Original Article

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Analysis of Magnetic Resonance Imaging of Brain Tumour using Fuzzy Set Rules

Biotechnology Section

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ABSTRACT

Introduction: Cancer becomes life threatening once the expansion of tissues in human brain turns into an uncontrolled growth. In detection of brain tumours, Magnetic Resonance Imaging (MRI) images give better results when compared to Computerised Tomography (CT) scan and X-ray. Malignant tumours can be detected with the help of image processing and machine learning techniques. These techniques detect even a small abnormality in the human brain following a four-stage process which includes preprocessing, segmentation, feature extraction and optimisation.

Aim: To predict a brain tumour using Fuzzy minimum-maximum rule in MRI.

Materials and Methods: The medical challenge is how can we rapidly and precisely diagnose brain lesions. It is difficult when using standard image analysis to differentiate the benign and malignant lesions. Hereby, authors have used a Fuzzy imaging algorithm in data set of 253 brain tumour images of high grade tumour colllected from kaggle.com.This paper proposes a fuzzy min-max image processing algorithm. Image processing includes four stages- preprocessing, segmentation, feature extraction and accuracy detection. Brain tumours are located using various algorithms at each of these stages.

Results: There were more than 20 features which can be taken into consideration when using the Fuzzy image algorithm. The proposed method in its current form achieves an accuracy of about 95% by considering seven features.

Conclusion: The study revealed that age, shape, contour, blood supply, capsule of tumour, oedema, post contrast enhancement, cyst generation signal intensity of T-1 weighted image etc. were the important investigation parameters. Location and size are important to the domain experts, but due to their complexity these parameters are not considered here.

Keywords: Brain lesions, Fuzzy algorithm, Image processing, Oedema, Segmentation methods

INTRODUCTION

A common problem in the field of image processing is the extraction of geometric features. Over the years, several different approaches have been devised to extract these features. Decision Making is hard due to various features having minute dissimilarity across different cases.Therefore, there is a need is to generate a set of rules to predict the degree of malignancy in tumours.

Standard image analysis techniques alone make it difficult to differentiate the benign and malignant lesions. Consequently, there is a need for high accuracy techniques which can analyse scans of brain tumour automatically and have a capacity for prognosis. Brain tumour sores are simply characterised by relative intensity changes when compared to healthy tissues, and their shape, size and area vary significantly, which makes it impossible to use commonly used pattern recognition algorithms.The ever expanding number of patients and the digitization of records had resulted in an exponential growth in the amount of data. Thus, there is a need for an algorithm that can process this data automatically.

The degree of malignancy is used to describe the amount by which a benign tumour is converted into malignant tumour. In the proposed method, fuzzy set rules can be used to predict the degree of malignancy. Authors describe the relationship between the extracted features and degree of malignancy using the following parameters.

- Accuracy: According to domain experts, the accuracy rate in detection of these pattern must be over 80%.
- Robustness: Since precise analysis of shapes is difficult, adjectives such as round, ellipse and irregular are used to describe the shape.

Techniques detecting these patterns must be as sturdy as possible to reduce uncertainty [1]. Existence of plenty of tools aims to do useful research but it is hardly useful for clinicians, as most of the researches are theory based. Therefore, in future it will be the matter of research, to effectively merge the developed tools into more user friendly environments. Various techniques are described for brain tumour classification and detection [Table/Fig-1] [2-11].

Author and year of publication	Methodology used	Accuracy (%)
Kharrat A et al., (2010) [2]	Brain tumour classification as benign or malignant using hybrid method.	98
Arunachalam M et al., (2017) [3]	MRI brain tumour analysis as normal or abnormal using Neural Network (feed forward).	95
Albawi S et al., (2017) [4]	Brain tumour image classification of MRI image using convolutional neural network.	91
Paul JS et al., (2017) [5]	Classification of brain tumour as normal tumour/abnormal tumour using MRI dataset. Author used CNN for classification.	91.4
Ural B, (2018) [6]	Brain tumour detection using Probabilistic Neural network.	90
Rajan PG and Sundar C, (2019) [7]	Segmentation and region localisation using SVM.	98
Saxena P et al., (2019) [8]	Binary classification of brain glioma as normal or abnormal using CNN with transfer learning.	95
Ghoshal P et al., (2019) [9]	Classification of brain tumour using Advanced deep learning.	94.4
Ullah Z et al., (2020) [10]	Brain MRI image analysis using FFNN.	96
Khan HA et al., (2020) [11]	Brain tumour detection using CNN.	97

