A Systematic Approach for Brain Tumor Detection Using Machine Learning Algorithms

T DHARAHAS REDDY [1] V VIVEK[2]

[1]PG Scholar, Department of CSE, Faculty of Engineering & Technology, Jain University, Bangalore – 562 112
[2]Assistant Professor, Department of CSE, Faculty of Engineering & Technology, Jain University, Bangalore – 562 112

Abstract: The excessive growth of cells induces cancer in every part of the body. The irregular growth of cells in the brain induces a brain tumor.Intracranial pressure inside the brain is increased by the brain tumor, Due to that pressure brain changes from normal structure to abnormal structure. By using the fractional dimension we can detect irregular or abnormal structures of the brain. Gliomas is one form of adult brain tumor. Gliomas originate in glioma cells and affect adjacent tissues.Diagnosis of irregular brain pictures are crucial for patient care, especially during the initial stage of the disease. Various brain imaging techniques have used computer-aided diagnosis (CAD) machine learning to detect irregular brain images.For patient care, the diagnosis of abnormal brain images is critical, Especially in the initial phases of disease. Various brain imaging methods have used computer-assisted diagnosis (CAD) machine learning to detect irregular brain images. Magnetic resonance imaging (MRI), Diffusion tensor imaging (DTI), Computer tomography (CT), Single-photon emission computed tomography(SPECT), and Positron Emission Tomography (PET) techniques are used. In these techniques MRI is the best and most commonly used technique. MRI is used because it has capable of providing information about soft tissues and it does not have any radiations that affect human beings.

Keywords- MRI, Brain tumor segmentation, Classification, Preprocessing.

I. INTRODUCTION

The abnormal development of brain cells is considered a brain tumor.The growth of the tumor in the brain depends on the health status of the individual. The brain tumor is broken down into two forms, malignant and benign.The brain tumor that extends into adjacent cells is considered malignant and the tumor that does not spread into adjacent cells is considered benign. Once more, the brain tumor is divided into primary and secondary based on the region of interest. The tumor that emerges from the brain itself is considered primary and is considered a secondary brain tumor, the tumor that occurs from other parts and spreads to the brain.Magnetic resonance imaging (MRI), Diffusion tensor imaging (DTI), Computer tomography (CT), Single-photon emission computed tomography(SPECT), and Positron Emission Tomography (PET) techniques are used. In these techniques MRI is the best and most commonly used technique. MRI is used because it has capable of providing information about soft tissues [1]. In brain image classification MR images are assigned into a tumor and non-tumor groups. Brain imaging classification is a challenging task and only performed by experienced doctors and radiologists. Early diagnosis can improve the health of the patient. There is a method for image classification based on fractional dimension [2]. There are four steps for the detection of the tumor, They are preprocessing, Feature extraction, Classification, and preprocessing [3]. MR images are collected using normal subject brainimages (BRAINS) image bank. Brain's picture bank is made up of multiple MR images including T1, T2, T2 *, and FLAIR (Fluid Attenuated Inversion Recovery) [4].Jenitta and Samson Ravindran proposed an approach that uses Local Pattern Descriptor (LPD) and Gray-level Co-occurrence Matrix (GLCM) to extract image characteristics [6].With the support of machine learning and high-dimensional design wrapping, Yong Fan, Hengyi Rao, Joan Giannetta, and Hallam Hurt proposed an approach of using structural and functional MR images for brain disease diagnosis [8].

Kushaggr Sharma, Shivang Sharma, and Rahul Prajapat proposed an approach which uses machine learning approaches like nearest neighbor along with SVM. Features are extracted with the help of GLCM by using principal component analysis (PCA) [9]. For brain tumor segmentation Virupakshappa and Basavaraj Amarapur proposed a modified level set segmentation approach [13].

The article is structured as follows: Methods under section 2. Section 3 sets out the comparison of the paper. The results reported in Section 4. Section 5 introduces the conclusion.

II. METHODS

Detection of the abnormal brain using 2D-Discrete Wavelet Transform, Probabilistic PCA, and RSE Classification [1].

Within this paper the segmentation of brain tumors is carried out using preprocessing, extraction of features, reduction of features, and classification. Wiener filter is used in preprocessing for noise reduction, 2D-DWT for extraction of features, PPCA for reduction of features, KNN used as a classifier to determine whether the image is normal or abnormal.

In this paper four datasets are used. DS-66 consists of 66 axial T2 weighted images, DS-90 consists of 90 axial T2 weighted images, DS-160 consists of 160 axial T2 weighted images, DS-255 consists of 255 axial T2 weighted images. Gif images are taken and modified to JPG format. Previously, images were transformed to grayscale images in RGB format.

