DOCNN: Double Optimized Convolution Neural Network for Brain Abnormalities Segmentation via MRI

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Research Article

Keywords: Double Optimized-CNN, ABC algorithm, Black widow spider algorithm, Brain Tumor Segmentation, Magnetic resonance imaging

Posted Date: April 22nd, 2022

DOI: https://doi.org/10.21203/rs.3.rs-1526430/v1

DOCNN: Double Optimized Convolution Neural Network for Brain Abnormalities Segmentation via MRI

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Abstract

Brain Image segmentation is the predominate approach used to conquer an isolated anomaly portion of MRI image through proper thresholding strategy adapted in the deep learning model. Hence, it can converge to desire fitness value and thereby, finds optimistic solution to best threshold effectively. However, it may face high computational complexity because of meta-heuristic search of multi-level thresholding in order to console accuracy as well as efficiency. In this paper, an effective segmentation of abnormalities on magnetic resonance imaging (MRI) images using Double Optimized Convolution Neural Network (DOCNN) is proposed. In this method, first, Ant Bee Colony (ABC) algorithm along with Sugeno Fuzzy (SF) logic set is used to extract the salient features by knowing depth of penetration into tissues textures. Thereby, a cell infectious radius and spreading ratio is easily calculated. Second, a best optimistic threshold value is identified without creating any additional complexity by using back widow spider algorithm. When compared to other existing approaches such as Equilibrium optimization (EO), Particle swarm optimization (PSO), Slap swarm optimization (SSO), Genetic algorithm (GA), Firefly algorithm (FA), and Gray wolf optimization (GWO), With Other Deep Learning Models (CNN, RNN, LSTM) the proposed algorithm takes less computational complexity and high accuracy in terms of infectious portion detection. It has proved by estimated parameters such as specificity, precision, and sensitivity, Jaccard index and Dice coefficient index.

Keywords: -- *Double Optimized-CNN; ABC algorithm; Black widow spider algorithm; Brain Tumor Segmentation; Magnetic resonance imaging*

I. Introduction

Many radiologists says that the handling patient with different levels of brain nerves related problem (especially various stages of brain tumors) is being critical task which has required advance computerized based diagnosing system to provide visually enhanced image for accurate anomaly detection and infectious tissue segmentation. Usually, MRI images are preferred for easy segregation of affected and un-affected tissue portions. But it is available in large volume, due to this, processing time goes long and manual operators (radiologist) frustrated of their regular diagnosing campaign which may leads into medical errors. Thereby, it can be avoided, by using advance MRI scanners associated with specialized graphical tools which has categorized tumors region into number of isolation parts in more accurate and faster. Then, the process is referred as Image Segmentation. In addition to this, automatic segmentation process is programmed which gives clear understanding of tumors characteristic with respect to its size, shape, volume, location and type. However, it needs appropriate segmentation algorithm to obtain the desired result. In general, there are five basic techniques are developed based on predefined attributes such as edge, region, threshold, artificial neural network (ANN) and fuzzy for fully automated image segmentation process. In edge-based method applies mathematical operators (Sobel and Laplacian) to measure the pixel intensity variation based on that target boundary is constructed. But, its accuracy level come down in presence of large brain tissues (Cerebrospinal Fluid (CSF), White Matter (WM) & Gray Matter (GM)) and gray level distribution is extremely in wider range. Consequently, region-based method taken for its advance segmentation producer in which a feasible solution can be obtained for inhomogeneous brain images even sustain wide distribution of gray levels. In case of threshold-based method, interested region is isolated from the background by setting appropriate threshold limit which is directly influence the sensitivity and selectivity function. According to the threshold limit, different functions may induce during segmentation. In recent time, researchers prefer ANN for producing an optimistic results and less computational time to access large dataset. Because, it has different set of training parameters and ensures large segmentation banks. The clustering concept is predominately used for image segmentation due to its easy accessibility of large dataset and complex structure. In this, fuzzy c mean clustering is utilized in the proposed framework due to its silent features which is given as follows: (i) assign membership to data points using different fuzzy logic set, (ii) allocate data point to multiple clusters once it satisfies criterion of all, (iii) identify objective function in minimum iteration. The feature extraction is process of collecting data point from the image for further processing to reach out the desired target result. It is possible only if the proper selection of feature is made otherwise, incorrect attributes identifies which may affect the segmentation process. In the proposed framework deployed the Gray Level Co-occurrence Matrix (GLCM) for its effectiveness in the gray level intensity measurement concerned. The optimization techniques provides best suitable solution for any specific target and its computational time values depend on the number of parameters consider on evaluation stage for achieving global solution. Based on that, many optimization techniques are developed and author used the artificial bee colony (ABC) optimization because of its limited number of parameters considered. The parameters such as pixel count, weight vector, pixel difference, cross over probability, mutation probability, and number of adjustment & pitch compensating rate. Later, author utilized Black Widow optimization for further enhancement of segmentation process. It has following advantages such as (i) average convergence ratio, (ii) less iteration involved to reach global solution, (iii) adaptive changes in local parameters. Hence, single stage optimization is not reached the desired the search target to exact analysis of infectious spread and accurate target location detection. It can be resolved by developing heuristic algorithm assisted two-stage optimization that adopted to examine the brain abnormality recorded using MRI scanned image of various modalities.

The organization of paper is given as follows: Section 2 describes contributions of recent articles towards methodologies. In section 3, Authors elaborates the pre-processing, FCM segmentation, and optimizations technique proposed in the research elaborately. The detailed description of proposed a novel Double Optimized Convolutional Neural Network (DOCNN) algorithm and their respective Pseudo code is discussed in section 4. Section 5 briefs the performance of the proposed algorithm in comparison with other traditional methods availed in the literature. Finally, conclusion and future scope is given in section 6.

