Open Comput. Sci. 2021; 11:380–390 DE GRUYTER

Research Article

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Segmentation of MRI Brain Tumor Image using Optimization based Deep Convolutional Neural networks (DCNN)

https://doi.org/10.1515/comp-2020-0166
Received Apr 28, 2020; accepted May 28, 2020

Abstract: Segmentation of brain image should be done accurately as it can help to predict deadly brain tumor disease so that it can be possible to control the malicious segments of brain image if known beforehand. The accuracy of the brain tumor analysis can be enhanced through the brain tumor segmentation procedure. Earlier DCNN models do not consider the weights as of learning instances which may decrease accuracy levels of the segmentation procedure. Considering the above point, we have suggested a framework for optimizing the network parameters such as weight and bias vector of DCNN models using swarm intelligent based algorithms like Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Gray Wolf Optimization (GWO) and Whale Optimization Algorithm (WOA). The simulation results reveals that the WOA optimized DCNN segmentation model is outperformed than other three optimization based DCNN models *i.e.*, GA-DCNN, PSO-DCNN, GWO-DCNN.

Keywords: Brain image segmentation, CNN, PSO, GWO, WAO

1 Introduction

Image analysis is a primary function in medical diagnosis and test [1, 2]. The major health issues in the world are brain irregularities like tumor and brain stroke. It involves the public irrespective of femininity and ecology. Generally, the brain abnormality is diagnosed on a predefined procedure constructed by experienced doctors. The brain images kept under a control environment. Once the recording process is finished, the required information from the patient is executed in a screening procedure by guided or automatic methods to review the causes and condition of severity. The evaluation process is executed with the patient to control and cure the abnormalities after the screening process [3].

Generally, the state of the brain is calculated based on channel and multiple channel EEG signals. It is evidenced by the outside electrodes or the brain images documented by MRI imaging advances [4–7]. Earlier lessons prove that the in-sequence of the brain is necessary to categorize and confine the abnormalities as contrasted to the strong brain signs [8]. Other methods can be applied to plot brain signals and use images to put reason and area of brain abnormalities. In content, a soft computing directed actions be used to observe the CT and MRI brain images [9, 10]. MRI grasps a variety of modalities style such as T1 T1C, T2 and DW [11, 12, 14]. The observable of irregularity in T2 and Flair are better and aimed for testing. To assess the brain anomaly, some soft computing methods are implemented. Some mechanisms also propose to apply a single step or two step process to segment the irregular part for a selected MRI piece [11, 15, 16]. Many of these processes are fine for few modalities, for example flair and T2. The heuristic algorithms supporting two steps occurrence are widely accepted to challenge this pitfall. It is inspected better in the brain abnormalities verification by MRI of Varity of modalities.

Palini *et al.* [8] implements otsus thresholding procedurean advance soft-computingsoft computing to divide sion the flexible brain tissues [4, 5]. Chaddad [17] applied Gausian mixture method to extract features of MRI brain tumor. Day *et al.* [6] used genetic algorithm to eliminate brain MRI noise

A specified estimation of advance brain tumor segmentation is discussed by Rajinikantha and Satapthy [9]. The authors realized a variety of heuristic measures to split the irregularities of brain MRI recorded by different modalities. They state that image a fusion technique is needed to improve the correctness of brain MRI assessment [13]. Amin *et al.* [4, 5] suggested a unique advance of deep a learning approach to mine the irregular parts of the brain MRI.

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Every deep learning and machine learning approach has advantages and disadvantages. The assessment process of MRI brain images should well organized and consistent to take out and asses the ROI of brain images [19]. Already a remarkable study has been done to implement evolutionary/swarm to assess brain MRI segmentations [9, 13]. The work done by Author [20] adopted a new tactic using Jaya algorithm. This work confirms that Jaya algorithm is easy compared to previous heuristic algorithms. The study used the chan-vese technique to extract the tumor part in processed brain images. The quality of execution is verified by a better assessment among the mined tumor part and the images in GT [9]. Author [28] test the optimization of CNN using two different datasets *i.e.*, Dermquest and DermIS. The outcomes can be balanced with different techniques like AlexNet, Ordinary CNN, VGG-16, and ResNet etc. Their proposed method achieved better performance.

In this paper [29], a DCNN Model is considered. The Adapt Ahead optimization algorithm enriches the accuracy and decreases losing functions from the training procedure of the model. In this version of training procedure, version-based optimisation algorithms are presented to test the loss in evaluation contrasted to the optimization algorithm that was proposed. This algorithm is more suitable than other marketing algorithms that are based on the BRATS Dataset. From the reviewed literature, we noted that neural system models give promising outcomes in almost each and every field. Convolutional neural networks also perform well in image processing. Optimization algorithms have been employed in these neural network models to set optimized values for model parameters. This combination enhances the performance of the model by converging it faster. As such, we got motivated to use this hybrid composition of optimization algorithms with deep learning neural system for segmentation of brain images. In this context, we propose a hybrid framework to extract the tumor section by optimization based on the DCNN model to mine the irregular part in the (2D) slices of the MRI brain images. We consider swarm-based optimization algorithms like genetic algorithm (GA), particle swarm optimization (PSO), gray wolf optimization (GWO) for comparison [20]. These optimization algorithms have proved their efficacy in almost all research domains.