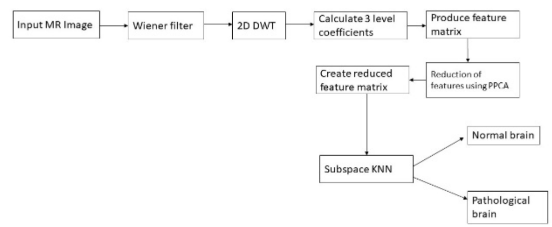


Fig.1: The proposed model

Wiener filter is used to decrease noise. Incase if the image is blurred it can be retrieved by using inverse filtering. The DWT is used separately in each dimension, in a case involving 2D images.A description of an image of a pathological brain MR with its wavelet decomposition of three stages. Therefore, at each scale there are four sub-band images. The subband LL is used for the other 2D-DWT and can be considered as the image approximation part while the subbands LH, HL, and HH can be considered. In this paper the authors selected the harr wavelet.

After extracting the features by using 2DWT, PPCA is used for feature extraction. PPCA is used to reduce high dimensional data to low dimensional data. The ensemble is a classifier that includes multiple classifiers to get more accurate predictions when compared to an individual model. In classification RSE is used to decrease the error rate.

After classification authors compared their proposed model with the existing model by calculating Sensitivity, Specificity, Accuracy, Precision. Sensitivity is used to determine that the person is having a disease. Specificity is used for determining that the person does not has a disease. Accuracy is used to measure how many diagnostic tests are performed.

The implementation is implemented by using MATLAB-2016. By implementing the proposed model the authors gained an accuracy of 99.20%.

MR Brain Classification Images focused on the analysis of the fractal dimensions [2].

In this paper the proposed approach is divided into four phases i.e. preprocessing, Gray matter, and White matter extraction, FD calculation, Classification. There are two preprocessing processes, i.e. skull stripping and contrast enhancement, that are used in preprocessing.

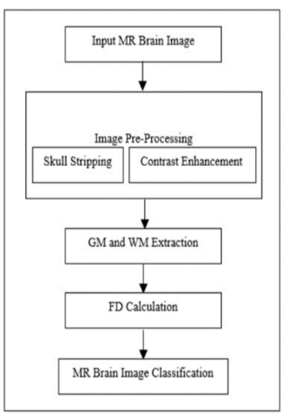


Fig.2: The proposed model

90 images are used in that 45 are non-tumored and 45 tumored T1 MR brain images. Skull stripping is used to remove details of additional sections other than brain tissue. Gray matter and white matter extraction are done by using the FCM clustering algorithm. Irregularity of brain structure is identified by using the Fractional dimension. Box counting, fractionally modified box-counting, and piecewise triangular prism area (PTPSA) are different methods of fractional dimension. The authors have used the box-counting method in this proposed approach. Classification is done after FD calculation. In the classification, section authors found whether the input MR image is tumored or not. The fractional dimension is used in the classification for determining that the image is tumored or not and got 100% accuracy.

Comparison of Brain Tumor Segmented Classifiers [3].

In this paper, the authors presented a discriminative segmentation method for a brain tumor. The detection of tumors is divided into four phases, They are preprocessing, Feature extraction, Classification, and preprocessing. For segmentation there are a lot of classifiers to be used the best classifiers are SVM, Ada boost, and Random forest. The authors compared all the classifications and their performances.

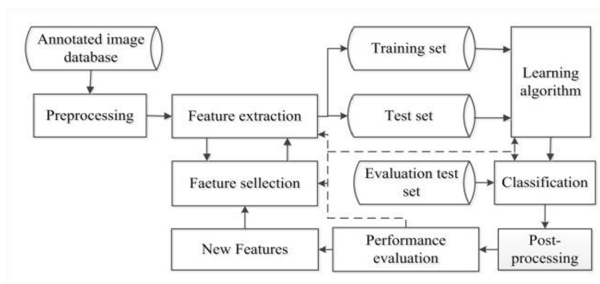


Fig.3: The proposed model

In this paper there are three artifacts analysis by authors. The three artifacts are inhomogeneity, Noise, Intensity nonstandardness. For inhomogeneity they applied N4 filter in the ITK package.

First-order operators, High order operators, Texture features, Spatial content features are some features used in this paper. The authors convert the task of image segmentation into a task of pattern recognition by removing certain features.

The random ensemble forest classifier is based on two random forests. Ada boost is the first algorithm for adaptive boosting. This analysis also uses the classifier SVM. The benefits of SVM in the classification are its robustness and precision.The disadvantage of SVM is It cannot be solved to optimize the quadratic programming problem.

By testing all classifiers random forest is more accurate when compared to ada boost and SVM.

Brain Images of Normal Subjects(BRAINS) [4]

Brains is an image bank that allows us to add new images.Brains image bank consists of images of people from 15 years to 81 years of age. The brain's image bank is composed of images from T1, T2, T2 *, and FLAIR (Fluid Attenuated Inversion Recovery).Brain image bank architecture is based on an extensible Database Toolkit for Neuroimaging (XNAT).Brains image bank import images and those images are to be checked whether these images are healthy or not. Textual data passes through data cleaning. In data cleaning it checks the format, coding. Database Quality Assurance is used to ensure image quality assurance. It contains the DICOM image data. The database Relation is used to map the original ID of patients and subjects studying IDS to their assigned ID of brain subject.

