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PERFORMANCE ANALYSIS OF SVM AND DEEP LEARNING WITH CNN FOR BRAIN TUMOR DETECTION AND CLASSIFICATION

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Abstract

A brain tumor occurs when abnormal cells form within the brain. In diagnosis of the disease medical imaging has many advantages. Many people suffer from brain tumor, it is a serious and dangerous disease. A proper diagnosis of brain tumor is provided by the medical imaging. The detection and classification of tumor from brain is an important and difficult task in the medical field. The brain tumor detection technique in the MRI images is very significant in many symptomatic and cure applications. Tumor detection and classification are very hard because of high quantity of data in MRI images. One essential part in detecting the tumor is image segmentation. The segmentation provides an automatic brain tumor detection technique in order to increase the precision, yields with decrease in the diagnosis time. The goal is to detect the tumor from the MRI images and extract the features from the segmented tumor and finally classify it. The image detection and classification include image acquisition, image preprocessing, denoising, image segmentation, feature extraction and classification. The input image is pre-processed using wiener filtering and the noise is removed using Edge Adaptive Total Variation Denoising (EATVD) technique. Once the noise is removed from the image, it is used for segmentation process, where Mean Shift Clustering is used. The segmented tumor undergoes features extraction stage, where Gray Level Co-occurrence Matrix (GLCM) features are used. In the last stage images are classified either as tumorous or non-tumorous. Classification is done using Support Vector Machine (SVM), Deep Learning with Convolutional Neural Network (CNN). Early detection of the tumor region can be achieved without much time lapse in the calculation by using this efficient classifier model. This system presents a prototype for detecting objects based on SVM that classifies images and assesses whether the image is cancerous. While comparing the accuracy of these classifier, CNN would provide high accuracy. The simulation results obtained for brain tumor detection and analysis are done with minimum computational time and with reasonable accuracy. This proposed system is tested using PSGIMSR (PSG Hospitals, Coimbatore) dataset and implemented using MATLAB software.

Keywords:

Wiener filter, Edge Adaptive Total Variation Denoising, Gray Level Co-occurrence Matrix, Support Vector Machine, Convolutional Neural Network

1. INTRODUCTION

In the advanced imaging technology, diagnostic imaging has become an indispensable tool in medicine today. X-ray angiography (XRA), magnetic resonance angiography (MRA), magnetic resonance imaging (MRI), computed tomography (CT) and other imaging modalities are heavily used in clinical practice. Such images provide complementary information about the patient. Due to increase in the complexity in the medical field it requires latest advances in computer technology in order to reduce the cost and make possible to develop automation [1].

A tumor occurs when abnormal cells form within the brain. Some of the ways for diagnosing brain tumor are MRI scan, CT scan and biopsy of the head etc. In CT scan technique image of the brain is taken from several angles and is studied altogether. In the magnetic imaging techniques, the radio waves are utilized to locate as well as to obtain a digital image of tissues present in the brain. In fact, the traditional MRI method is a very difficult task and time-consuming even for a skilled person, which will also depend on the expert's experience on the expected results. Similarly, it is consequential to obtain a method to provide doctors with an accurate and fully automatic technique as the manual analysis of such images requires training and experience and will often lead to wrong diagnostics.

The growth of the tumor occupies space within the skull and affects with normal brain activity. Brain tumor is classified into two type as normal brain and abnormal brain [3]. There are two types of tumors: malignant or cancerous tumor and benign tumors. Cancerous tumor can be divided into primary tumor that start within the brain and secondary tumor that have spread from somewhere else, known as brain metastasis tumor. Brain tumor detection in medical images forms an essential step in solving several practical applications such as diagnosis of the tumor and registration of patient images obtained at different times.

