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A Review on an Efficient Technique for Detection and Classification of Early Stage Tumor

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Abstract— **To reduce the death by tumor disease it is important for the classification and identification of the early stage tumor for diagnosis. The brain tumor is categorized into two types those are primary and secondary brain tumor. Again, primary brain tumor is categorized into two types those are malignant and benign tumor. Benign tumor is non-cancerous it does not affect other parts but malignant brain tumors are cancerous they may spread into spine of our body. This paper reviews various techniques utilized to classify the brain tumors with the help of MR images. Brain tumor classification can be divided into four phases as preprocessing, segmentation, feature reduction and extraction, classification. As segmentation is important step to classify the brain tumors. Median filter is efficient to eliminate the noise. Combination of K means cluster and otsu binarization is enough for segmentation. DWT (Discrete wavelet transform) and GLCM (Grey Level co-occurrence matrix) efficient for transform and spatial feature extraction. PCA (Principal component analysis) reduces the feature vector to maintain the classification accuracy of brain MRI images. For the performance of MRIs classification, the significant features have been submitted to KSVM (kernel support vector machine). The proposed system will reduce processing time and better accuracy can be achieved. The proposed method is validated on BRATS 2015 dataset.**

Index Terms— **K-means; DWT; GLCM; PCA; KSVM; MRI Classification.**

I. INTRODUCTION

The formation of abnormal cells in the brain leads to brain tumor. Benign and malignant are the two main kinds of tumors. The tumor which starts in the brain itself is known as primary malignant tumor. Secondary tumors (metastasis tumors), spread from elsewhere. There are four grades of brain tumors according to the American Brain Tumor Association and World Health Organization [2]. Benign tumors, which are slow growing are Grade I and grade II, and are also known as low-grade tumors. Malignant tumors, which are rapid growing are grade III and grade IV and are called high-grade tumors. It is significant to detect brain tumor at the early stage and it is necessary to identify the tumor area and segment the tumor images.

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Magnetic resonance imaging (MRI) and computed tomography (CT) scans are two diagnostic modes which show the internal structure of the brain. MRI is an imaging technique which provides the information about human body. Due to high contrast of soft tissues and spatial resolution of brain, it is mandatory to diagnose the brain tumor by MRI component. It does not produce radiation and is non-invasive, which make it more proficient than other techniques [4]. It has a several benefits compared to remaining imaging techniques. Operator performance causes noise in MRI images and this noise leads to inaccuracies classification. It is not easy to detect and classify the brain tumors. Due to the misplaced edges, noise, low contrast of medical images it is hard to get information from these images [31]. It includes few processes, such as image segmentation, enhancement, feature selection and extraction, feature classification and reduction. The noise is reduced by using different filter methods. Gaussian, speckle, Salt and pepper noise are additive noises of MRI images and can be removed by Averaging filter, Adaptive filter, Un-sharp masking filter, Median filter and Gaussian filter [6]. Averaging filter gives the good result by computing MSE. Median filter removes the noise based on PSNR [17]. Significant step for the detection of tumor area is segmentation. The separation of image into distinct parts as per their similar properties can be done by using clustering. Clustering is one of the unsupervised segmentation methods. K-means and Fuzzy C-means algorithm are two mostly used clustering techniques. K-means clustering is an effective way that uses a fixed number of clusters prior to classify a set of data [24]. The feature extraction can be done by using Gray Level Co-occurrence Matrix (GLCM) and Discrete wavelet transform (DWT). Spatial feature extraction can be done by using GLCM and transform feature extraction can be done by DWT. The high dimensional space patterns can be made by statistical method known as principal component analysis (PCA). The multidimensionality and number of variables can be reduced by PCA and it enables the exploring of date in an easy way [40]. The classifier on the basis of machine learning comprising of supervised and unsupervised learning has become popular in recent years. K-NN, SVM and ANN are included in supervised learning. Self-organization feature map (SOFM) and fuzzy c-means are included in unsupervised [3]. The advantageous features of SVM are regularization, low test error rate, kernel trick and absence of local minima.

The tumor classification and detection has been done by employing various techniques till now. But these techniques have drawbacks such as lack of accuracy, intensity inhomogeneity, noise, time complexity, computational complexity, feature selection, extraction and reduction, etc. DWT with KSVM classifier is proposed to overcome these limitations and also classification of the tumor is done with high accuracy by using this classifier, which denoising and segment the image, extract and reduce the feature, select the proper features for accurate classification of the tumor as benign and malignant tumor from MRI image.

