

Morphological Image Processing Approach Using K-Means Clustering for Detection of Tumor in Brain

Meenakshi S R¹, Arpitha B Mahajanakatti², Shivakumara Bheemanaik³

Department of Biotechnology Engineering, Dayananda Sagar College of Engineering, Kumaraswamy Layout, Bangalore 560078 India

Abstract: *The brain is the anterior part of the central nervous system. Along with the spinal cord, it forms the central nervous system (CNS). Brain tumor is an abnormal growth caused by cells reproducing themselves in an uncontrolled manner. Magnetic resonance imaging (MRI) is the commonly used technique for diagnosis of brain tumors. In MRI, the amount of data obtained is very large to manually analyze and interpret. Segmentation is an important process in medical image analysis and it is a challenging problem due to noise present in the input images. Clustering is an efficient method for biomedical image segmentation. In this study, we propose to use K-means clustering algorithm under Morphological Image Processing (MIP). The input to this algorithm is an MR image of the human brain. The position of tumor objects is detected from an MR image by using a clustering algorithm. This enhances the tumor boundaries more precisely and the performance is evaluated based on execution time and accuracy of the algorithms. It produces the reliable results that are less sensitive to error.*

Keywords: Morphological Image Processing (MIP), Magnetic resonance imaging (MRI), Brain tumor, Clustering, Morphological operations, K-means clustering, Image segmentation

1. Introduction

Along with the spinal cord, the brain forms the central nervous system (CNS) which is the anterior most part of the (CNS). The cranium, a bony box in the skull protects it. The adult human brain weighs on average about 1.5 kg [1] with a volume of around 1260 cm³ in men and in woman with a volume around 1130 cm³ in women, although there is significant individual variation.

A brain tumor or intracranial neoplasm occurs when abnormal cells formed within the brain. There are two main types of tumors, one is malignant or cancerous tumors and another one is benign tumors. The cancerous tumors can be divided into primary and secondary tumors. The primary tumors further classified based on the type of tissue in which they arise [2-4]. The most common brain tumors are gliomas that begin in the glial (supportive) tissues. There are many types of gliomas, which contains astrocytomas arise from small, star-shaped cells called as astrocytes. They grow anywhere in the brain or the spinal cord. In adults, astrocytomas often arise in the cerebrum. In children, it occurs in the cerebrum, the brain stem and the cerebellum [5]. A grade III astrocytoma is occasionally called anaplastic astrocytoma. A grade IV astrocytoma is called as glioblastoma multiforme [6]. Oligodendrogliomas occur in the cells that produce myelin (the fatty covering that protects nerves). These tumors usually occur in the cerebrum. It grows slowly and do not spread into adjacent brain tissue. Ependymomas commonly develop in the lining of the ventricles. They may occur in the spinal cord. These tumors can develop at any age, most common in childhood and adolescence [7]. There are other types of brain tumors that do not begin in glial tissue. Meningiomas grow from the meninges. They are usually benign, because these tumors grow slowly, meningiomas may grow quite large before they cause symptoms. They arise most often in women between

30 and 50 years of age. Secondary brain tumors are tumors caused from cancer that originates in another part of the body. These tumors are not the same as primary brain tumors. Treatment for secondary brain tumors depends on where the cancer started and the extent of the spread and other factors, such as the patient's age, general health, and response to previous treatment of the patient.

An estimated 23,380 adults (12,820 men and 10,560 women) in the United States are diagnosed with primary cancerous tumors of the brain and spinal cord this year (<http://seer.cancer.gov/statfacts/html/brain.html>). Brain tumors are the second most common cause of cancer death in men ages 20 to 39 and the fifth most common cause of cancer among women age 20 to 39. About 4,300 children and teenagers are diagnosed with a brain or central nervous system tumor this year. More than half of these are in children i.e., younger than 15. An estimated 69,720 new cases of primary brain tumors are expected to be diagnosed in 2013 and includes both malignant (24,620) and non-malignant (45,100) brain tumors [8]. In India, about 160 people per 1 lakh of the population are suffering from brain tumor. About 60% of these patients suffer from the most aggressive form of cancer known as glioblastoma.

