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OPTIMIZED DEEP NEURAL NETWORKS FOR SEGMENTATION OF BRAIN TUMOUR FROM MR IMAGES

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Abstract : **For numerous applications in the field of medical analysis, the localization and segmentation of brain tumours from magnetic resonance imaging (MRI) are challenging and important tasks. Many recent approaches used the four modalities T1, T1c, T2, and FLAIR because each brain imaging modality provides distinct and important details related to each area of the tumour. In this project, to obtain a flexible and effective brain tumour segmentation system, first, we propose a preprocessing approach to work only on a small part of the image rather than the whole part of the image. In the second step, as we are dealing with a smaller part of brain images in each slice, a simple and efficient Convolutional Neural Network is proposed. Two network one is 3D CNN and other is U-Net is designed and ensembled.Finally to achieve good results Particle swarm optimization is designed to achieve the global best feature for segmentation of brain tumour. The matlab is used for performing experimental evaluation.**

IndexTerms **– 3D CNN,U-Net,Particle swarm optimization,matlab.**

I. INTRODUCTION

One of the most dangerous tumours in the world is a brain tumour. It develops when a particular kind of brain cell, known as a malignant cell, starts to expand rapidly. The number of patients having a brain cancer diagnosis has considerably increased over the past 30 years, affecting many people all over the world.

Early diagnosis of brain cancer is important since it allows for diagnosis and treatments. Depending on the location, nature, and size of the tumour, radiotherapy, surgery, chemotherapy, or a combination of these treatments may be used to treat brain tumours. Medical imaging is employed to confirm the presence and identify certain features of various types of brain tumours. There are several other medical imaging techniques, but the two that are most commonly used to detect brain cancer are magnetic resonance imaging (MRI) and computed tomography(CT) scans.

Magnetic resonance imaging (MRI) techniques are becoming more frequently used for tumour identification and assessment also for monitoring and predicting patient outcomes.Accurate brain segmentation is important for both diagnostic and treatment planning of the tumour. The difficulty of tumour segmentation in multi-modal MRI scans is due to appearance of tumour in several shapes and sizes. MRI has quickly become a popular method. Examples of such MR-images are shown in Figure(1)

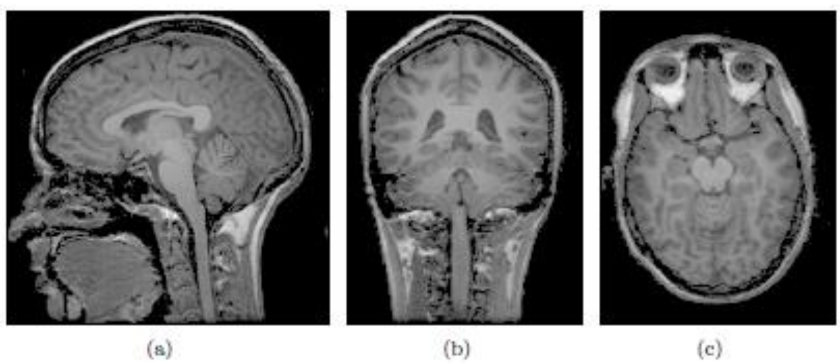

Figure 1. Examples of structural magnetic resonance images. The images show slices of a human head viewed from (a) sagittal, (b) frontal and (c) horizontal directions.

II. Related works

Numerous studies have shown how important Deep learning (DL) is in facilitating and enhancing the effectiveness of human practices.DL algorithms can help neuroradiologists to monitor and plan for the disease by accurately segmenting the cancerous areas.Semantic segmentation tasks are better handled by deep learning algorithms than by traditional, context-based computer vision techniques.

Deep Learning Algorithms:

It was proposed a 2D U-Net architecture for the automated segmentation of brain tumours [1].To minimise the issue of class imbalance in the data and improve network efficiency, a variety of data augmentation approaches were used in conjunction with the soft dice loss function. A neural network that had previously been utilized for the job of brain parcellation was improved by Fidon et al. [2] and modified for the input of multimodal MRI data. In order to connect the frontend and backend of a network, ScaleNet used a merging process rather than concatenation, making it scalable and generalised. Le et al. [3] developed an architecture that combined a fully convolutional network with the standard variational level set (VLS).

