I. J. Engineering and Manufacturing, **2023, 2, 40-51**
Published Online on April 8, 2023 by MECS Press (http://www.mecs-press.org/)
DOI: 10.5815/ijem.2023.02.05

Interpolation Method for Identification of Brain Tumor from Magnetic Resonance Images

Sugandha Singh*
Department of Computer Science, Babasaheb Bhimrao Ambedkar University, Lucknow, 226025, India
E-mail: singhsugandha3@gmail.com
ORCID iD: https://orcid.org/0000-0002-9202-8507
*Corresponding Author

Vipin Saxena
Department of Computer Science, Babasaheb Bhimrao Ambedkar University, Lucknow, 226025, India
E-mail: vsax1@rediffmail.com
ORCID iD: https://orcid.org/0000-0003-1035-1704

Received: 06 September, 2022; Revised: 21 October, 2022; Accepted: 24 November, 2022; Published: 08 April, 2023

Abstract: During the past years, it is observed from the literature that, identification of the brain tumor identification in human being is gaining popularity. Diagnosing any disease without manual interaction with great accuracy makes computer science research more demanding, therefore, the present work is related to identify the tumor clots in the affected patients. For this purpose, a well-known Safdarganj Hospital, New Delhi, India is consulted and 2165 Magnetic Resonance Images (MRI) of a single patient are collected through scanning, and interpolation technique of numerical method used to identify the accurate position of the brain tumor. A system model is developed and implemented by the use of Python programming language and MATLAB for the identification of affected areas in the form of a contour of a patient. The desired accuracy and specificity are evaluated using the computed results and also presented in the form of graphs.

Index Terms: MRI; Segmentation; Interpolation Method; Brain Tumor and Newton Divided Difference Method.

1. Introduction

Due to the evolution of digital signal processing in the late 1970's, the identification of digital images as a part of image processing is gaining popularity in the recent years. In this process, the digital image is segmented into a number of pieces which may be uniform or non-uniform forming the numerous segments. The goal of segmenting the digital image is to analyze more meaningful features to change the representation of digital image. When an image is too large taken from the high resolution of scanning devices, then the digital image segmentation is needed, which means partitioning the digital image into several parts that have similar or different texture features. The process of the partitioning of digital images is achieved through region-based, edge-based or boundary-based methods. In the present work, an attempt is made to evaluate the segment regions of Magnetic Resonance Images (MRI) related to brain tumor images and diagnose the effective tumor by the proposed algorithm. The brain tumors increase as age increases in frequency; the vast mass of brain tumors diagnosed in the young patients. The pilocytic astrocytoma type of tumor highly occurs in the young patients. The gender difference shows that gliomas are more highly occur in men and meningiomas brain tumor occur in women. The sample images of the MRI brain with different slices are depicted below in the following figure 1.

For the proposed work, exhaustive literature is surveyed and it is found that there are more than hundred types of brain tumors which may cause as cancerous or non-cancerous. It is an abnormal growth of tissues causes due to unregulated proliferation of the cell. There are two types of brain tumor that are diagnosed generally in human brain are cancerous and non-cancerous. The cancerous brain tumors are medulloblastoma which is malignant brain tumor and observed very commonly in the children. Medulloblastoma exclusively occurs in the cerebellum. Invasive Meningioma is also a cancerous brain tumor invades in brain tissue and it is highly aggressive brain tumor. Other cancerous brain tumors are rhabdoid tumor which is highly malignant tumor which occurs in posterior fossa and supratentorial compartment in the young children. Whereas, non-cancerous brain tumors are meningioma, pituitary adenoma and hemangioblastoma, etc. The primary brain tumor is meningioma that is diagnosed by the experts in more than 30% to all other brain tumors. It is arising from the meninges of the brain usually attached to the dura and compresses the brain structure and symptoms appeared according to the compressed structure of brain. Meningioma is grade1 type tumor that has low risk of recurrence. Atypical meningioma is grade2 level which has high rate of recurrence and more aggressive than grade1. Anaplastic Meningioma is grade3 tumor. In addition to this, pituitary adenoma tumor arises from pituitary gland and slow growing tumor. It produces symptoms of visual disturbances and menstrual problems.

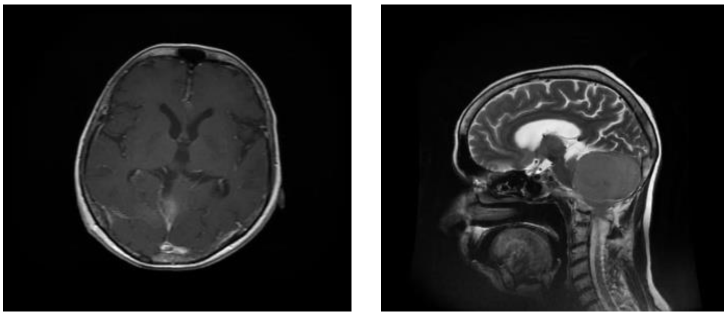

Fig. 1. Different slices of MRI human brain

2. Related Work

By considering the aforesaid objective, exhaustive survey on identification of brain tumor images have been done, therefore, it is necessary to describe some of the important contributions of scientists and engineers during the past years. In the year 2012, Angel and Jayakumari [34] proposed an algorithm to quantify the image segmentation process through reliable tests with high quality rate. Further, in the year 2014, Swe Zin and Aung Soe Khaing [33] proposed morphological operation for feature extraction-based technique to detect the tumor.

In the year 2015, Vaishnavee and Amshakala [35] elaborated self-organizing map clustering to detect brain tumor. Before segmenting brain image, the histogram equalization used for feature extraction to increase segmentation accuracy and gray level co-occurrence matrix used to avoid misclustered regions. In the same work, Principal Component Analysis (PCA) and proximal support vector machine based classier used to detect the tumor from MRI brain image and also increased accuracy. Ivana et al. [12] introduced the validation problem in the brain MRI segmentation.

In the year 2016, Nayak et al. [25] proposed a method feature extraction techniques using two-dimensional Discrete Wavelet Transform (DWT), feature dimensionality reduction using Probabilistic Principal Component Analysis (PPCA) and classification using the AdaBoost algorithm with random forests for automated and accurate diagnosis. In the same work, three magnetic resonance image datasets are used with dataset of 66, 160 and 255. Pereira et al. [28] used Convolutional Neural Network (CNN) approach to detect and segment tumor. Hasan et al. [11] proposed an automated method to segment the tumor for different image slices of MRI brain, and to increase the performance of tumor detection.

