AN ENHANCED BRAIN TUMOUR MRI SEGMENTATION AND CLASSIFICATION USING MORPHOLOGICAL AND SUPPORT VECTOR MACHINE

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ABSTRACT

In this development a dynamic segmentation tool for the detection of brain tumor is used to help clinician and researchers in radio surgery applications. Segmentation is a vital role in medical image processing, where clustering technique widely used in medical application particularly for brain tumor detection in magnetic resonance imaging (MRI). We use MRI because of its provide accurate visualize of anatomical structure of tissues. Usually tumor occupies the locations of normal tissues and their intensity characteristics differ from the surrounding normal tissues. Though the intensity characteristics of tumor region and surroundings normal tissues differs but in T2 scan the tumor intensity characteristics are very close to CSF. This project describe segmentation method consists of two phases. In the first phase, the MRI brain image is acquired from patient database. In that film artifact, noise is removed then converted images RGB to Gray conversion also used median filter. Log method and sobel method used for edge detection. In this enhancement image involved feature extraction using by morphological operator. Next the second phase (MR) image segmentation support vector machine is used to accurately identify the principal tissue structures in these image volumes. Finally the numbers of affected cells are counted using the row and column wise scanning method. In this paper clustering method that have been used for segmentation in MRI are reviewed.

Key-Words: MRI, Sobel method, Morphological operator, Median filter, SVM;

1. INTRODUCTION

Medical Imaging is technology that can be used to generate images of human body. These images are processed or analyzed by experts who provide clinical prescription based on their observations. Ultrasonic, X-ray, Computerized Tomography, & Magnetic Resonance Imaging (MRI) are quite seen in daily life, through different sensory systems are individually applied [3]. In this paper we’re only concerned about one of the application of Medical Imaging i.e. Brain Tumor Detection, Segmentation, & Classification. Segmentation of tumors on medical images is not only of high interest in serial treatment monitoring of “disease burden” in oncologic imaging, but also gaining popularity with the advance of image
There are about 130 different types of brain tumors. Most brain tumors develop from the cells that support the nerve cells of the brain called glial cells. A tumor of glial cells is a glioma. Around 45 out of 100 (45%) of all primary brain tumors are gliomas. There are 3 main types of glioma. Astrocytoma, Oligodendroglioma, Ependymoma. A fourth type is called unspecified glioma, which is where the type is not clear or there is a mixture of cell types. Brain stem gliomas are particularly difficult to treat, whatever their grade. The brain stem is a very complicated and delicate part of the brain and completely removing the tumor is not likely to be possible. Astrocytomas are the most common type of glioma in both adults and children. A third of all brain tumors (34%) are astrocytomas. They develop from cells called astrocytes. The astrocytes are the cells of the brain that support the nerve cells (neurons). Astrocytomas can be slow growing (low grade) or fast growing (high grade). Some are very localized (focal). This means it is easy to see the border between the tumor and normal brain tissue on a scan or during an operation. Focal astrocytomas are more often diagnosed in children and are not common in adults. Other astrocytomas are called diffuse. These do not have a clear boundary between the tumor and normal brain tissue. Anaplastic astrocytoma (also called grade 3 astrocytoma) and glioblastoma multiforme (GBM or grade 4 astrocytoma) are the most common type of brain tumor in adults. These are malignant (high grade) brain gliomas. They can sometimes spread to other parts of the brain. Anaplastic astrocytoma is a rare malignant brain tumor. Astrocytomas are tumors that develop from certain star-shaped brain cells called astrocytes. Astrocytes and similar cells form tissue that surrounds and protects other nerve cells found within the brain and spinal cord. Anaplastic astrocytoma is a primary grade III (malignant) brain tumor. Anaplastic astrocytoma comprises about 4 percent of all primary brain tumors diagnosed in the United States. An anaplastic astrocytoma can start out as a grade III tumor or a reoccurrence of a lower-grade, previously treated grade II astrocytoma. Anaplastic astrocytoma can occur at any age, even childhood. The average age of patients developing this disease is about 40 years. These tumors occur in the brain more than in the spinal cord. Glioblastoma multiforme (GBM) also known as Grade IV Astrocytoma is the most common and most aggressive malignant primary brain tumor in humans, involving glial cells and accounting for 52% of all functional tissue brain tumor cases and 20% of all intracranial
tumors. GBM is a rare disease, with an incidence of 2–3 cases per 100,000 person life-years in Europe and North America. It presents two variants: giant cell glioblastoma and gliosarcoma. About 50% of the patients diagnosed with GBM die within one year, while 90% within three years.