The organization of rest of the paper is described as follows. Section 2 elaborates the preliminaries and details of optimization algorithms. The working principle of the proposed method *i.e.*, optimization based DCNN model is elaborated in section 3. Section 4 focuses on experiments and discussing the result. Finally, the conclusion of this study is presented in section 5.

2 Material and methods

Neural network presents notable performance in various research works. To handle complex applications, researchers have assumed the development of typical neural networks. The most important and advanced neural network is the deep learning neural network. In this work, we use optimization algorithm in a convolution neural network, like particle swarm optimization (PSO), genetic algorithm (GA), gray wolf optimization (GWO) and whale optimization algorithm (WOA). The use of these optimization techniques in the training process is to optimize the output of the result vector on DCNN and advance segmentation accuracy. This study the MRI brain tumor images from BTARTS 2015 dataset. This dataset contains 220 subjects with high grade and 54 subjects with low grade gliomas. For testing, 53 subjects with mixed high- and low-grade gliomas were used.

2.1 Particle swarm optimization (PSO)

Particle swarm optimization (PSO) is a population based stochastic approach. It is used to solve nonstop and distinct optimization problems. In PSO, a simple of possible solution is called particle. It reaches a global solution by updating its position and velocity. In PSO, no particle dies or gets eliminated rather it continuously upgrades itself towards better and improved moves while exploring the space of an optimization dilemma.

2.2 Genetic algorithm (GA)

The restriction and also un-constraint optimization issue is solved with genetic algorithm (GA). It can be a more customary selection process that imitates the all-natural advancements. The process is most currently modifying a populace of remedies to generate a population of points at each iteration. The best point in the population approaches an optimal solution. It works by using the generated points to produce the offspring. At the path of the solution that is optimal/optimally, the inhabitants grow after productions.

2.3 Gray wolves optimization Algorithm (GWO)

Gray wolves optimization is a new meta-heuristic, novel optimization algorithm globally used to get global optimum solution. It mimics the nature of hunting mechanism by following the management hierarchy, four types of grey wolves are used to achieve the hierarchy of guidance in this optimization algorithm. They are alpha, beta, delta, and omega. To get the global optimum value, three major steps of hunting are followed: search for prey, encircle the prey and attack the prey as elaborated in [25].

2.4 Whale optimization algorithm (WOA)

Whale optimization Algorithm [22] maximize problems by mapping humpback whales' monitoring activities. Feeding method (the behavior) can also be seen from humpback whales. The whales make the bubbles utilizing feeding. This algorithm consists of a few measures; bubble-net foraging operation of humpback whales, exploring for prey, and encompassing prey.

Encircling prey

The victim is located by humpback whale and then encompasses it. The finest application solution that is the best solution obtained that is much closer to the actual solution. After getting the finest candidate solution, the options or agents make an effort to revise their positions in the path of broker or perhaps the best hunt alternative utilizing equations (1) and (2)

$$D = |C.X^*(t) - X(t)| \tag{1}$$

$$X(t+1) = X^*(t) - A \cdot D \tag{2}$$

Wherever t is the existing loop A along with Do are coefficient vectors, X^* is the place Vector of the best solution, and also X suggests the positioning vector of a solution, || could be your total value. The vectors A along with C are computed as follows:

$$A = 2a \cdot r - a \tag{3}$$

$$C = 2 \cdot r \tag{4}$$

Where's that a is linearly decreased from 2 to 0 within the span of the iteration and r is an arbitrary digit [0, 1].

Bubble-net attacking method

The technique is utilized by Whales to strike the prey. It is made of two strategies:

(a) Shrinking Encircling Mechanism

In this strategy, the whales analyze by decreasing the worthiness of equation (3). Note the array of A is additionally reduced from the value of "that a". In different hand, A is really a value in the interval $[a, a]$ where a person is decreased across iterations' manner. Putting random worth for A [−1, 1], the book location of an internet research agent might be described anywhere between the very first position of this agent and also the position of the current best agent.

(b) Spiral Updating Position

In this process, a spiral formula is made between the job of whale and prey to mimic the exact whirl-shaped movement of humpback whales as follows

$$D' = |X^*(t) - X(t) \tag{5}$$

$$X(t+1) = D \cdot e^b l \cdot \cos(2\pi l) + X^*(t) \tag{6}$$

Where prey, b is invariable and vector D (is now the space among the whale) defines the shape, l is random in [−1,1] and is a factor-by-factor multiplication. Assuming A probability of 50%, choosing either or the surrounding movement, spiral model motion is simulated during iterations of the algorithm got using the following equation:

$$\begin{cases} X(t+1) = X^*(t) - A \cdot D & \text{if } p < 0.5 \\ D \cdot e^b l \cdot \cos(2\pi l) + X^*(t) & \text{if } p \geq 0.5 \end{cases} \tag{7}$$

Wherever p is an arbitrary numeral in [0, 1].

Search for prey

In the bubble-net process, humpback whales attempt to find prey arbitrarily as this layout's precise placement is not clear. The growth phase having A in space [−1, 1], the hunt agent can steer from a benchmark subway and also hunt representative will be revised coping to select from search agent, in the place of their lookup broker found so far. Both acts devise the subsequent.

$$D = |C \cdot X_{rand} - X| \tag{8}$$

$$X(t+1) = X_{rand} - A.D \tag{9}$$

Where X_{rand} is a arbitrary location vector.

Hunt agents improve their location based on the above details. The capacity of high-level studying comprehension of WOA is because to the placement updating procedure for Whales using equation (9). Equations (6) and (2) show that the WOA algorithm will be able to afford high regional optimum evasion and the convergence speed in the iteration approach.