A brain tumor usually involves a neurological examination, brain scans, and/or an analysis of the brain tissue. A neurological examination is a series of tests to measure the function of the patient's nervous system and physical and mental alertness. A brain scan is a picture of the internal structures in the brain. A specialized machine takes a scan in much the same way a digital camera takes a photograph. The most common scans used for diagnosis is MRI. MRI is a scanning device that uses magnetic fields and computers to capture images of the brain on film. It provides pictures from various planes, which helps doctors to create a three-dimensional image of the tumor. The MRI detects signals emitted from normal and abnormal tissue provides clear

images of most tumors. MRI uses radio frequency and magnetic field to obtain the image of a human body without using ionized radiations. Imaging plays an important role in the diagnosis of brain tumors [9,10].

The structure and function of the brain can be studied noninvasively by doctors and researchers using Magnetic Resonance Imaging (MRI). MRI strongly depends on computer technology to generate or display digital images. It takes a long time for diagnosis without using image processing techniques. Segmentation is an important process in the most of the medical image analysis. It is very difficult to perform brain surgeries without using image processing techniques. Detecting brain tumors from MR Images is a complex medical process and cannot be done without image processing techniques. Structures like tumor, brain tissue and skull cannot be identified without image segmentation. Image Segmentation is necessary to extract complex information from images. In the present study, brain tumor image analysis is performed using k-means clustering algorithms [11].

2. Materials and Methods

2.1 Hardware requirements

The computer with Pentium IV processor (2.6 GHz) and 512 MB RAM with Windows 7 was used for the study. The tools used for the image analysis is MATLAB (VERSION R2012B).

2.2 Brain images

The MR images of normal brain and brains with tumors were obtained from various sources. The MR images of brain tumor patients were of different age groups and medical conditions (Table 1).

Table 1: Magnetic resonance images of brains used in the study

Age of the patient	Sex	Condition
40	Male	Normal
40	Male	Multicystic lesion
57	Male	Glioblastoma
30	Male	Glioblastoma
38	Female	Astrocytoma
62	Male	Glioblastoma
42	Male	Glioblastoma
10	Male	Glioma
73	Male	Glioblastoma
41	Male	Epidermoid brain tumor
4	Male	Craniopharyngioma paediatric tumor
35	Female	Astrocytoma
40	Male	Glioma
42	Male	Ganglioglioma
40	Female	Astrocytoma

2.3 Image enhancement

In order to improve the visual effects of the image for image recognition, MR image pre-processing or enhancement is needed, which mainly includes color image to grayscale, image smoothing and sharpening. Image smoothing is to

eliminate noise and improve image quality. The purpose of image sharpening is to make the tumor edges, contour lines and image details clearer. The same process will be applied to the real target image.

In image enhancement, image filtering is useful for many applications, including smoothing, sharpening, removing noise, and edge detection. A filter is defined by a kernel, which is a small array applied to each pixel and its neighbors within an image [12]. In most applications, the center of the kernel is aligned with the current pixel, and is a square with an odd number 3, 5, 7, etc. of elements in each dimension. The process used to apply filters to an image is known as convolution, and may be applied in either the spatial or frequency domain [12, 13].

2.4 K-means clustering

The K-means clustering algorithm is commonly used for segmentation of multi-dimensional data. K-means works by assigning multidimensional vectors to one of K clusters, where K is given a priori. The aim of the algorithm is to minimize the variance of the vectors assigned to each cluster. The algorithm is iterative after each vector is assigned to one of the clusters, the cluster centers are recalculated and the vectors are re-assigned using the new cluster centers.

K-means clustering is a partitioning method. The function K-means partitioning data into K mutually exclusive clusters, and returns the index of the cluster to which it has assigned each observation. Unlike hierarchical clustering, K-means clustering operates on actual observations (rather than the larger set of dissimilarity measures), and creates a single level of clusters. The distinctions mean that k-means clustering is often more suitable than hierarchical clustering for large amounts of data [14].

K-means treats each observation in data as an object having a location in space. It finds a partition in which objects within each cluster are as close to each other as possible, and as far from objects in other clusters as possible. Any one parameter can be chosen from five different distance measures, depending on the kind of data used for clustering. Each cluster in the partition is defined by its member objects and by its centroid, or center. The centroid of each cluster is the point to which the sum of distances from all objects in that cluster is minimized. K-means computes cluster centroids differently for each distance measure, to minimize the sum with respect to the measure that is specified.