Bahadure et al. [2] investigated comparative study for various segmentation methods and compare the segmentation results by comparing different segmentation methods. Shree and Kumar [30] proposed noise removal technique and extraction features using Gray-level Co-occurrence Matrix (GLCM) and DWT-based technique used with brain tumor region growing segmentation. Further, in the year 2018, Khalila et al. [21] proposed classification method to classify brain image and extract features using GLCM. Devkotaa et al. [6] used mathematical morphological reconstruction method to automatically detect brain tumor.

Wadhwa et al. [14] reviewed literature on recent methods of brain tumor segmentation of MRI images and also evaluated the performance to different methods. Anaraki et al. [1] proposed the architecture of the CNN using genetic algorithm. Further in 2020, Lin et al. [22] proposed neural network model for brain tumor segmentation using multi modal magnetic resonance images. Deb and Roy [8] proposed an algorithm to detect brain tumor using adaptive fuzzy deep neural network and frog leap optimization technique. Yuvaraj et al. [15] detect brain tumor by investigation based on multi-perspective scaling convolutional neural networks model. Khosravanian et al. [17, 18] satisfied the results for glioma brain tumor segmentation due to super pixel fuzzy clustering and gives accurate segmentation results. The author also proposed a region-based level set technique to segment image using intensity inhomogeneity. Sun et al. [32] proposed 3D fully convolution network and apply multi-pathway architecture for feature extraction to extract features from multi-modal MRI images. Punn and Agarwal [26] performed tumor segmentation on the preprocessed multi-modal images using 3D deep neural network.

Ding et al. [4] developed end-to-end two stage generative adversarial neural network-based segmentation method. Maheshwari et al. [23] proposed hybrid clustering methods of k-means and fuzzy c-means algorithms to detect brain tumor and algorithm evaluated in synthetic and real time datasets. Burje et al. [3] proposed an algorithm using soft computing to detect effected regions of brain tumor and compares with different existing segmentation methods. Kumar et al. [19] proposed work on adaptive k-nearest neighbor classifier which is used to classify an image and tumor regions are segmented using optimal possibilistic fuzzy c-means clustering algorithm. Kumar and Manivannan [20] introduced k means clustering algorithm to segment and applied fruit fly algorithm for gabor filter and also increases the classification accuracy using multi kernel support vector machine. Pooja et al. [29] proposed a work on a comparative study of different segmentation techniques like threshold based, edge detection, region growing, watershed, and k-mean clustering techniques. These techniques are evaluated and the performance of the different methods are qualitatively analyzed by classifying the tumors from the MR brain images based on the area of segmentation, number of pixels and processing time. Sasikala et al. [16] proposed fractional order BAT algorithm with fuzzy c means to detect brain tumor. In the same work, delaunay triangulation and fractional order nature methods are applied to segment the lesion from brain. Khairul Islam et al. [13] introduced an enhanced brain tumor detection algorithm based on the template-based k-means (TK) with super pixels and PCA. Weiss et al. [30] developed CNN for segmentation of brain. Wu et al. [36] proposed method to promote the performance of commodity segmentation, an UNet-based neural network and more residual UNet methods are used for segmentation. Saleem et al. [31] introduced in the first step to segments the tumor into sub-regions as non-enhancing tumor, edema, and enhancing tumor and performed the prediction on each MRI volume, normalize to z-score and center cropped from 240 x 240 x 155 to 128 x 128 x 128 voxels. Mamatha and Krishnappa [24] proposed the graph-based method to rectify the complex structure of MRI. In the same work, MR images are preprocessed using boundary detection method. For further processing, segment MRI images using fuzzy c-mean clustering and graph cut techniques are used. Chen et al. [5] proposed a hybrid approach for glioma detection and segmentation on different MR sequences and trained a lightweight convolutional neural network to detect glioma and mask the effected region to process large bunch of MRI images. El-Haget al. [9] elaborated the method for MR and Computed Tomography (CT) images applied non-sub-sampled shearlet transform with modified central force optimization technique to calculate more optimized fusion results from the quality metrics. In the same work, interpolation technique is used to get a high-resolution image from the low-resolution and the interpolation technique applied to enhance fusion results before segmentation and then, the threshold and the watershed segmentation methods are used sequentially to restrict the tumor region. Gunasekara et al. [10] proposed deep learning architecture, to classify using deep convolutional neural network and region-based CNN is used on the classified images to localize the tumor, after that the tumor boundary is contoured for the segmentation process by using the chan-vese segmentation method. Mohan et. al. [27] also developed a method for measuring perfusion indices in brain tissues and also generates hemodynamic parameters used decomposition-based deconvolution techniques. Dhar et al. [37] proposed edge detection method and applied divergence operation to compute Laplacian of image, then to decrease sample rate of image using down sampling technique. [38] proposed support vector machine and Lagrange multiplier to optimize constraints on x-ray images. [39] fuzzy logic approach used on skin images and apply classification methods, also calculate performance evaluation metrics. [40] surveyed traditional image detection and deep learning based methods and analyze the limitations to detect objects.

3. Materials and Methods

The present work is based upon the identification of tumor tissues, inside the image taken during the MRI scan test technique. The MRI of brain image has been done using three Tesla Philips MRI scanner with sense head coil and acquiring images in following sequences:

Axial: T1W, T2W, FLAIR, T2*GRE, DWI, T1C+
Sagittal: T2W, T1C+
Coronal: T2W, T1C+

In the proposed work, two MRI images are selected of sagittal and axial for further processing. The images that have been selected for processing containing T1C+ sequence of MRI image. The image of patient that has been selected labelled as atypical meningioma refers that is more aggressive type of tumor and it is grade2 tumor which is addressed by World Health Organization (WHO). It is acclaimed that different clinical factors of radiographic features do not accurately analyze grade1 from grade2 meningiomas. Usually, these tumors grow rapidly and have more heterogeneous imaging visualizations, and highly orientation to recur early. A block diagram is designed with the detailed explanations and represented in the following figure 2 and briefly described below:

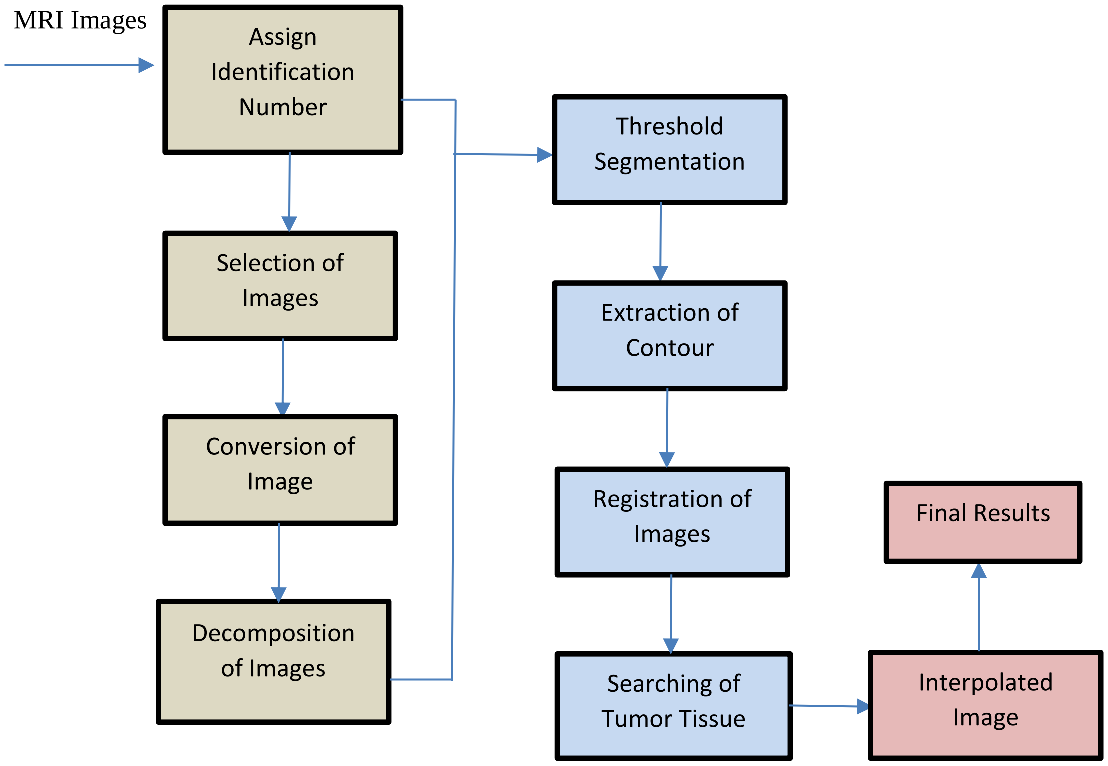

Fig. 2. System model for proposed method

3.1 Assign identification number

In the present work, 2165 MRI images have been considered of a single patient and each MRI image is in DICOM format which has been assigned its identification number.

3.2 Selection of image

By the use of MATLAB function, each image is resized pixels as 256*256 and thereafter two images are selected of single patient for implementations. These two images of MRI brain tumor represent atypical meningioma type tumor as shown below in figure 3

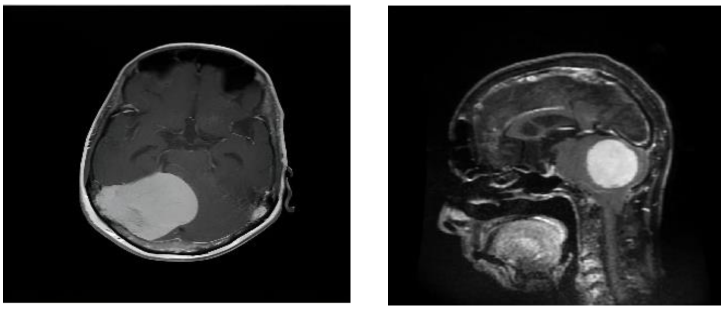

Fig. 3. Selection of two original MRI images

3.3 Conversion of image

The above two-colored images consisting of RED, GREEN, BLUE (RGB) colors are having three channels in the form of RGB. In MATLAB, these images have M*N*3 array of color pixel, where each color pixel is in the form of RGB triplet having specified spatial location. Thereafter, these images are converted into gray images which is represented as a single channel and consisting of M*N array whose values have been scaled to represent intensities. The grayscale conversion of images is shown below in figure 4.

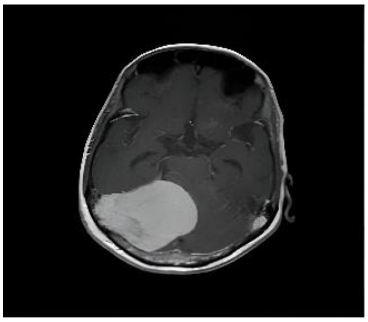
Image4(a)

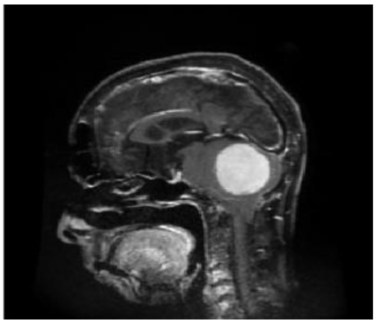
Image4(b)

Fig. 4. Representation of grayscale image

3.4 Decomposition of image

After selection and conversion of image into grayscale, consisting of M*N array size, a decomposition technique is used as given below;

$$A = LU \tag{1}$$

Where, A is M*N matrix and it is decomposed into two matrices, one is L called as lower triangular matrix while U is upper triangular matrix. The images are decomposed into two parts lower and upper triangularization form. The decomposed images shown in figure 5 as Image1(a) and Image2(a) represents lower triangular part, whereas Image1(b) and Image2(b) represents the upper triangular image. The images are decomposed using lower triangular function “tril” whereas for upper triangular decomposition “triu” function have been used.

