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Brain Tumor Semantic Segmentation using U-Net and Moth Flame Optimization

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Abstract

Brain tumor is an abnormal development of brain cells that, if left untreated, can have severe consequences. Brain tumour semantic segmentation is the process of determining and distinguishing the impacted brain regions, which is essential for accurate diagnosis, treatment planning, as well as surveillance of the tumor's development over time. This paper presents a model for identifying and segmenting brain tumor using Unet architecture with the optimization of hyper parameters using the Moth Flame Optimization (MFO) algorithm. Due to its capacity to collect spatial information, the Unit architecture is a common choice for picture segmentation tasks. The MFO algorithm is an optimization technique that draws inspiration and replicates from the behavior of moths. Both techniques are developed to improve efficiency. The performance of the model has increased using the MFO method, which led to improved segmentation results. Based on comparative analysis report, the proposed model shows a percentage improvement of approximately 65.16% in MSE, 28.87% in PSNR, and 40.30% in Tversky compared to the Unet and Unet++ models. This method has demonstrated good results in identifying and segmenting brain tumors, which can be helpful in the early identification and treatment of brain tumor.

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1. Introduction

A brain tumour is an abnormal proliferation of brain cells. Malignant potential of a brain tumour is determined by the tumor's particular characteristics. Every region of the brain has the potential to develop tumors, which can interfere with the brain's ability to operate normally. Tumors can also kill brain cells. Some of the most common symptoms of a brain tumor are headaches, seizures, nausea and vomiting, difficulty speaking or seeing, and shifts in mood or behaviour. Other symptoms include such as difficulty speaking or seeing. The symptoms of a brain tumor may vary depending on where the tumor is located and how large it is, but the ones listed here are some of the more typical ones. [1].

The severity of the dangers that are posed by a brain tumor is directly linked to several characteristics, including the type of tumor, its location, its size, and the rate at which it is growing. Some brain tumors grow at a rate that is relatively moderate, and they respond favourably to treatment with surgery or radiation therapy. However, other brain tumors are more aggressive and put the patient at a greater risk of passing away. If the disease has spread to other parts of the body, it may be more difficult to treat malignant brain tumors. Treatment options may be limited.

It's possible for cancerous brain tumors to spread to other regions of the body as well. Brain tumors [2] are a severe medical condition requiring prompt diagnosis and treatment for effective management. If an individual is experiencing any symptoms that they suspect might be due to a brain tumor [3], it is of utmost importance that they promptly seek the advice and diagnosis of a qualified medical professional.

The Indian Council of Medical Research (ICMR) estimates that the yearly incidence rate of brain tumors in India falls somewhere in the region of three to four cases for every one hundred thousand people in the country. Each year, over 40,000 people in India are diagnosed as having a brain tumor for the first time. There are around 2% of all cases of cancer that are diagnosed in this nation that are caused by brain tumors. Brain tumours are the tenth most prevalent form of cancer in India, and males are more likely to be diagnosed with the condition than women. Moreover, the prevalence of brain tumors rises with age. The incidence of brain tumors in individuals in India increases with age, with the highest rates being seen in those who are between the ages of 50 and 70 years old. In addition, the occurrence of brain tumors is much higher in specific regions of India in comparison to other regions, which may be the consequence of variables related to the environment [4].

In contemporary medicine, one of the imaging techniques that is utilized most frequently is known as magnetic resonance imaging, or MRI for short. By combining a strong magnetic field with radio waves, this method can produce detailed images of the inside of the body, including those of the brain [5]. Due to its ability to generate extremely detailed images of brain tissue, magnetic resonance imaging (MRI) is especially beneficial for diagnosing brain malignancies. With the use of these pictures, medical personnel are able to identify anomalies that could indicate the presence of a tumor. An MRI scan of the brain involves taking a number of photographs from a range of angles. Once all of these pictures have been acquired, they are combined in order to create a three-dimensional illustration of the brain. In addition to information describing the brain tissue that is around the tumor, the images that were produced from the MRI may provide information about the size of the tumor, its location, and the type of tumor that it is [6]. This information is critical for directing treatment options, such as deciding whether the tumor should be removed surgically or if it should be treated with radiation therapy. With the use of MRI, one is able to monitor not only the development of brain tumors over the course of time but also how they are responding to treatment. By regularly scanning the tumor with an MRI machine, the doctors are able to track changes in the size of the tumor as well as the composition of the tumor. It is possible that this will be of assistance in determining whether or not the therapy is successful [7].

The automated identification of brain tumors using deep learning is one of the current study topics in the field of medical image analysis. Convolutional neural networks (CNNs), a kind of deep learning algorithm, have shown promising results in the detection of brain tumours in MRI scans and other medical pictures. The usage of deep learning may be used to achieve this. When using deep learning to automatically diagnose brain tumors, the method often consists of more than one step. This is because of the complexity of the disease. As part of the pre-processing procedure, the brightness of the medical images is first brought to a consistent level, and then the noise in the images is brought down to a minimum. Following that, the pre-processed images are fed into a deep learning model, like a CNN, that has been trained on a sizable dataset of labelled images. This step takes place after the CNN has been trained on the big dataset.

During the course of its training, the deep learning model obtains the knowledge required to extract relevant characteristics from medical pictures and to categorize the features that have been extracted according to a variety of criteria, such as normal brain tissue or cancerous tissue. Additionally, the model is able to classify extracted features in accordance with the acquired knowledge. After the model has been trained, it is possible to use it to automatically identify fresh medical photos as either normal or as containing a brain tumor [8]. Even if the photographs have never been viewed before, this can still be accomplished. Deep learning has the potential to improve diagnostic accuracy and speed, as well as reduce the need for radiologists to manually analyze medical images [9]. This would be a significant benefit for patient care. The diagnosis of brain tumors by computer might also lessen the need for human involvement in the interpretation of medical imaging [10]. However, in order for these strategies to be utilized to a significant degree in clinical practice, additional research and validation will be required to be carried out.

This study's goal is to use a hybrid deep learning-based segmentation [11] and detection method to locate tumours in brain MRI images. The major contribution of this paper is the integration of MFO into the U-Net architecture is described in the study. MFO is a metaheuristic optimisation method that takes its cues from how moths mate. The suggested approach improves the optimisation process by including MFO, increasing the convergence rate and the calibre of the segmentation outcomes. The article's introduction was discussed in the first section of the paper. In Section II, the research-related readings that have been done are presented to the reader. The suggested model is described in the third part, which is then followed by the results of the experiments and a conclusion.