This paper introduces a method that is performed by focusing on major challenges and problems in medical imaging such as image detection and classification for detecting and classifying brain tumors. The detection of tumors consists of image acquisition, pre-processing, denoising, segmentation, extraction and classification of features. Image segmentation is one of the most important tasks in tumor detection. Initially, the MRI image input is pre-processed using wiener filter, followed by denoising where the technique of Edge Adaptive Total Variation is used. Following denoising is a segmentation task consisting of mean shift clustering and content-based active contour techniques that would extract the tumor from the MRI images. The next stage in the proposed system is feature extraction, where GLCM features from the segmented image. Finally, the classification is done using Support Vector Machine (SVM), Deep Learning with Convolutional Neural Network (CNN). In image processing it is usually necessary to perform high degree of noise reduction in an image before performing higher-level processing steps, such as edge detection [3], smoothing filters is used to remove noise from an image. Each pixel is represented by three scalar values representing the red, green and blue chromatic intensities. At each pixel studied, a smoothing filter takes into account the surrounding pixels to design an accurate version of this pixel. By taking neighbouring pixels into considerations, extreme 'noisy' pixels can be represented. In research and technology such as geographic information systems, digital images play an important role as well as being the most vital part in the field of medical science such as ultrasound imaging, X-ray imaging, computed tomography and MRI. A very large portion of digital image processing involves restoring images. Specific segmentation method is not found to extract vasculature from every medical images modality. While techniques like clustering, segmentation etc., employ pure intensity-based pattern recognition techniques such as thresholding followed by connected component analysis, edge detection methods are applied explicitly in the tumor models to extract the tumor contours [2].

Based on the image quality different pre-processing methods are used for segmentation. On the other hand, methods like low pass filtering, unsharp masking techniques are applied in the post-processing in order to overcome the problems arising over segmentation. There are six main categories by which medical image segmentation algorithms and techniques can be divided as pattern recognition techniques, model-based approaches, tracking-based approaches, artificial intelligence-based approaches, neural network-based approaches and object detection approaches. In this paper, mean shift clustering is used for segmenting the tumor from the brain. Extraction of the feature is a process of attribute reduction. Contrary to the selection of features classifying existing attributes by prediction, the removal of features transforms the attributes [8]. Feature extraction projects a data set to a smaller number of dimensions with higher dimensionality. In this paper gray scale co-occurrence matrix (GLCM) features are extracted which is used for training the network [4] [7].

The purpose of the classification process is to categorize all pixels in a digital image into one of several classes or themes of land coverage [20]. Then, this categorized data can be used to produce thematic maps of the land cover in an image. Multispectral data are normally used to perform classification and the spectral pattern present in the data for each pixel is used as the numerical basis for categorization. The aim of image classification is to identify and portray the characteristics that occur in an image in terms of the object or type of land that these characteristics represent on the ground as a unique gray level (or color). The main aim of this paper is to detect the position, boundary and the type of tumour automatically based on the symmetry information of MRI. Clinical diagnostics can be aided as the key reason for brain tumors to be detected. The goal is to develop a tumor proof algorithm that provides a method for tumor detection in MRI brain images by combining various procedures. The scope of this work is to bring some useful information to the users in a simpler way, particularly for the patient's medical staff.

2. LITERATURE REVIEW

A lot of research has been studied for brain tumor segmentation. Some of the recent research methods are discussed here. The paper outlines lab work using artificial neural network for brain tumor detection using MRI images [12]. This paper detects tumor area by darkening tumor portion and enhances the images for detection of brain tumor. The methods used are image acquisition, preprocessing, image enhancement, thresholding and morphological operation. Median filter is used in preprocessing to remove noise. A high pass filter is applied to digitized MRI image to get Enhanced image. The threshold segmentation is based on threshold value which converts Gray scale image into binary image. The purpose of morphological operator is to separate the tumor part of the image. In the areas of image analysis and computer vision, Active Contour models have been widely used. The contours are driven to reach the boundary of the object by minimizing the fitting energy for contour-based image segmentation. There are two types of active contours: Active parametric contours and active geometric contours [10]. In terms of curve function, parametric active contours are formulated and highly dependent on curve parameters. Geometric active contours do not involve curve parameterization and can naturally and effectively handle contour topological changes [9].

