Kalpa Publications in Computing
Volume 19, 2024, Pages 1–12
Proceedings of 6th International Conference on Smart Systems and Inventive Technology

PSO based MR Image Segmentation for Brain Tumor Detection

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Abstract

Brain tumor segmentation is an essential step that is important for the diagnosis and treatment planning in healthcare. Brain MRI images are preprocessed in accordance with the suggested approach before data is gathered and ready for further analysis. The suggested study introduces a new strategy that uses the bio-inspired Particle Swarm Optimization (PSO) algorithm to segment brain tumor images. To improve accuracy and dependability, the segmentation model's parameters can be adjusted. Standard measures like Accuracy, Precision, Sensitivity, Jaccard index, Dice Coefficient, Specificity are used in performance evaluation to measure the effectiveness of the suggested PSO-based segmentation approach. The overall accuracy of the suggested method is 98.5%. Subsequent performance analyses yield better results of 91.95%, 87.01%, 92.36%, 90%, and 99.7% for Dice Score Coefficient, Jaccard Index, Precision, Sensitivity, and Specificity, respectively. Therefore, this method can be a useful tool for radiologists, supporting them in diagnosis of tumor in brain.

Keywords — Brain Tumor, Swarm Intelligence, Particle Swarm Optimization, Magnetic Resonance Images.

I. INTRODUCTION

An uncontrolled growth of cancer cells in any part of the body is called a tumor. A subset of aberrant cells that develop within or around the brain are known as brain tumors. Brain tumors account for more than 90% of primary Central Nervous System (CNS) tumors. In 2020, there were 308,102 estimated cases of primary brain or spinal cord tumors diagnosed worldwide. The survival rates for brain tumors have not changed much in recent years, despite years of research. In contrast, many other tumors have seen major improvements in survival rates. Roughly 3.9% of brain tumour diagnoses occur in children between the ages of 0 and 14. It is anticipated that in 2023 there would be 3,920 new cases of primary paediatric brain tumours diagnosed. When it comes to solid cancers in children [9] aged 0 to 14, brain tumors are the most often diagnosed type and also the main cause of death from childhood cancer.

Brain tumour segmentation is the process of automatically classifying malignant brain tissues according to the types of tumours by identifying them. Manual segmentation of brain tumor is usually prone to error and consumes a lot of time. Due to the intricate structure [7] of the brain and the challenges involved in differentiating between normal and abnormal cell growth, accurate tumour class prediction at a faster rate is difficult. Thus, a quick and precise method for segmenting brain tumours is required. Computer-aided detection has lately garnered a lot of recognition as a solution to this problem[3]. However, the following factors like poor quality of available images[10] and intensity levels pose problems in effective visualization of images. There are a lot of existing strategies that segment tumors. But their accuracy values[6] do not yield a precise solution to the doctors identify tumors.

Over the years, there has been a notable shift towards more advanced approaches, including machine learning, deep learning, image processing techniques, graph methods and traditional clustering. Deep Learning models, especially large architectures like U-Net, can be computationally expensive and demand substantial hardware resources(e.g., GPUs).In high-dimensional spaces, Deep Learning models could struggle to learn meaningful interpretations, especially if the data at the disposal is constrained. Machine learning models, including Support Vector Machine (SVM) and Random Forest, rely on labeled training data for learning. Some conventional clustering techniques, like K-means, Fuzzy c-means, assume that the clusters are spherical and equally sized, which may not accurately represent the complex shapes and sizes of brain tumors. They may also get stuck in local optima and struggle to find a global optimal solution. For the reasons described above, brain lesion segmentation is still a difficult problem in computer vision and medical image processing. As researchers continue to explore innovative avenues, optimization algorithms like PSO have been integrated, aiming to enhance parameter tuning and overall performance in brain tumor segmentation tasks. Due to its ability to adjust complicated images and to fine-tune the parameters of image segmentation algorithms, Swarm Intelligence algorithms[12][14] have become more and more popular in recent years.

