

Brain Image Segmentation to Diagnose Tumor by Applying Wiener Filter and Intelligent Water Drop Algorithm

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Abstract—Segmentation of image has wide application in the field of medical, military, surveillance, etc. This work segments medical resonance image for detection of tumor in brain where work identify three parts in the image. First is skull, second is brain and third is tumor. Presented paper includes description of image segmentation in unsupervised manner where proposed model identify all segments of image without any training. Here, wiener filter preprocessed the input images by removing unwanted information from the image matrix. Filtered image then passed in Intelligent Water Drop (IWD) genetic algorithm for finding representative pixel value sets of image segments. Graphical water drop movement in the IWD algorithm has representative pixels value set selection accuracy. Experiment is performed in real dataset of brain tumor and detection is done by taking reference of ground truth images. Proposed model evaluated average precision value 0.98 and average accuracy 96%. Hence, when results is compared with existing methods then it is obtained that proposed segmentation work increased the segmentation evaluation parameter values.

Index Terms—Brain tumor detection, digital image processing, genetic algorithm, image segmentation.

I. INTRODUCTION

Digital image processing applications in image segmentation, provides support for medical image diagnosis, digital object detection in videos, change detection analysis, etc. Image segmentation leads to separation of image pixels into two or more cluster sets as per feature set, fitness function, etc [1]. Large number of research paper have been published on digital image segmentation in last few decades for resolving different issues. Some of papers are to identify background, some identify objects, pay per hour for medical image diagnosis [2]. So algorithms proposed in this kind of papers are under low level engineering where images are segmented as per pixel values into few clusters. Images were taken from different resources, environment so some noise were present in it then some of noise removal techniques for also proposed by scholars for enhancing digital image segmentation efficiency.

Number of techniques for image segmentation work were proposed and differentiated on the basis of their feature vectors extracted from input image and such features are edge,

Manuscript received January 15, 2021; revised April 11, 2021. This work was completed in Research Centre Institute of Engineering and Technology, Devi Ahilya Viswavidyalaya, Indore, India for advancement work of author's (First Author) PhDs thesis work.

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corner, histogram, wavelets, etc. Each of proposed algorithm for image segmentation reduces false pixel assignment [3]. Image processing holds an important position in the medical field having the form of magnetic resonance image, ultrasound images, X-ray, tomography study, etc. These medical images improve understanding of doctors or medical practitioners and provide treatment [4]. As per the experience of medical practitioners, identification of tumor in brain region was done but due to manual involvement, accuracy of detection varies and risk of treatment gets increases. So need of some automatic algorithm was required for the diagnosis of tumor in the brain region for improving the medical prescription accuracy, rate of development, change detection etc. Hence image segmentation for this kind of treatment have its own role. Some of MRI machines were developed with this facility for supporting the human experience [5].

Paper is structured into few sections first is introduction then second section elaborate various research work done by scholars in field of image segmentation. Further in third section paper explanation of IWD is given. Fourth section has detailed the proposed genetic based image segmentation model for detection of brain tumor with block diagram explanation. In fifth section paper compares performance of proposed model with other algorithms. Finally, paper get conclude with findings of proposed model.

II. LITERATURE SURVEY

The author [6] proposed a new rough to fine (CFM) method for brain tumor segmentation. considered hierarchy included preprocessing, deep classification of networks and post-processing. Preprocessing was used to generate image patches for all MR images and the deep learning network output was a grievous image patch. The high-level abstract function extracted from the input using the stacked auto encoder framework for identifying patches of images. After that classification results were mapped into a binary image, the final segmenting result was achieved with a morphological filter. For the analysis of the proposed method, the experiment was used for the brain tumors segment for each patient data package.

The author [7] presented the Convolutional Neural Networks in which multi-succession magnetic resonance images were grouped for tumor detection in brain region. Various CNN were given that focused on MAGNETIC RESONANCE IMAGE patches, cuts and volumetric multi-planar cuts without any preparation. Two existing ConvNets (VGGNet and ResNet) models prepared in ImageNet dataset, through a calibrating of the last scarcely

any layers, likewise test the reasonableness of move examination to the mission. The Leave one tolerant out assessment plot was applied to evaluate ConvNets output. ConvNets outcomes shown that it accomplished better accuracy in all situations when arranged for a multi-planar volumetric informational collection.