3 Proposed Hybrid Frameworks

Although there are variety of research outcomes found on the brain tumor image segmentation and classification process, the outcomes are far way from being fine gained. Individual research techniques are recommended for the new height of excellence. The entire brain tumor recognition schemes rely on suitable pre-processing methods for achieving consistency and quality correctness. A regular segmentation formula for MRI brain tumor using DCNN should facilitate handling the issues that have been discussed in the literature for quality input for brain MRI segmentation stage. The complete automatic model for segmentation approach for MRI brain tumor by DCNN uses the following steps as well as the framework depicted in Figure 1.

i) Image pre-processing: It consist of following three steps
   a) Read image
   a) Resize image
   a) Remove noise
ii) Segmentation of image using optimization based DCNN framework and filtering of ROI object based on histogram.
iii) Validation has to be done with ground truth and then the final decision has to be made.

Initially we read the image, resize the image and deploy MICO bias correction method to remove noise from brain image slices. Optimized DNN algorithm is used in the subsequent step to identify brain tumor.

This procedure at first takes a 2D MRI slices as the experiment picture to be processed and the pre-processing phase eliminates noise and prepares a correct image using MICO scheme. This scheme is a proven error minimization technique. Rajinikant and Ratapthy [9] focused on skull removal which is required to design an automatic bug analysis scheme.

3.1 Pre-processing stages with MICO noise removal method in MRI Brain Image

Intensity at homogeneity could be complex in brain MRI brain tumor segmentation. From the tests of prejudice field improvement, we used the MICO method [21] to assess the bias field and cyst segmentation that depends in 2 multiplicative parts on breakdown of an MRI image. This is an energy minimization strategy to streamline joint bias field estimation which is exhibited in Figure 2. BRATS utilize multi-institutional pre-operative MRIs and targets the segmentation of heterogeneous (in appearance, shape, and histology) mind tumors, particularly gliomas. The MRI picture set of each individual includes many different strings including T1, T2-weighted, T1-weighted, along with FLAIR, together using an annotation of both edema, improving tumor, together side tumefaction. For more details about the BRATS statistics set, we employed the BRATS 2015 schooling data set which is freely available, whilst the BRATS difficulty is stored.

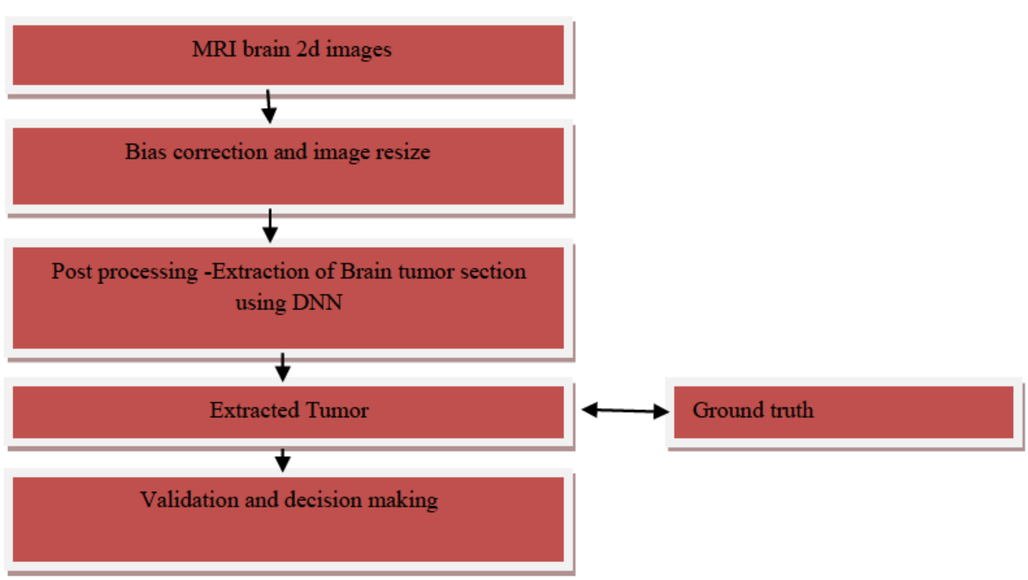

Figure 1: A general deep learning framework for automatic brain tumor segmentation