II. Related Works

In this section, a detailed literature survey has been made on medical image processing methodology and techniques. There are significant number of works contributed for identifying accurate detection of the infectious occupancy in the human body by using conventional as well as soft-computing (SC) based techniques. In earlier days, a normal traditional approach recognized the abnormalities section by applying image fusion method based on Discrete Wavelet Transform (DWT). It provides reasonable pre-processing of MRI image and removed non-readable noisy components using spatial filtering a technique like Gaussian filters [1]. However, the textures color of the brain image affected after applying Image fusion technique. Hence, color contract problems are associated in this method. This problem is overcome by using superior visualization by shift-invariant shearlet transform (SIST) with regional statistics to preserve minimum color distortion and maintain the inner dependency in different high pass frequencies [2]. Here, edge indexing (QAB/F) and mutual information (MI) are evaluated which may take much time to compute the specific task. Then, in order to improve the analyzing strategy of human abnormalities through segmentation approach involved in which entre region is split into number of small region based on threshold value obtained from standard reference image. The adaptive threshold algorithm is used for performing structural based analysis on liver region [3]. It achieved 96% of accuracy in segmentation process and thereby, identified the abnormalities. In addition to this, graph cut and labeling methods, most used for its performance and accuracy [4]. However, it required highly human interactions to capture MRI image in different position in order to acquire their desired structural content. Later, they have concentrated only on specific growing region (lung nodule) with help of quasi-Monte Carlo method which is type of nonlinear mapping [5]. It includes local adaptive algorithm operated under seed selection process collects the feature extraction by mapping fuzzy sets and then extended into accessing coordinate of the probability model involved in the expectation-maximization (EM) algorithm [6-7] performs clustering operation based on cluster head selection. However, it undergoes non-linear adjustment of pixel intensity leads to appear artifacts and degrades the visual quality of the image. It is addressed by possibility based fuzzy approach that minimized the noisy occupancy levels at the end of segmentation phase [8-11]. It improves the neighboring pixel intensity which maintained the quality of the segmented portion. Further, enhanced the segmentation operation, fuzzy C-means (FCM) algorithm is presented and updates its membership function by evaluating fuzzy factor and kernel weigh metric [12-14]. As a result, obtained an efficient segmentation based on clustering strategy. Recently, advance mechanism learning based segmentation is implemented where Convolutional neural network structure is used for training samples through back propagation from supervised and unsupervised approaches [15]. By this way, pre-processing time is reduced and weight updating is done with help of multilayer perception neural network [16]. After this model, a topological based mapping process is initiated for fast trace out of target region in which one-two stage SOM neural network is involved [17-19]. In this, entropy-gradient segmentation algorithm is applied to minimize the color segmentation problem and strong training phase to maintain the tradeoffs between tumors detection and classification [20]. Suppose a special case like tumors classification, semi-supervised method is used which perform feature mapping by self-organizing approach that direct proper modal analysis and produce enhanced segmentation results [21-25]. Rarely, local window grid (3x3) mapping is used due to lower computational complexity. However, it needs histogram equalization based on vector optimization approach [26-30]. Hence, single stage optimization is not reached the desired the search target to exact analysis of infectious spread and accurate target location detection. It can be resolved by developing heuristic algorithm assisted two-stage optimization that adopted to examine the brain abnormality recorded using MRI scanned image of various modalities [31-33]. In this paper, an attempt has been made to develop two stage optimization algorithms (artificial bee colony and Black Widow) for quality detection and evaluation of tumors tissues located in human brain region. In this algorithm, first, extract the salient features of healthy brain MR scan image set as a reference image. It is being compared with the patient MR scan image to estimate cell infectious radius and spreading ratio. Then, it followed by segmentation by using clustering strategy in order to acquire depth of penetration into tissues textures as well cell constraints.

III. Methodology

Figure 1 shows the flowchart of the proposed a novel Double Optimized Convolutional Neural Network (DOCNN) algorithm. The overview of working operation of proposed (DOCNN) algorithm is described as follows. First of all, input MR scan image undergo pre-processing function by using Gaussian filter in order to extract the salient features of healthy brain MR scan image set as a reference image. It is being compared with the patient MR scan image to estimate cell infectious radius and spreading ratio. Then, it followed by segmentation by using clustering strategy in order to acquire depth of penetration into tissues textures as well cell constraints. The quality cluster head is identified after evaluating its membership function with help of Euclidean distance and update weight value involved in the FCM clustering strategy. In addition to this, CNN provides favourable and unfavourable criterion which may helpful to reach minimum membership function much faster. Then, selected segmented region further undergoes first level of parametric optimization is carried by ABC algorithm. It gives two optimistic parameter values which includes local best and global best parameters. Thereby, set the threshold value for obtaining best pixel position which can trace out the entire tumour portion in the affected region. In addition to this, second level of parametric optimization is carried by Black Widow algorithm in which provide assured optimistic parameter for estimating actual radiated region of tumour cell along with fluid rate present in the affected location. The proposed algorithm combines two optimization algorithms which include ABC and Black Widow for better prior detection of infectious portion and radiologist make easy to operate to remove deadly tissues members from human body. When compared to other existing approach, the proposed algorithm takes less computational complexity and high accuracy in terms of infectious portion detection. It has proved by simulation results, such as Sensitivity, Specificity Mean Square Error (MSE) and Peak Signal to Noise Ratio (PSNR). The image data base is acquired from authorized health centres and hospitals.

(a) Gaussian filter and clustering strategies of FCM

The scanned MR image is subjected into pre-processing phase in order to detect the extract board or boundary of the tumour region. Because, mostly, MR scanned image is suffered by Gaussian type of noisy portion accumulate more in the sensitive area due to low level intensity values. Thereby, the Gaussian filter is used to reduce the noisy part and also minimize the pre-processing time which will leads to perform segmentation as early as possible compared with Contrast limited adaptive histogram equalization (CLAHE).

$$G_f = g_{\min} + 1\big/\sqrt{2\pi\alpha}\, e^{v_i^2/2\alpha^2} \qquad (1)$$

Once, the boundary is identified properly then, FCM based clustering strategy is followed to get effective segmentation phase. It is fully depends on Euclidean distance and weight updating of individual pixel present in the infectious spread region. The number of segmented region (cluster group) is formed and each as quality cluster head (CH) which is selected by its minimum Euclidean distance and weight value is being compared with reference standard image. The region where large number of pixel intensity occupancy is scheduled to make more clusters rare than small number of pixel intensity and also the number of pixel count varies between clusters. Because, maximum number of pixel occupancy region may contain actual information about infectious spread. The proper selection of membership function plays significant role in the segmentation process. The CHs selection can be defined form membership functions whose mathematical model is given as follows.

$$J(\mathrm{U},\mathrm{V})=\sum_{i=1}^{C}\sum_{k=1}^{M}\delta_{ik}\left\|x_k-v_i\right\|^2+\alpha\sum_{i=1}^{C}\sum_{k=1}^{M}\delta_{ik}\left\|\overline{x_k}-v_i\right\|^2 \tag{2}$$

Where, X_k be the reference image and its possible number of pixel count be the x_k. Similarly, V_i be the input MR scanned image and its possible number of pixel count be the v_i. then, N_k be the set of neighboring possibility after compared with reference image and δ_{ik} is the membership function is measured by surrounding pixel. The trapezoidal and triangular membership functions represents boundary values (low, very low, high, very high, near, far, few, many, very small and very large) respectively. The cluster size of each group can be selected from input parameters with their linguistic variables.

