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A NOVEL APPROACH TO BRAIN TUMOR DETECTION

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ABSTRACT

An intracranial mass of abnormal cells in the brain that have grown out of control is referred to as brain tumor. Based on the type of tissue involved and the location of the tumor, brain tumors are classified as benign (non-cancerous) or malignant (cancerous). Brain tumor prognosis attributed lot of significance in successful treatment. Magnetic Resonance Imaging (MRI) is proved to be a most accurate diagnostic tool for human soft tissue analysis. However brain tumor segmentation and classification is a cumbersome process, as magnetic resonance images are inherently noisy in nature. In this work Support Vector Machine (SVM) classifier is used to classify the MRI images as normal and abnormal (tumor). Features are extracted from the segmented images and the clustered to improve the SVM classifier accuracy. Statistical analysis is performed with 10 fold cross validation to find the robustness of the classifier. Experimental result shows 96.5 percent accuracy while testing with MRI brain tumor images from IMRI Volumetric Non-Rigid Registration-Dataset.

KEYWORDS: Magnetic Resonance Imaging, Support Vector Machine, Brain Tumor, Statistical analysis, Cross Validation.

I. INTRODUCTION

Uncontrolled proliferation of abnormal cells is referred to as brain tumor. Brain tumors are termed as primary, if those originate in the brain. The secondary tumors originate at other body parts and spread to the brain through metastasis. Primary brain tumors can be benign (non-cancerous) or malignant (cancerous), whereas secondary brain tumors are malignant. Both primary and secondary tumors are dangerous and could prove fatal if not detected in early stage. As the space inside the skull is very limited, the growth of tumor inside the skull could increase the intracranial pressure causing edema, reduced blood flow, displacement, and degeneration of other tissues that control important body functions. Survival rates of the affected individual with brain tumors vary widely, depending on the type of tumor [2], however for brain tumor prognosis and successful treatment therapy planning, early and accurate tumor diagnosis is imperative.

Medical imaging is becoming a very important aspect in clinical applications from diagnosis to treatment [1]. Magnetic Resonance Imaging (MRI) is a very important diagnostic tool for analysis of human soft tissue. Magnetic resonance imaging is popularly used in diagnosis of brain tumor because, it is a non-invasive technique. However the diagnosis is inherently challenging due to the large variance and complexity of tumor characterization in images, such as size, structure, location and intensities and can only be performed by professional radiologists. Also Magnetic resonance images contain noise caused by operator performance that could pave path to inaccuracies in classification.

Nowadays use of computers in clinical diagnosis is extensive and spread across a wide range of medical applications such as cancer prognosis, artery thickening, brain tumors etc. Magnetic resonance imaging is the ultimate option available at the present for study of tumors as it efficiently finds the tumor types, size and the tumor location. In magnetic resonance imaging method, the image is formed by magnetic field, radio waves and a computer and there is no known significant side effects for exposure of radiation. Magnetic resonance imaging technique reveals greater details of soft human tissues. Brain tumor is often symptomatic, however in absence of symptoms, in some cases brain tumor is revealed while scan is performed for some other cause. Researchers in the recent past have put-forth several ideas for successful diagnosis of brain tumor, some of the relevant ones are reviewed here.