The suggested methodology provides more accuracy than other algorithms. It incorporates a PSO algorithm with inspiration from biology to segment the image into many parts for additional examination. This property of PSO allows to find solutions in regions that may be challenging for other algorithms. It performs well in high-dimensional search spaces making it ideal for complex problems that require a large number of variables. It is adaptive to dynamic environments and can handle diverse datasets. It is capable of adjusting its parameters according to the working conditions, i.e, any variations in noise levels or image quality. It provides faster convergence in terms local and global which helps in finding the solution effectively. PSO is therefore beneficial for the segmentation process of brain tumors. Finally, the Experimental and Performance Analysis is carried out. A number of metrics, namely Dice Coefficient and Jaccard Index are applied for experimental evaluation. Further analysis is done by calculating Accuracy, Precision, F-Score, Specificity and Sensitivity.

II. RELATED WORKS

There are a few studies that use brain tumor segmentation for various purposes. M. Ali et.al., (2023) [1] developed two segmentation networks, a U-net and a 3D- CNN, in a significant but straightforward combinative technique that produces more accurate and exact predictions. The suggested ensemble obtained dice scores of 0.750, 0.906, and 0.846 for the enhanced tumor, complete tumor, and tumor core, respectively, on the validation set which is very less than the dice coefficient of the proposed method. K. Bhima, et al., (2023) [2] proposed a framework which is robust and efficient when compared to traditional classification algorithms. The suggested framework for tumor analysis showed an accuracy of 98.23% ± 1.1%. A. G. Eker et al., (2023) [3] aim to conduct brain tumor segmentation using transfer learning-based techniques like XceptionNet, ResNet, InceptionNet and VGG architectures with basic models like U-Net and FCN and it obtained a dice score of 0.9169. M. R. Goni et al., (2022) [4] offered two key changes to the U-net model: a sharp block a grid-based attention block. The test demonstrated Jaccard score of 86.84% and a dice score of 92.75%. W. Huang et.al., (2022) [5] used improved two things while utilising UNet techniques Feature pooling block (FPB) is created as the decoder that procures an average dice score of 0.8169.

A. Hussain et al.,(2020) [6] incorporated a watershed segmentation strategy which uses GLCM techniques to extract characteristics from previous phases. Then, a few images were classified using SVM. The accuracy of 93.05% is observed, which is less accurate than the accuracy of the suggested system. Jaspin, K., et al., (2023) [7] developed a Multi Class Convolutional Neural Network model(MCCNN) to detect tumors in brain MRI images. This approach offers less complexity. With 99% and 96% accuracy in Experiment I and Experiment II respectively, this system provides a remarkable performance. Logeswari, T et al., (2020) [8] depicts a two-phase segmentation algorithm. First, noise and film artifacts of brain tumor images are eliminated. Then, for image segmentation, Hierarchical Self-Organizing Maps (HSOM) are used. HSOM yields accuracy of 80.01%, sensitivity of 78.2%, specificity of 85.4%, precision of 71.14%, recall of 72.34%, F-measure of 78.25% and DSC of 83.63%. The proposed strategy outperforms this algorithm with higher values in the assessment. X. Liu et al.,(2023) [9] developed nnU-Net and SegResNet. The results (Dice scores of 0.859±0.229 for the enhancing region and 0.880±0.072 for the total tumor, respectively) were obtained with nnU-Net pretraining. With greater evaluation scores, the suggested approach performs better than this method A. Mishra et al.,(2023) [10] examines Anisotropic filters, morphological techniques and threshold-based segmentation to remove noise from MRI images and distinguish the damaged region from the normal one. This method uses older techniques for segmentation.

Natarajan, A, et al., (2019) [11] gave an advanced automatic segmentation technique that relies on swarm intelligence and machine learning. The brain tumor region in magnetic resonance imaging (MR) is to be segmented using a fuzzy logic with spiking neuron model (FL-SNM).It results DSC of 91.2% accuracy of 94.87%, sensitivity of 92.07%, precision of 89.36%, recall of 88.39% specificity 99.34% and F-measure of 95.06%. With greater evaluation scores, the suggested approach performs better than this method. M. N, et al.,(2023) [12] incorporated a K-means clustering technique and an algorithm based on social behaviours of salps, the Salp Swarm Optimisation method is a nature-inspired metaheuristic optimisation method. The efficacy of the suggested system is confirmed via DSC of 83.44% which is relatively lower to the DSC of proposed technique.

