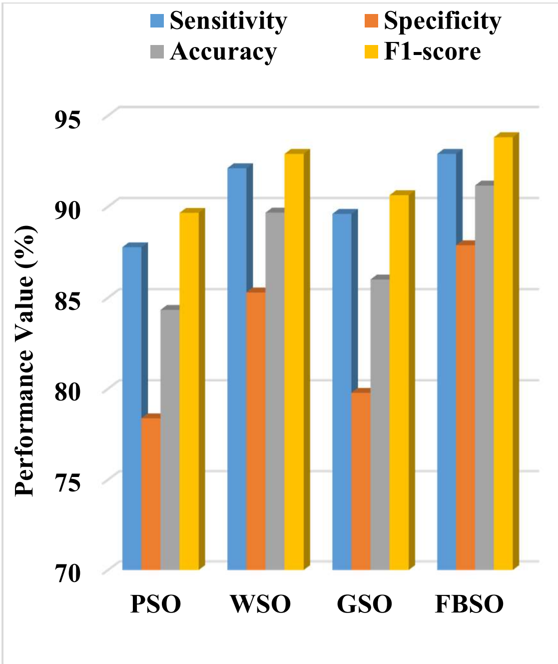

Fig 1. Comparative Analysis Between The Existing Optimization Techniques

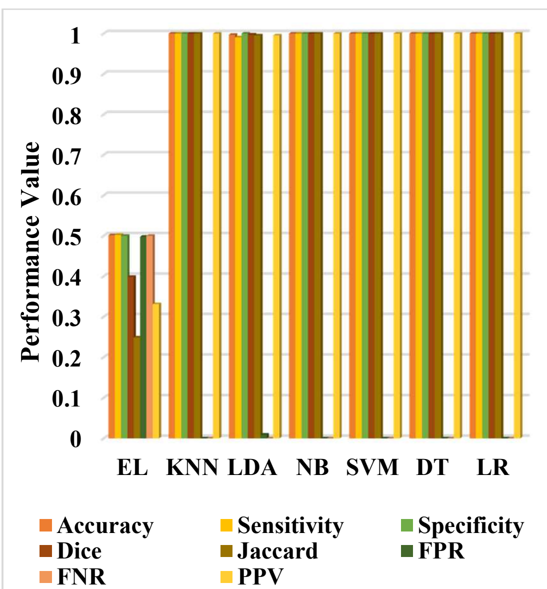

Fig 2. Comparative Analysis Between The Classification Approaches For BRATS 2015 Dataset

As shown in Fig 2 to Fig 4, the performance of various classification techniques [15] are compared for the images obtained from the BRATS dataset 2015, 2016, and 2017, which includes the techniques of Ensemble Learning (EL), K-Nearest Neighbor (K-NN), Linear Discriminant Analysis (LDA), Naïve Bayes (NB), SVM, Decision Tree (DT), and Linear Regression (LR). Then, this analysis shows that an improved performance values of the techniques are highly depends on the working and operating conditions of the image processing techniques.

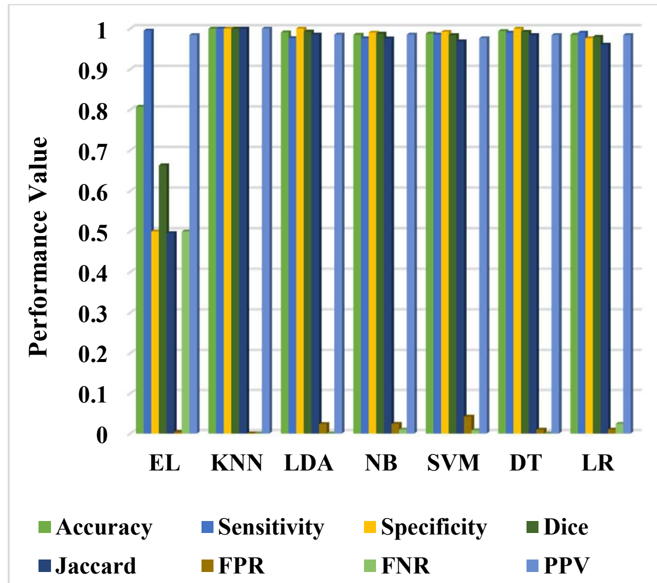

Fig 3. Comparative Analysis Between The Classification Approaches For BRATS 2016 Dataset