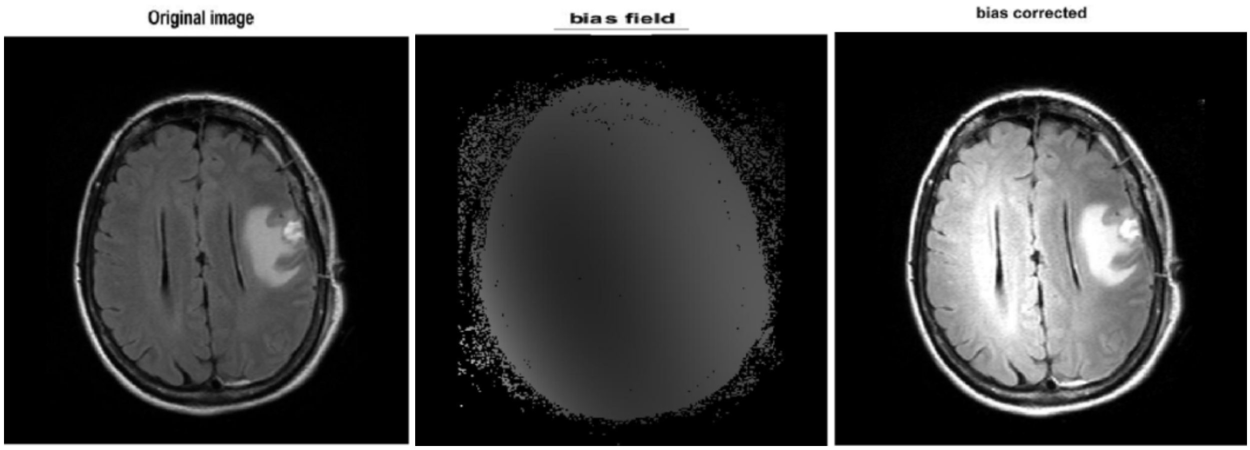

Figure 2: MICO bias corrections

3.2 Optimization based CNN model for brain MRI image segmentation

In CNN based image segmentation; a segment of an image has to feed as input to it which in turn levels the pixel. The CNN cannot process the entire image at once. So, the image is scanned and each time several pixels are filtered till the entire image is mapped. In our work, a convolutional neural network with optimization framework is proposed as depicted in Figure 3. In the proposed framework, the output image of the CNN converges to the expected image by adjusting the network parameters of the CNN with the use of optimization algorithms like WOA, GWO, GA, and PSO. We have focused on two popular optimization techniques to optimize parameters of CNN for the segmentation process using the whale optimization algorithm and Wolf optimization algorithm. The objective function's fitness value is calculated by comparing the output image of the CNN and manual doctors prescribed segmented image (GT).

The optimization algorithms evaluate their fitness values to obtain the optimized learning parameter of the CNN model.

The working procedure of proposed research work consists of following steps:
Training Phase:

1. Initialization – Initialize the learning coefficient of CNN. Consider the weight vector of CNN as a swarm of optimization algorithm. Initial swarm group size is equal to 50. Number of iterations to be set, in our case we have set it to 50 or till converges.
2. Training process of CNN will start with each swarm optimization algorithm and the first image of the input data set.