Outlining the tumor contour is a major step in planning spatially localized radiotherapy. On T1 images acquired after administration of a contrast agent (gadolinium), blood vessels and the parts of the tumor, where the contrast can pass the blood-brain barrier are observed as hyper intense areas. MRI uses three electromagnetic fields, a very strong static magnetic field to polarize the hydrogen nuclei, called the static field, a weaker time-varying field for spatial encoding, called the gradient field and a weak radio-frequency field for manipulation of the hydrogen nuclei to produce measurable signals, collected through a Radio Frequency antenna. A tumor is a mass of tissue that grows as out of control of the normal forces that regulate growth.

There are various types of tumors of which brain tumor is the cause of one quarter of all cancer deaths. The complex brain tumors can be separated into two categories depending on tumor origin as primary and metastatic tumors. Primary brain tumors are tumors that arise from cells in the brain or from the covering of the brain. A secondary or metastatic brain tumor occurs when cancer cells spread to the brain from a primary cancer in another part of the body. Several automatic tumor segmentation methods which are rapid and time preserving have been developed[2]. The Central Nervous System and peripheral nervous system are the two main nervous system present in the brain structure and it consists of Gray Matter and White Matter. The Gray Matter control brain activity and cortex region cover the brain which is made of glial cells and the gray matter nuclei (colostrums) are located deep within the white matter. The militated axons are considered as white matter fibers that connect the cerebral cortex with other brain regions [4]. The cerebrospinal fluid (CSF) consists of nutrition rich glucose, salts, enzymes and WBC’s present between the lower part of brain and spinal cord. The meanings are present in the intra cranial of brain and act as protective layer. The cerebrum parts of brain is divided into two
hemisphere regions, the right and left cerebral hemisphere and consists of four lobes including parietal, frontal, temporal and occipital lobe at the back of the brain. The diencephalon layer is the central structure of the brain and consists of thalamus, hypothalamus and pituitary gland and communicated through ventricles [5]. Clustering is the most popular method for medical image segmentation, with fuzzy c-means (FCM) clustering and expectation–maximization (EM) algorithms being the typical methods. The applications of the EM algorithm to brain MR image segmentation were reported [6] and [7]. A common disadvantage of EM algorithms is that the intensity distribution of brain images is modeled as a normal distribution, which is untrue, especially for noisy images. The FCM algorithm has also been employed by many researchers [8] presented a knowledge-based classification and tissue labeling approach to initially segment MR brain images using the FCM algorithm, and introduced an expert system to locate a landmark tissue by matching it with a prior model[9] segmented brain MR images using an artificial neural network (ANN), and compared the performance with FCM. FCM was shown to be superior on normal brains, but worse on abnormal brains with edema, tumor, etc. Pham and Prince [10] extended the traditional FCM algorithm to deal with MR images corrupted by intensity in homogeneities. Unfortunately, the greatest shortcoming of FCM is its over-sensitivity to noise, which is also a flaw of many other intensity-based segmentation methods. Since medical images are first requirement of manually select seed points. Selection of seed points is based on user criteria. It is also iteration based method, like clustering algorithms. The algorithm steps for region growing technique are below [11]. In a preprocessing step, the noise is jettisoned and to instigate the image appropriate for the ensuing stages. In segmentation stage, the neoplasm regions are dissected over region growing method. In feature extraction, certain explicit feature will be extorted by manipulating texture as well from intensity. On the classification stage, the kernel based SVM is fabricated and smeared to training of support vector machine (SVM) to maneuver automatic detection of tumor in MRI images [14]. The Proposed system consists of multiple phases. First phase consists of Preprocessing and segmentation, the second phased consists of first order and second order GLCM (Gray level Co-occurrence Matrix) based features extraction from segmented brain MR images. Third phase classify brain images into tumor and
non-tumors using Feed Forwarded Artificial neural network based classifier. After classification tumor region is extracted from those images which are classified as malignant using two stage segmentation process [15]. In the proposed method the MRI Brain image classification of tumors is done based on Fluid vector flow and support vector machine classifier. In this method Fluid Vector Flow is utilized for segmentation of two dimensional brain tumor MR images to extract the tumor and that tumor can be projected into the three dimensional plane to analyze the depth of the tumor. Finally, Support vector machine classifier is utilized to perform two functions [16]. FVF is utilized for segmentation of two dimensional brain tumor MR images to extract the tumor and projected into the three dimensional plane to analyze the depth of the tumor [19]. In this paper a simple strategy for the automatic segmentation of tissues in magnetic resonance images of multispectral classification based mainly on minimum Euclidean distance is presented. From a set of 3D images in the T1,T1 modalities with gadolinium contrast, T2 and FLAIR and its segmentation reference descriptors for each tissue type are obtained through the centric of each class, which are used to classify new input images [21]. In practice, however, you come across often in images suffer from various kinds of artifacts that do fail the classification algorithms. Also the effect of noise, often present in the signal characterizing the MR images, makes the complex segmentation methods. The proposed work takes its value in two areas of the magnetic resonance imaging (MRI).
segmentation. Proper segmentation can be performed on images without noise, therefore examines some of the algorithms that operate in the spatial domain and in the wavelet domain. There is also an advanced algorithm segmentation that is able to well classify the pixels of the images [22]