The author [8] built up a DLF (Deep Learning Framework) for brain tumor sections and has anticipated the endurance of glioma by methods for Magnetic Resonance Image. This paper utilized different 3 Dimension CNN engineering sets for MRI tumor detection rule. This diminished model inclination and improved execution efficiencies. They selected solid endurance properties utilizing a decision tree and cross approval. An irregular backwoods model was in the long run evolved to assess the patients by and large endurance.

The author in [9] built up a prescient Machine Learning Model for the analysis of brain tumors. Routine blood tests must require substantially more data than even the most prepared specialists by and large acknowledge. They built up an AI prescient model in which neurological patients were tried for mind tumors normally. Review assessment of 68 sequential brain tumors and 215 control patients for the nervous system science administration has affirmed the model.

In the paper [10], another digital image division/segmentation strategy was proposed by joining the FCM bunching calculation with an unpleasant set hypothesis. To start with, the quality worth table was built dependent on the division/segmentation consequences of FCM under various bunching numbers and the digital image was separated into a few little districts dependent on the undefined relationship of characteristics. At that point, the weight estimations of each quality were gotten by esteem decrease and utilized as the premise to ascertain the distinction among areas and afterward the likeness assessment of every locale is acknowledged through the identicalness relationship characterized by the distinction degree. At last, the equality connection characterized by closeness was utilized to blend areas and complete digital image division/segmentation. Paper has identified few Problems mentioned in following points 1. In binary masked image was required to remove the background. Hence work was static as the mask was different for different set of images. 2. Calculation of information table for each image was compulsory for finding the segmentation class of sub images, this increased execution time. 3. In Pre-processing , input image description was not detailed like noise removal or skull identification. 4. Given Classification accuracy is 96%, which can be further enhanced.

Our proposed model removed noises from image through wiener filter then segmented the image by using Intelligent Water Drop algorithm. It also avoided drawbacks specified for paper that is summarized in above paragraph. Our proposed model is dynamic in nature and increases adoptability of tumor detection by fulfilling objectives i.e. 1. To apply pre-processing filter to remove noise from input image. 2. To Develop dynamic skull detection and removal technique. 3. Increase the tumor detection accuracy.

III. INTELLIGENT WATER DROPS

IWD takes its motivation from common natural phenomena. IWD copies the conduct of streaming of water drops with the waterways. In light of the above property of flowing water, a keen algorithm was developed by Shah Hosseini [11]. In this every single intelligent water drop was expected to have three significant properties. First is the measure of soil that each water drop conveys with it, spilling out of one water node to another. Second is the speed of the water drop, that increment or diminishes according to the collected soil along the way. Total soil conveyed by the water drop relies on the speed of the streaming water drop.

Fig. 1 shows the speed of the water drop increments marginally when moving through the stream bed with more soil. The speed of the subsequent water drop increments when moving through the stream bed or with less soil.

As Intelligent Water Drop Algorithm is inspired from nature/Biological conduct it comprises all the properties of hereditary calculation like populace age, wellness estimation, choice, hybrid and transformation while discovering arrangement of an issue.

Our proposed model is particular for Image Segmentation by utilizing Weiner channel and Intelligent Water Drop calculation by discovering delegate pixel esteem sets of a digital image section. Subtitles are depicted in segment beneath.



Fig. 1. Water drops moving through stream beds with more and less soil [11].

IV. PROPOSED MODEL

This section describes proposed ISWIWD (Image Segmentation by Weiner and Intelligent Water Drop) model which is working for brain image segmentation. It's block diagram is shown in Fig. 2. Whole work is divided into three module i.e. first is image for pre processing, second is written for skull part removal and third section elaborate working of segment representative pixels finding.