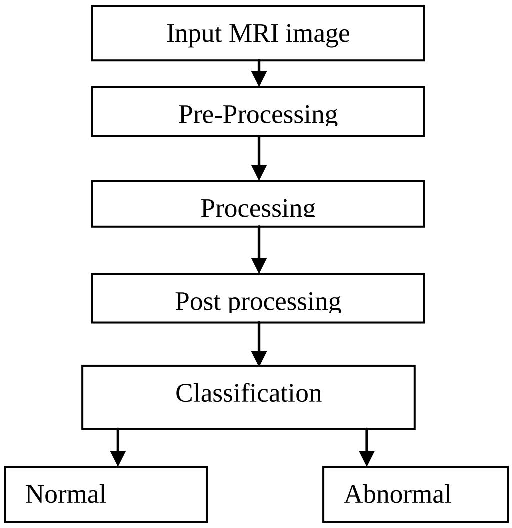

Figure 1: Brain tumor classification and detection methodology

A . Pre Processing

The detailed information of brain can be obtained by the MRI images and are considered as the input images. Input dataset is used in the form of X= $\{x_1, x_2, \ldots x_n\}$. The BRATS dataset is used for the collections of images.

The first stage of this system after the preparation of the dataset is preprocessing. Some types of noise affect the magnetic resonance images which leads to degradation of the resolution [7]. The preprocessing stage enables the improvement in image quality by suppressing the noise and it also enhances the resolution of the images. De-noising and filtering at this stage is done by median filter.

B. Processing

The processing stage includes K -means clustering and Otsu binarization. Conversion of image into binary format is done by Otsu binarization and which finds the binarization threshold automatically. It is commonly used thresholding technique. The binary image from gray-level image in image processing and in computer version can be obtained by this technique which also performs the clustering-based image thresholding. The binary image further processed by significant clustering algorithm known as K-means. Grouping of pixels is termed as clustering. Defining the number of k clusters has to be done first. The cluster centers k is selected in random way. The calculation of distance between the pixels and the cluster centers is carried out next. Distance formula is used for the comparison of each pixel with every cluster center. The pixel is transferred to a cluster which is at a shortest distance from the pixel compared to all. This process is continuous until the clustering criterion converges.

C. Post Processing

Feature reduction and extraction are carried out in postprocessing. The process of feature extraction includes the extraction of significant information such as texture, color features, contrast and shape of an image. Here spatial feature extraction has been performed by GLCM and transform feature extraction is done by DWT. The relative position of pixel in an image is obtained by a statistical method called GLCM. The first texture-based technique of feature extraction was presented by R.M. Haralick. It calculates the occurrence of a pixel i having intensity I in relation with other pixel j with distance d and angle ϴ. The element of the GLCM is formed by pixel i with the total number of occurrences. Resultant matrix is used to determine the features after the calculation of GLCM. The measurement of correlation, energy, contrast and homogeneity is carried out in this study. The features are extracted from the segmented image by DWT. Images are converted to frequency domain from the spatial domain. The low pass and high pass filters are used for filtering the image in both horizontal and vertical direction to perform the actual DWT. The division of image in each DWT level includes coefficients: LL, LH, HL and HH. The LL sub-bands (approximation coefficient) obtained by using the low pass and high pass filters in the horizontal and vertical directions respectively. Remaining sub-bands are called as detailed coefficients. More detailed information is extracted from the tumor using DWT. Classification complexity is increased by extra unnecessary features, require more storage memory and prolong the computational time. Thus, feature reduction is considered as a part of our proposed system. Wavelet transform dimensionality can be reduced by Principal Component Analysis (PCA) method. The reduction of data dimension as per their variance and importance is done by. Emphasis of differences and similarities in standards of data and their expression is performed by PCA. Patterns can be compressed and their dimensions can be reduced, once they found without losing much of information. This reduction is useful for data representation, image compression, calculation reduction which are essential for the further processing.