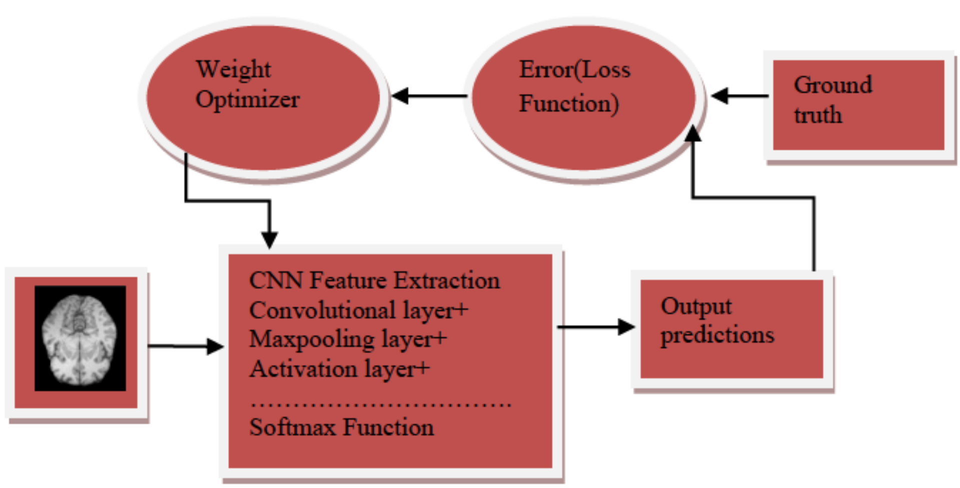

Figure 3: Proposed Framework: Optimization based CNN

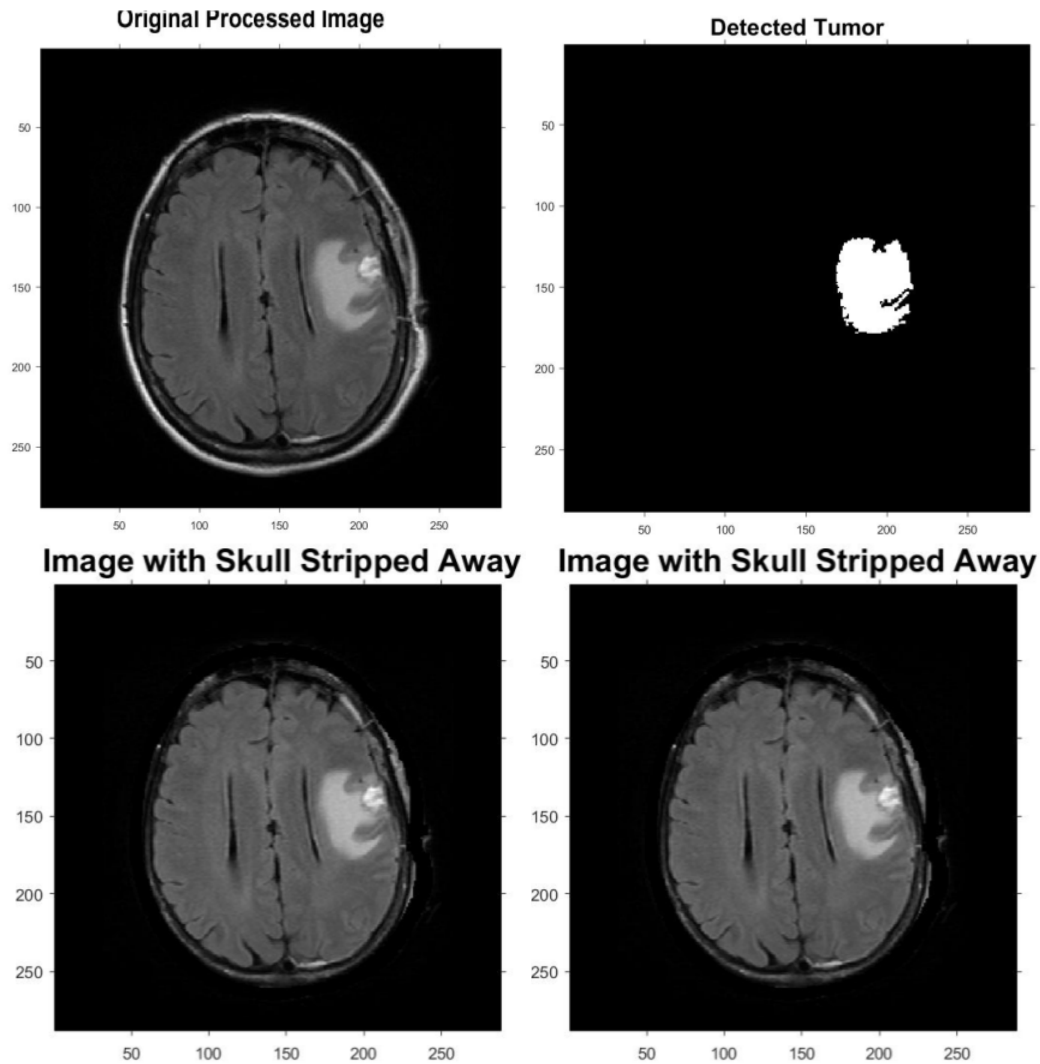

Figure 4: The segmentation results

3. In this process, once all the swarm or weight vectors have been applied, then it needs to be updated using the updating equation of wolf optimization algorithm.
4. Similarly, all the training images will be applied one by one with procedure mentioned in step 3 till the loss function of CNN model becomes negligible or converges.
5. Once the loss function converges, then we need to freeze the parameters of the CNN model by selecting the individual of the population obtained in the final iteration.

Testing Phase:

1. Once the training procedure with above steps is completed along with 60000 MRI brain image training samples, the testing of the model is carried out with the rest of the 1000 tests brain images.
2. Each of the test brain image sample has to be applied to the trained model with the frozen parameter values obtained from the training phase.
3. Output of the proposed model will be obtained and recorded to validate the model.

Figure 4 demonstrate the identification of tumor using DCNN optimization with skull eliminations.

Table 1: Parameter Values of PSO, GA, GWO and WOA

	PSO parameters for proposed algorithm		GA parameters for proposed algorithm		GWO parameters for proposed algorithm		WOA parameters for proposed algorithm
1.	Number of Particles=16	1.	Number of population=16	1.	Number of wolves=16	1.	Number of wolves=16
2.	Maximum Number of Iterations=100	2.	Maximum Number of Iterations=100	2.	Maximum number of iterations=100	2.	Maximum number of iterations=100
3.	Inertia Weight=1	3.	Mutation Coefficient (alpha)=0.2	3.	Alpha wolf initial value= inf.	3.	Initial search agent value= inf.
4.	Inertia Weight Damping Ratio=0.99	4.	Elite count=Roulette wheel selection	4.	Beta wolf initial value=inf.	4.	Acceleration co-efficient= linearly decrease
6.	Personal Learning Coefficient=1.5			5.	Delta wolf initial value=inf.		
8.	Global Learning Coefficient=2.0			6.	Acceleration co-efficient= linearly decrease		

