International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

“Analyzing the Performance of SVM-ACO Classifier and Hybrid Optimization Techniques in MRI Brain Tumor Segmentation for Early Prognosis”

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Submitted: 16/07/2023 **Revised**: 04/09/2023 **Accepted**: 23/09/2023

Abstract: In MRI images, automated methods are used to generate images of the human body's interior organs for clinical study. A key component of many medical evaluations is image segmentation. There are manual, automatic, and semi-automated methods for segmenting a region. The technique presents a hybrid process for classifying and identifying brain tumours using MRIs (magnetic resonance imaging). The first step of the suggested method corresponds with the pre-processing of MR images, which includes the denoise filter, cranium stripping, and other techniques. The following stage is FE (feature extraction), which is different from MR images of brain tumours, of brain MRI using Local Binary Pattern along with a histogram. Brain tumours are categorised using the SVM (Support Vector Machine) based on many types of characteristics. The third phase focuses on a decision compound that classifies Support Vector Machine and (ACO) Ant colony optimisation is dependent on decision rates concerned with confidence criteria to support the final distinctive result. Since a genuine human brain and artificial MRI data set were used in the trials, 158 MR images total normal MRIs and 100 aberrant MRIs were obtained. On both training and testing data images, it was determined that the categorization accuracy was 98.99% accurate.. The classifier differentiates the cancer with rather good accuracy and provides the radiologist with confirmation. The early detection of brain tumours and other brain disorders, as well as the planning of their treatment, depend on the medical image segmentation of brain images. MRI segmentation is a labor-intensive task best left to medical professionals. For the purpose of early diagnosis and treatment of brain tumours, this research needs to provide some fresh hybrid picture segmentation and classification techniques. In order to increase the reliability of the fuzzy c-means clustering (FCM) perspective for segmenting the images, local spatial information is typically supplied to an objective function.

Keywords: *Medical Image Segmentation, Ant colony Optimisation (ACO), Social Spider Optimisation (SSO), SVM (Support Vector Machine), Local Binary Pattern (LBP) and Glioma Histogram Brain Tumour, Feature Extraction (FE),Classification of tumor, Magnetic Resonance Images (MRI),.*

For the proper understanding of the content, we bifurcated the paper in the following sections: i) Performance Evaluation of SVM-ACO Classifier for MRI Brain Tumor ii) Segmentation using Hybrid Optimization Techniques.

Section-I

1. Introduction:

A brain tumour results from an accumulation of unintended growth of a cell in a brain or major spinal canal. Two fundamental cancer kinds are exploratory brain tumours and rapturous brain tumours. The meningioma brain tumours initially cause cancer in many body parts before spreading to the brain, whereas the preceding brain tumours start and remain in the brainiac itself. Epoch is not a characteristic of brain malignancies; rather, it is more frequently observed in older individuals. Approximately 70000 people with brain tumours have received a diagnosis in recent years from all over the world. Additional 4600 children between the ages of 0 and 19 who had brain tumours have been examined. Along with males between the ages of 20 and 39, brain tumours are the second- and third-leading causes of tumor-related fatalities among children under the age of 20[1-2]. One of the more prevalent sorts of malignant next leukaemia is tumorous brain cancer. In addition to the imaging procedure, performance of brain tumour instances is excluded. The field of brain MRI image segmentation approaches for cancer identification had seen a lot of effort in previous years. The literature analysis has noted automated and semi-computerized processes for segmenting brain tumours. User involvement is required for the detection of brain tumours using semi-computerized methods [3–5]. The skilled radiologists completed decision-making tasks with a significant level of accuracy and care. Computerised assisted analysis tools had been developed [6] and [7] for greater extraordinary precision and discrimination in the pharmaceutical category of brain tissue. Various strategies are used into the segmentation processes based on category that uses FE (features extraction).

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The research proposed a method for automated classification of brain tumors based on varying degrees of resolve. The propound method removes two different texture types, particularly LBP and the brain's MRI's greyscale intensity histogram.. Next, classification of SVM is used to classify texture type, since the SVM depends on a certain degree of confidence, which is ultimately useful; this is observed by analyzing the rates of choice class synthesis and grouping [8]. The provided approach amalgamation delivers uncertain results in such circumstances, in contrast to synthetically producing a category outcome of not only malicious but also amiable while the confidence levels are decreasing.