Pereira. S, et al, (2016) [13] explored an autonomous segmentation strategy on Convolutional Neural Networks kernels after researching tiny 3x3 grids. CNN yields accuracy of 91.5%, sensitivity of 90.8%, specificity of 97.72%, precision of 86.41%, recall of 85.47%, F-measure of 87.54% and DSC of 88.78%. IN terms of assessement values, the proposed approach yields better results than this method. K. Ramudu, et al., (2022) [14] granted a hybrid approach known as MPSO-ADF-a combination of modified particle swarm optimization (MPSO) and anisotropic diffusion filter (ADF). This technique also uses a Support Vector Machine Classifier (SVM). This method utilizes a machine learning technique with MPSO which may be more complex. R. Sumathi, et al.,(2019) [15] proposed the Image segmenting technique using Modified Cuckoo Search Optimization with Morphological Reconstruction Filters which provides 97% accuracy. The proposed approach yields better results than this method. M. Thilagam et al., (2020) [16] used the Fuzzy C-means algorithm to analyze brain MRI images for tumor segmentation, and they talked about how fuzzy clustering can be applied for accurate segmentation. Fuzzy c-means is a conventional clustering technique that may get stuck in local optima and struggle to find a global optimal solution.

III. METHODOLOGY

The proposed methodology is carried out with the help of MATLAB as a simulation tool. It begins with data collection and preprocessing. This step is then followed by a Bio inspired PSO algorithm to segment the image into several components for further analysis. Then the PSO output is visualized as clusters and the segmented output is displayed. As the last step, the performance evaluation for the proposed method is conducted. This flow is shown in Fig. 1.

A. *Data Collection*

The data for segmentation of brain tumor is collected from kaggle. The BRATS benchmark datasets are collected as input images for the segmentation of brain tumor. The dataset consists of brain images with tumor. Fig.2 shows some brain tumor images

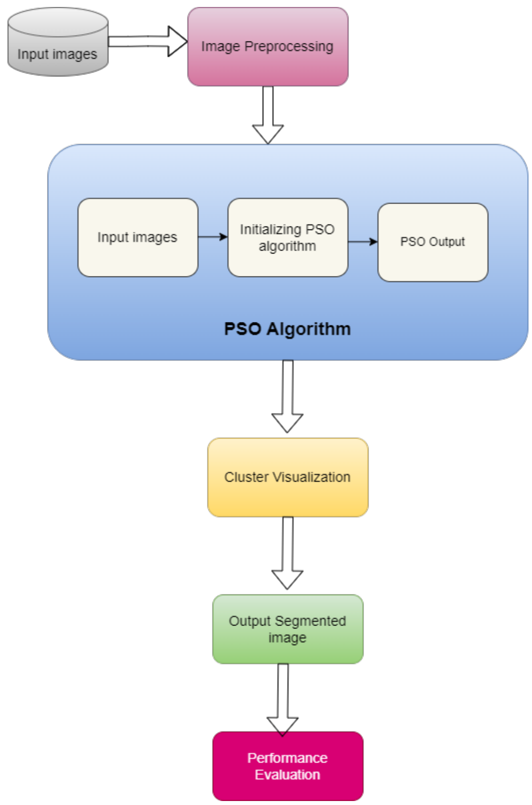

Figure 1: System Architecture of Brain Tumor Segmentation

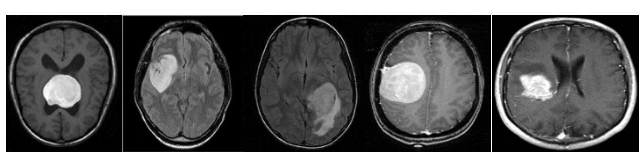

Figure 2: Tumor images

B. ***Image Pre-processing***

Standardisation of the obtained images is the first step in image preprocessing, which guarantees uniformity in pixels and brightness. By enhancing the image quality requires the application of necessary preprocessing techniques like noise reduction and intensity normalisation. Skull removal by threshold method is a medical image processing technique used to isolate and eliminate the skull region from images, such as brain scans. Threshold method involves setting a specific intensity threshold in medical images to differentiate skull pixels from brain tissues. This threshold is determined based on observed intensity values, and pixels exceeding it are identified as part of this skull and removed or labelled. The method realises on the inherent contrast between skull and brain tissues, making separation straightforward. However, its success hinges on clear contrast and selecting and appropriate threshold value.