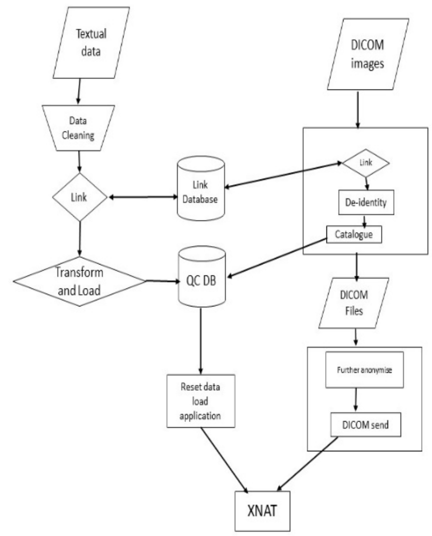


Fig.4: The proposed model

Brain image data bank consists of two web interfaces i.e. primary and secondary. Primary also called a guest interface. The secondary interface is only for brains project team and collaborators.

Initially users access the data through guest interface only. Once the user selected which type of image that they wanted and they have to fill the data access request form.

Data is to be provided to users via separate servers in compressed packages in DICOM format and textual data in CSV.

MRI Brain Tissue Identification Using Unattended Methods of Optimized Extenics [5].

In this paper authors have selected the correct pixel vectors to be clustered centers using standard deviation goal generation procedure. Classification is achieved with the help of optimal correlation functions based on extents.

This paper contains images of PD, T1, and T2. The method of target generation is done by using the relatively low likelihood criterion to look for targets. At the edges of clusters, targets will be skipped over but those on the edges of non-clusters will be found.When these goals are implemented in images segmented by merge, it does not affect the final output. For this analysis, the appropriate cluster centers must first be identified, since they will be used to determine the Interaction function of each cluster's extension set. For this purpose it is important to generate an appropriate target to be the center of each cluster.

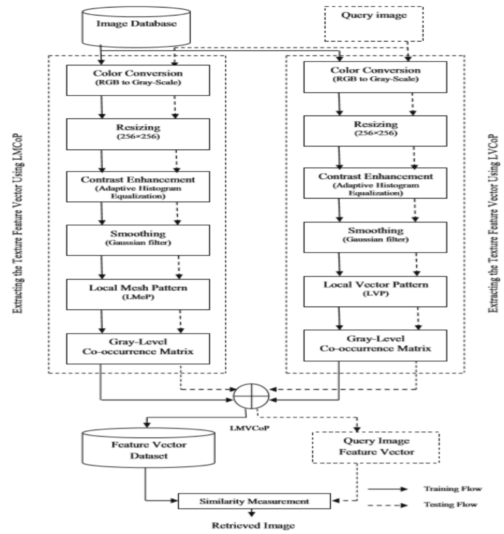
The lesser the standard deviation, the more concentrated the distribution of the data is. Otherwise, the data would be scattered further.

Finally, to make the measurement more accurate and simpler, the distances from the edges to the centers of all the sets are made equal. The extension sets identified with an extenics-based correlation function can also include all the sets during the optimization process, since the greater the extension set, the better the extenics-based correlation value will be. Hence the extenics-based correlation function is updated in this study to describe that the bigger the extension set is.

There are several metaheuristic algorithms which are used academically. Comparatively, PSO programming is simpler and easier to implement. So, it's applied in this analysis. X is the source of multi-spectral images in the extenics-based correlation function, M is the cluster center identified by the standard deviation target generation method, and r is the variable to determine the size of the cluster extension collection, also the target to be optimized in this analysis.Therefore the r in the modified simple correlation function based on extenics is defined as the particles in the PSO. Nonetheless, particle quality has to be evaluated during the PSO cycle if replication occurs each time. Ultimately, the findings obtained are applied to the classification of MRI brain images to obtain the findings of the GM, WM, and CSF classification.

Image recovery focused on a co-occurrence pattern for local mesh vectors [6].

In this paper the proposed approach is divided into preprocessing, Extracting features, and



retrieval. Feature extraction is done using the local mesh co-occurrence pattern and the local mesh vector co-occurrence pattern. The local mesh vector co-occurrence pattern was Planned to concatenate the local mesh co-occurrence pattern. The GLCM fusion with the local mesh pattern and the local vector pattern produces LMCOP and LVCOP.

In pre-processing, MR Image is pre-processed and turned to a grayscale image. After pre-processing, the image is normalized using contrast enhancement of the adaptive histogram equalization. Adaptive histogram equalization transforms the lower local contrast to a higher contrast.The smoothing process is done for reducing noise by using a Gaussian filter.