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- The capabilities of Back Propagation Neural Network (BPN) and Radial Basis Function Neural Network (RBFN) to classify the brain MRI images into normal or abnormal categories have been investigated in [3]. The researchers have demonstrated that RBFN outperformed the BPN in terms of classification accuracy resulting 85.71%.
- Classification of brain tumor in MR images using genetic algorithm and support vector machine is discussed in [4]. Spatial Gray Level Dependence Method (SGLDM) is used to extract optimal features from a wavelet based texture feature set. Genetic algorithm is used to select the required texture features for training the support vector machine classifier for classification.
- Detection of contour of brain tumor and its geometrical dimension using segmentation and histogram thresholding is explained in [5].
- Automatic detection and classification of brain tumor is proposed using Adaptive Gray level Algebraic set Segmentation Algorithm (AGASA) in [6]. The Statistical Features were extracted from the detected tumor texture using first order statistics and gray level co-occurrence matrix (GLCM) based second order statistical methods. A decision system was developed for the grade detection of tumor using these selected features.
- Classification of brain tumor in MR images using feed forward and back propagation neural networks classifiers is proposed in [7]. Discrete wavelet transform is used for feature extraction and principal component analysis is used for reduction of dimensionality.
- Brain tumor classification using probabilistic neural network is presented in [8]. Feature extraction is performed using principal component analysis and classification is carried out by probabilistic neural network. The researchers have demonstrated that PNN classifier is faster and provide good classification accuracy.
- Tumor classification framed with the help of correlation filters to spell tumor subtype concealed in characteristically expressed genes is demonstrated in [9]. Two correlation filters namely Minimum Average Correlation Energy (MACE) and Optimal Tradeoff Synthetic Discriminant Function (OTSDF), were put to ascertain whether a test sample tally with the templates combined for each subclass.
- A bilateral filtering method based on wavelet to reduce the noises in MR images is introduced in [10]. Bilateral filtering of approximate coefficients increased the efficiency of denoising. The denoising scheme was adapted to Rician noise. This filtering method enhanced the visualization and diagnostic quality of the image.
- Automatic classification of medical images in to normal and abnormal based on image features and automatic abnormality detection is proposed in [11]. K-Nearest Neighbor classifier is used for classifying the image using the Euclidean distance. SVM have high approximation capability and much faster convergence. Normal image is displayed as resultant normal image and the abnormal image is passed to the next phase for further processing.
- A bounding circle is used for accurate demarcation of the boundary of the tumor, along with correct visual location of the tumor in [12]. This study assisted in diagnosis decision whether the tumor is present or absent along with the exact size of the tumor.

In this study, a novel technique based on SVM classifier is used to classify the brain MR images into either normal or abnormal based on its features that are extracted from the segmented image is discussed. The organization of rest of the paper is as follows. In Section 2, the proposed algorithm is described. The methods and materials involved in the proposed technique for brain tumor classification is presented in Section 3. The experimental results are discussed in section 4. Finally, conclusion is discussed in Section 5.

II. PROPOSED ALGORITHM

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The framework for the brain tumor detection system is shown in Figure 1.