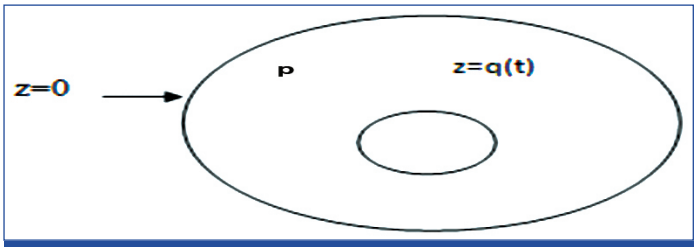
[Table/Fig-1]: Review on work done in ascending order of years [2-11].
CNN: Convolutional neural network; FFNN: Feed forward neural network; SVM: Support vector machines; MRI: Magnetic resonance imaging

The proposed fuzzy logic is the extension of previous work done on prediction of malignancy [12]. The previous research is based on the parameters identification and fuzzification to predict the degree of malignancy. The work can be elaborated by defining fuzzy rules, also the oedema distance calculation plays a significant role for

degree prediction of malignancy. Hence, this study was used to calculate fuzzy rule, oedema distance and survival rate.

MATERIALS AND METHODS

This study was conducted at Department of Electronics and Communication, University Institute of Technology, RGPV, Bhopal, Madhya Pradesh, India, from January 2020 to September 2021. In this study data set of 253 brain tumour images of high grade tumour collected from kaggle.com was considered to predict malignancy. In the following notation, t represents time and z is used to represent the space co-ordinate(s). Thus, authors can give a mathematical description of a tumour can be treated as z=q(t). We consider p to be the boundary [Table/Fig-2].



[Table/Fig-2]: Mathematical description of a tumour.

In this framework, healthy brain tissue is analysed in two different ways:

- A solid phase having neurons and glial cells, and
- A liquid phase consisting of interstitial fluid, blood, and any dissolved components.

Mass and momentum of both solid and aqueous balances are applied. The mass exchange terms are chosen to encourage the maintenance of healthy homeostasis, whereas the choice of stress tensors and momentum transfer terms are based on the assumed mechanical properties of each phase.

Tumour ranges between

$q(t)<z<p$

Volume fraction of mass substance of healthy tissue=r (z, t)

Volume fraction of fluid substance of healthy tissue=s (z, t)

Growth rate of tumour tissues (with velocity V) and stress tensors [13]

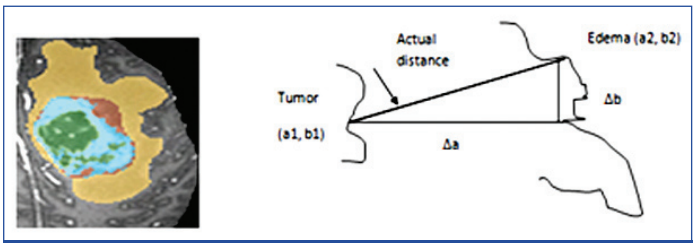
$=V_r$ and V_s and σ_r and σ_s

As the mass and fluid phases are not compressible, so to find mass balance partial derivative is used with respect to time and space.

$(r)_t+(V_r r)z=Y_r$

$(s)_t+(V_s s)z=Y_w$

This model help us to find tumour growth rate, healthy tissue remodeling rate, and the mechanical properties of brain tissue, that affect tumour induced oedema result in increased intracranial pressure. Thus, authors calculate the actual distance between tumour edges and oedema boundary using Pythagoras theorem [Table/Fig-3].



[Table/Fig-3]: Pythagoras theorem.