The Image segmentation is the process of partitioning a digital image into multiple segments. The goal of segmentation is to simplify or change the representation of an image into the more meaningful information and which is easier to analyse. Segmentation plays an important role in analysis of medical images for computer-aided diagnosis and therapy. Segmentation is the challenging and complex task in medical imaging due to the imprecise nature of images [1]. For neurological pathology clinical study and research fully automatic brain tissue classification from magnetic resonance images (MRI) is very important. The important task is to segment the MR images into different classes especially gray matter (GM), white matter (WM) and cerebrospinal fluid (CSF) accurately. The useful diagnostic information can be known from regional volume calculation [6]. In neurodegenerative disorders such as Alzheimer disease, in movement disorders such as Parkinson or Parkinson related syndrome, in white matter metabolic or inflammatory disease, in congenital brain malformations or perinatal brain damage, or in post-traumatic syndrome, quantization of gray and white matter volumes are considered for calculations.

A multi stage approach using random forest for brain tumour classification and segmenting them using fast bounding box was proposed [18] [5]. The combined approach of gray level co-occurrence matrix (GLCM) and gray level run length matrix (GLRLM) texture feature extraction methodologies is used in this work for classififying the tumour. In this proposed system a comparison is done for classifying the accuracy for the dataset which contains 120 cases of MRI images. The results show that multi stage approach outperforms the reference methods and achieves better accuracy in classifying Glioma or Meningioma and segmenting the tumour. An important observation in this work is that multi stage approach uses hierarchical classification method which boosts performance significantly. Decisions obtained by applying a hierarchical classification for every single classification task is better than the best individual classification algorithm [5].

These system brain MRI methods have been verified as a significant way to find the brain tumor [14]. The hybrid methodology of gathering support vector machine and fuzzy c-means clustering for classification gives precise result for identifying the brain tumor. For future work, a hybrid SVM algorithm should be proposed to achieve a better accuracy rate and less error rate [16]. In future work, different data mining techniques can be used to train to improve classifier performance using different kernel functions, and data sets can also be increased. A prototype for object detection with SVMs was presented in [15], which can achieve real-time performance while maintaining high detection accuracy. 82% of the accuracy is achieved and 81.48% of the positive predictive values (PPV) are calculated. The True Positive Cases are 22; True Negative 5 is 22; False Positive 5 is 22. The same prototype can also be used for different applications regardless of the size of the window, the number of support vectors and the size of the image. Many researches were done to automate the segmentation and diagnosis of brain tumors using Deep Learning networks. In the research [17], multiple convolutional networks are used to segment the brain tumors for diagnosis process. The MRI image modalities like T1-weighted, T2-weighted are given more consideration in the segmentation process. In this method, the 3D image voxels are input into a 2D CNN model. Four CNNs are developed with different block sizes to compare the performance of each model. The accuracy is reasonable compared to the algorithm of Bauer and Menze. The output of the said method is a segmentation of brain tumor out of the whole brain MRI image. It does not predict whether the tumor is either benign or malignant or which tumor type it is.

K-Means Clustering n observations into K clusters in which each pixel belongs to the clusters by minimizing an objective function in such a way that the sum of squares within the cluster is minimized [11]. It starts with initial K cluster centres and it reassigns the observations to clusters based on the similarity between the observations and cluster centre. Automation of detection and segmentation of brain tumors in MRI images is a very challenging task due to occurrence of high degree of gray-level similarity in the image. There is a fully automated two-step segmentation process of brain MRI images. In the first step, skull stripping is performed by generating a skull mask from the MRI image and in the second step, an advanced K-means algorithm improvised by two-level granularity-oriented grid-based localization process based on standard local deviation is used to segment the image into gray matter, white matter and tumor region and then length and breadth of the tumor is assessed. This research paper presents a method based on image characteristics and automatic detection of abnormalities to automatically classify medical images in two classes Normal and Abnormal [13]. Statistical texture functionality is derived from normal and abnormal pictures. We used the KNN classifier to classify the image [19]. The KNN classifier performance against the kernel-based SVM classifier (Linear and RBF). The calculated confusion matrix and result shows that KNN receives an 80 percent classification rate higher than the SVM classification rate.