(b) CNN based Feature Extraction

The feature extraction is an important stage after successfully image segmented into small units. It extracts silent features from each unit which will be feed for advance future analysis to identify the irregular attributes associated in the segmented process. It has obtained by appropriate statistical parameters measured using the image's gray level intensity. Hence, it has helpful to classify affected tissues portion as well as pattern observation problem. According to CNN, second order statistical parameters are involved to compute the textural feature set based on that gray level intensity (minimum 14) is created for each pixel and made reasonable adjustment with neighbouring pixel. Initially, two-dimensional matrix is used to evaluate the spatial property of image where changing pixel intensity according to the occupying frequencies. First, neighbouring pixel appears right hand side of the reference pixel may adjust its pixel intensity value between minimum and maximum threshold limit (i.e. 2 to 256). In addition to this, CNN also provides favourable and unfavourable criterion which may helpful to reach minimum membership function much faster and it further pass over the first level of optimization (ABC algorithm). Because, it involved entropy and contrast is an examine features can clearly shown the higher and lower pixel intensity variation. The training and test phase operation is discussed as follows.

(i)Training Phase:

- Initializing the number of iteration is carried out for finding weight vector and Euclidean distance for effective CH selection. Approximately, set the cluster group size is equal to 30 or it will be adjusted to convergence range.

- Clustering feature sets are extracted in the CNN training phase for identifying extract feature mapping with ground truth images.
- By using equation of $d_{\min}(i)$ and $w(i+1)$ as mentioned in the pseudo code are updating regularly based on the instant weight vector of each frame.
- Similarly, it has continued for all other data sets using step: 6 and 7 in the pseudo code for estimate the cost function as closer to desired target based on the favorable and unfavorable criterion derived from CNN extraction model.
- Once the cost function is converged, then it is fixed for selecting best threshold value by setting local and global factor using ABC and BW optimization algorithms.

(ii) Testing Phase:

- Testing phase is activated if the CNN parameters are not converge then further updating is carried in the weight vector for withstanding best threshold value.
- Every sample output is recorded and it is being validated after entire sample undergoes double optimization algorithms.

(c) Optimization algorithms

In this section, describes the operational steps involved in the two well-known optimization algorithms are Ant Bee Colony (ABC) and Black Widow for better detection of infectious portion and radiologist make easy to operate to remove deadly tissues members from human body.

(i) ABC Optimization:

It is used to find an optimized image for quality analysis of anomaly features appears in each segmented part and the step of pixel intensity optimization of ABC has been given below.

1. The reference pixel is taken after measured the centroid from in and around neighboring pixels intensity. Every iteration, check the threshold limit of pixel, if it is beyond the limit, then, update the present intensity range otherwise, check for next iteration.
2. It updates the pixel population, neighboring pixel difference and centroid point. Thereby, it moves closer to desired point where feature extraction can be efficient.
3. At regular time interval, each Cluster head has chosen based on the updated probability occurrence value of desired membership function. Thereby, find the best possible solution from neighboring pixel of CHs. Hence, the probability occurrence value is obtained by,

$$P_{i,j} = \frac{(\tau_{i,j})^{\alpha}(\eta_{i,j})^{\beta}}{\sum_{j\in N}(\tau_{i,j})^{\alpha}(\eta_{i,j})^{\beta}} \left\langle \therefore \tau_{i,j} = \frac{1}{d_{i,j}} \right. \tag{3}$$

Where, $\tau_{i,j}$ be the updated pixel intensity of next CH selection from source CH, $\eta_{i,j}$ be the intensity range indicator of each pixel and $d_{i,j}$ be the distance between reference pixel and target pixel associated CH.

$$\eta_{i,j} = \frac{x_k - v_i}{\sum_{k \in N} x_k} \tag{4}$$

It regulates the relative weight of the probability occurrence value. In this optimization, the reference pixel effectively evaluate the target pixel intensity at centroid point from a source pixel to corresponding CH depends on the higher probability occurrence value.

(d) Back Widow Optimization:

It is also an another important optimization algorithm provides best possible solution in terms of clustering strategies especially looking for specific outcome expected from the event. It takes minimum measuring parameters such as population size, maximum iteration number and number of design variables. It utilizes the external adjustable criterion in which pixel intensity optimization can be made, thus, obtained best solution that may nearest to feasible solution.

Double Optimized Convolutional Neural Network (DOCNN) Algorithm.

The proposed DOCNN optimization algorithm is described in detail as follows.

Step1: The input MR scan image is pre-processing by using Gaussian filter. It reduces the artificial noise component present on edges of object appears on scanned image. In the filtering process, the optimum number of set sample can be encounter with respect to the distance of neighboring pixel value. It helps lot to do feature extraction (mean and standard deviation) further pre-defined quantity pixel for doing segmentation process.

Step2: The quality cluster heads (centre pixel value) are identified after evaluating the average weighted value of pre-defined quantity pixel from reference image with the excepted distance. Thus, finds uneven distribution of neighboring pixel and calculate minimum Euclidean distance by comparing pixel present in both reference image and input MR scan image.

$$D(t)_{Euclidean} = \min\left\{\sum_t \left(x_k(t) - v_i(t)\right)^2\right\} \tag{5}$$

The membership function selection is achieved after reached the minimum Euclidean distance which shows a best matching unit from effective learning rate of α.

$$v_i(t+1) = v_i(t) + \alpha * G_f * \left(x_k(t) - v_i(t)\right) \tag{6}$$

Where, 't'refer to be iteration terms and $\alpha(t)$ is the learning rate of function with respect to time instant ($\alpha_0 = 0.99$). That is, $\alpha(t) = \alpha_0 * e^{(-t/2T)}$.

Step3: The sufficient number of segmented blocks is generated with help of minimum membership function associated to FCM clustering strategy. The optimistic number of cluster heads with minimum membership function is evaluated by using equation (3) given below.

$$seg_{Optimum} = \min J(\mathrm{U},\mathrm{V}) \tag{7}$$

Where, $\mathrm{U} = (\delta_{ik})_{C\times N}$ is the membership matrix and $\mathrm{V} = (v_1, v_2, ...v_C)$ be the set of identified cluster heads. The Euclidean distance and weight value is continuously updated until get the minimum value of pixel distance as well weight value. In addition to this, GLCM provides favorable and unfavorable criterion which may helpful to reach minimum membership function much faster and it further pass over the first level of optimization (ABC algorithm). Because, it involved entropy and contrast is an examine features can clearly shown the higher and lower pixel intensity variation.

$$A = \begin{cases} 1 \quad if \quad J(\mathrm{U},\mathrm{V}) = x_k \ \& \ J(\mathrm{U},\mathrm{V})\big|_{\delta_{ik}} = v_i \\ 0 \qquad\qquad elsewhere \end{cases} \tag{8}$$