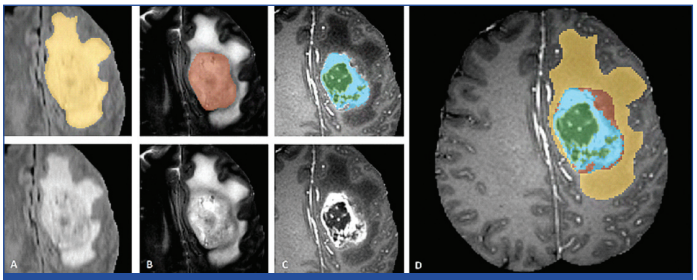
$\Delta a=a_2-a_1$

$\Delta b=b_2-b_1$

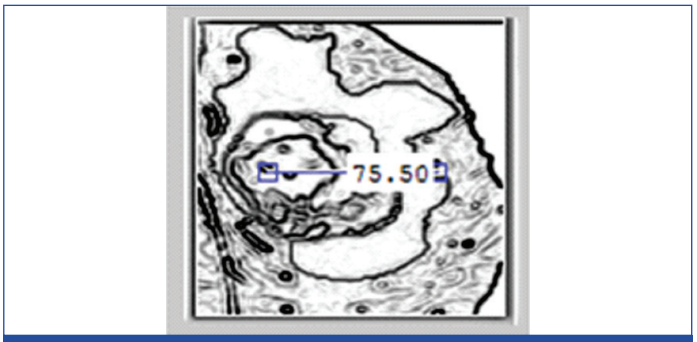
Distance between oedema and tumour boundary

$D=\sqrt{(\Delta a)^2+(\Delta b)^2}=\sqrt{(a_2-a_1)^2+(b_2-b_1)^2}$

Malignancy can be predicted using fuzzy imaging. In fuzzy logic, a number is assigned to brain features depending upon the range of the tumour and oedema size. Normally tumour range from 2.3-9.0 cm, minor oedema are smaller than 1 cm, major oedema are larger than or equal to 1 cm. The largest range for extension of oedema is from 2.5 cm to half the size of the hemisphere [Table/Fig-4]. Horizontal distance between oedema and tumour boundary shown in [Table/Fig-5].



[Table/Fig-4]: Database reference- BraTS IEEE TMI paper. Images patches in data set moves from left to right. (A) Tumour region is represented by yellow, it is visible in T2-Flair B) Core region is visible in red colour; C) Enhanced tumour structure with cyst is visible in blue/green colour; D) Final image at the right corner represents oedema (yellow), non-enhancing solid core (red), necrotic/cystic core (green), enhancing core (blue).



[Table/Fig-5]: Horizontal distance between oedema and tumour boundary.

Cyst cavity is defined as a feature in fuzzy imaging as:

- Not Present- 0
- Small- 1 thus ≤½ of the total tumour.
- Large- 2 thus ≥½ of the total tumour.

Fuzzy imaging algorithm should be used for symptoms of the same feature. Assuming that set containing a range of possible symptoms i.e the set contains more than one valid element. The range can be defined in between max_i and min_i, where $max_i>min_i$ is always valid.

Consider various features F_i, for each feature F_i there is a set of all possible symptoms of that feature V_i. Then a medical case can be recorded as $\{(s_1,s_2,s_3,\ldots, s_n),(a_1,a_2,a_3,\ldots, a_m),d,Id\}$ where $s_1, \ldots, s_n$ represent symptoms on different features and si $\in$, V_i; d denotes the result of diagnosis; and Id is the identity of the case.

Let V_i contains all possible values from max_i to min_i. If the membership value of V_i at k^{th} element is s_{ik} and similarly at j^{th} element is s_{ij}. Then we can apply the fuzzy rule using the following equation.

$$\mu_{is}(v_{ik}) = \max\left[0, 1-\lambda \frac{|s_{ij} - s_{ik}|}{max_i - min_i}\right]$$

The sensitivity parameter taken for this research was $\lambda=1$. It indicated the how quickly changes occurs in the model. When the normalised distance between s_{ij} and s_{ik} increases, the sensitivity parameter dictates how fast the membership value goes to zero. The sensitivity parameter was 1 for round, 0.5 for ellipse and 0 for irregular shape.

Now all valid symptoms descriptions can be arranged in ascending order according to the shape/size of the tumour, to form the list. Considering seven medical symptoms s_{ij} ($1 \le j \le 7$); the sub parameters can be further mapped. After mapping numerical representation is like: (x_1, x_2, x_3,…,x_p).