Shen et al. [4] proposed a fully convolutional network (FCN), trained to learn boundary and area tasks, and it was successful in extracting context from MRI scans with a relatively low computational cost. Pereira et al. [5] developed an FCN using a similar architecture that captured more complex features through feature recombination and added a recalibration block to the structure. With the use of a one-pass computational strategy, Zhou et al. [6] introduced a multi-task CNN that integrated and trained on the many tasks of brain tumour segmentation in terms of their association. This accelerated the inference process. A scribble-based, weakly-supervised U-Net was proposed by Ji et al. [7]

In this paper, we suggest an ensemble of two networks, a 3D CNN and a U-Net, in an unique yet simple combinative approach that yields more precise predictions than uniform weighting. The objective is to develop an automated brain tumour segmentation system that will delineate tumours into intra-tumoural classes successfully and more accurately than current approaches. In comparison to the most recent models, our proposed approach produces outcomes that are comparable, and in some cases even better.

III. Materials and methods

For the diagnosis and assessment of brain tumours, radiologists frequently use magnetic resonance imaging (MRI) technology. It offers multiple complementary 3D MRI modalities, including T1-weighted, post-contrast T1-weighted (T1ce), T2-weighted, and fluid-attenuated inversion recovery, that are acquired based on the level of excitation and repetition times.Figure 2 represents the block diagram of the proposed methodology.

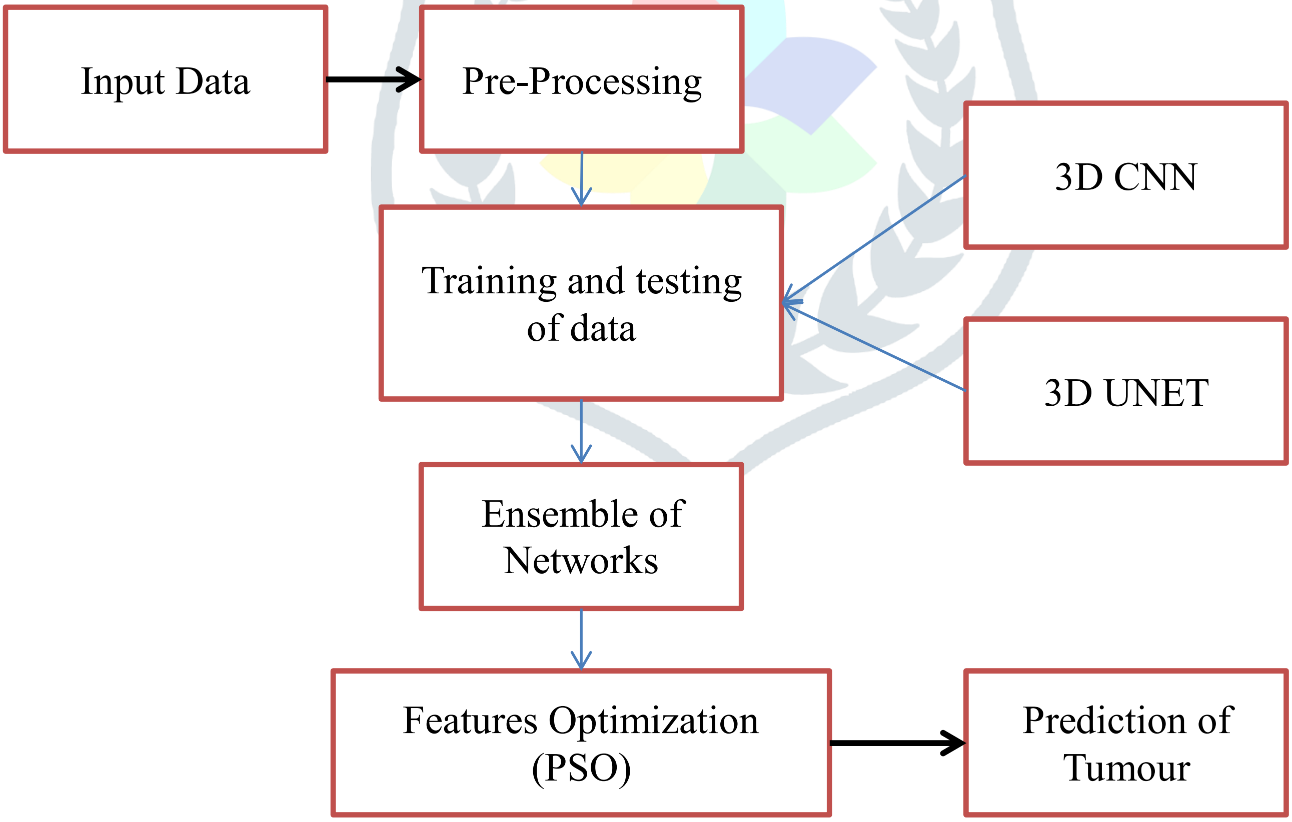

Figure 2: Block diagram of proposed model

A.DATASET USED:

We make use of the 2020 Brain Tumour Segmentation Challenge (BraTS) dataset, the training setis used to develop the models and validation set to assess the proposed ensemble.