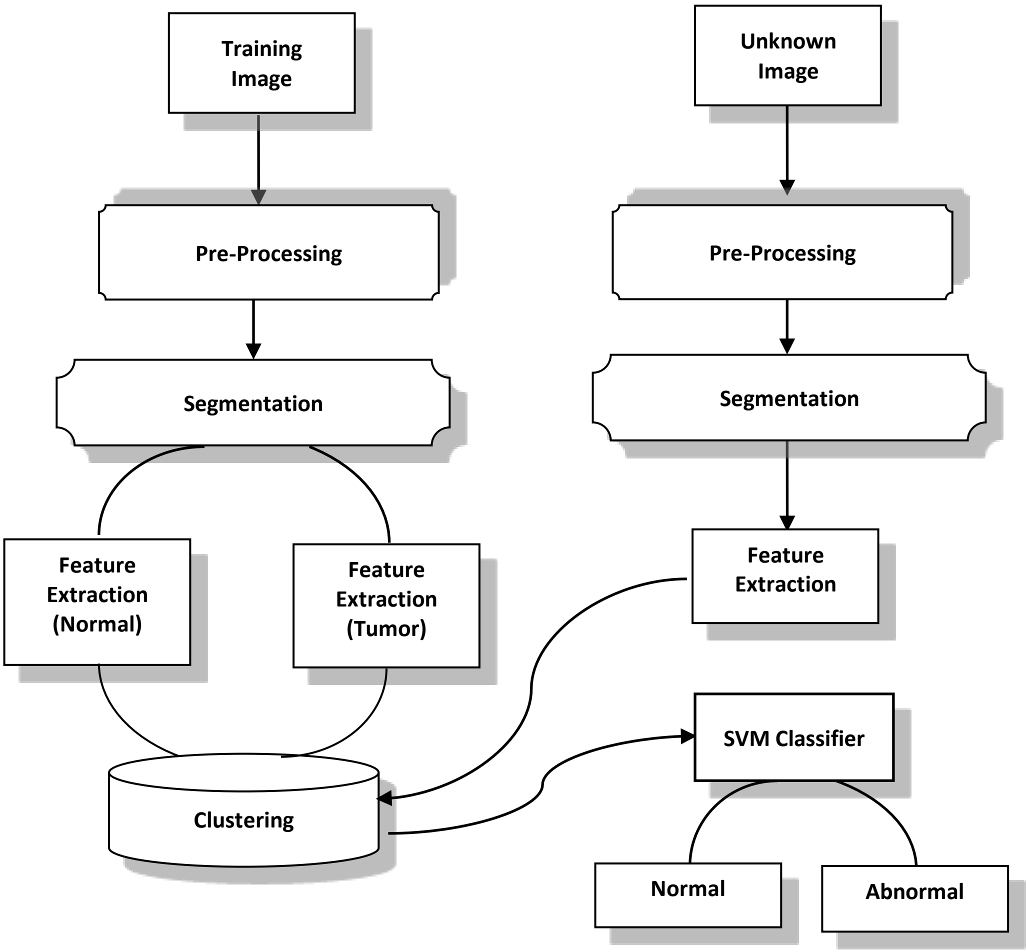

Fig. 1 Automated System for Brain tumor detection in MR images

The SVM based brain tumor detection system has been implemented using three different stages namely, the active contour based segmentation, feature extraction and clustering, and SVM based detection. Any image processing algorithm necessarily has a pre-processing stage preceding the main processing stages. The pre-processing is done to remove the noise and artifacts such as background and patient information in the magnetic resonance images. In the segmentation stage active contour based segmentation is used to segment the MR images. Features are extracted from the segmented images and clustered by K-means algorithm to increase the SVM classifier accuracy. The clustered features forms a feature set, which is used to train the SVM classifier. Figure 2 shows the brain magnetic resonance images. The trained SVM classifier is used to classify a given brain MR images as normal or abnormal. The detailed procedure for the aforementioned CAD system is explained in the section 3.

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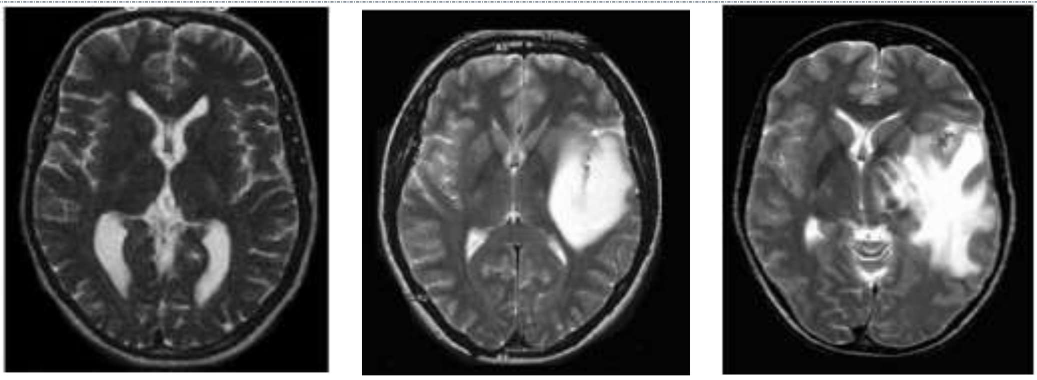

(a) *(b)* *(c)*

Fig. 2 MRI images (a) Normal Brain Image, (b) and (c) Tumor Brain Images.

III. MATERIALS AND METHODS

In this section, the database for brain MR images used in this work is discussed. Also a detailed study on active contour segmentation method, feature extraction, clustering and SVM classifier based classification is carried out.

3.1 Image Database

The proposed technique is evaluated using the MRI brain tumor images from IMRI Volumetric Non-Rigid Registration-Dataset. The dataset contains unprocessed pre-operative and intra-operative data stored in a parent directory called Original. Inside this directory, there are 10 subdirectories called Case 1… Case 10. Each of these directories contains data corresponding to each image dataset. The images can be accessed and processed with 3D Slicer [13]. A total of 40 brain MR images were downloaded, out of which 23 are tumor and 17 are normal cases. Hereafter these 40 images are referred as database.