K-means uses an iterative algorithm that minimizes the sum of distances from each object to its cluster centroid, over all clusters. This algorithm moves objects between clusters until the sum cannot be decreased further. The result is a set of clusters that are as compact and well-separated as possible. The details of the minimization can be controlled using several optional input parameters to K-means, including ones for the initial values of the cluster centroids and for the maximum number of iterations [15].

Algorithm for K-means clustering

K-means algorithm includes

1. Let $X_1 \dots X_N$ are N data points in the input image, let k be the number of clusters which is given by the user.
2. Choose $C_1 \dots C_k$ cluster centres.
3. Distance between each pixel and each cluster centre, which is called as centroid is found.
4. The distance function is given by $J = |X_i - C_j|$ for $i=1 \dots N$ and for $j=1 \dots k$, where $|X_i - C_j|$, the absolute difference of the distance between a data point and the cluster centre indicates the distance of the N data points from their respective cluster centres.
5. Distribute the data points x among the k clusters using the relation $x \in c_i$ if $|x - c^j| > |x - C_j|$ for $i=1, 2, \dots, k, i \neq j$, where denotes the set of data points whose cluster.
6. Updated cluster centre is given as, $C_k = i$, for $i=1, \dots, k$, where i is the number of objects in the dataset, where k is the number of cluster and C is the centre of cluster.
7. Repeat from Step 5 to Step 8 till convergence is met for all data points.
8. After segmentation and detection of the desired region, there are chances for misclustered regions to occur after the segmentation algorithm, hence morphological filtering is performed for enhancement of the tumor detected portion. Here the structuring element used is disk shaped [16]. Figure 1 represents the flow chart for the K-means clustering.

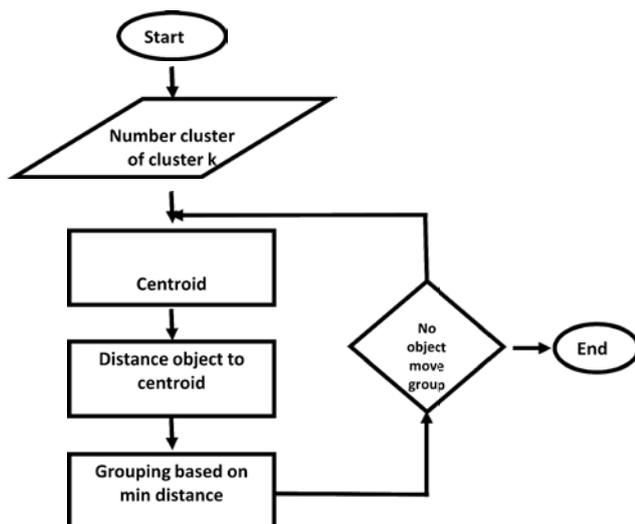


Figure 1: Flow chart of K-means clustering algorithm

2.5 Morphological segmentation

Morphological operations involve filtering a label map such that the boundary of a labeled region either grows (dilation) or shrinks (erosion). Sequences of morphological operations can augment manual segmentation by filling in small holes or breaking connections between regions. Thresholding is another filtering method that is used to label pixels whose grayscale values are in a desired range.

Morphological processing is constructed with operations on sets of pixels. Binary morphology uses only set membership and is indifferent to the value, such as gray level or colour, of a pixel [17]. Morphological image processing relies on the ordering of pixels in an image and many times is applied to

binary and grayscale images. Through processes such as erosion, dilation, opening and closing, binary images can be modified to the user's specifications [18]. Binary images are images whose pixels have only two possible intensity values. They are normally displayed as black and white. Numerically, the two values are often 0 for black, and either 1 or 255 for white. Binary images are often produced by thresholding a gray scale or colour image, in order to separate an object in the image from the background. The color of the object (usually white) is referred as the foreground color. The rest (usually black) is referred to as the background colour. However, depending on the image which is to be a threshold, this polarity might be inverted, and in which case the object is displayed with 0 and the background is with a non-zero value [19]. Some morphological operators assume a certain polarity of the binary input image so that if we process an image with inverse polarity the operator will have the opposite effect. For example, if we apply a closing operator to a black text on white background, the text will be opened.