<u>Step4:</u> Each segmented block is applied to ABC optimization algorithm in which two optimistic parameter values are identified such as local best (γ_{local}) and global best (γ_{global}) parameters. After that, the threshold value is set for obtaining best pixel position which can trace out the entire tumors portion in the affected region.

$$v'_i(t+1) = \begin{cases} x_k + \phi_k\left(x_k(t) - v_i(t)\right) & v_i(t) < v_i(t+1) \quad ; \quad \gamma_{Local} \\ \qquad x_k & \qquad otherwise \qquad ; \quad \gamma_{Gobal} \end{cases} \tag{9}$$

<u>Step5:</u> Let as denote $\left(O_1(t)_{ABC_{threshold}}\right)$ be the threshold value obtained from first level optimization using ABC algorithm. It consists of two scalar values namely $\min\left(O_1(t)_{ABC_{threshold}}\right)$ and $\max\left(O_1(t)_{ABC_{threshold}}\right)$ respectively.

$$O_1(t)_{ABC_{threshold}} = \left\{ \frac{\min\left(O_1(t)_{ABC_{threshold}}\right) + \max\left(O_1(t)_{ABC_{threshold}}\right)}{2} \right\} \tag{10}$$

<u>Step6:</u> In addition to this, global best (γ_{global}) parameters are combined to take average value which in turn selects the new threshold value $\left(O_1(t)_{Threshold(ABC)}\right)_{Updated}$

$$\left(O_1(t)_{ABC_{threshold}}\right)_{Updated} = O_1(t)_{ABC_{threshold}} + \gamma_{Gobal} \tag{11}$$

<u>Step7:</u> Then, second level optimization is followed by Black Widow algorithm and its segmented value is denoted as BW_{seg}. normally, it contains previous iteration updated nearest neighboring pixel values (i.e. $BW_{seg} = v'_i(t+1)$). Sometime, after first level segmentation few pixel intensity remains same due to artifact noisy present. It checks the condition for re-evaluation of optimum parameter is required by using Eq. (12).

$$\left(BW_{seg}\right)_{Updated} = \left(BW_{seg}\right) > \left(O_1(t)_{ABC_{threshold}}\right)_{Updated} \tag{12}$$

Step8: The actual radiated region of tumors cell is estimated along with fluid rate present in the affected location using Eq. (13).

$$\mathrm{Img}_{Tumor\_Seg} = \left(BW_{seg}\right) - \left(BW_{seg}\right)_{Updated} \quad (13)$$

The different form of affected region can be identified through these values such as $\left(BW_{seg}\right)$, $\left(BW_{seg}\right)_{Updated}$ and Img_{Tumor_Seg}.

Step9: Eq. (14) gives addition of two terms Img_{Tumor_Seg} and $\left(BW_{seg}\right)_{Updated}$ which explore deliverance of results than others. In that shows the high accuracy in terms of infectious portion detection as well as estimate radiated region.

$$\mathrm{Im}\,g_{Final\_Seg} = \mathrm{Img}_{Tumor\_Seg} + \left(BW_{seg}\right)_{Updated} \quad (14)$$

(e) Pseudo code of proposed DOCNN

Algorithm: DOCNN	
#1	**Initiation of parameters:** $\alpha, p(f), g_{\min}, X_k, v_i, \delta_{ik}$
#2	Apply Gaussian filter for removal of artefact components using Eq. (1)
CNN based feature extraction and clustering starts:	
#3	**Set** no of possible neighbours pixel per cluster N_R
#4	Calculate minimum Euclidean distance and Weight updating
#5	**for** i=I to N_R do
#6	$d_{\min}(i) = \min\left(\sum_i (x_k - v_i)^2\right)$
#7	$w(i+1) = w(i) + \alpha * (x_k - w(i))$
#8	**End**
First Level Optimization (ABC algorithm):	
#9	Initialize no of segmented block denoted as $SN = \{x_1, x_2, x_3 .... x_k\}$
#10	**for** i=1 to SN do
#11	Apply a greedy selection process between v_i and x_k and select the better one
#12	Obtain local best (γ_{local}) and global best (γ_{global}) parameters
#13	Continues check: **if** $\left(O_1(t)_{ABC_{threshold}}\right) = \min\left(O_1(t)_{ABC_{threshold}}\right)$
#14	Retain previous state value
#15	**else if** $\left(O_1(t)_{ABC_{threshold}}\right) = \max\left(O_1(t)_{ABC_{threshold}}\right)$
#16	Again, update (γ_{local}) and (γ_{global})
#17	To get $\left(O_1(t)_{ABC_{threshold}}\right)_{Updated}$ by taking average of min, max and global values
#18	**End**
#19	**End**

Second Level Optimization (Black Widow algorithm):	
#20	Set BW_{seg} value
#21	**for** i=1 to SN do
#22	Continues check: **if** $\left(BW_{seg}\right)_{Updated} = \left(BW_{seg}\right) > \left(O_1\left(t\right)_{ABC_{threshold}}\right)_{Updated}$
#23	Then, further re-evaluation of optimum parameter is required
#24	**Else**
#25	Retain previous state value
#26	**End**
#27	**End**
#28	The actual radiated region of tumour cell is estimated $\mathrm{Img}_{Tumor\_Seg} = \left(BW_{seg}\right) - \left(BW_{seg}\right)_{Updated}$
#29	The different form of affected region can be identified by $\left(BW_{seg}\right)$, $\left(BW_{seg}\right)_{Updated}$