To differentiate a normal and a tumour cell, various features are taken into consideration-

a) **Shape/size:** Uneven shape/size of cell, however in cancerous cell nuclear membrane pores are increases (x_1).

b) **Temperature and blood flow:** It is high near cancerous cells (x_2).

c) **Protein requirement:** Ribosomes and polysome are responsible for production of proteins. It is necessary for the cell growth process. In case of cancerous cell level of free ribosomes and polysome increases (x_3).

d) **Golgi apparatus:** It exports protein and other lipids, in malignant cells Golgi apparatus is poorly developed (x_4).

e) **Peroxisomes:** Peroxisomes are involved in various metabolic reactions and are found only in cancerous cell, this parameter is involved in various metabolic reactions. Malignant cells change their enzyme content, such as the reduction of acid or alkaline phosphates, distance of cell from center and so on (x_5, …, x_n).

In this paper, fuzzy set rule-based image processing approach is proposed to detect degree of malignancy.

Steps for Mathematical Calculations

1. Age and gender of volunteers is considered.
2. Different features symptoms (s_1, s_2,……s_n) are recorded.
3. For different fuzzy regions evaluate the value of count.
4. For each term calculate maximum count region.
5. Estimate V_i; set containing all possible symptoms on F_i
6. Considering F_i ($1 \le i \le 2$); malignant and benign, all its valid descriptions can be sorted accordingly.
7. Sub parameters mapping to s_{ijk} ($1 \le k \le r$); r is the total no. of sub parameters. Final mapping outcome can be presented as (x_1, x_2, x_3,……,x_p).

In general, a membership function can be calculated by some defined rules.

$$N\ rule\ (case) = \min e \in V^t_{age,\ edema,\ cyst,\ blood\ supply} \left(\max \mu_{age}, e, \max \mu_{cyst}, e, \max \mu_{blood\ supply}, e, \max \mu_{edema}, e \right)$$

N rule=Age (20-70), Oedema (middle, heavy), Cyst (≥½ of the total tumour), Blood supply middle (affluent), then high grade tumour.

Oedema extension and necrosis are important factors related with the overall survival of patient [14-16]. Data for calculating survival probability has been given in [Table/Fig-6]. For estimating overall survival Hazard Ratio (HR) and 95% Confidence Interval (CI) were the important estimating factors:

t (in days)	No. of failure (d)	No. at risk (r)	Hazard rate (d/r)	Censoring	Survival probability	Cumulative distribution function	95%CI
0	0	20	0/20	0	1-0/20=1	0	=P±1.96*SE 0.625±1.96 * 0.07 =0.48 to 0.762 =48 to 76%
100	1	19	1/19	1	1(1-1/19)=0.47	0.53	
200	1	18	1/18	0	0.47(1-1/18)=0.44	0.55	
300	1	17	1/17	1	0.44(1-1/17)=0.18	0.81	
400	1	16	1/16	1	0.18(1-1/16)=0.17	0.83	

[Table/Fig-6]: Represents overall survival rate, data for above table is referred from [15].
ecdf, by default, produces the cumulative distribution function values;
95% confidence interval=effect size±1.96×Standard error of the effect size (SE),
Where SE=√[P×(1-P)]/N
P=Number of responses to treatment, N=Number of subject

$$\text{Hazard Ratio (HR)} = \frac{\text{Probability of healing first}}{\text{Probability of not healing first}} = P/(1-P)$$

$$\text{Else, } P = \frac{HR}{1+HR}$$

HR=1 means 50% chance of treatment

95% confidence interval=effect size±1.96×Standard error of the effect size (SE)

Where $SE = \sqrt{[P \times (1-P)]/N}$

$$P = \frac{\text{Number of responses to treatment}}{\text{Number of subject (N)}}$$

Major oedema and necrosis are prognostic indicators for shorter OS (HR 2.274, P=0.015; HR 2.215, P=0.001, respectively) [17].