D. Classification

The reduction of structural risk can be done by original support vector also known as binary classification method presented by Vapnik. SVM is on basis of supervised techniques and is used for the problems from one-class to multiple-class classification [13]. SVM is utilized as kernel machine. The kernel enables to fit the maximum-margin hyperplane into transformed feature space, which is the significant effect of kernel trick. MRI classification is performed by KSVM. Box constraint, auto scale and kernel are the families of SVM. The selection of kernel support vector machine is on the basis of wide range of functions, such as polynomial, linear, and gaussian radial basis (GRB).

II. LITERATURE SURVEY

Arakeri et al., (2013) proposed an accurate and automatic computer-aided diagnosis (CAD) system on the basis of group of classifiers such as SVM, ANN and KNN to characterize the brain tumors as malignant or benign on MRI images. In pre-processing stage, the noise is suppressed by employing median filter. To segment the brain tumor on each 2D MRI image they used combination of modified FCM clustering and wavelet decomposition technique. The feature selection and ranking steps are involved in the techniques of feature selection. The feature ranking using information gain method, which selects the subset of features based on the information contribution associated with the class variable. Feature selection is done by using ICA (independent component analysis). Classification is done by using 3 classifiers such as SVM, ANN and KNN. The proposed CAD system reduces the computational cost and operational complexity as it performs the analysis of brain tumor in 2D features, which eliminates processing of entire 3D tumor volume. They collected 550 patients' MRI images from shirdi sai cancer hospital manipal, India. By using these 3 classifiers they achieved better accuracy such as SVM (96.42%), ANN (94.18%) and KNN (89.09%).

Amien et al., (2013) instead of CAD, they used MRI images due to time consumption. They proposed the classification of brain images by employing Back-Propagation Neural Network (BPNN) which is on the basis of Pearson correlation coefficient. The proposed system consisting of 3 stages. Enhancement in the contrast and suppression of noise are done in preprocessing. Secondly, the classification of the brain tumor is performed by extracting the texture features and reduction of dimensionality are performed by using PCA and BPNN. They 58 MRI images of 3 MRI human brain dataset and they achieved 96.8% of accuracy.

Jayachandran A. *et al.*, (2013) proposed a technique which consists of four stages. The reduction of noise is done by using anisotropic filter in the first stage. They obtained the texture features related to MRI images in the second stage. The feature reduction is done by utilizing principles component analysis in the third stage. The supervisor classifier based FSVM is utilized to classify tumor as normal and abnormal brain MR images at the last stage. They collected 80 MRI images of non-tumor and tumor from south Indian area severity and analysis includes the processing the images and they achieved 95.80% of Classification accuracy.

Kharmega Sundararaj *et al.*, (2014) presented the automatic brain tumor classification in CT images. The four stages of this method are preprocessing, extraction of features, feature classification and reduction. Gaussian filter is employed to reduce noise and to ensure the compatibility of image for features extraction. Extraction of intensity and texture based features are done in the second stage to classify. More accurate and efficient classification is achieved with the help of PCA by reducing the feature space dimensionality in the next stage. Experimental images are classified into abnormal and normal with the help of two classifiers during the stage of classification. The first and second classifiers are on the basis of k-nearest neighbour and Linear SVM respectively. They achieved 94% of accuracy in Linear SVM and 92% accuracy in k-NN by collecting 50 CT brain images from Department of Radiology, Rajah Muthiah Medical College Hospital (RMMCH). There are 10 normal and 40 abnormal brain images out of 50 CT brain images.

Natteshan *et al.*, (2015) proposed a technique known as Computer Aided Diagnosis (CAD) to classify the brain MRI automatically into non tumor and tumor. Contrast Limited Adaptive Histogram Equalization (CLAHE) and wiener filter are used to preprocess the input images. The tumor region is then extracted using the intensity metric. Support Vector Machine (SVM) and Neural network classifiers are used to classify the brain tumor. They collected 9 non tumor and 83 tumor affected grayscale images from DICOM. They achieved accuracy of 85.40% with the help of SVM classifier provided quadratic kernel function, which performs more efficient than Radial Basis Function (RBF) kernel function (83.61%).