A. Image Preprocessing

In image processing, wiener filter is very prominent method for removing unwanted data from the image [12]. In our method, input image (as shown in Fig. 3(a)) was transformed into two dimensional format where pixel value ranged between 0 to 255. Image was reshaped further in order to apply matrix operations by the same approach that is used in [13]. Wiener filter removed an additive noise and reduced mean square error, as it's linear estimation of original image. Hence mean (μ) and variance (σ^2) of each pixel were estimated by Eq. 1 and Eq. 2.

$$\mu_{x,y} = \frac{1}{XY} \sum_{m,n \in N} I(m,n) \quad (1)$$

$$\sigma_{x,y}^2 = \frac{1}{XY} \sum_{m,n \in N} I(m,n)^2 - \mu^2 \quad (2)$$

$$I(x,y) = \mu + \frac{\sigma^2 - v^2}{\sigma^2} (I(x,y) - \mu) \quad (3)$$

Changes as per Weiner filter was done by Eq. 3 where v^2 is noise variance.

B. Image Skull Removal

Filtered image (as shown in Fig. 3(b)) was further processed into two dimensional format where pixel values ranged between 0 and 1. Here binary conversion was done by applying otsu method. Otsu is a method to find gray threshold value for binary conversion. Binary conversion removed skull part of an image. Otsu provided threshold values for portioning the image into black and white color as shown in Fig. 4(a). Once binary image format obtained then scanning of image, left to mid in a row and right to mid in a row took place. While scanning from left to mid in a row, proposed module point first white pixel position and then first black pixel position. So all pixels from first white to first black pixel were considered as skull part in the row as shown in Fig. 4(b). Similarly while scanning from right to mid in a row, proposed module point first white pixel position and then first black pixel position. So all pixels from first white to first black pixel were considered as skull part in the row as shown in Fig. 4 (c). Once skull part of the image was identified and removed then resetting of gray scale image values to 0 was done. So output of this module was again a two dimension matrix whose pixel value ranged in 0 to 255. Fig. 4(c) is processed brain region from image.

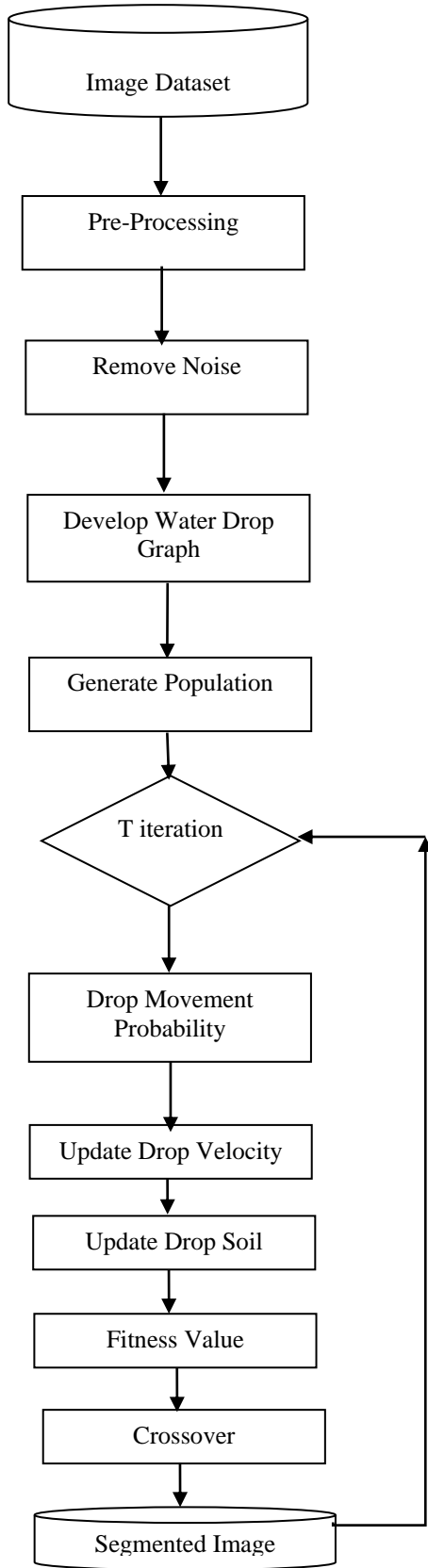


Fig. 2. Block diagram of proposed model.

where I is an input image, m and n are pixels position to filter, $N \times M$ are pixels surrounding where $N=M=3$, m and n are positioned in $N \times M$ block.