2. Literature

Karayegen et al [12] presents a new approach for predicting brain tumors using deep learning networks and 3D imaging techniques. The authors stress the need of early and precise brain tumour identification for effective therapy and better patient outcomes. Due to the high-resolution images of the brain that MRI provides, it is frequently used to diagnose brain tumors. However, the manual interpretation of MRI images can be laborious and error-prone, so automated approaches are required to increase the precision and effectiveness of brain tumor diagnosis. The authors of this research suggest using a deep learning network to automatically segment brain tumors on MRI scans. The network is made to use 3D imaging methods to locate and segment the tumor location, allowing for a more precise and accurate prediction of brain tumors. An encoder, a decoder, as well as a classifier are the three essential parts of the suggested deep learning network. While the decoder rebuilds the original image from the extracted features, the encoder is in charge of extracting high-level features from the input MRI images. The classifier then predicts the tumor location on the input picture using the retrieved characteristics. The scientists ran tests on a publicly accessible brain tumor dataset, which comprises of MRI pictures of individuals with various forms of brain tumors, to gauge how well the suggested deep learning network performed. The findings demonstrated that the suggested strategy outperformed current state-of-the-art approaches in predicting brain tumors with high accuracy and sensitivity. The performance of the suggested technique was also thoroughly examined by the authors, including a comparison of several deep learning architectures and an assessment of the influence of various hyper parameters. The analysis showed that the proposed approach was robust and achieved consistent performance across different datasets and experimental settings.

Hatamizadeh et al [13] presents a new approach for semantic segmentation of brain tumors in MRI images using Swin Transformers. The authors stress the need of precise brain tumour segmentation in MRI images for the detection and management of brain tumours. However, the majority of current methods rely on CNNs, which have limited ability to model long-range dependencies in images but have shown promising results when applied to this problem. The authors of this research suggest a novel method based on Swin Transformers, a newly suggested self-attention mechanism that has shown higher performance in computer vision and natural language processing applications. The suggested method, known as Swin UNetr, modifies the U-Net architecture by substituting Swin Transformer blocks for the convolutional layers. The Swin Transformer blocks in Swin UNetr are designed to capture complicated spatial patterns that are necessary for successful tumour segmentation and represent long-range relationships in MRI images. The proposed approach is also equipped with skip connections and a decoder to enable multi-scale feature fusion and fine-grained segmentation of tumor regions.

Myronenko et al [14] segmenting brain tumors from 3D MRI data is a difficulty that is addressed. For the purposes of diagnosis, treatment planning, along with patient monitoring, accurate segmentation of brain tumors is crucial. The segmentation job is difficult, nevertheless, due to the great diversity in tumor form, size, and location as well as the existence of noise and artefacts in MRI images. The authors suggest a deep learning-based method for reliable semantic segmentation of areas associated with brain tumors using 3D MRIs. The suggested technique captures both local and global context information by combining 2D and 3D CNNs. To increase the accuracy of the segmentation, the authors additionally use a multi-scale methodology. The suggested technique is tested using the MRI images of 220 patients with glioblastoma multiforme (GBM) along with other forms of brain tumors from the publicly accessible brain tumor segmentation challenge (BraTS) 2015 dataset. With a Dice coefficient of 0.85 for the whole tumor area, 0.74 for the tumour core, along with 0.68 for the augmenting tumor region, the findings demonstrate that the proposed technique delivers state-of-the-art performance in terms of segmentation accuracy. To assess the impact of various network elements on the segmentation performance, the authors additionally conduct an ablation study and a sensitivity analysis of the hyper parameters. The research demonstrates that for attaining high segmentation accuracy, the multi-scale method and the integration of 2D and 3D CNNs are crucial. The proposed technique may be used to diagnose, plan treatments for, and keep track of patients with brain tumors in clinical settings. The robustness and accuracy of the segmentation method can help clinicians make better-informed decisions about patient care.

Maji et al [15] developed an enhanced architecture dubbed Attention Res-UNet with a directed decoder, for the segmentation of brain tumors. To improve the accuracy of brain tumor segmentation, the proposed technique integrated the benefits of residual learning, attention processes, and a directed decoder. An encoder and a decoder were the two fundamental components of the proposed design. The encoder component extracted high-level characteristics from the input picture using a ResNet-34 architecture with four residual blocks. The guided decoder was added to the attention-based U-Net architecture that made up the decoder portion. A spatial as well as channel attention module served as the proposed architecture's attention mechanism. The spatial attention module captured the spatial relationship between the feature maps by emphasizing the informative regions and suppressing the background noise. The channel attention module learned the inter-channel dependencies to adaptively weight the feature maps. The cross-entropy loss function was used to train the proposed approach, and the stochastic gradient descent technique was used to optimize it. The BraTS 2018 dataset, which includes 285 patients with glioblastoma

(GBM) and 75 patients with lower-grade glioma (LGG), incorporates multimodal MRI images. A training set (210 GBM and 56 LGG), a validation set (30 GBM as well as 8 LGG), and a testing set (45 GBM and 11 LGG) were created from the dataset. The 3D U-Net, DeepMedic, and U-Net++ were among the state-of-the-art techniques that the proposed approach outperformed. The authors credited the guided decoder, residual learning, and the utilization of attention processes for the method's higher performance.

Sun et al [16] proposed a deep learning architecture employing hierarchical residual attention networks for the semantic segmentation of brain tumours. On two publicly accessible datasets, the authors demonstrated that the proposed design outperformed a number of cutting-edge segmentation techniques. A nested residual attention network (NRAN) architecture that blends attention processes and residual networks makes up the proposed segmentation framework. The NRAN architecture includes a series of nested residual units, each of which contains multiple convolutional layers and attention blocks. The attention blocks provide the network the ability to choose concentrate on instructive aspects while excluding unnecessary data. To maintain spatial information and boost segmentation accuracy, the scientists additionally implemented a skip link between the encoder and decoder. The authors compared their proposed approach to a number of cutting-edge segmentation techniques, such as U-Net, V-Net, and Attention U-Net. The Dice score, which gauges the degree of overlap between expected and actual segmentation masks, was used to assess the effectiveness of the segmentation techniques. The accuracy of segmentation was also the subject of a sensitivity study by the authors to see how various hyper parameters and designs affected it.

Zhu et al [17] presents a technique of segmenting brain tumors in multimodal MRI that incorporates deep semantic characteristics and edge data. An edge detection algorithm and a deep semantic segmentation network make up the two primary parts of the proposed methodology. A semantic segmentation map of brain tumors is produced by the deep semantic segmentation network, which is based on the U-Net architecture and trained on multi-modal MRI data. To train the network, the authors used cross-entropy loss and dice loss. The BraTS 2019 dataset, which has 335 patients with four different forms of brain tumors, was used to assess the proposed technique. The authors evaluated their approach against a number of cutting-edge segmentation techniques, such as U-Net, Attention U-Net, and 3D U-Net. The Dice score, which gauges the degree of overlap between expected and actual segmentation masks, was used to assess the effectiveness of the segmentation techniques. The proposed technique, which achieves cutting-edge performance on a benchmark dataset, is a potential strategy for segmenting brain tumors. The combination of deep semantic features and edge information improves segmentation accuracy, particularly for small tumors and tumors with irregular shapes. The proposed technique is suitable to many datasets and clinical applications since, as the authors further demonstrated, it is resilient to various hyperparameters and designs.