B.PREPROCESSING:

We only concentrate on a small portion of the image to extract the most important features, in contrast to many other current deep learning algorithms that use the entire image. The genuine negative results are significantly reduced by eliminating these pointless uninformative components. Additionally, by employing such an approach, we can avoid using a convolutional model that is too complex. Four brain modalities—T1, FLAIR, T1C, and T2—are used to increase the final segmentation's accuracy. We perform normalisation for the employed modalities to make the MRI data more uniform and eliminate the anisotropic effect (particularly for the FLAIR modality). This method results in an output image with zero mean and unit variance for a medical brain imaging.

C.TUMOUR REPRESENTATION IN EACH SLICE:

In this research, we discovered that the tumour's size and shape constantly changed or increased in size in successive slices. The tumour appears in the initial slices in any imaginable area of the image. The tumour will then stay in the same spot within the image in the succeeding slices, but it will grow larger. The tumour size will then begin to decrease after reaching its largest size until it then disappears completely. The primary benefit of using the four brain modalities outlined above is their distinct ability to identify specific tumour components. A tumour must also be located in all three of its components in each of the four modalities, which must then be combined to create a solid item.

D.DEEP LEARNING ALGORITHMS USED:

Network One: 3D-CNN

In this paper, an ensemble CNN model that includes local and global data from several MRI modalities has been proposed. Chen first created a 3D CNN, which is the first model in this ensemble. For volumetric segmentation, it employs a multifiber unit with weighted dilated convolutions to extract feature representation at many scales. We expand their work by optimizing the model for better segmentation.Figure 3 represents 3D CNN Network.

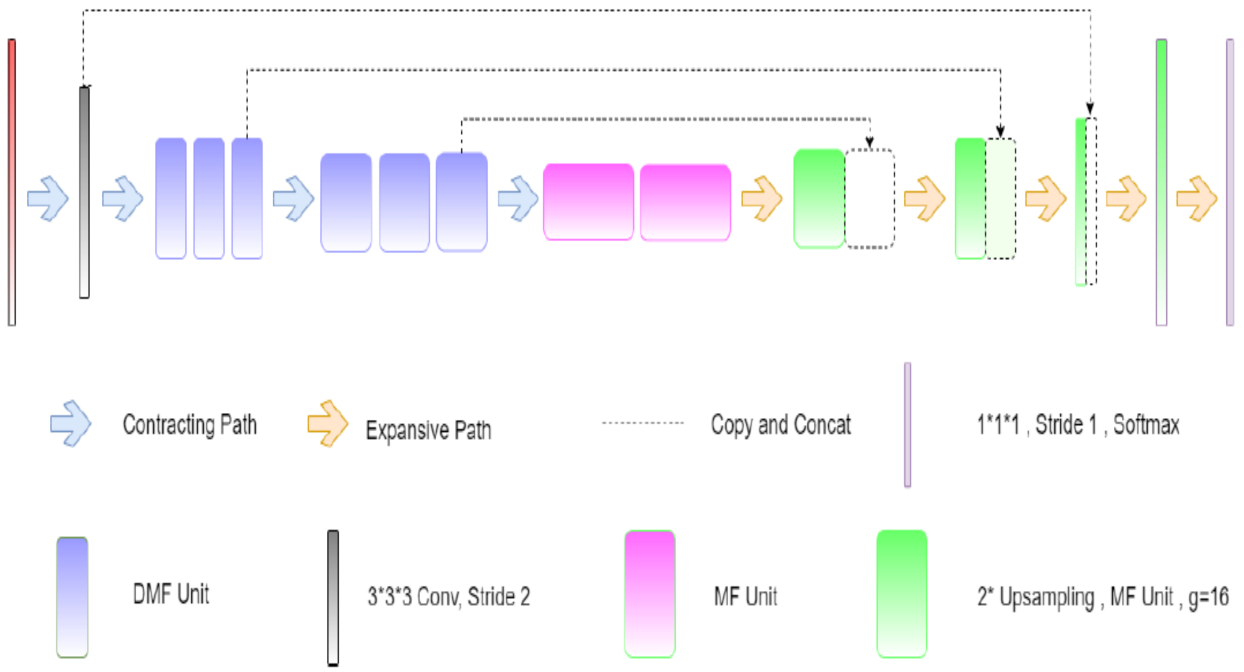

Figure 3: 3D-CNN model

Network Two: 3D UNET

The second model in our ensemble is a 3D U-Net variant that differs from the conventional U-Net architecture; in which leaky ReLUs are used in place of the ReLU activation function and instance normalization is used instead of batch normalization.figure 4 represents 3D UNET network.