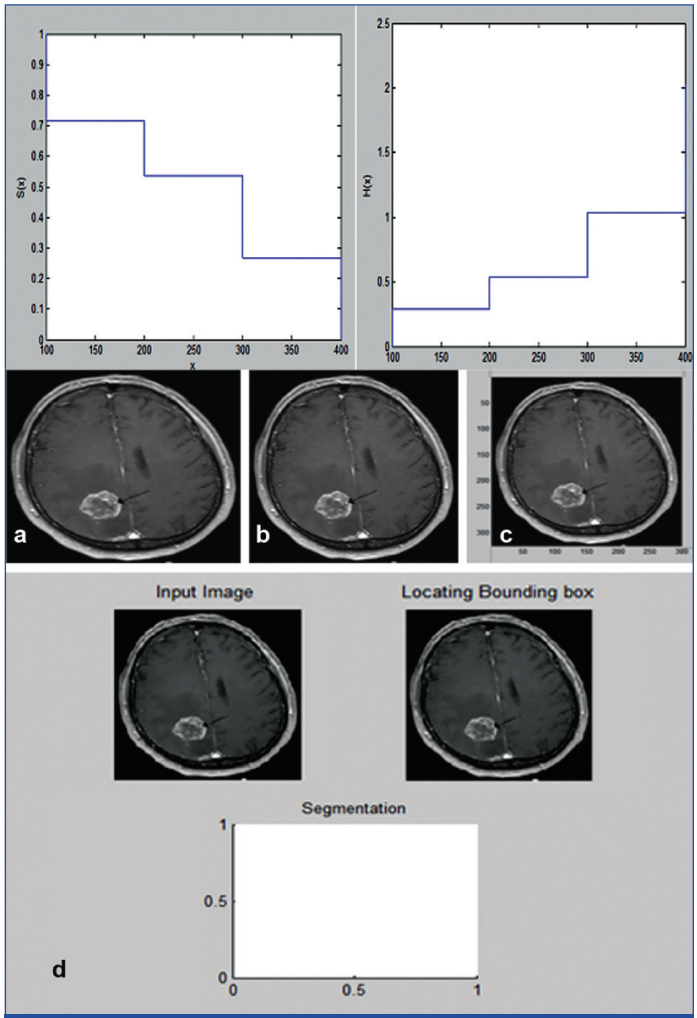
Steps for Post Processing of Magnetic Resonance Images

To obtain noiseless, smooth, and enhanced region of interest, post processing of MR images is necessary.

Stage 1- Preprocessing of the brain MR images

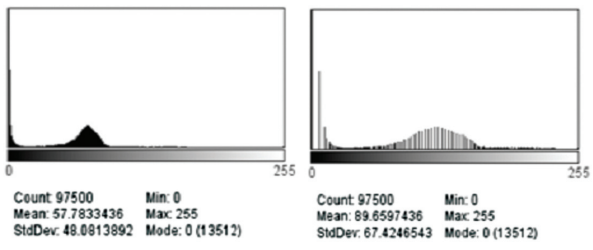
Preprocessing stage includes MR brain image acquisition, resizing the image, Region of interest Localisation (RL) and enhancement. To apply morphological operation on medical (MRI) images, the first step is to reduce contrast between consecutive pixels using Anisotropic Diffusion Filter.

a) Image is converted into grey scaled image. [Table/Fig-7] depicts the input greyscale image, bounding box and segmentation image.

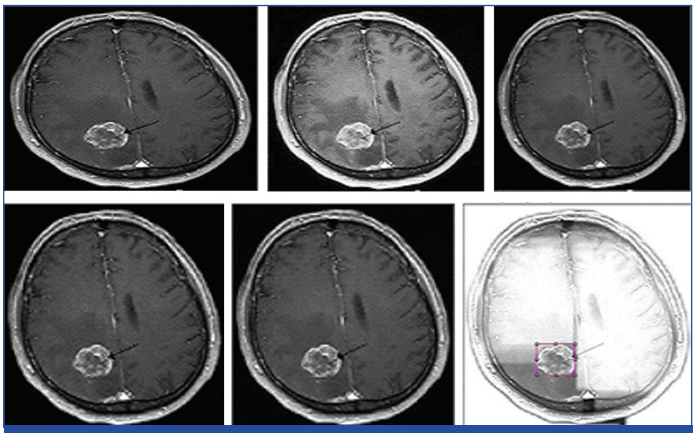


[Table/Fig-7]: (a) Input image; (b) Grey scaled image; (c) scaled image; (d) bounding box and segmentation.

b) Image histogram equalisation is used to enhance the images. Canny and Sobel operators are used for edge detection and gradient computation. [Table/Fig-8,9] are image histogram of pre and post processing images.