3. PROPOSED SYSTEM

The proposed system is to detect and classify the brain tumor, which involves pre-processing, denoising, segmentation, feature extraction and classification stages. The software and device that are used for implementing this proposed system is MATLAB R2017b with Intel core i5 processor and 16GB RAM capability. Specimen images were collected from PSGIMS&R, PSG Hospitals, Coimbatore which is used for training and testing the proposed system. The MRI image dataset that is obtained from PSGIMS&R consists of 10 different cases in which a few sample cases are taken as the input for detection and classification. After consultation with the radiologist, the axial T2 FLAIR weighted, digitized in 512×512, 12 bit per pixel images from the MR Avanto 1.5 T MRI scanner was selected as the input data. The first stage classifies a normal and abnormal image into two classes. Two metrics were calculated to evaluate the classification efficiency: (a) the training performance (i.e. the proportion of cases properly classified in the training process) and (b) the test performance (i.e. the proportion of cases properly classified in the testing process).

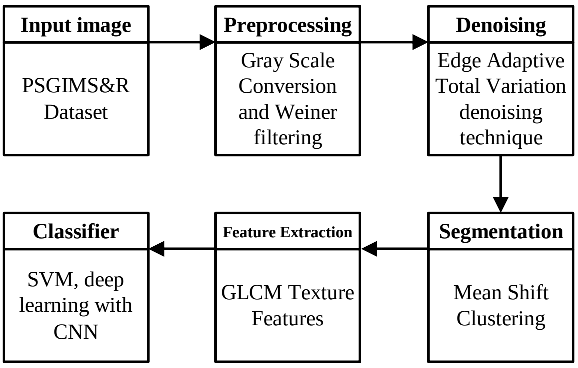

Fig.1. Overview of the proposed system

Initially the MRI image is taken as the input and it is preprocessed using wiener filter. The wiener filter would remove the noise present in the image, and it would blur the image. The pre-processing stage is followed by Denoising, where Edge Adaptive Total Variation technique is used. The main objective of the denoising is to eliminate the unwanted signal present in the input image. The denoised image is further taken to the Segmentation process in which Mean Shift Clustering is used to cluster the pixel that are of similar properties. Finally, the clustered output is used for extracting the features which is done in feature extraction phase and the extracted features are used for classification of tumor. In the classification stage Support Vector machine, deep learning with CNN are used. These are used for classifying the MRI images into tumorous or non-tumors. The overview of the proposed system is given in Fig.1.

3.1 PRE-PROCESSING

Pre-processing is a common name for image operations at the lowest abstraction level-both input and output are intensity images. The aim of the pre-processing is to improve the image data that suppresses unwanted distortion or improves certain image features important for further processing. The different categories of image pre-processing methods depending on the size of the pixel neighborhood used to calculate the new pixel brightness are as follows.

- Transformations of pixel brightness
- Transformations of geometry
- Pre-processing methods that use the processed pixel's local neighborhood
- Image recovery requiring knowledge of the entire image
- Other pre-processing image classifications exist

Images gained from various MRI modalities are influenced by ancient rarities, for example, movement and field inhomogeneity. A MRI can be utilized to assess cerebrum, neck, and spinal string issues. It can likewise enable parental figures to take a gander at issues with the chest, heart, mid-region, joints, or veins. The filtering of Wiener makes an optimal compromise between inverse and noise smoothing filters. It removes the added noise and simultaneously reverses the blurring. In the case of window sizes 3×3, 5×5, 7×7, 13×13 and 23×23 and the like, the quality of the filtered image differs.