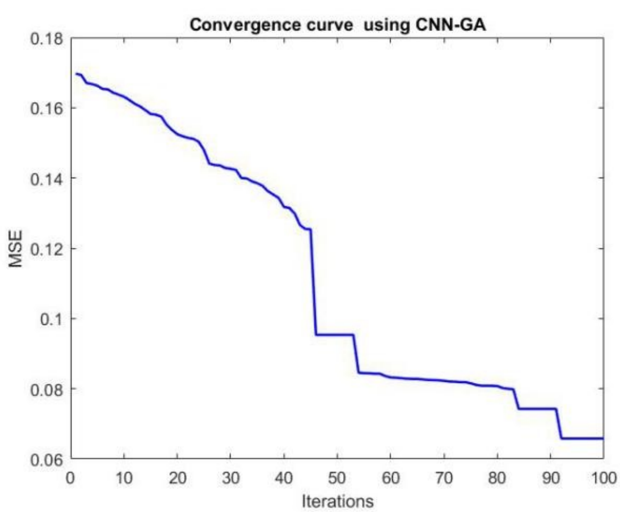

Figure 5: Convergence curve of CNN-GA

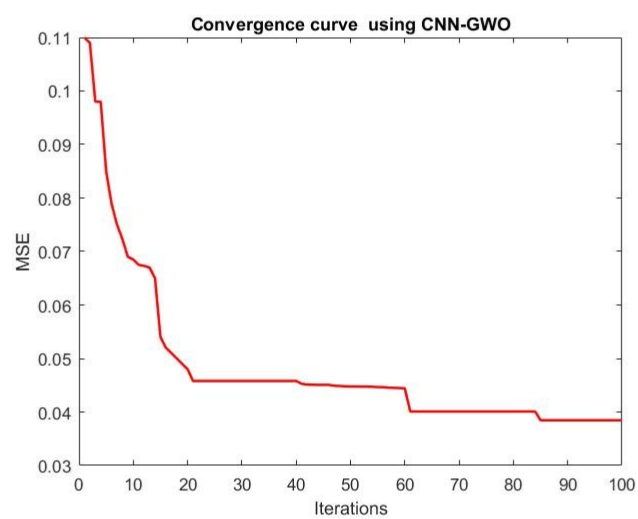

Figure 7: Convergence curve of CNN-GWO

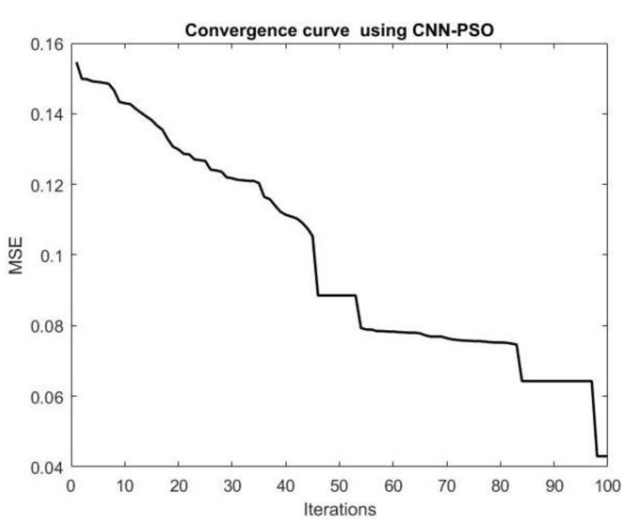

Figure 6: Convergence curve of CNN-PSO

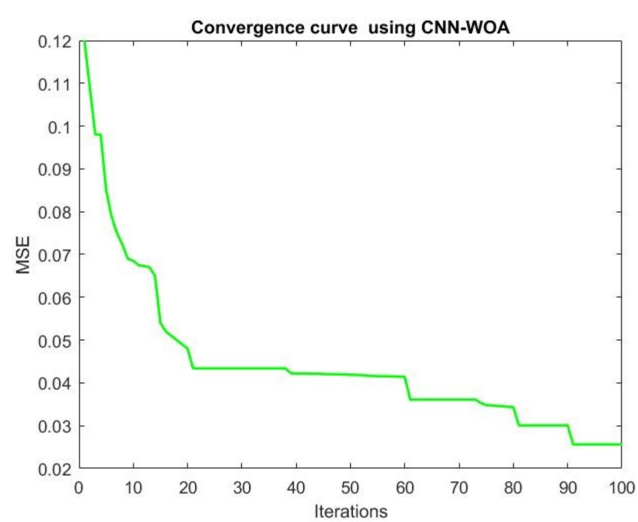

Figure 8: Convergence curve of CNN-WOA

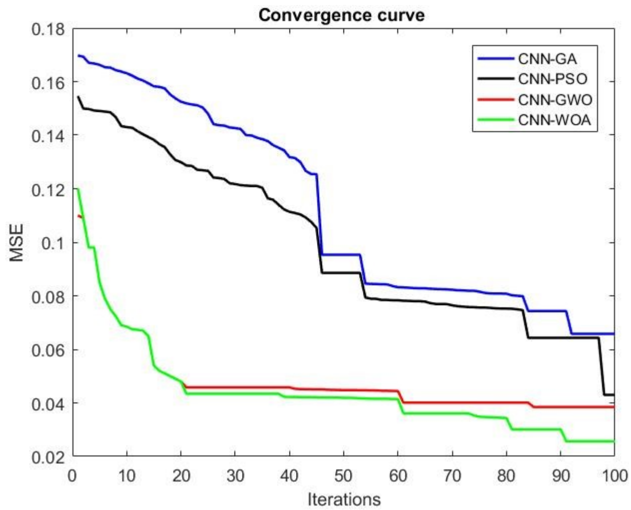

Figure 9: Comparison result of Convergence curve of different proposed models

4 Experiment and Result Discussion

The research work has carried out by demonstrating the outcomes of the proposed model applied on brain MRI of BRATS 2015 database for performance analysis of the proposed method.

The experiments follow the steps required to train and segment the brain tumor with CNN optimization.

1. The result of CNN process is optimized by the output vector of CNN with whale optimization (WOA). Whale optimization serves to make the value of the loss function on CNN to be at minimum.
2. The outcome vector will be improved if the solution of current whale value has less error than the earlier vector output.
3. The whale optimization will continue till the convergence solution is found.
4. After the CNN training, the model will be tested using the testing data (Ground truth).
5. The outcomes of the CNN vector represent the accuracy of CNN to predict the actual value of brain tumor segmentation with contrast to the ground truth.

Here we have used the different parameters for different optimization technique for our simulations as illustrated the table below.

In this paper, we have proposed to apply optimization algorithm in deep convolution neural network to optimize its network parameters such as weights and biases. The proposed model is tested with MRI brain tumor image for segmentation with respect to the validation indexes such as specificity, sensitivity and accuracy.