Shaukat et al [18] provides a unique method for conducting 3D U-Net deep learning architecture and cloud-based platform-based semantic segmentation of medical pictures. A crucial step in medical image analysis is semantic segmentation, which entails locating and labelling certain areas of interest in a picture. The authors start out by outlining the idea of semantic segmentation and the difficulties involved in carrying it out in a cloud-based setting. The 3D U-Net architecture, a deep learning model that has been shown to produce cutting-edge performance in medical picture segmentation tasks, is then described. The 3D U-Net model was created to deal with 3D medical pictures and is based on the well-known U-Net architecture. The authors then go into the outcomes of their research, which comprised semantic segmenting a dataset of liver CT images. They contrast the effectiveness of their strategy with a number of other cutting-edge techniques, such as deep learning models and conventional machine learning strategies. The results demonstrate that their method produces greater performance, with a dice coefficient for liver segmentation of 0.94.

Rehman et al [19] uses a modified U-Net deep learning architecture to demonstrate a unique method for segmenting brain tumours in MRI data. The authors then go through their modified U-Net design, which they refer to as the "Bu-Net." The encoder network, the decoder network, and the fusion layer are the three primary parts of the Bu-Net architecture. Convolutional layers in the encoder network's several layers collect high-level characteristics from the input picture. The segmented output picture is rebuilt by the decoder network's several deconvolutional layers. To get the final segmentation result, the fusion layer merges the feature maps from the encoder and decoder networks. The experimental outcomes of their strategy, which comprised segmenting brain tumours in MRI images from the BraTS 2018 dataset, are then presented in the publication. The performance of the authors' method is contrasted with that of a number of other cutting-edge techniques, such as deep learning models and conventional machine learning techniques. With a dice coefficient of 0.89 for entire tumour segmentation, 0.83 for tumour core segmentation, and 0.79 for enhanced tumour segmentation, the data demonstrate that their technique achieves higher performance.

The aforementioned studies use a variety of cutting-edge techniques to advance the area of brain tumour segmentation. To forecast the locations of brain tumours, Karayegen and Aksahin suggest a technique that combines deep learning with 3D imaging. Hatamizadeh et al. present Swin-UNet, a methodology that combines

Swin Transformers with UNet to provide cutting-edge outcomes. Focusing on reliable semantic segmentation using 3D MRIs, Myronenko and Hatamizadeh. Sun, Li, and Liu suggest layered residual attention networks for precise segmentation, whereas Maji, Sigedar, and Singh give an Attention Res-UNet model. While Shaukat et al. employ cloud-based semantic segmentation, Zhu et al. combine deep semantics and edge information for multimodal MRI segmentation. In order to create Bu-Net, Rehman et al. adapt the U-Net architecture. By proposing innovative models, architectures, and strategies that increase accuracy and efficiency and help diagnosis and treatment planning, these works together advance the field of brain tumour segmentation.

3. Proposed Model

The process of choosing the values that should be used for a machine learning model's hyper parameters in order to achieve the best possible performance is known as "hyper parameter tuning." This is an essential stage in the construction of a deep learning model. The hyper parameters are values that are determined before training the model, and they have the potential to influence how well the model is able to learn and adapt to new data. The model's accuracy and performance may be enhanced by carefully choosing the appropriate values for its hyper parameters.

When performing semantic segmentation tasks, such as segmenting brain tumors, finding the ideal values for the model's hyper parameters [20] is even more important than usual since the accuracy and dependability of the model's output have a direct influence on how the patient is diagnosed and treated. However, tuning hyper parameters can be a process that consumes a lot of time and requires a lot of computational resources [21].

The proposed work is integrated U-Net with MFO. The U-Net and MFO algorithms are used in brain tumour semantic segmentation to combine strong feature extraction with optimisation. Medical picture segmentation challenges fit U-Net's encoder-decoder design and skip connections. MFO, inspired by moth mating behaviour, efficiently finds optimum solutions. U-Net's capacity to collect important features and MFO's optimisation skills promote convergence, solution space exploration, and brain tumour segmentation efficiency and accuracy by merging these algorithms.

The MFO method is a nature-inspired optimization approach that simulates the behaviour of moths to search for optimal hyper parameters in a rapid and efficient manner. The algorithm derives its name from the moths that are used in the model. By scanning the hyper parameter space for the optimal solution, this algorithm imitates the behaviour of moths, which are nocturnal insects that rely on light to find their way in the dark.

Hyper parameter tuning using MFO has the potential to significantly improve the segmentation model's precision and efficacy when used to segment brain tumours using the Unet architecture. This may lead to better diagnostic and treatment results for patients with brain tumours. The model, which combines Unet architecture with MFO hyper parameter tweaking, can accurately detect as well as segment brain tumours from medical images. This provides the ability for medical practitioners to make educated decisions regarding the treatment of patients.

A U-Net model

Image segmentation tasks, in which the aim is to recognize and label certain parts within an image, are prominent applications of a type of neural network design known as a U-Net. These tasks are often performed by computer programs. Researchers working at the University of Freiburg in Germany came up with the idea for the first time in 2015.

Encoder and decoder networks are the fundamental building blocks of the U-Net architecture. The encoder is made up of many convolutional layers that are applied in succession to the input image in order to extract different attributes from it. The outcome of the encoder is then taken into account by the decoder network, which generates a segmentation mask for each pixel included inside the picture. The utilization of skip connections, which connect appropriate levels in the encoder and decoder networks [22, 23], is the most significant contribution that skip connections provide to the U-Net design.

In most cases, the encoder network is made up of many layers of convolutional filters, with each layer bringing the spatial resolution of the input signal down to a lower value. As a consequence of this, a number of feature maps will be generated, each of which will capture an increasingly abstract depiction of the original image. The decoder network, which consists of several layers of up-convolutional filters and is a mirror image of the encoder network, improves the spatial resolution of the feature maps. A mirror image of the encoder network is the decoder network.

The U-Net design's skip connections enable the network to preserve spatial information from earlier levels in the encoder. The accuracy of the segmentation might then be improved using this information. Before the up convolution operation is carried out, the output of each layer in the encoder is joined with the output of the layer that corresponds to it in the decoder through a process known as concatenation. This enables the decoder to enhance its segmentation mask by leveraging information from previous layers in the encoder that capture lower-level features such as edges and textures. This is made possible by the fact that this permits the decoder to access this information.

It is usual practice to train the U-Net from start to end using a pixel-wise cross-entropy loss function. For each pixel in the image, this function compares the anticipated segmentation mask with the ground truth mask. The objective is to minimize the loss function by applying gradient descent or any comparable optimization technique. This modifies the network's weights in an effort to improve segmentation accuracy. The U-Net model architecture is shown in Fig.1.