Morphological Segmentation details the segmentation for identifying the tumor in the brain. The proposed approach utilizes mathematical morphology operations for the segmentation. The morphological operations are applied to the grayscale images to segment the abnormal regions. Erosion and dilation are the two elementary operations in Mathematical Morphology. An aggregation of these two represents the rest of the operations [20].

2.6 Image compression

In order to reduce the redundant information in the image data Compression techniques are used which facilitate the storage, transmission and distribution of images (e.g. JPEG, PNG, TIFF, and GIF). JPEG provides an exceptional quality at high and mid bitrates. However, the quality is unacceptable at low bit-rates (e.g. below 0.25 bpp). The current JPEG standard provides some resynchronization markers, but the quality still degrades when bit-errors are encountered. JPEG was optimized for natural images. JPEG2000 is a new compression standard used for still images, it is projected to overcome the loopholes of the present JPEG standard. JPEG2000 standard uses the wavelet and sub-band technologies. Some of the markets targeted by the JPEG2000 standard are printing, internet, remote sensing, digital photography, E-commerce, mobile and digital libraries. This standard provides lossy compression with a superior performance at low bit-rates and also provides lossless compression with progressive decoding. Applications such as digital libraries/databases and medical imagery can benefit from this feature [21]. This standard incorporates a set of error resilient tools to make the bit-stream more robust to transmission errors. In this mode, regions of interest (ROI's) can be defined. These ROI's can be encoded and transmitted with better quality than the rest of the image.

3. Results and Discussion

3.1 K-means clustering algorithms output window

In the present study, identification of brain tumour image and segmentation is carried out using K-means clustering algorithm. It is implemented and executed using MATLAB. The graphical user interface window named GUI1 and Tumor Detection System. For user, the size, colour, text and text font are defined in code result of the window executed. The C number indicates the number of cluster entered and it is used for image processing. In first part its location for input image, by clicking load button it will lead to the location of image stored in file of user computer. Different format of images can be uploaded. After loading an input image its respective filtered image will be executed in two different forms in an adjacent box as written in program. Hence the filtered image is now considered as input to next step and its morphological segmented image will be executed. In this box all features of tumor such as area, orientation, centroid, intensity, and variance, median are showed and all these features are displayed for particular image of brain. This is important notation because these feature values are constant for particular image and for number of cluster so accurate result can be obtained. In the last result box i.e. in approximated region if tumor is present it will display text as "tumor". Then image compression has to be done for given image hence save image option carries this operation. The resultant image can be saved in any format of image which is used for future studies. In the present study, 15 MR images were used for the analysis using K-means clustering algorithm (Table 1). In this research article, eight MR image analyses are represented.

The brain MR image of 40 year man suffering from multicystic lesion was analysed for tumor detection using K-means clustering algorithm (Figure 2). The input image is MR image (Figure 2A). Using MATLAB image analysis and image processing toolboxes used for Noise removed using a median filter. The pre-processed image is given for image segmentation using K-means clustering algorithm. The image pixels were considered as 128*128 pixels. Main concept in MATLAB is to convert pixels as matrices so 128*128 pixels are converted into matrices of different sizes. Matrix size is decided by cluster number which will be entered in execution window. Such as for C number 3 the matrix size is 3*3 and for C number 4 matrix size is 4*4, here number of clusters are 6 hence matrix size is 6*6. As size increases the time taken for identification of tumor also increases and there is a possibility of obtaining less accurate result. In the matrix for every unit a centroid is calculated and it is based on the distance between the centroid and unit of the matrix. It will assign values to each unit as zero or one based on intensity gradient. The pixel intensity is represented within a given range between a minimum and a maximum, inclusive. This range is expressed as a range from 0 (total absence, black) and 1 (total presence, white), with any fractional values in between as an abstract way [22]. Only one value unit are considered for clustering. In Figure 2B, filtered images, segmented and approximated region of tumor is shown. K-means is an iteration process and it will perform clustering till the distinct clusters are formed. The characteristic feature of given image are displayed (Figure

2). The white region in the Figure 2 clearly indicates the presence of tumor in the brain. The K-means clustering algorithm improved the quality of the image for further treatment of the patient.