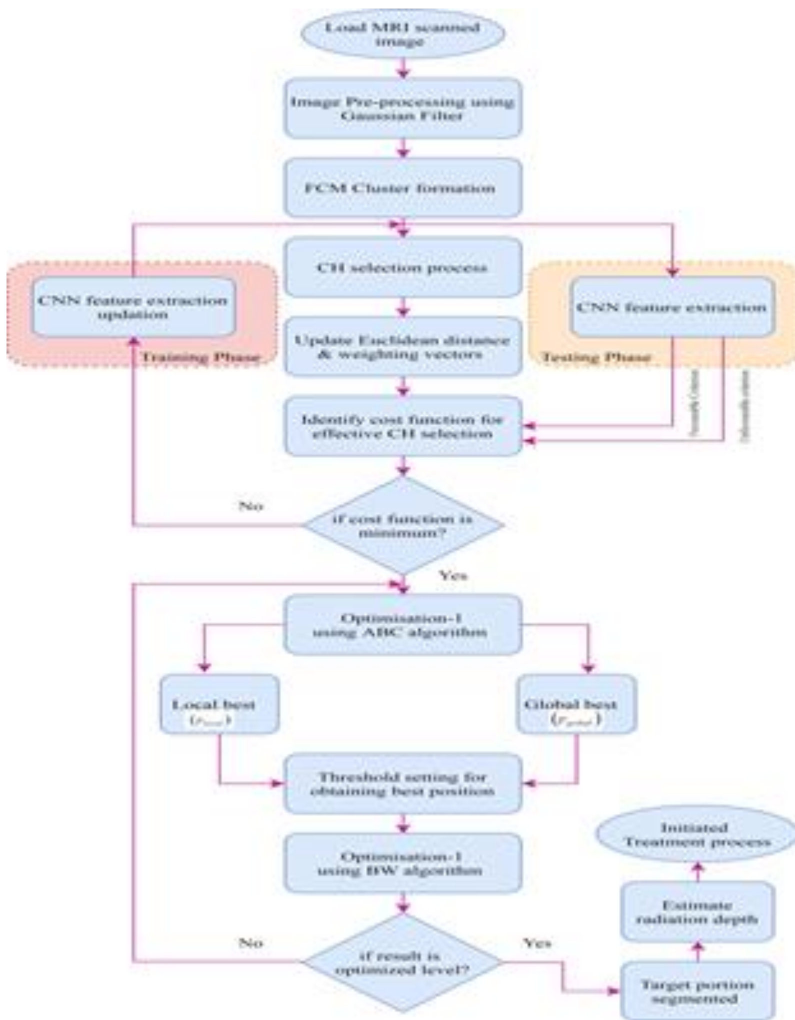


Figure 1: Flowchart of the proposed a novel double optimized convolutional neural network (DOCNN)

V. Result and Discussion

In this section explores the qualitative and quantitative evaluation of segmented image carrying different tumor complaints associated with MRI scanned brain images. The proposed DOCNN framework is accurately identified the tumor region by enhancing the visual quality of segmented image through double optimization approach includes Black Widow and ABC. The BW-ABC-CNN output is comprehensively compared with other existing PSO-RNN, GWO-LSTM algorithm results to understand the progressive improvement achieved by proposed DOCNN framework towards the tumor region detection. The brain region is usually occupancy of large number of tissues which is classified into Cerebrospinal Fluid (CSF), White Matter (WM) & Gray Matter (GM). The deadly inactive tissues undergone cell manipulation process and further develop into tumor block. It is very much difficult to find infectious level of the tumor block in these multifaceted tissue layers. Thereby, it is necessary to have an efficient soft computing technique which can identify the infectious level as well as tumor size accurately. In this paper, a novel double optimization framework is proposed to enhance the accuracy of detection process in the segmented images and also fulfilled the target detection efficiently. For analysis purpose, nearly, 25 clinical brain images are taken from BRATS 2019 dataset with different carcinoma tumor complaints such as Primitive Neuro-Ectodermal, Meningioma and Astrocytoma. The proposed work mainly focus on proper segmentation of MR image based on FCM clustering, extract statistical features of individual segmented image through BW-ABC-CNN and further enhance the segmented image using double optimization approach (ABC and Black Widow algorithm). The output of the proposed framework compared with the traditional methods using key performance metrics like Mean Squared Error (MSE), Dice-Coefficient index (DOI), and Peak Signal to Noise Ratio (PSNR).

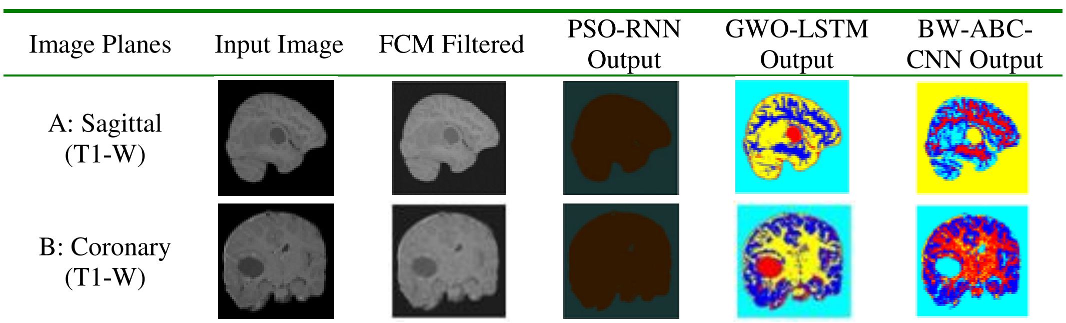


Fig.1 Segmented output image associated with Primitive Neuro-Ectodermal Carcinoma (PNEC) complaint

In fig.1 shows the BW-ABC-CNN segmented output image associated with Primitive Neuro-Ectodermal Carcinoma (PNEC) complaint. For better visualization of the infectious portion, consider the input image in three different structural views includes axial, sagittal and coronal slice. It is clearly represented in fig.1 (A) – (C). While analyzing the PNEC affects MRI scanned images, it is inferred that there are many round shape cells having closer appearance which is difficult to isolate the tumor region alone from high degree of similarity region. The proposed framework has given proper segmentation of CSF, WM & GM regions and visually enhanced the segmented image for tumor region detection in the PNEC affects MRI scanned images. It is evidently shown in the fifth column of fig.1 (A) – (C) respectively. Thus, implies the proposed DOCNN framework achieved high accuracy of tumor region detection and obtained reasonable segmentation of CSF, WM & GM regions as compared with FCM and GWO-LSTM results.

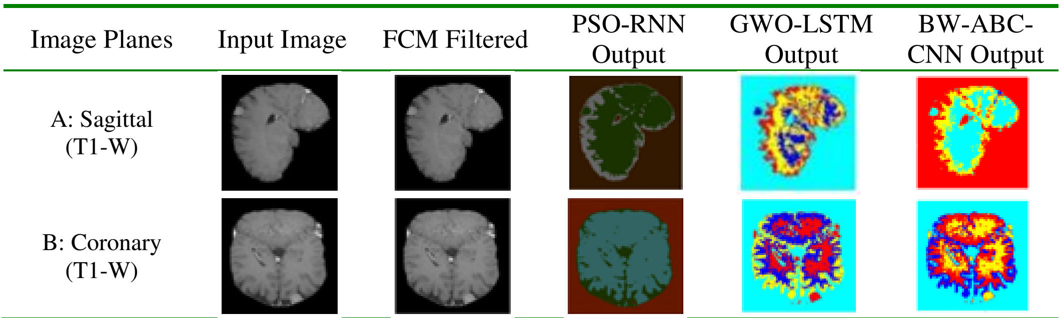


Fig.2 Segmented output image associated with Meningioma tumor complaint

In fig.2 shows the BW-ABC-CNN segmented output image associated with Meningioma tumor complaint. It is normally formed in the outer membrane of human brain especially outlet point towards spiral cord. Hence, it has appeared narrow curved like cylindrical structure which is similar to other tentorium layers. Therefore, it is very much indeed to segment infectious portion from the non affected region. The partial detection of tumor is obtained by FCM and GWO-LSTM due to irregular segmentation output which is clearly shown in the third and fourth column of fig.2 (A) – (C) respectively. As a result, poor segmentation of CSF, WM & GM regions and visual quality of segmented image is seriously degraded. It has been augmented by the proposed BW-ABC-CNN framework, which can improvise by making proper segmentation and enhanced the accuracy of tumor region detection as compared with PSO-RNN and GWO-LSTM results. It is evidently proven in the fifth column of fig.2 (A) – (C) respectively.