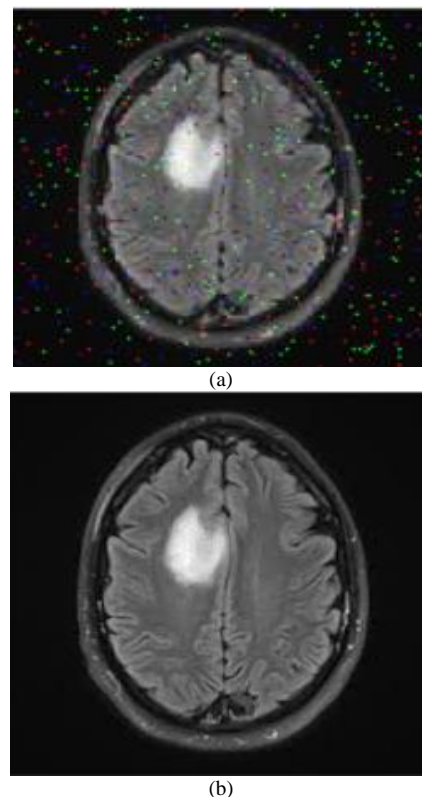


Fig. 3. (a) Input image (b) Image after pre-processing.

C. IWD Genetic Algorithm

In the IWD genetic algorithm, each pixel acts as a water drop where one drop move towards other drop and soil between the drop positions is less. So soil act as distance between the pixel values [14]. In our model, this movement

of pixel or water drop created segments in the image. Output of this module was segment representative pixel values

Develop Water Graph : First phase of this intelligent water drop genetic algorithm was to develop a graph where each node is pixel and other distance between them act as weight of graph [15]. Soil of the graph acts as graph weight which was estimated by Eq. 4.

$$S(i, j) = \text{Euclidian}(i, j) \quad (4)$$

where i, j are pixel values belongs to image and S is the soil matrix of pixels.

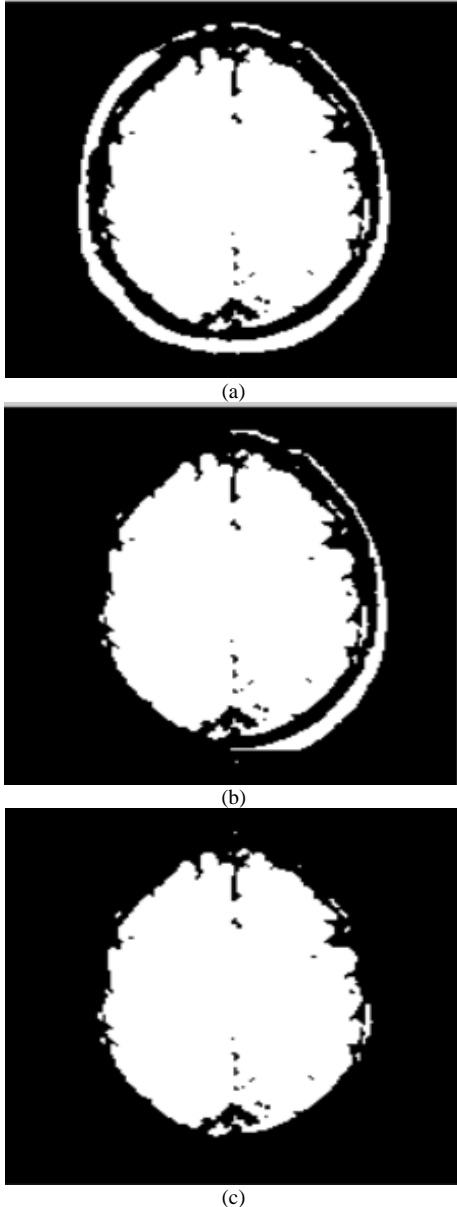


Fig. 4. (a) Binary image, (b) Image after removing left skull region, (c) Image after removing right skull region.