3.2 DENOISING

Digital images, for example geographic information systems, play an important role in research and technology and are key to medical science such as ultrasound imaging, X-rays, Computed Tomography and MRI. The restoration of images includes a very large part of digital image processing. Restoration of images is a degradation method that takes place during the capture of the image. Degradation due to electronic and photometric sources is caused by sound and blurring. Blurring represents a bandwidth reduction of images caused by an imperfect image formation process, such as relative motion among the camera and the original scene or a distorted optical system. Noise is the undesirable signal that impairs the original signal and degrades the visual quality of digital images. Principal sources of noise in digital images are imperfect instruments, problems with process of data acquisition, natural interference, transmission and compression. The denoising of images is the pre-processing step in photography, research, technologies and the medical science in which the image has been degraded in some way and needs to be restored before further processing. Edge Adaptive Total Variation Denoising is one of the techniques of noise removal that this proposed system employs.

3.3 SEGMENTATION

Segmentation partitions an image in different regions that contain similar attributes for each pixel. The regions should be strongly linked to described objects or features of interest, which are meaningful and useful for image analysis and interpretation. The segmentation is the first step from low-level image processing to convert a gray or color image into one or more other images to high-level image description in terms of features, objects and scenes. The success of the image analysis depends on the reliability of the segmentation, but an accurate image partitioning is usually a very difficult problem. The techniques of segmentation are either contextual or non-contextual thresholds. In this proposed system two different types of segmentation techniques such as Mean Shift Clustering and Content based Active Contour model are used for the analysis and results are compared.

3.4 FEATURE EXTRACTION

The component extraction includes improving the measure of assets required to depict an extensive arrangement of information precisely. When performing examination of complex information one of the real issues originates from the quantity of factors included. Examination with a substantial number of factors for the most part requires a lot of memory and calculation control or an order calculation which over fits the preparation test and sums up inadequately to new examples. This is a strategy for catching visual substance of pictures for ordering and recovery. Crude or low dimension picture highlights can be either broad highlights, for example, extraction of shading, surface and shape or area explicit highlights. In this proposed methodology gray scale co-occurrence matrix (GLCM) algorithm is used in-order to extract the true surface feature for the advancement in the estimation of image. The four highlights specifically, Energy, Contrast, Correlation and Homogeneity are figured utilizing MATLAB.

3.5 CLASSIFICATION

Classification between objects is an easy task for humans, but for machines it has proven complex. Higher capacity computing and high-end and cheap video cameras have created an interest in algorithms for the classification of objects, along with the growing need for automated video analyses. A simple grading system consists of a camera that is mounted high above the zone in which images are recorded and thus processed. Classification includes image sensors, pre-processing, detection and division of objects, extraction of functions and classification of objects. Classification systems are a database containing predefined patterns which are to be classified into the proper category compared to detected objects. Classifying images is an important and demanding task in different fields of application such as biomedical imagery, biometry, widespread surveillance, vehicle navigation, industrial visual inspection, robot navigation and remote sensing. This proposed system is used for classifying the brain tumor by the Support Vector Machine (SVM) and deep learning using the Convolution Neural Networks (CNNs).

4. SIMULATION RESULTS AND DISCUSSIONS

The Fig.2 shows the input image with tumor is given as the MATLAB input. This image is then preprocessed using wiener filter by adding speckle noise.

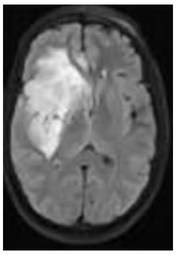

Fig.2. Input image with tumor

In the pre-processing stage very few amounts of noise are removed, and it is blurred using wiener filter, as shown in Fig.3. The process of the wiener filter is analysed by varying the window size of the filter as 3×3, 5×5, 7×7, 13×13, 15×15, 23×23. When the size of the window is high then the resolution would be minimum while restoring the image. Hence, a 3×3 window size is taken for the pre-processing stage.