The coordination of this suggested strategy is as follows. Division II depicts the classifier and FE approaches that were included in a recommended procedure. Division III provides a summary of a recommended process and expresses, in particular, its first stages. Division IV provides explanations along with findings from the study. Division V wraps up the suggested approach and describes a potential endeavour.

2. Related Works

A. FE

We need to make sure to have the proper arrangement for the piece's dimension first. This configuration was specifically designed to work with A4 report dimensions. Surface details and greyscale aggressiveness were both eliminated by the performance of the essential MRI from the original image. The LBP operator concludes a simple a histogram of 256 bins is employed for both Local Binary Patterns (LBP) and grayscale intensity in texture analysis. This encompasses a detailed description of the analytical weave, which in turn, establishes the specific type of regional weave. This approach offers a unified representation incorporating both analytical and structural characteristics.

B. H S I

The grey-scale emphasis histograms represent a occurrence of individually lustre values in MRI. It's a progression of the person in line with scaling, rotating, and translation [8]. The two histograms are of benign and harmful tumours.

C. L B P

The LBP, resembles the outward appearance, were more or less implied [9]. The 8-bit digital number that is emitted from the image element area is what the LBP of image elements often refers to. According to the sign for a removal consequence, 1's or 0's were assigned for duration. Intended for 3*3 blockage, a weight for a central picture element eliminated with the intention that each of its bordering picture elements is 8 was appointed. A developed bit was then linked and ciphered into an eight-bit binary numeral for each of the adjacent image parts.

3. Methods & Materials

Fig. 1 provided a summary of a suggested approach. The next part will provide information on each step of the technique.

A. Feature Extraction

This technique calls for elementing the ROI (region of interest), more especially, the cancer areas of the pictures, in order to eliminate key characteristics from MRI brain imaging. Robotic ROI subdivision in MRI brain images is said to as a difficult task [10]. This analysis is interested in different types of tumours and is also decided to properly segment the ROI of each picture. ROI segmentation is the procedure of characterising the ROI of a source frame. By automatically choosing a specific location in frame & entering the rectangle's dimensions technique during ROI segmentation, the ROI will be drawn as a rectangle on frame. The growth of the brain tumours produces exact surface characteristics and regional intensities. As a result, it decided to divide the entire collection of images into several partnerships.

B. ACO-SVM Classifier

ACO and linear SVM both have classification results and beliefs that were used as classifiers for their respective distinctive characteristics. Brain tumours are classified as Normal or Abnormal using the ACO-SVM classifier. Additional aberrant tumours are categorised as malign or benign. To find the optimal response, an artificial ant was developed. Each ant creates a solution as the initial stage in problem-solving. The second stage compares the routes discovered by various ants. The third phase also updates the path's value or pheromone. One of the supervised learning techniques employed for categorization encompasses Support Vector Machines (SVMs). The activity and examination sub-sets of the data set mentioned in the next section were separated. A working information set for determining the optimal hyper-plane dependent margin maximization between two categories was also something that SVM was familiar with. By making the following efforts, a new instance y moves in the direction of rank:

The process involves standardizing all training sets (y) in the view of a preparation representative's mean (μ) & SD (σ)

$$y1 = (y - \mu)/\sigma \quad .... (1)$$

$$Ma = \sum_{i=0}^{n} \quad \alpha\, ik(Vi, y1) + c \quad .... (2)$$

Where Vi represented the kernel process (focuses output $(Vi, y1)$ over here in backdrop), n stood for $Vi's$ dimensions, Vi was aided in vector setup, is the alpha significances for, and c was leaning. If $Ma \geq 0$, then, at that point, y is delegated an individual from the biggest group (amiable), but was previously classified as a member of a dual-level (malevolent). Images of a hyper-plane are important for an achieve memory. The suggested technique lays out the conviction status for a model y established its importance Ma along with S D (σ) for decision rates for the test subset (spontaneous model) in accordance with the following three rules.