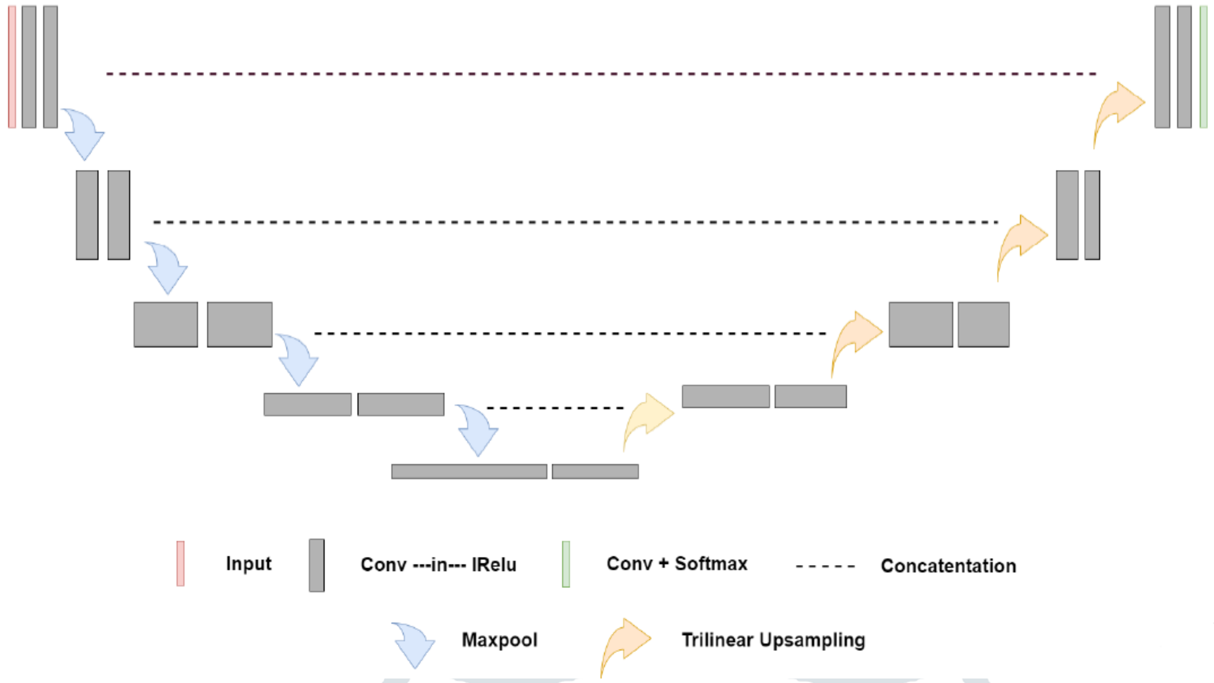

Figure 4: 3D UNET Model

E.ENSEMBLE OF NETWORKS:

The predictions (probability maps) produced by the two models are not simply averaged to create the ensemble. We combine the results from the two models after carefully evaluating a technique known as variable ensembling. To acquire the relevant segmentation pictures, we independently test these trained networks on the validation set. On the online BraTS server1, these predictions from the various models are independently assessed to see how well they segregate the tumour areas. Then, we compare the dice scores of the two models to determine which network performs better and is more accurate for each particular tumour location.