1.1 ARCHITECTURE OF BRAIN

The brain is a soft, spongy mass of tissue. It is protected by the bones of the skull, Three thin layers of tissue (meanings), water and fluid (cerebrospinal fluid) that flows through spaces between the meanings and through spaces (ventricles) within the brain. The brain directs the things we choose to do (like walking and talking) and the things our body does without thinking (like breathing). The brain is also in charge of our senses (sight, hearing, touch, taste, and smell), memory, emotions, and personality.

Fig 3. Brain Tumor Anatomy

A network of nerves carries messages back and forth between the brain and the rest of the body. Some nerves go directly from the brain to the eyes, ears, and other parts of the head. Other nerves run through the spinal cord to connect the brain with the other parts of the body. Within the brain and spinal cord, glial cells surround nerve cells and hold them in
place. The three major parts of the brain control different activities.

1. **Cerebrum:** The cerebrum uses information from our senses to tell us what is going on around us and tells our body how to respond. It controls reading, thinking, learning, speech, and emotions. The cerebrum is divided into the left and right cerebral hemispheres. The right hemisphere controls the muscles on the left side of the body. The left hemisphere controls the muscles on the right side of the body.

2. **Cerebellum:** The cerebellum controls balance for walking and standing, and other complex actions.

3. **Brain stem:** The brain stem connects the brain with the spinal cord. It controls breathing, body temperature, blood pressure, and other basic body functions.

**1.2 BRAIN TUMOR**

Tumor develops when the normal workings of a cell go wrong and the cell becomes abnormal. The abnormal cell keeps dividing making more and more abnormal cells. These eventually form a lump (tumor). Not all tumors are cancerous. Doctors can tell if a tumor is cancerous by removing a small sample of tissue or cells from it. This is called a biopsy.

![Brief Brain Anatomy](image)

**Fig 4. Normal cells vs Tumor cells**

A brain tumor that is cancerous (malignant) can grow into nearby tissue. Cancer cells from the tumor may spread from where the cancer first started to other parts of the brain. Primary brain tumors do not usually spread to other parts of the body. Certain brain tumors may spread to the spinal cord.

**Benign** brain tumors do not contain cancer cells. Usually, benign tumors can be removed, and they seldom grow back. The border or edge of a benign brain tumor can be clearly seen. Cells from benign tumors do not invade
tissues around them or spread to other parts of the body. A benign brain tumor may become malignant.

**Malignant** brain tumors contain cancer cells. Malignant brain tumors are generally more serious and often are lives threatening. They are likely to grow rapidly and crowd or invade the surrounding healthy brain tissue. Very rarely; cancer cells may break away from a malignant brain tumor and spread to other parts of the brain, to the spinal cord, or even to other parts of the body. The spread of cancer is called metastasis.