Anitha. V *et al.*, (2016) introduced an approach called two-tier classification for classification methodology and the segmentation is performed by employing adaptive pillar K-means algorithm. Discrete wavelet, transform blend wavelets are used to extract the feature from neural network trains and K-nearest neighbor are used for consequent train of the resultant filter factors. The preferable performance i.e., the classification of brain tumors in double training process is done two-tier system compared to traditional method of classification. It is implemented in MATLAB R2013a. The patterns of the same classes having small intra-cluster distances and patterns of different classes having large inter-cluster distances enable the classification algorithm to work in a proficient way. The problem of this work is overlapping of different classes patterns with feature space and can be resolved with the help of two-tier classification method whose aim is to suppress the feature space dimensionality and to enhance the classification efficiency. In two-tier method of classification, initial training of extracted features is performed by the SOM (self-organizing map) neural network followed by the KNN classifier. The advantageous features of two-tier classification include deterministic reproducible results and better final distortion. They collected 65 MRI images and they achieved 94.28% accuracy.

Singh *et al.*, (2016) proposed method comprising Preprocessing, segmentation and classification. Segmentation is performed by fuzzy c-means clustering algorithm, feature extraction is done by gray level run length matrix (GLRLM) and classification is performed by artificial neural network (ANN). For training and testing phase, they collected 120 real brain MRIs of which 60 abnormal and 60 normal and they achieved 87.50% accuracy, 75% of Sensitivity and 100% of specificity.

Abd-Ellah *et al.*, (2016) proposed CAD system comprising five steps namely MRI preprocessing to eliminate background noise, combination of K-means clustering and Otsu binarization for image segmentation, DWT approach for feature extraction, and PCA method for features dimensionality reduction. MRI classification is performed by kernel support vector machine (KSVM) and they collected 80 MRI images, out of which 70 abnormal and 10 normal images. The 100% accuracy is achieved by GRB kernel compared to 83.5% of linear kernel, 72.5% by multilayer perceptron (MLP) kernel, and 97.5% by polynomial kernel.

Alfonse *et al.*, (2016) proposed method consist of data acquisition, preprocessing, segmentation is done by employing adaptive thresholding and expectation maximization (EM) algorithm. Fast Fourier Transform (FFT) is employed to extract the feature from MRI data set, Minimal-Redundancy-Maximal-Relevance criterion (MRMR) is used for the selection of features and SVM classifier is employed to classify and to select most valuable features. they collected 100 MR images, among which 20 are normal and 80 images have tumor. The format of image is DICOM with size 512 x 512. They achieved 98.9% of accuracy.

Saha *et al.*, (2016) proposed rough sets method and impreciseness of set boundaries representation is advantage of rough sets. They collected 100 MRI images from BRATS 2013 and 2015 and they achieved 93.43% of sensitivity.

Amin *et al.*, (2017) proposed Gaussian filter for noise reduction and improve the image quality. Action and SVM is used for classification of brain tumor. They collected 85 images (39 healthy images and 46 images having tumor) from Nashtar Hospital Multan, 100 images from Harvard dataset in which 65 images are tumor and 35 images are healthy and 126 patient's images from Cancer imaging archive (TCIA) organized RIDER brain image data. They achieved 97.1% accuracy, 91.9% sensitivity and 98.0% specificity.

Bahadure *et al.*, (2017) proposed Berkeley wavelet transformation (BWT) to segment brain tumor and SVM based classifier to improve the accuracy. They collected 22 images of 15 patients from the Digital Imaging and Communications in Medicine (DICOM) dataset and expert radiologists. They achieved 94.2% specificity, 96.51% accuracy and 97.72% sensitivity.

Banerjee *et al.*, (2018) by using multi-sequence MR images they proposed Deep Convolutional Neural Networks (ConvNets) to classify the brain tumors. Three ConvNets proposed by them are trained from scratch, on slices, MRI patches, and multiplanar volumetric slices and they applied this method on existing two ConvNets models for pre-trained VGGNet (16 layers), and ResNet (50 layers) architectures have been applied for transfer learning which are trained on the ImageNet dataset. The ConvNets performance can be evaluated by Leave-one-patient out (LOPO) testing scheme. Multi-planar volumetric dataset is employed to train the model and better accuracy can be achieved by ConvNet. They collected 32 samples of 277 MRI images and utilizing multi-planar MRI slices, they accomplished 97.19% of accuracy.

Shree *et al.*, (2018) proposed gray-level co-occurrence matrix (GLCM) to extract the features, and to improve performance and complexity reduction, DWT based brain tumor region growing segmentation has been done. To classify brain tumors, the classifier called probabilistic neural network has been utilized. They collected 25 images of DICOM dataset to get 650 samples, out of which, the infected brain tissues are 18 and others are normal. They made use of trained dataset from websites known as www.diacom.com and test dataset. They achieved 100% accuracy.