IWD Population Generation: Population of genetic algorithm consist of chromosome where probable solution is chromosome. In this work segment representative pixel set acted as population chromosome. Segment representative pixel sets were generated randomly. IWD Population P consist c number of sets and each set have s number of segment then Eq. 5 used to generate population.

$$P \leftarrow \text{IWD_Population_Generation}(c, s, I) \quad (5)$$

Drop Movement Probability: As image I was segmented into s class, so each representative pixel moved toward other pixel of image as per soil value. So movement probability of water drop help in this selection using Eq. 6.

$$DMP(i, j) = \frac{FS(i, j)}{\sum_{K=1}^N FS(i, k)} \quad (6)$$

$$FS(i, k) = \frac{1}{\delta + WS(i, k)} \quad (7)$$

$WS(i, k) = \text{Soil}(i, k)$ if minimum (Soil (i , all element)) > 0,

Otherwise $WS(i, k) = \text{Soil}(i, k) - \text{minimum}(\text{Soil}(i, \text{all element}))$.

where WS is Weighted Soil, FS is Feasible Solution, δ is constant value range between 0 to 1.

Modify Drop Velocity and Soil Values: Here i^{th} drop velocity (DV) was updated by Eq. 8 when it moves towards j^{th} drop.

$$DV(t+1) = DV(t) + \frac{v_1}{v_2 + v_3 + \text{Soil}(i, j)^2} \quad (8)$$

i^{th} drop soil was updated by Eq. 9 when it moves towards j^{th} drop.

$$\Delta S(i, j) = \frac{S_1}{S_2 + S_3 + T(t+1)^2} \quad (9)$$

$$T(t+1) = \frac{HD}{DV(t+1)}$$

HD is heuristic durability, a constant value ranged between 0 and 1.

$$\text{Soil}(i, j) = (1 - \beta_L) * \text{Soil}(i, j) - \beta_L * \Delta S(i, j)$$

where $v_1, v_2, v_3, s_1, s_2, s_3$ and β_L are constant range between 0 and 1.

Fitness Function: Fitness value of chromosome depends on the segment pixel representative set. So it's an summation of minimum distance between the segment representative pixels to the segmenting pixel of image. Chromosome having minimum summation value was considered as best solution in the current iteration population.

$$F_c = \sum_{x=1}^{\text{Column}} \sum_{y=1}^{\text{Row}} \text{Min}(P_{c,s} - I(x, y))^s \quad (10)$$

where in above Eq. 10 F_c is fitness value of c^{th} chromosome in the population P and $P_{c,s}$ is representative pixel in c^{th} chromosome and s^{th} segment.

IWD Crossover: As population need updating so crossover operator performed this changes where each chromosome in the population get modified as per best segment representative pixel set in a current iteration. Hence lowest fitness value of the chromosome acted as best solution and random position pixel value was replaced in this crossover operation.

This updated population chromosomes were further analyzed to identify that new chromosome solutions are better as compared to previous parent or not. following

conditions considered for changes i.e. in case new chromosome found better, then replace parent solutions in population otherwise parent will continue and new will discard.



Fig. 5. Tumor region in image.

Segment Image: After completing maximum number of T iteration IWD genetic algorithm stopped its execution and fitness value of final population considered as segment representative pixel set. This pixel set segmented whole image into tumor and non tumor region as shown in Fig. 5. Tumor region is represented by white color while other portion of image is black.