We demonstrate the convergence behavior of the different optimization algorithms used in DCNN for reducing errors (MSE). During the process, the co-efficient of algorithm

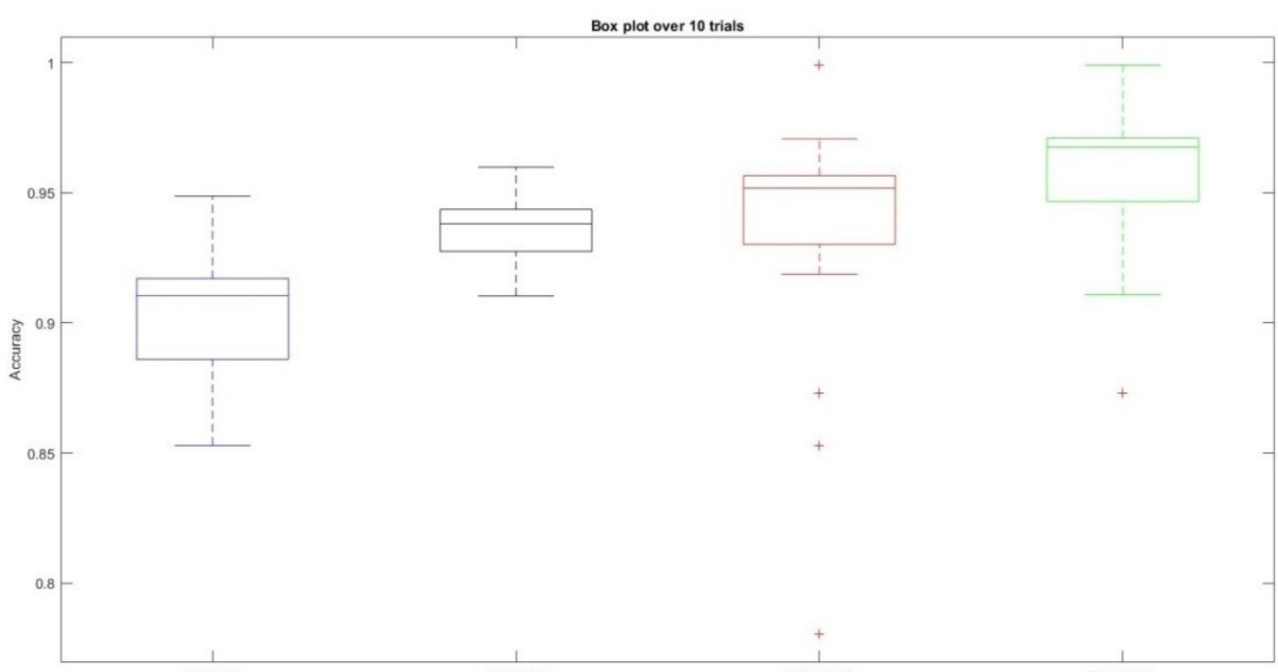

Figure 10: Accuracy of different proposed models *i.e.*, CNN-GA,CNN-PSO,CNN-GWO and CNN-WOA

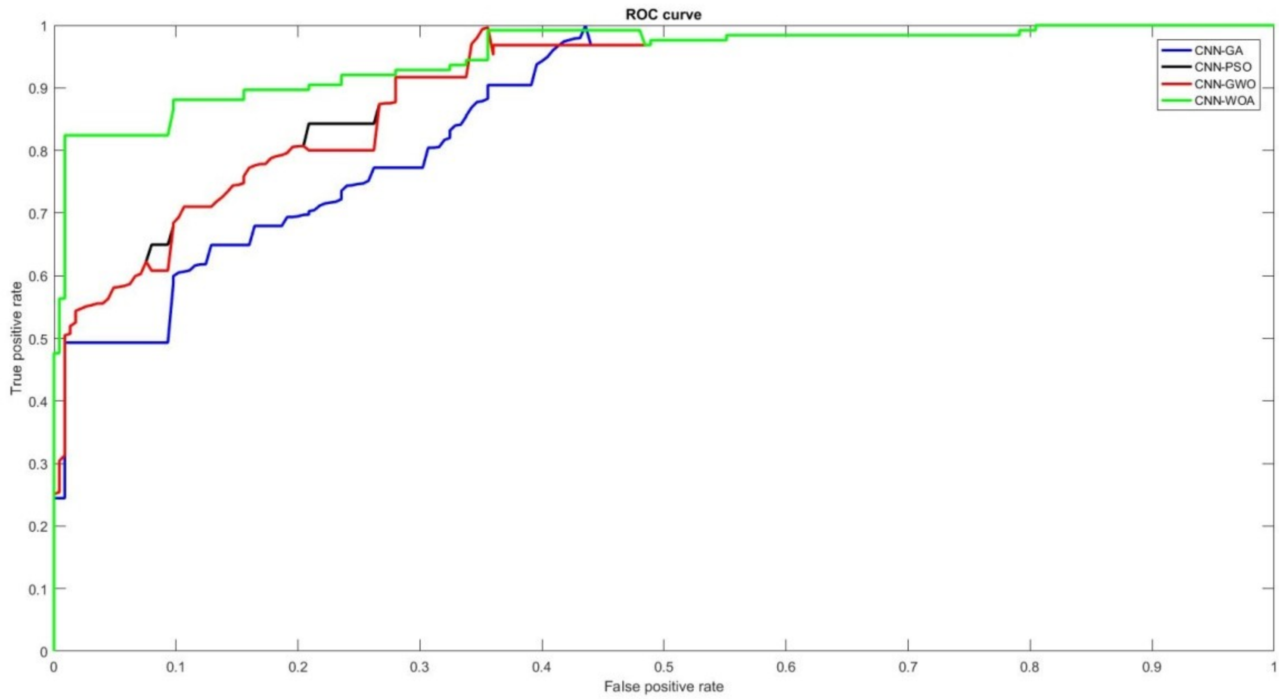

Figure 11: ROC curve between true positive rate and false positive rate between proposed algorithms