Fig.5: the Proposed approach

After preprocessing, Feature extraction is done by using local vector co-occurrence and local mesh co-occurrence. Both local vector co-occurrence and local mesh co-occurrence results are combined i.e.

LMVCoP =wLMCoP + (1−w) LVCoP

Measurement of similarity between the feature dataset vector and the query image vector feature is completed in retrieval, and output values are sorted in Increasing order. The image with the minimum difference reaches a higher position. User requests that the images retrieved to be displayed in the graphical user interface.

The framework proposed communicates with the user by means of GUIs. Preprocessing is used to convert the query image into a grayscale image. After preprocessing grayscale image is resized with the help of a scaling algorithm. Image features are to be enhanced by using a contrast enhancement algorithm. Noise is reduced with the help of Gaussian smoothing. LVP and GLCM are used for extracting features.Finally, the LVCoP map is obtained.

MRI brain classification SVM (support vector machine) [7].

Data sets taken in this paper are 32 images. In that 32 images 22 images are abnormal images and 10 normal images. The datasets consist of T2 flair weighted and axial images. Axial images are chosen because they strongly indicate abnormalities. The extraction of features is done by wavelet transform. Daubechies-4 (DAUB4) wavelet is used for extracting features.

The main objective of the extraction feature is reducing the original set of data by calculating those properties. Classification of the extraction feature shall be performed. The extracted features will be used as input for the classifier. SVM will be used as a classifier.

In SVM there are two steps i.e. training and testing. Extraction is done by using MATLAB 7.9. By using classifier authors can declare whether the image is normal or not.

Brain Irregularity Diagnosis Using both structural and functional MR images [8].

The proposed approach consists of data definition, preprocessing, extraction function, selection of hybrid features, and SVM classification.

49 datasets are used in this study. 25 are parental cocaine-exposed patients and 24 are socio-economically patients.

By using Siemens 3.0T Trio scanner all structures and fundamental scans are obtained. Three density maps are obtained, i.e. a white matter map, a gray matter map, and a functional feature map.Gray matter, white matter tissues are obtained by segmenting each MR image into three tissues for each subject, i.e. Grey matter, white matter, and cerebrospinal fluid.

For feature extraction statistical regional features extraction method is used. After extracting some of the regional features, the authors represented brain images of each subject, i.e. all the regional features calculated from three feature maps, i.e. M1,M2, M3. M3.

Nonetheless, some regional features are less effective than others, so that they have chosen some effective features to increase the efficiency of the classifier. The hybrid feature selection algorithm is used to pick regional classification apps. SVM is used for classification purposes. The rate of classification is 91.8 percent for both structural and functional brain MR images.

Function Extraction focused on the classification of MRI using ML [9].

In this paper the proposed methodology consists of contrast enhancement, Extracting features, First-order statistical and second-order statistical features, PCA, KNN, SVM.

The images of MRI T1 are taken as input images. In contrast enhancement, the input images are transformed to a grayscale

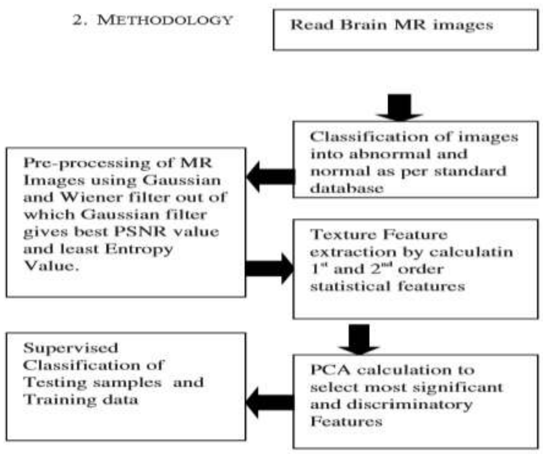


image.Wiener filters and Gaussian filters are used to minimize noise levels. Statistical features track and evaluate the spatial distribution of the gray level by measuring the local characteristics at each point.

The widely used statistical features are the characteristics of co-occurrence and the variations in the gray level. First-order statistics from the original image are calculated. The features derived from statistics of the first order are mean, standard deviation, skewedness, energy consumed and randomness. The second-order depends on the relationship between the pixel pair, i.e. the pixel and the adjacent pixel. Properties are measured using GLCM.

Fig.6: The proposed approach

GLCM selects two pixels at the same time. They're a reference and a neighbor pixel. Neighbor pixel is the right one of each reference pixel and expressed as (1,0) i.e. 1 is the x-direction and 0 in the y-direction. Each pixel of the image becomes a reference pixel, starting from the upper left order to the lower right.

PCA has the highest data value and equally decreased fashion for additional main components. To implement PCA, the dataset originates in a manner in which columns carry the variables for each corresponding image in a row.

KNN and SVM are used as a classifier. KNN is a lazy algorithm for computing. It plots the features of the picture by busting the nearest neighbors to the k. The core concept of KNN is to classify simple data in line with the nearest 'k' of the data set.

