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Modified Social Group Optimization Based Deep Learning Techniques for Automation of Brain Tumor Detection–A Health Care 4.0 Application

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Now-a-days, Segmentation is essential in diagnosing severe diseases wherever there is a scope for image processing. In this work, hybridization of most popular and metaheuristic algorithms with Conventional Neural Network (CNN) has been proposed. As a part of the study, jelly fish and Modified Social Group Optimization Algorithms (MSGOA) are used. The CNN weights and the corresponding hyper parameters are modified or designed with the help of the respective metaheuristic approach of the algorithm. This certainly improved the efficiency of the segmentation which is measured in several metrics of bio-medical image processing. The accuracy, loss, Intersection over Union (IoU) are some of those metrics which are employed in this study for better understanding of the algorithm's effectiveness. Further the detection process is simulated consuming 100 iterations uniformly in either of the algorithms. The proposed methodology has efficiently segmented the tumor portion. The simulation has been carried out in MATLAB and the results are presented in terms of computed metrics, convergence plots and segmented images.

Keywords: Brain tumor, Classification, Modified social group optimization algorithm (MSGOA), Prediction, Segmentation

Introduction

Brain Tumor (BT) occurs due to the abnormality of cells in the tissues of brain. The BT is categorized briefly as primary and metastatic. The BT can also be considered as collection of unpredictable cells that form in the brain. Under the primary category, the abnormality can be seen in the brain itself. However, in the meta-static, any other part of the body can be affected. Similarly, the tumor can be malignant or benign. The malignant tumor is considered as cancerous, while the benign tumor is non-cancerous. The cancerous tumors are quite dangerous and can be life risking too.[1–4]

Further, there is a varied categorization of the tumor based on the magnitude of malignancy. However, it is evident from the analysis of the data available that a benign tumor can also create an irreparable effect on the subject's health. Cerebral tumors are considered the most widely recognized diseases of the sensory system, causing harm to numerous human well-being and death. In this case, the most well-known cerebral tumor in adults is glioma,[5,6] which will stimulate the memory of the most depressed patient. The clinical picture of tumors during treatment assesses the progression of infection.[7] Examples of imaging techniques are Magnetic Resonance Imaging (MRI), Single photon emission computerized tomography (SPECT), Positron Emission Tomography (PET), Computed Tomography (CT) images, and spectroscopy.

K-means clustering blended with fuzzy C-means clustering system can be used for the semantic segmentation of MRI images.[8] Threshholding and level set division techniques are used to provide efficient cerebral tumor identification. This method can obtain parts of unlimited computational time for the image segment of the K-means group. Similarly, it can get the best conditions of ambiguous C-references in precision fragments.[9] The adaptive regulated strip-based MRI image cerebral tumor segment obscure C-marker boxing system had potential gains for adaptation to the local system.[10] It has been updated with the power to reduce image sophistication, the possibility of collection boundaries, and computational costs. However, these techniques do not achieve the best fragmentary effects on the MRI image.[11,12] Recently, to achieve the best-segmented results in MRI images, the deep learning model has

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been utilized with Artificial Intelligence (AI) techniques such as Genetic Algorithm, Particle Swarm Optimization, Whale Optimization Algorithm, and Grey Wolf Optimization.[13–15]

In this paper, the most recent metaheuristic algorithm called modified social group optimization algorithm is used.[16] The MSGOA has expressed its excellence in solving many engineering problems in manufacturing industry and electromagneticfields.[17,18] So far, the application to brain tumor classification and prediction has not been done. Considering the efficiency, the MSGOA is used to control the weights of the deep CNN network applied for brain tumor detection and classification. The deep learning techniques blended with MSGOA forms a hybridized MSGOA-DL network. Further, the discussion on the latest research findings on this topic is listed in the Section-Literature Survey, while the methodology is explained in the next Section, followed by the Section-discussion on implementation results with comparative analysis between JFA and MSGOA.

Literature Survey

Several techniques of semantic segmentation in medical images are proposed. Weighted Bee Swarm Intelligence blended with the K-means clustering can perform multi-site tumor segmentation of MRI images.[19] The technique handles the segment boundaries to obtain the best possible solution. Cerebrospinal fluid, pale matter, and white matter were separated using the proposed calculations. It is also invested combines a wide range of features made from different layers of the U-Net.