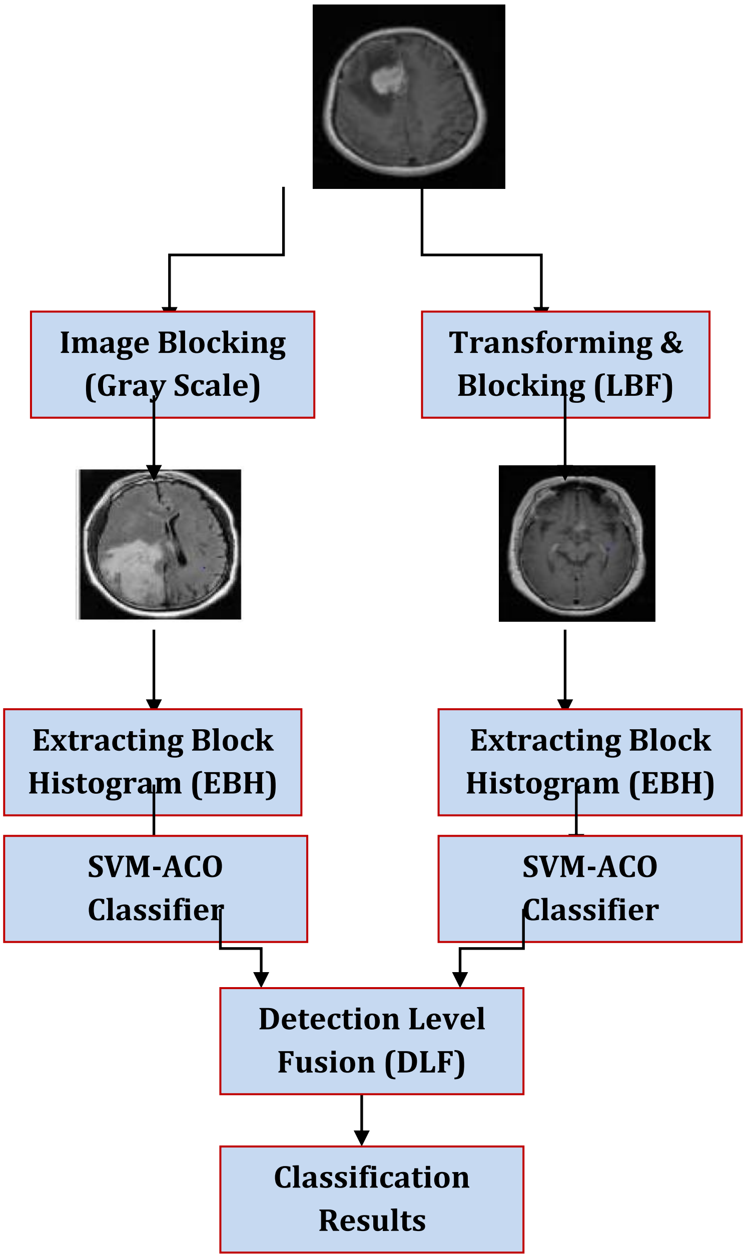


Fig-1: Block illustration for suggested technique

Rule 1: If Ma ≥ (α) or Ma ≤ (-α), then the outcome is finalized along with H L (undeniable level certainty).

Rule 2: If Ma ≥ (α /2) and Ma < (α), or (Ma ≤ (-α /2) and Ma > (-α)), then the decision is concluded with M L (mid-level certainty).

Rule 3: When Ma < (α / 2) or Ma > (-α / 2), the evaluation is then conducted with L L (low level certainty)

C. DLF and SVM-ACO

This recommended strategy achieved a D L F (Decision Level Fusion) methodology relying on 2 fundamental reasons in line with these three directions observed in the preceding region. If both the traits (L B P-H) are precisely classified in MRI, better. The second is whether or not the MR pictures are divided into several groups. Determine numerous potential regulations for various scenarios based on these two difficulties:

Step 1:

In collaboration, MR pictures were rated according to an exact type of texture (LBP-H): A combination assurance is higher conviction non-harmful on the off chance that L B P positions scan as non-harmful through H L S C and an immediate histogram sorts it as non-harmful (amiable) in the company of H L self-confidence (SC). The techniques, type classification based on two distinct weaves, have classified an MRI as non-malignant by H L S C. A different situation is when results are unfavourable among M L S C, the choice working histogram for the M R I is unfavourable with M L S C, and the decision for the MRI utilising L B P was unfavourable with M L S C. It was possible to classify MRI as non-benign by way of H L S C using histograms and textures and classify an exact MR image as non-amiable in the middle of L L S C involving LBP in the assurance combination is non-amiable with M L S C upto an issue couldn't be concluded giving like H L alongside it couldn't give like L L the assurance lies among H L and L L S C.