**Stages of Tumor**

Different stages of tumors are given as follows:

- **Stage0** - A typical cells in a normal anatomical configuration.
- **Stage1** - Tumor limited to the local anatomical site.
- **Stage2** - Involvement of ipsilateral regional lymph nodes.
- **Stage 3** - Involvement of contra lateral lymph nodes.
- **Stage 4** - Involvement of a distant site.

The stage together with an assessment of the degree of differentiation is very important for treatment planning and for determining cancer diagnosis.

### 1.3 MAGNETIC RESONANCE IMAGING

A magnetic resonance imaging instrument (MRI scanner), or "Nuclear Magnetic Resonance (NMR) imaging" scanner as it was originally known, uses powerful magnets to polarize and excite hydrogen nuclei (single proton) in water molecules in human tissue, producing a detectable signal which is spatially encoded, resulting in images of the body. The MRI machine emits a RF (radio frequency) pulse that specifically binds to hydrogen. The system sends the pulse to the area of the body to be examined. The pulse makes the protons in that area absorb the energy needed to make them spin in a different direction. This is the "resonance" part of MRI. The RF pulse makes them (only the one or two extra unmatched protons per million) spin at a specific frequency, in a specific direction.

![Fig 5. MRI Acquisition](image)
The particular frequency of resonance is called the Lamoure frequency and is calculated based on the particular tissue being imaged and the strength of the main magnetic field. MRI uses three electromagnetic fields: a very strong (on the order of units of teslas) static magnetic field to polarize the hydrogen nuclei, called the static field; a weaker time-varying (on the order of 1 kHz) field(s) for spatial encoding, called the gradient field(s); and a weak radio-frequency (RF) field for manipulation of the hydrogen nuclei to produce measurable signals, collected through an RF antenna. Unlike CT, MRI does not involve the use of ionizing radiation and is therefore not associated with the same health hazards. For example, because MRI has only been in use since the early 1980s, there are no known long-term effects of exposure to strong static fields (this is the subject of some debate; see 'Safety' in MRI) and therefore there is no limit to the number of scans to which an individual can be subjected, in contrast with X-ray and CT.

2. PROPOSED SYSTEM

The proposed method consists of two stages namely Preprocessing, and segmentation. In the first stage median filter is applied for noise reduction and to make the image suitable for extracting the features using morphological operator. In the second stage, support vector machine and morphological operator used to segmentation process the tumor is extracted from the MR image and its exact position and the shape also determined. of tumor tissue with accuracy and reproducibility comparable to manual segmentation. In addition, it also reduces the time for analysis. To reduce computational costs, we embedded the proposed method in a multi resolution framework. The results of segmentation as given above are at par with the recent medical standard. Moreover the success rate of the segmentation in images of brain MRI taken from all the three angles is quite high and satisfactory.

2.1 THE ARCHITECTURE

The methodology for abnormality segmentation uses 1) a set of pathology-free images in order to calculate an objective function measuring similarity to a healthy brain 2) a test image (with abnormalities) for which the objective function is maximized. All images are co registered and the mean image is calculated and subtracted from them. The solution is based on partitioning the spatial domain into overlapping, equally sized blocks in random locations.
The algorithmic steps are the following. First, the test image is scanned and a random block is selected (among the not already scanned locations). By concatenating the image intensities in the block, the test vector $x_0 \in \mathbb{R}^d$ is constructed, where $d$ is the number of dimensions (e.g., number of voxels in the block). The same block is then extracted from all pathology-free images forming the training vectors $V_{n \times d}$, where $n$ is the number of subjects. The training set $V$ is used to calculate an objective function $l(x)$ the optimization of which gives a new vector $\hat{x} \in \mathbb{R}^d$ that is “less abnormal” and also as similar as possible to the original vector $x_0$.