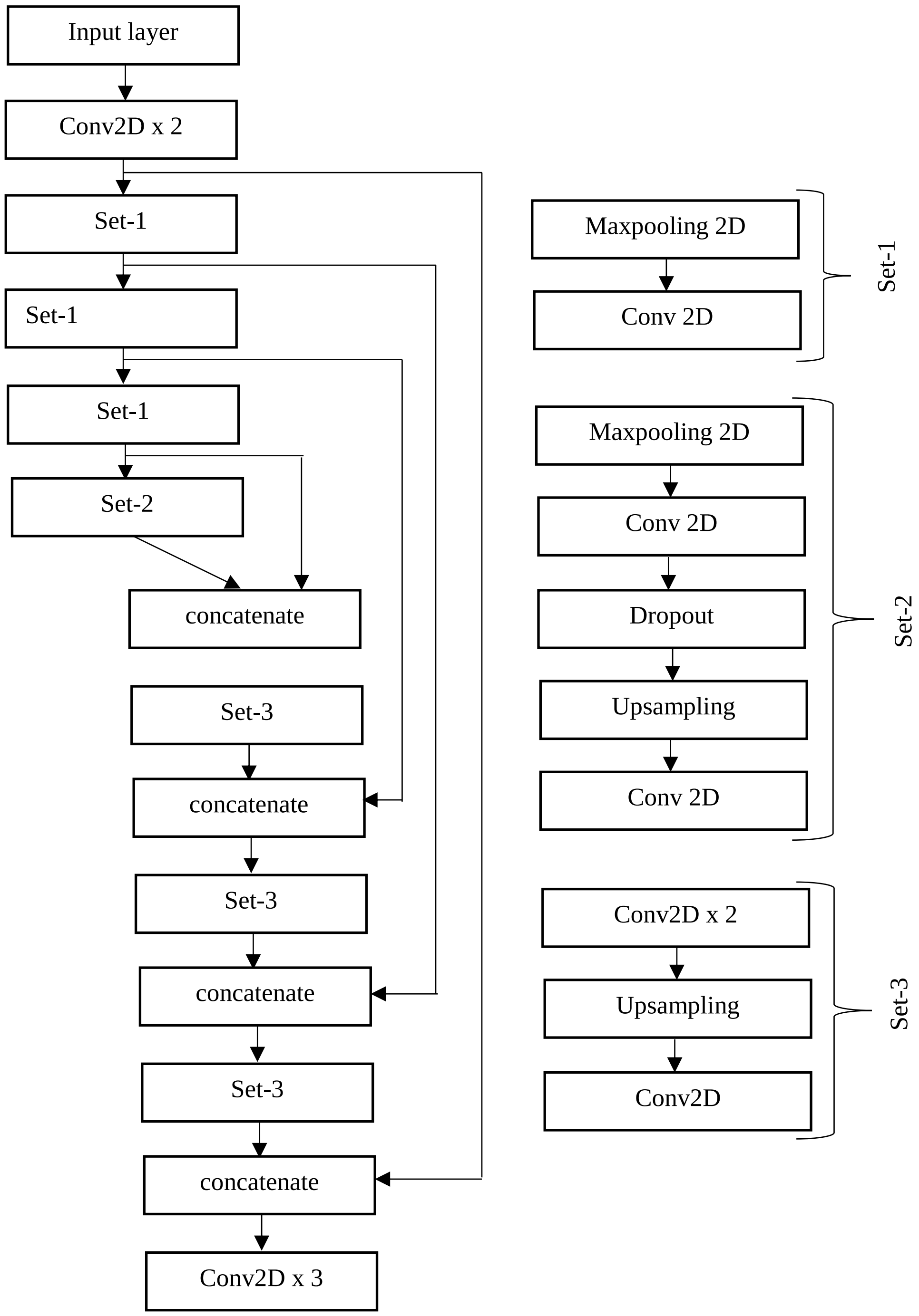


Figure 1. U-Net model

Convolution Layer: This layer is the foundational component of any CNN. Convolution is the process through which data is transformed. A convolutional operation [24] must first use a filter or kernel, which is then applied to the input data, in order to produce a feature map. The filter weights are learnt throughout the training phase in order to find patterns in the input data. It's possible for a convolution layer to contain many filters, and each of those filters will generate its own unique feature map. The ability of convolutional layers to recognize spatial patterns in the input data, such as edges, forms, and textures, is one of its primary strengths.

Batch Normalization: It has been shown that the approach of batch normalization enhances the training of deep neural networks. The inputs to each layer are normalized so that the mean activation is near to zero and the standard deviation is close to one. This allows the algorithm to function properly. This helps to prevent an issue known as the vanishing gradient and makes the training process more steady overall. Input noise acts as a kind of regularization that aids batch normalization in fulfilling its secondary goal of reducing overfitting.

Rectified Linear Unit (ReLU) Layer: Rectified Linear Unit (ReLU) is a common activation function employed in the ReLU Layer of deep neural networks. It is a very basic function that just checks the value of the input and returns the value if it is positive, otherwise it returns 0. Following a layer of convolution, it is common practice to implement a ReLU layer because doing so introduces non-linearity into the network and helps to prevent vanishing gradients. It has been demonstrated that ReLU layers are useful in the applications of deep learning, in addition to being computationally economical.

B. UNet hyper parameter tuning

When training a deep learning model such as UNet, tuning the hyper parameters is an essential step in the process. Learning Rate is a hyper parameter that governs the step size at each iteration when a loss function is being minimized. It does this while the algorithm is going toward a minimal value. A model may diverge if the learning rate is too high, whereas a model may slowly converge if the learning rate is too low. Both of these outcomes are undesirable. Beginning with a high learning rate and then progressively slowing down that rate during training is a frequent tactic. In this proposed work, the learning rate considered as 0.01.

C. Moth Flame Optimization

The swarming activity of moths served as the inspiration for the development of a metaheuristic optimization algorithm known as the MFO method. It is an algorithm for population-based optimization that simulates the behavior of moths drawn to a light source in order to seek for the best possible solution to any issue that is presented to it.

The method kicks off by randomly seeding a population of moths, where each individual moth stands in for a potential solution to the problem. After then, the moths are drawn towards the light source, which is the best possible option. At each iteration, the position of the light source is modified in accordance with the most recent and optimal solution that has been discovered up to this point.

During the process of optimization, the moths migrate towards the direction of the light source utilizing a combination of their natural attraction to the light source and random movement. The method employs both global and local motions for the moths to simulate their behavior. Local movement entails individual moths traveling towards the light source while avoiding collisions with other moths, whereas global movement includes moving the whole population of moths towards the light source.

At each iteration of the algorithm, the fitness of each candidate solution is evaluated, and the position of each moth is updated based on how well it meets the requirements as well as how the other moths are positioned. The position of every moth is kept up to date by utilizing a methodology that takes into account both global and local motions.