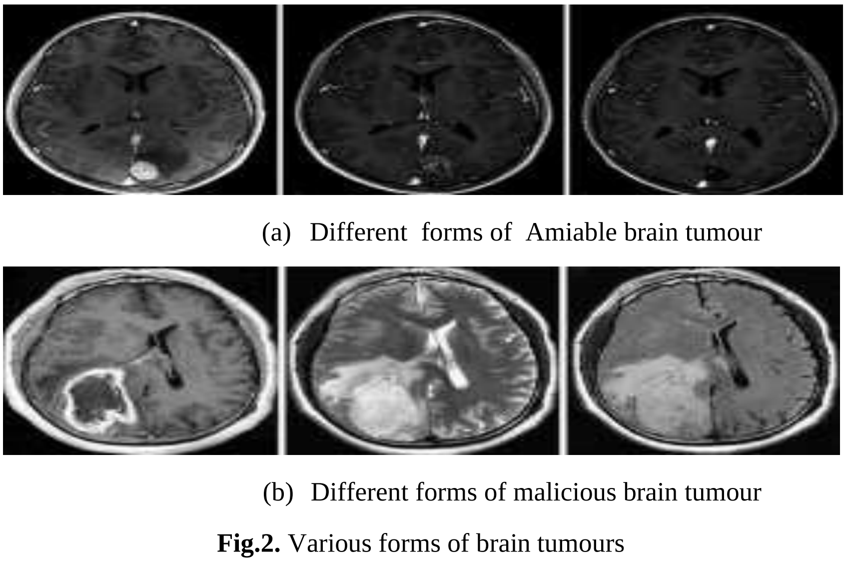
Step 2:

Both histograms and LBP classified an MRI as non-benign within HL SC; however, the problem was an uncertain resolution that could not classify the MRI as long as both features classified the MRI as different types and it was not possible to determine which component has a certain classification; thus, this could not classify the MRI. Equally textures (LBP-H) were classified as several modules by the MRI. Other odd circumstances include the classification of the identical MR images as non-malignant in HL SC using histograms and non-benign in LL SC using LBP features.

4. Experiments & Results

A . BRAIN TUMOR DATA-SET

Every picture utilised in this suggested technique is a M R I of medical procedure including an craniectomy with retracted incision & was selected as the most representative facsimile of the conclusive histology by Fig.2 which shows several sample MRI’s of benign and benign brain tumoursin data cllection. A total of 158 MR images from 158 individuals were collected. This was done intentionally to produce a response that could handle significant numerically distinct issues. Meningioma, Schwannoma, Pituitary adenomas, Hemangioblastomas, Craniopharyngioma, and Choroid plexus papillomas are just a few examples of the six categories of amiable tumours that commonly develop from brain-related tissues. There are also six categories of malicious tumours, including gliomas, acoustic neuroma, astrocytoma, chordoma, CNS lymphoma, Because different types of non-malignant tumours and different types of non-benign tumours have different traits, these varied sorts of sub-groups can imitate categorical development.



(a) Different forms of Amiable brain tumour

(b) Different forms of malicious brain tumour

Fig.2. Various forms of brain tumours

B. TESTING PROTOCOLS

One type of inequality concerns between the quantity of malignant and benign cells are included in the suggested process information set. In order to create the level dataset for the various category, the assumption of the down-sampling method and chose 58 benign issues that were above 110 and 58 malignant concerns that were over 100 [11,12]. 18 matches with decreasing, consequence-specific criteria for the outcomes and replication research. Separately, taking 58 MR images—

58 benign and other 58 from 100 malignant—as an unexpected example, we rigorously train a classifier (SVM), that achieve classification on test illustrations, later on measure the perfection while carrying the standard of accuracy throughout the course of 18 rounds.

This strategy uses a leave out the procedure for stratified cross-validation test to work the compelled number of activity examples: splitting a model information data into 56 doubles, each of which has 5 benign and 5 malignant tumours, additionally, a double has been employed to assess the remaining data on the side of the training process.

C. RESULTS & DISCUSSION

The subsection features a number of investigations. A preferred testing method is determined through the accuracy of category prediction using SVM classification and addressing issues of overpopulation. The next inquiry focused on the growth of the belief-founded decision-synthesis category. The results of diagnosis class combination versus the impact of conventional feature class combination will next be investigated. The recommended method included tests from 1*1 to 9*9 partnerships together with a blocked established approach that removed the LBP-H characteristic. Because block recognises small-scale components rather than large-scale features, the exactness was increased by extending the block's scope, whereas behind block 4*4 the exactness is amended or progressively diminished. The optimum outcome is offered by block 4*4 for all possible patients. Figure 3 and Table 1 display the category metrics for classifying brain tumor MR images into benign or malignant using different classifiers..