**List of Modules**

The algorithm has two stages, first is pre-processing of given MRI image and after that segmentation. Steps of algorithm are as following:

1) Give MRI image of brain as input.
2) Convert it to gray scale image.
3) Apply median filter to enhance the quality of image and feature extraction using sobel with log method and Morphological operator.
4) Compute SVM method segmentation.
5) Finally output will be a tumor region

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**Fig2.1 Proposed System Architecture Design**

**3. PREPROCESSING**

The aim of pre-processing is an improvement of the image data that suppresses unwanted distortions or enhances some image features needed for further processing.
3.1 IMAGE DETECTION

In Image detection, Median filter is used for preprocessing. Median filtering is a nonlinear method used to remove noise from images and very effective at removing noise while preserving edges also salt and pepper type noise. The median filter works by moving through the image pixel by pixel, replacing each value with the median value of neighboring pixels. The pattern of neighbors is called the window which slides, pixel by pixel over the entire image pixel, over the entire image. The median is calculated by first sorting all the pixel values from the window into numerical order, and then replacing the pixel being considered with the middle (median) pixel value then use Canny Edge Detection Algorithm. The Canny Edge Detection Algorithm processed following steps

(i). Smoothing: Blurring of the image to remove noise. To decrease the influence of noise and smooth the image using Gaussian Smooth Mask.

(ii). finding gradients: The edges should be marked where the gradients of the image has Large magnitudes. Computing derivatives of the image using vertical and horizontal Sobel Operator, so to get the derivatives along both x and y directions, based on which we can get the final gradient magnitude and the norm direction of the edge. Hence two images in this step, one derivative magnitude image and one image recording the gradient directions of corresponding pixels.

\[ |G| = \sqrt{G_x^2 + G_y^2} \] ……… (1)

\[ \Theta = \arctan \left( \frac{G_y}{G_x} \right) \] ………… (2)

\[ K_{GX} = \begin{pmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{pmatrix} \] ………… (3)

\[ K_{GY} = \begin{pmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{pmatrix} \] ………… (4)

\[ |G| = \sqrt{G_x^2 + G_y^2} \] ……… (5)

\[ |G| = |G_x| + |G_y| \] ………… (6)

\[ \Theta = \arctan \left( \frac{|G_y|}{|G_x|} \right) \] …………(7)

(iii). Non - maximum suppression:

Only local maxima marked as edges. Round the gradient direction to nearest 45°, corresponding to the use of an 8-connected neighborhood. Compare the edge strength of the current pixel with the edge strength of the pixel in the positive and negative gradient direction. I.e. if the gradient direction is north (\(\Theta = 90^\circ\)), compare with the pixels to the north and south. If the edge strength of the
current pixel is largest; preserve the value of the edge strength.

(iv). Double thresholding:

Possible edges are determined by thresholding. The edge-pixels remain after the non-maximum suppression step is marked with their strength pixel-by-pixel. Many of these will probably be true edges in the image, but some may be caused by noise or color variations for instance due to rough surfaces. This method to differentiate

\[ d_Q([I_1], [I_2]) = \min_{x \in [I_1], y \in [I_2]} d_T(x, y) \]

The two related metrics allows us to go between and . In particular, any computation relating to a metric on can be equivalently formulated using its corresponding -invariant metric. The median filter is normally used to reduce noise in an image, somewhat like the mean filter. However, it often does a better job than the mean filter of preserving useful detail in the image. This class of filter belongs to the class of edge preserving smoothing filters which are non-linear filters. This means that for two images \( A(x) \) and \( B(x) \):

\[ \text{median}[A(x) + B(x)] \neq \text{median}[A(x)] + \text{median}[B(x)] \]

These filters smooth the data while keeping the small and sharp details. The median is just the middle value of all the values of the pixels in the neighborhood. Note that this is not the same as the average (or mean); instead, the median has half the values in the neighborhood larger and half smaller. The median is a stronger "central indicator" than the average. In particular, the median is hardly affected by a small number of discrepant values among the pixels in the neighborhood. Consequently, median filtering is very effective at removing various kinds of noise. The median filter considers each pixel in the image in turn and looks at its nearby neighbors to decide whether or not it is representative of its surroundings. Instead of simply replacing the pixel value with the mean of neighboring pixel values, it replaces it with the median of those values.