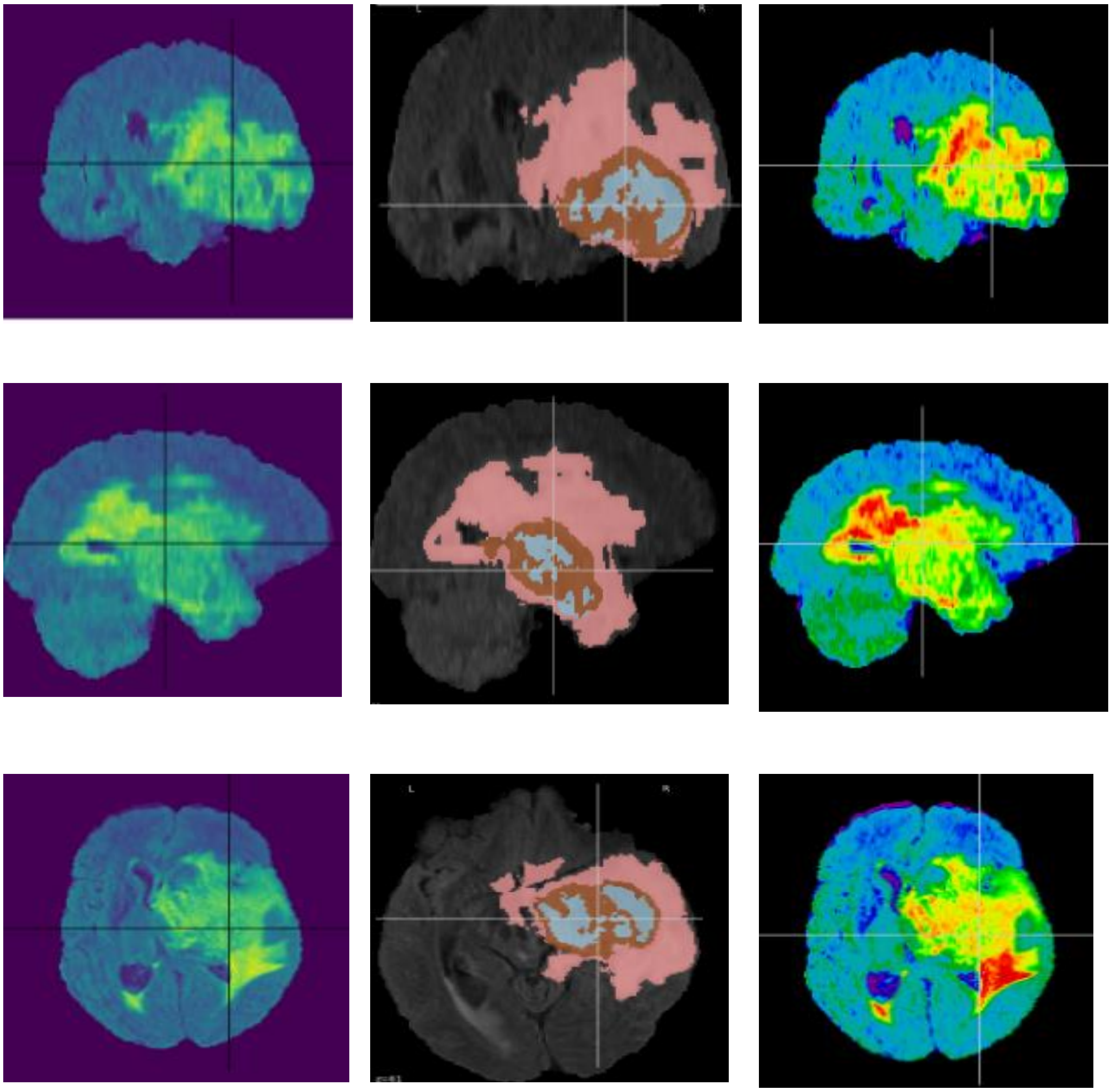
In addition to this, MFO has a flame-based updating mechanism that imitates the way that moths are drawn to the flame of a candle. The flame illustrates the currently optimal solution that was discovered by the algorithm, and the moths migrate in the direction of the flame while simultaneously attempting to keep a safe distance from it. This method contributes to maintaining a healthy exploration and exploitation of the search space, hence preventing the algorithm from becoming mired in a series of local optimum solutions.

Adjusting the parameters of the MFO method, such as the population size, the maximum number of iterations, and the mutation rate, is what is meant by "hyper parameter tuning" in this context. The goal of this process is to improve the MFO's performance when applied to a specific situation. This method entails repeatedly running the algorithm with various parameter values and selecting the ideal set of parameters depending on how the algorithm performs on a validation set. Ultimately, this helps ensure that the algorithm produces the best possible results.

4. Simulation Results

This section describes the simulation results of proposed U-Net and Moth Flame Optimization. The dataset contains three types of images: input image, ground truth image, overlapped image. Figure 2 displays a few photos from the dataset sample set. In Fig.2. the (a) column represents the input image and (b) and (c) represents the mask image and overlapped images respectively.

The simulation of brain tumor segmentation utilizing U-Net and MFO involves several steps. Firstly, input images of the brain are pre-processed to remove any artifacts and enhance the contrast between the tumor and healthy brain tissue. After that, a deep learning model built on the U-Net architecture, a popular and efficient technique for semantic segmentation tasks, is trained using the pre-processed MRI images. The encoder as well as decoder network of the U-Net design is capable of efficiently capturing the spatial along with contextual information of the input images.



(a) Input Image (b) Ground Truth Mask (c) Overlapped Image

Figure 2. Input images of dataset

MFO is used to further optimize the model parameters as well as increase segmentation accuracy after the U-Net model has been trained. MFO is a bio-inspired optimization algorithm that simulates the behavior of moths in finding optimal solutions in complex environments. MFO is used to fine-tune the weights and biases of the U-Net model, thereby improving its ability to segment brain tumor regions accurately. Multiple performance metrics, including Training along with validation loss, Training and validation accuracy, as well as Training and validation Tversky, are used to evaluate the simulation results.