Table:1 Performance analysis of various classifiers with proposed methods

Various Classifiers	Accuracy %	Sensitivity%	Precision %	F- Score %	Specificity%
K N N	91.75	88.66	89.86	89.35	87.27
A N F I S	88.95	89.6	88.25	86.1	91.76
N B	81.75	84.27	82.58	85.35	86.65
D T	91.97	86.75	88.85	89.27	86.65
N N	92.56	88.7	89.85	89.36	92.91
PM	97.98	96.75	98.16	97.02	96.29

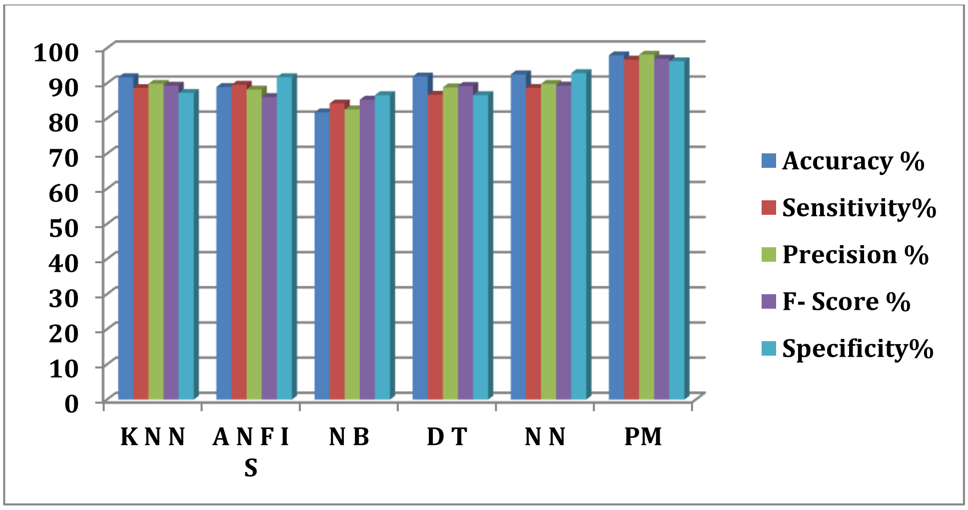


Fig-3: Graphical evaluation of classifier performance using the proposed methods.

5. Conclusion

This innovative method employs computational machine learning (ML) for validation, will soon be able to distinguish between distinct MRI brain pictures is shown. This anticipated approach offers a brand-new class determination fusion methodology and SVMACO, which provide the expected type of result and a type of estimate confidence (H L, M L, L L). This original analysis revealed strong relationships between the confidence and accuracy class categories. When compared to SVM-ACO classification, which anticipates contrasting findings separately, the combinational approach didn't provide broad level. Such belief-based estimate findings using the recommended method were more significant than those using antiquated categorization systems that indicate accuracy's, and they were also closer to validity in the examination of situations that were very difficult to classify.

Section-II

1. Introduction:

The process of segmenting a digitised medical image into different parts is known as "medical image segmentation." The target is to clarify image investigation and create a more interpretable representation, medical image segmentation is used. It aids in pinpointing the borders and the edges image segmentation partitions an image into a set of distinct zones based on certain criteria that together encompass the full image [13]. As a result, medical image segmentation is essential for diagnosis. It is a difficult endeavour since medical pictures frequently have poor contrasts, a wide range of abnormalities, or diffuse boundaries. Computed tomography (C T) or magnetic resonance imaging (MRI) can be utilized for further investigation of the architecture of the brain. Compared to a CT scan, an MRI scan is more useful for diagnosis. Primary brain tumours impact less than 2% of all malignancies or roughly 250,000 people worldwide each year. People can develop 150 distinct kinds of brain tumours. Indeed, there are two kinds of tumors: amiable and malicious. Amiable tumors have grown throughout the brain. Malicious tumors are commonly referred to as "brain cancer" since they can spread outside of the brain.

The segmentation of the whole tumour (W T), tumour core (T C), and improved tumour (E T) may all be done more precisely with the use of information that clinical practitioners can get from MR imaging. Radiation treatment and surgical resection are concentrated on the TC and ET regions. WT is an edoema caused by tumour extrusion into nearby tissues and tumour cell release. Compared to WT, TC and ET frequently have fuzzier edges & take up significantly small space. It is significantly more difficult to distinguish accurately between TC and ET due to these characteristics. By isolating just the necessary regions, medical picture segmentation enables the processing of anatomic data with more specificity. It can lessen noise's impact and enhance image quality. [14].