Krishna *et al.*, (2018) made the classification and detection of brain tumors into benign and malignant by employing Particle Swarm Optimization (PSO) based Local Linear Radial Basis Function Neural Network (LLRBFNN) model. They collected 200 MRI images of normal and abnormal images for testing and training dataset from the Alzheimer's disease Neuro imaging Initiative (ADNI) public database and Harvard medical school architecture and they achieved 98.7% accuracy.

Kavin Kumar *et al.*, (2018) proposed a transform called Poisson unbiased risk estimator- linear expansion of thresholds (PURE-LET) to denoising an image and for feature extraction, they used combination of Multi-Texton Microstructure Descriptor (MTMD) and Modified Multi-Texton Histogram (MMTH). Feature extraction of the image is done by Gray Level Run Length Matrix (GLRLM) and GLCM, and for classification purpose they used SVM and KNN. The extracted features are used to train Extreme Learning Machine (ELM) and are employed for classification of images. They collected 46 normal and 44 tumor training dataset images and 21 normal and 23 tumor testing images. They achieved accuracy with SVM classifier is 95%, with KNN classifier 80% and with ELM classifier 91%.

Deepa *et al.*, (2019) proposed method which consists of feature extraction, preprocessing, fusion to accomplish high accuracy in classification, and selection. The average filter is employed to reduce variation in intensity of images in the preprocessing step. The orientation, locality, and frequency are extracted by Gabor wavelet feature extraction which gives texture information to classify. The small subset of features is selected by kernel principal component analysis (KPCA) to enhance the relevancy and to suppress the redundancy of the feature. The GRBF of feature fusion gives the information distinguished from the features having multiple sets. To classify a fused feature adaptive firefly backpropagation neural network is employed. They collected images from the BRATS 2015 dataset comprising 81 MRI images, with 11 normal images, 55 images having malignant tumor and 15 images having benign tumor. They achieved 99.85% of specificity, 99.84% of Accuracy and 97.24% of sensitivity.

Mallick *et al.*, (2019) used deep wavelet autoencoder (DWA) technique to compress image. The deep neural network (DNN) ensures the further classification and has impact on sinking of the feature. The comparison of performance of DWA-DNN classifier has been done with other classifiers such as DNN or autoencoder-DNN, and it has been noticed that the proposed method superior compared to existing methods. Interpretation of medical image dataset is time-consuming process and it is challenging task to handle them. The proposed DWA-DNN classifier gives best result in terms of specificity, accuracy, sensitivity. They collected 19 patients MRI image from RIDER in DICOM format. They achieved 93% of accuracy.

Song *et al.*, (2019) proposed a noninvasive automatic diagnosis system which is on the basis of machine learning to detect gliomas. Size normalization, standardization, background noise removal, have been done to get standard images. The improvement in the low-contrast standard brain images is done by modified dynamic histogram equalization. Further, pyramid histogram of the oriented gradient, hybrid features, gray-level co-occurrence matrix, intensity-based features and modified completed local binary pattern are extracted from the enhanced images. The particle swarm optimization along with KSVM is adopted to train classifiers. They collected 120 patients original brain MRIs out of which, 81 images are having glioma, 68 images having other kinds of tumors and 57 normal images from shengjing hospital of china medical university and they achieved 98.36% of accuracy, 99.17% of sensitivity, and 97.83% of specificity respectively.

Shakeel P *et al.*, (2019) For classification of brain tumor, (MLBPNN) machine learning based back propagation neural networks system is proposed, which helps pathologists to improve the exactness of threat location and help doctors in studying the picture cell by using bunching calculations and order by recoloring phones qualities. Fractal dimension algorithm is used to extract and then important features are selected by multi fractal detection technique for complexity minimization. The integration of imaging sensor is done through wireless infrared imaging sensor to transfer the data of tumor to clinician to examine the condition of wellbeing and for ultrasound measurements level control, especially for elder patients living in remote zones. Testing and training are two processes in MLBPNN. The classification of tumor images is class I database for area < 500 and Class II Database for area > 500. In testing, holes filling is done for the image that has to be tested. This highlights the tumor part by filling the area around tumor helps to find the tumor location exactly Imerode function is used. Accuracy is estimated and tumor area is calculated and thus classified as class I or Class II. They collected 30 MRI images of 21 abnormal and 9 normal from surgical planning laboratory (SPL) dataset and they achieved 93.33% of accuracy, 71.42% of sensitivity and 88.88% of specificity.