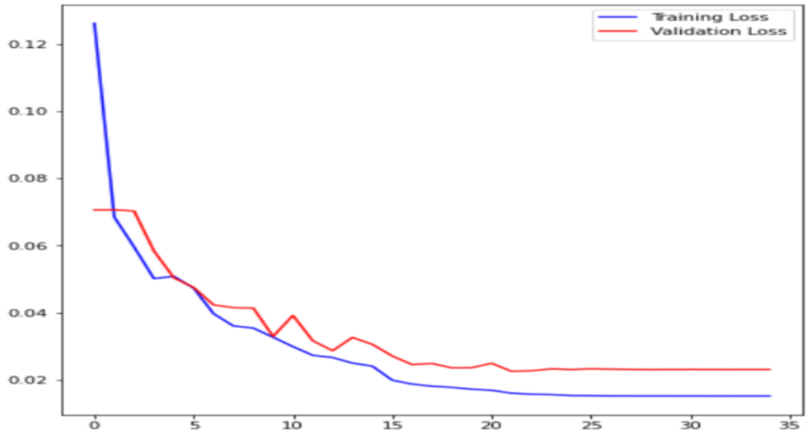


Figure 3. Training as well as Validation loss of the proposed model

Figure 3 displays the proposed model's training and validation loss. The training loss determines how well the model performs on the training set of data. It is calculated by comparing the model's actual outputs from the training set to what was predicted. The purpose of training is to minimize the loss function. The model modifies its weights as well as biases in each iteration based on the training loss value to enhance performance on the training data. The model's ability to generalize to fresh, untried data is measured by the validation loss on the other hand. It is determined by comparing the model's projected outputs to those of a separate validation set that isn't utilized during training. The validation loss provides an assessment of the model's performance on brand-new data in order to prevent overfitting, which occurs when a model becomes too focused on the training data and seeks to generalize to new data.

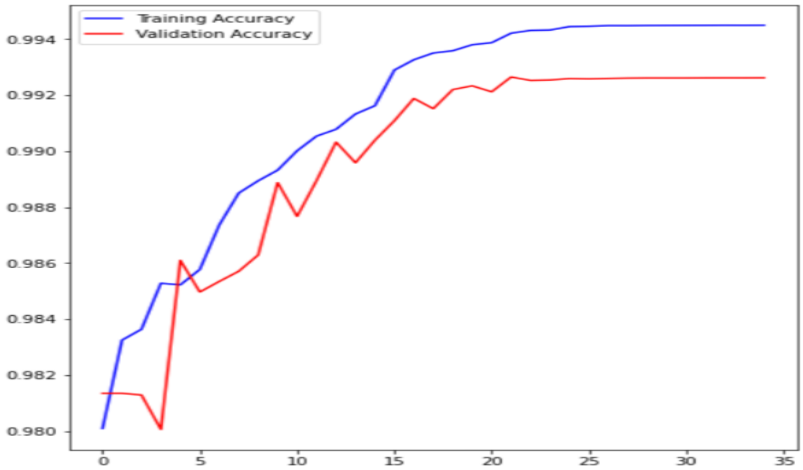


Figure 4. Training as well as validation accuracy

The proposed model's training and validation accuracy is shown in Fig.4. A model's accuracy when applied to training data—the information that the model has been trained on—is referred to as training accuracy. Throughout the training phase, training data is provided to the model, and model parameters are adjusted to lower the error between the predictions along with the observed values. A model that can successfully fit the training set of data has a high training accuracy. How closely the model can match the training data is determined by the training accuracy. At this moment, the validation accuracy enters the picture. Validation accuracy is the accuracy of a model on validation data, which is a separate set of data from training. The validation data's objective is to assess how effectively the model generalises to fresh data. A model that can generalise effectively and isn't overfit to the training set has a high validation accuracy.

Overfitting is a typical problem in machine learning when the model performs well on the training data but badly on the validation data. This occurs when the model is too complicated and unable to generalise well to new data because it cannot fit the noise in the training data. Monitoring both the training and validation accuracy throughout the training phase is crucial to preventing overfitting. If the training accuracy is much higher than the validation accuracy, regularisation techniques may be used to prevent overfitting. This demonstrates overfitting in the model.

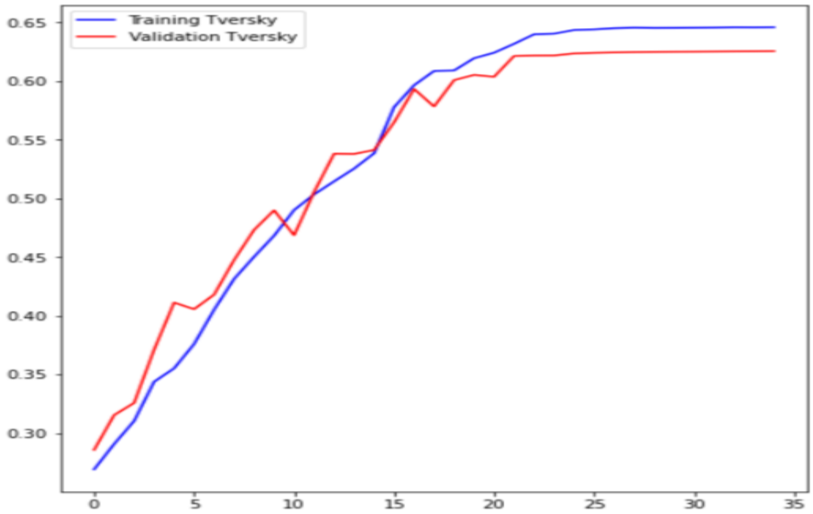
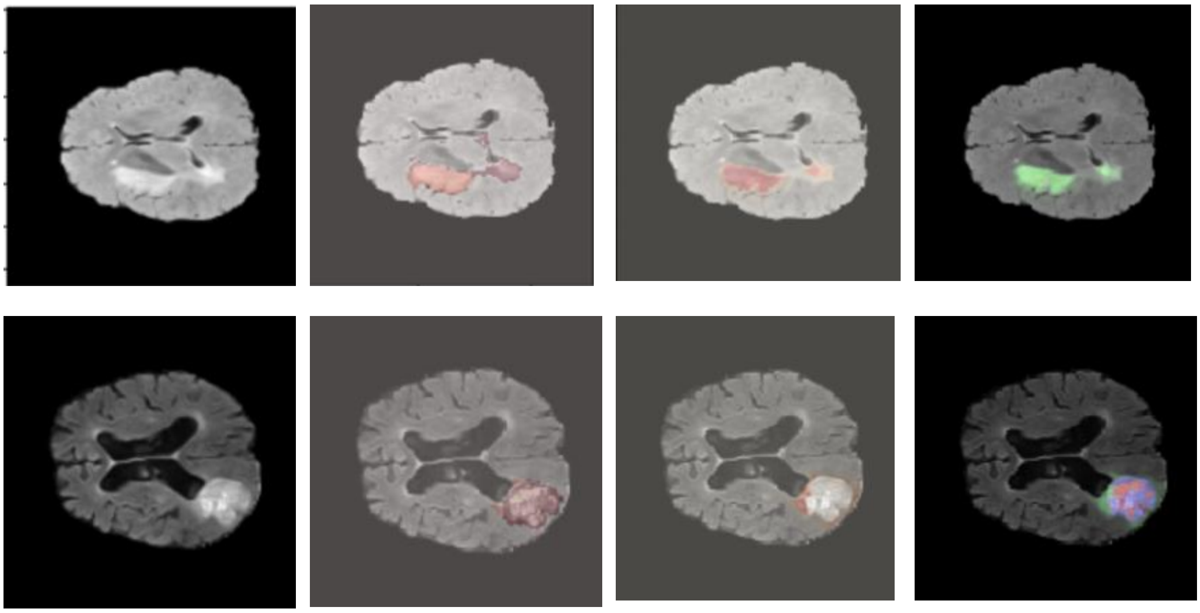