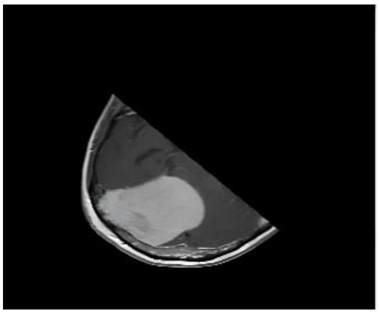
Image5 (a)

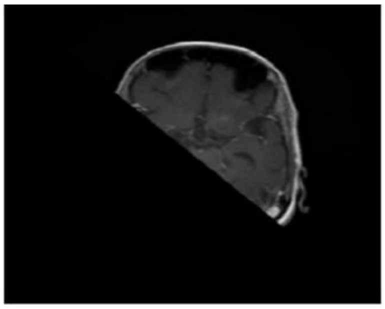
Image5 (b)

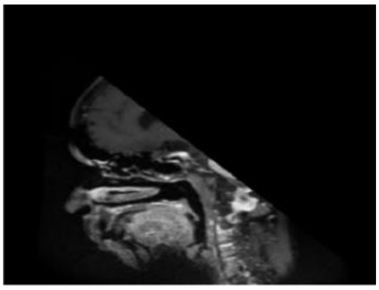
Image5 (c)

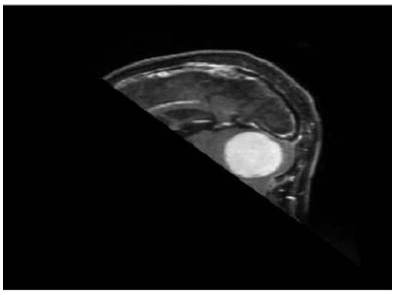
Image5 (d)

Fig. 5. Decomposition of image

This technique is applied in the proposed work to optimize pixel values. After applying these two functions to decomposed an image into lower and upper triangular matrix, the values of lower and upper triangular matrices are converted into one-dimensional list.

3.5 Threshold segmentation

In this technique, the images are partitioned into smaller pieces that have similar features and characteristics. These features and characteristics are extracted from the grayscale images. This method divides the pixel intensities into groups. Let us consider, if f (i, j) is an image and its gray conversion is g (i, j) where, i= 1 to M, j=1 to N, then the threshold value can be selected for using following formula,

$$g(i,j) = \begin{cases} 0 \; if \; f(i,j) < T \\ 1 \; if \; f(i,j) \geq T \end{cases} \tag{2}$$

Which is having maximum threshold value as T.

3.6 Extraction of contour image

In the proposed method, initial rectangular contour region is extracted, from the structure of the human brain. The morphological operations are applied on the MRI images. For this purpose, firstly images were resized and then apply the threshold value. After that the images are converted into binary image. In the partially processed image, morphological operations have been applied and details on solidity and areas of the persuasive locations were obtained. The minimum value for both parameters has been determined from statistical average of contrasting MRI images containing tumor.

The morphological operation used to extract features. It partitions the images by smoothing image size details, contouring boundaries and localize the region of interest (ROI) around a pixel. The basic morphological operations consist of dilation, erosion, closing and opening.

The variables I and D are considered as image and design elements respectively, then the erosion of a binary image I can be structured by a design element D denoted as I ⊖ D which produces a new binary image as g = I ⊖ D with ones in all locations (x, y) of a design element's origin at which that design element s fits the input image I as given below:

$$g(x,y) \; = \begin{cases} 1 \; if \; D \; fits \; I \\ 0 \; otherwise \end{cases} \tag{3}$$

The erosion of I with D is defined below:

$$I \; \ominus \; D_2 \approx \; (I \; \ominus \; D_1) \ominus D_1 \tag{4}$$

The dilation of an image I by a design element D (denoted as $I \; \ominus \; D$ construct a new binary image g = I ⊕ D with ones in all locations (x, y) of a design element's origin at which that design element D hits the input image I as given below:

$$g(x,y) \; = \{1 \;\; if \; D \; fits \; I \; 0 \;\; otherwise \tag{5}$$

Dilation and erosion have the opposite effects to each other. In dilation operation a layer of pixels is appended to the inner and outer boundaries of the region.

The results of the depicted method are shown in figure 6

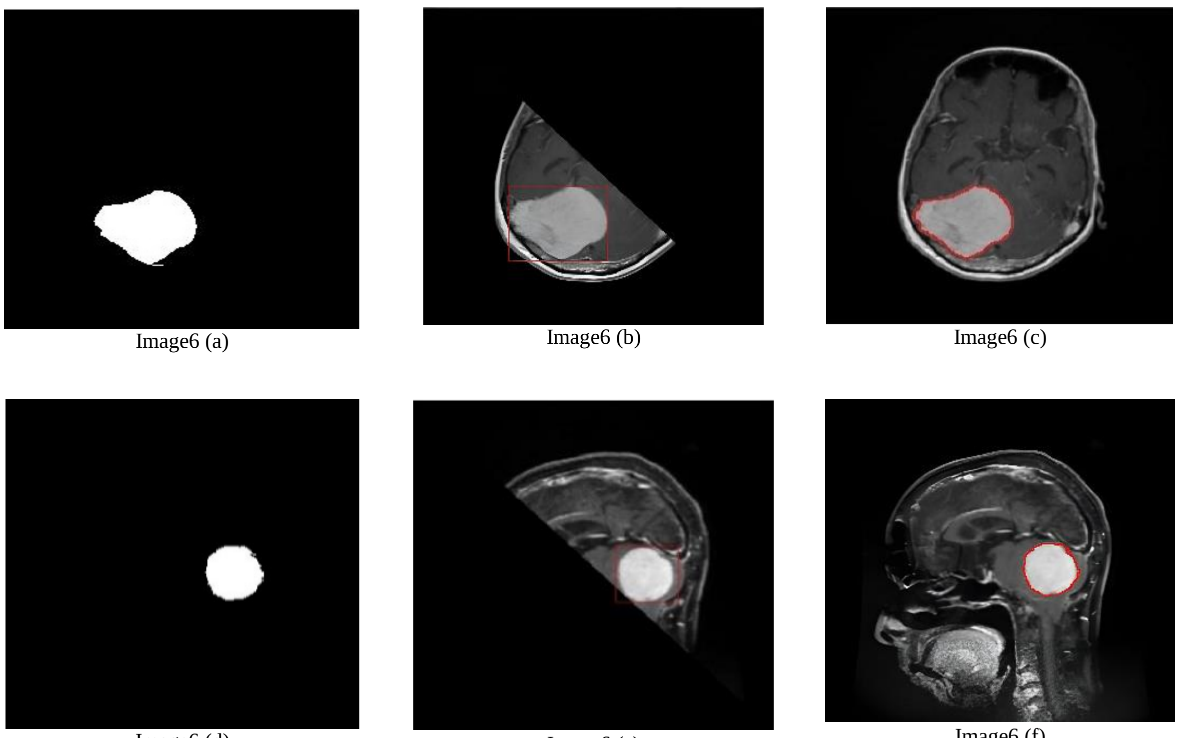

Fig. 6. Contour extraction for segmentation of tumor

In the figure 6 column wise, Image6(a) and Image6(d) shows segmentation results which are segmented using threshold method, while Image6(b) and Image6(e) represents the rectangular contour in red over the decomposed images, whereas Image6(c) and Image6(f) shows the tumor outline by applying image filling, eroding and subtracting operations.