Rajesh T *et al.*, (2019) The proposed method includes classification of tumor and extraction of features. For the extraction of features, they used (RST) Rough set theory and for the classification of MRI brain images as abnormal and normal particle swam optimization neural network (PSONN) is tested. They collected 90 images, 60 images are utilized for testing and 30 for training and they achieved 95% of accuracy as compared to RST-FFNN (Feed-forward neural Network) and RST-FSVM.

Polepaka *et al.*, (2019) The proposed method consists of tumor region identification, preprocessing and tumor region classification. In the preprocessing the filter method is used to reduce the noise and to recognize tumor region location of filtered image they used Bounding Box (BB) algorithm. Exact tumor location is classified by Support Vector Machine (SVM). They collected 101 MRI brain images and they used 50 images of 35 tumor images and 15 without tumor images from openly available dataset from website and they achieved 100% of segmentation accuracy compared with (EDPSO)

Enhanced Darwinian Particle Swarm Optimization of accuracy 95% and Particle Swarm Optimization (PSO) of accuracy 92%.

Deepika *et al.*, (2019) The proposed method consists of Preprocessing, segmentation, dimension reduction, and classification. Extraction of features from preprocessed images is done by local binary pattern (LBP) technique and to convert into grayscale images T2-weighted preprocessing is applied on MR Images. PCA is utilized for feature reduction. In order to classify MR image is abnormal or normal the minimized feature set is directed to SVM classifier. They utilized benchmark dataset Brats15 and Midas: database of human brain which are Healthy. This dataset includes 180 abnormal and 100 normal images, out of 280 MR images. They achieved 100% of accuracy, sensitivity, and specificity.

Rani *et al.*, (2019) the performance of k-means, fuzzy c-means clustering and KIFCM (integration of k-means and fuzzy c-means) are tested and they proposed ostu thresholding and support vector machine (SVM). They collected 152 images from Brain Web (Simulated Brain database) dataset including MNC extension. 22 brain tumor images from Digital Imaging and Communications in Medicine (DICOM) is second dataset. The third one is 81 images from BRATS dataset. The fourth one is Medinfo and the final dataset is 17 images are gathered from the Harvard Medical School website. They achieved accuracy of 95.45%.

Abiwinanda *et al.*, (2019) proposed convolutional neural network for tumor segmentation and CNN is guided using 3064 T-1 plodding CE-MRI images of brain tumor. They collected images from Jun Cheng previously utilized in his paper. The dataset includes 1426 images with meningioma, 930 images with pituitary tumors and 708 images with glioma. In their guiding phase, they level the images which are utilized to guide the CNN for each tumors class. Among all available images, they utilized only 700 images, 500 of those images were utilized for guiding phase and other 200 images for validation phase. They achieved 94.68% of accuracy.

Thillaikkarasi *et al.*, (2019*)* To classify the tumor efficiently and automatically they proposed novel deep learning algorithm (kernel based CNN) including M-SVM. This work includes some steps they are preprocessing, feature extraction, image classification and brain tumor segmentation. By Laplacian of Gaussian filtering method (LoG) along with Contrast Limited Adaptive Histrogram Equalization (CLAHE) the MRI image is improved and on the basis of tumor shape, position and surface features, brain features can be obtained. Consequently, based on the selected features image classification is performed by utilizing M-SVM. They collected 40 MRI images of 25 patients and are classified into two types abnormal and normal. They achieved 84% of segmentation accuracy.

Sharma *et al.*, (2019) proposed Differential Evolution algorithm along with OTSU method and collected 56 MRI images of 56 patients consisting 18 patients who are healthy and 38 brain tumor patients and gained 94.73% of accuracy.

Thah *et al.*, (2019) proposed Enhanced Convolutional Neural Networks (ECNN) with accession of loss function by BAT algorithm for Skull stripping and for spontaneous classification of brain tumor and image improvement algorithms are utilized for pre-processing. They collected dataset from BRATS 2015 and they concluded that current CNN method gives only 89% accuracy whereas the proposed ECNN model gives higher accuracy of 92% respectively.