Unsupervised Domain Adaptation (UDA)[20] is proposed to modify the model to new methods based on unindexed objective area information. Basic UDA calculations allow the focus on source space to allow information, which may not be reliable in clinical imaging due to security concerns. In this work, a security for the UDA created a calculation in the mandatory system where the source area information was blocked. This thinking was based on encrypting data from source experiments into a prototype distribution, which was used as a moderate scattering to correct objective partial conduction with source space rotation. Here, we reveal the adequacy of our computation by distinguishing between sophisticated clinical picture semantic segmentation approaches in two clinical semantic segment datasets.

The Fully Convolution Dense Dilated Network is yet another technique for enhancing the accuracy and segmentation efficiency.[21] The domain adaptation network (DANNet)[22] depends on the semantics of the image without actually taking the attributes in to account. It uses a conflicting product with marked daytime database and unnamed database, which features roughly adjusted day-night image galleries. In particular, for unnamed day-night image galleries, use the pixel-level expectations of static article classifications in a daytime image to separate its partner evening image as a dummy administration. Also, just as with raising the expected accuracy of small items, plan a re-weighing procedure to deal with the mis-representation brought about by the mis-designation between day-night film competitions and daytime film predictions.

Proposed Methodology

Several automatic semantic segmentation techniques were developed as efficient and effective semantic segmentation is an interesting study with medical applications. The automatic brain tumor semantic segmentation faces different problems such as varying types and sizing of brain tumors. Some of them are related to tissue anomalies and contrast level as the brain tumour is relatively small. Additionally, the multi resolution scanners and acquisition methods are increasing unpredictable intensity changes among tumour and brain. In recent years, the deep learning methods are interesting attention to manage different automatic recognition. Especially, the deep learning CNN network has been increased to provide efficient results for recognition, classification and segmentation. Hence, in this paper, MSGOA-DL is developed to semantic segmentation of the medical images. The block diagram of the proposed methodology is illustrated in Fig. 1.

Results and Discussion

The implementation of the algorithms to the problem statement and the corresponding results pertaining to the above methods are presented in this Section as follows.

Metrics of Interest

The performance is evaluate using certain metrices, these are

a) Loss: The pixel wire loss is computed in terms of logarithmic of loss which then summed up through all the classes. This is represented as:

$$\text{loss (pixel)} = \sum_{classes} Y_{true} log(Y_{Pxd}) \quad \ldots (1)$$

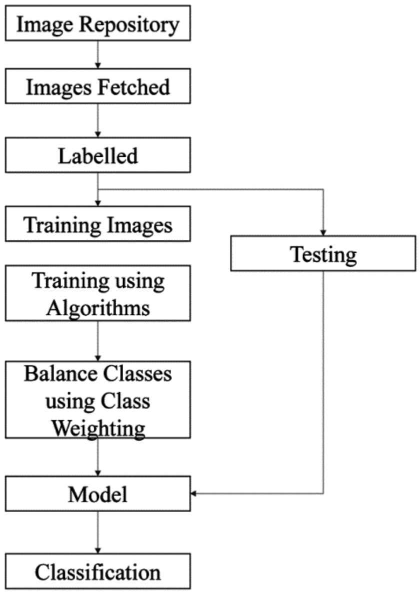

Fig. 1 — Methodology of Proposed Method

This is progressed through all the pixels and referred as loss.

b) Accuracy: Pixel accuracy is one of the simplest possible metrics of used to analyse the image. However, it severely suffers from visual imbalance.

c) Intersection over Union (IoU): it is another metrics used to have a validation of the accuracy. This is often referred as accord index. The metrics is also simple and has the ease of computation. The calculation is carried out using the following expression.

$$\text{IoU} = \frac{TP}{TP+FP+FN} \quad \ldots (2)$$

Initially, all the pixels from the picture are labelled a pixel can be represented as P_{min}. The labelling can be represented as follows:

$$P_{min} = \begin{cases} 0 \quad Healthy \\ 1\, Meningionla \\ 2 \;\; Glicoma \\ 3 \; Pituitary \end{cases} \quad \ldots (3)$$

The following function is evaluated for the classification.

$$f_{eval} = \frac{|\rho_{mn} == l|}{|\rho_{mn} > 0|} > Threshold \quad \ldots (4)$$

The corresponding label is computed as

$$l = \begin{cases} arg\{\max(f_{eval} > 0)\} & Classified \\ \quad negetive & Non - classified \end{cases} \quad \ldots (5)$$

Modified Social Group Optimization Algorithm (MSGOA)

The MSGOA is an advanced or well modified version of SGOA developed by Satapathy *et al*. The algorithms are yet another metaheuristic approach for solving multimodal engineering problems. The algorithm is showed its excellence in terms of performance when compared with other contemporary algorithms like Artificial Bee Colony (ABC), Simulated Annealing (SA), Partial Swarm Optimization (PSO) etc. The conventional SGOA has two phases referred as improving and acquiring phase.