To extract the tumor region and to eliminate other features in the image, morphological operations are applied. The morphological operations are used after the segmentation process have been done to detect tumor area accurately and shaped the tumor region exactly. The consolidation results of image are shown all together in figure 7 in which input original brain tumor image and converted into grayscale after that bounding box is created to extract the region of interest shown in green color rectangular contour shape. For this purpose, minimum and maximum threshold value is calculated to detect tumor region and then tumor is outlined.

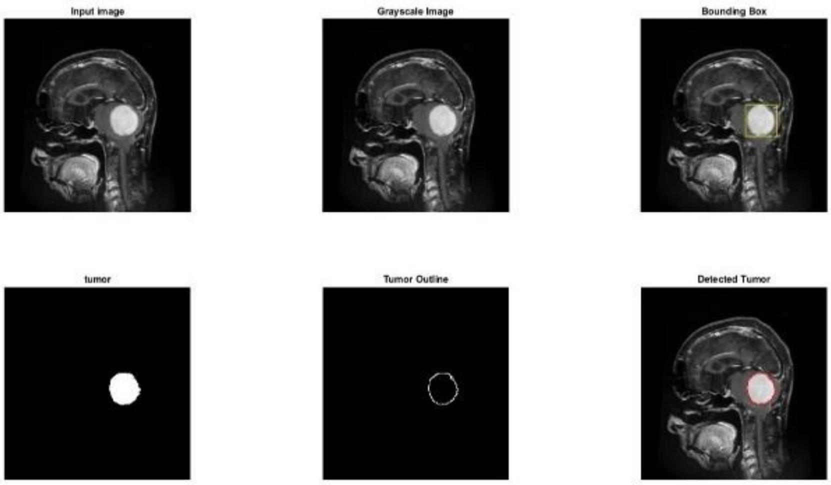

Fig. 7. Consolidation results of image

3.7 Registration of image

After extracting contour region and detection of tumor images, the registration of all tumor images of one patient is done by the use of MATLAB. In the process of representing brain tumor shape, the same type of images may be recognized as different types due to rotation and scaling. Therefore, the input image must be registered before applying subsequent operations. The alignment of image has been done by calculating centroid of the tumor region and then translation is applied to get the image at the centered position. The results of the desired approach have been given below in figure 8

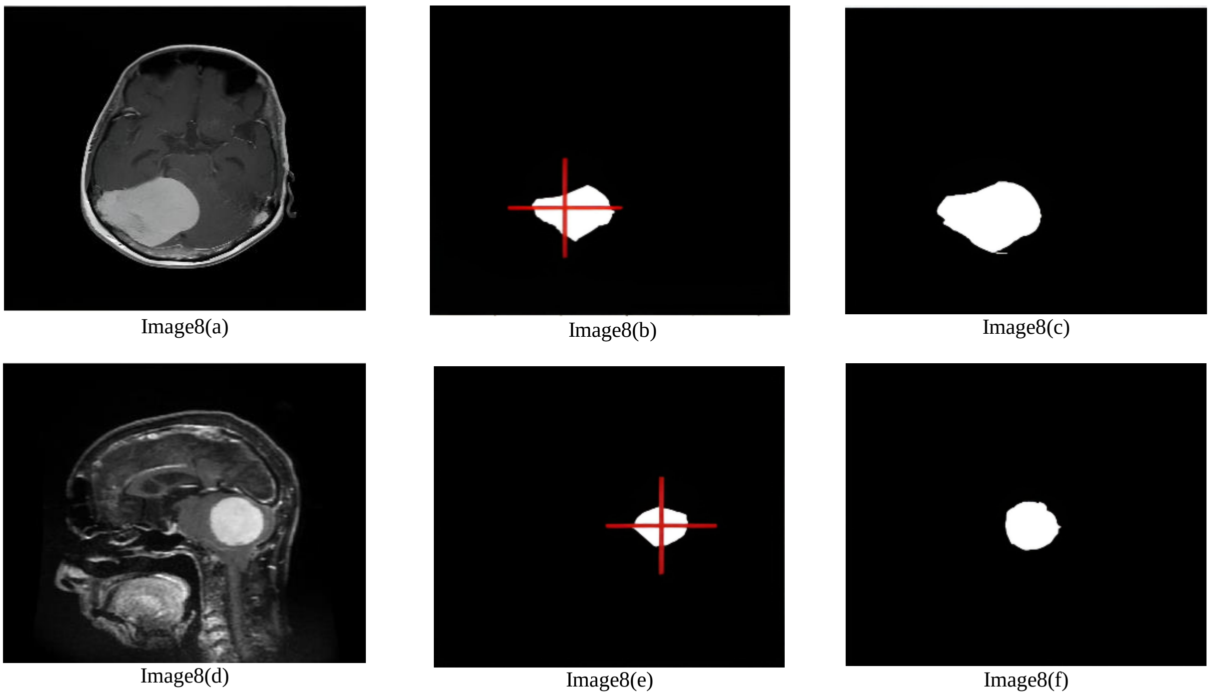

Fig. 8. Alignment of images at centered position

3.8 Searching of Tumor Tissue

For searching the tumor tissues, an approach of numerical method is applied by the use of newton divided difference interpolation technique which evaluates the pixel value of y after giving inputs as x and exact location of effected region is obtained. The value of y is calculated for region of interest and it is most suitable technique is used when the interval difference is not same for all sequence of values. Let us consider the pixels as (x_0, y_0), (x_1, y_1) ………… (x_M, y_N), then one can obtain the value of y by using following formula;

$$y = y_0 f_0 + y_1 f_1 + \ldots\ldots\ldots\ldots + y_N f_N \tag{6}$$

Where,

$$f_0 = f\,[x_0, x_1] = \frac{(f(x_1) - f(x_2))}{(x_1 - x_0)}$$

$$f_1 = f\,[x_0, x_1, x_2] = \frac{(f\,[x_1, x_2] - f\,[x_0, x_1])}{(x_2 - x_0)}$$

$$\vdots$$

$$f_k = (x - x_{k-1}) * f[x_0, x_1, \ldots x_k] \tag{7}$$

The newton divided difference method is symmetric with respect to the value i.e., independent of the order of arguments.
Therefore,

$$f[x_0, x_1] = f\,[x_1, x_0] \tag{8}$$

$$f[x_0, x_1, x_2] = f\,[x_2, x_1, x_0] = f\,[x_1, x_2, x_0]\ and\ so\ on \tag{9}$$