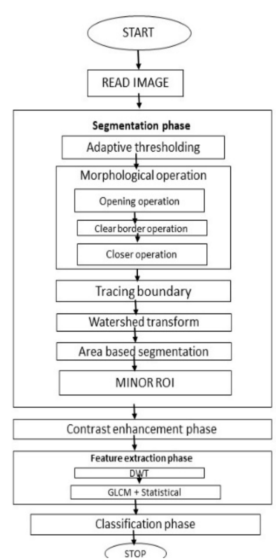
SVM is used to evaluate data and perform pattern recognition. SVM is used for the study of classification and regression. SVM is trained using 30 abnormal data and 23 normal data.

The accuracy that comes out after performing the proposed model is 95.45%.

Detection and classification of fetal brain disorders using machine learning techniques [10].

The main aim of this paper is to early identify the fetal brain defects before the birth of the fetal. Authors proposed an algorithm that could detect several MR image anomalies by using a versatile and simple approach with low computational costs.

The set of data used in this paper is composed of 227 images. The method proposed is composed of four phases i.e. Segmentation, enhancement, extraction, and description of the features. The fetal brain is surrounded by



amniotic fluid and cerebrospinal fluid (CSF).

Fig.7: The proposed approach

By using segmentation fetal brain is extracted. Threshold T is used to separate the image pixels into foreground and background. After pixel separation the new binary "I binary" image will be created from the original I image.

After extraction of the fetal brain there will be some maternal tissues connected to the outer part of the fetal skull. By using morphological operations these maternal tissues are removed then the new binary image I close is generated.For I close image, boundaries are to be traced and categorized into boundaries of parents and children, and the image obtained is called the I region. To eliminate other connections, segmentation is applied to the I region, then the image is called I watershed. Step of contrast enhancement is applied to enhance the consistency, contrast of the region of the brain and it also enhances the accuracy.

Four-level decomposition of 2D-DWT is applied to the image in feature extraction to remove the features. A feature matrix is generated after the 4-decomposition levels are obtained that contain the approximate horizontal, vertical and diagonal coefficients of the fourth level of decomposition. The function matrix is used for texture analysis to extract features such as contrast, strength, correlation, homogeneity in the images by using the gray level covariance matrix. Other features in that picture are also extracted which include Mean, Standard deviation, Variance, Root mean square, Smoothness.

LDA is used in classification operations and reduction of dimensionality. It uses hyperplanes to split data into two groups or more.

SVM is one of the machine learning techniques that is based on the principle of statistical learning.

Also, KNN is one of the machine learning methods, and it is one of the best machine learning classification algorithms.

Ensemble classifier is a combination of multiple classification models used to improve a single predictive model output.

LDA is used in classification operations and reduction of dimensionality. It uses hyperplanes to split data into two groups or more.

SVM is one of the machine learning techniques that is based on the principle of statistical learning.

Also, KNN is one of the machine learning methods, and it is one of the best machine learning classification algorithms.

Ensemble classifier is a combination of multiple classification models used to improve a single predictive model output.

Design of a support structure for the classification of MRI brain scans by Radiology Decision [11].

The main goal of this paper is to develop models for ML, such as SVM, LR, RF, and XGB.

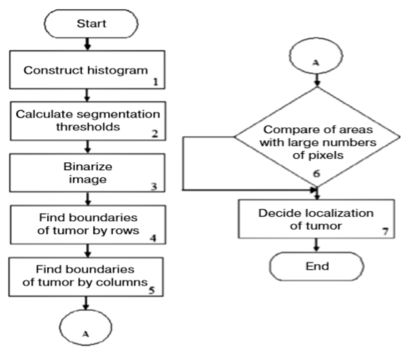
Study results have two outcomes, i.e. primary outcome and secondary outcome. The primary result is the creation of an algorithm for better classification. The secondary outcome is to define main words that may or may not differentiate adherence to acr. Secondary findings help create an MRI.

Using the technique, the free-text fields containing the initial findings of the patient before the MRI scan are cleaned in the pre-processing stage. Text mining algorithms that are intended to derive useful information from the words cannot effectively detect negated medical conditions.

These terms can also allow processing speed to be improved by removal. The algorithms have been tested using the term eliminate sparse matrix that eliminates rare occurring terms that are missing in 99.9 percent of documents.

The ML algorithms used in this paper include SVM, LR, RF, and XGB.

Logistic regression is used to evaluate the relationship between multiple predictors of a



binary or multinomial response.

SVM is also one of the techniques of ML that are based on statistical learning theory.

Random forest and XG boost are both among the best algorithms in machine learning.

SVM, LR, RF, and XGB were trained with 80% of the data and the RF and XGB showed the best overall results with 89.81% and 90.64% accuracy.

An automated solution for the segmentation of brain tumors on MRI images [12].