3.2 Training Phase

In this phase, pre-processing is performed for the entire brain MR images in the database and then the images of the training set are segmented and subsequently the visual content features such as texture, shape, mean intensity, edge strength, area and bounding region are extracted. All the extracted features are clustered to obtain the feature set combination. The SVM is trained by using the clustered combination to categorize the brain MR image into normal or abnormal.

3.2.1 Pre-processing

It is indispensable to perform pre-processing on the brain MR image for increasing the quality of the image as well as for making the feature extraction more reliable. In this stage, the noises in the images are removed, then the black background and the existing artifacts such as the written label etc. are also removed by using the cropping technique. Cropping removes the unnecessary parts of the image particularly peripheral to the area of interest. The cropping operation was made automatically by sweeping through the image and cutting the superfluous regions of the image horizontally and vertically that have the mean below a certain predefined threshold value.

3.2.2 Segmentation

Image segmentation refers to the process of partitioning an image or, representing an image into something that is more meaningful and easier to analyze. Image segmentation aims at locating objects and boundaries (lines, curves, etc.) in images. Image segmentation is of two types namely, edge based and region based segmentation. In edge based segmentation, the object to be segmented should have its boundary visible in the image as a prominent edge. In region based segmentation, the region of the object in the image should have a different statistic in some feature space, compared to its surroundings; these functions are combined with information on the shape of the region being extracted.

Active contour model (**Snakes)** is used for brain MR image segmentation. The active contour model is a framework in computer vision for tracing an outline from a noisy 2D image. Active contours are suitable for brain MR image region extraction because, the brain MR image is a well-defined curve and is capable of being treated in a particular way to the curve approximation characteristics of active contours.

The active contour model is defined by an energy function. The energy function, which is minimized, is a weighted combination of internal and external forces. The internal forces regulate the ability of the contour to stretch or bend at a specific point while preserving some degree of geometric smoothness. The external forces

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attract the contour to specific image features. The snake's general form represents a contour by a vector having the arc length s [14]. The Equation for the energy measure is given in equation 3.1.

$$E_{snake} = \int \left(E_{int}(v(s)) + E_{ext}(v(s)) + E_{image}(v(s))\right) \ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.1)$$

Here E_{int} is the internal energy of the contour due to bending or discontinuities,
E_{ext} is the optional external constraints energy and
E_{image} is the energy from the image forces.

In turn the internal energy E_{int} that maintains the snake's structure and resists singular deformations is given in equation 3.2.

$$E_{int} = \frac{1}{2}(\alpha(s)|v_1(s)|^2 + \beta(s)|v_1(s)|^2) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.2)$$

The values of α and β at a point determine the extent to which a contour is allowed to stretch or bend. If α is zero, discontinuities can occur at that point. If β is zero, curve discontinuities (i.e. a 90° sharp corner) are permitted. The derivatives in equation 3.2 are approximated using finite differences and are given in equations 3.3 and equation 3.4.

$$\frac{dv_i}{ds} \cong |v_i - v_{i-1}|^2 + (y - y_{i-1})^2 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.3)$$

$$\left|\frac{d^2v_i}{ds^2}\right|^2 \cong |v_{i-1} - 2v_1 + v_{i+1}|^2$$
$$= (x_{i-1} - 2x_i + x_{i+1})^2 + (y_{i-1} - 2y_i + y_{i+1})^2 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.. (3.4)$$

Applying snakes to brain MR image is a trivial task. The uncertain location of the brain contour means that initial placement is critical. The brain region is the largest feature in the brain MR image, which is useful in the threshold portion of the algorithm to determine which object is the brain. The image contains dark backdrop with low intensity level and relatively small brighter fragments. The strong tissue structure with lower intensity level is considered as background and the brighter region is the tumor. In this stage, the tumor object is extracted based on the threshold value, which should make a compromise between the elimination of the background and detection of the accurate tumor region with good descriptions of the shape which is crucial for the feature extraction. The intensity values of the filtered image that are greater than the threshold value belong to the tumor. However it is impossible to achieve 100% separability between noise and tumor region for more complicated situations. The threshold value is extracted based on the experiments as follows.