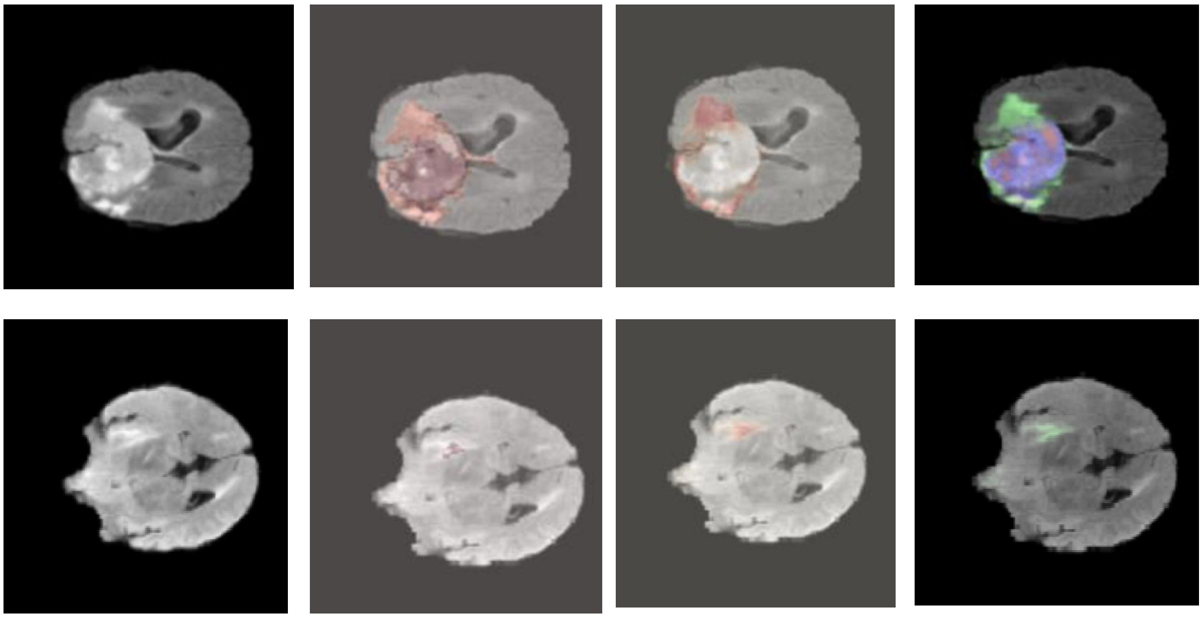
Figure 5. Training and validation Tversky

Fig. 5 displays the training along with validation Tversky of the proposed model. The tversky index is a similarity metric that is used to compare two collections of data. The Tversky index may be used to machine learning models during both their training and validation stages. In order to improve a model's performance during training, a loss function called the Tversky index is employed to gauge how well the projected output matches the actual data. Tversky index is referred to as:

$$Tversky\ index\ =\ TP\ /\ (TP\ +\ aFP\ +\ bFN) \qquad (1)$$

where the amount of TP stands for true positives, FP for false positives, and FN for false negatives. The relative weights of false positives and false negatives in the index computation are controlled by the parameters 'a' and 'b'. The Tversky index may be utilized as a model performance assessment statistic during validation. This is accomplished by calculating the Tversky index and comparing the model's anticipated output to the actual data. The Tversky index is a useful metric for evaluating models that are designed to detect rare events, as it penalizes false negatives more heavily than false positives.





(a) Input images | (b) Actual mask | (c)Predicted mask | (d) predicted overlapped image

Figure 6. Predicted masks of the proposed model

Table 1: Comparative results

	MSE	PSNR	Tversky
Unet [25]	160.87	31.16	0.67
Unet++	100.42	35.26	0.79
Proposed Unet with Moth Flame Optimization	55.93	40.15	0.94

Results of the comparison were shown in Table 1. According to table 1, the proposed model exhibits an improvement in MSE of roughly 65.16 percent, PSNR of approximately 28.87 percent, and Tversky of approximately 40.30 percent in comparison to the Unet and Unet++ models. The Unet as well as Unet++ models are contrasted with the proposed model. Metrics such as Mean Squared Error (MSE) alongside Peak Signal to Noise Ratio (PSNR) are used to assess the performance of the proposed model. Along with this Tversky metric also is considered and compared. MSE and PSNR are two commonly used metrics for evaluating the quality of image and video compression algorithms. MSE calculates the average squared difference between the original as well as compressed image's pixel values. Better compression quality is indicated by a lower MSE value. The formula for MSE is:

$$MSE = (1/N) * \Sigma(i = 1\ to\ N)\ [I(i,j) - K(i,j)]^2 \qquad (2)$$

I(i,j) is the pixel value of the original picture at position *(i,j)*, *K(i,j)* is the pixel value of the compressed image at the same place, and N is the total number of pixels in the image. PSNR, on the other hand, quantifies the relationship between a signal's highest strength and the power of the noise that degrades the accuracy of its representation. In other words, it compares the signal power to the noise power. Higher PSNR values indicate better compression quality. The formula for PSNR is:

$$PSNR = 10 * log10\ [(MAX^2) / MSE] \qquad (3)$$

where MAX is the highest pixel value that the picture may contain. Decibels (dB) are often used to express PSNR. The choice of measure relies on the particular application and needs. Both MSE and PSNR have benefits and drawbacks. While MSE is simple and easy to compute, it may not always correspond well with perceptual quality. PSNR, on the other hand, is often used in video compression applications where preserving as much visual quality as possible is important. Overall, the U-Net and Moth Flame Optimization approach that has been described is a successful one for precisely identifying and segmenting brain tumor locations in MRI data. Deep learning-based segmentation combined with optimization methods like MFO may enhance segmentation performance and improve the detection and management of brain tumors.

5. Conclusion

If untreated, a brain tumour is an uncommon development of brain cells that may have serious effects. Brain tumor semantic segmentation is the process of identifying and separating the parts of the brain that are affected by the tumor, which is crucial for accurate diagnosis, treatment planning, and monitoring of the tumor's growth over time. In this study, a model for identifying and segmenting brain tumors using Unet architecture with hyper parameter tuning using the MFO algorithm was presented. The Unet architecture is commonly used for image segmentation tasks due to its ability to gather spatial information. The MFO algorithm is a nature-inspired optimization strategy that imitates the behavior of moths. The effectiveness of the model was increased by combining the two methods. The MFO approach increased the model's performance, which led to better segmentation outcomes. This approach showed promising results in identifying and segmenting brain tumors, which can be beneficial in the early detection and treatment of brain tumors. Overall, the study demonstrated that the combination of Unet architecture and the MFO algorithm can be an effective approach for brain tumor semantic segmentation.