\[ \text{Original} \rightarrow 4 \times \text{Zoom} \rightarrow 7 \times 7 \text{ Window} \rightarrow \text{Filter} \]

\[ \text{Filtered Original} \rightarrow \text{Zoom} \rightarrow \text{Filtered Window} \]

Figure 3.1: Median filter process

Orientation image lie between 1 and 8, depending on which of the 8 kernels produced the maximum response value greater than T2
are also selected as edge pixels. The Sobel operator is used in image processing, particularly within edge detection algorithms. Technically, it is a discrete differentiation operator, computing an approximation of the gradient of the image intensity function. At each point in the image, the result of the Sobel operator is either the corresponding gradient vector or the norm of this vector. The Sobel operator is based on convolving the image with a small, separable, and integer valued filter in horizontal and vertical direction and is therefore relatively inexpensive in terms of computations. On the other hand, the gradient approximation which it produces is relatively crude, in particular for high frequency variations in the image. The operator consists of a pair of 3×3 convolution kernels as shown below. One kernel is simply the other rotated by 90°. These kernels are designed to respond maximally to edges running vertically and horizontally relative to the pixel grid, one kernel for each of the two perpendicular orientations. The kernels can be applied separately to the input image, to produce separate measurements of the gradient component in each orientation (call these Gx and Gy). These can then be combined together to find the absolute magnitude of the gradient at each point and the orientation of that gradient.

4. SEGMENTATION USING SVM

Our proposed method, we impersonate the final segmentation step. Here we utilization the kernel based Support Vector Machine classifier to classify the image into tumors or not. In 1995, Support Vector Machine (SVM) has been corroborated, which is an effective supervised classifier and accurate learning technique. It is descended from the statistical theory invented by Vapnick. It fabricates efficacious classification results in several application domains, for e.g. medical diagnosis [15] [16]. SVM adheres to the structural risk minimization principle from the statistical learning theory. Its kernel is to hegemony the real risk and classification competence in order to encompass the margin between the classes and condense the true costs [17]. A support vector machine searches an optimal unscrambling.
Linear SVM is the simplest case in which the input patterns are linearly discernible. There exists a linear function of the form

\[ f(x) = W^T + bx \]  

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Such that for each training example \( x_i \), the function yields \( f(x_i) \geq 0 \) for \( y_i = +1 \) and \( f(x_i) < 0 \) for \( y_i = -1 \). Hence, training samples from the two different classes are separated by the hyper plane.

\[ f(x) = W^T + bx = 0 \]  

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### 4.1 RBF kernel based SVM

The linear SVM classifier can be eagerly substantial to a nonlinear classifier by relishing a nonlinear operator to map the input pattern \( x \) into upper dimensional feature space. The non-linear classifier is defined the equation (13). hyper plane between members and non-members of a particular class in a high dimension feature space [18].

\[ f(x) = W^T \phi(x) + b \]  

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\[ \min J(W, \xi) = \frac{1}{2} \|W\|^2 + C \sum_{i=1}^{l} \xi_i \]  

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The data with linear separability may be analyzed with a hyperplane and the linearly non separable data are analyzed with kernel functions such as higher order polynomials, Gaussian RBF portrayed as Polynomial kernel \( k_1 \) is    \( \text{Where } p \text{ is the order of the kernel} \)

Radial basis function (RBF) \( k_2 \) is: The learning process undertaken by a radial-basis function (RBF) network irrespective of its Theoretical background may be visualized as follows. The linear weight associated with the Output unit(s) of the network tend to evolve on a different “time scale” compared to the Nonlinear activation functions of the hidden units. Thus, as the hidden layer’s activation functions evolve slowly in accordance with some nonlinear optimization strategy, the output layer’s weights adjust themselves rapidly through a linear optimization strategy.