Let $a = \{a_{ij} | 1 \leq i \leq r; 1 \leq j \leq c\}$ be the brain MR image after pre-processing, then threshold, $T = \mu + k\sigma$. Here μ and σ are the mean and standard deviation of the image model given by equations 3.5 and 3.6 respectively. The value of *k* is selected experimentally. Using the pixels greater than the threshold value, the brain MR image is segmented.

$$\mu = \frac{1}{i * j}\sum_{i=1}^{r}\sum_{j=1}^{c} a_{ij} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.5)$$

$$\sigma = \sqrt{\frac{1}{i * j}\sum_{i=1}^{r}\sum_{j=1}^{c}(a_{ij} - \mu)^2} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.. (3.6)$$

3.2.3 Feature Extraction

After segmentation of the brain MR images, the relevant features are extracted from the segmented images. The selected features for the classification process should return an accurate specificity for the MR image under investigation, and also it should emphasize the dissimilarity between normal and tumor. Using image processing techniques, the features such as texture, shape, gray level intensity, edge strength, area and bounding region are extracted from the segmented images. Each and every feature can be obtained from different process such as, Gabor filter, gray Level Difference Method (GLDM), gray level histogram and Sober algorithm.

Particularly, the shape feature plays an important role in the classification of the normal and tumor and in this proposed technique, Gabor filter based shape features is retrieved. In this approach, 2D odd-symmetric Gabor filter is designed for shape extraction, which is described in the equation (3.7).

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$$G_{(x,y)} = \exp\left(-\frac{(xcos\theta_k + ysin\theta_k)^2}{\sigma_x^2} + \frac{(xcos\theta_k - ysin\theta_k)^2}{\sigma_y^2}\right).\cos(2\pi f_i(xcos\theta_k + ysin\theta_k) + \varphi) \ldots (3.7)$$

Here f_i provides the central frequency of the sinusoidal plane wave,

σ_x and σ_y represents the standard deviations of the Gaussian envelope along the $x - axis$ and $y - axis$. We set the phase $\varphi = \pi/2$ and compute each orientation as $\theta_k = \frac{k\pi}{n}$ where $k = \{1..n\}$ and n is a real number. Several common textures consist of small textons that are usually very large in number, and are perceived as isolated objects. The elements can be placed more or less regularly or randomly. The texture features act as a support feature for segment based classification methods and in this technique. The texture features are extracted by using the gray level difference method (GLDM). In the GLDM, diverse images are created in four directions and then a feature vector is generated by linearizing the gray level histograms of these four new images. The texture features extraction is performed based on the following steps.

Step 1: Four difference images are created in the four directions i.e., north-east, north-west, south-east and south-west. Then the probability distribution function is created from the gray level histograms of these four new images. The step distance is given as *d* and the four difference images are

Image (i, j) - Image (i, (j + d))
Image (i, j) - Image ((i – d), (j + d))
Image (i, j) - Image ((i + d), j)
Image (i, j) - Image (i - d) ,(j - d))

Step 2: The probability distribution function is created from the cumulative sum of the gray level histograms of these four new images. Each probability function is given the length of 256.

Step 3: The four probability distribution functions are joined to form a feature vector of length 1024.

The bounding box indicates the position of the segmented image and the area is computed from actual number of pixels in the region. The Sober algorithm based edge strength is retrieved. The mean intensity feature is calculated using equation 3.8.

$$\psi = \frac{1}{m \times n} \cdot \sum_{i=1;\, j=1}^{m;n} SI_{ij} \qquad (3.8)$$

The features such as shape, texture, bounding region, mean intensity, area and edge strength are extracted and then the extracted features are clustered using K-means clustering to form the feature vector for training the SVM classifier.

3.2.4 Clustering of Features

In this step, the clustering is performed on the extracted feature for improving the classifier performance. The combinations of several features are considered to be vital in ascertaining whether the MR image being cosidered is normal or abnormal. In order to find which combination of features will provide an accurate separation between normal and abnormal, a clustering is performed on the extracted feature set.