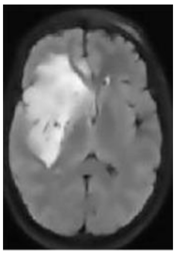

Fig.3. Weiner Filtered Image

Table.1. Error metrics obtained by varying the window size of the wiener filter for PSGIMSR dataset

Window Size	Peak-SNR value	SNR value	MSE value	SSIM value
3×3	28.6522	7.2485	74.258	0.06982
5×5	26.9685	17.4568	73.6475	0.6874
7×7	243669	17.258	70.8741	0.6556
13×13	24.3698	13.588	67.1214	0.66741
23×23	20.2368	11.3648	64.9871	0.63842

The second process is denoising followed by preprocessing, where EATVD technique is used to eliminate the noise content in the image. The result is shown in the Fig.4. The denoised output is used to calculate the peak signal to noise ratio (PSNR) value, signal to noise ratio (SNR) value, structural similarity (SSIM) value and mean squared error (MSE) value. Although a higher PSNR generally indicates that the reconstruction is of higher quality. Higher the SNR value means more amount of noise is removed.

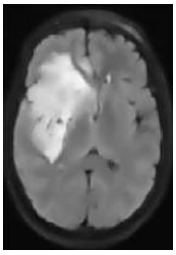

Fig.4. Denoised image

However, as per least squares results, it is slightly biased towards blur. SSIM has been developed to have a quality reconstruction metric that also considers the similarity of the edges (high frequency content) between the denoised image and the input image. These values are compared by varying the window size of the filter as 3×3, 5×5, 7×7, 13×13, 15×15, 23×23 etc. The error metrics obtained by varying the window size of the wiener filter is for PSGIMSR datasets is shown in the Table.1 and their EDTV values are given in Fig.5.

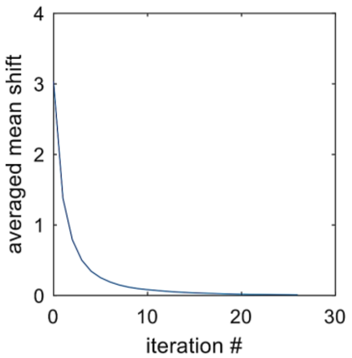

Fig.5. EDTV (Averaged mean shift value = 0.0091619)

The segmentation is done using Mean Shift Clustering (MSC) algorithm. The outcome of the MSC algorithm returns the average mean shift value. When the value of the average mean shift is high then the segmentation would have more coverage, which is given in the Fig.6. The segmentation is also based on the number of iterations that must undergo for segmenting the tumor. By default, the iteration is taken as 100. When the number of iterations increases more than the limit it may leads to loss in the information.

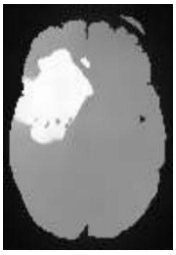

Fig.6. Mean Shift Clustering Image

For the given input image, the average mean shift value is maximum as the number of iterations increases. This model is used to extract the boundary region of the tumour and extract it separately from the MRI image. Furthermore, the initial image does not need to be smoothed, even though it is noisy and thus the boundary locations are very well detected and preserved. The mean-shift algorithm with color and spatial information in color image segmentation is in generally successful for few cases. However, in some cases, the color and spatial information are not enough for superior segmentation. Mean Shift is a non-parametric clustering approach that does not take the form of the distribution and the number of clusters into consideration.

The GLCM features like contrast, correlation, energy, homogeneity, mean, standard deviation, entropy, RMS, variance, smoothness, kurtosis, skewness are extracted from the segmented results. Based on the features extracted the boundary of the tumor can be identified. The feature extracted are stored as database that is used for training and testing the network. The sample features of PSGIMSR is given in the Table.2.