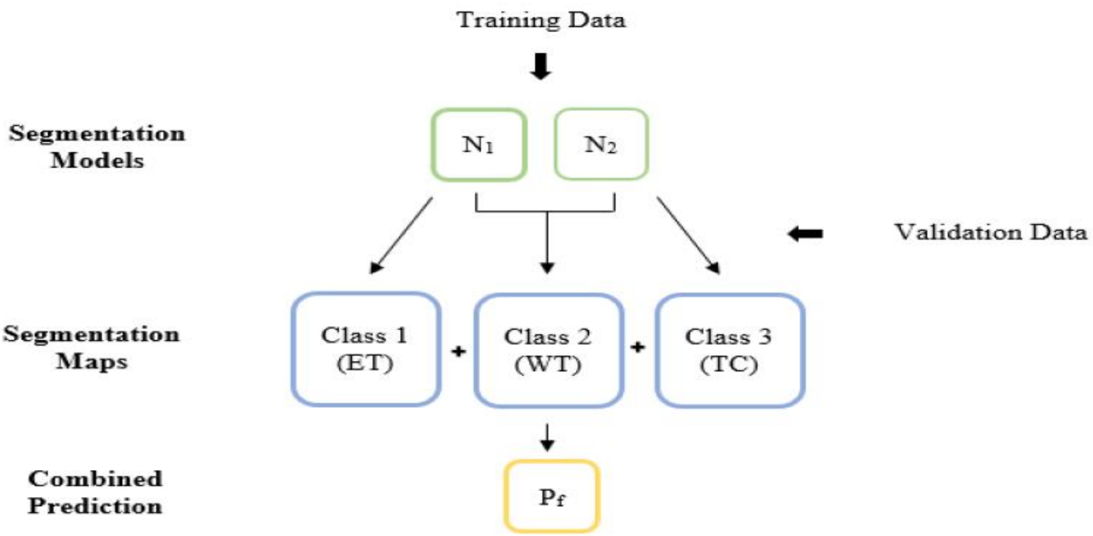

Figure 5:Ensemble Architecture where N1 represents 3D CNN and N2 represents 3D UNET

F.OPTIMIZATION OF ENSEMBLE DATA

The use of optimization techniques enables any application to achieve the greatest features available worldwide. In this research, particle swarm optimization (PSO) is taken into consideration to figure out the best tumour segmentation portions. The last layer of CNN employs this optimization strategy to extract the best features possible. The features will be chosen based on the PSO process, and the PSO process is explained in detail.

H. PARTICLE SWARM OPTIMIZATION

Particle swarm optimization (PSO) is a computational technique that aims to solve a problem as efficiently as possible by repeatedly attempting to raise the quality of a candidate solution. A population of possible solutions, here referred to as particles, are used to solve a problem, and these particles are moved throughout the search space in accordance with a straightforward mathematical formula over the particle's position and velocity.[8] In addition to being led toward the best known positions in the search space, which are updated as other particles find better places, each particle's movement is also impacted by its local best known position. This is expected to guide the swarm toward the most effective solutions.

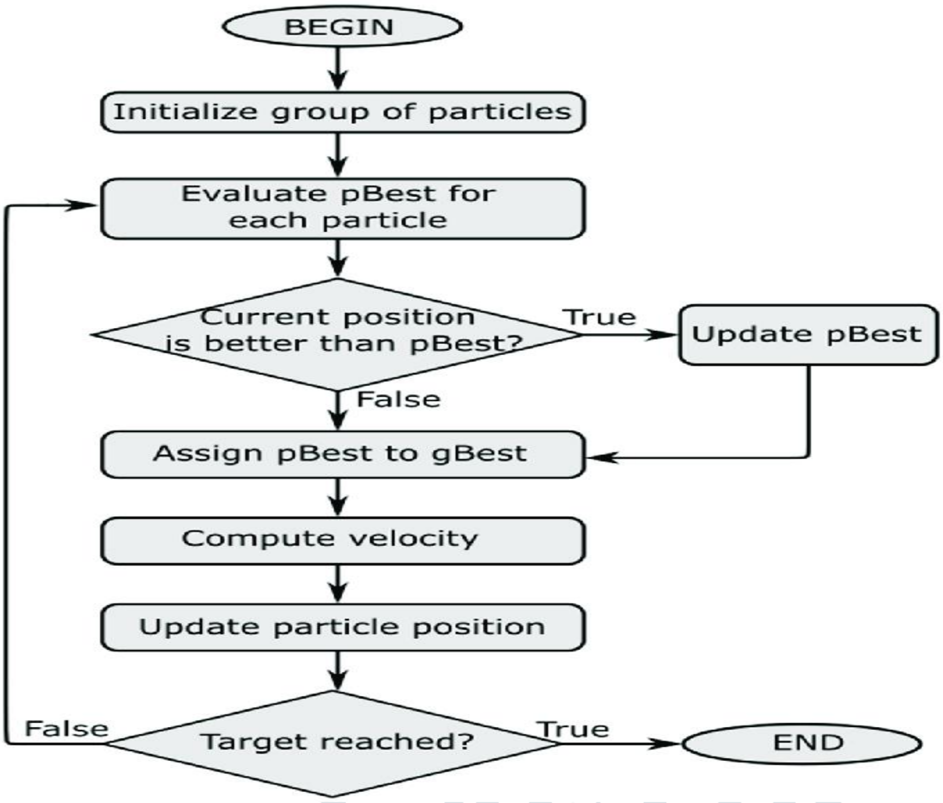

Figure 6:Flowchart of PSO

IV. Results

Evaluation Metrics:

Metrics for the enhancing core (EC), tumour core (TC, including necrotic core plus non-enhancing core), and entire tumour(WT, including all classes of tumour structures) are used to evaluate the success of the technique.The assessment metric used to calculate the overlap between the ground truth and the predictions is the Dice Similarity Coefficient (DSC).

EC

The enhanced core tumour is believed to indicate areas where the blood-brain barrier has been compromised, which is frequently observed in high-grade gliomas.

TC

In addition to transitional/pre-necrotic and necrotic areas that are a part of the non-enhancing portion of the tumour core, the NET also reflects non-enhancing tumour regions.

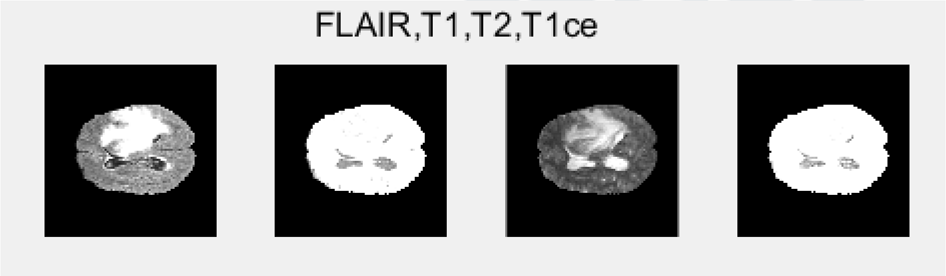

Figure 7: input images flair,T1,T2,T2ce

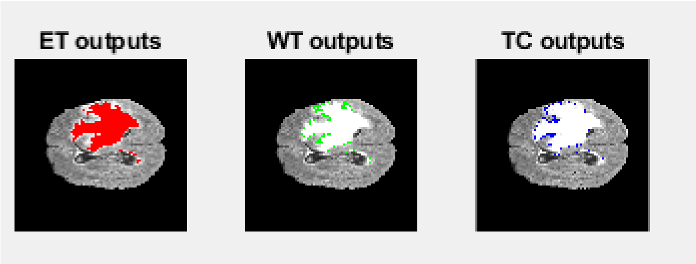

Figure 8 output images using CNN + UNET

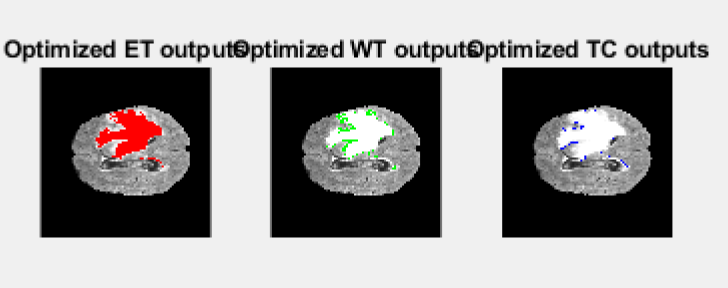

Figure 9 output images with ensemble optimized technique(PSO)

Table 1: comparison table for different Algorithms

Sl. No	AT SLICE VALUE 80	ET	WT	TC
1	CNN + UNET	0.8334	0.9886	0.9681
2	ENSEMBLE OPTIMIZED NETWORK(PROPOSED)	0.8769	0.9891	0.9851

V. Conclusion

In this work, we have described an ensemble of two networks that are typically used to perform the task of biomedical image segmentation. According to the multimodal MRI scans provided by the BraTS 2020 challenge dataset, the ensemble successfully creates highly accurate segmentation of brain tumours, which compares favourably with predictions produced by different other state of art models. The extracted features are optimised by using particle swarm optimization techniques, which also increase the accuracy of tumour detection. The proposed optimized ensemble offers an automated and impartial way to provide brain tumour segmentation to support clinical disease planning and patient care.

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