Figure 2: Analysis of MR image of 40 year old man diagnosed with multicystic lesion. **A.** Input MR brain image. **B.** Loading of a brain image, its filtered, segmented and approximated region of tumor

Similarly, the brain MR image of 30 year old man diagnosed with glioblastoma was used for analysis (Figure 3). The input image is MR image (Figure 3A). The characteristic feature of given image are calculated and displayed (Figure 3B). The image obtained after the analysis clearly showed sharp white region which correlated with the tumor in the brain (Figure 3). Therefore, K-means clustering is an efficient method for the analysis of MR imaged to identify the tumors in the brain.

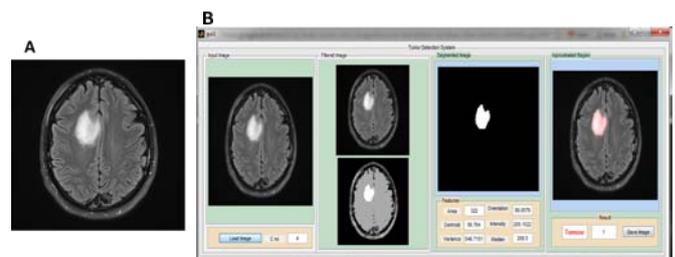


Figure 3: Analysis of MR image of 30 year old man diagnosed with glioblastoma. **A.** Input MR brain image. **B.** Loading of a brain image, its filtered, segmented and approximated region of tumor.

To compare the results obtained from the brain tumor MR images, normal brain MR image of 40 year old man was analyzed using K-means clustering algorithm (Figure 4). The results obtained clearly indicated that there was no white spot on the brain image (Figure 4B).



Figure 4: Analysis of normal brain MR image of 40 year old man. **A.** Input MR brain image. **B.** Loading of a brain image, its filtered, segmented and approximated region of tumor.

Similarly, brain MR image of 38 year old woman diagnosed with astrocytoma was analyzed to detect the tumor using K-means clustering algorithm (Figure 5).

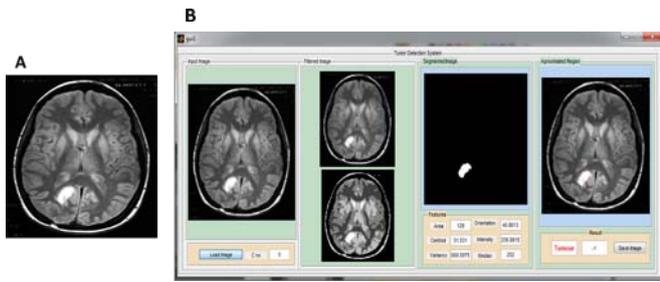


Figure 5: Analysis of brain MR image of 38 year old woman diagnosed with astrocytoma. **A.** Input MR brain image. **B.** Loading of a brain image, its filtered, segmented and approximated region of tumor.



Figure 8: Analysis of brain MR image of 4 year old boy diagnosed with pediatric craniopharyngioma tumor. **A.** Input MR brain image. **B.** Loading of a brain image, its filtered, segmented and approximated region of tumor.

The MR image of 10 year old boy diagnosed with glioma was used for detection of tumor using K-means clustering (Figure 6). Similarly, MR image of a person suffering from epidermoid brain tumor (Figure 7), 4 year old boy diagnosed with pediatric craniopharyngioma tumor (Figure 8) and a person suffering from ganglioglioma (Figure 9) were used to detect tumors using K-means clustering algorithm. After analyzing the results obtained indicated that K-means clustering algorithm is helpful in detecting tumors in brain from MR images. This method can be further used to diagnose tumors and treat the patients in feature. Taken together, K-means clustering algorithm is an efficient method to detect tumors in MR images of brain and can be used in detection of tumors.

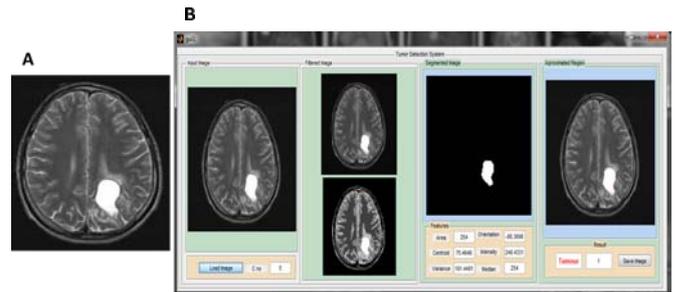


Figure 9: Analysis of brain MR image of 42 year old man diagnosed with ganglioglioma. **A.** Input MR image of brain. **B.** Loading of a brain image, its filtered, segmented and approximated region of tumor.