The Important point is that the different layers of an RBF network perform tasks, and so it is reasonable to separate the optimization of the hidden and output layers of the network by using different techniques, and perhaps by operating on different time scales. There are different learning strategies that we can follow in the design of an RBF network, depending on how the centers of the radial-basis functions of the network are specified. The main problem with the method of fixed centers just described is the fact that it may require a large training set for a satisfactory level of performance. One way
of overcoming this limitation is to use a hybrid learning process, consisting of two different stages: Self-organized learning stage, the purpose of which is to estimate appropriate locations for the centers of the radial basis functions in the hidden layer. Supervised learning stage, which completes the design of the network by estimating the linear weights of the output layer. Although batch processing can be used to implement these two stages of learning in is preferable to take an adaptive (iterative) approach. For the self-organized learning process we need clustering algorithm that partitions the given set of data points into subgroups, each of which should be as homogeneous as possible. One such algorithm is the k-means clustering algorithm, which places the centers of the radial basis functions in only those regions of the input space where significant data are present. Let m denote the number of radial-basis functions; the determination of a suitable value for m may require experimentation. Let \( t_k(n) \) denote the centers of the radial-basis functions at iteration n of the algorithm.

**Initialization.** Choose random values for the initial centers \( t_k(0) \); the only restriction is that these initial values are different. It may also be desirable to keep the Euclidean norm of the centers small.

**Sampling.** Draw a sample vector \( x \) from the input space \( h \) with a certain probability. The vector \( x \) is input the algorithm at iteration n.

**Similarity matching.** Let \( k(x) \) denote the index of the best-matching (winning) center of input vector \( x \). Find \( k(x) \) at iteration by using the minimum-distance Euclidean criterion:

\[
k(x) = \arg \min_k \| x(n) - t_k(n) \|, \; k = 1, 2, 3, \ldots, m
\]

Where \( t_k(n) \) is the \( k \)th radial-basis function at iteration n.

**Updating.** Tweak the centers of the radial-basis functions, by exploiting the update rule:

\[
t_k(n+1) = \begin{cases} 
    t_k(n) + \eta [x(n) - t_k(n)], & k = k(x) \\
    t_k(n), & \text{otherwise}
\end{cases}
\]

**Continuation.** Augmentation n by 1, back to step II, and carry on the progression until conspicuous vagaries are perceived in the centers. In non-linear SVM, the original data set is transformed to upper dimensional data, the parameter of the decision function \( f(x) \) has satisfied the following minimum criteria: \( f(x) \) has satisfied the following minimum criteria. In this section, we present the basic characteristics of the RBF neural
network architecture (Haralambos et al., 2008) and the proposed training method for developing neural network classifiers. An RBF neural network is a special three-layered network. The input nodes pass the input values to the internal nodes that formulate the hidden layer. The non-linear responses of the hidden nodes are weighted in order to calculate the final outputs of the network in the output layer. A typical hidden node in an RBF network is characterized by its center, which is a vector with dimension equal to the number of inputs to the node. The activity value \( y \) of the lead node is the Euclidean norm of the difference between the input vector \( y \) and the node center \( \hat{y}_1 \) and is given by:

\[
v(y) = ||y - \hat{y}_1||
\]

The output function of the node is a radically symmetric function. A typical choice, which is also used in this work, is the Gaussian function:

\[
f(v) = \exp(-v^2 / \sigma^2)
\]

Where \( \sigma \) is the width of the node. In the proposed training method, the calculation of the hidden node centers is based on the fuzzy means clustering algorithm (Darken C et al., 1995), while the connection weights are obtained using linear regression. The fuzzy means clustering algorithm initially produces a fuzzy partition in the input space, by defining a number of triangular fuzzy sets on the domain of each input variable. Multidimensional grid of the input space is produce using centers of these fuzzy sets. The knots of the grid constitute the set of candidates for becoming hidden node centers. The rigorous selection algorithm is chosen using the most appropriate knots and is used as centers in the produced RBF network model.
5. CONCLUSION

An automatic brain tumor MR image segmentation performance analysis using SVM based segmentation method is proposed for brain tumor segmentation in heterogeneous MRI images. The proposed SVM used it is clearly shown the various methods which can detect the brain tumor with improved Accuracy, Sensitivity and Specificity. that can be effectively used for segmenting MRI brain images with high level of accuracy. The data distribution in each sub manifold was important for the classification, and to learn the relationship between the data distribution and reconstruction error norm. We evaluated the proposed method using both synthetic data and public available brain tumor image data. In both problems, our method out performed competing methods computed using the proposed algorithm capture image sharpness and features to a higher degree.

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