Let $N = \{Fb(k)_i | 1 < k \leq m; 1 < i \leq n\}$, $Ab = \{Fm(l)_i | 1 < k \leq m; 1 < i \leq p\}$, be the extracted feature set of the normal and abnormal MR brain image, where 'm', 'n', and 'p' are the total number of extracted features, the number of normal and the number of abnormal elements in the database respectively. The clustering process is performed using the K-means clustering.

Figure 3 shows the flowchart describing the process of the K-means clustering algorithm. In the K-Means clustering, initially the cluster number K is determined and then the centroid or center of these clusters is assumed. One can take any random object as initial centroid or the first K-object in the sequence can also serve as the initial centroid. Then the K-means algorithm will perform the following three steps until convergence.

Iterate until stable (no object move group);

1. Determine the centroid coordinate,
2. Determine the distance of each object to centroid,
3. Group the objects based on minimum distance.

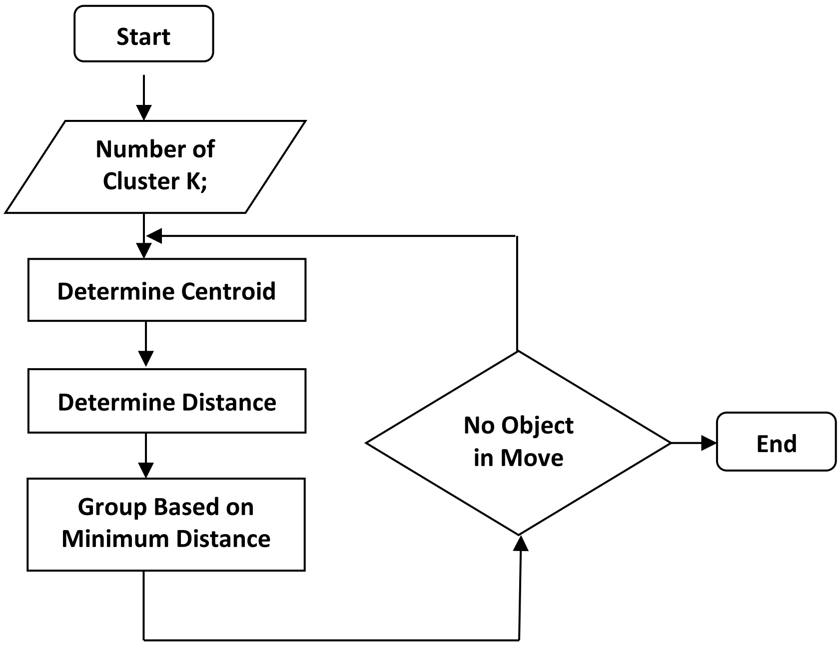

Fig. 3 Flowchart of K-means Clustering Algorithm

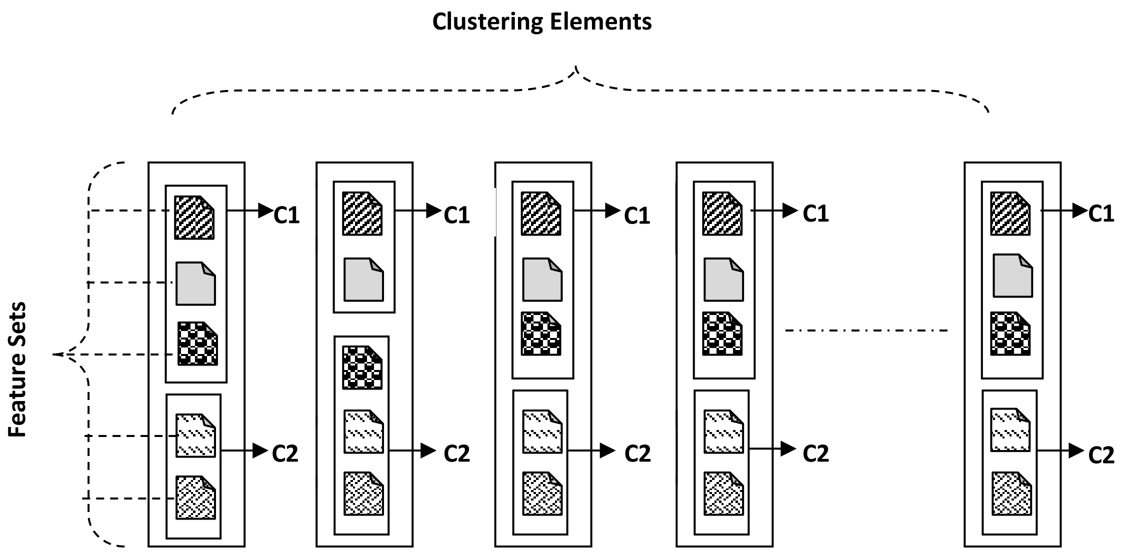

Fig. 4 Clustering of Feature Set

3.2.5 Feature Set Clustering

In the clustering, the extracted features of every normal and abnormal element in the database are clustered separately using the K-means clustering. The every ith elements '*k*' features having same dimension elements are clustered individually by using the k-means algorithm. Figure 4, illustrates the clustering of feature sets containing the similar dimensions. In the Figure 4, the clustering elements represents the feature set of each brain MR image in the database. In local clustering, every elements feature is clustered locally using the K-means algorithm and provides the clusters C1 and C2. The frequent occurring cluster C_f is used for the training purpose.

3.2.6 SVM Based Training

SVMs are the most popular and robust class of algorithms that utilize the idea of kernel substitution and which are commonly called as kernel methods. The training set of instance-label pairs are given as (x_i, y_i); i = 1 …l where $x_i \in R^n$ and $y \in \{1, -1\}^l$, the Support Vector Machines (SVM) [15, 16] require the solution of the optimization problem, i.e., the SVM intends to minimize an error function given in Equation 3.9.

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$$\min_{w,b,\xi} \frac{1}{2} w^T w + c \sum_{i=1}^{l} \xi_i \qquad (3.9)$$

with the following constraints

$$y_i(w^T \phi(x_i) + b) \geq 1 - \xi_i \, , \xi_i \, \geq 0$$