It is essential to have sophisticated and efficient techniques for identifying these brain tumours. Even though there are many effective techniques available, new advancements are required to simplify clinical diagnosis. Technological developments offer a variety of effective segmentation techniques, simplifying diagnosis. Modern neural network techniques such as Deep Learning and Machine Learning can be successfully applied in classifying along with predicting the images of the brain. This is achieved through robust feature extraction and segmentation techniques applied to these medical images. [15]

This work develops an automated combinational method for identifying and pluck out glioma in MRI images of the brain by fusing F R F C M and S S O. The FRFRCMSSO metaheuristic algorithm is advised because it creates the best clusters, attempts to stabilize the exploration and exploitation difficulty, and provides the most effective answers to optimisation issues. The document is laid out as follows: Section 1 purposefully provides a complete summary of the research and its approaches. An explanation of the data-set utilised in this investigation is provided in Section 2. A suggested segmentation and clustering methods are explained in Section 3. The results of the suggested strategy's successful execution are addressed in Section 4. The ideal outcome of the advised strategy is outlined in Section 5.

2. Description of Data-Set

The dataset of MRI brain images employed in this research was sourced from the BraTS challenge. Figure 4 enumerates the different publicly accessible glioma datasets

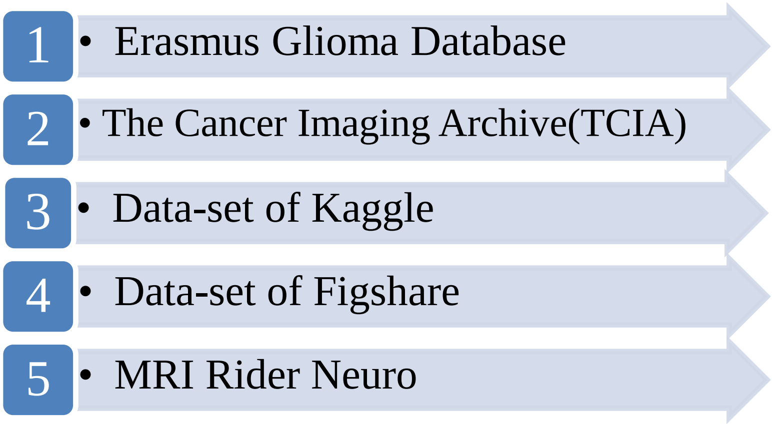


Fig-4: Dataset of brain tumor

We used MR brain images from 2013, 2015, and 2018 in this study, datasets for the 2019–2020–2021 BraTS challenge.

3. Proposed Procedure

A. Fast & Robust F C M (F R F C M)

In order to enhance the accuracy of image segmentation, local spatial information is often incorporated into the objective function. This is important because the FCM algorithm can be sensitive to artifacts. On the other hand, the inclusion of local spatial information typically necessitates a lengthy computation process due to an iteratively estimate of the Euclidean the separation of pixels within cluster centres and nearby local physical neighbours. The efficient fuzzy technique FRFCM described in this research appears to be both significantly faster and more reliable than FCM. To provide noise resistance, the spatial information of the neighbours is first provided via morphological reconstruction. The goal function is then modified based on the spatial information of the neighbouring pixels and the distance between the pixels in the cluster centre [16]. Because it does not need calculating the distance between pixels inside nearby clustering centres and spatial neighbours, an F R F C M approach is simpler and faster than traditional procedures. Furthermore, membership filtering may efficiently improve the membership partition matrix, making it helpful for dissecting pictures with noise. The suggested technique not only yields superior results but also demands less computational time compared to previous methods, according to experimental experiments on medical pictures [17]. We noticed that the recommended FRFCM has the considerable capabilities based on the prior examination.

1. Due to the inadequacy of the distance of redundant estimate, FRFCM has a very low computational cost.

2. FRFCM may produce good picture segmentation accuracy because it incorporates MR and membership filtering, which effectively uses spatial information.

B.Social Spider Optimization (SSO)

It is a population-based heuristic that imitates the social spider's cooperation [18]. SSO uses two different species of search agents known as spiders: male and female. Based on its sex, each agent is put through a variety of evolutionary set operators that approximate the different cooperative behaviour seen in a colony. The elimination of exploitable weaknesses in various SI approaches, such as an unsuitable exploration-exploitation ratio and rapid convergence, is made possible by individual classification. SSO, in contrast to some other effective approaches, avoids particle concentration in advantageous spots, avoiding important drawbacks like a high rate of convergence to inadequate solutions or a constrained balance of exploitation and exploration. These characteristics have encouraged the use of the SSO approach to solve a number of issues.