Materials used for this study are taken from two databases i.e. 12 images from Vladimir and 44 images from Riyadh. The first stage involves segmentation by constructing image brightness and identifying the points in that image that correspond to the maximum and minimum tumor region brightness (Figure 8. Block 2).

Fig.8: The proposed approach

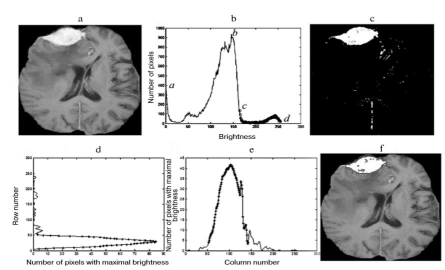
Figure 9 represents the steps of the brain tumor segmentation process by using MRI images.

Fig.9: Images of the process

The initial image is (9 a) indicating the segmentation region. The picture with values for brightness strength in which the tumor is outlined in circles.

Figure 9 represents the original image (a); The image histogram created with the intensity of the brightness within which the tumor is located in circles (b); A binary image with a luminosity point between the upper and lower brightness threshold limits (c); Total brightness pixels are distributed by rows(d); Total brightness pixels allocated by column (e); and BT segmentation output on initial image (f).In Fig. 9b (image histogram) The x-axis shows intensity values for light, and the y-axis shows the pixel count.

In fig 9 b the image's brightness intensity is zero which corresponds to the image's black



background.

The second mode (9 b) has the highest number of pixels with gray matter, which is the point of reference. The minimum brightness value of the tumor region on the right side of the second mode defines the boundary of the transition from low to higher brightness, which characterizes a potential boundary for the tumor to begin. Points c and d (Fig. 9b) define the lower and upper threshold limits of the image's brightness. This picture is characterized by pixels with only brightness intensities between the brightness threshold's upper (point d) and lower (point c).

The second step is the determination of tumor boundaries. The boundaries are calculated by measuring the mean values of pixels with maximum brightness in each row (fig 8. Block 4) and column (fig 8. Block 5) respectively.

The sensitivity and specificity rise from 89% to 99%.

Brain tumor segmentation technique focused on cognitive MRI using a modified level set process [13].

The authors in this paper suggested an updated level-set approach for the segmentation of brain tumors. Preprocessing is done for removing noise and segmentation is done for MR images.

The technique proposed shall consist of two steps.

I. Preprocessing
II. Segmentation

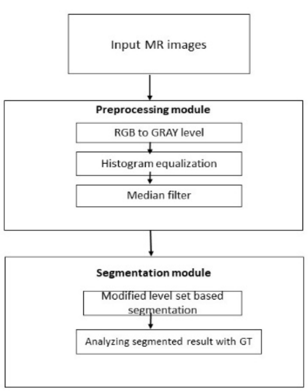


Fig.10: The proposed approach

MR images are taken as data, and noise reduction is achieved by preprocessing. To that the processing complexity, the conversion of color to gray is performed on MR images. Preprocessing to eliminate unnecessary noise is performed with the help of histogram equalization and median filtering technique.

When the picture is represented by near contrast values being bright or dark at the same time in histogram equalization then this approach is helpful. Equalization of the histograms is a mapping of gray levels "u" as "x." Tests are used to alter the strength of each pixel across their local neighborhood. The primary segmentation goal is to separate the ROI. After the image has been preprocessed, it is segmented by an updated level set procedure.The glioma images are to be graded in the segmentation system into high-grade gliomas to low grade gliomas and segmented by an updated level of the segmentation process. The drawbacks of level set segmentation are the required velocity for the level set function to continue. The segmentation of the adjusted level set increases the accuracy of the segmentation. Instead of a Gaussian filter, the level set segmentation approach uses anisotropic diffusion since the Gaussian filter takes longer to reduce image information. With the help of PMD filter noise is completely removed. This approach is executed in MATLAB platform and the accuracy obtained is 99.3%.

A classification technique that uses Bayesian fuzzy clustering to segment and identifies brain tumors [14].

Segmentation and classification are essential components of brain tumor identification. There are some drawbacks because it takes an immense amount of time and is successful in decision making. The authors proposed an automatic classification method that used the HCS optimization algorithm to train the Multi-SVNN Classifier to resolve the above challenges.

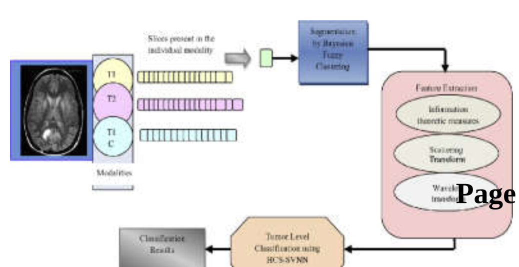


Fig.11: The proposed approach

BT segmentation is done through the Bayesian fuzzy clustering method, and classification is done through the SVNN model based on the HCS optimization algorithm.