Here, the training vectors x_i is mapped into a higher dimensional space by the function ϕ and subsequently SVM finds a linear separating hyper-plane with the maximal margin in this higher dimensional space. c > 0, represent the penalty parameter of the error term. Also $K(x_i, x_j) \equiv \phi(x_i)^T \phi(x_j)$ is called the kernel function. Thus by reducing the error function, the SVM learns the extracted feature set x_i effectively in order that it can categorize the normal or abnormal that are analogous (similar) to the training set.

3.3 Classification Phase

From the training gene data, the SVM learns well about the class in which the normal or tumor is present. Once the SVM is trained properly, it achieves the capability to classify any brain MR image dataset in the similar fashion. In the classification phase, all the features that are used in the training process are extracted for testing the brain tumour image in a similar manner and subsequently the clustering of the features is performed and the SVM-testing process is carried out using the extracted feature set combination. The features set is given to the trained SVM and therefore the class of the given brain MR image is obtained efficiently.

IV. RESULTS AND DISCUSSION

Active contour based segmentation of brain MR image is developed based on morphological operation. The objective of this segmentation is to extract the proposed features from the brain portion only. Feature extraction is carried out and the features having similar values are clustered using K-means algorithm to generate a feature vector, that is used to train the SVM classifier. Once the SVM classifier is trained, classification of any unknown image can be done accurately. The SVM classifier performance is tested with the training data with clustering and training data without clustering. Experimental results shows that training the SVM classifier method with clustering outperforms the training the SVM classifier method without clustering. Figure 5 shows the performance comparison of both the methods. The results shown in the graphs are averaged from 10-fold cross validation experiments. Classification accuracy of 96.5% is achieved by classifying with SVM classifier and clustering of features using the expression 3.10. The other metrics used to analyze the system such as sensitivity, precision and F-score using the expressions 3.11, 3.12 and 3.13 respectively. Results shows high classification accuracy of 96.5% is achieved while classifying the database images.