In the improving phase, the first in the social group has been identified and treated as the groups best. The best individual is further used to inspire every individual in the group and improve. This is given in the following steps of the algorithm:

Algorithm 1:

for i = 1 to L
for j = 1 to M
$P_{new}(i,j) = \left[c * P_{(ij)} + r * gb_{(j)} - P_{(ij)}\right]$
end
end

Following the improving phase, the corresponding acquisition phase is introduced, in the later phase, an individual interacts with the only the first in the group, but also with any other random individual. The step has a two folded advantage in which, the individual not only explores hut also exploits the knowledge of other randomly picked individual. This is explained in the algorithm as follows:

Algorithm 2:

for i = 1 to L
for j = 1 to D
Update individual with respect to random chosen individual P,
$P_{new}(i,j) = P_{(i,j)} + r_1 * \left|\left[P_{(i,j)} \sim P_{(r,j)}\right]\right| + r_2 * \left[gb_{(j)} - P_{(i,j)}\right]$
end
end

In the MSGOA version, the new parameters known as self-awareness probability (SAP) have been introduced. The SAP refers to the characteristics of individual featuring the awareness that he/she inherently possess. This characterizes an individual and discriminates among other in terms of the ease an individual possesses which makes him unique.

In this step, the individual updates its own knowledge with respect to the best in the group along with a randomly chosen individual. However, if the individual's position is inferior to the randomly picked one, then the decision of updating the individual with respect to the randomly picked and the groups best or the bounds is made with respect to the considered SAP.

Algorithm 3:

for i = 1 to L

if $\left(f(P_i) < f(P_r)\right)$

if $(rand > SAP)$

$P_{new}(i,j) = P_{(i,j)} + r_1 * \left|\left[P_{(i,j)} \sim P_{(r,j)}\right]\right| + r_2 * [gb - P_i]$

else

$P_{new}(i,j) = l_b + r * (u_b - i_b)$

end

end

end

Performance Analysis

The initial step involves in benchmarking the labelling process. This labelled image helps in segmentation process as a preprocessing step. This is demonstrated in Fig. 2. The input image is Fig. 2(a) while the corresponding segmented and labelled image in Fig. 2(b). The proportion of the brain and the tumor is depicted in Fig. 2(c) for better understanding. The process of simulation-based experimentation has been performed initially using ideal JFA, which is followed by MSGOA. In either case the CNN has been the common factor. The number of iterations has been kept constant at 100.

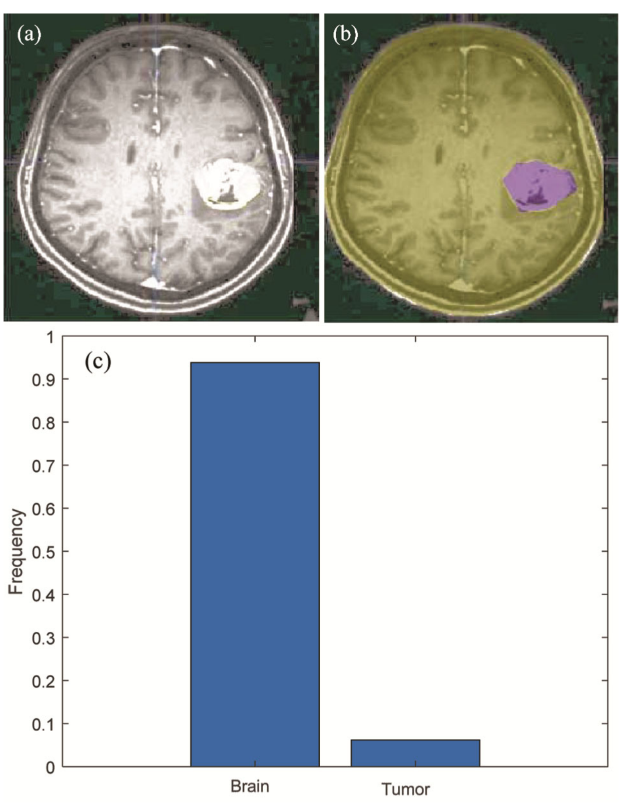

Fig. 2 — (a) Input image and corresponding (b) labelled image, (c) labelling index