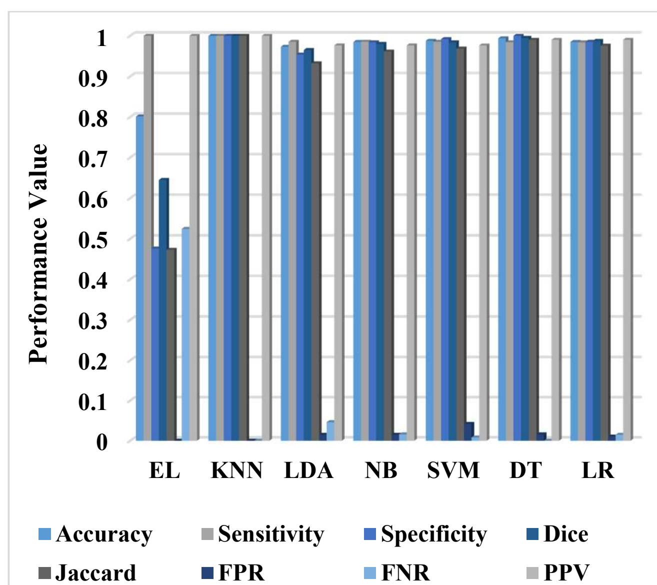

Fig 4. Comparative Analysis Between The Classification Approaches For BRATS 2017 Dataset

Table 6. Analysis Of Conventional Brain Tumor Detection Approaches

Authors & Year	Technique	Description	Advantages	Disadvantages
Arunkumar, et al [52] & 2019	K-Means clustering integrated with Neural Network (NN)	It intends to detect the abnormality or brain tumors by incorporating the functionalities of k-means and NN techniques.	Easy to implement Fast processing	Cluster prediction is difficult Due to the ordering of clusters, the final result of classification may affect.
Sajjad, et al [51] & 2019	Data augmentation with deep CNN	It aims to categorize the grade of tumors by tuning the parameters of DNN.	It has the ability to handle the complex features Better accuracy	It requires more training data for processing. High computational complexity
Wang, et al [46] & 2017	Cascaded Anisotropic – CNN Model	The main aim of this work is to improve the segmentation result by estimating the optimal solution for multi-class segmentation.	Optimal values increase the accuracy of computation It has the ability to handle large datasets	Requires more time consumption High false positives
Dey, et al [40] & 2019	Social Group Optimization (SGO) – ANFIS Model	It objects to accurately extract the tumor portion by computing the thresholds using knowledge updating procedure.	High predictive accuracy No overlapping	Difficult to understand Complexity in algorithm design
Lavanya Devi, et al [39] & 2017	PCA – PNN based classification	This technique is used to segregate the tumor spread area by clustering the objects based on the distance measure.	Better optimization Simple estimation Fast processing	Increased misclassification results It does not has the ability to handle large dimensional data
Varuna shree and Kumar [37] & 2018	DWT – PNN	Here, the identification properties of image such as shape, color and texture have been considered for improving the detecting performance.	It does not require any prior knowledge Better accuracy Optimal number of features	It requires more time for computation Reduced efficiency
Matthew, et al [34] & 2017	DWT – SVM	It applied the otsu thresholding approach and morphological operations for developing an automatic tumor detection system.	Accurate classified outcomes Simple designing	Binary classifier

5. RESEARCH ISSUES AND LIMITATIONS

Due to the increased complexity of medical images, it is very difficult to process the images for disease identification and diagnosis. Also, it is very complex to obtain an increased accuracy and reduced false positives in MRI brain tumor detection. Because, the brain images have different size, shape, intensity, and location, hence it consumes more time for accurately segmenting the tumor affected region from the given image. This study objects to review the image processing techniques used for segmenting and classifying the tumor affected portions with increased accuracy. Still, this work requires to perform an in-depth analysis for extracting the features of medical images. Since, the detection performance and accuracy of classification are highly depends on the features of image. In most cases, the classifier requires an increased amount of time for training the features in order to predict the classified result. Hence, this review requires to validate the performance and results of feature extraction and optimization techniques.

6. CONCLUSION

This paper presents the detailed survey on various image processing techniques used for processing the medical brain MRIs. Also, it investigates the related problems and importance of detecting tumor by using the soft-computing techniques. The main intention of work is to identify the abnormality of brain images by developing an automated system using the segmentation and classification techniques. Here, the techniques are surveyed and studied under stages of preprocessing, feature extraction, optimization, segmentation, and classification. Also, it discusses about the benefits and demerits of these techniques based on its operating principles and characteristics. Moreover, the essential parameters used for validating the performance of these techniques are analyzed with its estimation models. From this review, it is studied that the entire performance of brain tumor detection system is highly depends on the factors of improved quality of image without noisy contents, most-suited feature attributes of the normalized image, accurate image segregation with edge preservation, and efficient classifier with training and testing phases. Moreover, the complete and efficient medical imaging system must ensures the properties of reduced designing complexity, high accuracy, minimal time consumption for training samples, and reduced false positives. According to this study, it is suggested that MRI brain tumor segmentation and classification system is entirely depends on the quality of image and segmented region of interest. Also, is important to obtain the reduced error rate, misclassification output, computational complexity, increased detection accuracy, minimized training and testing time. Therefore, it is more essential to develop an efficient segmentation based classification system for accurately localizing the tumor region from the MRI brain images. Moreover, the feature optimization helps to efficiently reduce the time consumption by optimally selecting the features for training the data model of classifier.

In future, this work can be extended by implementing an advanced segmentation and classification models for precisely detecting the tumor region with its exact location.

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