C. ***Particle Swarm Optimization – Based Segmentation***

In this project, a nature-inspired Particle Swarm Optimization(PSO) algorithm (Fig 3)is employed. In the first step, the PSO algorithm is commenced by initializing a swarm of particles. Then, an objective function is defined with PSO parameters, and then the particles move and modify their locations. After this, the particles converge towards an optimal solution to provide the global best solution. This computational optimization strategy was motivated by fish and birds social interactions. When it comes to segmenting images, use of the PSO method is to streamline the process of identifying or dividing regions of interest within an image.

Algorithm

Begin Algorithm
Input: *PSO's initial parameters (nPop, MaxIt, w, c1, c2).*
Output*: Global best position*
Set the particle positions at random initialization.
Analyse each particle's fitness.
Set the global and local optimal locations and costs
for it = 1 to MaxIt for every particle.
    Update Rate
    Put constraints on velocity
    Update your position.
    Assess the level of fitness
    Current local self
    Update global best
Return the global best position
End Algorithm

The above pseudocode represents the flow of Particle Swarm Optimization(PSO) algorithm. In this pseudocode, five parameters are given. The parameters are nPop, MaxIt, w, c1 and c2 represents the particle size(number of particle or population), maximum number of iterations, weight that controls the previous velocity of the particles, personal (local) learning coefficient and global learning coefficient respectively. Subsequently, each particle's fitness is assessed once its placements are randomly assigned. Next, the costs of the particles alongside the local and global locations are initialized. Iterations are started in the for loop between 1 and a maximum number (MaxIt). Every iteration updates the locations and velocities of particles, and each particle's fitness is assessed., global and personal(local) best positions are updated. Then, after all the iterations are completed, the global best position is returned as output.

The formulation of PSO algorithm is:

$$\boldsymbol{s_i(t+1) = w.s_i(t) + m_1 . n_1 . (q_i - r_i(t)) + m_2 . n_2 .(q_g - r_i(t))}\text{-----------------}\mathbf{(1)}$$

$$\boldsymbol{R_i(t+1) = r_i(t) + v_i(t+1)}\text{----------------}\mathbf{(2)}$$

$$\boldsymbol{\text{If } f(R_i(t+1) < f(q_i), \text{ then } q_i = R_i(t+1)}$$

$$\boldsymbol{\text{If } f(q_i) < f(G), \text{ then } G = Q_i}$$

Where $H_i(t)$ indicates the location of particle *i* at time *t,* $S_i(t)$ denotes the velocity of particle *i* at time *t*, *W* signifies inertia weight , q_i the best- known position of particle *i,* Q_g is the best-known position in the population, m_1 and m_2 are coefficients of acceleration and n_1 and n_2 are arbitrary integers in the range of 0 and 1.

Here's a breakdown of the key components and steps involved in PSO-based segmentation:

A. ***Initialization***

To begin, the algorithm generates a swarm of particles, each representing a possible answer in the search space. In terms of image segmentation, each particle is assigned a set of attributes that define a segmentation approach.