[Table/Fig-8]: Preprocessing and Postprocessing Image Histogram.



[Table/Fig-9]: Contrast Enhancement- Histogram Equalisation with Saturation.

c) The contrast between targets and their backgrounds is enhanced using contrast enhancement techniques which involve modifying the pixel values so that more of the offered range is used. [Table/Fig-6] respectively show the original grayscale filtered image and contrast enhancement image i.e. enhanced filtered image.

Stage 2- Shape boundary representation and segmentation stage

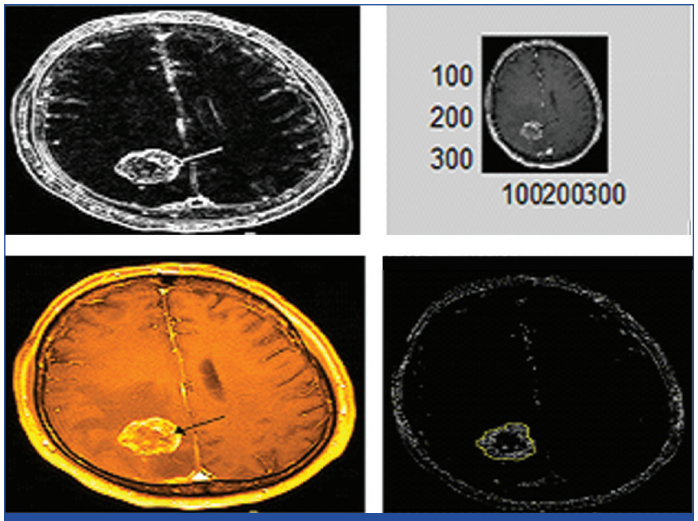
This includes edge detection, region of interest localisation and segmentation using spectral transforms. Generalised Hough transforms are used for circular region detection [18]. [Table/Fig-10] depicts image after edge detection and hot organ tumour representation for tumour high intensity outline detection.

Stage 3- Feature extraction stage

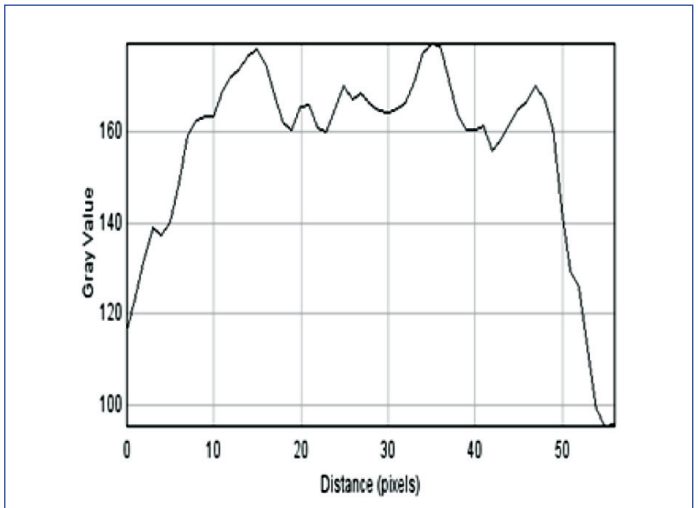
This step includes extraction of high intensity pixels and morphometric measurement-invariant features for indexing. [Table/Fig-11] includes extraction of high intensity pixels to locate ROI and its profile plot.

RESULTS

The flow chart for fuzzy reasoning algorithm shown in [Table/Fig-12]. The dataset analysis represents total of 253 brain tumour images with



[Table/Fig-10]: Edge Detection and Hot organ tumour representation and Tumour high intensity outline detection.