TP = True Positive: A tumor image is classified as tumor.

TN = True Negative: A normal image is classified as normal.

FP = False Positive: A tumor image is classified as normal.

FN = False Negative: A normal image is classified as tumor.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \ldots\ldots\ldots\ldots\ldots\ldots (3.10)$$

$$Sensitivity = \frac{TP}{TP + FN} \ldots\ldots\ldots\ldots\ldots\ldots (3.11)$$

$$Precision = \frac{TP}{TP + FP} \ldots\ldots\ldots\ldots\ldots\ldots (3.12)$$

$$F - Score = \frac{TN}{TN + FP} \ldots\ldots\ldots\ldots\ldots\ldots (3.13)$$

The performance of the SVM based brain tumor detection system with clustering of features is shown in table 1

Table 1 Performance of SVM based classification system with feature clustering

No. of Iterations	No of Test Images	Correct Result	Accuracy	Sensitivity	Precision	F-Score
1	40	40	1	1	1	1
2	40	39	0.975	0.958333333	1	1
3	40	39	0.975	1	0.956521739	0.944444444
4	40	38	0.95	0.956521739	0.956521739	0.941176471
5	40	38	0.95	1	0.913043478	0.894736842
6	40	38	0.95	0.92	1	1
7	40	37	0.925	0.954545455	0.913043478	0.888888889
8	40	38	0.95	0.92	1	1
9	40	40	1	1	1	1
10	40	39	0.975	0.958333333	1	1
Average			0.965	0.966773386	0.973913043	0.966924665

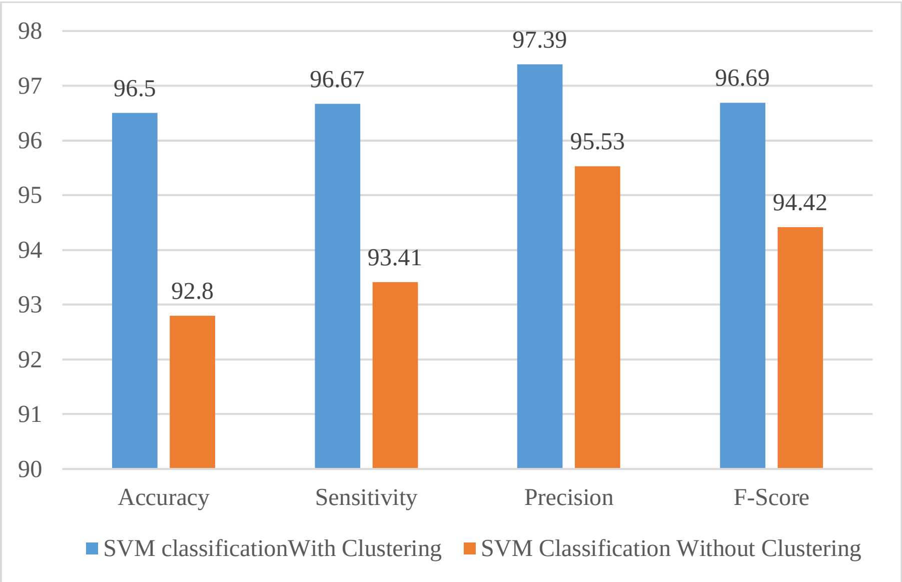

Fig. 5 Comparision of SVM Classifier performance with and without clustering

V. CONCLUSION

In this work, SVM classifier based detection system is implemented. The brain MR images are processed with 3D Slicer software and saved in the jpg format. A dataset of 40 (23 tumor and 17 normal) was used for this implementation. The images were preprocessed and segmented using active contour method for feature extraction. The extracted features were clustered using K-means algorithm and the clustered feature set were used to train the SVM classifier. An accuracy of 96.5% was obtained while classifying the dataset images with 10-fold cross validation method. The SVM classifier was also trained with the un-clustered features to classify the brain MR images. But results have demonstrated that, trained SVM classifier with clustered feature set outperformed the trained SVM classifier with un-clustered feature set.

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