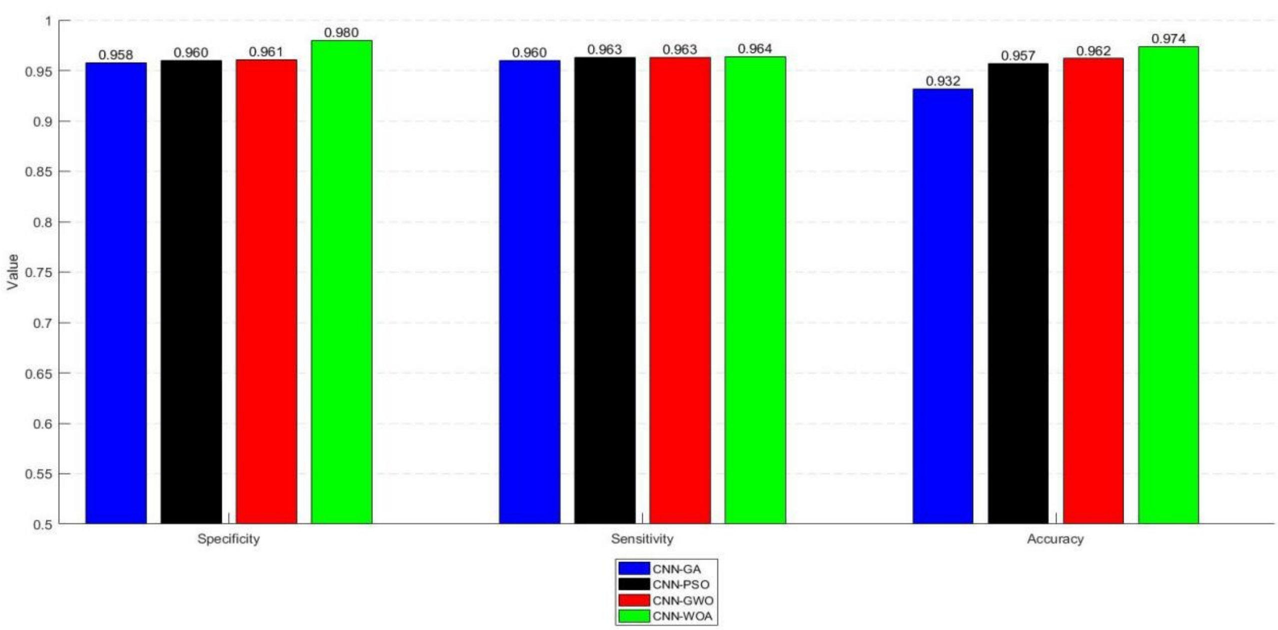

Figure 12: Comparison of different proposed algorithms

was decreased gradually with iterations and consequently the more linearly decreased algorithm was found efficient.

As shown in the Figure 12, the accuracy of the proposed model along with Whale optimization algorithm gives better result as compared to other optimization techniques like PSO, GA and GWO for CNN model based on BRATS 15 dataset. From the convergence curves of each individual model shown in Figures 5 to 8 and the comparison of the convergence characteristics of all 4 models in Figure 9, we observed that the DCNN algorithm model is converges faster by not getting trapped into local minima. To validate this model, the accuracy of the 4 models and ROC curves can also be plotted with the rate and false positive rate in Figures 11 and 10 respectively.

5 Conclusions and Future Work

Deep convolutional neural network extracts the relevant features automatically. In order to get optimized learning parameters of the network, swarm optimization-based algorithms are applied in CNN network to make more suitable and faster to learn from training samples. In this investigation we used the 4 optimization algorithms such as (*i.e.*, WOA, GWO, GA, and PSO) to enhance the performance and reduce the loss function in DCNN training model. During testing, the accuracy record for GA, PSO, GWO and WOA guided DNN was 0.958, 0.960, 0.961, 0.980 and 0.960, 0.963, 0.963, 0.964 and 0.932, 0.957, 0.962, 0.974 in specificity, sensitivity, and accuracy respectively. These performance measures are presented in the form of bar chart in Figure 12 and it is clearly visible from the figure that WOA-DCNN model performs better than the other 3 optimizations based DCNN models.

Future work: The optimization based DCNN model can be applied in other image processing tasks, like object detection, classification and segmentation. The brain images are not enough to detect the malignant nature of the brain, so we need to supply other information such as symptoms and/or any test reports for accurate prediction. This may be the case of Big Data, which can be difficult to handle in limited memory space and less parallel GPUs. One of the limitations of the proposed hybrid model is the more computation time. Thus, this problem can be addressed with progression of GPU and the use of libraries that allocate multiple GPUs diagonally for parallel processing. This may reduce the computation time of optimized based DCNN model and can be able to achieve better performance in the parallel environment.

Conflict of Interest: Authors state no conflict of Interest.

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