Chander *et al.*, (2020) They proposed that MRI image can be divided into multiple segments by adaptive k-means clustering and by using Support Vector Machine classifier segmented images are classified. They collected forty MR images of malignant and Benign tumors from Harvard University medical Image Repository. They achieved 93% of accuracy using linear kernel method and segmentation accuracy is 99.7%.

Chaudhary *et al.*, (2020) They proposed K-Means for segmentation and DWT is used to extract features. For the classification between malignant and benign tumor SVM is applied at last. They used 6 images for testing their code from Rajendra institute of medical science and they achieved 94.6% of accuracy.

Vijh *et al.*, (2020) To find the optimal threshold value, adaptive particle swarm optimization including OTSU is proposed. In order to eliminate the noise and enhance the image quality Anisotropic diffusion filtering is employed on brain MRI. For performing classification and guiding the convolutional neural network, data is provided by extracted features. They collected 40 MR-free non-tumored images and 61 IBSR (Internet Brain Segmentation Repository) tumored images of magnetic resonance and gained 98% of accuracy.

Ansari M *et al.*, (2020) proposed median filtering to denoise the image and Morphological Operation for Image Segmentation. The DWT and GLCM is utilized for feature extraction and SVM are utilized for segmentation of brain tumor as benign and malignant. They used 5 MRI images for testing their code these images are JPEG/JPG format and they achieved 98.91% of accuracy.

Gokulalakshmi *et al.*, (2020) proposed SVM classifier and K-means clustering for classification. For feature extraction

Grey-Level Co-occurrence Matrix (GLCM) and Discrete Wavelet Transformation (DWT) are used. They collected 750 samples of 30 images from DICOM dataset and They achieved 94% of accuracy.

Chander P *et al.*, (2020) proposed adaptive K-Means clustering algorithm for segmentation and SVM classifier is used for classification. Discrete Wavelet Transformation (DWT) and Grey-Level Co-occurrence Matrix (GLCM) are utilized for feature extraction. Forty MR images of malignant and Benign tumor are collected from Harvard University medical Image Repository. They achieved 99.7% of segmentation accuracy and 93% of Classification accuracy.

A. Review table

Table 1. Review table of classification methodologies.

Sl. No	Authors	Year	Methods	Dataset	Accuracy
1	Arakeri	2013	SVM+ANN+KNN	550 patients MRI images from shirdi sai cancer hospital, manipal, India	SVM(96.42%)ANN(94.18%)KNN(89.09%)
2	Amien	2013	BPNN+PCA	58 MRIimages of 3 MRI human brain dataset	96.8%
3	Jayachandran	2013	Anisotropic filter+ FSVM	80 brain MRI images	95.80%
4	Sundararaj	2014	Gaussian filter + PCA+KNN +Linear SVM	50 CT brain images of which 10 are of normal brain images and 40 are of abnormal brain images from Department of Radiology, Rajah Muthiah Medical College Hospital (RMMCH)	KNN(92%), Linear SVM (94%)
5	Natteshan, N	2015	Wiener filter+CLAHE+ SVM	83 tumor and 9 non tumor gray scale images from DICOM	Quadratic kernel function (85.40%), RBF(83.61%)
6	Anitha,V	2016	Adaptive piller K-means algorithm+SOM +KNN	65 MRI images	94.28%
7	Singh	2016	FCM+GLRLM+ ANN	120 MRI images 0f 60 are normal and 60 abnormal images	87.50%
8	Abd-Ellah	2016	DWT+PCA+ KSVM	80 MRI images of 10 are normal and 70 are abnormal	GRB(100%), linear kernal (72.50%), MLP(97.5%)and polynomial kernal(97.5%)
9	Alfonse	2016	EM+FFT +MRMR +SVM	100 MRI images of 20 are normal and 80 are abnormal	98.9%
10	Saha	2016	Rough sets	100 MRI images from BRATS 2013 to 2015	93.43% sensitivity
11	Garima	2016	Naive Bayes+SVM	110 brain MRI images is from Yatharth Hospital, Noida	Naive Bayes (87.23), SVM(91.49%) of efficiency
12	Amin	2017	Gaussian filter+SVM	85 images of 46 are tumor and 39 are non tumor images from Nashtar Hospital Multan and	97.1%