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References

[1] Arabahmadi, M., Farahbakhsh, R., & Rezazadeh, J. (2022). Deep learning for smart Healthcare—A survey on brain tumor detection from medical imaging. Sensors, 22(5), 1960.

[2] Tao, A., Sapra, K., & Catanzaro, B. (2020). Hierarchical multi-scale attention for semantic segmentation. arXiv preprint arXiv:2005.10821.

[3] Arif, M., Ajesh, F., Shamsudheen, S., Geman, O., Izdrui, D., & Vicoveanu, D. (2022). [Retracted] Brain Tumor Detection and Classification by MRI Using Biologically Inspired Orthogonal Wavelet Transform and Deep Learning Techniques. Journal of Healthcare Engineering, 2022(1), 2693621.

[4] Sharma, A. K., Nandal, A., Dhaka, A., Koundal, D., Bogatinoska, D. C., & Alyami, H. (2022). [Retracted] Enhanced Watershed Segmentation Algorithm-Based Modified ResNet50 Model for Brain Tumor Detection. BioMed Research International, 2022(1), 7348344..

[5] Ravì, D., Bober, M., Farinella, G. M., Guarnera, M., & Battiato, S. (2016). Semantic segmentation of images exploiting DCT based features and random forest. Pattern Recognition, 52, 260-273.

[6] Chattopadhyay, A., & Maitra, M. (2022). MRI-based brain tumour image detection using CNN based deep learning method. Neuroscience informatics, 2(4), 100060.

[7] Wei, Y., Liang, X., Chen, Y., Shen, X., Cheng, M. M., Feng, J., ... & Yan, S. (2016). Stc: A simple to complex framework for weakly-supervised semantic segmentation. IEEE transactions on pattern analysis and machine intelligence, 39(11), 2314-2320.

[8] Soomro, T. A., Zheng, L., Afifi, A. J., Ali, A., Soomro, S., Yin, M., & Gao, J. (2022). Image segmentation for MR brain tumor detection using machine learning: a review. IEEE Reviews in Biomedical Engineering, 16, 70-90.

[9] Rezaei, M., Yang, H., & Meinel, C. (2020). Recurrent generative adversarial network for learning imbalanced medical image semantic segmentation. Multimedia Tools and Applications, 79(21), 15329-15348.

[10] Simpson, A. L., Antonelli, M., Bakas, S., Bilello, M., Farahani, K., Van Ginneken, B., ... & Cardoso, M. J. (2019). A large annotated medical image dataset for the development and evaluation of segmentation algorithms. arXiv preprint arXiv:1902.09063.

[11] Alalwan, N., Abozeid, A., ElHabshy, A. A., & Alzahrani, A. (2021). Efficient 3D deep learning model for medical image semantic segmentation. Alexandria Engineering Journal, 60(1), 1231-1239.

[12] G. Karayegen and M. F. Aksahin, "Brain tumor prediction on MR images with semantic segmentation by using deep learning network and 3D imaging of tumor region," Biomedical Signal Processing and Control, vol. 66, p. 102458, 2021. DOI: 10.1016/j.bspc.2021.102458.

[13] Hatamizadeh, A., Nath, V., Tang, Y., Yang, D., Roth, H. R., & Xu, D. (2021, September). Swin unetr: Swin transformers for semantic segmentation of brain tumors in mri images. In International MICCAI brainlesion workshop (pp. 272-284). Cham: Springer International Publishing.

[14] Myronenko, A., & Hatamizadeh, A. (2020). Robust semantic segmentation of brain tumor regions from 3D MRIs. In Brainlesion: Glioma, Multiple Sclerosis, Stroke and Traumatic Brain Injuries: 5th International Workshop, BrainLes 2019, Held in Conjunction with MICCAI 2019, Shenzhen, China, October 17, 2019, Revised Selected Papers, Part II 5 (pp. 82-89). Springer International Publishing.

[15] Maji, D., Sigedar, P., & Singh, M. (2022). Attention Res-UNet with Guided Decoder for semantic segmentation of brain tumors. Biomedical Signal Processing and Control, 71, 103077.

[16] Sun, J., Li, J., & Liu, L. (2021). Semantic segmentation of brain tumor with nested residual attention networks. Multimedia Tools and Applications, 80, 34203-34220.

[17] Zhu, Z., He, X., Qi, G., Li, Y., Cong, B., & Liu, Y. (2023). Brain tumor segmentation based on the fusion of deep semantics and edge information in multimodal MRI. Information Fusion, 91, 376-387.

[18] S. Shaukat, M. A. Khan, and A. Rehman, "A state-of-the-art technique to perform cloud-based semantic segmentation using deep learning 3D U-Net architecture," BMC Bioinformatics, vol. 23, no. 1, pp. 1-12, Jun. 2022, doi: 10.1186/s12859-022-04794-9.

[19] Rehman, M. U., Cho, S., Kim, J. H., & Chong, K. T. (2020). Bu-net: Brain tumor segmentation using modified u-net architecture. Electronics, 9(12), 2203.

[20] Vimala, S. Krishnan, V. Raj, M. Kumar, A. Janakiraman, M. "Object Detection Using Deep Learning," Journal of Journal of Cognitive Human-Computer Interaction, vol. 6, no. 1, pp. 32-38, 2023. DOI: https://doi.org/10.54216/JCHCI.060103

[21] Serizawa, T., & Fujita, H. (2020). Optimization of convolutional neural network using the linearly decreasing weight particle swarm optimization. arXiv preprint arXiv:2001.05670.

[22] Liu, P., Dou, Q., Wang, Q., & Heng, P. A. (2020). An encoder-decoder neural network with 3D squeeze-and-excitation and deep supervision for brain tumor segmentation. IEEE Access, 8, 34029-34037.

[23] Zatarain Cabada, R., Rodriguez Rangel, H., Barron Estrada, M. L., & Cardenas Lopez, H. M. (2020). Hyperparameter optimization in CNN for learning-centered emotion recognition for intelligent tutoring systems. Soft Computing, 24(10), 7593-7602.

[24] Pei, L., Bakas, S., Vossough, A., Reza, S. M., Davatzikos, C., & Iftekharuddin, K. M. (2020). Longitudinal brain tumor segmentation prediction in MRI using feature and label fusion. Biomedical signal processing and control, 55, 101648.

[25] Aghalari, M., Aghagolzadeh, A., & Ezoji, M. (2021). Brain tumor image segmentation via asymmetric/symmetric UNet based on two-pathway-residual blocks. Biomedical signal processing and control, 69, 102841.