In fig.3 shows the BW-ABC-CNN segmented output image associated with Astrocytoma Carcinoma tumor complaint. The region of infectious mainly on astrocytes which is star shaped structure made up of glial cell groups. Usually, it appears low intensity region where the tumor isolated part is difficult to trace out. But, the proposed BW-ABC-CNN framework is reasonable good for intensity variation in which effectively detected the tumor region and also achieved better segmentation of CSF, WM & GM regions. It is evidently proven as compared with PSO-RNN and GWO-LSTM results which are given in the third and fourth column of fig.3 (A) – (C) respectively. The BW-ABC-CNN segmented output image has maintained proper tradeoff between edema portion and tumor region in turn induced healthy diagnosis of the Astrocytoma Carcinoma tumor complaint. It is clearly inferred in the fifth column of fig.3 (A) – (C) respectively.

In fig. 4 shows the segmented output results of both low and high-grade glioma images. From the fifth column of fig.4 (A) – (E), inferred that the BW-ABC-CNN segmented output image has maintained proper tradeoff between low and high-grade glioma and provided healthy diagnosis of detected tumor region complaint. In fig. 4 illustrate the segmented output of the proposed BW-ABC-CNN framework processed on the high and low brain images received from the BRATS 2019 dataset. The experimental results conveyed that the proposed BW-ABC-CNN framework holds effective and robust segmentation on MRI scanned images, and the same can be verified with ground truth images.

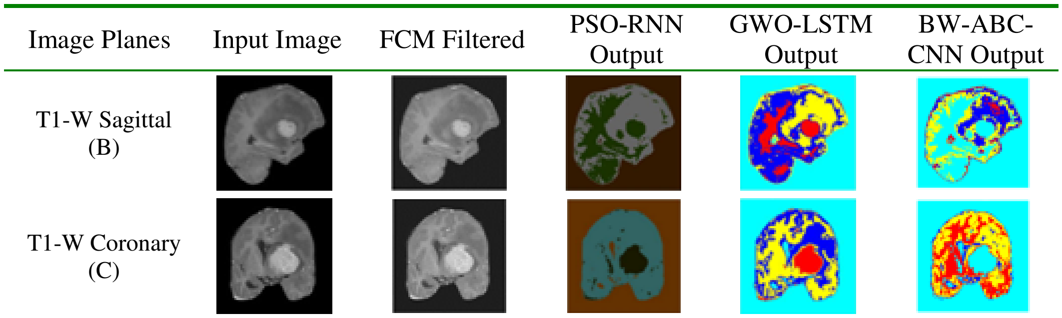


Fig.3 Segmented output image associated with Astrocytoma Carcinoma tumor complaint

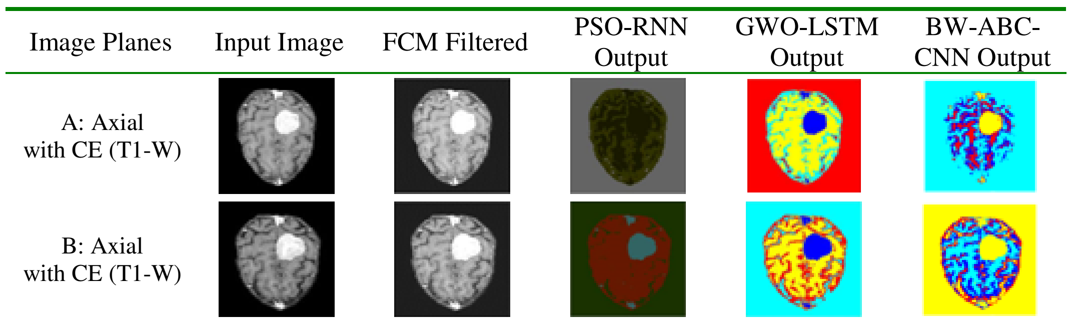
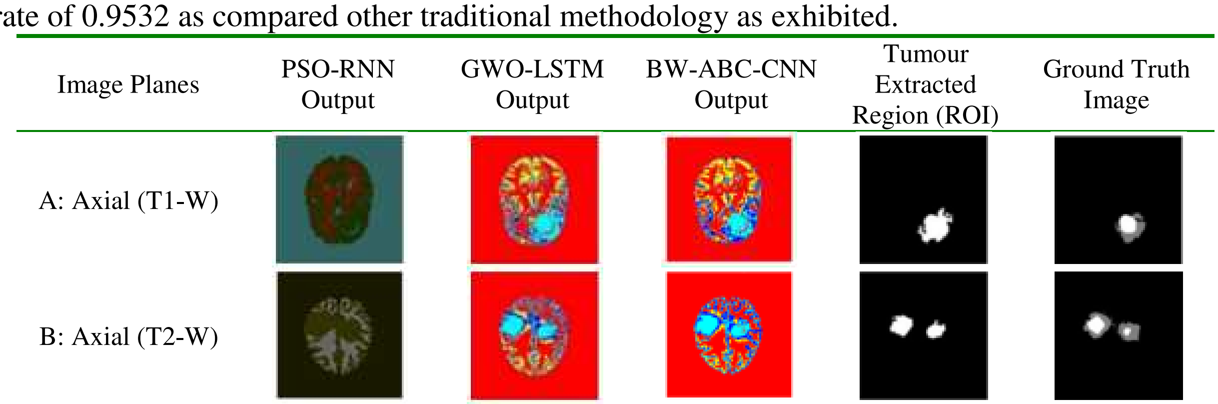


Fig. 4 shows the segmented output results of both low and high-grade glioma images.