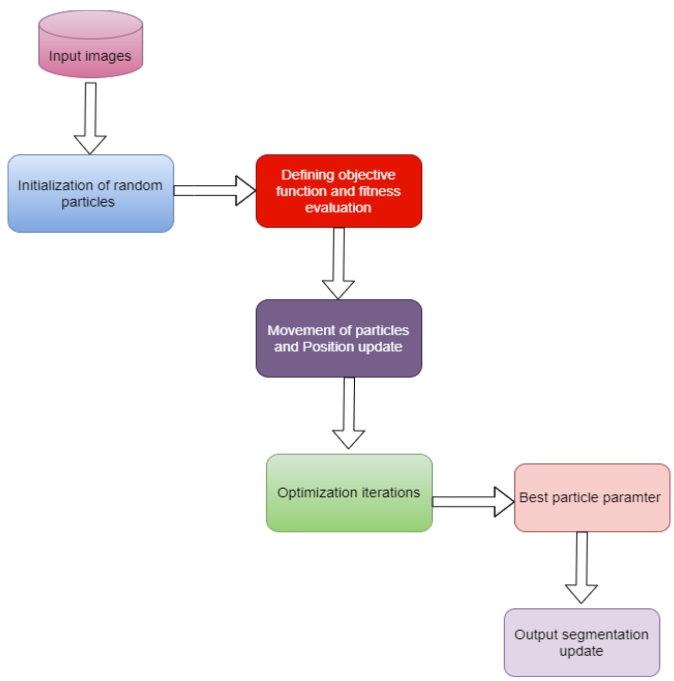

Figure 3: Particle Swarm Optimization Architecture

B. Objective Function

The performance of segmentation approach is measured using an objective or fitness function. This function assesses how well the segmented zones match the intended or ground truth segmentation when it comes to image segmentation.

C. Particle Movement

Based on its own prior experiences as well as those of its neighbors, every particle modifies its location in the solution space. The optimization process, which seeks to identify the combination of factors that reduce or maximize the objective function, is what drives this movement.

D. Optimization Iterations

The algorithm iteratively refines the positions of the particles over multiple iterations. As the particles move through the solution space, they converge towards an optimal solution that represents an effective segmentation strategy.

E. Segmentation Update

At the end of the optimization process, the parameters for the segmentation strategy are provided by the best-found solution (particle) . Using this data, the input image is segmented into discrete areas according to the optimization's specified criteria.

D. ***Cluster Visualization and Output***

The output from the PSO is identified and converted into four distinct clusters. Clustering is done implicitly. Then the segmentation results are visualized with different clusters. Out of which, the user-input cluster number is chosen, and the output is displayed.

IV. IMPLEMENTATION

In fig.4, to enrich the resolution of the input image, preprocessing techniques namely noise reduction and intensity normalization are applied. The image is then transformed into a skull-stripped image.

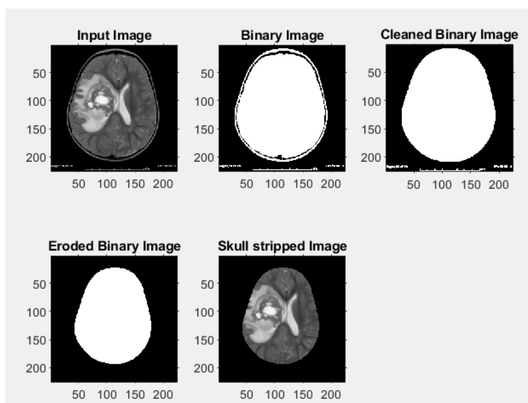

Figure 4: Preprocessing of input image

In the fig.5, pre-processed image is then segmented using PSO algorithm. The best solution is identified and the output image is visualized as four clusters with four distinct parts of the given brain tumor input image.

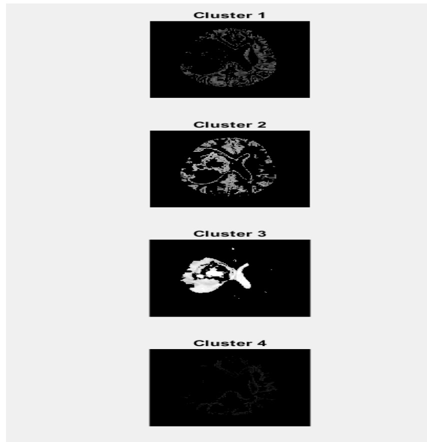

Figure 5: Image segmentation using PSO.

As the next step, the user inputs the cluster number i.e, the region that is likely to have a tumor as shown in the fig.6. Then user entered number is selected for further analysis.