Table.2. Feature extraction for various image sets for PSGIMSR dataset

Features	Image sample 1	Image sample 2	Image sample 3
Mean	0.005273	0.005671	0.003869
Standard Deviation	0.089659	0.089635	0.089731
Entropy	1.89451	2.16453	2.46141
RMS	0.089802	0.089802	0.089802
Variance	0.008059	0.008066	0.008065
Smoothness	0.951501	0.954745	0.935042
Kurtosis	34.5611	36.8149	20.4204
Skewness	3.12135	3.28541	1.81771
IDM	1.84505	2.95678	1.50355
Contrast	0.42436	0.432425	0.331479
Correlation	0.135197	0.099307	0.093482
Energy	0.850171	0.852803	0.789385
Homogeneity	0.955292	0.955248	0.939014

The Table.3 gives the performance measurements of SVM classifier. For training this network, datasets are taken with 10 cases which consists of 40 image sets and for testing the network, 20 image sets are taken. The MRI image is classified as No tumor or MRI with tumor (Benign and Malignant). The number of iterations taken for classifying the tumor is 700 and four different types of kernel like RBF, linear, polygonal and quadratic are used. Performance that are measured from this classifier are computational time, classification rate, error rate, sensitivity, specificity, positive predicted value, negative predicted value, and accuracy for different kernels. By varying the kernel function and number of iterations, the accuracy can be attained maximum. When the iterations are minimum the accuracy is also minimum and the time taken for classifying is low, similarly when the number of iterations is increased, maximum accuracy is attained, and computational time is high.

Table.3. Output performance measurement of SVM classifier for PSGIMSR dataset

Image Set	**Test image 1**	**Test image 2**	**Test image 3**
Computational time in seconds	11.983	10.677	12.076
Classification rate	0.5	0.6	0.5
Error rate	0.5	0.4	0.5
Sensitivity	0.4	0.4	0.4
Specificity	0.6	0.5	0.6
Positive Predictive Value	0.5	0.4444	0.5
Negative Predictive Value	0.5	0.4545	0.5
RBF accuracy in %	80	100	90
Linear accuracy in %	90	90	80
Polygonal accuracy in %	80	90	90
Quadratic accuracy in %	90	80	90
Best accuracy among the above kernel in %	90	100	90
Overall accuracy in %	85	90	87.5
Tumor type	Benign	Malignant	No tumor

The CNN classifies the MRI image into two classes and the data size of the classifier is 20 image sets are taken and trained. The neural network has 19 hidden layers and 1 output layer. The data division is considered as random and training method used is scaled conjugate gradient. This network has 1000 neurons and it would be computed for 7000 epochs. The output data that are taken for training and the performance measures are given in the Table.4.

Table.4. CNN training parameters and outcomes for PSGIMSR dataset

Parameters	**Values**
Number of classes	2
Size of the dataset	40
MSE	0.132964
Number of hidden layers	19
Data division	Random
Training method	Scaled Conjugate Gradient
Number of epochs	7000
Number of neurons	1000
Training time	0.2996 seconds
Gradient	0.1444
Number of output layer	1
CNN training accuracy in %	89.2105

This network would return the performance of the training network, confusion matrix of the training and testing network, the training state plot of the CNN and the entropy plot of the network. The best validation is obtained at the epoch 0 and the best validation performance value is $2.2204e^{-16}$. This validation performance is taken for the cross entropy and the total number of epochs.

The network is tested with 20 sample images of PSGIMSR datasets. The network would be tested for 7000 epochs for each image samples, the best performance validation can be attained in different epochs based on the type of the tumor it classifies. This network returns the tumor type, area or size it occupies in the brain, testing time, and classification accuracy. The performance measurements of CNN testing are specified in the Table.5 for PSGIMSR datasets correspondingly. The Convolutional neural network consists of various layers such as average pooling layer, classification output layer for a neural network, 2D convolutional layer, dropout layer, fully connected layer, rectified linear unit layer etc.