The detailed analysis can be carried on BRATS 2019 dataset for identifying the similarity index occurs between detected tumor region and its ground truth images. It is evidently shown that the proposed BW-ABC-CNN framework has achieved accurate detection of tumor region by enhancing the visual quality of segmented image for maximum number of images available in the BRATS 2019 dataset. It is clearly exhibited in fig.5-(d), (e) for high grade and fig. 5- (k), (l) for low grade images. It has conveyed the proper identification of boundaries of affected region and reduced number of false detection due to improper segmentation of the tumor portion. On the whole, the proposed BW-ABC-CNN framework yield maximum protection against false detection by extracting similarity index between closer regions which has been improved in the rate of 0.9532 as compared other traditional methodology as exhibited.



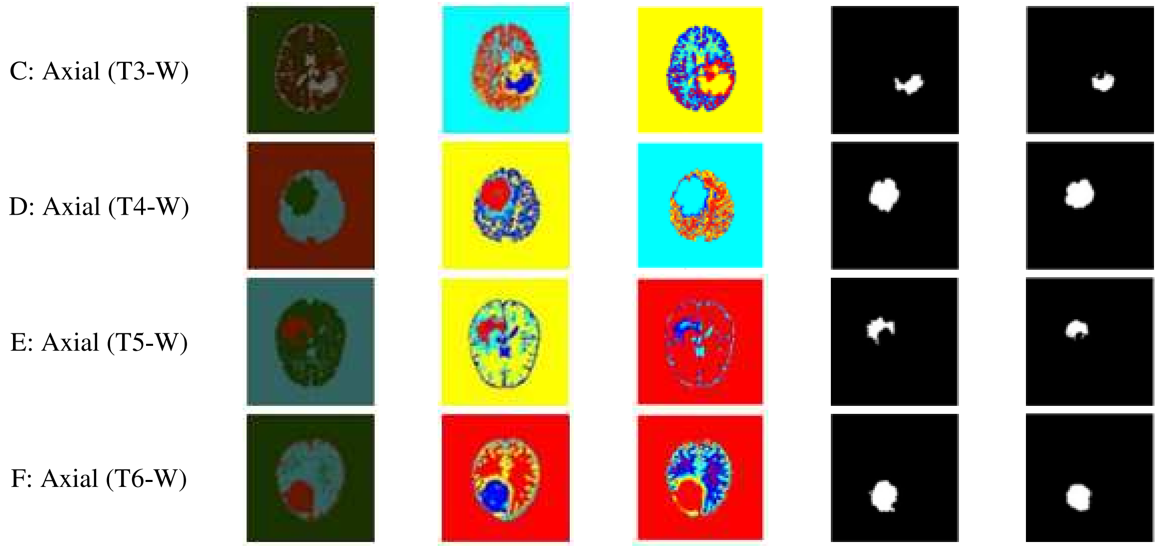


Fig.5 Identifying the similarity index occurs between detected tumor region and its ground truth images.

(a) Performance Evaluation Metrics

(i) Mean Squared Error Index (MSE)

It is evaluating parameter used to calculate the performance accuracy of proposed BW-ABC-CNN framework by analyzing variation observed between input image and processed (output) image. Usually, errors are induced at every stage of image processing which can be estimated by using MSE. Even if the variation is too low, MSE can give the accurate error value irrespective of intensity scale variation. Visually, there is no much difference observed in the processed image but it has error occupying at the high- and low-level intensity region. The mathematical expression for MSE is given below.

$$MSE = \frac{1}{R \times C} \sum_{i=1}^{R} \sum_{j=1}^{C} \left\{ In\_\mathrm{Im}\,g(\mathrm{i,j}) - Out\_\mathrm{Im}\,g(\mathrm{i,j}) \right\}^2$$

Where, $In\_\mathrm{Im}\,g(\mathrm{i,j})$ and $Out\_\mathrm{Im}\,g(\mathrm{i,j})$ denotes the input image and output image with maximum row size of R and column size of C respectively. Based upon the value, the performance accuracy has been evaluated. In fig.9 shows the MSE comparison chart between proposed BW-ABC-CNN framework and other traditional methods. It is clearly shows that the BW-ABC-CNN segmented output image has occupied less error around 1.006 which is reasonably low as compared with other PSO-RNN and GWO-LSTM results. Thus, indicate the proposed BW-ABC-CNN framework is more effective in terms of high and low level intensity variation.

(ii) Peak Signal to Noise Ratio (PSNR)

It is another evaluating parameter to measure noise induction associated in the processed image. It has included wide range of spectral components to which the signal strength can be measured. PSNR value purely depends on intensity of noisy component that can vary with respect to signal strength. It is clearly noticed that the proposed BW-ABC-CNN framework produced high PSNR value which represents minimum occupancy of noise intrusion in the processed segmented image. In general, it has been measured in decibels that can accommodate wide range of values. It is given by

$$PSNR = 10\log_{10}\left(\frac{(P_{\max})^2}{MSE}\right)$$

Where, $P_{\max}$ represents the maximum range of pixel values (i.e. $P_{\max} = 255$). The experimental results of proposed BW-ABC-CNN framework obtained the PSNR value around 50.983 dB which is comparatively high with respect to other traditional methods.

(iii) Jaccard Index or Tanimoto Coefficient Index (TC)

It is defined as ratio of pixel overlapping function occurs between segmented image and ground truth image. Otherwise, it is also defined as correlation metric which brings similarity index associated with processed image and input image. That means, the correlation metric filled with 0's and 1's which represents minimum and maximum correlation existence between two images. It is also referred as Intersection over Union (IoU). When mentioned in percentage, the proposed BW-ABC-CNN framework produces an average TC value of 65.30%, which is superior to the other peer algorithms stated in this work like GWO-LSTM (28.23%), and PSO-RNN (21.54%), and the same is exhibited in Fig. 5.

(iv) Dice Coefficient Index (DOI)

It is kind of another correlation metric as similar to Jaccard Index. It can measure closer similarity appears in the low level intensity region of both segmented image and input image. It gives additional weight factor to ensure the accuracy of correlated coefficient values obtained when having closer similarity associated in the intensity scale. It is mathematically expressed as

$$DOI(r,c) = \frac{2\times(r\cap c)}{r+c}$$

The correlated coefficient values changes between 0 and 1. Where, '0' denotes low similarity index and 1 denotes high similarity index. It exhibits that the proposed BW-ABC-CNN framework produces the best DOI value of 81.9% (expressed in percentage) compared to other traditional methods specified in this work. Similarly, accuracy of the proposed BW-ABC-CNN framework has produced maximum accuracy (98.12%) in percentage as compared with GWO-LSTM (96.76%), and PSO-RNN (92.23) respectively. It is clearly observed that the high accuracy percentage is obtained by using proposed BW-ABC-CNN framework, as mentioned din Table.1. Thereby, it supports earlier prediction of infectious depth as well as promotes proper treatment by the authenticated surgeon.