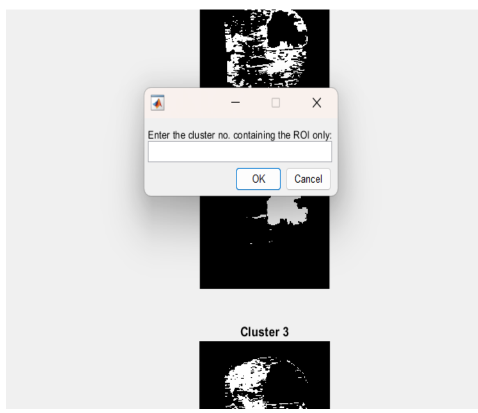

Figure 6: User inputs cluster number

In the final step, the output image with the tumor is displayed. This is illustrated in fig.7.

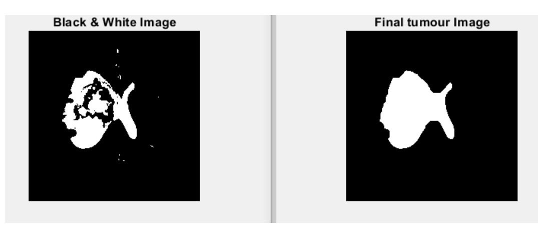

Figure 7: Final Output image

V. PERFORMANCE ANALYSIS

The PSO-based segmentation results and the ground truth annotations are assessed to determine how well the suggested technique performs. The segmented output image and the ground truth image are similar with higher performance. The graph depicts the evolution of particles over time. The x- axis signifies the number of iterations and the y-axis signifies the cost values. A descending trend of the curve as depicted in fig.8 indicates that the particles converge towards an optimal solution(best cost) by encountering a greater number of iterations. Thus, the global best solution is acquired.

Metrics / Images	Accuracy	Precision	Sensitivity	F-Score	Dice Coefficient	Jaccad Index	Specificity
Image 1	0.98298	0.99749	0.81319	0.89596	0.89596	0.81154	0.9998
Image 2	0.90611	0.57571	0.87831	0.69552	0.69552	0.53318	0.90998
Image 3	0.98277	0.99749	0.81086	0.89454	0.89454	0.8092	0.9998
Image 4	0.99298	0.96441	0.94923	0.95676	0.95676	0.91711	0.99688
Image 5	0.99048	0.97675	0.90355	0.93873	0.93873	0.88453	0.99811
Image 6	0.98995	0.97766	0.89077	0.9322	0.9322	0.87301	0.99829
Image 7	0.9929	0.99486	0.90732	0.94908	0.94908	0.90309	0.99963
Image 8	0.98979	0.99032	0.86009	0.92062	0.92062	0.85292	0.99938
Image 9	0.99429	0.91516	0.9859	0.94922	0.94922	0.90334	0.99477
Image10	0.99687	0.97562	0.95298	0.96417	0.96417	0.93081	0.9989
Image11	0.99737	0.97533	0.96195	0.96859	0.96859	0.9391	0.99893
Image 12	0.99829	0.97555	0.9825	0.97901	0.97901	0.95889	0.99896
Image 13	0.99868	0.98553	0.98165	0.98359	0.98359	0.9677	0.9994
Average	0.9857	0.9236	0.90017	0.91954	0.91954	0.87015	0.99702

Table.1: Performance Analysis results

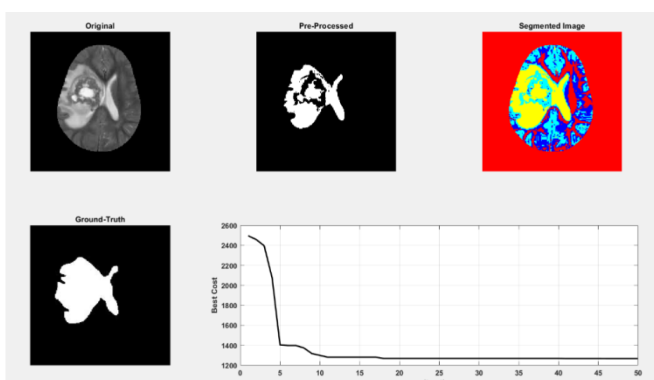

Figure 8: Performance Analysis of segmentation using PSO

To deduce false negatives, false positives, true negatives and true positives for this comparison, a confusion matrix is used. Then, segmentation evaluation is carried out on dataset of 13 images (numbered from image 1 to image 13) using a number of metrics and the average is computed.