Figure 6: Analysis of brain MR image of 10 year old boy diagnosed with glioma. **A.** Input MR Brain image. **B.** Loading of a brain image, its filtered, segmented and approximated region of tumor.

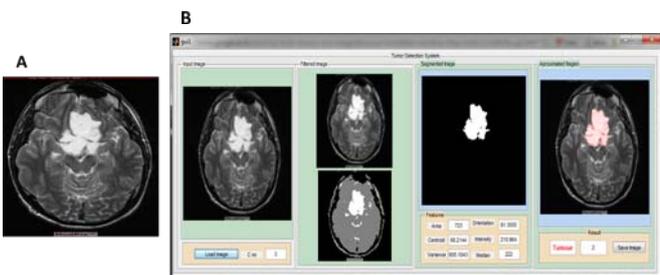


Figure 7: Analysis of brain MR image of 41 year old man diagnosed with epidermoid brain tumor. **A.** Input MR brain image. **B.** Loading of a brain image, its filtered, segmented and approximated region of tumor.

4. Conclusions

In the proposed method, segmentation and K-means clustering is combined for the improved analysis of MR images. The results that interpret unsupervised segmentation methods are better than the supervised segmentation methods. A pre-processing is required to screen images in the supervised segmentation method. The image segmentation method also requires considerable amount of training and testing data which significantly complicates the process. However, the image analysis of noted K-Means clustering method is fairly simple when compared with frequently used fuzzy clustering methods. Here, it is shown that JPEG2000 is a new compression standard for still images intended to overcome the shortcomings of the existing JPEG standard. It also provides loss of less compression with progressive decoding. The applications of digital libraries/databases and medical imagery can benefit from this feature. The standard incorporates a set of error resilient tools to make the bit-stream more robust to transmission errors. In this mode, regions of interest (ROI's) can be defined. These ROI's can be encoded and transmitted with better quality than the rest of the image. K-means based segmentation process to detect brain tumor is implemented.

5. Acknowledgements

We thank Mr. Deepesh, Knowx Innovations, Bangalore for his technical help during this research project.