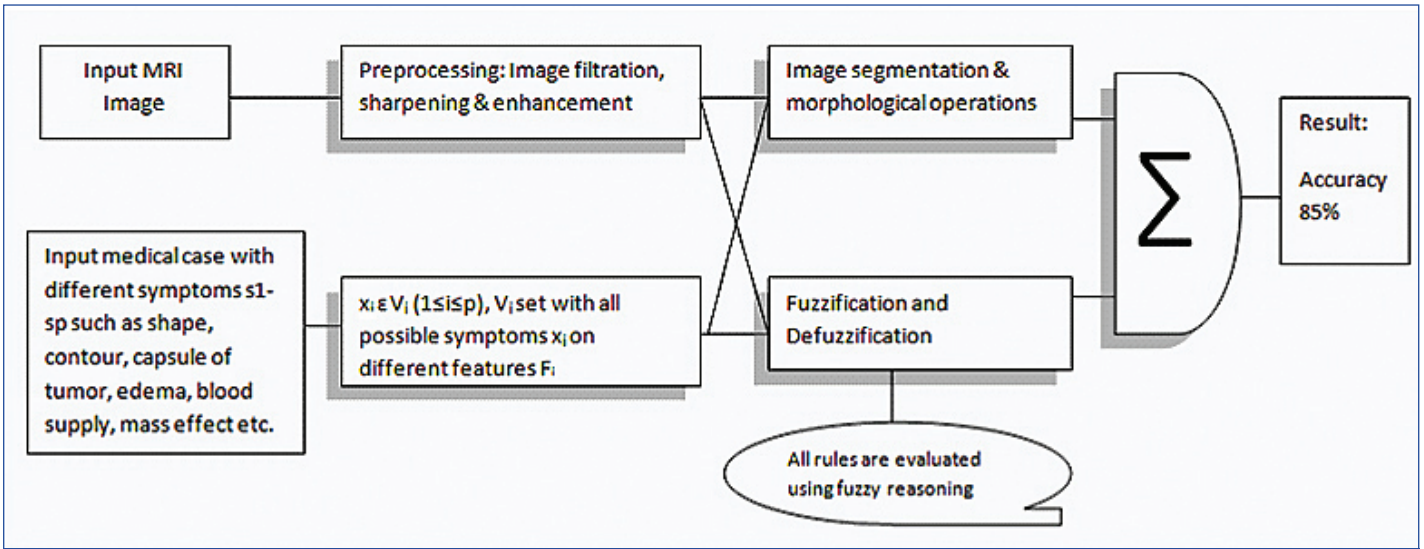
[Table/Fig-11]: Profile Plot of ROI.

True Negative=98, False Negative=12, False Positive=6 and True Positive=143.

For the above dataset, the accuracy, sensitivity and specificity were 95%, 93% and 94% respectively [Table/Fig-13].

DISCUSSION

The MRI plays an important role in the primary evaluation of brain glioma of patients under clinical supervision. Dealing with uncertainty and even missing values requires gathering numerous cases to interpret the relationship between MRI finding and degree of malignancy.



[Table/Fig-12]: Flow chart for fuzzy reasoning algorithm.

Different algorithms	Accuracy (%)
Multi Layer Perceptron network (MLP)	96.1
Decision tree algorithm (ID3)	94.4
Nearest neighbor	96.2
Fuzzy Min-Max Neural Network (FMMNN)	86.5
Fuzzy rule extraction	95.9
Proposed	95

[Table/Fig-13]: Dataset of Different Algorithms.

Limitation(s)

The present study was limited by small number of images studied and only a single set of rules was applied.

CONCLUSION(S)

Magnetic resonance imaging is the initial stage in brain tumour detection. Due to existence of uncertainties and irregularity in tumour shapes and sizes their need to predict malignancy using fuzzy set rules increases.This improves the classification ability of a simple set of rule and constitutes an advantage over traditional decision rules. In the present study, seven features have been used. The overall accuracy of the proposed method was nearly equal to the other methods mentioned in the study. This accuracy was achieved by using a single set of rule. To increase accuracy rate, number of features can be increased.

Ongoing research in medical image processing (edge detection and segmentation of images) aims to enhance the accuracy, specificity, and computational velocity, as well as maximising computational speed and minimising the manual interaction. Combining segmentation methods i.e, discrete and continuous, can lead to considerable improvements. Real-time data handling capability will also be a crucial aspect. Using fuzzy set rules in tumour image analysis of larger data sets may be useful in detecting the degree of malignancy.

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