The performance analysis yields a Dice coefficient of 91.95% and a Jaccard index of 87.01%. Subsequent analyses yield results of 98.5%, 92.36%, 91.95%, 90%, and 99.7% for accuracy, precision, F- Score, sensitivity, and specificity, respectively as shown in Table.1.

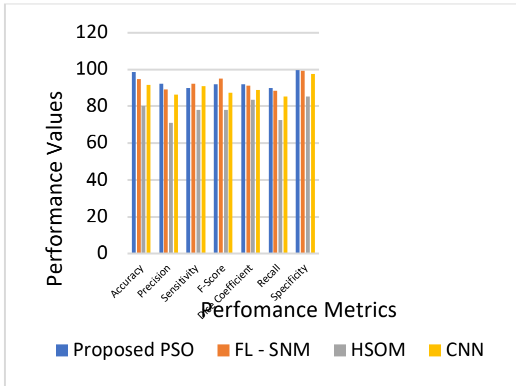

Figure 9: Comparative Analysis of algorithms

In fig.9, a comparative analysis is carried out in a bar graph. The proposed algorithm is compared with three other algorithms called FL-SNM[11], CNN[13] and HSOM[8]. The assessment is evaluated based on accuracy, precision, sensitivity, F- Score, Dice Coefficient, Recall and Specificity of the algorithms. FL-SNM results in DSC rate of 91.2%, sensitivity of 92.07%, specificity of 99.34%, accuracy of 94.87%, precision of 89.36%, recall of 88.39% and F-measure of 95.06%[11] . HSOM yields accuracy of 80.01%, sensitivity of 78.2%, specificity of 85.4%, precision of 71.14%, recall of 72.34%, F-measure of 78.25% and DSC of 83.63%[8]. CNN yields accuracy of 91.5%, sensitivity of 90.8%, specificity of 97.72%, precision of 86.41%, recall of 85.47%, F-measure of 87.54% and DSC of 88.78%[13].

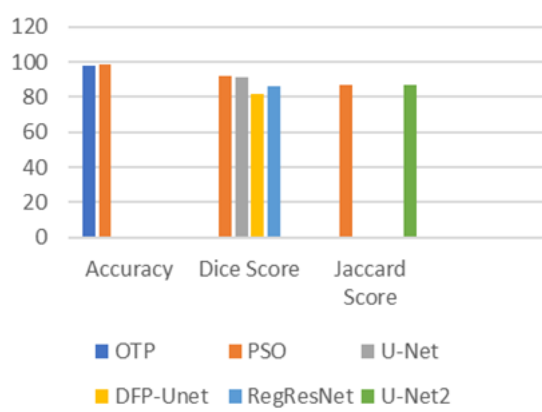

Figure 10: Comparative Analysis of algorithms

In Fig.10, a comparative analysis is carried out in a bar graph. The proposed strategy is compared with five other algorithms called OTP[2], U-Net[3], U-Net2[4], DFP-Unet[5], RegResNet[9]. The assessment is evaluated based on accuracy, Dice Coefficient, Jaccard score of the algorithms. OTP results in accuracy rate of 98.23%, and U-Net yields a DSC of 91.69%, DFP-UNet yields DSC of

81.69% and RegResNet yields a DSC of 85.9% and the Jaccard score of U-Net2 is 86.84%.From this we understand that the proposed strategy outperforms the other three algorithms with higher values in the assessment.

VI. CONCLUSION

This research explores the utilization of a nature-inspired Computational Intelligence algorithm called PSO algorithm for the segmentation of brain tumor. This project implicitly performs a clustering visualization which renders a systematic segmentation of tumors into distinct clusters. The segmented output is then procured by the user selection of the cluster which is likely to be the tumor region. The objective of the strategy is to provide significant understanding about the possibilities of bio-inspired optimization methods for raising the accuracy of brain tumor segmentation. The research results with a remarkably high average accuracy rate of 98.5%. Thus, making the algorithm ideal for the recognition and isolation of tumors in medical image segmentation. The future work for the project may involve further optimization and validation on larger datasets. By collaborating with medical professionals to validate the algorithm's performance in clinical settings. Consider participation in clinical trials to assess the impact on patient outcomes. These are the works that can be implemented in the project in the future.

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