The development of the edema is established using MRI. Patient brain images are processed in four separate modalities, including T1, T2, T1c, and Flair. The extraction of the function is achieved by using theoretical methods, transforming the scattering, and transforming the wavelet. Classification is achieved using multi-SVNN. The area of the edema tumor is defined by using Bayesian fuzzy clustering authors. Bayesian Clustering Fuzzy is used for segmentation. The extraction method for the app has three major phases.First is a theoretical measure of knowledge, second is transform scattering and third is transforming wavelets.

The wavelet transform is applied to obtain the mean, Variance, Entropy so that classification efficiency is enhanced. The proposed classification classifies 4 levels i.e. Level 1 non-tumor, Level 2 Edema, Level 3 Core tumor, Level 4 Enhanced tumor.

The multi-SVNN submitted follows the layered approach. Upon extraction of the app the extracted features are fed to multi-SVNN individually.

SVNN1 training is focused on Non-Tumor Segment characteristics. SVNN2 is trained using the features of the edema section, SVNN3 is trained using core tumor features, and the enhanced tumor function is used for SVNN4 development. When a new classification feature arrives the new feature is classified then features are known as a non-tumor category. With the aid of level 2 we can identify the weather the tumor may or may not be present in the section. If it is an edema section then SVNN3 defines whether or not the tumor is the core tumor because it is not completed as an enhanced tumor. The accuracy obtained through this process is 93%.

III. COMPARISON

S.NO	PAPER METHODS	ACCURACY
1	2D-DWT + PPCA + RSE	99.20
2	Fractal Dimension Analysis	100%
3	Classifier comparison	-
4	BRAINS	-
5	Optimized Extenics-based Methods	-
6	Local Mesh Vector Co-occurrence Pattern	-
7	Support vector machine	65%
8	Structural and Functional	-
9	SVM	95.45%
	K-NEAREST NEIGHBOUR	77.27%
10	LDA	79%
	SVM	79%
	Ensemble Subspace Discriminate	80%
11	Logistic Regression	57%
	SVM	81%
	Random Forest	90%
	XGBoost	91%
12	Automated segmentation algorithm	-
13	Modified level set method	99.3%
14	Bayesian HCS-based multi-SVNN	93%

IV. RESULTS

MR images are taken as inputs and preprocessing is done for that image. Feature extraction is done by using 2D-DWT. After feature extraction, Feature reduction is done by using PPCA. After feature reduction classification is done by using the RSE classifier. The proposed model is done using MATLAB. The accuracy obtained in this model is 99.20% [1]. In this paper there are two preprocessing methods are there i.e. skull stripping and contrast enhancement. Gray matter and white matter extraction are done by using the FCM clustering algorithm. Irregularity of brain structure is identified by using the Fractional dimension. After that classification is performed then the accuracy obtained in that method is 100% [2]. In this paper there are three artifacts analysis by authors. The three artifacts are inhomogeneity, Noise, Intensity now standardness. The random forest ensemble classifier is built on two random forests. Ada boost is the first adaptive boosting algorithm. The SVM classifier is also used in this study. By testing all classifiers random forest is more accurate when compared to ada boost and SVM [3]. BRAINS is the bank of pictures. Brains image bank consists of images T1, T2, T2 *, and FLAIR [4]. In this paper, the classification of MRI brain tissue is achieved using unsupervised methods based on optimized extenics[5]. Preprocessing is used to convert the query image into a grayscale image. After preprocessing grayscale image is resized with the help of a scaling algorithm. Image features are to be enhanced by using a contrast enhancement algorithm. Noise is reduced with the help of Gaussian smoothing. LVP and GLCM are used for extracting features. Finally, the LVCoP map is obtained [6]. The extraction of the feature is done using Wavelet Transform. The main aim of the extraction of the function is to decrease the original dataset by measuring certain properties. The classification of the extraction function is performed after. The extracted characteristics will be used as input to the classifier. Uses SVM as a classifier [7]. The statistical geographic features extraction approach is used for the extraction of the features. After extracting some regional features, authors represented each subject's brain images, i.e. by all regional features computed from 3 feature maps i.e. M1, M2, and M3. SVM is used for ratings. For both structural and functional brain MR pictures, the classification rate is 91.8% [8]. In this paper the proposed methodology consists of contrast enhancement, Feature extraction, First-order statistical and second-order statistical features, PCA, KNN, SVM. The accuracy obtained in this method is 95.45% [9]. The method proposed is composed of four phases i.e. Segmentation, enhancement, extraction, and classification of the features. The fetal brain is surrounded by amniotic fluid and cerebrospinal fluid (CSF). The classification accuracy is calculated. LDA got an accuracy of 79%, Linear SVM got an accuracy of 79%, KNN got an accuracy of 73%, and RS ensemble got an accuracy of 80% [10].The main objective of this paper is to develop models for machine learning, such as LR, SVM, RF, and XGB. LR, SVM, RF, and XGB were trained against 80% of the data and it emerges that the RF and XGB had the best overall results with 89.81% and 90.64% accuracy[11]. Using the Automated System for Segmenting Brain Tumors on MRI Images improves the sensitivity and specificity from 89% to 99% [12]. The accuracy obtained by using theCognitive MRI technique for brain tumor segmentation using an updated level set approach is 99.3% [13]. By using Bayesian HCS-based multi-SVNN the accuracy obtained in this method is 93% [14].