Proposed Algorithm:

1. Input: I // Image
2. Output: SI // Segmented Image
3. $I \leftarrow \text{Reshape-Image}(I)$
4. Loop 1: X // X number of row in I
5. Loop 1: Y // Y number of column in I
6. $m \leftarrow \text{Mean}(I(x,y), M, N)$
7. $v \leftarrow \text{Variance}(I(x,y), m, M, N)$
8. $I(x,y) \leftarrow \text{Weiner}(I(x,y), v, M, N)$
9. EndLoop
10. EndLoop
11. $B \leftarrow \text{Otsu}(I)$
12. $I \leftarrow \text{Remove_Skull}(B, I)$
13. Soil $\leftarrow \text{Develop_Water_Graph}(I)$
14. $P \leftarrow \text{IWD_Population_Generation}(c, s, I)$
15. Loop 1: T // T : Number of iterations
16. DMP $\leftarrow \text{Drop_Movement_Probablity}(\text{Soil})$
17. Loop 1: N // Number of Nodes in Graph
18. DV $\leftarrow \text{Update_Velocity}(\text{DMP}, \text{Soil})$
19. Soil $\leftarrow \text{Update_Soil}(\text{DMP}, \text{Soil})$
20. EndLoop
21. $F \leftarrow \text{Fitness-Function}(P)$
22. $G \leftarrow \text{Best_Chromosome}(F)$
23. $P \leftarrow \text{Crossover_operator}(G, P)$
24. EndLoop
25. $F \leftarrow \text{Fitness-Function}(P)$
26. $SI \leftarrow \text{Segment}(F, I)$

V. EXPERIMENT AND RESULTS

Experimental work of proposed model was performed on MATLAB software having machine configuration of 4GB RAM, windows 7 operating system and I3 processor. Results were compared with existing algorithm FCMRS (Fuzzy C Mean and Rough Set) proposed in [10].

A. Dataset

Experiment was performed on brain tumor Segmentation dataset (code 105) obtained from the repository maintained on URL <https://ijcsret.com/2017/12/14/computer-science/>. This dataset consist 100 images where 50 are original image and 50 are ground truth image set. Dimension of each image are not same so proposed model work on random size image.

B. Evaluation Parameter

Evaluation parameters value of segmented image was obtained considering the basis of ground truth images of dataset. So segmented images obtained from proposed and existing algorithm are system generate pixel class (Tumor or non tumor region). Formulas of evaluation parameters are [16]:

$$\text{PositiveLikelihood}(PL) = \frac{TP}{TP + TN} \quad (11)$$

$$\text{NegativeLikelihood}(NL) = \frac{TN}{TN + FP} \quad (12)$$

$$\text{Precision} = \frac{\text{True_Positive}}{\text{True_Positive} + \text{False_Positive}} \quad (13)$$

$$\text{Recall} = \frac{\text{True_Positive}}{\text{True_Positive} + \text{False_Negative}} \quad (14)$$

$$F_Score = \frac{2 * \text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}} \quad (15)$$

$$\text{Accuracy} = \frac{CC}{CC + IC} \quad (16)$$

Here CC = Correct Classification and IC = Incorrect Classification.

C. Results

Table I and Fig. 6 shows that precision value (calculated by Eq.13) of proposed model ISWIWD is better than FCMRS model proposed in [10]. ISWIWD considered noise removal by wiener filter which increased the accuracy of work. This paper has enhanced the tumor detection by utilizing genetic algorithm for tumor pixel values identification. Proposed model has improve the work precision value by 1.97%.

TABLE I: PRECISION VALUE BASED COMPARISON

Images	FCMRS	ISWIWD
Set 1	0.91638	0.939224
Set 2	0.982449	0.989285
Set 3	0.970936	0.971748
Set 4	0.992847	0.9929
Set 5	0.922616	0.988989

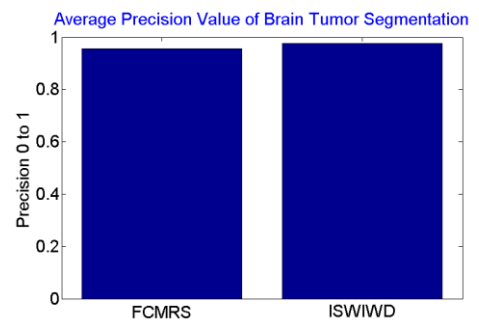


Fig. 6. Average precision value comparison.

Table II shows that use of Intelligent water drop genetic algorithm for segmentation has increased the recall value (calculated by Eq. 14) of ISWIWD model by 1.83%, as compared to FCMRS [10].