4. Implementation and Results

In programmes that aid in medical prognosis, image segmentation is absolutely essential. Medical pictures are ambiguous due to blurring, intensity inhomogeneity, and noise, making it difficult to segment the image information.

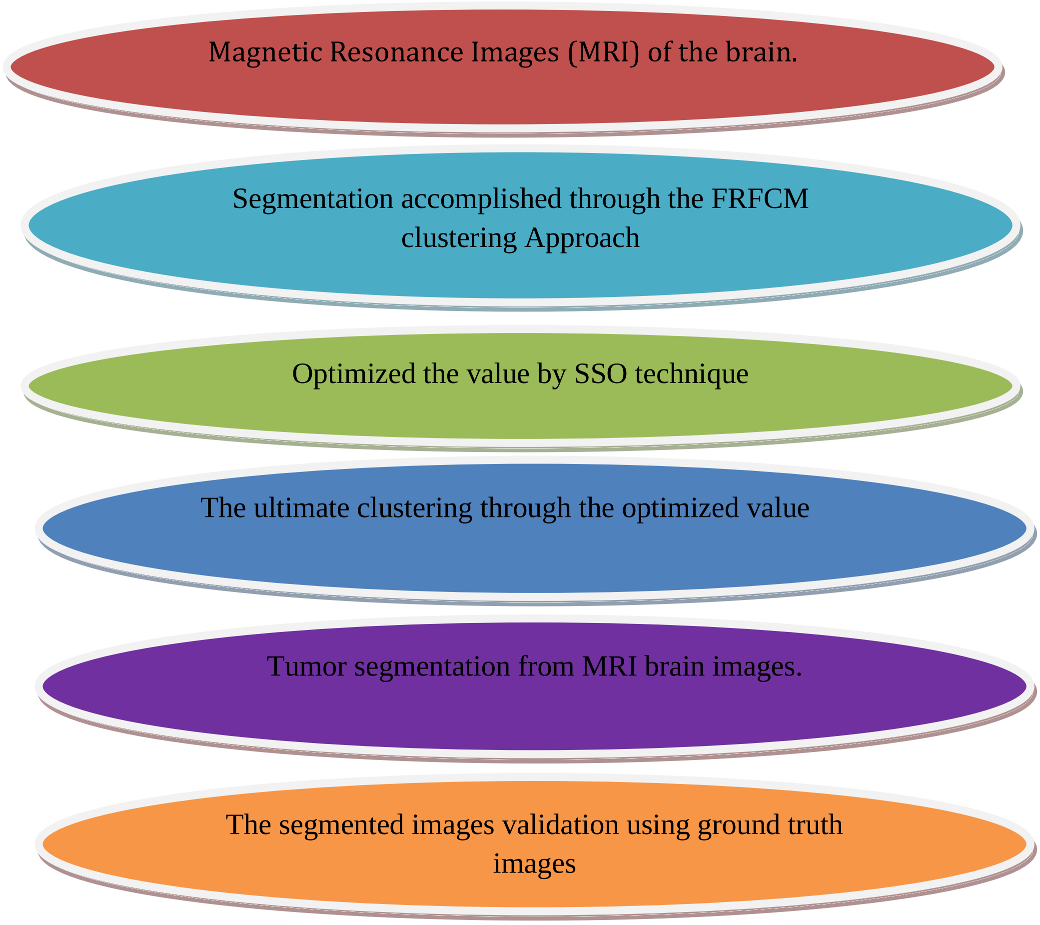


Fig-5: The suggested method's methodology

The FRFCM approach is much more convenient and much faster since it does not need calculating the distance between pixels inside clustering centres and local physical neighbours. Furthermore, membership filtering may efficiently improve the membership partition matrix, making it beneficial for segmenting noisy pictures.

To demonstrate the efficacy of the suggested SSOFRFCM, MR brain images containing a tumour are utilised as the test dataset in this instance. Using an input image as a mask image for F R F C M and a 3x3 structural square element, the marker image is produced. Furthermore, the membership filtering for both the fuzzy and window operations is carried out using a 3x3 median filter. SSO is tuned for clusters created using the FRFCM approach to get better segmentation outcomes. The process of the suggested FRFCM-SSO method is shown in Figure 5. Figure 6 depicts the processes in the SSO algorithm.