4. Experimental Results and Discussion

By the use of above materials and methods, MATLAB and Python programming used for finding the affected tissue of the patient. For this purpose, the following parameters are used:

(i) 2165 images of single patient with different sequences and views are taken out of which only two MRI images are selected for the implementation;
(ii) These images are in 512 X 512 size pixels which are resized as 256 X 256 pixels of images;
(iii) The sequences of both images are T1C+ which is contrast-enhanced MR is the standard for small metastases detection;
(iv) (x_i, y_i) for the interpolation points on the image;

4.1 Patient Detail

The real images of single patient have been collected from VMMC, Safdarjung Hospital, New Delhi, India, consulting the Department of Radiology. The age of patient is about 62 years and suffering from the atypical meningioma in right posterior fossa with mild obstructive hydrocephalus with involvement of right transverse of sinus.

4.2 Evaluation of Proposed Method

In the present work, two images of same patient are considered for proposed method one is axial and other image having sagittal views. These images contain brain MR scans from patient suffering from atypical meningioma. Patient MR scans consider for proposed work consists of T1C+ sequence MRI image. Each volume contains a set of three-dimensional brain scans image with size 512 X 512 pixels which are further resized into 256 X 256 and converted into grayscale.

In the proposed method, a mathematical approach has been used to localize tumor on the basis of pixel values. The newton divided interpolation technique is useful when the interval difference is not same for all sequence of values. For this approach a newton divided difference interpolation technique utilize for plotting y by giving value of x.

Algorithm 1

Step 1: Assigning the identification number to each MRI image;
Step 2: Registering each image of single patient with 2 views depicted in figure 3;
Step 3: Selection of original MRI images are depicted in figure 4;
Step 4: Conversion of RGB color image into grayscale are depicted in figure 5;

Step 5: Decomposition of image for identification of contour through LU decomposition;
Step 6: Threshold segmentation is done for breaking the image into smaller pieces;
Step 7: Extract the contour region consisting of area of tumor;
Step 8: Searching of tumor region through Interpolation technique;

By the use of above algorithm (x_i, y_i) are collected pixels having definite region as x_i, i=1 to 256 and y_j, j= 1 to 256 and concept of newton divided difference technique is used through following pseudocode:

```
For x in range(width)
For y in range(height)
r, g, b = pixels [x, y]
x1 = array(x)
x2 = arrange(x1)
y1 = array(y)
y2 = arrange(y1)
function newton_divided_diff (x, y)
n = len(y)
coeff = zeros ([n, n])
coeff [:, 0] = y
for j in range (1, n)
for i in range (n - j)
 coeff [i][j] = \
(Coeff [i + j] [j - 1]) – coeff [i] [j - 1]) / (x [i + j] – x [i])
Return coeff
Function newton_polynomial (coeff, x_d, x)
n = len(x_d) – 1
p = coeff [n]
for k in range (1, n + 1)
p = coeff[n-k] + (x - x_d [n - k]) * p
x = array ([65, 95, 130, 140])
y = array ([150, 190, 160, 210])
p_s = newton_divided_diff (x, y) [0,:]
x_n = arrange (290,382,3)
y_n = newton_polynomial (p_s, x, x_n)
plot (x_n, y_n)
plot(img)
```

The results of the proposed algorithm are shown in the figure 9

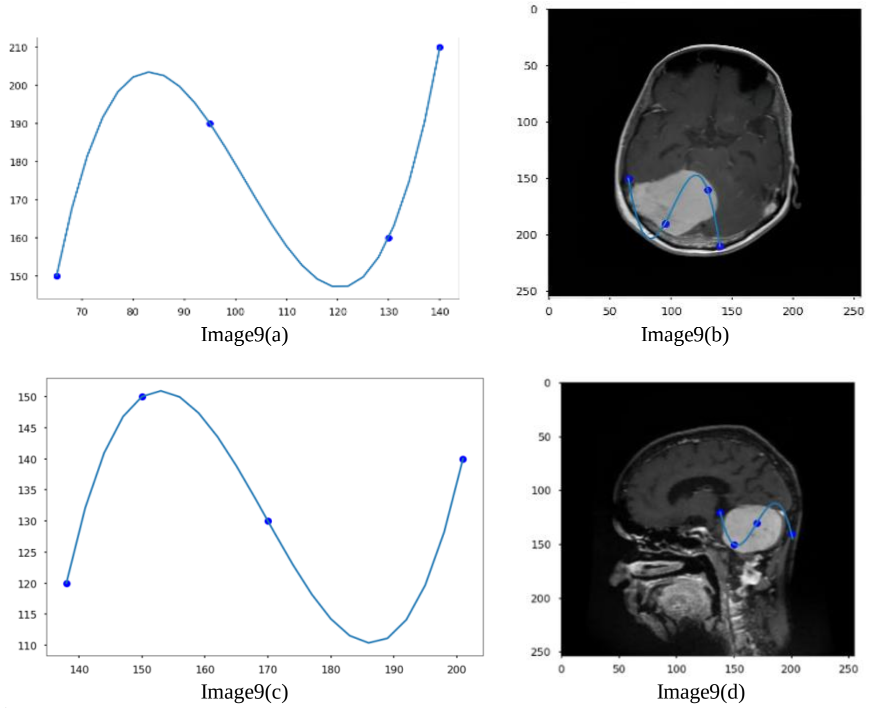

Fig. 9. Representation of tumor cell

By the use of pseudocode, the pixel values as observed through threshold segmentation of image are inputs and to localize the tumor identification value as y on different x values. After that, plot is constructed over the tumor area and tumor cell is obtained which is given in table 1.