This helps in better comparison. In every iteration, the respective image metrics are computed and recorded for the performance analysis in terms of the correspondence convergence characteristics. In every iteration the corresponding objective function is evaluated which depends on the image. In this case, the convergence plots are presented for both the algorithms in which the computed loss and the respective accuracy are measured in percentage are accordingly plotted.

The plot presented in Fig. 3 refers to the convergence feature of JFA. The accuracy observed large charges for every iteration during the initial stage. However, later witnessed smaller change and settle at its best value with in the 100th iteration. Similarly, the case with the corresponding loss function, where in the loss linearly decayed and reached lower values initially and there by consistent through all the iterations.

Following this in Fig. 4, the corresponding accuracy and loss function are displayed for MSGOA. The rate of accuracy increase was a bit slow when

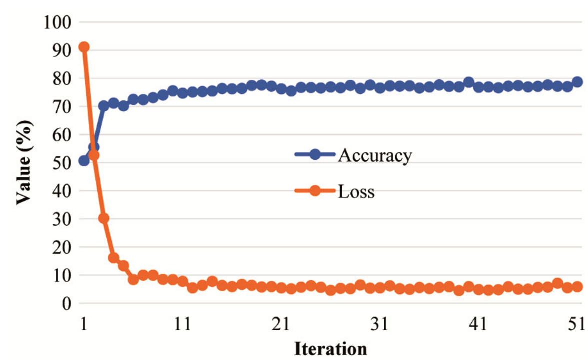

Fig. 3 — Convergence of accuracy and loss for the jelly fish algorithm

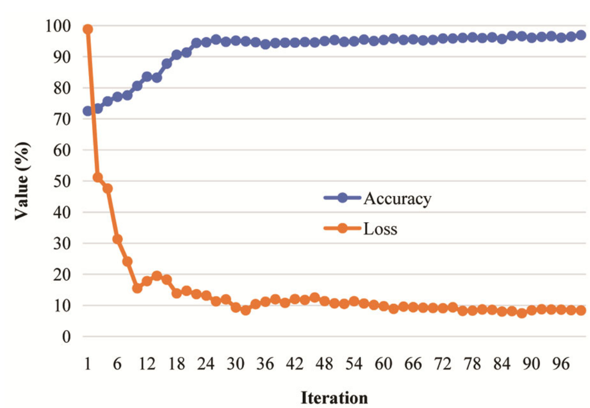

Fig. 4 — Convergence of accuracy and loss for the SGOA algorithm

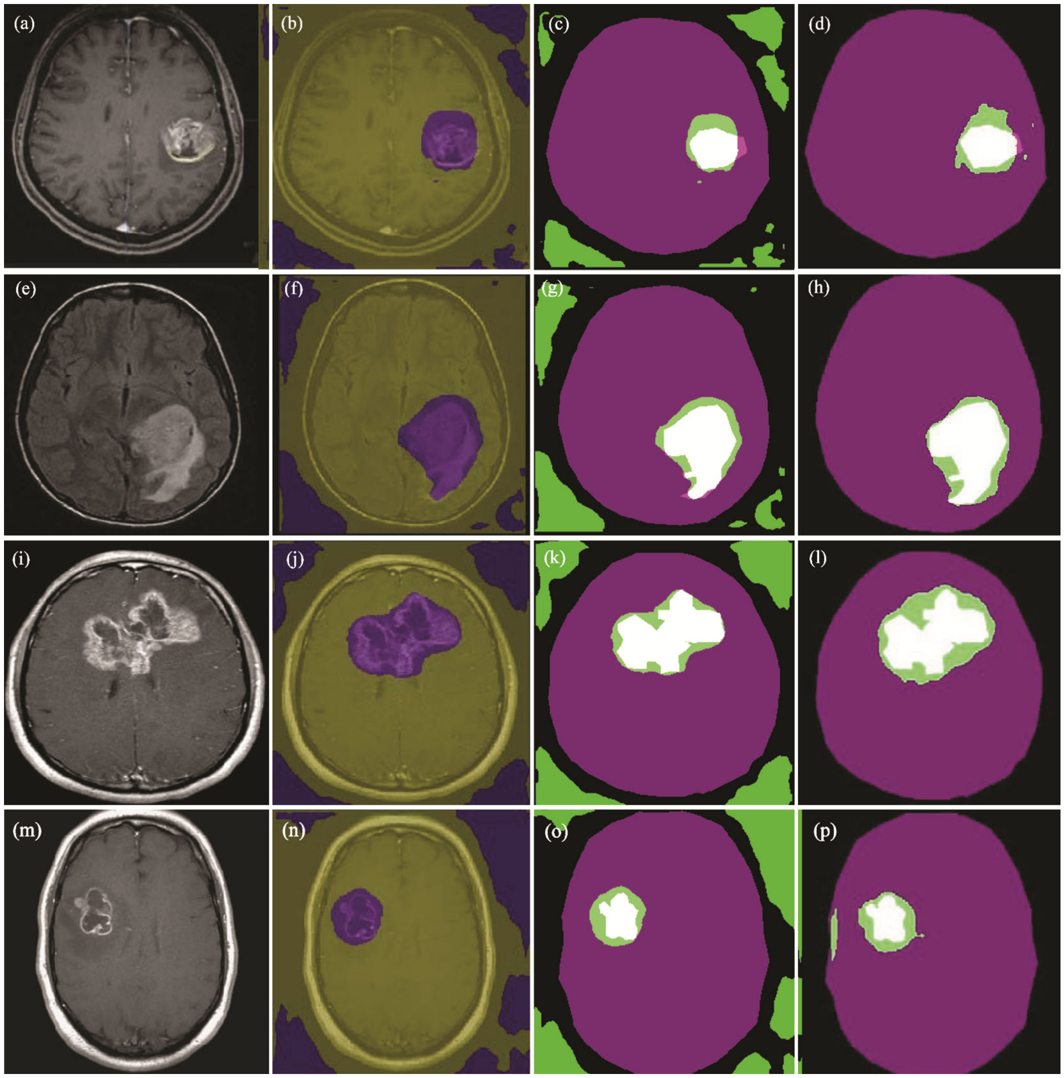

Fig. 5 — (a, e, i, m) input images, (b, f, j, n) labelled images, (c, g, k, o) JFA segmented images and (d, h, l, p) MSGOA segmented images

compared with JFA in MSGOA. However, initial point was much better in MSGOA that is over 70%. Further, the loss function also expressed the behavior on similar line with the corresponding change being slow in initial iterations there by soon settling at lower values and consistent further to levels below 10%.