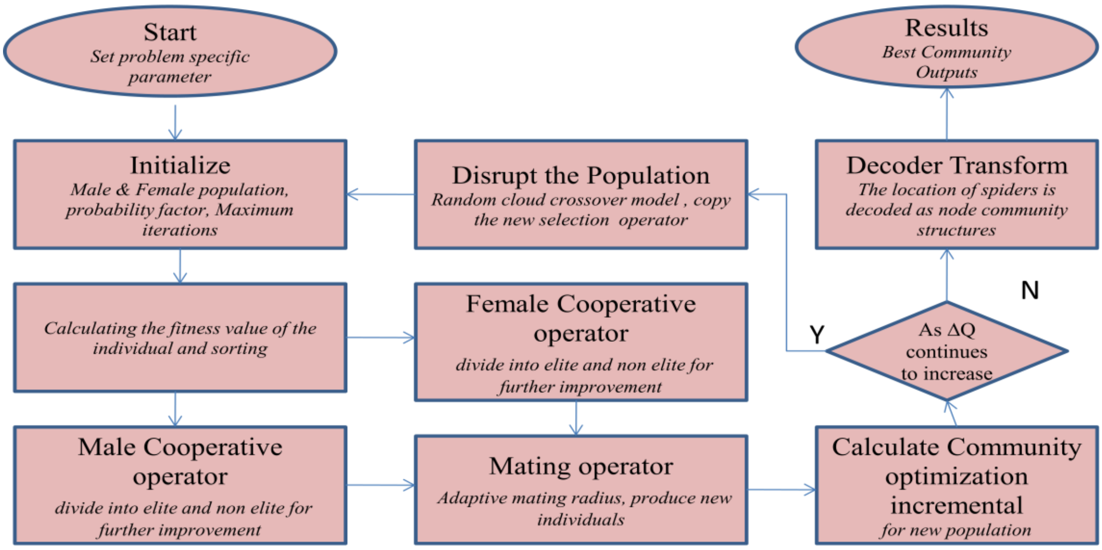


Fig-6: SSO Algorithm

DATA-RESOURCE	DATA-SET	Time	MSE	P S N R	T C	D S
BRATS Challenge Data-set	2013 L G	22.67 23.59	0.351 0.28	51.80 54.51	56.30 56.10	76.07 76.94
	2 015 H G	21.01 24.44	0.3667 0.229	51.11 55.08	55.28 57.30	77.73 78.10
	2018 L G	23.12 20.76	0.321 0.31	53.11 53.36	56.76 54.12	79.48 78.84
	2018 H G	24.47 24.11	0.35 0.31	52.84 53.26	57.26 58.18	79.46 76.75
	2019 L C	24.85 24.63	0.24 0.26	54.53 54.15	54.98 56.84	79.71 78.91
	2019 HG	22.36 22.24	0.38 0.40	52.38 52.17	59.89 57.85	79.79 78.76
	2020 W	21.58 22.26 20.74	0.23 0.39 0.21	54.70 52.36 54.99	58.45 59.27 60.45	76.40 75.26 78.62
	2021 LG	23.81.	0.2114	54.9128.	59.82	79.00
AVERAGES ALUES		22.89	0.3044	53.4341.	57.50	77.8089.

Table :2- The FRFCM-SSO method's performance in segmenting glioma from MRI images using various performance measures

This evaluation was conducted by contrasting the results to the ground truth images, the images having tumour parts of the BraTS MR brain images are specifically segmented. The performance metric values achieved are shown in Table 2. Performance measures like Peak Signal to Noise Ratio (P S N R), time, Mean Squared Error (M S E), Tanimoto Coefficient (TC), and Dice Score (DS) are assessed when segmenting the tumour from MR images. Following the confirmation of the qualitative and quantitative findings by skilled radiologists and real-world pictures, physicians may quickly diagnose patients and determine their courses of treatment.

5. Conclusion

We presented a novel technique for tumour delineation in MRI of brain that makes use of F R F C M and S S O. Traditional F C M's drawbacks are avoided, and similar/similar groupings of pixels are formed instead. In addition to attempting to prevent faulty or improper clustering partitions brought on by anomalies, it also works to keep computation costs as low as possible.

By assessing the tumour dissected picture utilising ground truth images, performance metric parameters, and the orthopedist's consideration, the efficiency of the procedure is shown.

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