Table.5. CNN testing outcomes for PSGIMSR dataset

Parameters	**Image Sample 1**	**Image Sample 2**	**Image Sample 3**
Epoch	68	164	207
Testing time (sec)	13.78	14.23	11.258
Gradient	$8.55e^{-06}$	$7.65e^{-06}$	$6.25e^{-06}$
Tumor type	Malignant	Benign	No tumor
Tumor area (mm)	4623	1025	Nil
Regression point	0.61989	0.56384	0.6685
Accuracy	0.0925	0.0975	0.0946
Sensitivity	0.7	0.5	0.64
Specificity	0.3	0.5	0.36

Based on the number of iterations or the number of epochs the performance of each image set would vary. The regression plot shows how the input and the target output matches, and blue line indicates the fit ratio and the dotted line represents the output or target. The final tumor detected image is given in the Fig.7.

Tumor Area = 1234 and it is Malignant

Fig.7. Tumor detected image

Table.6. Performance measurement comparison of classifiers by using PSGIMSR dataset

Selected parameter	**Accuracy (%)**		**Computational time (s)**		**Type of tumor**	
Classifier	**SVM**	**DCNN**	**SVM**	**DCNN**	**SVM**	**DCNN**
Image sample 1	87.5	91.87	10.805	12.36	Malignant	Malignant
Image sample 2	85	98.9	11.576	13.22	Benign	Benign
Image sample 3	82.5	94.2	11.12	10.21	No tumor	No tumor

The CNNs are designed to work with image data, whereas SVM is a more generic classifier. CNNs extract features while SVM simply maps its input to a certain high dimensional space where variations in class can be revealed. Learning objectives of SVM and CNN are different: SVMs seek to maximize their margin while CNNs do not maximize their margin. On comparing the computation time for both the network Deep learning with CNN is quite faster and the accuracy is more when compared with the support vector machine. The 94.2% accuracy is obtained by using Deep Learning with CNN classifier while SVM classifier has attained 87.5% accuracy. The number of iterations is fixed for all image sets and kernel type, but for CNN the maximum number of epochs is assumed, and the minimum number of epochs is required automatically to classify the MRI during classification. The comparison between the various parameters of SVM, CNN classifiers are specified in the Table.6. On comparing the results of the classifiers deep learning with CNN would result better when compared with the other classifiers with respect to accuracy and computational time.

5. CONCLUSION

The MRI image input is taken and a speckle noise is added, then pre-processed using wiener filter. The parameters used in the wiener filter include the noisy image, the type of noise used, the mean and the image variance. The pre-processed image is denoised using EDTV technique, where the SNR value obtained is high, the image resolution would be high when it is reconstructed. In the segmentation of color images, the mean shift algorithm with color and space data is generally successful, but in some cases, color and space information are not sufficient for superior segmentation. Mean Shift is a non-parametric clustering approach that does not consider the distribution form and the number of clusters. Consequently, Mean Shift can deliver better results of segmentation than model-based clustering systems, when used to segment historical images. The extracted characteristics are used to classify the image as the input. To improve classification accuracy, the multiple features of the image and selection of appropriate classification methods are effectively used. CNNs are intended to work with image data, while SVM is an increasingly nonexclusive classifier. CNNs separate qualities while SVM essentially maps its contribution to a specific high-dimensional space where contrasts in class can be uncovered. There are diverse learning destinations: SVMs are endeavoring to boost the edge, while CNNs are not doing as such. On contrasting the ideal opportunity for both system registering, Deep learning with CNN is quicker and more precise in contrast to the Support vector machine. An accuracy of 94.20% is accomplished by utilizing deep learning CNN classifier, while SVM classifier accomplished 87.50% precision. On looking at the computational time of the classifier, SVM is characterized in a brief timeframe contrasted with different classifiers. Comparing various parameters of SVM and Deep Learning with CNN, the results of the CNN classifier are better w.r.t computational time and accuracy.

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