With the corresponding tumor images, the MSGOA expressed its excellence and domination in all the categories. It has a peak accuracy of 98.29%, IoU reported to be 79.25% with the corresponding mean BF at 0.48. These are much better than the JFA which has its accuracy, IoU and mean BF recorded as 95.49%, 69.28% and 0.376 respectively.

Some of the images pertaining to input brain, labelled and segmented using JFA and MSGOA are displayed in Fig. 5(a)–(p). Though the naked visual perception of these images is almost similar, their corresponding image metrics convey the actual variation in the performance of the algorithm. The comparative analysis of the JFA and MSGOA are tabulated in Table 1.

Table 1— Comparative analysis

Label	Accuracy		IoU		Mean BF Score	
	JFA	MSGOA	JFA	MSGOA	JFA	MSGOA
Brain	97..57	99.58	97.29	99.20	0.86	0.92
Tumor	95.49	98.29	69.28	79.25	0.376	0.48

Conclusions

In this work, deep CNN network method is used for classifying glioma, meningioma, pituitary and no tumor grades. The MSGOA and JFA algorithms are used to enhance the performance of the DCNN. The proposed hybrid method proved to be capable of providing high precision results in terms of detection and classification of brain tumor. The proposed method technically avoids several intermediate steps. The methods can directly perform on the numerical or statistical data featuring the brain MRI scans. Hence, this does not involve in storing large volumes of high-resolution images of brain. The results are very useful to the practitioners as they are reliable and can serve as a ready second opinion for validations or assistance. The framework of establishing a real time environment with high-speed computing systems to provide live data analysis as compact system would be a best scope of future work.

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