V. CONCLUSION

There are many methods used to classify that the brain is having a tumor or not. The different methods used in this paper are Preprocessing, Feature extraction, Feature reduction, Classification, Segmentation. There are different wavelets, filters, and different segmentation methods that are used in preprocessing to eliminate the noise and to increase the clarity of the image. DAUB4 is one of the wavelets used in preprocessing and the Gaussian filter is used for decreasing the noise. Contrast enhancement is used to increase the clarity of the image. There are different methods like 2D-DWT, Scattering transform, Statistical regional features that are used for extracting the features. There are different methods like PPCA is used for feature reduction. There are different types of classifier algorithms are there in machine learning. SVM, LDA, LR, XG boost, Ensemble, RSE are used to classify the image is having a tumor or not. This process is done using MATLAB software.

REFERENCES

1. Zhang, Y., Yang, J., Wang, S., Dong, Z., & Phillips, P. (2017). Pathological brain detection in MRI scanning via Hu moment invariants and machine learning. Journal of Experimental &Theoretical Artificial Intelligence, 29(2), 299-312.
2. Benson, C. C., Lajish, V. L., &Rajamani, K. (2017, September). Robust classification of MR brain images based on fractal dimension analysis. In Advances in Computing, Communications and Informatics (ICACCI), 2017 International Conference on (pp. 11351140). IEEE.
3. Lefkovits, L., Lefkovits, S., Vaida, M. F., Emerich, S., &Măluțan, R. (2017). Comparison of Classifiers for Brain Tumor Segmentation. In International Conference on Advancements of Medicine and Health Care through Technology; 12th-15th October 2016, Cluj-Napoca, Romania (pp. 195-200). Springer, Cham.
4. Job, D. E., Dickie, D. A., Rodriguez, D., Robson, A., Danso, S., Pernet, C., ...& Waiter, G. D. (2017). A brain imaging repository of normal structural MRI across the life course: Brain Images of Normal Subjects (BRAINS). NeuroImage, 144, 299304.
5. Chen, R. M., Yang, S. C., & Wang, C. M. (2017). MRI brain tissue classification using unsupervised optimized extenics-based methods. Computers & Electrical Engineering, 58, 489-501.
6. Jenitta, A., &Ravindran, R. S. (2017). Image Retrieval Based on Local Mesh Vector Co-occurrence Pattern for Medical Diagnosis from MRI Brain Images. Journal of medical systems, 41(10), 157.
7. MohdFauzi Bin Othman, NoramalinaBt Abdullah, NurulFazrenaBt Kamal. MRI brain classification using support vector machine. 2011 International conference on (pp. 1288-1322). IEEE.
8. Yong Fan, Hengyi Rao, Joan Giannetta, Hallam Hurt, Jiongjiong Wang, Christos Davatzikos, and Dinggang Shen. Diagnosis of Brain Abnormality Using both Structural and Functional MR Images. 2006 International conference on (pp. 6585-6588).IEEE.
9. Kushaggr Sharma, Shivang Sharma, Rahul Prajapat, AnupamaBhan, AyushGoyal. Feature Extraction based Classification of Magnetic Resonance Images using Machine learning. 2019 International conference on (pp. 127-131).IEEE.
10. MahaA.Sharkas, OmneyaAttallah, HebaGadelkarim. Detecting and Classifying Fetal Brain Abnormalities using Machine Learning Techniques. International conference on (pp. 1371-1376).IEEE.

11. AlwinYaoxian Zhang, Sean Shao Wei Lamb, Nan Liub,c,YanPanga Ling LingChanc, PhuaHwee Tang. Development of a Radiology Decision Support System for the Classification of MRI Brain Scans. International conference on (pp. 107-115).IEEE.
12. Abdulraqeb, A. R., Al-Haidri, W. A., Sushkova, L. T., Abounassif, M. M., Parameaswari, P. J., &Muteb, M. A. (2017). An Automated Method for Segmenting Brain Tumors on MRI Images. Biomedical Engineering, 51(2), 97-101.
13. Amarapur, B. Cognition-based MRI brain tumor segmentation technique using modified level set method. Cognition, Technology & Work, 1-13.
14. Raju, A. R., Suresh, P., & Rao, R. R. (2018). Bayesian HCS-based multi-SVNN: A classification approach for brain tumor segmentation and classification using Bayesian fuzzy clustering. Biocybernetics and Biomedical Engineering.