Table 1. Localize value of x and y on tumor region

Input Image	X	Y
First Image	65, 95, 130, 140	150, 190, 160, 210
Second Image	138, 150, 170, 201	120, 150, 130, 140

This procedure is repeated till all affected tumor cells are collected and grouped in the form of tissue.

4.3 Performance evaluation metrics

The analysis of proposed system presents the quantitative approach. It evaluates accuracy and specificity evaluation metrics, and mathematically denoted as:

$$Accuracy = \frac{(TP + TN)}{TP + TN + FP + FN} \tag{10}$$

$$Specificity = \frac{(TP)}{(TN + FP)} \tag{11}$$

In Eq. (10 and 11), TP indicates the number of meningioma tumor pixels segmented correctly as a tumor, and TN represents the incorrectly as tumor, while FP shows the number of non-tumor pixels segmented incorrectly as tumor, FN represents the number of tumor pixels segmented incorrectly as normal.

The performance evaluation metrics used for the proposed method is calculated after acquiring the desired results. By using the proposed segmentation method, we examined the brain tumor. In the table 2, our evaluation metrics represents evaluation results that are able to find the brain tumor with high accuracy and specificity.

Table 2. Computation of accuracy and specificity

Input Image	**TP**	**TN**	**FP**	**FN**	**Accuracy (%)**	**Specificity (%)**
Image1	399	40256	1211	0	97.11	97.08
Image2	58979	398	945	0	98.43	98.42

5. Conclusion

Image processing algorithms developed to detect tumor and to optimize results to achieve great performance evaluation. The proposed framework is based on the use of segmentation and interpolation of MRI brain tumor images for better diagnosis of disease. In the proposed work threshold segmentation-based approach is used with morphological operations to locate the region of interest and then newton divided interpolation technique is applied for searching of tumor tissues. By using mathematical interpolation technique tumor region is localized. These techniques applied over the images by taking real images of single patient. The experimental result on the image shows that segmentation method can detect the tumor more accurately.

References

[1] Anaraki, A K. (2018): Magnetic resonance imaging-based brain tumor grades classification and grading via convolutional neural networks and genetic algorithms, Biocybernetics and Biomedical Engineering, 39, 63-74, https://doi.org/10.1016/j.bbe.2018.10.004.

[2] Bahadure, N. B. (2017); Comparative Approach of MRI-Based Brain Tumor Segmentation and Classification Using Genetic Algorithm, International Journal of Biomedical Imaging, 477-489, DOI: 10.1007/s10278-018-0050-6.

[3] Burje, S. (2021): Modified Image Segmentation Schemes for Detection & Identification of MRI Brain Tumor Infection, Turkish Journal of Computer and Mathematics Education, 12, 6604-6612, https://doi.org/10.17762/turcomat.v12i10.5518.

[4] Ding, Y. (2021): ToStaGAN: An end-to-end two-stage generative adversarial network for brain tumor segmentation, Neurocomputing, (2021), 462, 141-153, https://doi.org/10.1016/j.neucom.2021.07.066.

[5] Chen, H. (2021): A Hybrid Feature Selection based Brain Tumor Detection and Segmentation in Multiparametric Magnetic Resonance Imaging, Medical Physics, 48, 7360-7371, https://doi.org/10.1002/mp.15026.

[6] Devkotaa, B. (2018): Image Segmentation for Early-Stage Brain Tumor Detection using Mathematical Morphological Reconstruction, Procedia Computer Science, 125, 115-123, https://doi.org/10.1016/j.procs.2017.12.017.

[7] David, A. (2021): Automated multiclass tissue segmentation of clinical brain MRIs with lesions, NeuroImage: Clinical**,** DOI: 10.1016/j.nicl.2021.102769.