Table. 1 Comparative analysis of the IoU, accuracy and variance on brain tumor diagnosis using BRATS 2019 dataset.

Method	IoU (in %)	Accuracy (in %)	Variance (in %)
PSO-RNN Output	21.54	92.23	0.8
GWO-LSTM Output	28.23	96.76	0.6
BW-ABC-CNN Output	65.30	98.12	0.4

In order to ensure the quality measurement of anomaly detection and separation based on the effective classifiers. It is being tested by calculating the three important factors such as specificity, precision, and sensitivity that can be evaluated by using Equ. (15), (16) and (17).

$$\text{Precision}=TP/TP+FP' \tag{15}$$

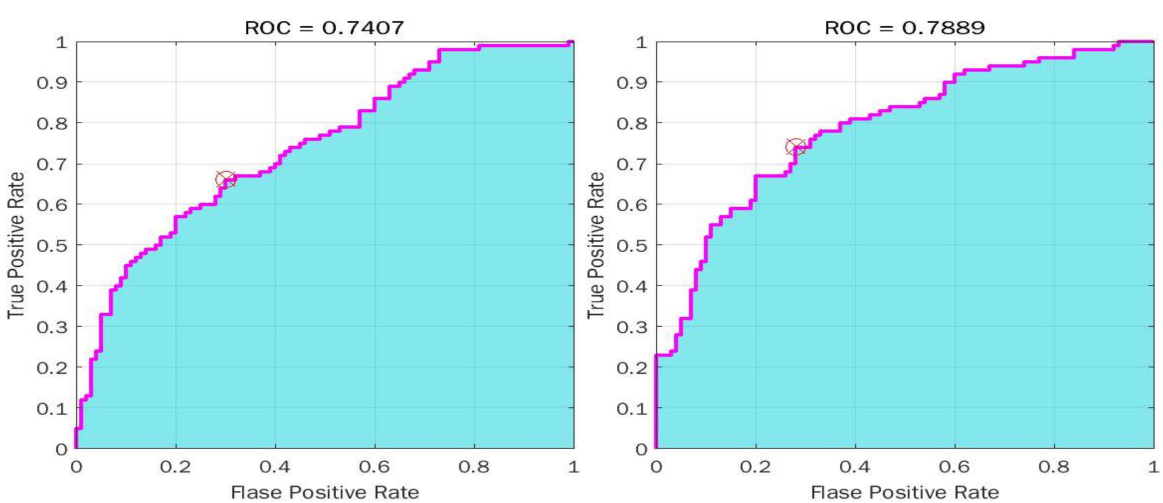
$$\text{Sensitivity}=TP/TP+FN' \tag{16}$$

$$\text{Specificity}=TN/TP+FP' \tag{17}$$

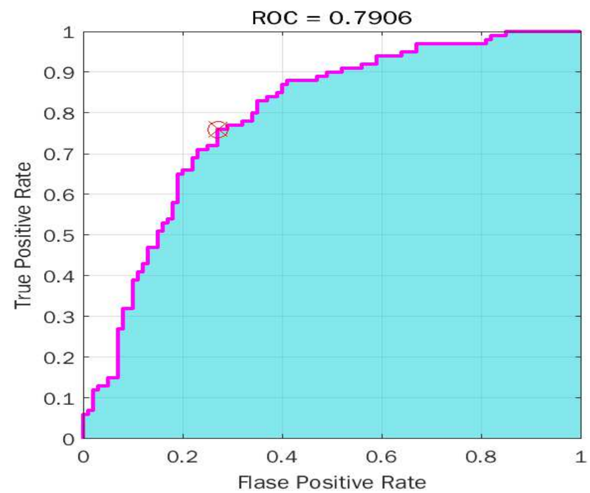
Where 'FP', 'TP', and 'TN' indicates false positives rate, true positives rate and true negatives rate respectively. Table.2 shows the anomaly detection results of the proposed BW-ABC-CNN framework that can segment target region accurately for three different tumor complaint includes Primitive Neuro-Ectodermal Carcinoma, Meningioma Carcinoma and Astrocytoma Carcinoma.

Table 2: Results of the proposed BW-ABC-CNN framework for anomaly detection and segmentation.

Tumor Compliant Type	Precision (in %)	Specificity (in %)	Sensitivity (in %)
Neuro-Ectodermal	96.16	94.79	95.42
Meningioma	95.00	96.07	97.55
Astrocytoma	97.25	97.30	98.15



(a) (b)



(c)

Fig.6 ROC interpretation curve (a) PSO-RNN, (b) GWO-LSTM and (c) BW-ABC-CNN

Fig.6 shows the ROC interpretation curve of the proposed BW-ABC-CNN framework on MRI image segmentation is being matched with GWO-LSTM and PSO-RNN respectively. It is clearly identified that the ROC value of 0.7407 is obtained by comparing both expected and predicted threshold value (true positive rate (TPR) and false positive rate (FPR)) of the PSO-RNN. It is clearly observed in Fig.6 (a). Similarly, the ROC value of 0.7889 and 0.7906 are obtained for both GWO-LSTM and BW-ABC-CNN respectively. It is conveyed that TPR and FPR are show significant improvement as well as tradeoff ratio maintained between two approach is clearly observed in Fig.8 (b) and (c) respectively.

Conclusion

In this paper, a new framework was proposed to conquer an isolated anomaly portion of MRI image through proper thresholding strategy. Based on this, accurate fitness value is obtained and thereby, finds optimistic solution to best threshold effectively by using Double Optimized Convolution Neural Network (DOCNN). That is, first, Ant Bee Colony (ABC) algorithm along with Sugeno Fuzzy (SF) logic set is used to extract the salient features by knowing depth of penetration into tissues textures. Thereby, a cell infectious radius and spreading ratio is easily calculated. Second, a best optimistic threshold value is identified without creating any additional complexity by using back widow spider algorithm. Thereby, a meta-heuristic search of multi-level thresholding is optimized and consoled accuracy as well as efficiency. It has reached out through effective classifier from feature extraction based on convolutional neural network. It exhibited that the proposed BW-ABC-CNN framework produces the best DOI value of 81.9% (expressed in percentage) compared to other traditional methods specified in this work. Similarly, accuracy of the proposed BW-ABC-CNN framework has produced maximum accuracy (98.12%) in percentage as compared with GWO-LSTM (96.76%), and PSO-RNN (92.23) respectively. In the future, high performance automated anomaly diagnosis system is super-imposed by altering structural modification in the proposed BW-ABC-CNN framework that can supports other medical complaints associated to the human body.

Funding Information

No funds, grants, or other support was received.

Ethics Approval

Not applicable

Consent to participate

Not applicable

Consent to Publish

Not applicable

Declaration of interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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