TABLE II: RECALL VALUE BASED COMPARISONS

Images	FCMRS	ISWIWD
Set 1	0.98203	0.995084
Set 2	0.988461	0.992106
Set 3	0.936821	0.953804
Set 4	0.922492	0.981652
Set 5	0.993147	0.990236

TABLE III: F-SCORE VALUE BASED COMPARISON

Images	FCMRS	ISWIWD
Set 1	0.947231	0.966347
Set 2	0.985446	0.990192
Set 3	0.953573	0.962692
Set 4	0.956377	0.987244
Set 5	0.956583	0.989612

Table III shows that F-Score value (calculated by Eq. 15) of proposed model ISWIWD is better than previous FCMRS model proposed in [10]. Proposed model pre-processing step of noise removal by Weiner filter has increased the precision and recall which ultimately enhance f-measure parameter as well. This paper has enhanced the tumor detection by utilizing IWD genetic algorithm for tumor pixel value identification. Proposed model has improved the f-measure value by 1.98%.

TABLE IV: PL VALUE BASED COMPARISON

Images	FCMRS	ISWIWD
Set 1	0.992088	0.985087
Set 2	0.998511	0.999195
Set 3	0.993341	0.993813
Set 4	0.996453	0.996282
Set 5	0.854066	0.986695

TABLE V: NL VALUE BASED COMPARISON

Images	FCMRS	ISWIWD
Set 1	0.0803695	0.035239
Set 2	0.0770235	0.0636132
Set 3	0.182979	0.176357
Set 4	0.34127	0.322319
Set 5	0.67075	0.547745

Table IV and V shows that proposed model increased the positive likelihood parameter value (calculated by Eq.11) while decreased the negative likelihood value (calculated by Eq. 12) in all set of images. This is achieved by utilizing the genetic algorithm as use of rough set reduces the pixel selection variety for segment representation.

TABLE VI: ACCURACY VALUE BASED COMPARISON

Images	FCMRS	ISWIWD
Set 1	90.0467	93.6814
Set 2	97.1351	98.059
Set 3	91.1805	92.8481
Set 4	91.6686	97.4908
Set 5	92.805	97.9706

Table VI and Fig. 7 shows the use of Intelligent water drop genetic algorithm for segmentation has increased the accuracy value (calculated by Eq. 16) of ISWIWD model by 3.58%, as compared to FCMRS [10]. Removal of skull has also increased the tumor and non tumor segmentation accuracy.

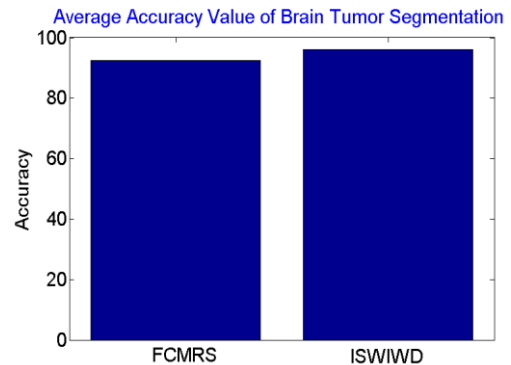


Fig. 7. Average accuracy value comparison.

VI. CONCLUSION

Segmentation of an image plays an important role in medical diagnosis. This paper has resolved this issue by developing a ISWIWD model for image segmentation where three regions are identified first is skull, second is tumor and third is non tumor. Proposed model has applied a weiner filter in the input image which removes unwanted information in form of additive noise. Skull portion of input MRI image may distract the segmentation therefore scanning of image from left to mid and right to mid was done to remove skull part. Finally unsupervised intelligent water drop genetic algorithm was used for the tumor region detection. Experiment was performed on real dataset where results were compared with FCMRS method. It is shown that ISWIWD has improved the work precision value by 1.97%, while accuracy value was enhanced by 3.58%. In future one can develop machine learning method to reduce detection time and improve accuracy as well.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

Ashish Kumar Dehariya conducted the research; Ashish Kumar Dehariya and Pragya Shukla performed experiment and analyzed the data; Ashish Kumar Dehariya wrote the paper under the guidance of Pragya Shukla. Both authors had approved the final version.

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