[8] Deb, D.; Roy S. (2021): Brain tumor detection based on hybrid deep neural network in MRI by adaptive squirrel search optimization, Multimedia Tools and Applications, 80, 2621–2645, https://doi.org/10.1007/s11042-020-09810-9.
[9] El-Hag, N. A. (2021): Utilization of image interpolation and fusion in brain tumor segmentation, International Journal for Numerical methods in Biomedical engineering, 37, https://doi.org/10.1002/cnm.3449.
[10] Gunasekara, S. R. (2021): A Systematic Approach for MRI Brain Tumor Localization and Segmentation Using Deep Learning and Active Contouring, Hindawi Journal of Healthcare Engineering, https://doi.org/10.48550/arXiv.2102.03532.
[11] Hasan, A. M. (2016): Segmentation of Brain Tumors in MRI Images Using Three-Dimensional Active Contour without Edge, Symmetry, https://doi.org/10.3390/sym8110132.
[12] Ivana (2015): MRI Segmentation of the Human Brain: Challenges, Methods, and Applications, Hindawi Publishing Corporation Computational and Mathematical Methods in Medicine, https://doi.org/10.1155/2015/450341.
[13] Islam, M. K. (2021): Brain tumor detection in MR image using superpixels, principal component analysis and template-based K-means clustering algorithm, Machine Learning with Applications, 5, https://doi.org/10.1016/j.mlwa.2021.100044.
[14] Wadhwa, A. (2019): A review on brain tumor segmentation of MRI images, Magnetic Resonance Imaging, 247-259, doi: 10.1016/j.mri.2019.05.043.
[15] Yuvaraj, D. (2021): Multi-perspective scaling convolutional neural networks for high-resolution MRI brain image segmentation, Materials Today: Proceedings, https://doi.org/10.1016/j.matpr.2020.12.199.
[16] Sasikala, E. (2021): Identification of lesion using an efficient hybrid algorithm for MRI brain image segmentation, Journal of Ambient Intelligence and Humanized Computing, DOI:10.1007/s12652-021-03060-9.
[17] Khosravanian, A. (2021a): A level set method based on domain transformation and bias correction for MRI brain tumor segmentation, Journal of Neuroscience Methods, 352, 0165-0270, https://doi.org/10.1016/j.jneumeth.2021.109091.
[18] Khosravanian, A. (2021b): Fast level set method for glioma brain tumor segmentation based on Superpixel fuzzy clustering and lattice Boltzmann method, Computer Methods and Programs in Biomedicine, 198, 0169-2607, https://doi.org/10.1016/j.cmpb.2020.105809.
[19] Kumar, D. M. (2021): MRI brain tumor detection using optimal possibilistic fuzzy C-means clustering algorithm and adaptive k-nearest neighbor classifier, Journal of Ambient Intelligence and Humanized Computing, 2867-2880, DOI:10.1007/s12652-020-02444-7.
[20] Krishnakumar, S.; Manivannan, K. (2021): Effective segmentation and classification of brain tumor using rough K means algorithm and multi kernel SVM in MR images, Journal of Ambient Intelligence and Humanized Computing, 6751–6760, DOI:10.1007/s12652-020-02300-8.
[21] Khalila, M. (2018): Performance evaluation of feature extraction techniques in MR-Brain image classification system, Procedia Computer Science, 127, 218–225, https://doi.org/10.1016/j.procs.2018.01.117.
[22] Lin, F. (2021): Path aggregation U-Net model for brain tumor segmentation, Multimedia Tools and Applications, 80, 22951-22964, https://doi.org/10.1007/s11042-020-08795-9.
[23] Maheswari, K. (2021): Hybrid clustering algorithm for an efficient Brain Tumor Segmentation, Materials Today: Proceedings, 37, 3002-3006, https://doi.org/10.1016/j.matpr.2020.08.718.
[24] Mamatha, S. K.; Krishnappa, H. K. (2021): Detection of Brain Tumor in MR images using hybrid Fuzzy C-mean clustering with graph cut segmentation technique, Turkish Journal of Computer and Mathematics Education, 12, 4570-4577.
[25] Nayak, D. R. (2016): Brain MR image classification using two-dimensional discrete wavelet transform and AdaBoost with random forest, Neurocomputing, 177, 188-197, https://doi.org/10.1016/j.neucom.2015.11.034.
[26] Punn, N. S.; Agarwal, S. (2021): multi-modality encoded fusion with 3D inception U-net and decoder model for brain tumor segmentation, Multimedia Tools, and Applications, 80, 30305–30320, https://doi.org/10.1007/s11042-020-09271-0.
[27] Pauliah, M. (2007): Improved T_1-weighted dynamic contrast-enhanced MRI to probe microvascularity and heterogeneity of human glioma, Magnetic Resonance Imaging, 25, 1292-1299, https://doi.org/10.1016/j.mri.2007.03.027.
[28] Pereira, S. (2016): Brain Tumor Segmentation Using Convolutional Neural Networks in MRI Images, IEEE Transactions on medical imaging, 1240-251, DOI: 10.1109/TMI.2016.2538465.
[29] Pooja, V. (2021): Comparative analysis of segmentation techniques on MRI brain tumor images, Materials Today: Proceedings, 47, 109-114, https://doi.org/10.1016/j.matpr.2021.03.723.
[30] Shree, N. V.; Kumar, T. N. R. (2018): Identification and classification of brain tumor MRI images with feature extraction using DWT and probabilistic neural network, Brain Informatics, 23-30, DOI:10.1007/s40708-017-0075-5.
[31] Saleem, H. (2021): Visual interpretability in 3D brain tumor segmentation network, Computers in Biology and Medicine, (2021), 133, https://doi.org/10.1016/j.compbiomed.2021.104410.
[32] Sun, J. (2020), Segmentation of the multimodal brain tumor image used the multi-pathway architecture method based on 3D FCN, Neurocomputing, 423, 34-45,https://doi.org/10.1016/j.neucom.2020.10.031.
[33] Zin, S.; Khaing, A. S. (2014): Brain Tumor Detection and Segmentation using Watershed Segmentation and Morphological Operation, International Journal of Research in Engineering and Technology, eISSN: 2319-1163 | pISSN: 2321-7308.
[34] Viji, A. K. S.; Jayakumari J. (2012): Performance Evaluation of Standard Image Segmentation Methods and Clustering Algorithms for Segmentation of MRI Brain Tumor Images, European Journal of Scientific Research, 166-179.
[35] Vaishnavee, K. B.; Amshakala K. (2015): An Automated MRI Brain Image Segmentation and Tumor Detection using SOM-Clustering and Proximal Support Vector Machine Classifier, IEEE International Conference on Engineering and Technology (ICETECH), DOI:10.1109/ICETECH.2015.7275030.
[36] Wu, Z. (2021), MR-UNet Commodity Semantic Segmentation Based on Transfer Learning, IEEE Access, 9, 159447-159456, DOI: 10.1109/ACCESS.2021.3130578.
[37] Dhar, Kishore K. (2022): Edge detection of image using image divergence and down sampling method, I. J. Engineering and Manufacturing, 3, 14-24, DOI: 10.5815/ijem.2022.03.02
[38] Omolara, A. Ogungbe (2022): Design and Implementation of Diagnosis System for Cardiomegaly from Clinical Chest X-ray Reports, International Journal of Engineering and Manufacturing, 3, 25-37, DOI: 10.5815/ijem.2022.03.02.
[39] Prashengit, Dhar; and Sunanda, Guha (2021): Skin Lesion Detection Using Fuzzy Approach and Classification with CNN, International Journal of Engineering and Manufacturing, 1, 11-18, DOI: 10.5815/ijem.2021.01.02.

[40] Diwakar; and Deepa, Raj (2022); Recent Object Detection Techniques: A Survey, International Journal of Image, Graphics and Signal Processing, Vol. 14, 47-60, DOI: 10.5815/ijigsp.2022.02.05

Authors' Profiles

Sugandha Singh received MCA from Babu Banarsi Das Technology and Management College in 2010 and thereafter received MTech degree from Banasthali Vidyapith in 2015 and presently research scholar of department of computer science in Babasaheb Bhimrao Ambedkar University, India. Her research interests include Medical Image Processing, Deep Learning and Visualization.

Prof. Vipin Saxena received his Ph.D. degree from Indian Institute of Technology, Roorkee, Uttarakhand, India. Presently, he is working as Professor in Department of Computer Science, Babasaheb Bhimrao Ambedkar University, Lucknow, India. He has published more than 190 research articles in the International and National Journals and Conferences, authored 05 books in the field of Computer Science and Scientific Computing, attended 55 International and National Conferences and received three National Awards for meritorious research work in the field of Computer Science. His research interests are Scientific Computing, Computer Networking and Software Engineering.

How to cite this paper: Sugandha Singh, Vipin Saxena, "Interpolation Method for Identification of Brain Tumor from Magnetic Resonance Images", International Journal of Engineering and Manufacturing (IJEM), Vol.13, No.2, pp. 40-51, 2023. DOI:10.5815/ijem.2023.02.05