				100 images of 65 are tumor and 35 are non tumor images from Harvard dataset of 126 patient's images from Cancer imaging archive (TCIA)organized RIDER brain image data.	
13	Bahadure	2017	BWT+SVM	22 MRI images of 15 patients from DICOM dataset and expert radiologist	96.51%
14	Shree	2018	DWT+GLCM+PNN	650 samples from 25 MRI images of 7 are normal and 18 are abnormal from DICOM dataset	95%
15	Banerjee	2018	ConvNets	32 samples from 277 MRI images	97.19%
16	Krishna	2018	PSO+LLRBFNN	200 MRI images from the Harvard medical school architecture and Alzheimer's disease Neuroimaging Initiative (ADNI) public database	98.7%
17	Kavin Kumar	2018	PURE-LET+MMTH+MTMDGLCM+GLRLM+SVM+KNN+ELM	46 normal and 44 abnormal MRI images	SVM(95%), KJNN(80%), ELM(91%)
18	Deepa, A	2019	Average filter+Gabor wavelet+KPCA+GRBF	81 MRI images of 55 are malignant tumor, 15 benign tumor and 11 normal images	99.84%
19	Mallick	2019	DWA+DNN	19 patients MRI images from RIDER	93%
20	Song	2019	GLCM+PSO+KSVM	120 patients original MRI images of 181 images with glioma,57 images with normal and 68 images with other kinds of tumors from shengjing hospital of china medical university	98.36%
21	Shakeel, P	2019	MLBPNN	30 MRI images of 21 are abnormal and 9 normal images from SPL dataset	93.33%
22	Rajesh	2019	RST+PSONN	90 MRI images are used for training and 60 are used for testing	95%
23	Polepaka	2019	BB+SVM	50 MRI images of 35 tumor and 15 non	100%

				tumor imagesfrom publicly available dataset from world wide web	
24	Deepika	2019	LBP+PCA+ SVM	280 MRI images of 180 abnormal and 100 normal images from MIDAS and BRATS2015	100%
25	Rani	2019	SVM+KIFCM	152 MRI images from brain web dataset ,22 MRI images from DICOM and 81 MRI images from BRATS dataset	95.45%
26	Abiwinanda	2019	CNN	708 MRI images with glioma, 1426 MRI images with meningioma , 930 MRI images with	
27	Thillaikkarasi	2019	Kenel based CNN+CLAHE+ MSVM	40 MRI images of 25 patients	84%
28	Sharma	2019	Dfferential evolution algorithm+otsu method	56 MRI images of 56 patients including 18 non tumor and 38 tumors	94.73%
29	Thaha	2019	ECNN	BRATS 2015	92%
30	Chander	2020	Adaptive K means clustering+svm	40 MRI images of Benign and malignant	99.7%
				tumors from Harvard University medical Image Repository	
31	Chaudhary	2020	K means+DWT+SVM	6 MRI imagesfor testing from Rajendra institute of medical science	94.6%
32	Vijh	2020	Adaptive PSO+OTSU	61 tumor and 40 non tumor MRI images from IBSR	98%
33	Ansari	2020	Morphologocal operation +DWT+ GLCM+ SVM	5 MRIimages for testing their code	98.91%
34	Gokulalakshmi	2020	K means+DWT+GLCM+SVM	750 samples of 30 MRI images from DICOM dataset	94%
35	Chander	2020	K means+DWT+ GLCM+ SVM	40 MRI tumor and non-tumor images from Harvard University medical Image Repository	93%

III. CONCLUSION

One of the leading diseases in the world is brain tumors. So, it is very important to detect and classify brain tumor at early stage. MRI brain images are widely utilized to classify brain tumors. Categorization of brain tumor from MRI is classified into four phases. Median filter is included in first phase preprocessing to eliminate the noise. Brain tumor segmentation using otsu binarization and K-means clustering is included in the second phase. Transform feature extraction utilizing DWT and spatial feature extraction utilizing GLCM are included in third phase. DWT is widely used to decompose the image and improve the resolution by removing the unwanted region. PCA is utilized to minimize the features to maintain the classification accuracy of brain MR images. The use of SVM along with the appropriate kernel techniques can help in achieving high accuracy.

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