References

- [1] A. Parent, M.B. Carpenter, Carpenter's human neuroanatomy. Williams & Wilkins. 1996.
- [2] M. Wrensch, Y. Minn, T. Chew, M. Bondy, M.S. Berger. Epidemiology of primary brain tumors: current concepts and review of the literature. *Neuro Oncol.* 2002; 4: 278-99.
- [3] D.N. Louis, H. Ohgaki, O.D. Wiestler, W.K. Cavenee, P.C. Burger, A. Jouvett, B.W. Scheithauer, P. Kleihues. The 2007 WHO classification of tumours of the central nervous system. *Acta Neuropathol.* 2007; 114: 97-109.
- [4] S.R. Chandana, S. Movva, M. Arora, T. Singh. Primary brain tumors in adults. *Am Fam Physician.* 2008; 77: 1423-30.
- [5] A. Mustaqeem, A. Javed, T. Fatima. An efficient brain tumor detection algorithm using watershed and thresholding based segmentation. *International Journal of Image, Graphics and Signal Processing.* 2012; 10: 34-39.
- [6] P. Kleihues, P.C. Burger, B.W. Scheithauer. The new WHO classification of brain tumours. *Brain Pathol.* 1993; 3: 255-268.
- [7] M.M. Ahmed, D.B. Mohammad. Segmentation of brain MR images for tumor extraction by combining K-means clustering and perona-malik anisotropic diffusion model. *International Journal of Image Processing.* 2010; 2: 1-34.
- [8] S. Pande, S. Herekar. A competent approach for revealing of brain tumor and its edges by means of segmentation and morphological operation. In *Proceedings of 4th SARC International Conference*, pp 5-9, 2014.
- [9] T.R. Jensen, K.M. Schmainda. Computer-aided detection of brain tumor invasion using multiparametric MRI. *J Magn Reson Imaging.* 2009; 30:481-9.
- [10] S. Rajeswari, T.K. Jeyaselvi. Support vector machine classification for MRI images. *International Journal of Electronics and Computer Science Engineering.* 2011; 1: 1534 - 1539.
- [11] N.R. Talegaonkar, P.N. Shinde, S.J. Shelke, S.D. Vaidya, A.G. Barathe, N. Wankhade, S. Kulkarni. An approach to automatic brain tumor detection in magnetic resonance Images. *Proceedings of IRF International Conference*, pp. 17 - 19, 2014.
- [12] Z. Afrose. Relaxed Median Filter: A Better Noise Removal Filter for Compound Images. *International Journal on Computer Science and Engineering.* 2012, 4: 1376 - 1382.
- [13] W. Gonzalez, "Digital Image Processing", 2nd Ed. Prentice Hall, 2008, pp. 378.
- [14] M.F. Kabir, C.M. Rahman, A. Hossain, K. Dahal. Enhanced classification accuracy on naive bayes data mining models. *International Journal of Computer Applications.* 2011, 28: 9-16.
- [15] H. Abghari, M. Mahdavi, A. Fakherifard, A. Salajegheh. Cluster analysis of rainfall-runoff training patterns to flow modeling using hybrid RBF networks. *Asian Journal of Applied Sciences.* 2009, 2: 150-159.
- [16] R.P. Joseph, C. Senthil Singh, M.Manikandan. Brain tumor MRI image segmentation and detection in image processing. *International Journal of Research in Engineering and Technology.* 2014, 3: 1 - 5.
- [17] K. Jayamani, R. Bagavathi. An FPGA based architecture for linear and morphological image filtering. *Proceedings of International Conference on Science, Engineering and Management*, pp. 219 - 226, 2014.
- [18] K.S. Talha, K. Wan, V. Chittawad, S.K. Za'ba, M.N. Ayob, Z.M. Razlan, A.B. Shahrman. Extracting features point of lip movement for computer-based lip reading system. *International Journal of Mechanical & Mechatronics Engineering.* 2014, 14: 48 - 53.
- [19] M.P. Paulraj, S. Yaacob, H. Desa, C.R. Hema, M. Hariharan, M. Ridzuan, A.B. Majid. Sign language into voice signal conversion using head and hand gestures. *Proceedings of the International Conference on Intelligent Systems and Control.* 2008.
- [20] P.K. Srimani, P.N. Angadi. Cumulative Techniques for Early Detection of Breast Cancer: A Review. *International Journal of Emerging Technologies in Computational and Applied Sciences.* 2014, 8: 481-489.
- [21] A. Skodras, C. Christopoulos, T. Ebrahimi. The JPEG2000 still image compression standard. *IEEE Signal Processing Magazine.* pp. 36-58, 2001.
- [22] P. Wu, T. Chen. Tutorial on JPEG for Still Image Compression in Advance Digital Signal Processing. 2013.

Author Profile

Meenakshi SR received the BE degrees in Computer Science Engineering from Sri Krishnarajendra Silver Jubilee Institute of Technology in 2011. She is now pursuing her M. Tech in Bioinformatics under Visvesvaraya technological University at Dayananda Sagar College of Engineering, Bangalore.

Arpitha B Mahajanakatti received the BE degree in Biotechnology Engineering from Dayananda Sagar College of Engineering in 2012 and M. Tech degree in Bioinformatics from PES Institute of Technology 2014. Now she is working as a Lecturer in the Department of Biotechnology Engineering at Dayananda Sagar College of Engineering. Her research interests are Structural Bioinformatics, Biostatistics and QSAR.

Shivakumara Bheemanaik is Associate Professor in the Department of Biotechnology Engineering at Dayananda Sagar College of Engineering, Bangalore since Nov 2012. He obtained his Ph.D. degree from Indian Institute of Science, Bangalore in 2005 and received his postdoctoral training at the University of Massachusetts Medical School, Worcester, Massachusetts, USA. Shivakumara Bheemanaik was a FASTTRACK Young Scientist in the Department of Biochemistry at the Indian Institute of Science, Bangalore, India. His interests include the Protein Biochemistry, DNA-protein interactions, Enzymology, Enzyme kinetics, Molecular Biology, Structural Biology, Comparative Genomics and Proteomics and Applications of Bioinformatics.